Developing an Activity-Based Model for City-Scale Cross-Sectoral Energy and Carbon Emissions Management

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April 2025

This thesis is submitted for the degree of Doctor of Philosophy

Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the preface and specified in the text. It is not substantially the same as any work that has already been submitted, or is being concurrently submitted, for any degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee.

Abstract

Emerging working patterns (such as home-based and flexible working) are becoming increasingly prevalent worldwide, reshaping how urban residents allocate their time and interact with the built environment. These structural shifts are changing the spatial and temporal distribution of energy demand in cities, posing new challenges and opportunities for sustainable urban energy management.

In response to the global climate emergency and the transformative effects of emerging working patterns, this thesis introduces a novel activity-based urban energy modelling framework that integrates the building and transport sectors. Acknowledging the limitations of conventional models that treat these sectors in isolation, the study develops a unified approach grounded in utility-maximisation theory, capturing the spatiotemporal dynamics of residents' activity chains. The framework comprises three sub-models: activity generation, spatial-temporal distribution, and energy demand simulation. Each subject to explicit time and budget constraints. This enables estimations of end-use energy demand across different locations and sectors, particularly in light of the behavioural shifts associated with flexible and remote working.

Empirical applications in Shanghai and Manchester reveal regional disparities in the adoption of flexible working patterns and their energy implications. In Manchester, home-based working reduces both travel and building energy demand, while in Shanghai, it results in increased residential energy use and transport activity. These findings highlight the complex interdependencies between urban form, human behaviour, and energy systems. The model also reveals how changes in activity chains redistribute energy loads across building types and times of day, with important implications for peak demand management.

This study develops a novel framework that captures new working influences in urban energy. By bridging behavioural dynamics with inter-sectoral energy modelling, this research provides a robust tool for policymakers to assess the systemic impacts of lifestyle shifts. The study offers actionable insights for designing integrated, context-sensitive strategies to support net-zero transitions in diverse urban environments.

Acknowledgements

I would like to express my deepest gratitude to my supervisor, Prof. Li Wan, for his unwavering guidance, support, and encouragement throughout my doctoral journey. His expertise and insightful feedback have been invaluable in shaping my research and improving my academic development.

I am very grateful for the valuable support provided by my degree committee members for their constructive critiques, valuable suggestions, and continued support throughout my thesis work.

I am also greatly indebted to my college advisor Dr Aylwyn Scally, my friends in Darwin College and fellow students in the Spatial Planning, Policy Studies, Urban Modelling, Digital Cities research group as well as Cambridge Centre for Smart Infrastructure and Construction, whose camaraderie and shared experiences have made this process both inspiring and enjoyable. Our discussions, collaborations, and moments of encouragement have been an unforgettable part of my progress and have enriched my academic experience.

In addition, I am profoundly thankful to my family members for their unconditional love and support, which has been a constant source of strength and motivation. Their belief in me has carried me through the challenges of this journey, and I owe them more than words can convey.

Finally, I am sincerely grateful for the financial support provided through my scholarships, as well as all the funding bodies of the grants, awards, and bursaries that I obtained, without which my work would not have been possible. These supports have enabled me to dedicate myself fully to my research and have been a cornerstone of my academic pursuits.

To all who have helped me along this path, thank you from the bottom of my heart.

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List of Abbreviations

ABA	Activity-based Approach
ABM	Agent-Based Modelling
AD	Activity Distribution
AERO	Activity Extraction with Rational Observation
AG	Activity Generation
AHTUS	American Heritage Time Use Study
AIC	Akaike Information Criterion
ALBETROSS	A Learning-Based Transportation Oriented Simulation System
ANOVA	An Analysis of Variance
AP	Activity Pattern
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
ATUS	American Time Use Survey
BEEM	BEirut Energy Model
BEMs	Building Energy Models
BIC	Bayesian Information Criterion
BNN	Bayesian Neural Networks
BSRED	Business Survey of Residential Electricity Distribution
BTED	Building and Transport Energy Demand
CARLA	Combinatorial Algorithm for Rescheduling Lists and Activities
CGE	Computable General Equilibrium
CIBSE	Chartered Institution of Building Services Engineers
CNNs	Convolutional Neural Networks
COAM	Community Occupant Agent Model

CRECS	Chinese Residential Energy Consumption Survey
DaySIM	Day Activity Schedule Simulator
DHW	Domestic Hot Water
DOE	Department of Energy
DRL	Deep Reinforcement Learning
EIA	Energy Information Administration
FEATHERS	Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS
FSM	Four-step Method
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GNNs	Graph Neural Networks
HECS	Household Energy Consumption Survey
HES	Household Electricity Survey
HETUS	Harmonised European Time Use Surveys
HMMs	Hidden Markov Models
HVAC	Heating, Ventilation, and Air Conditioning
ILM	Intrusive Load Monitoring
ILUTE	Integrated Land Use, Transportation, and Environment
ITLUP	Integrated Transportation and Land Use Package
LBS	Location-based Service
LSTM	Long Short-Term Memory
LUTI	Land Use and Transport Interaction
LILT	Leeds Integrated Land-Use/Transport
MASTIC	Model of Action Spaces in Time Intervals and Clusters

MATSim	Multi-Agent Transport Simulation
MDCEV	Multiple Discrete-Continuous Extreme Value
MDCP	Multiple Discrete-continuous Probit
MLPs	Multilayer Perceptions
MNL	Multinomial Logit
MTUS	Multinational Time Use Study
M-FRNN	Markov-feedback Recurrent Neural Network
NESO	National Energy System Operator
NL	Nested Logit
NILM	Non-intrusive Load Monitoring
OB	Occupant Behaviour
ONS	Office for National Statistics
PEBs	Pro-environmental Behaviours
RD	Recursive Dynamic
RECS	Residential Energy Consumption Survey
RFID	Radio Frequency Identification
RNNs	Recurrent Neural Networks
RSE	Recursive Spatial Equilibrium
RUT	Random Utility Theory
SEM	Structural Equation Models
SMARTS	Shanghai Metropolitan Area Residents Time-use Survey
STARCHILD	Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions
SUR	Seemly Unrelated Regression
TABULA	Typology Approach for Building Stock Energy Assessment

TASHA	Travel Activity Scheduler for Household Agents
TAZ	Traffic Analysis Zone
TMB	Time and Monetary Budget
TME	Travel Monetary Expenditure
TMY	Typical Meteorological Year
TS	Temporal-sequential
TTB	Travel Time Budget
TUS	Time Use Survey
UBEM	Urban Building Energy Modelling
UMI	Urban Modelling Interface
UKTUS	United Kingdom Time Use Survey

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Chapter 1 Introduction

1.1 Motivation

Cities accommodate around 55% of the global population (4.2 billion), generating more than 80% of global GDP (The World Bank, 2020), but also contributing about 64% of global energy consumption and 70% of greenhouse gas (GHG) emissions (International Energy Agency, 2020). In light of the planetary '*climate and environmental emergency*' declared by the European Parliament (European Parliament, 2019), it is essential for cities to take concrete and timely inter-sectoral actions to meet global energy and climate targets (International Energy Agency, 2021). The significance of urban energy management is further highlighted by global urbanisation trends, particularly in rapidly urbanising nations where large-scale rural-to-urban migration and income growth continue to drive increasing demands for space, resources, and mobility. Effective management of urban energy consumption and GHG emissions is thus crucial in determining global sustainability outcomes.

Cities are complex systems characterised by interdependencies across multiple sectors (Batty, 2010). Changes in the demographic structure and activity patterns of urban population are significantly influencing urban energy consumption and GHG emissions. Güneralp et al. (2017) with the building and transport sectors being leading emitters (Steemers, 2003). The interaction between land use and transport suggests that the building sector accommodates spatial demands from consumers and producers, while the transport sector provides access to activity destinations and in turn, determines the accessibility and hence attractiveness of locations. The interactions between population and the building and transport sectors fundamentally shape the temporal and spatial distribution of urban energy demand.

There has been extensive research on energy and carbon modelling for the building and transport sectors. However, several analytical gaps remain in literature. First, existing city-level energy model applications tend to consider buildings and transport as two separate and independent systems (Hong et al., 2020), thus unable to capture the inherent interdependences between the demand for floorspace and travel. Second, mainstream building energy models focus primarily on physical attributes of buildings such as the geometry and typological factors (e.g. high-rise vs low-rise) but tend to assume exogenous occupants' activity demand in buildings and overlook the influence of other activities beyond those occurring in the buildings of interest (e.g. the rise of homeworking hours as a result of flexible working). These behavioural factors, however, are key determinants of building energy intensity (Happle et al., 2018). Third, the COVID-19 pandemic has been transforming people's lifestyles globally, as a significant share of the workforce in cities has shifted to flexible/remote working. As a result, remarkable short-term energy demand fluctuation is observed during the pandemic (Jiang et al., 2021). However, understanding and managing the long-term impacts of changing working patterns on city-scale energy demand remains a critical task for urban energy research and practice.

This study builds on the activity-based approach in transport modelling and expands it as a unified framework integrating energy consumption in the building and transport sectors. The proposed theoretical model includes three sub-models: (1) activity generation, modelling aggregate activity choices of representative population groups; (2) activity distribution, distributing the generated aggregate activity demand in terms of location and frequency; (3) urban energy demand simulation, estimating building energy demand according to the activity demand and the transport energy demand as derived demand. All choices in the sub-models are subject to explicit time and budget constraints.

By bridging the building and transport sectors, the proposed model can simulate nuanced (activity-specific) end-use energy demand in buildings across locations and the associated energy demand for traveling between these locations, such that the inter-sectoral energy impact of flexible/remote working can be captured (e.g. people can engage in paid work from multiple locations and building types). This framework advances beyond previous efforts to integrate building and transport models by explicitly incorporating human activity factors underpinned by utility-maximisation theory. While conventional urban metabolism approaches often focus on aggregate mass and energy flows, our model accounts for individual-level decision-making processes through its activity-based approach. The proposed framework not only captures the spatial and temporal nuances of urban life but also robustly links activity choices with corresponding energy outcomes. In addition, our model simplifies the representation of complex systems by utilising representative population groups subject to explicit time and budget constraints. This provides a tractable and comprehensive method for investigating the interdependencies between building and transport energy demands, offering enhanced explanatory power and policy relevance.

The policy use of the model is demonstrated through model applications developed for (1) an urban neighbourhood in Shanghai, China, and (2) the city of Manchester, United Kingdom. After model calibration using empirical data, the calibrated baseline model will be used to estimate new activity demand based on assumptions on the adoption level of emerging working patterns. Using the simulated activity demand, energy demand and the associated emissions are estimated across residential, office, and passenger transport sectors. Policy implications will be drawn, which are expected to shed new light on a joined-up approach for achieving net zero for similar city-regions worldwide.

1.2 Research Objectives and Related Questions

This research aims to develop an activity-based modelling framework for cross-sectoral urban energy demand and carbon emissions simulation. Three research objectives and their associated research questions are proposed:

Objective 1: Identify key activity variables of residents affecting urban energy demand and understand their interdependencies

Based on this research objective, four related research questions are put forward:

(1-1) What resident activity variables influence urban building energy demand?

(1-2) How do these variables interact with one another as per existing energy modelling frameworks for buildings?

(1-3) What data can energy models utilise for model calibration and validation purposes?

Investigating the first two questions enables the research to identify key modelling variables and their interactions, revealing both the direct and indirect effects of residents' activity choices and associated travel choices on urban energy use. By identifying available data sources, a feasible model calibration and validation strategy could be developed.

Objective 2: Apply the activity-based approach to bridge the building and transport sectors for energy demand and emissions simulation

The second objective of this research is to establish a unified activity-based urban energy modelling framework that integrates the building and transport sectors. Based on this research objective, two related research questions are put forward:

(2-1) How an activity-based approach can capture the interdependencies between energy demand in building and transport systems?

(2-2) How to identify generic working patterns in terms of the time allocation across multiple locations and activity types?

Investigating the first research question entails a review of existing activity-based modelling frameworks and activity categorisations for standardised energy demand simulation, which informs the design of an integrated activity-based framework for urban energy modelling across sectors. The second question focuses on the identification of generic working patterns using time-use survey data.

Objective 3: Test the cross-sectoral energy implications of emerging working patterns using the new modelling framework

The proliferation of new working patterns, such as homeworking and flexible working, has generated significant impacts on time allocation of urban population. Based on the proposed activity-based energy modelling framework, the last objective is to test the energy implications of emerging working patterns across the building and transport sectors. The following questions are proposed:

(3-1) How do varying levels of flexible/remote working adoption influence activity, location and travel demand across the residential, office and transport sectors?

(3-2) How the above demand changes influence energy consumption and emissions?

(3-3) How flexible/remote working can be leveraged to reduce urban energy demand and carbon emissions?

Through scenario analysis, the first two questions quantify the impact of emerging working patterns on urban energy demand across the building and transport sectors. The third question focuses on policy implications.

1.3 Structure of The Thesis

The thesis is structured as follows:

Chapter 2: Review of existing Urban Building Energy Modelling (UBEM) frameworks

Addressing the first research objective, this chapter presents a systematic literature review of existing UBEM frameworks and key activity variables that influence the building energy demand. The review spans from 2004 to 2023, focusing on existing building energy models at urban and community scales. The review begins by analysing trends in the treatment of occupant-related variables in urban energy modelling over the past two decades, followed by a summary of key findings. Then, the chapter reviews how interrelationships of activity variables have been captured by existing models. Also, the review synthesises modelling methods and data sources from existing literature. The chapter concludes by summarising research gaps in existing approaches.

Chapter 3: Review of existing activity-based modelling frameworks for transport

Chapter 3 conducts a comprehensive literature review of activity-based modelling. The chapter begins by examining the theoretical foundations of activity-based models, including the evolution of time geography, the role of constraints and regularities in activity demand generation, as well as the link to transport energy demand/carbon emissions models. It then reviews the development of activity-based approaches and synthesises key representative activity-based models from transport research. Building upon the theoretical foundations, the chapter also extends the existing activity-based transport modelling framework and proposes an activity-based urban energy modelling framework that combines the building and transport sectors.

Chapter 4: Modelling Energy Effects of New Working Patterns: A Case Study of Shanghai, China

This chapter presents an empirical application of the new modelling framework through a case study of an urban neighbourhood in Shanghai, China. We employ time-use data collected from employed residents in Shanghai to identify typical post-COVID-19 working patterns through cluster analysis. The chapter develops a nested utility-maximisation model to simulate time-use characteristics across different working patterns, and discusses the model validation and calibration processes. Scenario analysis is conducted to identify energy demand variations in offices and residential buildings under different activity patterns.

Chapter 5: Activity-Based Urban Building and Transport Energy Modelling: A Case Study of Manchester, United Kingdom

Chapter 5 presents the second empirical case study applying the proposed theoretical framework at an urban scale in Manchester, UK. The chapter employs UK time-use survey data to identify working patterns across temporal and spatial dimensions. We develop an MDCEV model to simulate time-use patterns across different working patterns, validated and calibrated using public data. This chapter demonstrates the integration of activity-based models with existing UBEMs, where simulated time-use patterns serve as inputs for a bottom-up UBEM, constructed using local building data. The chapter examines energy transitions across residential, office, and transport sectors under various working patterns, and concludes with policy implications based on energy demand changes across the three sectors.

Chapter 6: Conclusion and Limitations

The final chapter summarises key findings, discusses research limitations, and proposes directions for future research.

Chapter 2 Review of existing UBEM frameworks

2.1 Background

UBEMs are increasingly being used in supporting sustainable development in cities (Ali et al., 2021; Sola et al., 2020). UBEMs can predict building energy demand and carbon emissions based on a building's physical attributes and assumptions on occupants' behaviour related to the building. UBEMs can help urban planners understand the impacts of different urban forms, building types, building density, and other factors on urban energy consumption, and inform energy-efficient urban development. For example, researchers employed the Urban Modelling Interface (UMI)-based supporting tool to design an energy-resilient neighbourhood in Dublin, Ireland (Buckley et al., 2021). In addition, UBEMs also show potential to contribute to intelligent urban power grid operation and management (Sola et al., 2020). For example, Barbour et al. (2019) developed a citywide UBEM in Boston and tested district-level photovoltaics-included gird management solutions.

In the post-COVID era, prevalent flexible working and remote working are reshaping the activity patterns of urban dwellers (de Haas et al., 2020; Liu et al., 2020), which may also accelerate ongoing structural changes in energy demand at the building and city levels (Ang et al., 2022). To cope with these complex activity trends and dynamic behaviour patterns, the research community promotes activity-based UBEM, also known as occupant-centric UBEM (Dabirian et al., 2022; Salim et al., 2020). These models focus on capturing the impact of changes in building occupancy, occupants' activity patterns, and energy-using behaviour.

2.1.1 Building Occupants and Energy Demand

Occupants' activity and behaviour pattens usually play important roles in building energy demands (Delzendeh et al., 2017). At the city and regional level, overlooking occupant-related factors can lead to significant estimation errors.

Occupant-related uncertainty has been recognised as a significant contributor to systematic discrepancy between simulated and observed urban building energy demand

(Dabirian et al., 2022). There are four primary reasons for this discrepancy: First, the spatial and temporal shifts in occupant activity pattens can cause corresponding changes in building energy demand; and certain occupant behaviours can have disproportionate effects on building energy consumption (Zhang et al., 2018). Second, at the urban scale, the occupant activity and behaviour patterns are usually heterogeneous and influenced by numerous external factors (e.g., interpersonal, environmental, and psychological factors) (Heydarian et al., 2020; Wang et al., 2023; Zhang et al., 2018). A narrow, sectoral focus on buildings can hardly capture such behavioural complexity. Third, the circular causality between the built environment and individual activity and building use patterns suggests that observed behaviour patterns can be both the cause and effect of building energy demand. Last, obtaining accurate occupants' behavioural data can be challenging due to privacy concerns and technical limitations.

Advancements in modelling techniques and data acquisition make it possible to simulate the interactions between occupants and buildings, especially how occupants' building usage pattens affect building energy demand. For instance, Virote and Neves-Silva (2012) developed a stochastic model of building occupancy patterns, while D'Oca and Hong (2014) utilised data mining methods to determine office window opening behaviour. However, in the post-COVID-19 era, new technologies and cultural shifts are driving unprecedented changes in residents' activity patterns, with complex implications for urban energy demand. Emerging lifestyles, such as remote working and online entertainment/shopping, further challenge the perceived interdependence between locations and activities, which represents a new change for UBEM.

2.1.2 Urban Building Energy Models

Beyond building-level energy simulations, Richardson et al. (2008, 2010) used time use data to establish a city-level residential building occupancy model, and Barbour et al. (2019) used mobile phone location data to build a district-scale model. Compared to Building Energy Models (BEMs), UBEM aims to assess building energy demands at urban and regional scales.

UBEMs can be broadly categorised into top-down and bottom-up models. Top-down models utilise aggregated data to analyse the correlation between energy consumption and socioeconomic indicators (e.g., regional economic development and household income) and environmental factors (e.g., temperature and humidity). The advantage of this approach lies in its simplicity, ease of data accessibility, leading to widespread application in urban energy management (e.g. Güneralp et al., 2017). However, the high level of abstraction and the lack of realistic representation of building-level physical and behavioural attributes remains a major analytical disadvantage.

In contrast to top-down models, bottom-up models focus on the micro level, first estimating individual building energy demands and then reflecting the aggregate demand pattern (Abbasabadi and Ashayeri, 2019; Ferrando et al., 2020). Two widely employed bottom-up strategies are statistical (data-driven) and engineering (physics-based) methods (Johari et al., 2020; Kavgic et al., 2010; Li et al., 2017). Data-driven models tend to estimate end-use energy demands of segmented population based on socioeconomic indicators, often using statistical methods such as regression and machine learning (Ferrando et al., 2022). The engineering approach computes energy demands primarily based on physical characteristics of the building stock (Shimoda et al., 2004), with a close interface with the building design and construction sectors.

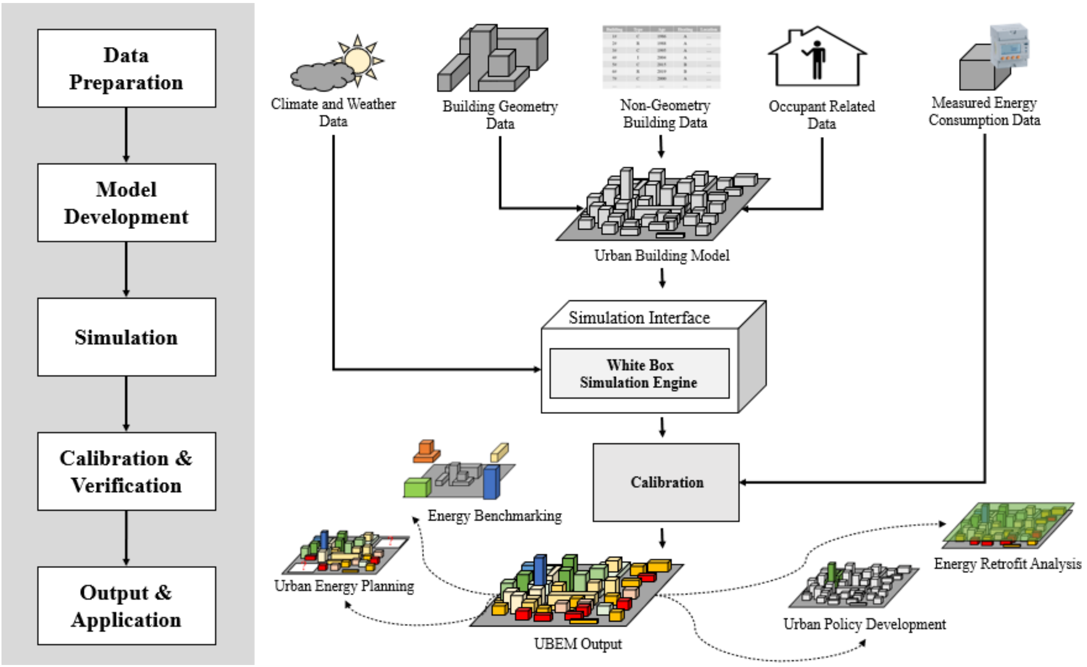


Figure 2.1 A typical workflow and data input of bottom-up UBEM

(Source: created by the researcher)

Figure 2.1 A typical workflow and data input of bottom-up UBEM illustrates a typical bottom-up UBEM workflow comprising five stages: (1) data preparation, (2) model development, (3) energy simulation, (4) calibration and verification, and (5) outputs. Primary UBEM data inputs include urban building geometry, non-geometric characteristics (e.g., age and materials), occupant-related data (e.g., occupancy schedules), climate/weather, and potentially measured energy use. The UBEM tools (e.g. *EnergyPlus*) usually establish a 3D model reflecting the physical features of buildings in the study area, and then combine it with local climate data to estimate stock energy demand. Finally, measured consumption data can be used to validate UBEM predictions.

In addition, some studies have developed hybrid models that combine statistical and engineering approaches. For instance, El Kontar and Rakha (2018) adopted clustering analysis and regression models to characterise occupant behaviour groups, and combine the occupant behaviour profile with UMI (Reinhart et al., 2013). The hybrid approaches compensate for the crude assumptions about occupants' behaviour and boundary conditions in typical engineering models. Simultaneously, it leverages the ability of engineering models to represent intricate energy-related building characteristics and systems. By accounting for both occupant-related factors and building physics, hybrid models can provide improved estimations of building energy consumption.

UBEM has undergone significant and unprecedented development over the past two decades, where several widely-used UBEM tools including UMI (Reinhart et al., 2013), CitySIM (Robinson et al., 2009), CityBES (Hong et al., 2016), SUNtool (Robinson et al., 2007), and TEASER (Remmen et al., 2018) have been sequentially developed. Among existing literature, how to better capture occupants' activity and behavoural patterns remains a key research focus. The following challenges have been identified in UBEM literature: (1) limited quality and accessibility of city-scale data; (2) boundary conditions which tend to overlook complex interactions between buildings of interest and their surrounding environment, and (3) complex occupant behaviours and activity patterns (Ali et al., 2021a; Ang et al., 2020; Ferrando et al., 2020; Johari et al., 2020).

The next sub-section will present a systematic review of UBEM literature.

2.2 Review Method

Figure 2.2 illustrates the workflow of the systematic review. The data source is from Web pf Science (WOS) system. A total of 4,381 studies are included in the initial search, 133 of which are selected for the final-stage review.

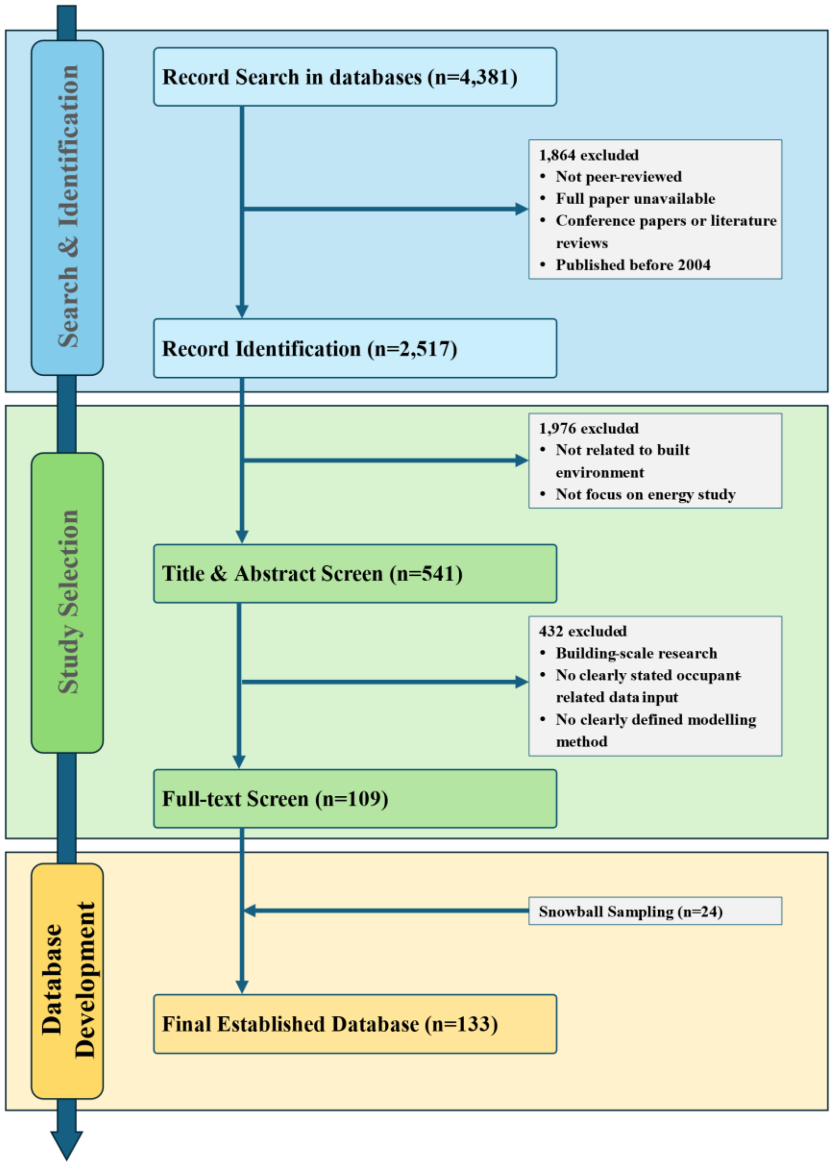


Figure 2.2 Database Development Process

(Source: created by the researcher)

The collection and processing of data is divided into the following steps. Firstly, the study conducted search by searching documents on Scopus by using the words TITLE-ABS-KEY(("region" OR "urban" OR "city" OR "district" OR "zone*" OR "community" OR "block" OR "neighbourhood") AND ("building" OR "residential" OR "housing" OR "non-residential" OR "commercial" OR "office" OR "school" OR "campus" OR "mall" OR "hotel" OR "industrial") AND ("energy" OR "electricity" OR "heating" OR "cooling" OR "lighting" OR "load") AND ("occupant" OR "user" OR "activity" OR "appliance use" OR "device use" OR "schedule" OR "occupancy" OR "presence" OR "time use" OR "behaviour" OR "action") AND ("model*" OR "simulation*")). This step obtained 4,381 documents.

Secondly, record identification was conducted. To ensure consistency and eliminate language barriers, only English-written literature was considered for inclusion in the analysis. Consequently, studies published in other languages were not included in the database. At this stage, the study selected documents following the criteria: (1) only peer-reviewed studies were considered, (2) full papers were available, (3) only technical papers and original articles were covered (conference papers and literature reviews were excluded), (4) publication time was between 2004 and 2023. The latest search was performed in December 2023. The search process resulted in a total of 2,517 outcomes.

Then, the selected documents from the previous step were screened. The study first focused on the title and abstract of the selected outcomes. At this stage, 1,976 documents were excluded because (1) the topics were not related to buildings or the built environment, or (2) the topics were not related to energy. The title and abstract screening kept 541 documents in the database for a full-text screen. In the full-text screening process, the study excluded documents that (1) had a study area containing less than two buildings (unless a multi-use building complex), (2) did not consider occupant-related data input, (3) the model aim was not to estimate building energy demand or to capture occupant-related variables for energy demand modelling, or (4) had no clearly defined modelling method. This process selected 109 studies for the database. Additionally, the study added 24 studies to the database through a snowball screening, making the final database size 133 documents.

2.3 Overview of selected literature

Figure 2.3 displays the publication timeline and geographical distribution of the selected publications' case studies. The figure visually illustrates the rapid development momentum of occupant-centric UBEM research: before 2015, such studies were generally published less than 5 times per year, while after 2015, a significant increase was observed. In 2023, 23 UBEM studies addressed the energy impacts of occupant activities and behaviours. Among all studies, cases from China (27) and the United States (18) received the most attention, followed by those from the United Kingdom (8) and Japan (8). Notably, most research cases were concentrated in developed countries in Europe, the United States, and East Asia: in addition to the United States and the United Kingdom, cases from Canada (7), Australia (5), Italy (5), Belgium (4), Switzerland (4), France (3), Spain (3), Hong Kong (2), and South Korea (2) were also observed. This may be attributed to the abundant research funding and effective, open, and high-quality data sources in these regions. Encouragingly, an increasing number of cases from developing countries emerged after 2015: in addition to mainland China, countries such as India (2), Brazil (1), Egypt (1), Lebanon (1), Malaysia (1), and Nigeria (1) were also represented. Although energy management in developing countries is gaining attention, the current development is imbalanced: the research community still needs more data and cases from Africa, Latin America, Central Asia, and South Asia.

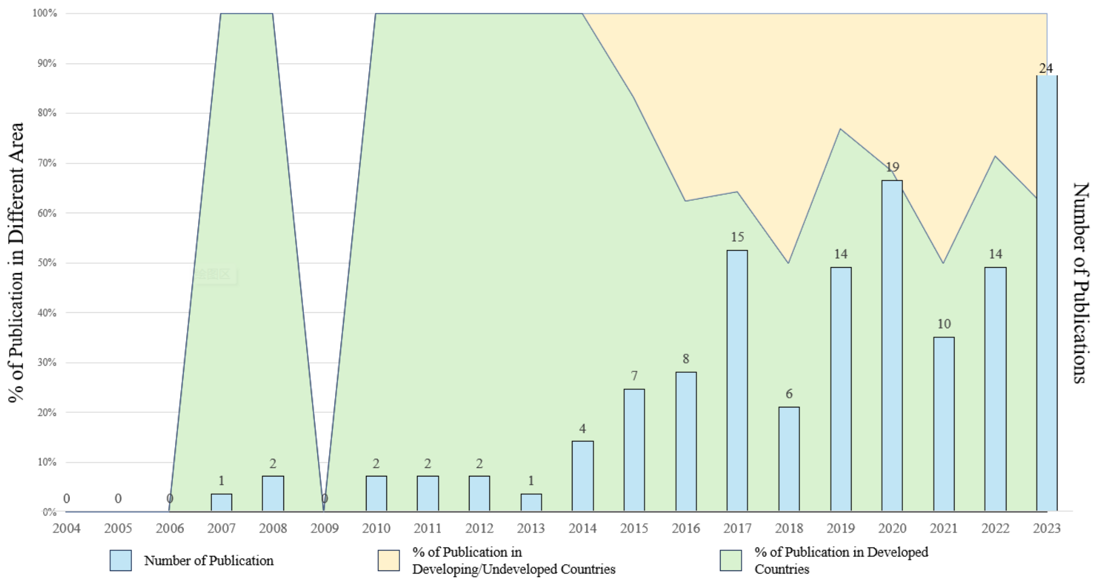


Figure 2.3 Number of selected publications per year by developed/developing country

(Source: created by the researcher)

It can be observed that prior to 2015, most research was concentrated in journals focused on building engineering and building science, such as *Energy and Buildings*, *Building and Environment*, and *the Journal of Building Performance Simulation*. In subsequent years, studies published in these journals, as well as in emerging building science journals like *Journal of Building Engineering*, *Buildings*, and *Building Simulation*, continued to dominate. However, it is noteworthy that the number of articles published in journals related to sustainability, energy, urban planning, and interdisciplinary fields has also increased. These journals include *Applied Energy*, *Sustainable Energy Technologies and Assessments*, *Environment & Planning B: Urban Analytics and City Science*, *Computational Urban Science*, and *Sustainable Cities and Society*. This data corroborates the trend of occupant-centric UBEM integrating with more urban systems and developing more interdisciplinary and diverse applications.

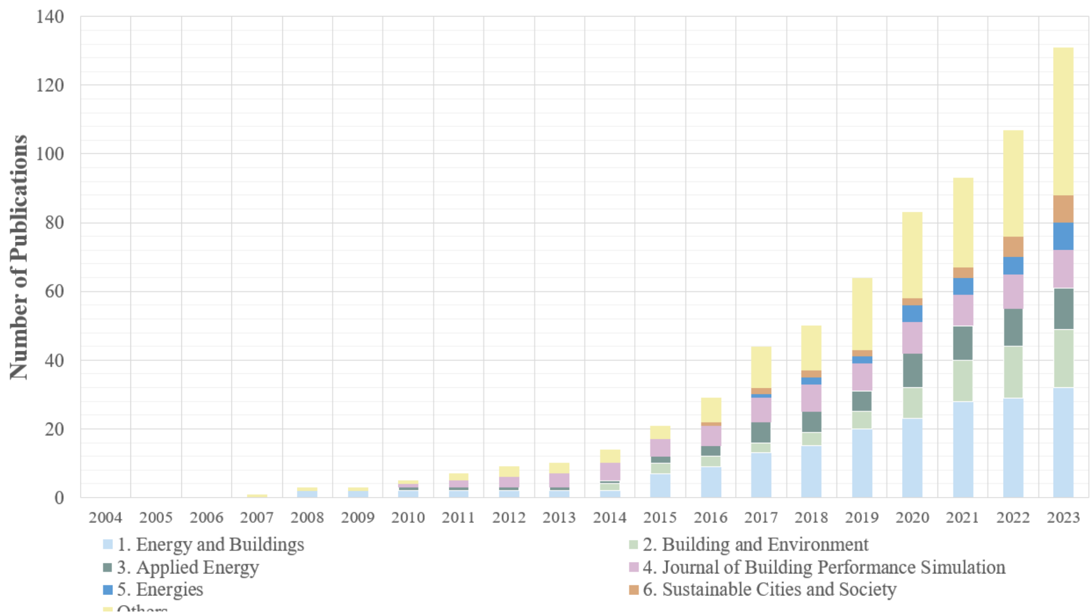


Figure 2.4 Cumulative Number of Selected Publications by Journal Over Time

(Source: created by the researcher)

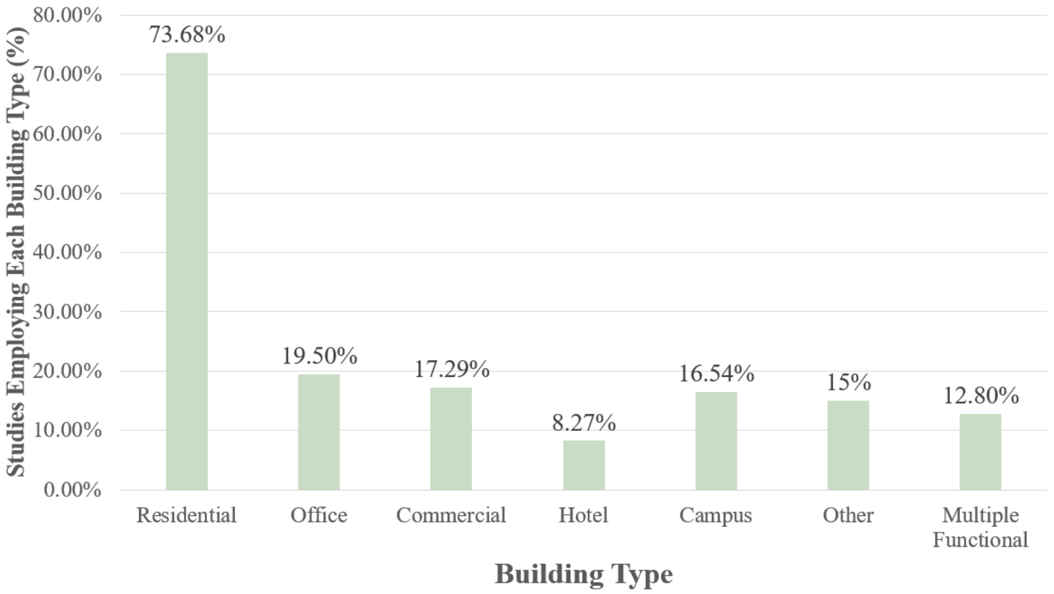


Figure 2.5 Proportion of Studies Using Each Building Type as Case Studies

(Source: created by the researcher)

Figure 2.5 displays the distribution of building types employed as case studies in the selected research. Over 70% of the 133 studies adopted residential buildings as the focus of their UBEM investigations. Additionally, approximately less than 20% of the studies in our database used office buildings, commercial buildings (such as shopping malls), and campus buildings, respectively. A small number of studies also concentrated on functional buildings like hotels, hospitals, transport hubs (e.g., stations and airports), and libraries. Approximately 12.5% of these 133 studies focused on multiple buildings with diverse functions within a district, some of which also considered occupant mobility between buildings.

Thematic review findings are presented in the following sections, starting from occupant-related variables in UBEM (Section 2.4), Data (Section 2.4), Occupant-related modelling methods (Section 2.5) and Future research directions (Section 2.6). A chapter summary (Section 2.7) is also provided at the end.

2.4 Review Findings: Occupant-Related Variables in UBEM

One of the main challenges in occupant-centric UBEM development is obtaining and processing the large number of variables related to the occupants. This section aims to summarise the critical occupant-related variables in UBEM studies and analyse their interactions.

As shown in Figure 2.6, based on the review results, this study categorises these variables into three groups: occupancy, activity pattern (AP), and occupant behaviour (OB). Occupancy mainly deals with the presence of occupants, including presence of occupants, occupant density (and number of occupants), and occupant status. AP describes the features of how the occupants allocate their time to different activities, mainly including activity type, activity location, activity time and duration, and activity sequence. OB is specific actions of the occupants that may affect the energy demand during the activities. OB includes direct energy-using/-saving behaviours, such as setting air-conditioning temperature, and indirect energy-using/-saving behaviours, such as opening windows and using shading systems.

In the database for this research, 116 (87.22%) of the 133 studies considered the impact of occupancy on the energy demand of buildings in the area. However, only 61 (45.86%) of 133 focused on the specific influence of OB, with only 9 (6.7%) studies considering the role of indirect energy-related behaviours. Furthermore, UBEM studies have not widely addressed the crucial role of AP in zonal or regional energy demand. Figure 2.7 illustrates the percentage of UBEM studies incorporating occupant-related variables.

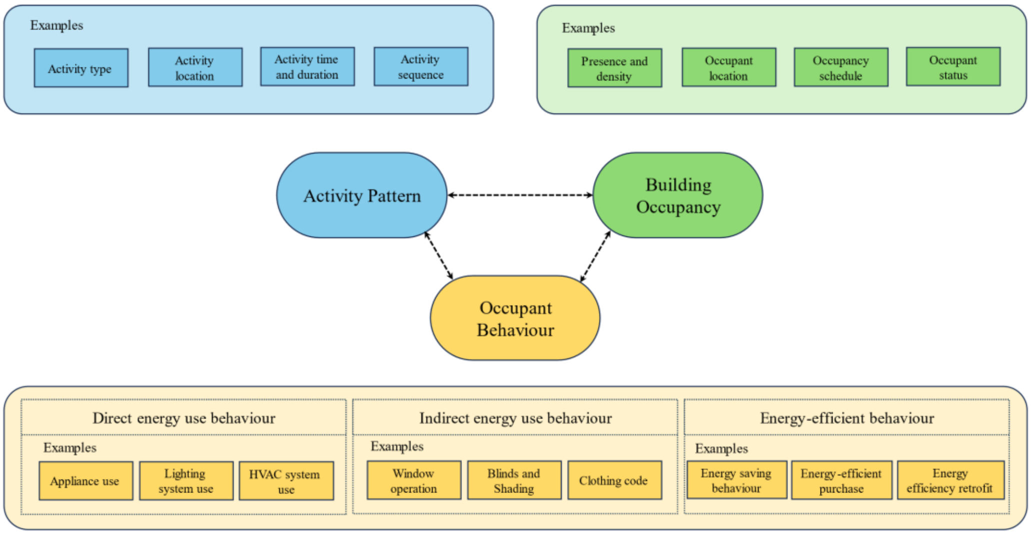


Figure 2.6 The category of occupant-related variables

(Source: created by the researcher)

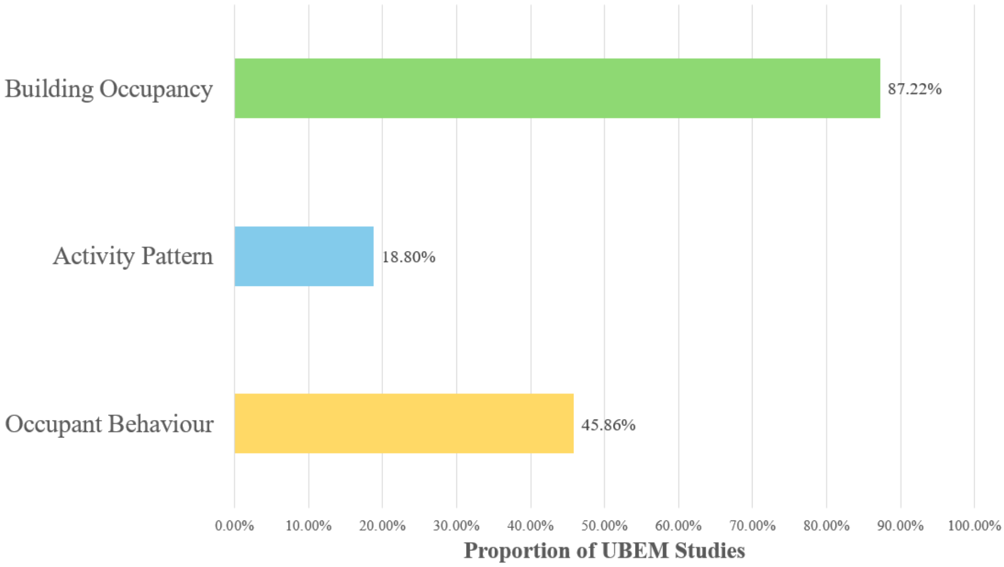


Figure 2.7 Proportion of UBEM Studies Incorporating Occupant-Related Variables

(Source: created by the researcher)

2.4.1 Occupancy

The occupant presence schedule is a pivotal factor extensively incorporated in UBEM studies (El Kontar and Rakha, 2018; Flett and Kelly, 2021; Happle et al., 2020). Numerous building standards and codes provide detailed occupancy schedules. For example, ASHRAE Standard 90.1 includes occupancy schedules for different building types, including residential, commercial, hotel, shopping mall etc. Additionally, the End-Use Load Profiles provided by the U.S. Department of Energy (DOE), the UK Chartered Institution of Building Services Engineers (CIBSE) Guide, and the Association of German Engineers in Germany also offer occupancy data.

Occupant presence exerts a direct and substantial influence on building energy demands, not only through additional heat generation but also by necessitating the operation of building systems to maintain indoor environmental comfort and the potential utilisation of appliances to facilitate anticipated activities (Happle et al., 2020). Furthermore, the zonal/regional building occupancy state reflects the spatial distribution of resident activities. For instance, as commuters depart their residences for workplaces in the morning, the occupancy in residential buildings declines, while the occupant density in office buildings rapidly increases.

The occupant amount/density are crucial factors to consider in UBEMs. Nejadshamsi et al. (2023) categorised this factor into two types: (1) real-count profiles, and (2) normalised profiles. The former refers to the actual number of occupants during each time interval. The latter is a normalised format of the actual count occupancy based on the maximum occupancy and capacity of each building for a specific time interval, which is also used in ASHRAE and DOE data. Many UBEM studies focusing on the residential sector adopt real-count profiles to reflect the impact of occupancy. This is because the number of occupants in residential units is usually small, and behaviour of an occupant can significantly affect energy demand. However, UBEMs considering office, commercial, and public buildings tend to adopt the latter approach due to their larger capacities and more complex space utilisation patterns, making them less sensitive to individual occupant behaviour changes. Thus, several cases opt for the second approach (Hou et al., 2020), including complex models encompassing multiple building types. For instance, Barbour et al. (2019) estimated the normalised occupancy profile of 1,330 buildings using mobile phone data. However, employing occupancy counts facilitates generating activity chains and capturing individual movements across multiple spaces or buildings within a region. Mosteiro-Romero et al. (2023) employed actual occupancy counts on campus to generate occupant AP profiles.

Another key factor is the occupant status (e.g., sleeping or active), can be seen as a simplified AP (Richardson et al., 2008, 2010). For example, Richardson et al. (2008) have distinguished between sleeping and awake occupants and defined the time when awake occupants are present in the building as active occupancy time. The variation in active occupancy times strongly correlates with appliance usage. In the UBEM practice, Aerts et al. (2014) classified residential occupants into three states: at home and awake, sleeping, and absent, while Mckenna et al. (2015) developed four states: not at home and inactive, not at home and active, at home and inactive, at home and active.

2.4.2 Activity Pattern

AP denotes the spatiotemporal distribution of individuals' activities within a given timeframe. The diverse APs of occupants exhibit varying energy intensities, leading to heterogeneous building energy consumption patterns (Ang et al. 2022; Delzendeh et al. 2017). Also, shifts in AP can potentially transform the spatiotemporal characteristics of energy demand (Barbour et al. 2019). Post-COVID-19, APs are transforming with remote work, e-commerce, and metaverse ubiquity (de Haas et al. 2020; Nikiforiadis et al. 2022). These dynamic trends underscore the pivotal role of AP in shaping urban building energy demand.

The widely considered AP dimensions encompass (1) activity type choice, (2) time and duration choices, and (3) location choices. The occupants' activity types interlink with their OBs, therefore influencing the energy intensity (Stankovic et al. 2016; Subbiah et al. 2013). Disparate activities necessitate varying energy types and intensities. High-intensity activities like cooking require substantial energy for devices like water heaters and stoves, contrasting lower-power devices for leisure (Webb 2006). In UBEM practice, Chiou et al. (2009; 2011) bootstrapped American Time Use Survey (ATUS) samples to represent time-use patterns of residents, consolidating household activity schedules for load profiles and occupancy. Diao et al. (2017) k-mode clustered ATUS in-home activities into ten patterns. Yamaguchi and Shinoda (2017) developed a stochastic discrete choice model prognosticating residential APs for urban energy demand, categorising routine and non-routine behaviours and accounting for household interactions. Chen et al. (2022) simulated sleep, personal care, cooking, laundry, absence, and leisure activities using Markov chains with duration sampling.

Transcending direct impacts on energy intensity, and spatiotemporal activity patterns of occupant dictate building occupancy. First, activity time and duration choices influence occupancy and appliance operation schedules (Fu et al. 2022). For example, the fixed work pattern of commuters dictates periodic occupancy fluctuations, like engendering office occupancy during workday diurnal hours. Second, activity location choices can also influence energy demands (Li et al. 2023). Occupant concentrations in locales may elevate energy demands, potentially creating spatiotemporal demand hotspots stressing power grids. Several UBEMs have considered the role of location choice. Mosteiro-Romero et al. (2023) simulated occupant AP and location choices using actual occupancy counts for 120 buildings. Marín-Restrepo et al. (2020) modelled the intra-office spatial variations.

In addition to the abovementioned factors, the frequency of occupant activities and secondary activities may also influence building energy demand. The frequency of occupant activities refers to how often they engage in specific activities (Bourgeois et al., 2006), while secondary activities are those that may occur alongside primary activities. Furthermore, several external factors have been shown to significantly influence occupant APs. For instance, occupants tend to engage in indoor activities in cold winter, increasing the building energy demands. However, only a very few UBEM research addresses the impacts of these factors, highlighting the need for further investigation (Aerts et al. 2014b; Bourgeois et al. 2006).

2.4.3 Occupant Behaviour

Occupant behaviour (OB) is another factor influencing building energy consumption, garnering widespread attention in building- and city-scale energy simulations. OB encompasses direct energy-use behaviours like electrical appliance/plug load, lighting, domestic hot water (DHW), and air conditioning/thermostat control usage, as well as indirect energy-use behaviours like window/blind operation and dress code selections modulating indoor environmental conditions or thermal comfort perceptions.

2.4.3.1 Plug Loads and Appliance Use

UBEM often employ plug load schedules to represent the usage of electrical appliances (Aydinalp et al. 2002; Ferrando et al. 2022). The schedules in residential dwellings heavily depend on occupancy and APs (Anand et al. 2019; Mahdavi et al. 2016). The family demographic composition substantially influences appliance usage: dwellings with elderly or children exhibit dispersed appliance use patterns, while single-occupancy households usually have concentrated usage schedules (Amoako et al. 2023; Wang et al. 2023). Compared with residences, office buildings have more concentrated and regular appliance usage schedules. Most UBEMs used deterministic models for appliance usage and plug load schedules. For instance, Zhang et al. (2023) employed statistical methods to determine plug load usage probability and appliance usage frequency for dormitories. Similarly, Osman et al. (2023) used TUS data to estimate usage frequency, duration, and energy consumption of 12 typical appliances. Aldubyan and Krarti (2022) employed a statistical model based on Saudi Arabian household plug load data. Alternatively, some adopted stochastic models. Flett and Kelly (2021) developed a Markov chains mode simulating appliance and hot water usage times by converting random numbers into times based on cumulative probability distributions, constrained by occupancy periods.

2.4.3.2 Lighting System Usage

Lighting systems account for 5-15% of energy consumption in buildings (Ryckaert et al. 2010). Their usage patterns depend on building occupancy schedules, APs, and several external environmental factors (Chi et al. 2018; Delgoshaei et al. 2017): Occupancy schedules determine lighting activation times and durations for different functional areas (Delgoshaei et al. 2017; Yun et al. 2012), while natural daylighting and climatic conditions also affect artificial lighting demand (Li and Lam 2001). Also, energy-saving behaviours and intelligent controls can significantly reduce lighting energy consumption (Nilsson et al. 2015; Staddon et al. 2016). There are several UBEM cases with deterministic lighting system use models. Aldubyan and Krarti (2022), for example, developed a residential lighting schedule model based on local daylighting conditions and statistical data across months. Some studies consider the influence of indoor activities on lighting system operation: An et al. (2017) proposed a model accounting for occupant presence and indoor illuminance levels, assuming occupants turn on lighting when illuminance drops below a threshold. Richardson et al. (2010) introduced a high-resolution household lighting demand model generating power demand curves using time-series active occupancy schedules, considering natural daylighting and occupants' activities.

2.4.3.3 Domestic Hot Water (DHW) Usage

Hot water provision generates significant energy consumption, accounting for 14% in the EU residential sector (Fuentes et al. 2018), and 18% in the US (Pérez-Lombard et al. 2008). Research usually focuses on domestic hot water (DHW) consumption in residential buildings due to its higher usage compared to other building types. Occupant APs impact the temporal distribution of DHW usage (Fuentes et al. 2018), typically during personal care (e.g., showering) and domestic work (e.g., cooking, and laundry), coinciding with peak demand periods when occupants are at home. Additionally, demographic and environmental factors also present significant influence (Fuentes et al. 2018; Rouleau et al. 2019; Xu et al. 2023), such as climatic factors, environmental awareness, and season (Ahmed et al., 2015, 2016). In the UBEM context, Osman et al. (2023) used cooking and showering times from TUS, and average hot water flow rates for these activities to estimate DHW consumption. Besides, the *Tool for Generating Realistic Residential Hot Water Event Schedules* (Hendron et al. 2010) generates annual DHW usage profiles for individual households by categorising consumption into five water fixture types. Rouleau et al. (2019) further enhanced this model by localising it to Quebec, Canada, and incorporating occupancy factors' influence on DHW usage.

2.4.3.4 HVAC Usage

HVAC systems account for over 50% of building energy consumption in some areas (Lam et al. 2008; Yao et al. 2005). HVAC usage pattern is complexly influenced by occupancy, AP, individual preferences, and environment (e.g., humidity, temperature) (Kharseh et al. 2014), and usually presents heterogeneous flexibility and complexity between residential and office contexts. In office buildings, HVAC systems are often centrally controlled, operating under predetermined strategies and schedules. Conversely, in residential environments, HVAC usage largely depends on occupants' personal temperature preferences and behavioural habits, allowing greater flexibility and on-demand adjustments to cater to individual comfort. Additionally, office activities are primarily sedentary, while residential activities like cooking, generate additional heat loads, imposing different demands on HVAC systems. In UBEMs, An et al. (An et al. 2017) determined the prevalent range of A/C temperature set-points through extensive surveys within the target community. Another research developed a residential HVAC usage model considering event triggers (occupant presence) and environmental triggers, assuming occupants adjust A/C operation in response to environmental conditions reaching certain thresholds (Liu et al. 2024).

2.4.3.5 Indirect Energy-Use Behaviours

There are some indirect energy-use behaviours influencing building energy demands. These behaviours, such as window and shading system usage, work by impacting the built environment. The usage of windows and shading systems involves a complex decision-making process influenced by physiological, psychological, social, physical environmental, and contextual factors (Fabi et al. 2012b). While many cases adopt deterministic models for simplicity, stochastic models have been employed to simulate window/blind usage behaviours. Robinson et al. (2007) developed SUNtool, incorporating a window usage behaviour model based on interaction probabilities and consequences. They compared three models to predict window usage: a single-probability Bernoulli process, a Markov chain model, and a hybrid model. Haldi and Robinson (2009) and Haldi et al. (2011) further extend this model to consider the impact of window opening on indoor air and illuminance, integrating it into CitySim. D'Oca and Hong (2014) employed data mining techniques to investigate window usage behaviour patterns of office occupants.

2.5 Review Findings: Data

This section critically examines prevalent data and data sources employed in modelling the occupation, activities, and behaviour of building occupants. These data sources are categorised into four distinct classes: (1) sensor-based data, (2) energy load data, (3) survey data, and (4) other emerging data. This discussion delves into a comprehensive exploration of these data collection methodologies, elucidating their roles and significance in UBEM research. Furthermore, the analysis evaluates their respective strengths and weaknesses within this context.

2.5.1 Sensor-Based Data

Numerous studies have employed monitors and diverse sensors within buildings to gather occupancy-related data (Chang & Hong, 2013). These sensors include image-based, motion, RF-based, and environmental sensors. The objectives of this approach are twofold: (1) capturing occupancy variables like number, activity durations, and positions of occupants; (2) understanding energy-related occupant-building interactions.

Building monitors and sensors serve as an important occupancy data source. Conventional approaches involve access control systems or ingress/egress monitoring (Erickson and Cerpa, 2010; Guan and Huang, 2015; Zhang et al., 2016). However, this approach might raise privacy concerns and require substantial investments. A more prevalent strategy entails the use of motion sensors (e.g., ultrasonic, vibration, PIR sensors) (Andrews et al., 2020; Dodier et al., 2006; Duarte et al., 2013; Sheikh Khan et al., 2021; Zhang et al., 2022), threshold sensors (e.g., pressure sensors at floor/mat, switch sensors) (Kim et al., 2018; Labeodan et al., 2015), as well as switch sensors (Jazizadeh and Becerik-Gerber, 2012), and mechanical sensors to discern occupancy within specific spaces. In a study analysing the occupancy status of 200 open-plan offices, the researchers employed light switch data recorded at five-minute intervals (Chang and Hong, 2013). The third strategy involves radio frequency-based sensors, such as radio frequency identification (RFID), Wi-Fi, Bluetooth, and Zigbee-based sensors (Natarajan et al., 2022; Shen and Plum, 2020; Tekler et al., 2020). Wang and Shao (2017) employed a Wi-Fi-based indoor positioning system to generate occupancy profiles by assessing the quantity and location of Wi-Fi devices within university library buildings. These sensors offer advantages such as deployment flexibility and broader coverage. In addition, more recent studies integrate various sensor types and develop a sensor network to further enhance accuracy and collect multiple types of data (Jin et al., 2014; Milenkovic and Amft, 2013).

In addition, sensors can constitute a crucial data source for examining OB. They can record appliance use behaviours with direct energy impacts and occupant interactions with the indoor environment and building systems, such as window use, A/C temperature settings, lighting control, and blind usage. Relevant sensors include light, carbon dioxide, humidity, temperature, and acoustic sensors. For instance, Andersen et al. (2013) employed carbon dioxide sensor data to model occupancy and window opening patterns in Danish residences. In a recent instance, Wu et al. (2023) analysed

HVAC usage among building occupants across 1,200 building units based on extensive online A/C monitors.

Sensor-based data offers robust accuracy in reflecting occupancy and OB, being pivotal for capturing human interactions with built environment and energy systems. However, sensor-based data also has certain limitations. Firstly, it only covers confined sensor-equipped areas like individual buildings or communities, making the economic feasibility of installing and deploying an adequate number of sensors diminish for extensive UBEM investigations. Secondly, most sensors capture occupant data within a specific spatial domain, making it challenging to trace activity chains across various spaces and locations. Although recent research has aimed to address broader occupant localisation through wearable sensors (e.g., smart bracelets and wearable positioning sensors), aligning occupant activities with corresponding location data remains a formidable challenge.

2.5.2 Energy Load Data

The building energy load can effectively reflect the appliance usage behaviour and activity patterns of occupants (Ahmad et al., 2016; Wang et al., 2019), and therefore, has been extensively utilised in UBEM research (Lazzari et al., 2022). For instance, Ang et al. (2023) proposed an approach combining smart meter data and open access statistic data to enhance building archetypes for district-level models. Similarly, Ferrando et al. (2022) employed smart meter data to create data-driven occupancy and electricity use schedules for archetypes. Aldubyan and Krarti (2022) assess the energy impact of short-term and long-term household activity changes on residential sectoral energy demand in Saudi Arabia.

However, most electricity meters and energy recorders merely provide the aggregate electricity consumption of a household over a defined period (monthly, weekly, or daily) (Wang et al., 2019). Thus, supplementary tools are typically required to obtain specific information about energy usage, involving two principal approaches: intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM). ILM employs a data collection strategy akin to sensor-based methods, utilising sensors to record the usage of individual electrical devices. Conversely, NILM employs an algorithm based on energy load data to infer the energy usage patterns of building occupants (Angelis et al., 2022). Hart (1985) first proposed the concept of NILM, which operates on the principle that specific load characteristics correspond to the operation of an individual appliance or equipment. Considering variables such as voltage, current, and power, each electrical device is represented by its unique energy consumption versus time waveform (Angelis et al., 2022; Wang et al., 2019). Compared to ILM, NILM is more cost-effective and easier to deploy in areas with multiple buildings, leading to its wider adoption in building energy research. NILM typically involves four stages: data acquisition, event detection, feature extraction, and load identification. The pervasive use of smart meters plays a crucial role in supporting data collection (Adams et al., 2021; Liao et al., 2014). As a novel form of digital electricity meter, smart meters can accurately measure the electricity consumption of a building unit and transmit the information. Hourly or half-hourly data from smart meters can be utilised to infer household occupancy, while higher resolution data enables the detection of usage patterns for various appliances.

Smart meter data plays a crucial role in building energy research by enabling the identification of activity types and time distributions among building occupants. For instance, Chen et al. (2010, 2013) employed smart meter data to infer occupant AP and generate AP profiles with six activity categories for building dynamics simulation. Furthermore, smart meter-based High-Resolution Intrusive Load Monitoring (HILM) can deduce specific energy consumption patterns and OB related to electrical appliance usage. For example, Liao et al. (2014) proposed AERO (Activity Extraction with Rational Observation), a method applied to a home area network service system that extracts low-level contextual information from a power strip-type smart meter, including time data on power consumption and the identification and location of appliances. Similarly, Belley et al. (2014) developed a two-stage algorithm to capture the usage of devices like bread machines, hot water kettles, coffee machines, blenders, and stereos. In addition to energy use, Vitter and Webber (2018) also employed NILM on water-meter data to classify DHW usage.

Energy load-based data, such as smart meter data, introduces innovative approaches to incorporate the impacts of occupant behaviour and activities into city-scale building energy research. However, this form of data encounters certain limitations. Firstly, the majority of energy load-based data necessitates inference through NILM algorithms rather than direct measurement, which has the potential to impact data accuracy, particularly in more intricate studies at larger spatial scales. Secondly, the absence of smart meters or similar devices in many communities hinders the provision of high-time-resolution energy load data. Thirdly, akin to sensor-based data, energy load-based data is inherently location-specific, concentrating on activities within a singular building unit. Consequently, the challenge arises in accommodating the spatial transfer of occupants between distinct buildings and establishing links between the spatial transfer of residents' activities and their corresponding energy requirements through activity chains.

2.5.3 Survey Data

Survey data, such as TUS data and household electricity survey (HES) data, are extensively employed in UBEMs to examine the roles of building occupant AP and OB (e.g., Chen et al., 2022; Flett and Kelly, 2021; Khalil and Fatmi, 2022; Sood et al., 2023; Yu et al., 2023). There are several advantages of applying survey data for capturing occupant-related variables in UBEMs. First, surveys can be tailored to meet the specific requirements of the study, with thoughtful sample selection and survey content enabling UBEM modellers to direct their attention towards particular areas, building types, or specific occupants (Osman and Ouf, 2021). Second, surveys can encompass a broader array of details pertinent to occupants' activities, including activity types, timing, and locations, allowing modellers to capture nuances, diversity, and evolving trends in AP and their energy implications (Torriti, 2014). Third, surveys can help incorporate a broader spectrum of factors relevant to occupants, including socioeconomic, psychological, and environmental variables, accommodating heterogeneity in AP and OB, thus enhancing the precision of UBEM predictions (Torriti, 2014). Lastly, survey data directly reflects the actual circumstances of AP of occupants, obviating the necessity for employing additional algorithms to infer activity patterns or energy-use behaviours.

TUS data represents the most commonly employed category of survey data in UBEM studies. TUS refers to a survey method designed to gather data on individuals' time allocation throughout the day. TUS questionnaires enable the collection of activity records over the course of a day, including information on activity types, durations, and locations, which are highly valuable for AP and OB simulation. For example, Osman et al. (2023) utilised Canadian TUS data to generate distributions for occupancy, lighting demand, appliance loads, and DHW usage for a bottom-up UBEM. Chen et al. (2022) employed ATUS data to develop an occupant-driven residential energy demand model for the US housing stock context. Fu et al. (2022) analysed the TUS data to establish residential occupancy profiles to support multi-scale UBEMs in China. Also, McKenna et al. (2015) developed a novel four-state domestic building occupancy model using UKTUS data.

Table 2.1 Typical time use survey data sources by country.

Country	Survey	Time (min)	Year	Sample Size	Reference
United Kingdom	UKTUS	10	2020/2024	2,165 (Mar to Apr 2020) 1,967 (Sep to Oct 2020) 3,722 (Mar 2021) 4,132 (Mar 2022) 3,611 (Nov 2022) 5,600 (Mar 2023) 3,659 (Sep 2023) 3,477 (Mar 2024)	(Office for National Statistics, 2024)
	CTUR 6-Wave TUS	10	2016/2021	1,011(2016) 1,004 (May 2020) 987 (Aug 2020) 1,358 (Nov 2020) 1,254 (Jan 2021) 1,282 (Aug 2021)	(Gershuny et al., 2022)
	UKTUS	10	2014/2015	9,388	(Sullivan & Gershuny, 2023)
Australia	Australia's Time Use Survey	15	2020/2021	7,062	(Australian Bureau of Statistics, 2020-21)
Belgium	Belgian Time Use Survey 2013 (BTUS13)	10	2013	6,400	(Glorieux et al., 2015)
Canada	Time Use Survey	15	2022/2023	Over 55,000	(Statistics Canada, 2024)
China	National Time Use Survey	15	2018	48,580	(National Bureau of Statistics of China, 2019)
	China's Third National Time Use Survey	15	2024	Over 107,000	(National Bureau of Statistics of China, 2024)
France	Enquête Emploi du Temps	10	2009/2010	15,300	(Insee[1], 2012)
Germany	Zeitverwendungserhebung	10 10	2022 2012/2013	19,526 11,400	(German Federal Statistical Office, 2022)
India	The Indian TUS	30	2019	4,47,250	(Hirway, 2022)

[1] Institut national de la statistique et des études économiques

Japan	Survey on Time Use and Leisure Activities	10 10	2021 2016	Over 190,000 Over 200,000	(Statistics Bureau of Japan, 2021)
Korea	Korean Time Use Survey	10	2019	Over 26,000	(Statistics Korea, 2020)
Spain	Time Use Survey	10 10	2009/2010 2002/2003	19,295 Over 9,500	(Spanish National Institute of Statistics[2], 2010)
Sweden	Swedish Time Use Survey	10	2010/2011	7,955	(Statistics Sweden, 2012)
The Netherlands	Dutch Time Use Survey	10	2016	2,757	(Roeters & Vlasblom, 2019)
Turkey	Turkish Time Use Survey	10	2014/2015	11,400	(Turkish Statistical Institute, 2016)
	Turkish Time Use Survey	10	2006	5,070	(Turkish Statistical Institute, 2014)
United States	American Time Use Survey (ATUS)	Activity Start-Stop Time	2003/2023	245,139 in total, of which: 20,720 (2003) 13,973 (2004) 13,038 (2005) 12,943 (2006) 12,248 (2007) 12,723 (2008) 13,133 (2009) 13,260 (2010) 12,479 (2011) 12,443 (2012) 11,385 (2013) 11,592 (2014) 10,905 (2015) 10,493 (2016) 10,223 (2017) 9,593 (2018) 9,435 (2019) 8,782 (2020) 9,087 (2021) 8,136 (2022) 8,548 (2023)	(U.S. Bureau of Labor Statistics, 2024)

[2] Instituto Nacional de Estadística (INE)

Many countries have established comprehensive TUS systems, providing historical data spanning long periods (Bauman et al., 2019; Fleming & Spellerberg, 1999). Table 2.1 lists some most widely used time use data sources. For example, the United States (Lundberg et al., 1934), the United Kingdom (Reeves and Reeves, 1913), and the former Soviet Union (Strumilin, 1925) had initiated regional or national TUS prior to World War II. The Multinational Comparative Time-Budget Research Project in the late 1960s established the groundwork for the prevalent TUS questionnaires (Szalai and Szlai, 1966). The American Heritage Time Use Study (AHTUS) has compiled over 60 years of time diary samples since the mid-20th century (CTUR, 2024). The harmonised European time use surveys (HETUS) are conducted as nationwide surveys in European Union countries (European Commission. Statistical Office of the European Union., 2016), with two rounds in 2000 and 2010. TUS has expanded to cover more regions in Asia and Africa, including South Korea (Korea, 2020), and mainland China (Jia, 2016; Pan, 2018). The Multinational Time Use Study (MTUS) contains 1.2 million days from 85 surveys across 26 countries (CTUR, 2024).

Many countries have conducted HES and provide publicly available data sources. Examples include the HES in the United Kingdom (Palmer and Terry, 2017), monitoring energy consumption, appliance ownership, labels, and energy-saving potential of 250 owner-occupied households across England from 2010 to 2011. Also, the U.S. Energy Information Administration (EIA) conducted the Residential Energy Consumption Survey (RECS), gathering data from a national sample of housing units, including demographics, energy use patterns, and housing unit characteristics. In Oceania, the Australian Bureau of Statistics leads the Household Energy Consumption Survey (HECS) and the Business Survey of Residential Electricity Distribution (BSRED), collecting information on household energy expenditure, consumption, behaviours, perceptions, and other characteristics (Australian Bureau of Statistics, 2013). In Asia, Philippine Statistics Authority (Philippine Statistics Authority, 2024) also conducted nationwide Household Energy Consumption Surveys in 1989, 1995, 2004, and 2011. Another significant data source is the Chinese Residential Energy Consumption Survey (CRECS) by Renmin University of China, with data from 2012, 2013, and 2014 available for academic purposes (Zheng et al., 2022).

Survey data also have some limitations for UBEM adoptions. First, the temporal resolution is strictly constrained by the questionnaire design, with the most common resolutions ranging from 10 to 30 minutes, as higher resolutions imply higher data collection costs and decreased respondent tolerance and accuracy. Second, surveys often yield cross-sectional data, necessitating regular data collection to capture trends in activity patterns, which are susceptible to financial and external influences, particularly in developing countries or underdeveloped regions. Third, survey data collected from building occupants might be subjective, and potentially influenced by social preferences and normative factors. Fourth, activity patterns and appliance ownership are influenced by complex cultural, economic, and environmental factors (Cabeza et al., 2018). For instance, Chinese households have fewer dishwashers and dryers compared to American households, while European households have fewer A/C than American households (Henderson, 2005). Therefore, UBEM for specific regions requires the use of data sources consistent with the local context.

2.5.4 Emerging Data Sources

Technological advancements have rendered several emerging data sources accessible for UBEM research. Typical examples of these data sources include mobile phone signal data, digital footprint data, social media data, and Wi-Fi connectivity data. These data sources offer rich and detailed user behavioural information, aiding researchers in more accurately simulating AP and OB of building occupants.

The application of mobile phone and digital footprint data is gaining traction in urban studies and UBEM research (Demissie et al., 2016; Jiang et al., 2013). Mobile phone signal data refers to information related to mobile phone communication within cities, collected and stored by mobile communication operators. Digital footprint data encompasses data generated by mobile applications, social media platforms, location services, and other sources. These data might enable UBEMs to discern the occupancy of different building/land parcels at specific times and model the flow between buildings. For instance, Barbour et al. (2019) employed the TimeGeo framework and utilised detailed call records to simulate the occupancy rates of various building types in the Boston metropolitan area, USA. Happle et al. (2020) collected usage data for retail and restaurant establishments in 13 different urban centres in the USA using web mapping services, creating data-driven schedules for each environment. Jiefan et al. (2018) conducted high-temporal-resolution building occupancy modelling using location-based service (LBS) data from mobile phone applications.

Furthermore, posts, check-ins, and tags on social media platforms can reveal individuals' activity trajectories. For example, by analysing geotags on Twitter, one can gain insights into people's activities and interests at different locations. Another valuable data source is Wi-Fi connectivity data. Lu et al. (2020) explored two methods for extracting typical occupancy schedules using social network-based data as input for building energy simulation: (1) text classification algorithms to identify whether individuals appeared in spaces where they posted on social media, and (2) LBS data collected by social media applications. Besides, Wi-Fi connection records can unveil occupancy characteristics of individuals in specific buildings or areas. For instance, Wi-Fi connection data from shopping centres, coffee shops, and public libraries can help understand AP and OB in these locations. Hou et al. (Hou et al., 2020) utilised Wi-Fi login data from a university campus to develop a model combined with nested copula dependence to describe the complex interactions between occupants in buildings within a district.

The aforementioned data sources are highly useful in analysing building or land occupancy density and trends. However, due to not every building occupant using the corresponding applications, connecting to Wi-Fi, or using specific mobile phone data carriers, these emerging data may not accurately reflect the occupancy trends of buildings or land at specific times. Another significant limitation is that these data cannot reflect the activities of building occupants within the buildings, as well as the sequence of activities between different buildings. This makes it challenging for UBEM to utilise these data in analysing spatial transfers of energy demand or conducting analyses of complete activity chains.

2.6 Review Findings: Occupant-Related Modelling Methods

Based on research in the literature, this study categorises the mainstream occupant-related modelling approaches in UBEM into three types: (1) deterministic approaches, (2) stochastic approaches, and (3) agent-based approaches. The stochastic model section will provide a detailed introduction to the application of Markov chain models, neural network models, and econometric models in UBEM.

2.6.1 Deterministic Approach

Deterministic approaches provide a straightforward means of modelling occupant activities in buildings. The fundamental precept is to incorporate activity patterns and regularities into the model to prognosticate building energy usage. In UBEM applications, deterministic approaches are among the most ubiquitous methods. These models can be further delineated into traditional deterministic schedules (i.e., static models) and rule-based models (i.e., dynamic models).

The static models employ fixed schedules to delineate occupancy, with building appliance/system use schedules related to various factors such as building typology, day of the week, and time of day. These immutable schedules are often derived from widely adopted standards and databases like ASHRAE, DOE, CIBSE, as well as questionnaire data or energy load data specific to the study scope. These standards provide a 24-hour schedule for each pertinent occupant activity variable required for the model, potentially stratified by building characteristics and utilisation, workday/non-workday, and season. For example, Krayem et al. (2019) developed a near-city-scale UBEM for Beirut, the BEirut Energy Model (BEEM), using residential occupancy and equipment usage schedules based on ASHRAE standards. Chen et al. (2021) generated workday and non-workday occupancy schedules to simulate building base/peak load, and occupancy through a case study in Glasgow. Sood et al. (2023) utilised the UKTUS data to establish more granular occupancy schedules for local residential buildings.

Rule-based deterministic models consider the influence of external environmental factors on occupant activities in buildings. For instance, occupants would illuminate when indoor illuminance falls below a threshold. Similarly, indoor temperature, illuminance, and air quality can affect occupants' use of windows, blinds, and lighting systems. Rule-based models connect each action with its environmental and time triggers to more accurately model adaptive behaviours. Their outputs comprise fixed thresholds that trigger occupant interactions with building systems/components. Examples include the rule-based algorithm proposed by Dorokhova et al. (2020) using sensor-based data to predict residential occupancy and A/C usage schedules, the models of Wang et al. (2016), An et al. (2017), and Gunay et al. (2017) considering solar irradiance, ceiling illuminance, and occupancy when simulating office lighting and blind use. By linking external factors with OBs, rule-based deterministic models enable more accurate predictions of occupant activities.

In summary, deterministic models allow for relatively simple and direct predictions of occupant activities by incorporating factors such as historical data, and seasonal variations into the model. This approach is suitable for building types or scenarios with well-understood occupant activities and offers computational efficiency.

2.6.2 Stochastic Approaches

Within stochastic approaches, occupant activities are modelled as random variables influenced by uncertainties like randomness of human behaviour and stochastic variations of external environmental factors. The prevalent stochastic approach in UBEM applications is occupant activity modules based on Markov chain models, while some studies have adopted neural networks and econometric models as alternatives. Compared to deterministic models, stochastic approaches better reflect real-world uncertainties and variabilities, though they are more complex, requiring more data and computational resources.

2.6.2.1 Markov Chain Models

Markov chain models have been extensively employed in ubiquitous UBEMs to simulate occupant-related variables. These models can describe diverse occupant activities with each activity representing a state in the chain. A transition matrix is established to quantify the probabilities of transitioning between states. Within UBEM, Markov chain models can depict transitions between activity states and incorporate probability distributions to simulate the randomness of activity durations and intensities. The theoretical underpinning of the basic two-state (at-home and out-of-home) Markov chain building occupancy model (Page et al., 2008) is presented in Equation (2-1):

$$P(t+1) = P(t)T_{11}(t) + \big(1 - P(t)\big)T_{01} \qquad (2-1)$$

*Let us consider two states: state **0** represents being out-of-home, and state **1** represents being at-home.* $P(t)$ *denotes the probabilities of at-home at the current time step, while* $P(t+1)$ *denotes the probabilities of at-home at the next time step. The transition probabilities are represented by* $T_{11}(t)$ *and* $T_{01}(t)$*, where* $T_{11}(t)$ *refers to the probability of remaining in the at-home state from one time step to the next, and* $T_{01}(t)$ *refers to the probability of transitioning from the out-of-home state to the at-home state at the next time step.*

Richardson et al. (2008) provided an early first-order Markov Chian application for two-state occupancy modelling. Widén and Wäckelgård (2010) covered three states (absent, present active, present inactive), using Swedish time use data to randomly simulate household energy consumption, and then they (Widén et al., 2012) extended the model to consider six activity states. Some studies have employed semi-Markov chain models to circumvent the influence of different times of the day on transition probabilities, which is neglected in traditional first-order Markov models (e.g., the probability of transitioning from other states to sleep is higher in the evening). A notable example is Wilke et al. (Wilke et al., 2013a) who used fitted Weibull PDFs to estimate activity durations and a random utility model (RUM) to estimate the impact of different types of individual variables on activity transitions, thereby simulating activity chains. Aerts et al. (Aerts et al., 2014a) combine Markov Chian Models with Clustering analysis to reflect the AP diversity. In addition, several studies have adopted discrete-time Markov models to (1) enhance time resolution and (2) focus on detailed energy-use behaviours in complex contexts, such as window opening, water heater use, lighting use, and office energy use behaviours. Haldi and Robinson (2009) employed a discrete-time Markov model to simulate window-opening behaviour. Baetens and Saelens (2016) developed the StROBe model based on a discrete-time Markov model for neighbourhood-level energy-use OB simulation.

In addition, some studies have employed higher-order Markov chains in occupancy and OB models. In first-order Markov chains, transition probabilities depend solely on the current state (known as "memoryless"). However, in higher-order Markov chains, transition probabilities depend on the current state and several previous states. The distinction between first-order and higher-order Markov chain models can be illustrated in Figure 2.8. Flett and Kelly (2021) developed a higher-order Markov Chain method for predicting domestic occupancy. Ramírez-Mendiola et al. (2019) utilised a variable-order Markov chain to capture residential occupant activity patterns, finding that the new model improved simulation outputs by 28% compared to traditional models.

	At-home Sleep	At-home Active	Out-of-home
At-home Sleep	$P_S \rightarrow S$	$P_S \rightarrow A$	$P_S \rightarrow O$

First-Order

Current State/Duration	At-home Sleep	At-home Active	Out-of-home
At-home Sleep / 0-2 Hrs	$P_{S2} \rightarrow S$	$P_{S2} \rightarrow A$	$P_{S2} \rightarrow O$
At-home Sleep / 2-4 Hrs	$P_{S4} \rightarrow S$	$P_{S4} \rightarrow A$	$P_{S4} \rightarrow O$
At-home Sleep/ 4-6 Hrs	$P_{S6} \rightarrow S$	$P_{S6} \rightarrow A$	$P_{S6} \rightarrow O$
At-home Sleep / 6-8 Hrs	$P_{S8} \rightarrow S$	$P_{S8} \rightarrow A$	$P_{S8} \rightarrow O$
At-home Sleep / 8+ Hrs	$P_{S8+} \rightarrow S$	$P_{S8+} \rightarrow A$	$P_{S8+} \rightarrow O$

Higher-Order

Figure 2.8 Difference between a first order and a higher-order Markov chain model

(adapted from Flett and Kelly, 2006)

Notes: In the first-order model, let us consider three states: at-home sleep (S), at-home active (A), and out-of-home (O). The transition probabilities are represented by $P_S \rightarrow S$, $P_S \rightarrow A$, $P_S \rightarrow O$, *where* $P_S \rightarrow S$ *denotes the probability of remaining in the at-home sleep state,* $P_S \rightarrow A$ *denotes the probability of transitioning from the at-home sleep state to the at-home active state, and* $P_S \rightarrow O$ *denotes the probability of transitioning from the at-home sleep state to the out-of-home state, all at the next time step. In the higher-order model, instead of using a single transition probability matrix, multiple matrices are employed corresponding to different sleep duration intervals, such as 0–2 hours, 2–4 hours, 4–6 hours, 6–8 hours, and 8+ hours. For instance, if an occupant has been asleep for 5 hours, the transition probability matrix for an occupant just took a 10-minute snap,* P_{S2} *would be used to determine the next occupancy state.*

Hidden Markov Models (HMMs) are statistical tools that can effectively model sequential and time-varying processes with underlying hidden states. In the context of urban building energy modelling, HMMs have shown great potential in capturing the stochastic nature of occupant behaviour and presence patterns. For example, by treating occupancy states as hidden variables and leveraging observational data, HMMs can learn and predict occupancy profiles. A case, Liisberg et al. (2016), have applied HMMs for indirect classification of OB and developed time-inhomogeneous HMMs to improve predictions.

2.6.2.2 Neural Network Methods

Neural network techniques are increasingly utilised for the development and prediction of activity models in UBEM (Chen et al., 2021; Wei et al., 2019) A neural network is a computational model comprising multiple artificial neurons, extensively applied to tasks such as pattern recognition, classification, regression, and prediction. Within UBEM, neural network approaches are extensively employed to simulate occupant AP and OB, predict activity types and durations, thus enabling more accurate forecasting of building energy consumption.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are among the most commonly used neural network techniques in UBEM. An RNN is a type of neural network architecture with recurrent connections, suitable for modelling sequential data. In UBEM, RNNs can be used to establish activity models that account for the time-series characteristics of occupant activities in buildings. By learning the sequential patterns from historical activity data, RNNs can predict future activity states. Wang et al. (2018) proposed a Markov-feedback Recurrent Neural Network (M-FRNN) algorithm for modelling and predicting occupancy. LSTM is a special RNN type that can better handle long sequences and long-term dependencies, thereby more accurately predicting future occupant activity patterns in buildings. Kim et al. (S. Kim et al., 2019) proposed an RNN-LSTM-based model for predicting occupant density in exhibition halls. Building upon this work, Jin et al. (2021) developed an RNN-based temporal-sequential (TS) analysis to predict residential occupancy within one week. Diarra et al. (2023) used non-intrusive sensor data to establish an RNN-LSTM model for predicting four different occupancy states in residential buildings.

Another emerging technology gaining momentum is Convolutional Neural Networks (CNNs). CNNs are primarily used for image data processing but are often employed in UBEM to handle variables related to building geometric data. However, CNNs can also be used to process activity patterns associated with spatial distributions. For instance, the spatial distribution of activities within a building can be treated as spatial data, and CNNs can learn spatial features and predict the spatial distribution of occupant activities. Gomez et al. (2018) were among the first to apply CNNs to indoor occupancy count estimation. Building upon this, Acquaah et al. (2020) developed two techniques for estimating occupancy in large rooms using thermal imaging data, with their proposed CNN model serving as the basis for indoor occupancy modelling. Arvidsson et al. (2021) constructed a CNN-based residential occupancy model. Unlike traditional models, their model does not require expensive high-resolution sensors or cameras but instead utilises multiple low-cost, low-resolution sensor data.

In addition to RNNs and CNNs, Bayesian neural networks (BNN), Multilayer Perceptions (MLPs), Graph Neural Networks (GNNs), and Deep Reinforcement Learning (DRL) have also shown potential for application in UBEM or occupant activity simulation. Furthermore, neural network-based models can provide support for more complex UBEM models. Khalil and Fatmi (2022) developed an agent-based model that also employed RNNs to simulate the time allocation of residential occupants between being at home and away.

2.6.2.3 Econometric Models

Some well-established econometric models, such as the gravity model and utility maximisation theory, have been developed to study occupant activity patterns and mobility, and have been widely applied in spatial economics, urban studies, and policy analysis. In recent years, some studies have extended these theories to the context of urban energy and integrated them with UBEM. This integration provides deeper insights into occupants' energy use behaviours in urban environments, thereby offering more effective support for urban energy planning and policymaking.

The gravity model is a classic economic model used to describe the flow of people or goods within a spatial context. Based on Newton's universal gravitation law, the model posits that the flow (e.g., population, goods, services) between two locations is inversely proportional to the distance between them and directly proportional to the sizes of those locations. In other words, the amount of flow depends on the attractiveness of the locations and the distance between them (represented by Equation (2-2)). It has widespread applications in urban studies and regional economics. Recent UBEM research has adopted the gravity model to simulate the spatial distribution of occupant activity patterns between buildings and, consequently, predict building energy consumption. For instance, based on the gravity model, Wu et al. (2020) developed a novel mobility-based approach to derive urban-scale building occupant profiles. Their study applied the approach to approximately 900 buildings in downtown San Antonio, Texas, using mobile positioning data for modelling. Additionally, Barbour et al. (2019) developed an occupancy density simulator covering over 80,000 buildings in the Boston region, utilising a large amount of passively collected mobile phone data and computing the distribution of occupant-driven energy loads.

$$F_{ij} = \frac{M_i \cdot M_J}{d_{ij}^{\beta}} \quad (2-2)$$

Where F_{ij} *denote the flow between zone* ***i*** *and zone* ***j***, M_i *and* M_j *represent the attractiveness of zone* ***i*** *and zone* ***j***, *respectively, and* d_{ij} *represent the distance between zone* ***i*** *and zone* ***j***. *The parameter* β *is a decay factor used to adjust the degree of influence that distance has on the flow.*

Apart from the gravity model, utility-based models grounded in utility theory from economics can also be integrated with UBEM. These models link individuals' activity choices to their utility or satisfaction derived from different activities (Guzman et al., 2023; Koomen et al., 2015; Macfarlane et al., 2021). Their application in UBEM primarily involves establishing models of occupant AP/OB to simulate their activity patterns and time-use allocation, thereby predicting building energy consumption.

Utility-based models' core is the utility function, which measures occupants' satisfaction with different activity patterns and time allocations, comprising factors such as comfort, convenience, and cost. Subsequently, a choice model is established based on the utility function to describe occupants' preferences and yield probabilities of different activity patterns. For example, Rovira et al. (2022) applied a utility-based model based on the Multiple-Discrete Continuous framework to simulate room occupancy patterns in UK residential buildings, deriving six patterns and incorporating factors like employment status, education level, age, and number of children.

On a larger scale, these models can support UBEM in revealing occupant flows between buildings and further explaining the spatial translation of energy demand, particularly for building types more sensitive to occupant density, such as commercial buildings and public facilities (e.g., office buildings, shopping malls, campus buildings). These models can account for detailed environmental and socioeconomic factors, aiding modellers in connecting different spaces and buildings through occupant activity patterns, thereby understanding the spatial and temporal distribution characteristics of urban energy demand.

2.6.3 Agent-Based Model

Agent-Based Modelling (ABM) is an approach that simulates occupant activity patterns and energy use behaviours in urban buildings by modelling the individual behaviours and interactions of agents. In ABM, each agent is treated as an independent entity possessing its own rules and preferences. These agents make decisions based on their individual characteristics and environmental conditions, interacting with one another and influencing each other's behaviours.

ABM can construct its modelling framework by adopting a combination of one or more techniques, depending on the context of interest. Chingcuanco and Miller's (2012) *Integrated Land Use, Transportation, and Environment* (ILUTE) model, an ABM that integrated multiple sectors such as residential, commercial, and transport, using a joint logit model of heating fuel and equipment choice as the core technique. Bustos-Turu et al. (Bustos-Turu et al., 2016) established an ABM for the London urban area to generate residential energy demand profiles, influenced by factors such as land use, energy infrastructure, and user behaviour, considering interactions between occupant activities and building energy demand four modules. Yu et al. (2023) showed the community occupant agent model (COAM) for community-level load simulation considering both occupant-building and building-building interactions. Mosteiro-Romero et al. (2020) developed an ABM called PopAp to model occupant presence at the district scale, following an approach inspired by transport models, assigning daily schedules to occupants in each building using information about the actual residents and their activities in the district.

The application of ABM in UBEM presents several advantages. Firstly, ABM allows for individualised modelling of each occupant within a building, considering their characteristics and preferences. This individualised simulation can more accurately reflect the behavioural differences and diversity among occupants in the real world. Furthermore, ABM can simulate the interactions and evolutionary processes among agents, enabling the model to dynamically adapt to changing environments and situations. This capability allows the model to better capture the evolution of occupant activity patterns in community or urban buildings. Thirdly, ABM can consider the spatial distribution and movement patterns of agents across different zones within a building, thereby more accurately modelling the building energy demand. Fourthly, ABM has the potential to account for various complex factors influencing occupant activity patterns and energy use behaviours, such as social networks and transport.

2.7 Review Findings: Future Research Directions

2.7.1 Cross-System and -Sector Integration

The diverse urban systems and sectors exhibit distinct energy consumption patterns, while they are also interconnected in the urban environment. The complexity of city presents challenges for energy modelling. Moving forward, community- and city-scale energy management should expand beyond existing tools to consider multiple interacting urban sectors for comprehensive energy management strategies. Two critical challenges emerge in developing new urban energy models:

First, the energy interaction between different building types requires future discussion and monitoring. Urban energy decision-making should account for changing building function boundaries driven by new technologies and social trends, resulting in more complex and dynamic energy demand patterns between different building types. For instance, emerging industries (e.g., live-streaming) and new working patterns (e.g., four-day work weeks) are reshaping the spatio-temporal characteristics of energy demand flows between residential and commercial buildings. Additional examples include the rise of mixed-use developments and the emergence of co-working spaces blurring traditional workplace boundaries.

Second, another direction is the capture of intricate interdependencies between urban sectors and their energy effects. An example is the energy demand flow between residential and transport sectors driven by EV charging behaviour. Other instances include the interaction between urban microclimate and building energy consumption, or the relationship between public transport availability and residential energy use patterns. Future urban energy models could couple and synchronously simulate various urban systems, encompassing multiple building types, facilities, power grids, transport networks, and urban microclimates. This integration requires effective data exchange mechanisms, coupling methodologies, and synchronisation controls to ensure accurate and reliable simulation outcomes.

Understanding these cross-system energy demand flows can significantly contribute to smarter grid operation decisions and urban or community energy hub planning. By integrating cross-system energy demands, decision-makers can obtain more precise urban energy consumption profiles, identify key drivers of energy use, and uncover potential opportunities for energy conservation and emission reduction. Through cross-system energy management schemes, decision-makers can work towards achieving spatio-temporal matching of energy loads, improving renewable energy utilisation efficiency, and reducing overall energy system operating costs. This holistic approach could also facilitate the development of innovative solutions such as district heating networks, integrated renewable energy systems, and smart grid applications that optimise energy flows across different urban sectors.

2.7.2 Capturing New Behaviour and Activity Trends

In recent decades, rapid advances in technology, alongside social and environmental changes, have been reshaping how urban residents live and behave These structural shifts pose a critical challenge for monitoring and managing the resulting fluctuations in city-scale energy demand.

From the OB perspective, new technologies and cultural shifts often lead to rapid changes and complex long-term impacts. For instance, the rise of social media has been associated with a notable decline in television usage in many regions. Another example is the evolution of office culture, where increasingly casual employee dress codes have influenced air conditioning temperature settings. Capturing these changes can help address uncertainties in UBEM and enhance the predictive capability of these models. Furthermore, the impact of energy-saving behaviour is gaining attention within academia (Han et al., 2013; Iweka et al., 2019; Wang et al., 2023). Numerous studies are exploring the psychological drivers behind various energy-saving behaviours and have developed a range of monetary and non-monetary interventions to encourage residents to adopt these behaviours (Nilsson et al., 2015; Xu et al., 2023). These interventions have shown significant effects in diverse types of buildings globally and are gradually being promoted. By capturing changes in residents' electricity usage under these interventions, UBEMs can consider the broader spatial impacts of different types of energy-saving measures and integrate them into comprehensive urban energy management plans.

Beyond behavioural changes, urban population activity patterns can alter the temporal and spatial distribution of energy demand, as well as its overall magnitude, affecting the operation and supply-demand balance of energy systems. In the post-COVID-19 era, novel productivity tools (e.g., Generative AI), working patterns (e.g., remote and flexible working) (Althoff et al., 2022; Yu et al., 2019), transport technologies (e.g., autonomous vehicles) (Nadafianshahamabadi et al., 2021), and shopping habits (e.g., online retail) (Dias et al., 2020) have accelerated changes in urban resident activities, leading to unpredictable fluctuations in energy demand. The next generation of UBEM tools will benefit from moving beyond traditional deterministic models, capturing the dynamic changes in urban energy demand driven by residents' activity patterns across time, space, and sectors. The models would enable tracking the trajectories of energy demand changes over the medium to long term by considering the evolving trends in residents' activity patterns, thus assisting urban policymakers in making informed energy planning and decision-making.

2.7.3 Occupant-Oriented Data Integration

Urban energy management would benefit from the integration of dynamic occupant-related data. In urban contexts, occupant-related variables exhibit both dynamic characteristics and mutual influences. For instance, AP can shape specific OB, such as appliance usage patterns, through continuous contextual transitions and resource availability. The existing urban energy models tend to simplify these interactions (Dabirian et al., 2022; O'Brien et al., 2020). However, these traditional approaches may compromise model accuracy, as energy demand is driven by multiple concurrent occupant-related factors. The isolated examination of singular variables (e.g., specific energy-use behaviours) often fails to capture the holistic perspective necessary for accurate modelling and predicting. Therefore, city-scale energy models require future expansion to understand and capture occupant-driven changes, which should encompass integration of multidisciplinary research findings as well as development of occupant-centric knowledge graphs. In addition, the new energy models could employ dynamic data sources (e.g., IoT devices, sensor networks) to capture real-time changes in occupant data. These enhancements would facilitate dynamic resource allocation in urban energy management, ultimately improving overall energy efficiency and power infrastructure resilience.

Another important objective of occupant-oriented data integration is to capture the impact of individual heterogeneity. Urban populations present significant variations across multiple dimensions, such as socioeconomic characteristics, cultural background, occupations, and personal preferences (Ren et al., 2024; Zhao et al., 2021). These heterogeneous factors directly influence energy consumption patterns. For instance, an environmentally conscious occupant might actively reduce energy consumption through careful adjustment of daily habits, whilst another might place less emphasis on energy conservation (Liu et al., 2021). Factors such as environmental education (Varela-Candamio et al., 2018) and sustainable policies (Han et al., 2013) are increasingly driving changes in energy consumption patterns through cognitive and behavioural shifts among individuals. Traditional aggregated models often overlook these microscale variations. Therefore, incorporating occupant-related factors into UBEMs can help precisely capture individual heterogeneity and the resulting variations in energy demand. Also, this process enables the development of customised energy interventions that address specific individual preferences (Xu et al., 2023), such as targeted programmes that consider the needs of elderly residents and shift workers.

Data silos have been an important challenge in occupant-oriented data integration. While future models aim to capture occupant-related variables and their dynamic changes through novel data sources to enhance model adaptability and accuracy, the integration of these sources presents considerable challenges. For instance, Microsoft's building footprint dataset provides data on billions of buildings across portions of the

USA and Canada, facilitating detailed and high-resolution UBEM development. Also, social media data can offer insights into attitudes and locations of residents, providing support for occupancy and behaviour modelling. However, these data often present heterogeneous spatiotemporal resolutions and formats. Also, the lack of standardisation across heterogeneous systems impedes direct data sharing and interoperability. Future urban-scale energy models will benefit from the integration of new data sources through semantic web technologies, enabling interoperability between occupant-related information and various urban system data, which can also support more intelligent queries based on semantic relationships, improving data utilisation efficiency and thereby achieving more refined and humanised energy management (Wang et al., 2025).

2.7.4 Mitigating Data Bias and Bridging Regional Gaps

UBEMs provide a platform that integrates urban residents, the built environment, and energy demands, forming a basis for dynamic tools and digital twins for urban energy management. These models often employ extensive datasets to capture resident-related dynamics, including building occupancy, OB, AP, as well as psychological and physiological information. However, the research community should pay further attention to the potential biases in these data and within the models, as they could have compound impact on energy justice and regional equity.

Reducing biases in data collection and input for UBEM is an essential direction for ensuring accurate and equitable energy management (Ali et al., 2021; Wang et al., 2025). The next generation of urban energy management tools will benefit from utilising more diverse data sources and employing cross-validation techniques to compare different data sources and identify discrepancies or biases (Bass et al., 2022; Garg et al., 2024). In addition, new energy modelling tools could adopt more inclusive sampling methods that cover all relevant groups in the data collection process, and continuously update and validate data to reflect new conditions and trends (Heidelberger and Rakha, 2022). Especially, the input data should include minority and marginalised populations, such as nighttime and gig workers, immigrants, and disabled residents. Furthermore, the discussions on building occupancy could expand beyond a focus on specific building types (e.g., residential buildings) to encompass more diverse contexts (e.g., hospitals, stations, pubs, and prisons) (Bass et al., 2022). These efforts will contribute to more accurate capturing and tracking of urban energy changes.

Another direction that warrants advancement is the focus on developing regions (Heidelberger and Rakha, 2022). Although our review indicates an increasing trend in research focusing on developing countries, UBEMs are primarily utilised in developed countries or high-density regions of developing countries. The scarcity of building- and occupant-related data in developing regions, attributed to various factors including community engagement limitations and insufficient communication infrastructure, poses significant challenges in analysing building energy demands and OB/AP in these areas. It is noteworthy that residents' activities, energy usage patterns, and occupant behaviours exhibit strong localised characteristics, which play critical roles in accurate energy simulation and effective strategy formulation. Therefore, supplementing, sharing, and standardising data from developing regions can significantly benefit urban energy research, practice, and sustainable development in these areas. Such efforts will promote regional equity from an urban energy perspective. More comprehensive and accurate data enable policymakers to formulate and implement energy policies more equitably, ensuring that minority groups and marginalised regions receive appropriate consideration (Katia et al., 2023). By incorporating these regions' specific needs into policy-making processes, social equity and inclusion can be enhanced.

2.8 Chapter Summary

This chapter presents a systematic review of how occupant-related factors are captured in existing UBEM literature published over the past two decades. The study confirms significant and growing scholarly attention to this topic. Especially, the research scope has expanded beyond building engineering to encompass interdisciplinary perspectives and implications. Our analysis reveals distinct geographical coverage of case studies: whilst the proportion of research from developing countries is increasing, the majority of cases remain concentrated in developed countries or rapidly expanding metropolitan areas in developing countries. Residential and commercial buildings dominate the research landscape, with limited discourse on other urban building typologies.

Our review categorises occupant-related variables into three primary classifications: activity patterns, building occupancy, and occupant behaviour. Existing models predominantly focus on building occupancy and direct energy-use behaviour of occupants, with a significant limitation in capturing evolving activity patterns and other occupant behaviours such as flexible working and associated lifestyle changes induced by the COVID-19 pandemic. Furthermore, this paper synthesises available occupant-related data sources into four categories: sensor-based data, energy-load data, survey data, and other emerging data sources. The study reviews representative applications of deterministic, stochastic, and agent-based approaches in modelling occupant-related variables from previous research.

Based on these analyses, four directions of future research are identified: (1) cross-system and cross-sector integration, (2) capture of emerging behavioural and activity trends, (3) occupant-oriented data integration, and (4) mitigating data bias and regional gaps in energy management. This comprehensive review provides crucial insights for both researchers and practitioners in urban energy modelling. Our findings underscore the necessity of incorporating more human factors in urban energy models. This work lays the foundation for future research that bridges the current gaps between technical modelling capabilities and the complex realities of human behaviour in urban energy systems.

Chapter 3 The Concepts of Activity-based Model

3.1 Modelling Activities under Constraints

3.1.1 Time Geography

Hägerstrand (1970) and Chapin (1974) first proposed the concept of time geography that provides an established framework for measuring and simulating how humans allocate time, as a scarce resource, among spatial activities through a bottom-up perspective. The basic assumption of time geography is that an individual's daily activity plan is subject to a limited time budget and mandatory participation in certain activities (Chapin, 1974; Hagerstrand, 1970). Therefore, individuals' activity pattern is not only driven by their desires but also governed by a set of time and space constraints (Asgari et al., 2019; Ellegård, 1999; Hägerstrand, 1989; Hägerstrand et al., 2009).

From the perspective of time geography, everyone is equal in front of time: people have the same amount of time every day (i.e., 24 hours or 1,440 minutes), and they physically exist in one and only one spatial location. The theory assumes that the passage of time has a constant speed. Since everyone must consume all available time, spatial existence of an individual can be measured by clock time, which contains three important parts: *past*, *now* and *future*. The *past* reflects what has happened, which cannot be changed but can have an impact on the *future*. The concept of *future* is the coming time, which contains many possible choices of activities, while only one will become reality when *future* becomes *past*. The concept of *now* is the moment when the *future* continuously becomes the *past*, and all individuals exist in this moment. *Now* constitutes a point in time at which an individual can take action and make changes. Clock time and indivisible individuals form the basis of time geography symbols (Ellegård, 2018).

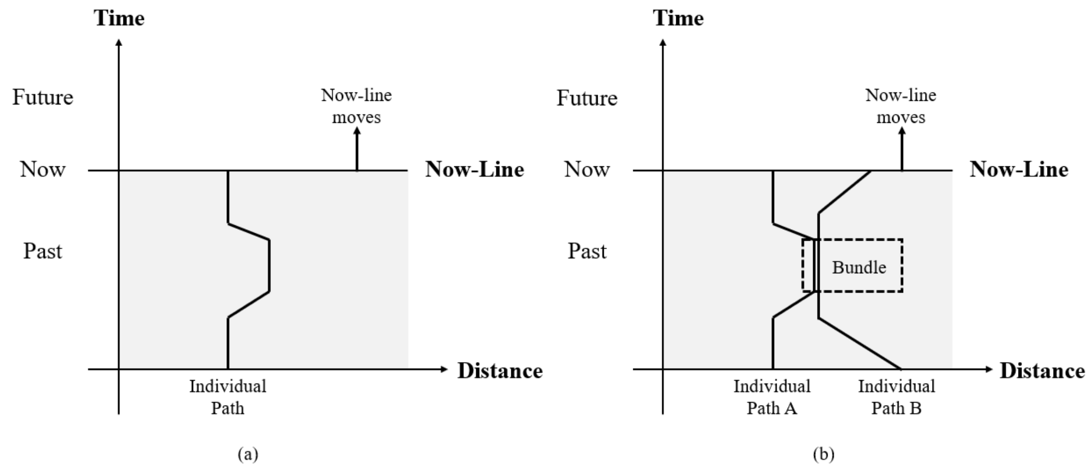


Figure 3.1 Simplified Two-Dimensional Individual Paths

(Source: author's own attribution)

In order to better explain the influence of space-time constraints on individual daily activities, time geography adopts a novel notation system, which accurately describes both the temporal and spatial processes that are difficult to explain by ordinary text-based description (Ellegård, 1999; Pred, 1984). The visual notation system is devised using the following concepts, *individual path*, *bundle of paths*, *space-time prism*, *project*, and *constraint* (Hagerstrand, 1970a; Hägerstrand, 1985). An *individual path* is a record of an individual's movement sequence in time and space (Hägerstrand et al., 2009). The individual path cannot present the individual itself, instead, it focuses on the individual's unique actions and trajectories in the *past* (Ellegård, 2018; Hägerstrand, 1985). In Figure 3.1(a), the solid line shows an individual path in a two-dimensional (i.e., time and distance) coordinate system. When the research object involves multiple individuals, their paths might appear simultaneously Figure 3.1(b). This is called a *bundle of paths* (Ellegård, 2018). Bundles are often used to illustrate collective activities.

Future contains more opportunities than the individual can realise, and the individual must choose only one path among the opportunities. The temporal and spatial scope of an individual's opportunity in the future is called a *space-time prism* (Hagerstrand, 1970a; Hägerstrand, 1989a). The space-time prism is determined by the individual's current geographic location, the maximum movable speed, and the time and space coordinates of the next determined behaviour. **错误!未找到引用源。** (a) shows a simplified space-time prism: the individual is now at location B and is scheduled to appear at location A at time A. The origin and terminal vertices point out the earliest start time and the latest end time for travel and potential out-of-home activities, which also reflects both perceived and fixed temporal thresholds (Soo, 2009). The shaded part represents all the locations where the individual has opportunities to appear between now and time A. As shown inFigure 3.2 (b), as the Now-Line advances upward, the individual path extends to position C. The time-space prism also shrinks with the extension of the individual's path, which means that there are fewer locations where the individual has opportunities to appear.

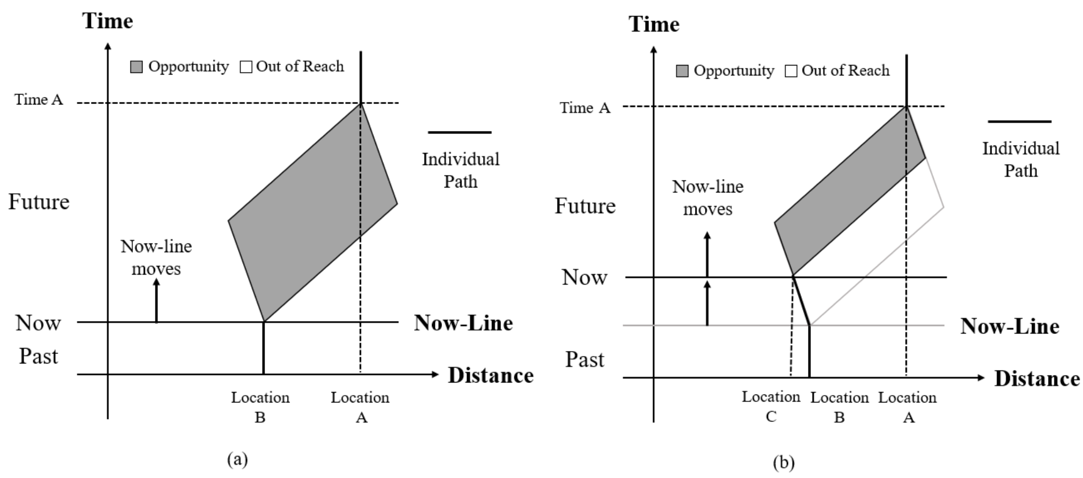


Figure 3.2 Simplified Two-Dimensional Time-Space Prism

(Source: author’s own attribution)

In time geography, *projects* reflect the activities carried out by individuals or groups to achieve a set goal. A project often contains multiple activities that contribute to achieving the set goal (Ellegård, 2018; Hagerstrand, 1970; Hägerstrand, 1985). However, many constraints exist in the process of completing these activities. According to Ellegård (2018), the concept of *constraint* is to specify the factors that confine individuals’ activity choices. Wegener and Fuerst (2004) classified the constraints into three types:

(1) *Capacity constraints*, refer to personal non-spatial restrictions on mobility, such as monetary budget, time budget, and availability of transport modes (e.g., car ownership).

(2) *Coupling constraints*, refer to “restrictions on the coupling of activities by location and time schedules of facilities and other individuals” (e.g., opening time of shops,

availability of families and colleagues).

(3) *Institutional constraints*, refer to “restrictions of access to facilities by public or private regulations such as opening hours, entrance fees or prices”.

Time geography has been widely used in activity-based urban development studies that use time-space prisms to evaluate the range of possibilities for conducting individual or organizational projects (Kwan, 1998a) or to model activity chains in time and space under various constraints (Asgari et al., 2019; Bradley et al., 2010a; F. Liao et al., 2013; Yoon et al., 2014; Yoon and Goulias, 2010). These space-time prisms can thus be regarded as accessibility measures, i.e., they measure potential areas of opportunity that can be realized under predefined constraints. The main factors that determine the space-time prism include: (1) location choice, and (2) travel choice. The location choice determines the vertex of the space-time prism. For example, the two most common locations of a full-time commuter’s daily activity frame are the home and work locations (Asgari et al., 2019; Yoon and Goulias, 2010). Both home and work locations are usually considered long-term choices and are rarely affected by short-term changes, e.g., travel conditions. The travel choice determines the travel speed, which in turn affects the boundaries of the space-time prism.

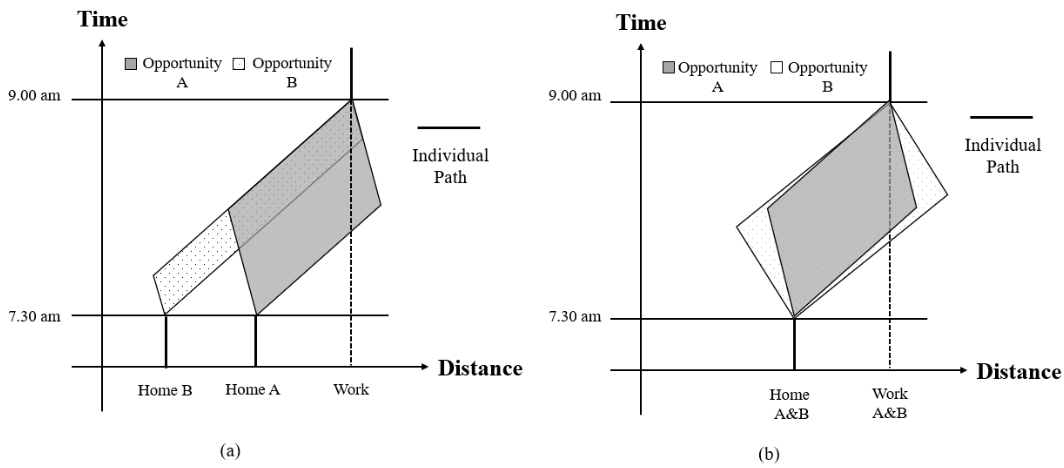


Figure 3.3 The Impacts of Location Choice (a) and Travel Choice (b)

(Source: author’s own attribution)

Figure 3.3 shows the influence of location and travel choices on the space-time prism. Figure 3.3 (a) shows that individual A whose home is closer to the work location has a larger space-time prism than individual B who lives further away from work, assuming the same travel speed between their respective home and work locations. Figure 3.3 (b) shows that individuals A and B, who have the same distance between home and work location but use different travel modes, have different space-time prisms. Individual B who uses a faster transport mode has a larger space-time prism.

3.1.2 Time and Monetary Budget

The concept of travel budget refers to an individual's average expenditure on travel, which tends to be relatively constant over time and across locations. Extensive empirical studies have confirmed the highly stable average travel time (Stopher et al., 2017; Van Wee et al., 2006; Zahavi & Talvitie, 1980) and the stability of travel monetary expenditure (TME) (Gunn, 1981; Zahavi, 1979; Zahavi & Talvitie, 1980). Both travel time budget (TTB) and monetary budget (TMB) are critical constraints in people's daily location and travel choices (Bocarejo S & Oviedo H, 2012; Smith et al., 2008). The stability of TTB and TMB, therefore, underpins the analytical validity of long-term demand forecasts in urban land use and transport planning (Anas, 2015; Metz, 2021; Schäfer, 2017). In this section, empirical evidence on the stability of TTB and TMB for travel will be discussed respectively.

3.1.2.1 Time Budget

Based on observations in the UK, Tanner (1961) first proposed the concept of a constant TTB, which was further articulated by Robinson et al. (1972). TTB refers to the amount of time allocated for travel. TTB has a strong behavioural root, which denotes that an individual would decide how much time to be allocated for travel, and subsequently maintain such time allocation plan, which in turn may entail certain schedule adjustments. For example, the observed time trade-off between working and non-commuting activities reflects the propensity of TTB planning. For modelling purposes, however, the full range of TTB is often difficult to measure empirically (Ahmed and Stopher, 2014). Thus, academia often employs the measurable daily or annual travel time expenditure (TTE) to infer the TTB of travellers in practice.

In the past 60 years, the research community has contributed a large number of empirical observations and discussions on the stability of TTE. Figure 3.4 summarises the empirical statistics in 19 city-scale and 10 country-scale travel surveys between 1955 to 2019 (source of data see). The results show the stability of the TTE over a wide range of time, income levels, and geographical and cultural settings. Although some studies found that TTE might slightly fluctuate with (1) socio-economic factors, (2) daily activity bundle, and (3) urban built environment (Asgari et al., 2019; Banerjee et al., 2007; Giuliano & Dargay, 2006; Van Wee et al., 2006), the stability of daily TTE has been well documented in literature, which is approximately 65 minutes hour per day (the red line in Figure 3.4).

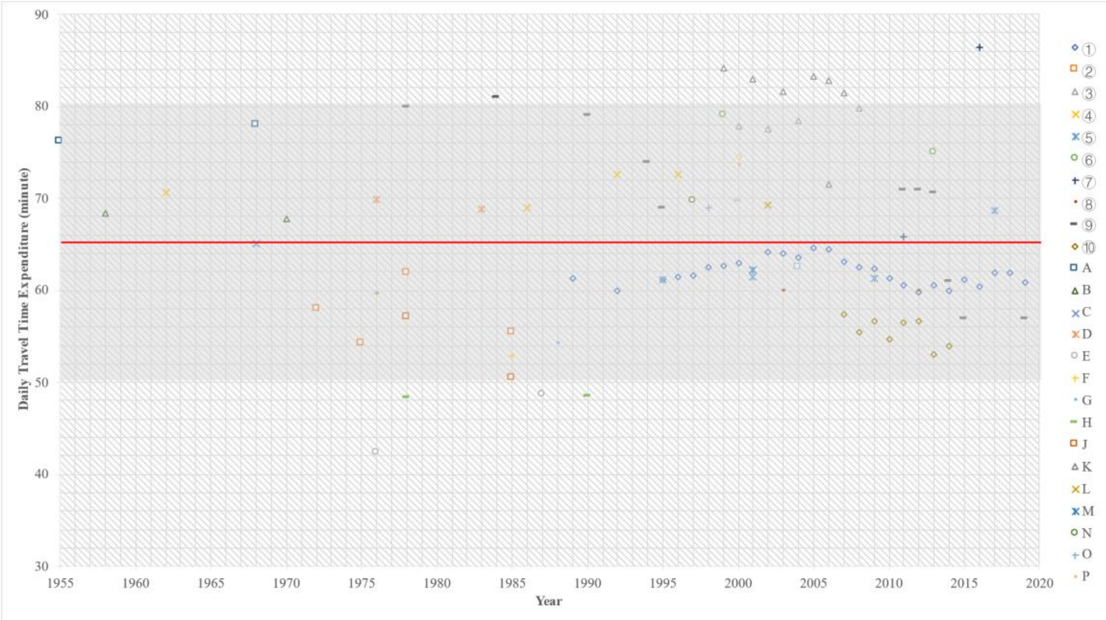


Figure 3.4 Daily travel time data from 10 countries/areas and 19 cities

(see data sources and notes in Table 3.1)

Table 3.1 Sources of Empirical Travel Time Data

Data Codename	Country/City	Year of Survey	Source of Data	Remark
Nation-Scale Observations				
①	England (UK)	1989 -2019	UK National Travel Survey (UK Department of Transport, 2020)	Short walks in 2002 and 2003 and short trips in 2007 and 2008 were underestimated. Data from 1995 onwards has been weighted, causing a one-off uplift in travel time between 1992/1994 and 1995/1997.
②	UK	1972/73 1975/76 1978/79 1985/86	UK National Travel Survey (UK Department of Transport, 2020)	

③	Germany	1999-2019	German Mobility Panel (KIT, 2020)	
④	The Netherlands	1962 1982/1986 1989/1992 1994/1996	(Hupkes, 1982; Schafer, 2011)	
⑤	US	1995 2001 2009 2017	US National Household Travel Survey (Hu & Reuscher, 2004; Hu & Young, 1999; U.S. Department of Transportation, 2011, 2018)	Only consider vehicle travel
⑥	Belgium	2013	Belgium National Time Use Survey (STATBEL, 2015)	
⑦	Finland	2016	(Official Statistics of Finland, 2018)	
⑧	Hong Kong (China)	2013	Thematic Household Survey （HK Census and Statistics Department, 2015)	
⑨	Sweden	2011 2011/12 2012/13 2014/15 2015/16	The Swedish National Travel survey (Official Statistics of Sweden, 2020)	
⑩	Denmark	2007-2014	Danish National Travel Survey (Department of Transport, 2015)	
City-Scale Observations				
A	Washington D.C.	1955/1968	(Zahavi & Ryan, 1978)	US
B	Twin Cities	1958/1970	(Zahavi & Ryan, 1978)	US
C	Amsterdam Oud-Zuid	1965	(Vidakavic, 1968)	The Netherlands
D	Paris	1976/1983		
E	Lille	1976/1987		
F	Lyon	1976/1985		
G	Marseille	1976/1988	(Bieber et al., 1994)	France
H	Bordeaux	1978/1990		
I	Toulouse	1977/1990		
J	Grenoble	1978/1985		
K	Australian Cities	2008-2016	(Stopher et al., 2017; Stopher & Zhang, 2011)	Australia
L	Lyon	2006	(Raux et al., 2011)	France
M	Grenoble	2002		

N	Rennes	2001	
O	Strasbourg	1997	
P	Brussels	1998-1999	Belgium
Q	Geneva	2000	
R	Bern	2000	Switzerland
S	Zurich	2000	

3.1.2.2 Monetary Budget

TMB refers to the ratio of monetary expenditure on travel to total household expenditure. Transport has been the third largest household expenditure category (following housing and food) according to the UK household expenditure survey series (ONS, 2020). TMB is another important constraint for people's travel choices.

There has been extensive evidence illustrating the stability of monetary expenditure on transport in different regions (Gunn, 1981; Schafer, 2000; Schafer & Victor, 2000; Zahavi & Talvitie, 1980). For example, Schafer (2000) compared the average TME of 26 countries from different years and concluded that they fluctuate around 10%. Schafer & Victor (2000) further found that, despite the rising oil prices during the two oil crises and following economic fluctuations, there were no significant TME fluctuations in American households. Also, the UK household expenditure survey data (ONS, 2020) (see Figure 3.5) show that the percentage of transport and housing expenditure combined is relatively stable (27% to 29%) over time.

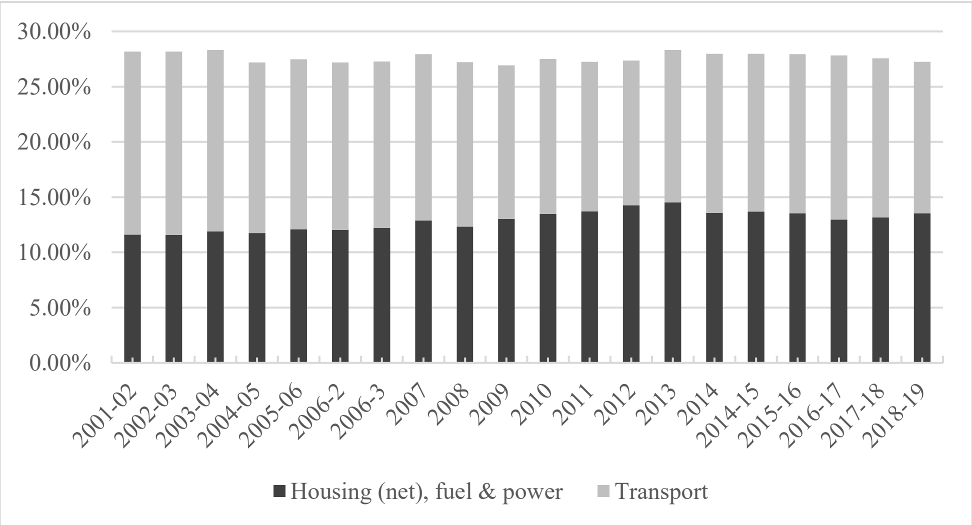


Figure 3.5 Share of Transport and Housing Expenditure in UK by Year

(Source of Data: UK Household Expenditure Survey (ONS, 2020))

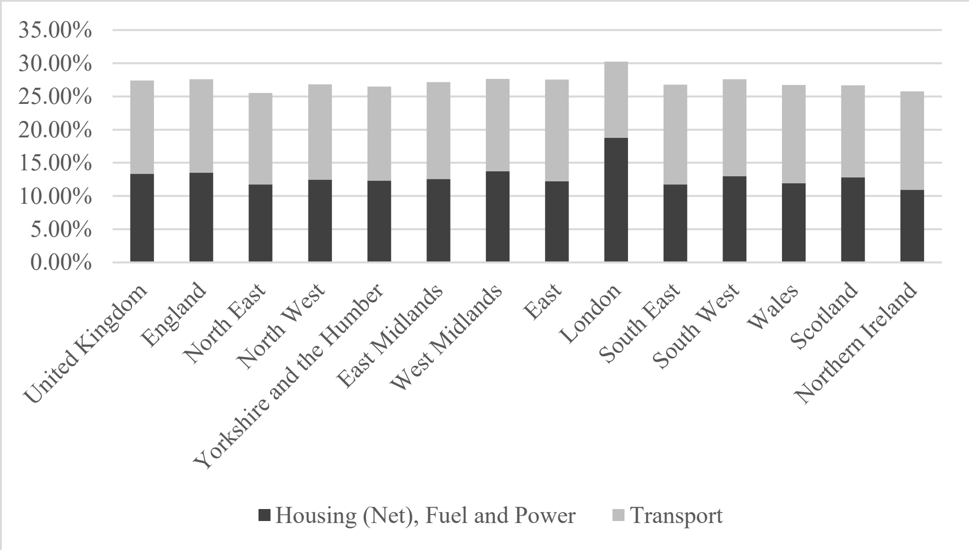


Figure 3.6 Share of Transport and Housing Expenditure in UK by Region

(Source of Data: UK Household Expenditure Survey[3] (ONS, 2020))

The regularity around TTE and TME has important policy implications for urban energy modelling. First, the stability over time and across locations demonstrates that people do not necessarily minimise their time and monetary expenditure on travel; instead, they maximise their activity needs and opportunities that can be achieved within their travel budget constraints (Wegener and Furst, 2004). Second, such longer-term regularity provides the empirical base needed for scoping the range of possibilities in terms of future demand for transport and building floorspace in post-pandemic cities, and the associated energy usage and carbon emissions. In light of the great uncertainties ahead, an analytical approach that is rooted in behavioural mechanisms of long-term stability would support informed policymaking. Third, it would be premature to assume that the budget constraints around travel would remain unchanged in post-pandemic cities. Nonetheless, by considering the possible changes of those constraints as *scenarios* (e.g., reduced or increased daily TTB), as opposed to modelling those constraints as *predictions*, established urban models could still be useful tools for quantifying the wider impact of alternative policy interventions thus supporting effective and sustainable recovery. However, to fulfil this task, existing urban models may need to explicitly incorporate such constraints in location/travel choice modelling,

[3] Employed the dataset *Family Spending Workbook 1: Detailed Expenditure and Trends* released by the Office for National Statistics (ONS) of UK

which may give rise to new model design and calibration-validation strategies.

3.1.3 Modelling Travel Behaviours and Carbon Emissions

Urban residents' travel behaviour significantly impacts the energy demand of the passenger transport sector and the associated greenhouse gas emissions. Within this context, urban transport models not only provide an analytical framework for understanding transport activities but also possess the potential to predict the environmental impacts of passenger transport systems (Hickman and Banister, 2019). These models adopt a spatial perspective, conceptualising travel demand as originating from the activity demands of various locations. These activity demands are interconnected through travel distances, residents' travel durations, and the speeds of various transport modes (e.g. cycling, cars, bus, and trains), collectively forming a foundational framework for examining energy consumption and carbon emissions in transport systems.

One critical factor is travel duration, which refers to the total time individuals spend on commuting and other activities (e.g. leisure). Travel duration directly influences energy demand and greenhouse gas emissions in the transport system. As noted by Hickman et al. (2013) and Hickman and Banister (2017), longer travel durations are often associated with increased energy consumption and higher carbon emissions. Consequently, reducing travel times or optimising their allocation emerges as a key strategy for enhancing energy efficiency in transport systems. Moreover, travel mode choice represents an important lever in managing urban transport energy demands. Different transport modes exhibit distinct energy consumption profiles and speeds. For instance, public transport, cycling, and electric vehicles hold substantial potential for reducing carbon emissions (Ercan et al., 2022; Hansan et al. 2019).

Changes in residents' activity patterns also have the potential to transform transportation energy dynamics. A direct example is the energy influence of COVID-19-induced travel behaviour change (Chapman et al., 2025; Schaefer et al. 2021). Also, flexible and remote working patterns could have complex influence on transport activities, profoundly influencing travel durations and mode choices. Zhang and Zhang (2021) report that these post-COVID-19 new working patterns could reduce peak-hour travel demand by 11%. This shift not only alters individual travel behaviours but also challenges conventional urban transport models (Chapman et al. 2025), creating new opportunities for improving energy efficiency. The interplay of technological advancements, evolving workplace cultures, and sustainable mobility strategies has emerged as a focal point for research on transport energy consumption.

3.2 Trip-Based Approach

There are two commonly adopted location/travel demand modelling approaches: the trip-based approach and the activity-based approach. The trip-based models (i.e., the four-step method, FSM), deal with each trip independently and employ a single trip as the fundamental measuring unit of analysis. The activity-based approach, however, treats travel as a derived, interconnected demand from activity participation (Bhat and Koppelman, 1999). The tour-based analysis is a core element in activity-based models (Hasnine and Habib, 2021). A *tour* refers to a trip chain containing a series of trips that start from and return to a specific location (commonly home). Figure 3.7 illustrates a typical tour with four trips (i.e., trip 1 to trip 4) that starts from and ends at Point A (home). This section focuses on the trip-based approach, which was the mainstream in urban modelling prior to the rise of ABA.

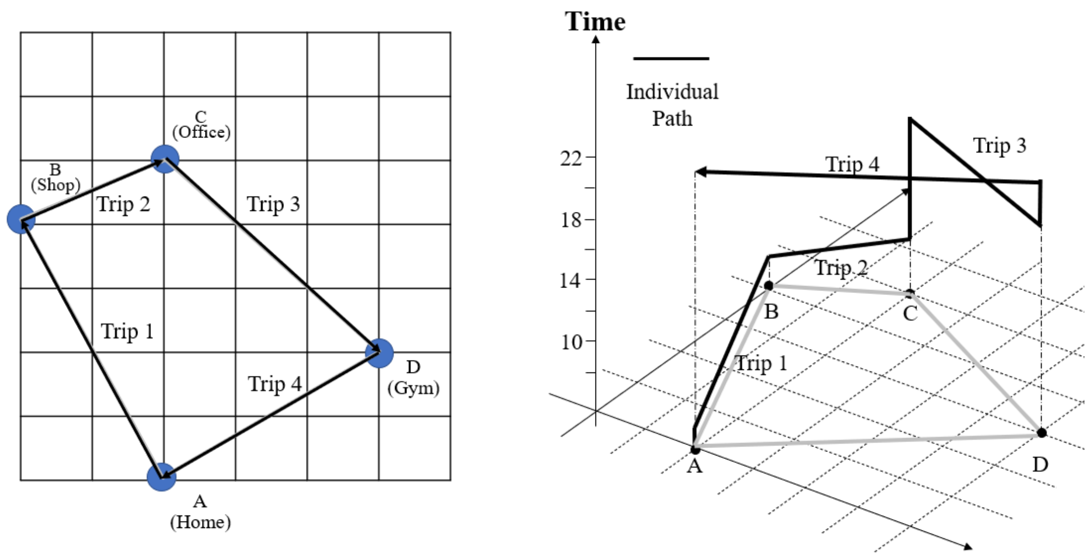


Figure 3.7 An Illustration of a Tour with Four Trips

(Source: author’s own attribution)

Transport planning through the use of trip distribution models started in North America (see Mitchell and Rapkin, 1954) and gained momentum in the 1960s. This process promoted novel urban modelling methods. In 1962, the *Chicago Area Transportation*

Study (CATS) first applied a novel trip-based modelling approach to predict urban transport demand. The extension of the CATS model (i.e., the FSM) has been the most widely used urban transport modelling method (Levin et al., 2019; J. G. McNally, 2007). This section first reviews FSM's theoretical structure, and then discusses its extensions and limitations.

3.2.1 Theoretical Structure

The four-step modelling process (see Figure 3.8) in FSM is as follows.

(1) *Trip Generation*. Trip generation determines the frequency of origins or destination of trips in each Traffic Analysis Zone (TAZ) by trip purpose, as a function of land use, household demographics and other factors.

(2) *Trip Distribution*. Trip distribution matches origins with destinations and required travel impedance (including time and/or money).

(3) *Mode Choice*. The step computes the proportion of trips between each origin and destination that use a particular transport mode.

(4) *Route Allocation*. The step allocates trips between an origin and destination by a particular mode to a route.

In terms of the modelling approach, according to McNally (2007, pp.38-39), FSMs tend to divide the study area into several TAZs and often employ TAZ as the spatial analysis unit. FSM uses external stations to simplify the interaction between the study area and the external area (including travel in, out and through the study area). In this process, growth factor models are commonly used to predict external flows. The internal activity system is usually represented by socio-economic and land use data. A network graph composed of nodes and links represents the transport system. Link is a one-way homogenous segment of a transport facility or service, which often exhibits related attributes such as length, speed, and capacity. Node is the link's endpoint, which often means the change of link attributes.

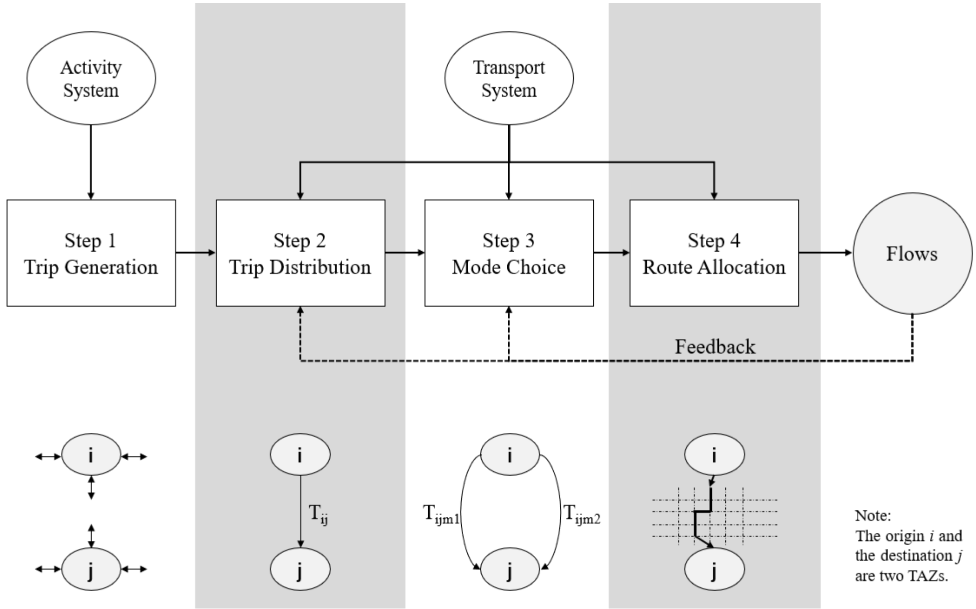


Figure 3.8 Four-Step Modelling Approach

(Source: author's own attribution, but adapted from McNally, 2007, pp.38)

There are three common approaches for modelling location and the associated travel choices: (1) spatial interaction approach, (2) utility-based approach, and (3) micro-simulation. The early-stage studies generally ground in traditional spatial interaction models, such as the gravity model[4] (Hansen, 1959; Lowry, 1964) and the entropy maximising theory[5] (Murchland, 1966; Wilson, 1969, 1970). The basic assumption of spatial interaction models is that flows are a function of (1) the attributes of the origin locations, (2) the attributes of the destination location, and (3) the friction of distance between the concerning origins and destinations. The general formulation of spatial interaction models represents the interaction between location i (origin) and j (destination) in the formula 3-1:

$$T_{ij} = f\left(V_i, W_j, S_{ij}\right) \qquad (3-1)$$

[4] The gravity model provides an analogy with Newton's law of universal gravitation. The model assumes that flows are proportional to the mass (e.g., GDP or number of activity) at originals and destinations, and inversely proportional to the friction (e.g., distance) between those locations (Hansen, 1959; O'Kelly et al., 2012).

[5] Entropy refers to the degree of disorder in a system. In the context of urban land use and transport system, the theory suggests that individual choices' probability distribution should satisfy the maximising entropy resulting from the relative location of workers, job and housing (Wilson, 1969, 1971). The spatial interaction model under Wilson's paradigm has been a realistic basis for predicting choices with known destination constraints (Ibeas et al., 2013).

where T_{ij} refers to the interaction between location i (origin) and location j (destination), V_i refers to attributes of origin i, W_j refers to attributes of destination j, and S_{ij} Measures the distance decay between i and j.

These spatial interaction models simulate aggregated trip flow based on zone-pair attributes. The gravity models, in particular, are highly operational and present the advantage of modest data requirements. Howsoever, several simplifying assumptions, such as mono-centricity, in these models, make it difficult to represent urban spatial heterogeneity and important urban market dynamics (Bhat, 2015).

The economic utility-based approach has become the mainstream for individual choice modelling. Those utility-based models draw on the random utility theory (RUT) and discrete choice model (McFadden, 1973). To capture the complex choice at the individual level, RUT models individual choice between alternatives as a function of the attributes of the alternatives and the decision-makers. The utility-based approach economic utility of choosing certain location/travel alternative using a bundle of deterministic attributes (i.e., observable parts) and a random component (i.e., unobserved parts). The RUT suggests that the utility that individual f choosing alternative i in the choice C_f can be represented in the following function:

$$U_{if} = V_{if} + e_{if} \tag{3-2}$$

where V_{if} refers to the observable part of utility and e_{if} refers to the unobserved part.

The probability that decision-maker f chooses the alternative travel mode or location i from choice set C_f can be represented in the following function:

$$P(i|C_f) = P[U_{if} \geq U_{if} \forall_j \in C_f] = P\left[U_{if} = \max_{j \in C_f} U_{jf}\right] \tag{3-3}$$

In practice, utility-based models often employ logit models for travel demand analysis. The logit models family assumes that the random utility is distributed as the extreme value distribution, such as Gumbel distribution (Gumbel, 1958). The multinomial logit (MNL) model and the nested logit (NL) model are the most prevailing ones for travel demand analysis (Ben-Akiva & Lerman, 2018).

The application of micro-simulation approaches in urban studies promotes disaggregate stochastic methods, such as cellular automata and agent-based modelling (ABM) (Acheampong & Silva, 2015). Those approaches employ a bottom-up approach: modelling the aggregate changes as the sum of the actions and interactions of disaggregate agent behavioural units. These approaches derive strength from their dynamic nature and temporal dimension. Due to limited individual behavioural data, early micro-simulation approaches often formulate behavioural rules based on subjective experience to achieve a higher degree of fit with reality under fixed boundary conditions. However, the stochastic and dynamic nature of the models and the lack of price-based assessments make such models difficult to quantify the long-term socio-economic impact of transformative changes, where the stability of individual-level behavioural rules tends to be in question.

3.2.2 Limitations of Trip-Based Models

With the improvement of data quality, the research community has been exploring more fine-grained transport modelling approaches. Limitations of the trip-based approach have been discussed extensively in existing literature (Davidson et al., 2007a; Hasnine & Habib, 2020, 2021; Kitamura, 1988; Rasouli & Timmermans, 2014a; Vovsha & Bradley, 2006). Two major limitations are summarised below:

(1) Conventional four-step models often assume exogenous trip rates (Rasouli & Timmermans, 2014a), which could render unrealistic, particularly when new development trends (e.g., transformative land-use or behavioural changes) are expected in post-pandemic cities.

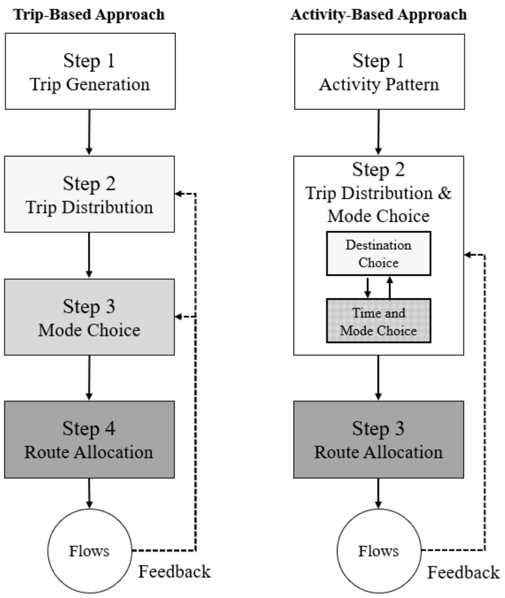
(2) The trip-based approach tends to assume the independence of each trip in location and travel mode choice modelling. For example, the mode choice for a commuting trip is independent of the possible off-work demand for leisure activities. This seems contradict to the real-world experience, where substitutions among trip purposes/modes and trip chaining are prevalent (Wan et al., 2021). Understanding the increasing interdependences among trips and between travel and non-travel activities in relation to spatial-temporal constraints is critical for capturing the possible travel behavioural changes and the associated energy demand.

3.3 Activity-Based Models

Since the 1960s, many researchers have argued that trip-based models ignored individual activity scheduling and trip-chains (Chapin, 1968, 1971; Jones et al., 1983). After Hägerstrand (1970) put forward the concept of time geography, the academia paid more attention to individual activity motivation in urban travel demand models

(Cullenand and Godson, 1975; Jones et al., 1983; Kitamura, 1988). In this context, the activity-based approach (ABA) for transport modelling emerged and has gained momentum since the 1990s (Axhausen and Gärling, 1992; Ben-Akiva & Bowman, 1998; Bowman & Ben-Akiva, 2001; Davidson et al.,2007; Dong et al., 2006).

The premise of ABA is that travel demands are derived from individuals' needs and desires of participating in activities. Some activities may occur at home, but others may occur out of their homes, which in turn generates the travel demand between home and activity locations. In addition to individual needs and desires, ABA also considers how complex activity sequences, interpersonal dynamics, and spatio-temporal constraints affect people's decision-making on their activity scheduling, location choices and trip-chaining (Castiglione et al., 2015).



Sub-Model Task	Comparison
What kind of activity	ABA considers interrelations and trade-offs across tours and trips
Where to go	ABA generates the trip-chain (tour) linking non-home-based and home-based trips.
What travel mode	ABA can control consistency of mode choices across dependent trips.
When to go	ABA can control consistency of time choices across tours and trips, while FSMs usually consider the peak vs non-peak difference only.
What route	ABA and FSM share similar route allocation (assignment) methods.

Figure 3.9 Comparing Steps in FSM and ABA

(Source: *author's own attribution*)

Based on the works of Castiglione et al. (2015), Davidson et al. (2007), and Hasnine and Habib (2020), this study compares the typical workflow in FSM and ABA, respectively, in Figure 3.9.

The trip-based approach and activity-based approach have some similarities, e.g., both models would identify trip origins and destinations and determine travel modes and routes. Unlike FSM, which relies on aggregate and often exogenous trip rates, ABA generates activities and hence travel demand endogenously by simulating daily or multi-day activity patterns (Davidson et al., 2007; Dong et al., 2006; McNally, 2007; McNally et al., 2000). The choice modelling in ABA models tends to imitate real-world activity decision-making processes by considering a host of activity demands in terms of types, frequency and sequence. To model locational/travel choices, both models can follow a utility-based approach (Bhat et al., 2004, 2016; Bowman and Ben-Akiva, 2001; Davidson et al., 2007; Liu et al., 2021), while ABA models often feature the modelling of trade-offs at various choice levels subject to explicit financial, spatial-temporal constraints hence a time geography perspective (see Section 2.2.1). For trip distribution, FSMs primarily focus on home-based trips, whereas non-home-based trips, if incorporated, are often modelled as a derivative of home-based commuting trips. By contrast, ABA can consider the chaining and sequence of trips of different purposes/origins. Finally, these two approaches share similar trip assignment methods (see a review of Rasouli and Timmermans, 2013).

Since the 1980s, the evolution of activity-based approaches has significantly enriched transport modelling by incorporating diverse theoretical and disciplinary perspectives. Following Arentze and Timmermans (2000), activity-based urban models can be categorised into four distinct types based on their theoretical underpinnings: utility-maximising models (in Section 3.3.1), single facet models (in Section 3.3.2), constraint-based models (in Section 3.3.3), and rule-based models (in Section 3.3.4). The ensuing discussion will delve into the unique characteristics of each model type, discuss representative models and their applications.

3.3.1 Utility-Maximising Models

The utility-maximising models are one of the two primary categories of activity-based models that represent the decision-making process of individuals when determining how to allocate their time, engage in activities, and select their travel patterns (Bhat et al., 2004b). Utility-maximising models assume that individuals choose their activity patterns by maximizing their perceived utility subject to constraints. These models measure the utility of different feasible alternatives, and then select the option that provides the highest utility. Constraints also exist in these models, which serve as boundaries within which utility maximization occurs. The microeconomic foundation and the interface with other spatial economic models are distinctive advantages of utility-maximising models. Examples of utility-maximising models include the CUSTOM (Habib, 2018), DaySim (Bowman et al., 2006), the CEMDAP (Bhat et al., 2004b) and the STARCHILD (Recker and Kitamura, 1985).

The STARCHILD (Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions) (Recker and Kitamura, 1985) is a representative utility maximising model (Recker et al., 1985). The model views travel as an output of a more basic process involving activity decisions and assumes that travel decisions are driven by the collection of activities that form an agenda for participation. The model considers travel behaviours as part of the temporal constraint for scheduling activities. Hafeizi et al. (2021) summarised the three-step, activity generation process in STARCHILD. In the first step, the model identifies all possible participation activities, subject to all constraints. In the second step, these choices are clustered into three to ten groups. In the third step, representative activity patterns are established for each group, and the model employs a multinomial logistic (MNL) model based on the utility function of different activity patterns and identifies the final activity choices.

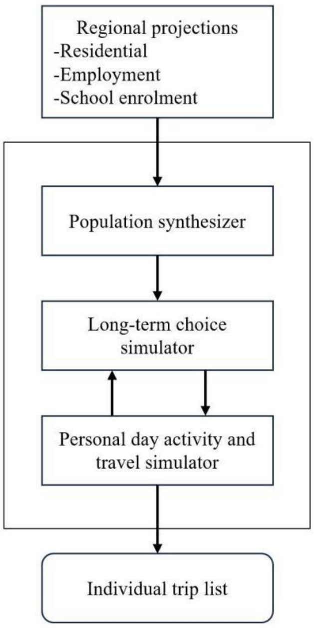


Figure 3.10 The system structure of DaySIM

(adopted from Bowman et al., 2006)

DaySIM (Day Activity Schedule Simulator) (Bowman et al., 2006) represents another important utility-maximising activity-based model (see Figure 3.10 for the model structure). DaySIM employs a day pattern approach that simulates complete daily activity patterns for individuals and households. It uses a hierarchical structure of models developed by Bowman and Ben-Akiva (2001) that work together to create realistic daily schedules. The system operates at four integrated levels: longer-term person and household choices, single day-long activity pattern choices, tour-level choices, and trip-level choices. At the highest level, it models long-term choices such as usual workplace location. At the intermediate level, it handles day-level decisions like which activities to pursue. At the detailed level, it determines specific timing, locations, and travel modes for each activity.

The advent of new data sources, such as sensor-based time use data and transit card data, coupled with the rapid advancement of discrete choice models, has paved the way for the development of increasingly sophisticated utility-maximising models. Over the past decade, these utility-maximising models have found numerous significant applications in urban research. For example, a recent utility-maximising model has addressed the challenge of modelling multi-day activity-travel demand by formulating a novel multivariate multiple discrete-continuous probit (MDCP) model system (Astroza et al., 2018). This comprehensive framework integrates two MDCP model components, one pertaining to weekday time allocation and the other to weekend activity-time allocation.

3.3.2 Single Facet Models

Many models focus on a single dimension of activity patterns of urban residents, such as activity frequency, activity timing, activity duration, or location choice, and do not strictly follow a tour-based structure. Depending on the input data (e.g. activity diary/time use data and other novel sources such as mobile phone signal data), single-facet models often adopt *ad hoc* model structures. The findings of these studies can be integrated with existing activity-based models.

Several papers in urban and transport research have examined various aspects of time allocation and activity engagement. For instance, Mesaric et al. (2022) explored the changes in transport activities and mode choices during COVID-19. Joubert and Waal (2020) employed Bayesian networks for activity demand generation and transport estimation. Yang et al. (2014) used mixed logit to investigate how context-dependent adjustments in activity-travel patterns affect energy consumption. Sharmeen et al. (2014) employed data collected in the Netherlands to investigate activity and travel demand and the dependency on life cycle and social network dynamics. Yang and Timmermans

(2013) used a multi-group simultaneous equations model and seemly unrelated regression (SUR) to explore the impact of fuel price fluctuations on people's activity-travel time expenditure. In addition, there are studies that employ structural equation models (SEM) to address complex causal relationships among socio-demographics, activity time use, and travel patterns (Cheng et al., 2019; Manoj & Verma, 2017).

3.3.3 Constraint-Based Models

In addition to single-facet models, the research community has also developed activity-based models that encompass multiple dimensions of activity patterns simultaneously and capture the interdependencies between these dimensions, for instance, the dependence of activity location and time on travel mode (McNally & Rindt, 2007). Early models of such are typically constraint-based, following the concept of time geography.

Constraint-based models are usually based on the feasibility assessment of specific activity patterns within particular time-space environments, also called behavioural paradigms or activity programs. The time-space environment is defined in terms of locations, attributes, available modes of transport network, and mode-specific travel times between locations. Capacity constraints, coupling constraints, and institutional constraintscan all affect the time-space environment (Wegener and Fuerst, 2004). For example, the opening hours of specific venues and transport services are typical constraints in these models. To test for the feasibility of possible activity sequences, combinatorial algorithms are often used. Arentze and Timmermans (2000) proposed a three-step process: (1) checking whether the interval between the end time of the previous activity and the start time of the next activity is sufficient to perform the activity of interest plus the associated travel time, (2) testing whether the activity falls in the time window of service provision, and (3) verifying that further conditions regarding the sequence of activities are not violated.

One classic and widely used constraint-based model is the Combinatorial Algorithm for Rescheduling Lists and Activities (CARLA), developed by (Jones et al., 1983c). CARLA is a computer model that explicitly represents the temporal constraints and linkages that influence the activity and derived travel patterns of an individual within a certain time period. The model employs a four-rule framework to generate activities and add them to individual schedules, including (1) logical rules that refer to the presumption of one unique activity at a time at one location, (2) environmental rules that refer to authority constraints such as access time restrictions to different places and travel times between locations, (3) inter-personal rules that refer to coupling constraints, and (4) personal rules that reflect personal preferences and individual heterogeneity (Lenntorp, 1976; Huigen, 1986). Also, CARLA employs two principles to optimise the activity pattern generation process: first, generating alternative activities in an ordered manner to avoid infeasible activity and travel patterns; and second, scheduling the activities with heuristic rules to reduce the total number of alternatives to be examined.

A number of models have been developed based on early constraint-based models such as PESASP (Lenntorp, 1976) and BSP (Huigen, 1986). It should be noted that Huigen (1986)'s BSP advanced the constraint-based models by considering the situation that adopting different travel modes to conduct different trips in the same activity chain. Building upon the PESASP model, Dijst (1995) and Dijst and Vidakovic (1997) developed the Model of Action Spaces in Time Intervals and Clusters (MASTIC). A distinct feature of MASTIC is to capture the role of lifestyles in influencing activity patterns (Hagerstrand, 1970b), which is inspired by studies on the heterogeneity of individual activity patterns (Kutter, 1981; Kwan, 1998b, 1999). The core concept of the model is the 'potential action space', denoting all action places that an individual can visit within a certain period of time. This space is located around one or two bases of personal relevance, referring to fixed place(s) where an individual spends a significant and regular amount of time, such as the home and workplace. Individuals typically leave these bases for only a limited amount of time, known as time windows, to engage in compulsory activities such as paid work. Events during the time windows may include visit(s) to accessible non-base locations, which then generate trip(s). Therefore, a journey is constrained by the time window from the temporal dimension, and by the potential action space from the spatial dimension (van Eck et al., 2005).

A potential action space is determined by four constraints: the distance between bases, the available time window, the travel time ratio, and the speed of the mode of transport. Van Eck et al. (2005) summarised three types of potential action space: circular, linear, and elliptic space. Figure 3.11 illustrates the differences between these three types (adopted from Van Eck et al. (2005)).

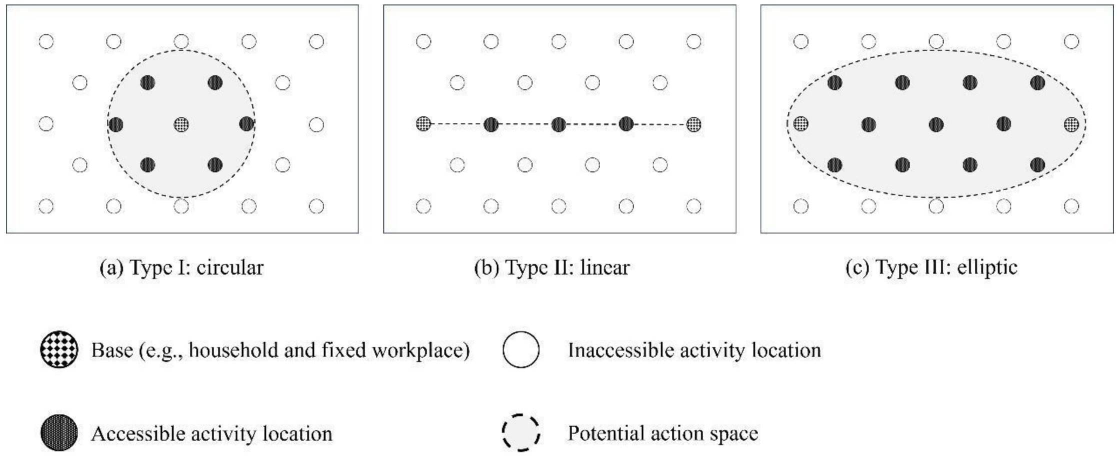


Figure 3.11 Three Types of Potential Action Space in the MASTIC

(Source: adopted from Van Eck et al. (2005))

3.3.4 Rule-Based Models

Rule-based models represent an alternative approach to utility maximisation and has been applied widely in activity-based transport models (Arentze and Timmermans, 2000; Timmermans and Arentze, 2011). These models operate on the principle that human decision-making in daily activity scheduling follows certain rules and heuristics, rather than purely utility-maximizing behaviour. The rule-based approach attempts to capture the cognitive processes people use when making activity and travel decisions, incorporating both constraints and preferences through a series of if-then rules and decision trees. This section reviews two models (ALBATROSS, FEATHERS) as distinguished examples of rule-based models.

ALBATROSS (A Learning-Based Transportation Oriented Simulation System), stands as one of the pioneering rule-based models, developed by Harry Timmermans, Theo Arentze and their colleagues (Arentze and Timmermans, 2000). Its primary strength lies in its ability to learn scheduling rules from observed activity-travel patterns using decision tree induction methods. The model considers various scheduling decisions sequentially, including activity selection, timing, duration, location, and transport mode choice. ALBATROSS's innovative feature is its capacity to capture complex interactions between different choice facets and adapt its rules based on empirical data, making it particularly effective in representing how people make activity-travel decisions in real-world contexts. Figure 3.12 illustrates the model architecture of ALBATROSS (adopted from Arentze and Timmermans, 2000).

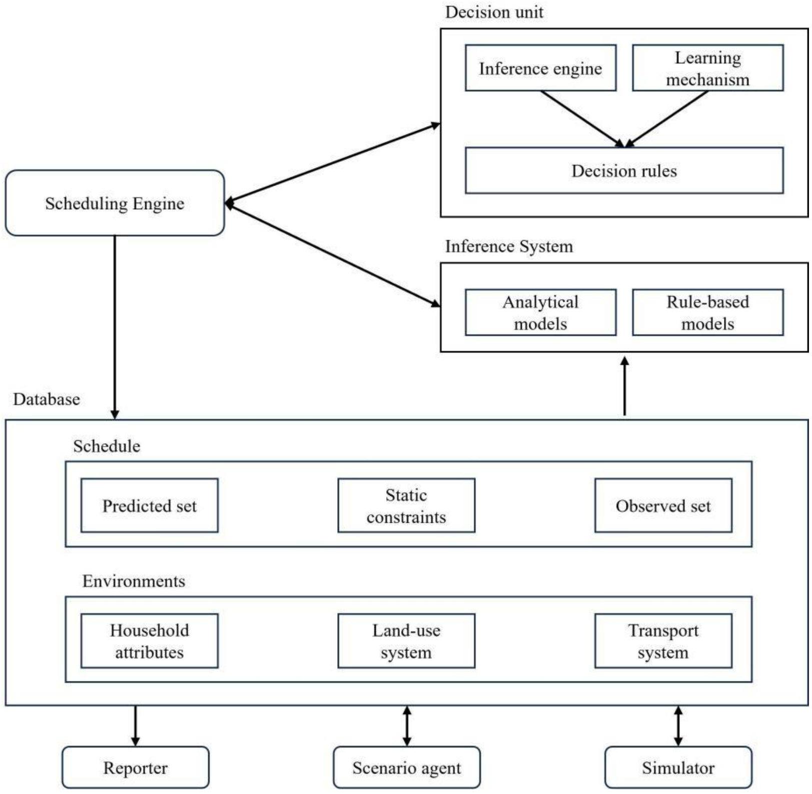


Figure 3.12 The system architecture of the ALBATROSS

(Source: adapted from Arentze and Timmermans, 2000)

The model is composed of three integral components: (1) a sequential decision-making process; (2) dynamically updated constraints on available choice options; and (3) a set of decision trees, serving as representations of individuals' decision-making behaviour at each step within the process model. ALBATROSS operates based on the premise of a predefined sequence of choice facets, established through a prioritised ranking of activities by their types and attributes. Drawing upon considerations such as travel companions, activity types, activity instances, activity sequencing, schedules, durations, and relevant details, ALBATROSS generates activity definitions. Its scheduling process model mirrors the way individuals shape their preferences and sequentially arrange them during the scheduling of activities. Thus, the model identifies choice options by considering dynamic constraints and devises a method to generate decision trees from data, along with establishing a rule for deducing decisions from the inferred trees.

Another example of the rule-based model is FEATHERS (Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS) (Bellemans et al., 2010). FEATHERS, building upon ALBATROSS's framework, extends the rule-based approach by incorporating evolutionary algorithms and enhanced environmental impact assessment capabilities. One of FEATHERS' key strengths is its ability to model the dynamic adaptation of activity-travel patterns in response to changing circumstances, such as policy interventions or environmental conditions. The model excels in simulating how individuals learn and adjust their behaviour over time, making it particularly valuable for assessing the long-term impacts of transportation policies and environmental measures. FEATHERS has been applied in many urban management scenarios (Bao et al., 2015) and in several regions and countries (Lee et al., 2012). For example, in Belgium, FEATHERS has been applied to investigate the potential impact of light rail initiatives on travel demand at a local network in Flanders (Bao et al., 2018).

3.4 Land Use and Transport Interaction (LUTI) Model

Hansen (1959) first reported the role of accessibility in urban land use and promoted the recognition that land use and transport markets interact with each other in urban development process. Urban spatial development (i.e., land uses) generates human activities that determine spatial interaction (i.e., transport) demands. Also, the transport system provides accessibility (reflected in travel time, cost, and distance) that so results in a change in urban spatial development (Wegener, 2004). Lowry (1964) first represented these interactions in an operational model (i.e., the *Model of Metropolis*), which gives rise to a variety of LUTI models, such as the MEPLAN model family (Echenique et al., 1969, 1990, 2013). In terms of the relationship between LUTI models and the transport models, the LUTI models feature replacing the trip generation module in four-step models with a land-use module. The land-use module simulates travel demand in relation to land-use changes, hence conforming to the generic LUTI framework. However, not all LUTI models are trip-based and there are a number of agent-/activity-based models adopting the LUTI framework. Figure 3.13 illustrates the theoretical structure of LUTI model.

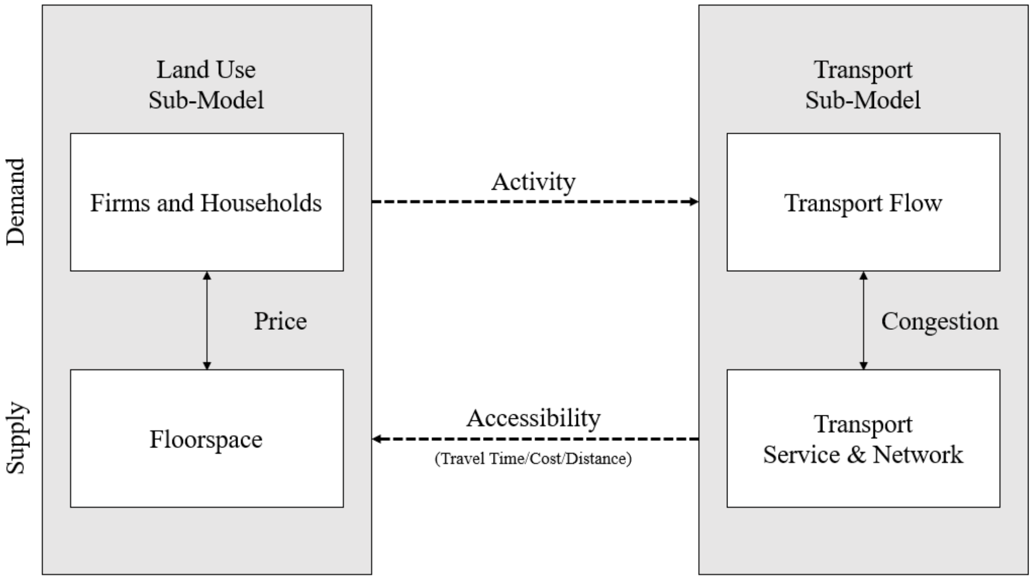


Figure 3.13 The Theoretical Structure of LUTI Model

Early LUTI models, such as Lowry's Model of Metropolis (Lowry, 1964), tend to be static (i.e. no explicit temporal scale in the model) and adopt spatial interaction models for simulating location choices. Lowry's model provides the conceptual framework of LUTI models, including the DRAM/EMPAL ITLUP model[6] (Putman, 1983, 1991, 1995) and the Grain-Lowry model (Garin, 1966), the LILT[7] model (Mackett, 1983, 1990, 1991) and the MEPLAN model (Echenique et al., 1969). In the past decades, the Lowry-type LUTI models have been advancing by absorbing novel theories, such as RUT (McFadden, 1973) and input-output analysis (Leontief, 1986), and advanced techniques, such as the technique for the optimal placement of activities in zones (TOPAZ) (Brotchie et al., 2013) and the integration with the geographic information system (GIS) tools.

The MEPLAN model, for example, is one of the widely-employed LUTI models based on input-output metrics (Echenique et al., 1969, 1990). In the MEPLAN model, the land-use sub-model not only computes the zonal distribution of households and

[6] ITLUP refers to the Integrated Transportation and Land Use Package developed by Putman (1983, 1991,1998), including two sub-models: the DRAM model (for residential location) and the EMPAL model (for employment). The ITLUP model has a Lowry-family update (i.e., METROPILUS) (Putman, 2010)

[7] LILT refers to the Leeds Integrated Land-Use/Transport model developed by Mackett (1983, 1990, 1991) of the University of Leeds.

employments, but also estimates the activity transactions between and within these markets for transport demands. The transport sub-model then conducts the travel mode estimation and travel route assignment, generating transport costs for locational choice updates in the land use sub-model (Echenique, 2011). The MEPLAN model has been applied in several cases, such as London (Williams, 1994), Leeds (Echenique et al., 1990) and Cambridgeshire (Echenique, 2011) in United Kingdom. The MEPLAN model also inspired a number of other LUTI models such as the TRANUS model (de la Barra, 1989; de la Barra et al., 1984), the PECAS model (Hunt et al., 2005) and the RSE model (Jin et al., 2013).

The incorporation of spatial equilibrium and agglomeration effects in LUTI models represents a new stage of development for LUTI models. In particular, the aggregate yet rigorous equilibrium conditions applied in computable general equilibrium (CGE) models (Bröcker, 1998; Taylor and Black, 1974) and the consideration of endogenous productivity growth in New Economic Geography models (Fujita, 1989; Fujita et al., 1999) further advance the analytical capability of LUTI models. Notable examples of the spatial equilibrium LUTI models include the RELU-TRAN model (Anas and Liu, 2007) and the RSE model (Jin et al., 2013). Despite the analytical advantage of spatial equilibrium models, one of the main criticisms is the difficulty of incorporating different rates of urban change processes in the CGE framework (see Table 3.2).

Urban development processes and policy interventions show enduring effects over time and different markets change at different speeds. For example, the established transport facilities (such as highways and airports) cannot immediately respond to the rapid transport demand changes after the COVID-19 outbreak. A key modelling implication is that, while the supply of energy and transport infrastructure and building floorspace could be modelled in a dynamic manner within CGE framework, e.g., through considering forward looking behaviour of agents (Bröcker and Korzhenevych, 2013), the increasing model complexity may undermine the operationality and interpretability of the model. Alternatively, the inertia-prone, path-dependent nature of the infrastructure sector could be modelled outside of the CGE framework, hence serving as supply constraints. Modelling the supply side as scenario inputs and updating them in a non-equilibrium manner over longer time horizon can also provide a desirable model interface for engaging with specific policy designs and goals. The design of non-equilibrium modules in spatial equilibrium models could draw insight from established micro-simulation models such as the IRPUD model (Wegener, 1982, 2011), the DELTA models (Simmonds, 1999, 2001; Simmonds and Still, 1999), and the URBANSIM[8] model (Waddell, 1998, 2000).

Table 3.2 The Timescale of Urban Change Processes

Speed	Change process	Stock affected	Response time (years)	Response duration (years)	Reversibility
Very slow	Transport construction	Transport networks	5-10	>100	Hardly reversible
	Land use change	Land use pattern	5-10	>100	Hardly reversible
Slow	Commercial/ industrial construction	Commercial/ industrial buildings	3-5	50-100	Very Low
	Residential construction	Residential buildings	2-3	60-80	Low
Medium speed	Economic change	Employment/ Firms	2-5	10-20	Reversible
	Demographic change	Population/ households	0-70	0-70	Partly reversible
Fast	Firm/ employment relocation	Workplace occupancy	<1	5-10	Reversible
	Residential mobility	Housing occupancy	<1	5-10	Reversible
Very Fast	Change in demand	Goods transport	<1	<5	Reversible
	Change in demand	Person travel	<1	<1	Reversible

 # Source: Wegener et al. (1986)

3.5 A New Framework for Activity-Based Urban Energy Model

Based on the above literature review, this section proposes an extended activity-based framework for urban energy modelling, aiming to address the research gaps identified from the literature.

Figure 3.14 illustrates the high-level structure of the proposed model. The distinct feature of the model is an activity-based framework that unifies the energy modelling in two conventionally separate sectors, namely buildings and transport. It is worth noting that this modelling framework is focused primarily on energy demand in homes and offices and for passenger travel, whereas energy demand in other non-domestic

[8] URBANSIM refers to the microeconomic model of location choice of households and firms developed by Waddell (1998, 2002). For more details, please refer to the official website of URBANSIM: http://urbansim.com.

buildings and for freight transport is not considered. We mark this simplification in a dotted line in Figure 3.14. The activity modelling is subject to explicit spatial-temporal constraints and supply constraints of buildings and transport. Such constraints could be recursively updated either by the model or by scenario assumption. This enables a wide range of energy demand scenarios to be explored, where the impact of radical policy changes (e.g., due to the climate emergency), disruptive technological advancement (e.g., large-scale uptake of zero-/low-emission vehicles) and transformative behavioural changes (e.g., flexible working) could be tested.

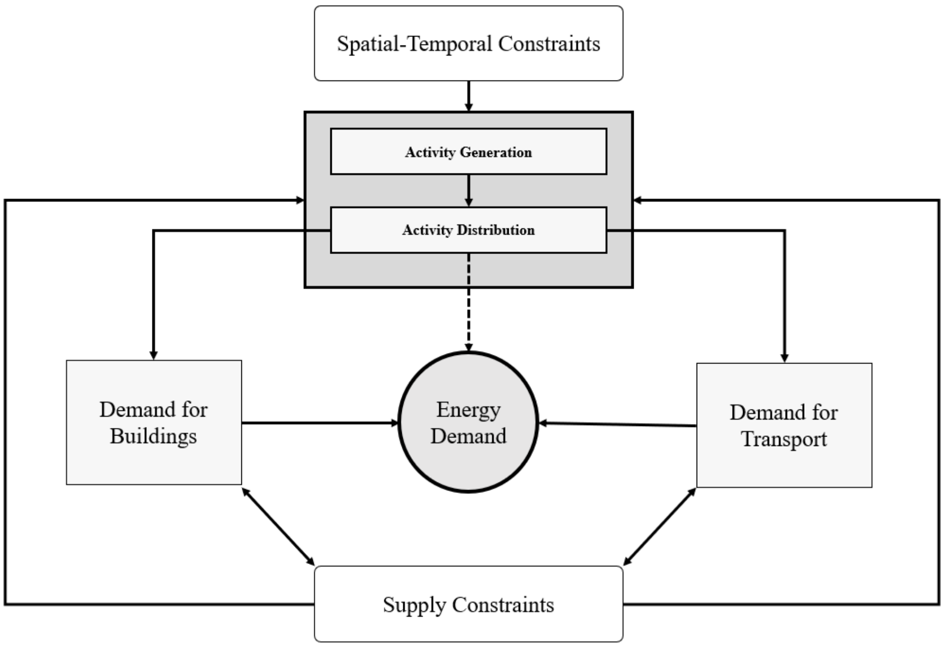


Figure 3.14 Conceptual Structure of the Theoretical Model

The theoretical model consists of four sub-models:

(1) The *Activity Generation* (AG) sub-model

The AG sub-model simulates aggregate activity choices of representative population groups of different socio-economic characteristics. This sub-model generates a general activity plan for individuals in terms of: (1) activity composition by broad activity type within the daily/weekly time endowment and (2) accumulated duration by activity type. The classification of activity types features a hierarchical structure, where detailed activity types will be consolidated into generic groups. The AG sub-model will be calibrated using observed activity data such as time use survey. The AG sub-model serves as an aggregate activity demand generator for the subsequent Activity Distribution (AD) model.

(2) The *Activity Distribution* (AD) sub-model

The AD sub-model distributes the aggregate activity demand in terms of (1) the locations by activity type, and (2) the frequency of engaging each activity type. The choice modelling in the AD model builds on established discrete choice models such as the MNL and nested logit model, subject to new model representations of various spatial-temporal and stock constraints. The primary output of the AD module is the activity schedule by representative population group. By disaggregating the activity demand spatially, it would give rise to building floorspace demand by location and floorspace type, and the associated travel demand to/from these locations.

(3) The *Building and Transport Energy Demand* (BTED) sub-model

The BTEM sub-model takes data from the AD module and simulates the energy demand in selected building types and for passenger travel. For the building sector, the sub-model employs a bottom-up engineering approach based on the endogenous building usage schedule data (from the AD sub-model) and exogenous building typological and geometric data (in the form of established building archetypes). For the transport sector, the sub-model would first simulate the modal split based on the origin-destination travel demand and travel time allocation obtained from the AD sub-model, and then calculate the associated energy consumption based on exogenous vehicle energy intensity data, i.e., fuel/energy consumption per distance travelled and by mode. Note that the proposed model is focused on 'what-if' impact assessment, as opposed to forecasting the probability or rate of change in the two sectors. In other words, transformative changes such as accelerated uptake of zero-/low-emission vehicles will not be modelled endogenously, but to be considered as scenario assumptions.

(4) The *Recursive Dynamic* (RD) sub-model

This module is proposed to update the supply-side constraints in a recursive-dynamic manner, i.e., the change of the supply constraints will be modelled between different time horizons. The RD sub-model is not a compulsory module in the framework. We deem that this is a desirable feature for practical policy analysis as the timing and phasing of major land/infrastructure development would require a clear temporal dimension in model output. The RD module can update the supply constraints according to (1) endogenous output from the AD and BTEM modules, and/or (2) exogenous policy interventions or market shocks as scenario-specific input. The updated supply constraints will take effect in the next time horizon. Although the RD module could take endogenous variables from other modules, we intend to use exogenous inputs, which helps to control the sensitivity of the model and reflects the inertia-prone nature of certain markets. The design of the RD module will draw insight from established urban microsimulation models such as IRPUD and Delta.

3.6 Chapter Summary

This chapter presents a comprehensive examination of activity-based models, tracing their theoretical foundations and evolutionary trajectory within urban transport and spatial analysis. Grounded in the seminal work of time geography pioneers, the chapter elucidates how human mobility is fundamentally constrained by temporal, spatial, and institutional factors beyond mere individual desires.

The narrative critically deconstructs traditional trip-based modelling approaches, particularly the FSM, which has long dominated urban transport planning. By exposing FSM's inherent limitations, notably its treatment of trips as independent, exogenous entities, the chapter advocates for a more nuanced approach that recognises the intricate interdependencies of human activities and travel behaviours.

Activity-based models emerge as a sophisticated alternative, offering a dynamic framework that generates travel demand endogenously by simulating multi-day activity patterns. The chapter meticulously categorises these models into four distinct types: utility-maximising, single-facet, constraint-based, and rule-based models. We explore each typology through re-visiting some representative models that demonstrate sophisticated techniques for understanding the human activity and mobility patterns.

Based on the review, this chapter proposes a new activity-based framework for urban energy modelling. The model comprises four interrelated sub-models: (1) *Activity Generation*, which simulates aggregate activity choices; (2) *Activity Distribution*, which allocates these activities spatially; (3) *Building and Transport Energy Demand*, which estimates sector-specific energy consumption; and (4) an optional *Recursive Dynamic* module that updates supply-side constraints over successive time horizons. This chapter highlights the importance of centring human beings and their activities in city-scale built environment modelling and analysis.

Chapter 4 Energy Effects of New Working Patterns: A Case Study of Shanghai, China

4.1 Background

Activity patterns of the population constitute a critical factor influencing energy demand across urban systems (Cantelmo and Viti, 2019; Jacobs-Crisioni et al., 2014; Wilke et al., 2013). For instance, the usage pattern of building occupants such as lighting, heating, cooling, and appliances, affects overall energy load of buildings (Cruz et al., 2024). At the urban scale, the spatial distribution of energy demand is contingent upon the locations where individuals reside, engage in occupational, personal and leisure activities, and how they travel between locations. Certain activities, such as office-based paid work or home-based leisure, can generate localised clusters of energy demand (Barbour et al., 2019). Temporal fluctuations in energy demand are also intertwined with the time use patterns of urban population: work, leisure, and sleep cycles exert profound influences on the timing and intensity of energy consumption (Friis and Haunstrup Christensen, 2016; Torriti, 2017). Thus, comprehending changing trends in the activity pattern of residents, alongside their spatial-temporal constraints and preferences for conducting activities, is crucial for prognosticating urban energy dynamics (Phoung et al., 2024) and developing resilient demand-side energy management strategies (Wiedenhofer et al., 2018).

The activity pattern changes caused by the prevalence of dual-income households (Lee and Lee, 2011) and other factors have occurred at a relatively gradual pace, often necessitating extended periods to manifest significant changes in building occupancy schedules and derived energy impacts. Therefore, many urban-scale building energy investigations employ deterministic models to simplify the roles of activity patterns. For instance, most engineering-based UBEMs utilise deterministic building occupancy schedules grounded in industry standards, e.g., ASHRAE codes, and aggregate activity data such as occupant densities and activity types (Doma and Ouf, 2023) as input for estimating building energy demand (Aldubyan and Krarti, 2022; Lin et al., 2023; Mylonas et al., 2024; Ren et al., 2012).

However, in recent years, dramatic productivity enhancements and rapid advancements in information and communication technology have disrupted the previously relatively stable activity patterns of urban population (Garikapati et al., 2016; Wang and Law, 2007). In particular, the widespread adoption of social distancing and lockdown policies during the COVID-19 pandemic stimulated a surge in the development of novel work modalities, such as flexible and remote work (Brynjolfsson et al., 2020; Franken et al., 2021). These new working patterns have substantially transformed time use patterns of urban population, resulting in structural changes in building occupancy and energy demand (Heffron et al., 2021; Jiang, et al., 2021).

The COVID-19 pandemic has normalised online meetings and remote collaboration, giving rise to novel work modalities such as remote/hybrid working and decentralised workspaces (Garrote Sanchez et al., 2021; Wohlers and Hertel, 2017). These changes can alter employees' choices of work locations, with more individuals opting for working from home, and/or in co-working spaces (Choudhury et al., 2021). The augmented flexibility in working patterns is also manifested in the temporal dimension, with many employees adopting dispersed working hours: flexibly selecting their preferred times to complete work tasks (Chen and Wan, 2024). These more malleable working patterns may impact the time allocation for other activities, thereby influencing activity choices of urban population (Wheatley, 2017; Yu et al., 2019). For instance, remote workers are relieved from daily commutes to physical offices, thus saving time which they can then use for other activities such as family and personal time, leisure activities, and extended work hours.

Another notable structural change is the rapid rise of side hustles in the post-COVID-19 era (Bates et al., 2019). A side hustle, also called as gig work and secondary occupation, is a form of supplementary employment or income-generating activity that individuals undertake alongside their primary job. It typically involves a flexible, entrepreneurial approach to utilising one’s spare time, enabling the development of additional skills or the pursuit of personal passions while diversifying overall income streams. The emergence of new social media platforms (such as TikTok) and service platforms (such as Uber, Grab, and Meituan) has brought possibilities for a significant increase in flexible employment opportunities (Oxendine, 2022; Peticca-Harris et al., 2020). During and after the COVID-19 period, global economic fluctuations and enhanced work flexibility have led more residents to pay attention to their job security. In mainland China, as one of the most prevalent forms of side hustles, the number of registered ride-hailing drivers surged from 3.291 million in February 2021 to 6.713 million in February 2024 (Ministry of Transport, 2024). For low-income residents and marginalised groups, engaging in side hustles or part-time work can enhance income diversification and establish a form of "safety net" (Ravenelle et al., 2021). However, managing multiple income streams may necessitate individuals to adjust their activity patterns to effectively balance work commitments across different roles or tasks (Bates et al., 2019).

In the post-COVID-19 era, these emerging working patterns have been largely sustained and further proliferated across myriad regions (Brynjolfsson et al., 2020; Vyas, 2022). The impacts of such structural changes have yet been fully captured by existing UBEMs (Dahlström et al., 2022). To bridge this gap, this paper aims to propose an activity-based urban energy model based on utility maximisation theory. The objectives are (1) to identify time-use characteristics of post-pandemic new working patterns, and (2) to simulate the potential impacts on energy demand across the housing, and office sectors. Using the SMARTS data, an online time use survey collected in 2022 in Shanghai, China, the calibrated and validated model is used to test a series of scenarios, examining the effects of flexible workplaces, flexible working hours, and side hustles. The model can simulate activity type, location, and duration choices of residents at different temporal junctures under new working mode scenarios. The findings of this research can contribute to addressing occupant-related uncertainties in city-scale energy management and potentially provide an interdisciplinary perspective aimed at promoting energy resilience and energy justice.

4.2 Data and Methods

Figure 4.1 delineates a three-stage analytical framework employed in this study. The initial stage encompasses time-use data collection and processing. The second stage focuses on model development and comprises two primary components: (1) identifying generic working modes across spatial-temporal and occupational dimensions, and (2) constructing a utility-based model for activity generation and allocation. The final stage is to evaluate the energy effects of emerging working modes through scenario analysis. A total of ten scenarios are developed.

Shanghai, China, has been selected as the case study site for this research for several compelling reasons. First, the timing of the questionnaire administration coincided with the city's recovery from an extended COVID-19 lockdown, thereby offering a unique opportunity to explore emerging post-pandemic trends in residents' time-use patterns.

Second, Shanghai's economic structure, dominated by finance, foreign trade, and technology, facilitates the adoption of new working practices. In addition, the friendly access to its demographic and urban environmental data further enhances its suitability for this study.

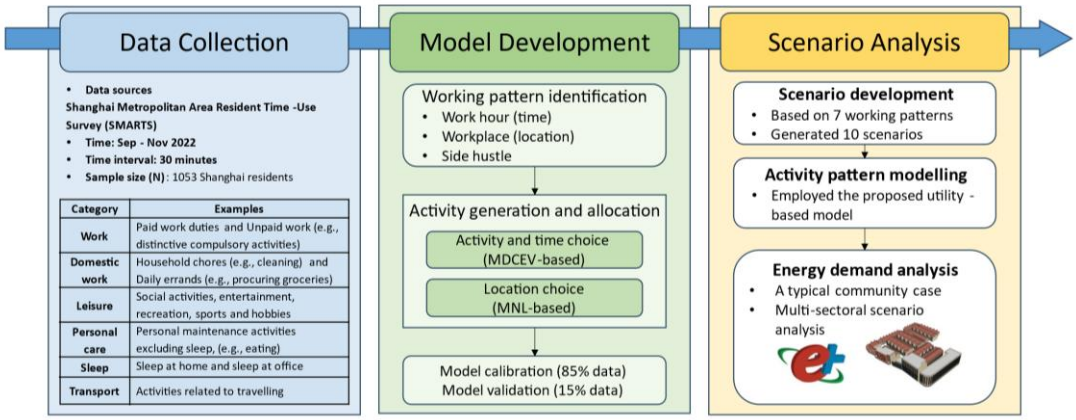


Figure 4.1 Research Framework

4.2.1 The SMARTS Data

Shanghai is recognised as one of the most densely populated and fast-growing cities in mainland China. The Shanghai Metropolitan Area Residents Time-use Survey (SMARTS) was distributed to local residents during September and October of 2022 to investigate changes in their lifestyles and to assess the implications of these shifts. The survey was conducted in two stages, with a pilot survey distributed in May 2022, and a final survey distributed in Sep 2022 after revisions informed by the pilot survey.

Respondents were invited to record their primary activities and locations at 30-minute intervals over the course of a single day. The survey also collected socio-demographic data, such as respondents' and their families' demographic profiles, employment status, primary residential location, and primary workplace location and the associated working pattern(s), and secondary occupation(s).

This study selects 1,053 respondents based on the following criteria: (1) have resided in Shanghai over 6 months (i.e. not short-term visitors), (2) economically active, (3) no nightshift working pattern, and (4) working for a minimum of two cumulative hours on the day of survey. This sample pre-selection helps to reduce the noise in the original survey data, facilitating the identification of new working patterns. This study uses randomly selected 85% of the data (i.e., 896) for model calibration, and the rest 15% (i.e., 157) for model validation.

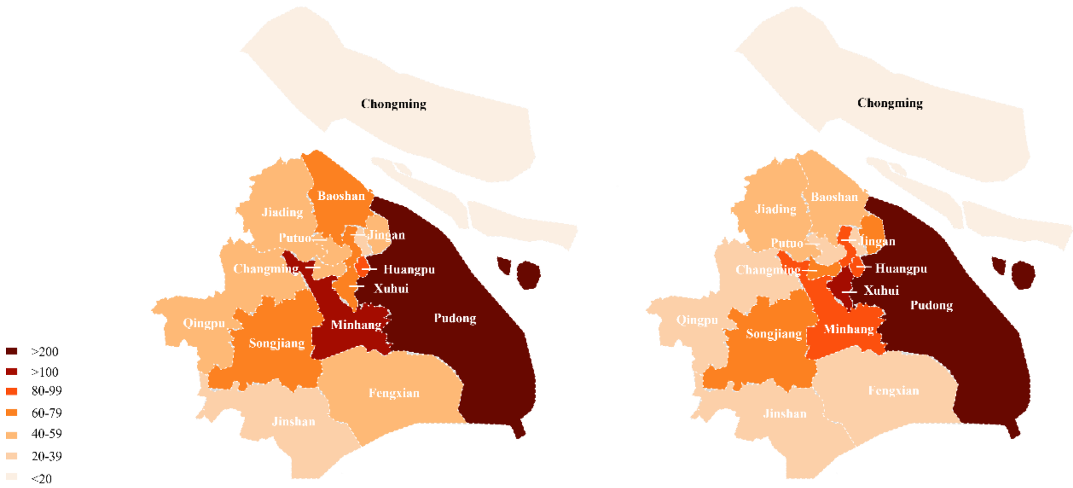
Table 4.1 summarises the socio-demographic characteristics of the selected respondents. The sample is broadly representative of the local employed population in terms of age, educational attainment, and household income distribution, despite marginal overrepresentation of female respondents (55.9% against 48.2% in the local census).

Table 4.1 Socio-Demographic Profile

Category	Variables	Number	Percentage
Gender	Male	464	44.06%
	Female	589	55.94%
Age	35 or younger	548	52.04%
	Older than 35	505	47.96%
Educational Level	Junior School or Below	27	2.56%
	High School or Equivalent	85	8.07%
	College Degree or Equivalent	143	13.58%
	Bachelor's Degree or Equivalent	637	60.49%
	Master’s degree or Equivalent	141	13.39%
	Doctoral Degree or Equivalent	20	1.90%
Family Yearly Income (CNY)	Less than 10,000	30	2.85%
	10,000 to 20,000	42	3.99%
	20,000 to 50,000	75	7.12%
	50,000 to 100,000	111	10.54%
	100,000 to 150,000	175	16.62%
	150,000 to 200,000	146	13.87%
	200,000 to 250,000	108	10.26%
	250,000 to 300,000	102	9.69%
	300,000 to 400,000	94	8.93%
	400,000 to 500,000	83	7.88%
	500,000 to 1 Million	67	6.36%
	1 Million to 2 Million	14	1.33%
	More than 2 Million	6	0.57%
Side hustle	Yes	31	2.94%
	No	1022	97.05%
Primary workplace location	Central districts	477	45.30%
	Suburban districts	576	54.70%
Primary residence location	Central districts	417	39.60%
	Suburban districts	636	60.40%

Figure 4.2 (a) and (b) show the geographical distribution of respondents' primary

residential and employment locations across administrative districts in Shanghai. Over half of respondents domicile and are employed in the nine non-central districts, corroborating the trends evidenced in the 7th National Population Census data.



(a) Primary residence distribution (b) Primary workplace distribution

Figure 4.2 Spatial Distribution of Respondents by Residence Location and Workplace

This study uses randomly selected 85% of the data (i.e., 896) for model calibration, and the rest 15% (i.e., 157) for model validation.

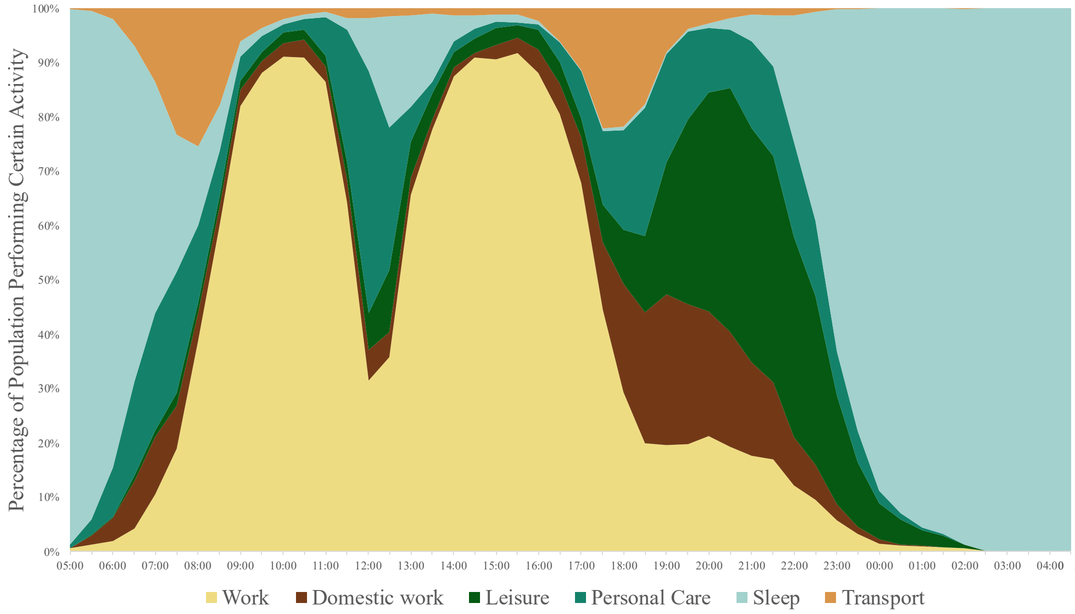
4.2.2 Data Processing

Activity types, timings, and locations are re-categorised for the purpose of this study. For activity types, original activity types are aggregated into 6 categories, based on the activity classification scheme adopted in the United Kingdom Time Use Survey (UKTUS) in 2014/15: (1) work, (2) domestic tasks, (3) leisure and entertainment, (4) personal care, (5) sleep, and (6) transport. The work category encompasses not merely paid employment but also unpaid work, such as voluntary overtime or locally distinctive compulsory activities. Domestic tasks encompass various household chores, including cleaning, culinary activities, gardening, and taking care of children and family members, as well as requisite daily errands like procuring groceries and paying utility bills. Leisure and entertainment broadly incorporate social activities, entertainment, recreation, hobbies, and sports. Personal care encompasses personal maintenance activities excluding sleep, such as eating and ablutions, while sleep is classified as a distinct category. Lastly, the transport category refers to activities related to travelling, including utilising various modes of transport and outdoor walking.

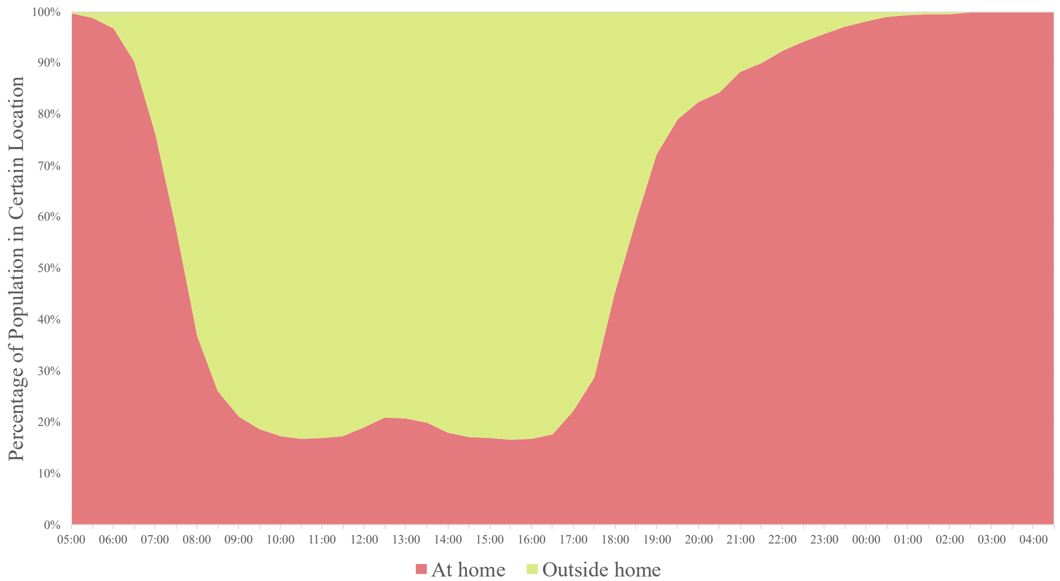
In addition, the study also categorises the activity timing and location. At 23:00, the proportion of respondents who were active (not sleeping) during the late night sharply declined (from 38.53% to 23.87%). This proportion remains at a low level until 05:00 and then increases, maintaining above 60%. Therefore, this paper focuses on usual active hours of the day (05:00-23:00), which are further categorised into 7 distinct periods: (1) early morning (05:00 to 08:00), (2) morning (08:00 to 11:00), (3) noon (11:00 to 14:00), (4) afternoon (14:00 to 17:00), (5) early evening (17:00 to 20:00), and (6) evening (20:00 to 23:00). The study distinguishes the location of activities by (1) at home and (2) outside home.

4.2.3 Descriptive analysis

Figure 4.3 (a) and (b) illustrate the aggregated time use patterns by activity type and location, respectively. The data reveals a rapid increase in the proportion of respondents leaving their homes between 06:00 and 09:00, with a concomitant rise in travel activities during this period, representing the morning peak time. Between 09:00 and 17:00, respondents primarily dedicated their time to work. The average duration of work activities was 503 minutes (8.4 hours) between 05:00 and 23:00. 33.90% of respondents engaged in a midday break, while 125 (11.87%) slept at home and 232 (22.03%) outside home (e.g., at workplaces). (b) demonstrates that the evening peak time travel is predominantly concentrated between 17:30 and 19:30. The proportion of time dedicated to domestic work and leisure and entertainment activities exhibited a notable rise between 19:00 and 22:30. After 23:00, the majority of respondents primarily engaged in sleep.



(a) Aggregated time allocation pattern



(b) Aggregated location choice pattern

Figure 4.3 Aggregated activity and location choice of respondents

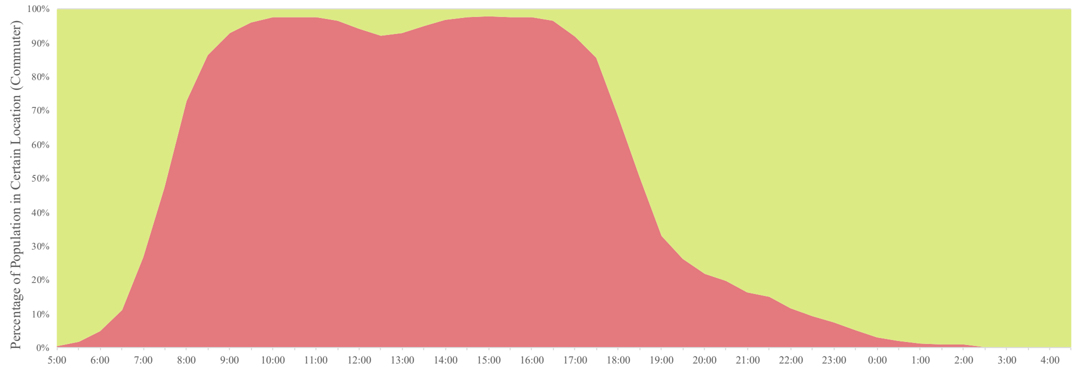
Figure 4.3 provides a summary of the patterns observed in the activity duration and timing choices of respondents between 5:00 and 23:00.

Table 4.2 Average activity duration and sample size by activity type and location

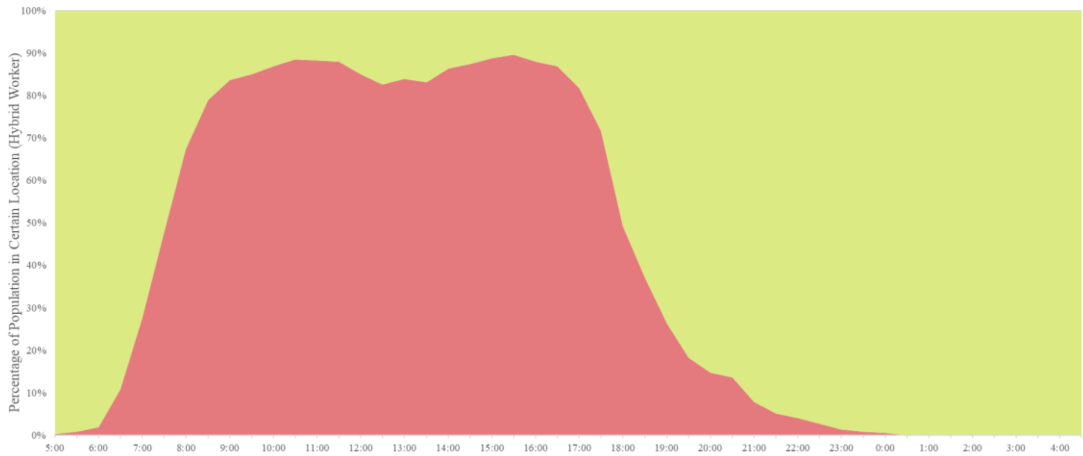
Location	Activity type	5:00-8:00	8:00-11:00	11:00-14:00	14:00-17:00	17:00-20:00	20:00-23:00	Total
At home	Work	3.56 (85)	19.91 (235)	13.19 (182)	20.91 (184)	15.61 (227)	21.08 (277)	94.27 (498)
	Domestic work	9.2 (229)	3.65 (94)	4.30 (96)	3.50 (72)	31.11 (570)	26.04 (444)	77.81 (769)
	Leisure	0.71 (19)	1.34 (31)	3.45 (76)	2.68 (54)	20.28 (383)	64.99 (701)	93.45 (770)
	Personal care	20.4 (547)	7.15 (203)	6.55 (171)	1.25 (31)	23.68 (604)	23.93 (577)	82.96 (963)
	Sleep	121.37 (1039)	8.52 (152)	6.89 (125)	2.34 (38)	0.77 (10)	23.36 (404)	163.25 (1048)
Outside home	Work	7.58 (163)	115.44 (883)	95.16 (887)	138.03 (881)	44.67 (661)	7.86 (96)	408.75 (927)
	Domestic work	0.80 (26)	2.25 (55)	2.36 (71)	1.74 (41)	4.44 (137)	1.25 (35)	12.85 (276)
	Leisure	0.71 (21)	1.88 (44)	7.01 (173)	2.93 (61)	7.44 (137)	6.41 (101)	26.38 (360)
	Personal care	1.77 (51)	2.85 (79)	26.78 (650)	1.77 (48)	6.52 (164)	2.02 (50)	41.71 (742)
	Sleep	0.14 (5)	0.26 (7)	11.94 (232)	0.94 (25)	0.06 (2)	0.43 (9)	13.76 (253)
	Transport	13.76 (337)	16.75 (434)	2.36 (61)	3.9 (105)	25.41 (564)	2.62 (67)	64.81 (793)

Note: Number without brackets: average duration (unit: minute); number in brackets: sample size

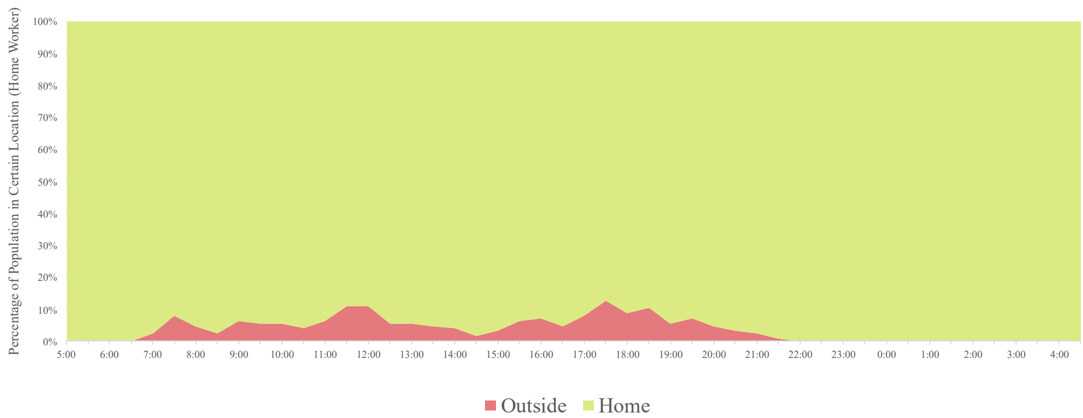
This study categorises working patterns based on the temporal and spatial distribution of their work activities. The classification of work location patterns refers to Chen and Wan (2024), distinguishing among homeworkers, commuters, and hybrid workers. Homeworkers complete all work activities at their residences. Commuters conduct all work activities outside their homes. Hybrid workers exhibit a combination of traditional commuting and homeworking. Adhering to this classification, the respondent pool comprises 553 commuters (52.52%), 374 hybrid workers (35.52%), and 126 home-workers (11.97%). Figure 4.4 shows the location choice pattern by work mode and by time of the day. Commuters tended to depart their residences between 07:00 and 09:00, returning home after 17:00. Hybrid workers spend about 10% of time during 08:00-17:00 on homeworking. Between 05:00 and 23:00, commuters allocate 11.2 (6.8) hours outside (at) their homes. Hybrid workers dedicated 9.7 (8.3) hours outside (at) their homes. Homeworkers spent 17.1 hours at home and 0.9 hours outside.



(a) Commuter



(b) Hybrid Worker



(c) Home Worker

Figure 4.4 Aggregated location choice pattern by work mode and by time of the day

4.2.4 Modelling methods

This section first introduces the methods employed for identifying latent working patterns and then the activity choice models.

In determining residential work patterns, this research employed a comprehensive analytical approach that systematically examined both temporal and spatial dimensions of work engagement. From the temporal dimension, a k-means clustering technique was applied to time-use survey data, which facilitated the identification of distinct work pattern clusters by disaggregating individuals' hourly work status. This statistical method enables the objective segmentation of work time profiles, providing a nuanced understanding of temporal work variations across the sample population. From the spatial dimension, work characteristics were categorised into three modalities following Chen and Wan (2024): homeworking, commuting, and hybrid working. Homeworking was defined as the complete execution of paid work activities within the residential environment, while commuting represented scenarios where all paid work occurred exclusively outside the home. The hybrid working category encompassed intermediate patterns, characterised by partial home-based paid work activities. This tripartite classification allows for granular analysis of spatial work dynamics, capturing the increasingly complex landscape of contemporary employment arrangements.

The activity modelling in this paper features a combined discrete and continuous choice problem (i.e. what activity type to engage and for how long) and a binary discrete choice problem (at-home or out-of-home to engage the given activity). The former is simulated using the established Multiple Discrete Continuous Extreme Value (MDCEV) framework (Bhat, 2005, 2008) and the latter is conducted using a logit model.

Bhat (2005, 2008) extended the Multiple Discrete-Continuous developed by Hanemann (1984) to the MDCEV model by introducing a multiplicative log-extreme value error term in the utility function. This structure shows three advantages in activity pattern modelling: First, it considers both discrete and continuous choices, enabling to capture of the situations where people choose multiple activities (e.g., work, leisure) simultaneously with different consumption intensities. Second, against traditional models, MDCEV elegantly handles corner solutions (situations where individuals spend zero time on certain activities) and satiation effects (diminishing marginal utility as more time is spent) (Baht et al., 2008). Third, the model explicitly accounts for the fixed budget constraint as well as the complementarity patterns between different activities, ensuring predictions are realistic and the total time allocated across activities sums to the available time (Palma et al. 2021). Therefore, the model has been gradually employed in budget-constrained choice modelling (Bhaduri et al., 2020; Khan et al., 2022; Palma et al., 2021; Rovira et al., 2022; Y. Zhang & Yao, 2022).

In this study, sleep at all times is identified as an outside numeraire good (activity) that is always consumed by each individual. The MDCEV utility function with an outside activity for a time-use allocation choice $\boldsymbol{X}$ in $\boldsymbol{K}$ alternative activities in $\boldsymbol{T}$ time junctures of residents with working pattern $\boldsymbol{p}$ is defined in function (4-1):

$$U_p(\boldsymbol{X}) = \sum_{t=1}^{T}\sum_{k=1}^{K} U_{ptk} = \frac{1}{\alpha}\psi_{\mathrm{p}1}x_{\mathrm{p}1} + \sum_{t=1}^{T}\sum_{k=2}^{K}\frac{\gamma_{kt}}{\alpha}\psi_{pkt}\left\{\left(\frac{x_{pkt}}{\gamma_{kt}}+1\right)^{\alpha}-1\right\} (4-1)$$

subject to time budget constraint $\sum_{t=1}^{T}\sum_{k=1}^{K} x_{pk} = B$

In equation (4-1), $U(\boldsymbol{X})$ is a quasi-concave, increasing, and continuously differentiable function. $\boldsymbol{x}$ is a vector of time allocation to activity 1, 2, …. K (K≥1) in time 1,2, … T (T≥1), $x_{kt} \geq 0$, for all $\boldsymbol{k}$ and $\boldsymbol{t}$. The $\boldsymbol{k = 1}$ indicates the outside good (Sleep), $\boldsymbol{p}$ is a vector representing the working pattern characteristics of individuals, including working time pattern $\boldsymbol{r}$, workplace choice pattern $\boldsymbol{l}$ and side hustle status $\boldsymbol{s}$. In most cases, the value of the parameter α tends to be positive but very small (no more than 1, and usually close to 0), resulting in $U_p(\boldsymbol{X}) \rightarrow \psi_{pkt}\gamma_{kt}\ln(\frac{x_{pkt}}{\gamma_{kt}}+1)$. ψ_{kt} represents the marginal utility of time consumption with respect to activity k. α and γ_{kt} are satiation parameters to provide a satiation effect by reducing the marginal utility with increasing time consumption. In our case, α is a constant and not associated with activity $\boldsymbol{k}$ and time $\boldsymbol{t}$. Also, γ_{kt} enables corner solutions by shifting the position of the point where the indifference curve is asymptotic to axes. B is the time budget, which is 18 hours in this case. z_{ktp} captures the observed attributes of activity $\boldsymbol{k}$ at time $\boldsymbol{t}$ for the decision-maker with working pattern $\boldsymbol{p}$, and ε_{ktp} represents unobserved utility. Thee base utilities $\psi_{ktp} = \exp(\beta' z_{ktp})$, where $\psi(x_{1p}, \varepsilon_{1p}) = \exp(\varepsilon_{1p})$ for $k = 1$, and $\psi(x_{ktp}, \varepsilon_{ktp}) = \exp(\beta' z_{ktp} + \varepsilon_{ktp})$ otherwise.

The probability that a respondent with working pattern ***p*** allocates their time to the first *M* activity-time combinations of ***a*** activities and ***b*** times (M ≥ 1, ***a*** ≥ 1, ***b*** ≥ 1) in the *K* activities and *T* Time is defined in equation (4-2):

$$P\left(e_{1_p}^*, e_{2_p}^*, e_{3_p}^*, \dots, e_{M_p}^*, 0,0,\dots,0\right) = [\prod_{i=1}^{M} f_i]\left[\sum_{i=1}^{M}\frac{1}{f_i}\right]\left[\frac{\prod_{i=1}^{M} e^{\frac{V_i}{\sigma}}}{\left(\sum_{t=1}^{T}\sum_{k=1}^{K} e^{\frac{V_k}{\sigma}}\right)^M}\right](M-1)! \qquad (4-2)$$

In equation (4-2), $\mathrm{f_{ip}} = \left(\frac{1\text{-}\alpha}{\mathrm{x_{ip}^*} + \gamma_{\mathrm{ip}}}\right)$, $e_{M_p}^*$ refers to the optimal time allocation from activity-time combination *i* to activity-time combination *M*, x_i^* refers to the optimal time allocation to specific activity-time *i*.

Then, the model can derive the activity allocation by activity type across the 6 time periods, excluding sleep (***k***=1). For each time period, the duration of sleep is calculated by subtracting the cumulative duration of all other activities from the total available time (i.e., 180 minutes) apportioned to that period.

After the MDCEV model, a logistic model is deployed to simulate the locational choice given the activity type and duration. The utility of a respondent with working pattern ***p*** performing activity ***k*** at time ***t*** outside home is presented in Equation (4-3):

$$U_{ktp} = \beta_{kt0} + \beta_{ktp} + \beta_{kt}D_{kt} \qquad (4-3)$$

where D_{kt} refers to the duration of activity ***k*** at time ***t*** outside home.

The next sub-section will introduce the building characteristics of the case study site which are key inputs to the building energy simulation model.

4.2.5 Case Study Site

To directly examine the energy impact of changes in residents' activity patterns, this study selected a typical community located in Shanghai as a case study and developed a simplified energy model to demonstrate the effects of new working patterns on different sectors and seasons. The community is situated in the central urban area of Shanghai and comprises 12 residential blocks and 4 office buildings. For the purposes of modelling, the case buildings were simplified, with offices assumed to function as open workspaces accommodating 1,020 occupants during peak hours, while the residential buildings house 2,290 residents.

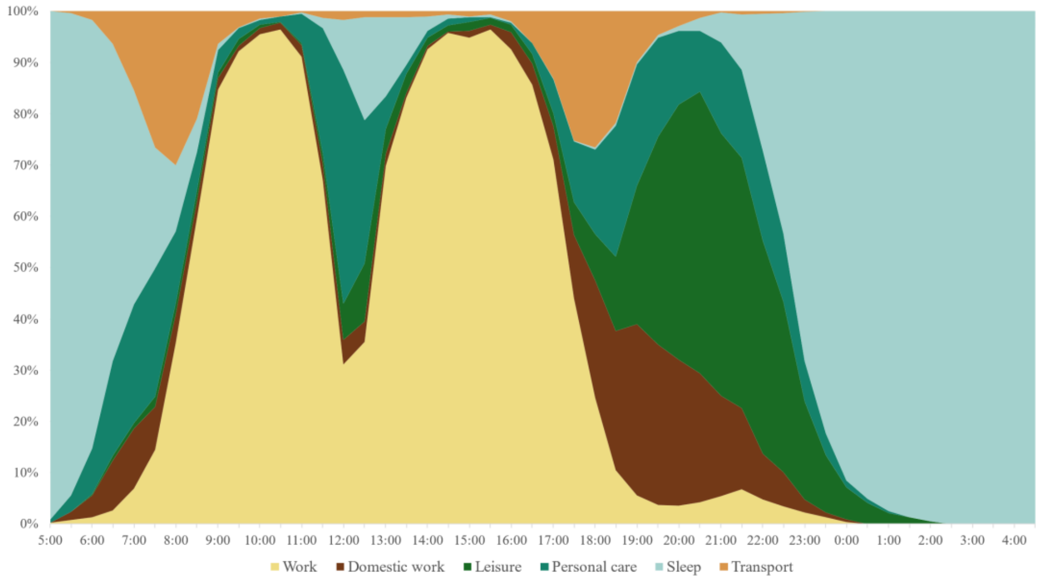
Within the energy model for this community, it was assumed that changes in residents' activity patterns would only influence building occupancy schedules. The generation of occupancy schedules accounted for both employed and non-employed residents. For employed residents, the schedules were derived from an activity choice model calibrated using the SMART data, whereas deterministic modelling was used to generate the schedules for non-employed residents. The analysis was conducted using DesignBuilder v7.0, powered by EnergyPlus v9.4.

4.3 Results

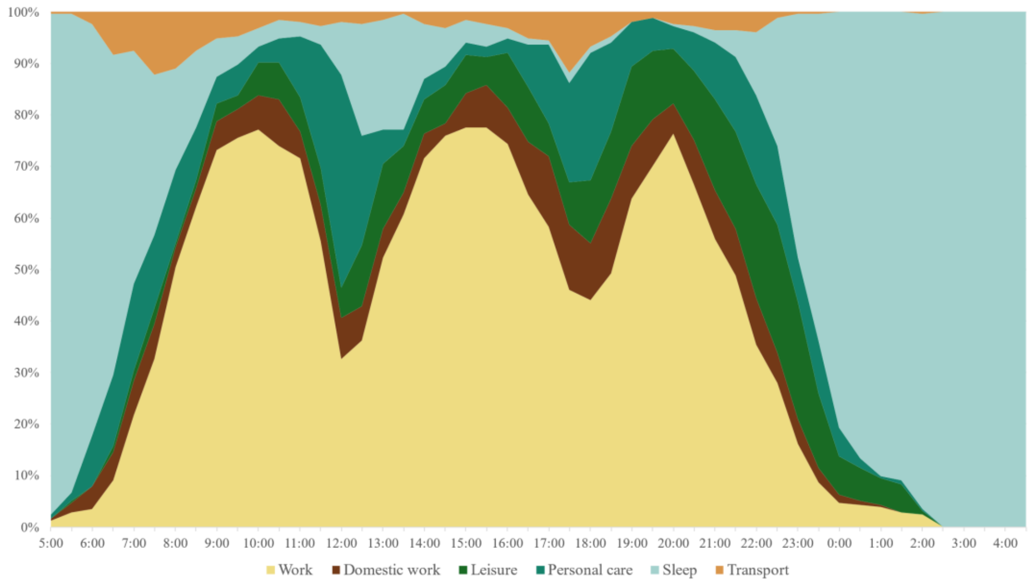
4.3.1 Identification of latent working patterns

Based on the temporal distribution of respondents' working hours between 5:00 and 23:00, this study employs the k-means clustering method to identify latent working patterns within each work mode. The Squared Euclidean distance and the Ward's linkage method are used to determine the optimal number of clusters, which is two. The two working patterns identified are: (1) traditional concentrated working pattern, and (2) the dispersed working pattern.

Table 4.3 presents the aggregated time allocation of the two working patterns. Figure 4.5 illustrates the time use characteristics by working pattern. The majority (n=799, 75.88%) of residents followed the concentrated working pattern. They tend to commence their workdays between 08:00 and 09:00, ending between 17:00 and 18:00. Their average total working time between 05:00 and 23:00 is 8.07 hours (483.94 minutes). After 18:00, this cohort allocated their time predominantly to other activities, notably domestic work (95.14 minutes), and leisure and entertainment activities (128.71 minutes).



(a) The concentrated working pattern



(b) The dispersed working pattern

Figure 4.5 Two distinct working patterns identified from cluster analysis

In contrast, respondents exhibiting the dispersed working pattern constitute a relatively smaller proportion (n=254, 24.12%). The residents in this cluster initiate their work activities slightly later than the first cluster and can allocate more time to non-work activities during the daytime. However, a substantial portion of this cluster continues work in the evening, forgoing leisure or domestic tasks, with a prolonged average working time of 9.38 hours (563.02 minutes) between 05:00 and 23:00, exceeding the other cluster. Consequently, their time dedicated to domestic work (76.54 minutes), travel (42.64 minutes) and leisure/entertainment (91.98 minutes) during this period is shorter than the first cluster. Nonetheless, time allocated for personal care and sleep exhibits marginal difference between the two working patterns.

Table 4.3 Aggregated time allocation by activity type and by working pattern (unit: minute)

Working pattern	Activity type	05:00-08:00	08:00-11:00	11:00-14:00	14:00-17:00	17:00-20:00	20:00-23:00	Total
The concentrated (n=799)	Work	7.92	139.04	113.32	167.35	47.83	8.49	483.94
	Domestic work	10.74	4.51	5.29	3.15	40.06	31.39	95.14
	Leisure	1.24	2.14	8.71	2.78	30.00	83.84	128.71
	Personal care	23.77	9.05	33.60	1.80	31.05	27.52	126.80
	Sleep	121.16	6.35	17.01	1.46	0.60	26.96	173.54
	Transport	15.17	18.92	2.07	3.45	30.45	1.80	71.86
The dispersed (n=254)	Work	21.26	123.78	92.72	132.52	99.45	93.31	563.03
	Domestic work	7.68	10.28	10.98	11.81	21.38	14.41	76.54
	Leisure	2.01	6.61	15.94	14.53	20.55	32.24	91.89
	Personal care	17.13	12.99	32.48	6.85	27.52	21.02	117.99
	Sleep	122.60	16.42	24.57	8.98	1.54	13.82	187.91
	Transport	9.33	9.92	3.31	5.31	9.57	5.20	42.64

Drawing upon the findings, this study identifies a total of 7 working patterns by considering three dimensions: working time, workplace, and side hustle. These dimensions are summarised in Table 4.4. From the perspective of working time, residents are divided into two categories: those with concentrated working patterns and those with dispersed working patterns. In terms of workplace, residents are classified as traditional commuters, home workers who exclusively work from home, and hybrid workers who combine both. Furthermore, the study distinguishes residents into two groups: workers with side hustle(s) and those without. In subsequent models, concentrated working, commuting, and no side hustle are used as the base category for each dimension.

Table 4.4 Categories of Working Patterns

Category	Working time (*r*)	Working location (*l*)	Side hustle (*s*)
Base	Concentrated working (*r*=1)	Commuting (*l*=1)	No side hustle (*s*=1)
Category II	Dispersed working (*r*=2)	Hybrid working (*l*=2)	With side hustle(s) (*s*=2)
Category III		Home working (*l*=3)	

4.3.2 Model Calibration

This study employs an MDCEV model to simulate the time allocation to 6 activity types in 6 time periods across the day. *Sleep* is considered the baseline activity. To enable in-sample validation, a random selection of 85% of the data (n=896) is used for model calibration, and the other 15% (n=157) is reserved for validation purposes. The study examines the goodness of fit of the model by checking the Log-Likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC). Both the AIC and BIC of the final model are below the constant model, which suggests an improvement in goodness-of-fit. The calibration results pertaining to the activity time-use component are presented in Table 4.5 and Table 4.6.

Table 4.5 Estimated baseline preference constants and translation parameters

Time period	Activity	Baseline preference (ψ)		Translation parameters (γ)	
		Coeff.	*t-ratio*	Coeff.	*t-ratio*
Early morning (5:00-8:00)	Work	-3.46	-26.01	1.35	9.20
	Domestic work	-2.65	-25.41	1.19	9.65
	Leisure and entertainment	-5.03	-18.16	1.21	4.02
	Personal care	-1.45	-18.20	0.82	14.49
	Transport	-2.17	-23.94	1.07	11.38
Morning (8:00-11:00)	Work	0.56	5.45	0.59	11.02
	Domestic work	-3.90	-24.08	1.31	7.20
	Leisure and entertainment	-4.95	-19.46	1.33	5.42
	Personal care	-2.84	-26.26	1.07	10.28
	Transport	-1.73	-20.91	0.92	12.81
Noon	Work	0.50	5.01	0.50	11.33

(11:00-14:00)	Domestic work	-3.95	-23.78	1.26	7.61
	Leisure and entertainment	-2.97	-26.26	1.17	9.84
	Personal care	-0.96	-12.65	0.62	16.17
	Transport	-4.39	-21.51	1.30	5.15
Afternoon (14:00-17:00)	Work	0.75	7.03	0.63	10.62
	Domestic work	-4.79	-20.37	1.46	6.02
	Leisure and entertainment	-4.73	-20.92	1.45	6.36
	Personal care	-4.49	-21.69	1.23	5.43
	Transport	-3.94	-23.47	1.22	6.22
Early evening (17:00-20:00)	Work	-1.05	-13.95	0.95	15.45
	Domestic work	-1.51	-18.96	1.08	14.66
	Leisure and entertainment	-1.95	-22.88	1.28	13.24
	Personal care	-1.22	-15.98	0.70	15.81
	Transport	-1.23	-15.59	0.82	13.94
Evening (20:00-23:00)	Work	-3.86	-26.72	1.06	9.77
	Domestic work	-1.81	-21.64	1.30	12.82
	Leisure and entertainment	-0.83	-10.83	1.31	15.03
	Personal care	-1.42	-18.18	0.83	15.06
	Transport	-4.33	-21.82	1.26	5.13

The baseline preference constants in

Table 4.5, also referred to as baseline utility, have no substantive interpretation but reflect the relative preference to participate in each category of activity-type-time-period. The computation of these baseline preference constants for each activity across distinct time periods takes into account the outside good (i.e. overall sleep) as the benchmark. Consequently, the majority of activities demonstrate negative baseline preference constants. However, an exception is observed during the daytime period (08:00-17:00), where work-related activities exhibit baseline preference constants greater than zero. This aligns with the common sense that work-related activities predominantly occur during these time periods.

The translation parameters serve two critical functions within the model. Firstly, they enable the accommodation of corner solutions, a phenomenon that arises when no time budget is allocated towards certain activity types for certain time periods. Secondly, these γ parameters act as satiation parameters, exhibiting an inverse relationship with the level of satiation for a given activity-type-time-period category. A lower value of the translation parameter is indicative of a higher satiation threshold for the given activity-type-time-period category, corresponding to a greater proportion of time allocated towards it. Conversely, a higher value of γ signifies a lower satiation threshold and, consequently, lesser time devoted to the activity-type-time-period category. According to the calibration results, individuals exhibit a stronger satiation effect when engaging in personal care activities during the morning and afternoon periods, in comparison to other time periods designated for such activities. On the other hand, the model indicates that individuals experience significantly stronger satiation effects when undertaking work activities during the early morning and evening periods, as opposed to the morning and afternoon periods.

Table 4.6 reflects that the advent of new flexible working arrangements has implications for baseline preferences across varied activity types and time periods. A blank cell (i.e., no parameter estimates) implies that the effect of the certain working pattern on baseline preference is insignificant. Flexible work schedules are associated with an enhanced baseline utility for non-work activities during conventional daytime hours, as well as an increased baseline preference for work activities in traditional off-work periods such as early evening and evening. Examining locational flexibility, hybrid workers who divide their time between the workplace and home exhibit elevated baseline utility levels in the morning, afternoon, and early evening periods. Conversely, remote working corresponds with a diminished baseline preference for transport activities across most time periods, reflecting the disutility nature of travel as a potential cause for engaging in remote working.

A binary logistic regression model is deployed to simulate the activity location choice (at-home or out-of-home given activity-type-time-period category). The location choice of transport activities is excluded from the model as all transport activities occur outside of home. We also employ Apollo (an established discrete choice modelling package for R studio) for the estimation.

Table 4.6 Estimated working pattern effects on baseline preference

Time period	Activity	Working pattern			
		Dispersed	Hybrid Work	Home Work	Side Hustle
Early morning (5:00-8:00)	Work	0.89 (5.02)	0.94 (5.26)	-0.74 (-2.31)	
	Domestic work	-0.47 (-2.16)		-0.91 (-2.95)	
	Leisure and entertainment		0.72 (1.88)		
	Personal care	-0.33 (-2.17)		-1.06 (-4.92)	-1.13 (-2.43)
	Transport				-1.13 (-1.81)
Morning	Work	-0.48 (-3.8)	0.28 (2.52)	-0.56 (-3.44)	-0.52 (-1.65)

(8:00-11:00)	Domestic work	0.56 (2.53)	0.29 (1.2)	0.86 (3.2)	
	Leisure and entertainment	0.86 (3.11)	0.93 (2.85)	0.98 (2.63)	0.69 (1.34)
	Personal care	0.25 (1.39)		0.42 (1.94)	
	Transport	-0.64 (-3.53)		-2.85 (-6.11)	-0.59 (-1.26)
Noon (11:00-14:00)	Work	-0.45 (-3.57)	0.23 (2.03)	-0.96 (-5.72)	-0.63 (-1.96)
	Domestic work	0.4 (1.89)	0.54 (2.25)	1.41 (5.53)	
	Leisure and entertainment	0.57 (3.23)		0.68 (3.24)	-1.23 (-1.97)
	Personal care			-0.29 (-1.72)	-0.65 (-1.88)
	Transport	0.39 (1.25)	0.38 (1.27)	-0.5 (-1.05)	0.74 (1.31)
Afternoon (14:00-17:00)	Work	-0.52 (-4.16)	0.22 (2.01)	-0.63 (-3.86)	-0.66 (-2.09)
	Domestic work	0.89 (3.62)	0.64 (2.03)	1.71 (5.46)	
	Leisure and entertainment	1.11 (4.70)	0.78 (2.67)	1.5 (4.87)	
	Personal care	1.09 (3.89)		-0.43 (-1.02)	0.86 (1.65)
	Transport	0.4 (1.49)	0.46 (1.86)	-1.03 (-2.07)	-1.11 (-1.08)
Early evening (17:00-20:00)	Work	0.92 (7.11)		-0.82 (-4.69)	-0.46 (-1.41)
	Domestic work	-0.75 (-4.97)	0.39 (3.1)		
	Leisure and entertainment	-0.55 (-3.45)	0.3 (2.19)	0.44 (2.37)	-0.43 (-1.12)
	Personal care				-0.52 (-1.49)
	Transport	-1.28 (-7.03)		-3.72 (-6.28)	-0.62 (-1.47)
Evening (20:00-23:00)	Work	2.49 (15.25)	1.5 (8.6)	0.44 (1.94)	
	Domestic work	-0.67 (-3.89)		-0.64 (-2.96)	
	Leisure and entertainment	-0.91 (-6.41)			
	Personal care	-0.16 (-1.12)		-0.57 (-3)	
	Transport	1.75 (5.93)	-0.8 (-2.55)	-3.28 (-3.19)	

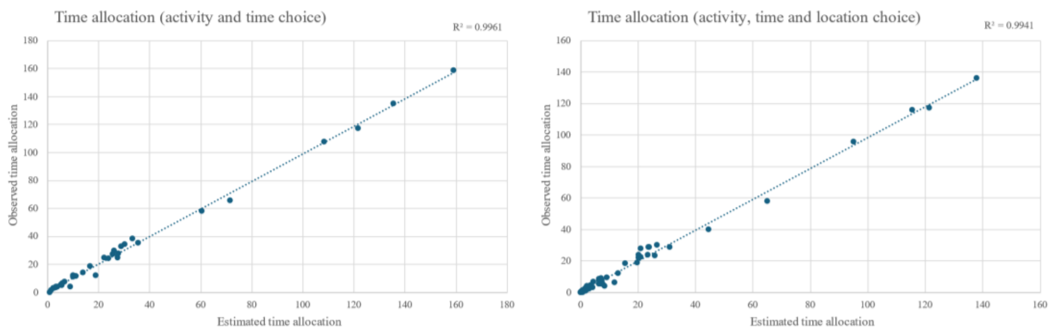
4.3.3 Model Validation

In this study, 15% of random samples (n=157) were used for model validation. Table 4.7 presents a comparison between the estimated and observed activity duration by activity type and location. The observed values were derived from the means of the holdout samples. For example, the observed average work-related time in early morning is 11.13 minutes, and the model estimated value is 11.53 minutes. Figure 4.6 presents the scatter plots between the estimated and observed. Specifically, Figure 4.6 (a) shows the validation results for the MDCEV time allocation model. In Figure 4.6 (a), each point refers to the estimated and observed time duration allocated to a specific activity type in a specific time period. Similarly, based on the MDCEV and logistic regression model, Figure 4.6 (b) shows the validation results for the activity location choice model, where each point refers to the estimated and observed time duration allocated to a specific activity-time-location category. Since all transport activities occur in outside-home locations, the location choice validation does not include transport activities to avoid goodness of fit inflation. The coefficient of determination (R-squared) for activity duration stands at 0.9961, while for the activity location choices is 0.9941. These high R-squared values suggested that the proposed model exhibits satisfactory predictive performance.

Table 4.7 Comparison between observed and estimated time use pattern

Time period	Activity	Observed total duration (min)	Estimated total duration (min)	Observed at-home duration (min)	Estimated at-home duration (min)	Observed outside duration (min)	Estimated outside duration (min)
Early morning (5:00-8:00)	Work	11.13	11.53	3.56	4.08	7.58	7.44
	Domestic work	10.00	10.97	9.20	9.57	0.80	1.40
	Leisure	1.42	1.52	0.71	0.74	0.71	0.78
	Personal care	22.17	24.69	20.40	23.77	1.77	0.92
	Sleep	121.52	117.05	121.37	117.05	0.14	0
	Transport	13.76	14.24	NA	NA	NA	NA
Morning (8:00-11:00)	Work	135.36	134.59	19.91	18.83	115.44	115.75
	Domestic work	5.90	6.71	3.65	4.57	2.25	2.13
	Leisure	3.22	4.04	1.34	1.80	1.88	2.24
	Personal care	10.00	11.92	7.15	8.96	2.85	2.96
	Sleep	8.77	4.18	8.52	4.18	0.26	0
	Transport	16.75	18.57	NA	NA	NA	NA
Noon (11:00-14:00)	Work	108.35	107.65	13.19	12.27	95.16	95.38
	Domestic work	6.67	7.27	4.30	3.29	2.36	3.98
	Leisure	10.46	11.66	3.45	4.03	7.01	7.26
	Personal care	33.33	38.54	6.55	8.30	26.78	30.24
	Sleep	18.83	11.82	6.89	5.42	11.94	6.40
	Transport	2.36	3.05	NA	NA	NA	NA
Afternoon (14:00-17:00)	Work	158.95	158.44	20.91	22.21	138.03	136.23
	Domestic work	5.24	5.44	3.50	3.59	1.74	1.85
	Leisure	5.61	5.22	2.68	3.10	2.93	2.13
	Personal care	3.02	3.48	1.25	1.06	1.77	2.42

	Sleep	3.28	3.50	2.34	3.33	0.94	0.17
	Transport	3.90	3.92	NA	NA	NA	NA
Early evening (17:00-20:00)	Work	60.28	58.27	15.61	18.20	44.67	40.07
	Domestic work	35.56	35.50	31.11	28.84	4.44	6.66
	Leisure	27.72	27.60	20.28	22.00	7.44	6.60
	Personal care	30.20	34.05	23.68	28.71	6.52	5.34
	Sleep	0.83	0.00	0.77	0.00	0.06	0.00
	Transport	25.41	27.2	NA	NA	NA	NA
Evening (20:00-23:00)	Work	28.95	33.01	21.08	27.91	7.86	5.10
	Domestic work	27.29	24.61	26.04	23.22	1.25	1.39
	Leisure	71.40	65.77	64.99	57.97	6.41	7.80
	Personal care	25.95	29.79	23.93	28.48	2.02	1.31
	Sleep	23.79	24.01	23.36	23.68	0.43	0.33
	Transport	2.62	2.81	NA	NA	NA	NA



(a) (b)

Figure 4.6 Scatter plots: Observed vs Estimated.

(a) activity duration; and (b) activity location

4.4 Scenario Analysis and Discussion

4.4.1 Scenario Design

The calibrated model is then applied to conduct scenario analysis to investigate how different compositions of the workforce in terms of working pattern may impact the aggregate activity patterns at the city level. In our analysis, the building occupancy, appliance/HVAC usage schedules, and the proportion of residents using different working modes in the baseline case were set entirely based on SMARTS data and case neighborhood statistics. In the baseline case, the proportion of residents using dispersed working was 24.12%, the proportion of residents using hybrid working was 35.52%, the proportion of residents using home-based working was 11.97%, and the proportion of residents using side hustle was 2.94%.

The design of the ten scenarios is summarised in Table 4.8, which can be categorised into four groups. The first group focuses on temporal flexibility, where Scenarios 1(a) and 1(b) assume 10% and 20% of workers with concentrated working patterns transitioning to dispersed working patterns, respectively. The second group addresses spatial flexibility, with Scenario 2(a) considering an increased share of hybrid workers, 2(b) assuming more home workers, and 2(c) representing an increase in both homeworking and hybrid working. The third group of scenarios addresses the emergence of side hustle, with settings similar to the first group. Scenarios 3(a) and 3(b) assume 10% and 20% of more workers engage in side hustle(s), respectively. In contrast to the first three groups, which primarily consider single dimension of working flexibility, the fourth group explores the combined effects of different types of flexibility. Scenario 4(a) integrates the settings of Scenarios 1(a), 2(c), and 3(a), representing an increasing prevalence of all types of flexibility. Building upon this, Scenarios 4(b) and 4(c) examine further popularisation of temporal and spatial flexibility, respectively.

Table 4.8 Summary of Scenario Design

Dimension	Scenario	Scenario description	Key indicators (only show changed items)
Baseline	0	Concentrated (75.88%) Dispersed (24.12%)	N/A
		Commuter (52.52%) Hybrid worker (35.52%) Home worker (11.97%)	
		No side hustle (97.05%) Side hustle (2.94%)	
Temporal flexibility	1(a)	10% concentrated to dispersed	Concentrated (69.29%), Dispersed (31.71%)
	1(b)	20% concentrated to dispersed	Concentrated (60.70%), Dispersed (39.30%)
Spatial flexibility	2(a)	10% commuters to hybrid working	Commuter (47.27%) Hybrid worker (40.77%) Home worker (11.97%)
	2(b)	10% commuters to home working	Commuter (47.27%) Hybrid worker (35.52%) Home worker (17.22%)

Dimension	Scenario	Scenario description	Key indicators (only show changed items)
	2(c)	10% commuters to hybrid working; 10% commuters to home working	Commuter (42.02%) Hybrid worker (40.77%) Home worker (17.22%)
Side Hustle	3(a)	5% without side hustle get side hustle(s)	No side hustle (92.21%), Side hustle (7.79%)
	3(b)	10% without side hustle get side hustle(s)	No side hustle (89.27%), Side hustle (10.37%)
Combined effects	4(a)	10% concentrated to dispersed; 10% commuter to hybrid working; 10% commuter to home working; 5% without side hustle get side hustle(s)	Concentrated (69.29%) Dispersed (31.71%) Commuter (42.02%) Hybrid worker (40.77%) Home worker (17.22%) No side hustle (92.21%) Side hustle (7.79%)
	4(b)	20% concentrated to dispersed; 10% commuter to hybrid working; 10% commuter to home working; 5% without side hustle get side hustle(s)	Concentrated (60.70%) Dispersed (39.30%) Commuter (42.02%) Hybrid worker (40.77%) Home worker (17.22%) No side hustle (92.21%) Side hustle (7.79%)
	4(c)	10% concentrated to dispersed; 25% commuter to hybrid working; 15% commuter to home working; 5% without side hustle get side hustles	Concentrated (69.29%) Dispersed (31.71%) Commuter (31.51%) Hybrid worker (48.65%) Home worker (22.472%) No side hustle (92.21%) Side hustle (7.79%)

4.4.2 Scenario Analysis Results

This section presents the findings derived from the contextual analysis conducted in the preceding part. It begins by examining changes in residents' time-use patterns across various work-mode scenarios, including (1) trends in location choices and (2) shifts in the allocation of activity durations. Subsequently, the section reports on the energy implications of these scenarios for the case community.

4.4.2.1 Activity location choices: At-home vs out-of-home

Table 4.9 presents the average at-home time across ten scenarios, with a breakdown by time period between 05:00 and 23:00, and the percentage change relative to the baseline scenario. The analysis reveals shifts in residents' temporal and spatial activity patterns across various work scenario interventions. Specifically, scenarios involving dispersed working patterns (1(a) and 1(b)) demonstrate a modest reduction in at-home time, primarily attributed to enhanced temporal work flexibility enabling increased spatial mobility. However, scenarios centred on home-based/hybrid working and side hustles predominantly exhibit increases in residential occupancy, with the most pronounced changes observed in the combined effects scenarios.

The temporal distribution of increased at-home duration is particularly significant during daytime hours, specifically between 08:00 to 17:00. These intervals witnessed substantial increases in at-home activities, with work-related tasks, domestic work, and personal care activities predominantly occupying the additional time. For instance, Scenario 2(c) demonstrated a remarkable 26.47% increase in domestic work time and a 23.11% increase in personal care activities during the noon period. The emergence of flexible work patterns appears to re-configure traditional activity patterns, enabling employed residents to integrate paid work, personal care, and domestic tasks more seamlessly throughout the day.

Table 4.9 Changes of at-home duration by time period of the day

Time period	S0	S1(a)	S1(b)	S2(a)	S2(b)	S2(c)	S3(a)	S3(b)	S4(a)	S4(b)	S4(c)
05:00-08:00	153.72	152.50 *-0.79%*	151.41 *-1.50%*	153.85 *0.09%*	155.10 *0.90%*	155.37 *1.08%*	154.22 *0.33%*	154.88 *0.76%*	154.78 *0.69%*	153.63 *-0.06%*	155.82 *1.37%*
08:00-11:00	38.47	40.96 *6.47%*	42.84 *11.36%*	38.78 *0.81%*	40.90 *6.32%*	47.02 *22.23%*	39.59 *2.91%*	41.05 *6.71%*	50.78 *32.00%*	52.87 *37.43%*	55.67 *44.71%*
11:00-14:00	31.84	32.71 *2.74%*	33.60 *5.54%*	32.59 *2.37%*	32.86 *3.21%*	40.68 *27.78%*	32.57 *2.30%*	33.41 *4.94%*	42.39 *33.15%*	43.39 *36.29%*	47.78 *50.08%*
14:00-17:00	30.92	31.93 *3.27%*	32.74 *5.89%*	31.58 *2.14%*	32.12 *3.89%*	40.27 *30.25%*	33.00 *6.73%*	35.34 *14.30%*	43.41 *40.40%*	44.41 *43.64%*	49.21 *59.16%*
17:00-20:00	94.41	92.68 *-1.83%*	91.27 *-3.33%*	95.80 *1.47%*	98.10 *3.91%*	101.31 *7.31%*	94.96 *0.58%*	95.67 *1.33%*	100.67 *6.63%*	99.15 *5.02%*	106.34 *12.64%*
20:00-23:00	159.10	155.19 *-2.46%*	151.82 *-4.58%*	159.85 *0.47%*	159.31 *0.13%*	161.00 *1.19%*	158.52 *-0.37%*	157.82 *-0.81%*	157.76 *-0.84%*	154.02 *-3.19%*	160.46 *0.85%*
Total	508.45	505.97 *-0.49%*	503.68 *-0.94%*	512.45 *0.79%*	518.39 *1.95%*	545.65 *7.32%*	512.86 *0.87%*	518.17 *1.91%*	549.79 *8.13%*	547.47 *7.67%*	575.28 *13.14%*

Note: S is for Scenario, for example, S1(a) refers to Scenario 1(a). S0 refers to the baseline. Unit: minute

A more granular examination of the time allocation reveals intricate patterns of activity redistribution across different time periods. The morning hours (08:00-11:00) show a shift towards increased sleep and personal care activities, particularly in scenarios with dispersed working patterns. This redistribution replaces time previously allocated to peak-hour commuting. The noon and afternoon periods (11:00-17:00) exhibit the most significant transformations, with substantial increases in paid work activities at home. Scenario 2(c), for example, showcases a 35.77% increase in at-home work time during the morning and a 37.46% increase in the afternoon compared to the baseline scenario. Also, this period sees a rise in domestic activities, with individuals leveraging increased flexibility to engage in personal care, and domestic tasks that were previously constrained by traditional work schedules.

From an energy demand perspective, these evolving work patterns potentially signal significant implications for residential energy consumption. The increased daytime occupancy, particularly during previously low-occupancy hours, suggests potential intensification of energy use for heating, cooling, and electronic devices supporting home-based work. Interestingly, while daytime energy demands may rise, the scenarios indicate a potential mitigation of evening peak electricity demand, with at-home time during typical post-work hours (20:00-22:00) marginally decreasing. This suggests a more distributed energy consumption profile that could contribute to a more balanced grid management and potentially reduce strain during traditional peak demand periods.

4.4.2.2 Activity type preferences

Table 4.10 presents changes in activity duration by activity type and location. The analysis is in line with the findings in section 5.4.2.1: while the aggregate work time remained relatively stable across scenarios (fluctuating within ±1.36%), there were significant reallocations of time between home and out-of-home activities. Work conducted at home demonstrated a consistent and substantial increase across all flexibility scenarios. Also, out-of-home work time experienced a corresponding decline, suggesting a fundamental restructuring of traditional work location patterns.

The out-of-home activity landscape reveals a sophisticated recalibration of temporal and spatial engagement, challenging conventional mobility narratives. Notably, out-of-home activities demonstrate counterintuitive patterns, with significant variations across different domains. Sleep and transport outside the home exhibited the most dramatic fluctuations, with out-of-home sleep time experiencing a remarkable 72.78% increase in Scenario 1(b) and out-of-home transport time rising by up to 28.33%. This suggests an emergent phenomenon of spatial diversification, where individuals are not simply reducing out-of-home activities but redistributing them more strategically. Leisure and personal care activities outside the home show more nuanced changes, oscillating between modest increases and decreases across scenarios. The data suggests a more complex social adaptation mechanism, where workplace flexibility enables more dynamic out-of-home activity engagement patterns, potentially reflecting a broader societal shift towards more flexible and multi-locational lifestyles.

Table 4.10 Changes of activity duration (min) by activity type and location

Activity	S0	S1(a)	S1(b)	S2(a)	S2(b)	S2(c)	S3(a)	S3(b)	S4(a)	S4(b)	S4(c)
Work (home)	93.96	98.08	102.41	98.19	97.31	117.45	95.40	97.98	125.41	129.70	144.69
		4.39%	*9.00%*	*4.51%*	*3.57%*	*25.01%*	*1.54%*	*4.28%*	*33.48%*	*38.04%*	*54.00%*
Domestic work (home)	71.96	69.20	66.58	72.53	73.02	75.00	72.90	73.77	73.59	70.81	75.77
		-3.83%	*-7.47%*	*0.80%*	*1.48%*	*4.23%*	*1.31%*	*2.52%*	*2.27%*	*-1.59%*	*5.30%*
Leisure (home)	88.38	85.32	82.37	88.17	91.65	93.78	89.07	89.73	91.44	88.42	93.94
		-3.46%	*-6.80%*	*-0.24%*	*3.70%*	*6.11%*	*0.78%*	*1.53%*	*3.46%*	*0.05%*	*6.29%*
Personal care (home)	98.95	97.62	96.51	98.73	99.53	101.61	98.92	99.04	100.54	99.23	101.79
		-1.34%	*-2.47%*	*-0.22%*	*0.59%*	*2.69%*	*-0.03%*	*0.09%*	*1.61%*	*0.28%*	*2.87%*
Sleep (home)	155.21	155.75	155.81	154.83	156.88	157.81	156.57	157.65	158.81	159.31	159.09
		0.35%	*0.39%*	*-0.25%*	*1.08%*	*1.67%*	*0.88%*	*1.57%*	*2.32%*	*2.64%*	*2.50%*
Work (outside)	408.60	407.92	406.75	406.48	398.97	380.91	403.60	397.72	373.05	372.01	354.55
		-0.17%	*-0.45%*	*-0.52%*	*-2.36%*	*-6.78%*	*-1.22%*	*-2.66%*	*-8.70%*	*-8.95%*	*-13.2%*
Domestic work (outside)	17.65	18.90	20.00	17.51	18.89	17.35	17.95	18.21	18.81	20.04	18.41
		7.10%	*13.33%*	*-0.78%*	*7.04%*	*-1.68%*	*1.72%*	*3.19%*	*6.59%*	*13.56%*	*4.32%*
Leisure (outside)	26.57	27.39	28.27	26.41	28.48	25.97	26.49	26.45	26.61	27.43	26.02
		3.07%	*6.38%*	*-0.62%*	*7.17%*	*-2.27%*	*-0.31%*	*-0.47%*	*0.14%*	*3.22%*	*-2.08%*
Personal care (outside)	44.55	46.58	48.22	43.95	44.54	41.65	44.47	44.31	43.08	44.97	40.61
		4.56%	*8.24%*	*-1.35%*	*-0.02%*	*-6.51%*	*-0.18%*	*-0.54%*	*-3.30%*	*0.94%*	*-8.84%*
Sleep (outside)	6.15	8.33	10.63	6.00	7.20	5.65	6.78	7.80	8.10	10.01	7.07
		35.39%	*72.78%*	*-2.48%*	*17.03%*	*-8.17%*	*10.20%*	*26.78%*	*31.66%*	*62.70%*	*14.91%*
Transport (outside)	55.52	70.51	69.03	71.25	67.68	67.21	71.18	70.53	65.40	64.20	62.72
		27.00%	*24.33%*	*28.33%*	*21.90%*	*21.05%*	*28.20%*	*27.03%*	*17.79%*	*15.63%*	*12.97%*

 # Note: S is for Scenario, for example S1(a) refers to Scenario 1(a). S0 refers to the baseline.

The emerging activity patterns also suggest a broader mobility implication. While peak-time commuting demand might decrease as a result of greater work flexibility, non-commuting travel demand stemming from activities like shopping, leisure, and entertainment may increase, leading to an overall increase in travel time budget. However, the energy implications of this change warrant further investigation, as transport-related carbon emissions do not necessarily increase proportionally with travel time. Without the reduced commuting time allocation, residents may opt for destinations closer to their homes and choose slower but more environmentally friendly modes of transport, such as walking, cycling, or public transit.

4.4.2.3 Community Case Study: The Energy Implication

This section reports the energy effects of the working pattern scenarios on the case community. Table 4.11 presents the annual energy consumption variations in the case neighbourhood under different scenarios, including a breakdown of loads by use (appliances, lighting, heating, and cooling) in residential and office buildings. The case-specific findings suggest that new working patterns tend to increase energy demand in the residential sector while reducing it in office buildings. The scenarios involving remote working patterns significantly impact energy demand derived from appliance/equipment usage, affecting both residential and office buildings. For instance, in scenario 2(b), an increase in homeworkers led to a 4.89% rise in appliance energy demand in residential buildings and a 5.29% decrease in office buildings. This indicates that new working patterns drive sectoral shifts in energy demand through changes in residents' activity patterns.

The nuanced energy demand variations extend beyond appliance usage to encompass comprehensive building performance metrics. Heating and cooling demonstrate significant sensitivity to changing occupancy patterns, with residential HVAC energy demands showing substantial increases across scenarios. The most pronounced scenario, 4(c), revealed a 13.35% increase in cooling energy and a 7.28% increase in heating energy for residential buildings. These variations are particularly noteworthy, as they reflect the extended home occupancy periods and the consequent intensification of energy systems' operational requirements. Interestingly, while residential energy consumption escalated, office building energy demands experienced corresponding reductions, suggesting a potential urban-scale energy demand rebalancing mechanism.

In our case community, new working patterns led to an overall increase in building energy consumption in the neighbourhood by 0.97% to 2.04%. However, this analysis primarily highlights the significant temporal and spatial shifts in energy demand due to new working patterns, rather than suggesting that these patterns hinder urban energy-saving efforts. This is because the floor area of residential buildings in this case is significantly larger than that of office buildings, amplifying the impact of residential buildings on total energy demand. Besides, new working patterns may also alter transportation and commercial demands, leading to complex effects on derived energy consumption.

Table 4.11. Detailed analysis for the annual energy load

Scenario*		Appliance (kWh)	Lighting (kWh)	Cooling (kWh)	Heating (kWh)	DHW (kWh)	Total (kWh)
0#	R	408,349.3	349,269.7	334,080.3	498,515.9	374,391.8	1,964,607
	C	394,598.9	511,353.0	150,540.8	670,651.6	N/A	1,670,331
1(a)	R	-0.22%	-1.33%	17.67%	3.02%	-	3.49%
	C	0.32%	0.08%	-0.13%	-0.22%	N/A	0.00%
1(b)	R	-0.23%	-2.45%	18.02%	2.74%	-	3.28%
	C	0.53%	0.14%	-0.23%	-0.44%	N/A	-0.03%
2(a)	R	0.71%	0.32%	16.88%	3.75%	-	4.02%
	C	-0.45%	-0.11%	0.15%	-0.23%	N/A	-0.21%
2(b)	R	4.89%	1.66%	15.40%	5.29%	-	5.27%
	C	-5.29%	-1.34%	-1.55%	-2.89%	N/A	-2.59%
2(c)	R	5.57%	1.94%	15.07%	5.55%	-	5.47%
	C	-5.71%	-1.45%	-1.60%	-3.12%	N/A	-2.81%
3(a)	R	0.95%	0.12%	16.92%	3.75%	-	4.05%
	C	-1.65%	-0.42%	0.41%	-0.93%	N/A	-0.83%
3(b)	R	1.93%	0.22%	16.60%	4.10%	-	4.30%
	C	-3.60%	-0.92%	0.95%	-2.02%	N/A	-1.80%
4(a)	R	6.70%	1.22%	14.95%	5.63%	-	5.58%
	C	-7.06%	-1.79%	-1.95%	-4.15%	N/A	-3.59%
4(b)	R	6.69%	0.10%	15.32%	5.34%	-	5.37%
	C	-7.00%	-1.78%	-1.89%	-4.48%	N/A	-3.70%
4(c)	R	10.71%	3.01%	13.35%	7.28%	-	6.88%
	C	-12.34%	-2.75%	-3.95%	-6.33%	N/A	-5.75%

*Note: # 0 refers to the Baseline situation, * R for the residential part, C for the office part.*

4.4.3 Policy Implications

The findings reveal that new working patterns may significantly impact the occupancy schedule of residential buildings, potentially leading to emerging energy demand patterns. During weekdays, the energy demand may shift from offices to the residential sector, as an increasing number of inhabitants embrace new working patterns. This shift necessitates a re-evaluation of existing energy distribution programme. For example, during hot summer days, the increase in homeworking may significantly elevate the residential cooling load and result in a surge of energy demand during daytime, in contrast to the usual peak of energy use in summer evenings. The new working patterns may engender enhanced temporal flexibility in transport activities, potentially precipitating more dispersed temporal patterns of electric vehicle charging and novel configurations of electrical grid load. These emerging trends pose new challenges for electricity generation and distribution.

Our findings can also contribute to the development of novel behaviour-oriented building energy-saving interventions. In light of the anticipated increase in building occupancy during daytime (08:00 to 17:00) due to flexible working, to enhance energy efficiency, building and facility managers can employ novel interventions to promote PEBs in work-related activities considering the emerging lifestyles under different working patterns. For example, promoting energy-efficient equipment use for remote and flexible working, and adopting monetary PEB incentives (Xu et al., 2023). In addition, with increasing propensity of remote workers to cook at home, energy-efficient and eco-friendly cookware and fuels could be promoted. Occupant-centric building energy renovation (Feng et al., 2024; Yu et al., 2023) and behaviour-driven building energy management solutions like norm-based interventions and subsidies for domestic energy retrofitting for flexible and hybrid workers can be considered.

The findings can also inform city-scale, inter-sectoral energy management strategies. For instance, during the hot summers and cold winters, traditional commuting patterns could be encouraged to reduce the excessive energy demand from dispersed, low-efficiency heating and cooling at home offices. In spring and autumn, working from home could be promoted to reduce long-distance commuting using private modes. Furthermore, enterprises may consider adaptive office space management plans such that seasonal variations in floor space demand could be leveraged to reduce rental/estate costs.

4.4.4 Limitations and Further Directions

First, the findings are context-specific. While the proposed model framework can be applied in more regions and countries, the findings of our case study have limited generalisability beyond the geography of Shanghai. The spatial extent of the case study site suggests limited representativeness of both the building stock and population in our case study. In particular, the buildings in this case study do not fully capture the variety of building typologies observed in the case study city. Notably, the diversity in building typology (e.g., mid-rise and high-rise building) and HVAC systems were not included but can be incorporated in future studies for more accurate sectoral demand results.

The second limitation is our study considers only the primary activity types, and thus multi-tasking in activity schedule is ignored. Residents often simultaneously engage in two or more activities, for example, using a washing machine while cooking, working or reading on public transport. The presence and optionality of such secondary activities can have considerable impacts on time use and location choices, hence affecting energy demand and emissions. Future research will benefit from incorporating agent-based modelling to handle multi-tasking as well as dynamic transitions and their impact on the urban environment and energy consumption.

Another important direction for future studies is to incorporate transport energy demand into the model. This case study does not include the transport energy demand for three reasons: (1) our activity data is recorded in 30-minute intervals, which could introduce bias in transport modelling; (2) the relatively small scale of the case study restricts the availability of local transport data, and (3) the transport demand of the study area is substantially influenced by activities conducted by outside residents. Future models that account for transport energy impacts, especially the energy influence of mode shifts, will enhance the comprehensiveness of energy management strategies within the proposed framework.

Fourth, another limitation of this case study is that its binary location categorisation, distinguishing solely between home and outdoor environments, overlooks the nuanced role of emergent third spaces (e.g., co-working centres and cafés), which may affect energy consumption patterns. These alternative workspace options could have a profound impact on residents' lifestyles and alter the spatial distribution of urban energy demand. Future urban energy research would benefit from a more in-depth exploration of these trends, capturing the interplay between third spaces and the conventional demands of residential and office environments.

Last, whilst the model demonstrated satisfactory goodness of fit in the case, the model calibration and validation are based on cross-sectional data, which means that potential transitions of lifestyles are not captured by the model. It is expected that understanding the transition of lifestyles over varying temporal scales (e.g. intra-week vs intra-month) in relation to flexible working schedules can shed further light on energy demand modelling and wellbeing of residents, which can be explored when longitudinal data becomes available in the future.

4.5 Chapter Summary

This research proposes a novel modelling framework to explore possible changes in workers' time use and location choices in light of the new working patterns such as flexible and hybrid working and side hustle. The modelling framework tackles the following two choice problems in a sequential manner, (1) what activity type to engage, when and for how long; and (2) where to conduct the given activity. The first problem is resolved by adopting the established MDCEV framework which is particularly suitable for simulating continuous-discrete joint choices, while the second problem is addressed by employing binary logistic models, which predicts the activity location choice between two options, i.e., at home and out of home. Time use survey data collected in 2022 from Shanghai is used for model calibration and in-sample validation. Scenario analysis is conducted to examine the possible impact of various future work scenarios (increasing temporal, spatial flexibility, increasing side hustle(s) and their combinations) on activity patterns and their broad locations. The analysis reveals that increased working flexibility would drive a shift of work activities towards residential locations and other places outside conventional offices. Furthermore, enhanced working flexibility is likely to lead to increased duration and timing changes in domestic work, leisure, personal care, and transport activities. This study is one of the early studies examining the behavioural impact of future work using empirical time use data from a fast-growing city region in a developing country context. The findings shed light on human-centric energy management at both building- and city-level. In spite of context-specific findings, the proposed method can be applied to other places with similar data resources. .

Chapter 5 Activity-Based Urban Building and Transport Energy Modelling: A Case Study of Manchester, United Kingdom

5.1 Case Introduction

Urbanisation represents one of the defining global trends of the 21st century. The World Urbanisation Projects (United Nations, 2018) reports that approximately 60% of the world's population will reside in urban areas by 2030. This rapid urban expansion has led to unprecedented energy demands, particularly in the building and transport sectors. The International Energy Agency (2021) reports that cities account for 75% of global energy consumption, with these sectors playing pivotal roles. In the United Kingdom, for example, the domestic and the transport sectors consumed 36,730 kto and 50,480 ktoe of energy use, respectively (Department for Energy Security and Net Zero, 2024). Understanding the dynamic changes in energy demand across these sectors provides new opportunities for smart sustainable cities and effective urban energy management (International Energy Agency, 2021).

Whilst numerous models and forecasting tools have been developed to address energy demands in these sectors (Ali et al., 2021b; Ferrando et al., 2020; Pye and Daly, 2015), existing research has predominantly focused on single-sector energy demand predictions (Hong et al., 2020; Keirstead et al., 2012; Sola et al., 2020), but paid less attention to the cross-sectoral interactions (Wang and Wan, 2025). For instance, some studies concentrate solely on residential electricity consumption whilst overlooking the interconnected energy demands of workplace and transport systems. Understanding the cross-sectoral interaction within the context of urban operations and emerging social trends, along with predicting temporal-spatial characteristics of energy demand, represents a critical step towards digital and smart urban energy management (International Energy Agency, 2021). Therefore, a holistic approach is essential to effectively capture the comprehensive nature of urban energy demands.

Activity-Based Approach (ABA), a modelling method that integrates human activity patterns into the core of urban built environment analysis (Wang and Wan, 2025), provides a promising solution to this challenge. This approach was first applied in transport modelling (Fu et al., 2025; Malayath and Verma, 2013; McNally and Rindt, 2007; Rasouli and Timmermans, 2014), it reflects resident demands and sector-specific resource allocation through the temporal distribution of activities across various spaces (Liu et al., 2021; Yin and Chi, 2021). ABA's unique ability to link multiple urban sectors through activity chains of population enables the capture of dynamic cross-sectoral interactions (Wang and Wan, 2025). However, due to data accessibility constraints and technical limitations in modelling tools, previous urban-scale energy analyses have rarely employed this approach systematically for understanding and simulating urban energy demand mechanisms.

Understanding cross-sectoral energy demand dynamics in urban environments provides a more comprehensive perspective for urban energy management. To address this research gap, this study aims to develop an activity-based urban energy model that bridges energy demands across residential, office, and transport sectors. We propose a utility-based framework for activity demand generation and allocation within urban environments, which can be integrated with existing sector-specific energy models. The model has been calibrated and validated using UKTUS 2014/2015 data (Gershuny and Sullivan, 2017). Through a simplified case study of the Manchester city region, we examine energy demand variations across residential, office, and transport sectors under different working pattern scenarios. This model development a new analytical tool to support an inter-sectoral approach to promoting urban sustainability.

The remainder of this chapter is structured as follows: Section 5.2 introduces the modelling framework. Section 5.3 details the data sources, case study background, and activity and energy modelling methods. Section 5.4 presents the working pattern identification process, activity model calibration and validation, and scenario analysis results. Section 5.5 examines the energy implications of various scenarios. Section 5.6 presents policy recommendations for urban planning and energy management, model limitations and suggestions for future research.

5.2 The Model Framework

The Activity-Based Approach (ABA) traces its origins to time geography established by Hagerstrand (1970, 1989) in the 1970s. Time geography represents a new way of understanding human activities not as isolated events, but as sequences interwoven through space and time, constrained by physical capabilities and environmental conditions. Building upon this paradigm, transport modelling has extensively adopted ABA to investigate the underlying motivations and patterns of travel behaviour, leading to the rapid development of various activity-based models. These include ALBATROSS (A Learning-Based Transportation Oriented Simulation System) (Arentze and Timmermans, 2000; Timmermans and Arentze, 2011), MATSim (Balmer et al., 2009), TASHA (Hao et al., 2010; Roorda et al., 2008; Yasmin et al., 2015), FEATHERS (Galland et al., 2014), and SACSIM (Bradley et al., 2010).

The potential of activity-based models extends beyond transport. For example, some studies applied ABA with LUTI models to predict outcomes ranging from short-term facility accessibility to long-term business activities and population relocation (Lopes et al., 2019; Niu, 2024; Niu and Li, 2019). Knapen et al. (2012) and Shahrier et al. (2024) extended the existing activity-based models to predict the impact of electric vehicle adoption on transport carbon emissions. Mosteiro-Romero et al. (2023) and Wang and Wan (2025) advocated for further application of the activity-based research paradigm across multiple dimensions of built environment analysis. Their objectives included (1) enhancing the predictive capability of urban built environment models regarding emerging demands and lifestyles of urban population, and (2) understanding the interactions between urban sectors to promote cross-sectoral resource integration and decision-making.

Building upon Wang and Wan (2025), we propose an activity-based framework for city-scale energy demand simulation (see Figure 5.1). The framework comprises two main components: (1) the activity model (marked in yellow), and (2) interconnected sectoral energy models. As the core of the entire activity-based framework, the activity model focuses on residents' activity patterns and time use characteristics. This component first determines residents' activity demands under existing spatial-temporal-economic constraints (termed *activity generation*), followed by allocating these activity demands to different practices, locations, and sectors (termed *activity distribution*). The energy model then integrates population activity demands into energy models for different sectors, capturing how these activity demands influence each sector and their derived energy demand changes. The final step synthesises these model predictions to understand cross-sectoral urban energy dynamics.

The energy model is developed based on existing bottom-up UBEM structures, including three sectors: residential buildings, offices and transport. In the residential sector, the model can capture how time allocation pattern changes affect energy demand, via changes in residential occupancy schedules and building services (such as lighting and heating systems) and appliance usage patterns. In the transport sector, the model can predict changes in residents' travel demand derived from activity demand. Flexible/remote working has blurred the boundary between homes and workplaces. For simplicity, it is assumed that energy consumption of home-based work activities belongs to the residential sector.

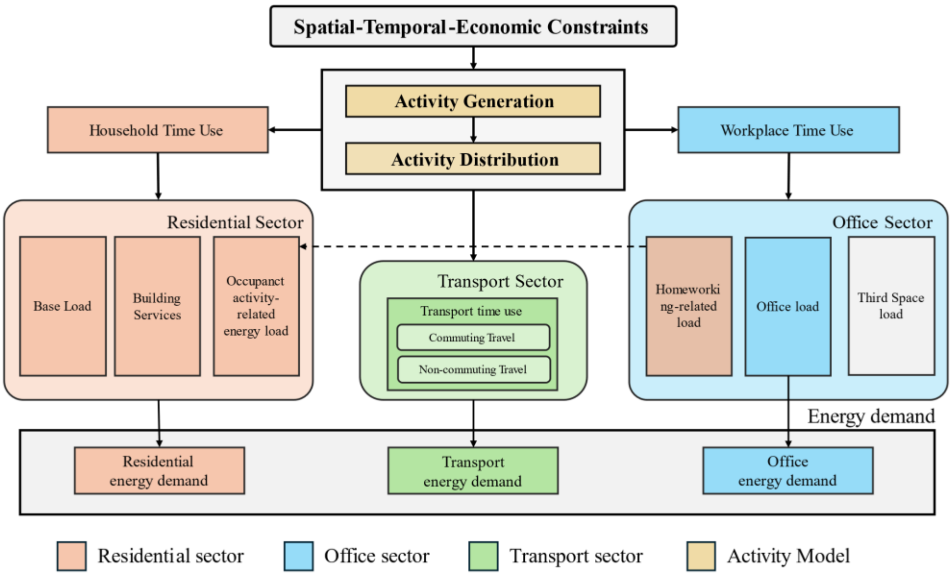


Figure 5.1 The Proposed Activity-Based Energy Modelling Framework

5.3 Data and Methods

5.3.1 Overview

Manchester (see Figure 5.2) is the largest financial centre in the UK outside London, with an economy dominated by financial services, media, and professional services. The concentration of knowledge-intensive sectors makes it a good case for examining the impact of new working patterns (Adekoya et al., 2022; Haywood, 2010).

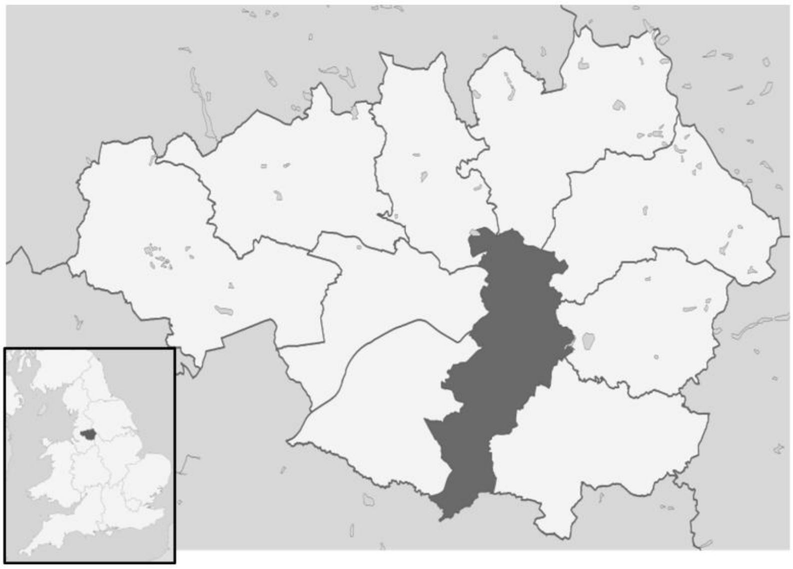


Figure 5.2 The geographic location of Manchester

Figure 5.2 illustrates the workflow of this study. The study employs the UKTUS 2014-2015 (Gershuny & Sullivan, 2017) for the activity model development. UKTUS is a large-scale household survey conducted in the United Kingdom, providing data on how individuals aged 8 and above spend their time. To streamline the modelling process, the research re-categorised the UKTUS data according to activity types, locations, and transport modes. Furthermore, aligned with our research objectives, the study classifies the survey observations based on weekdays versus weekends and employment status. This classification methodology enables a more accurate representation of activity patterns across different demographic groups and time periods, thereby enhancing the model's accuracy and practical utility.

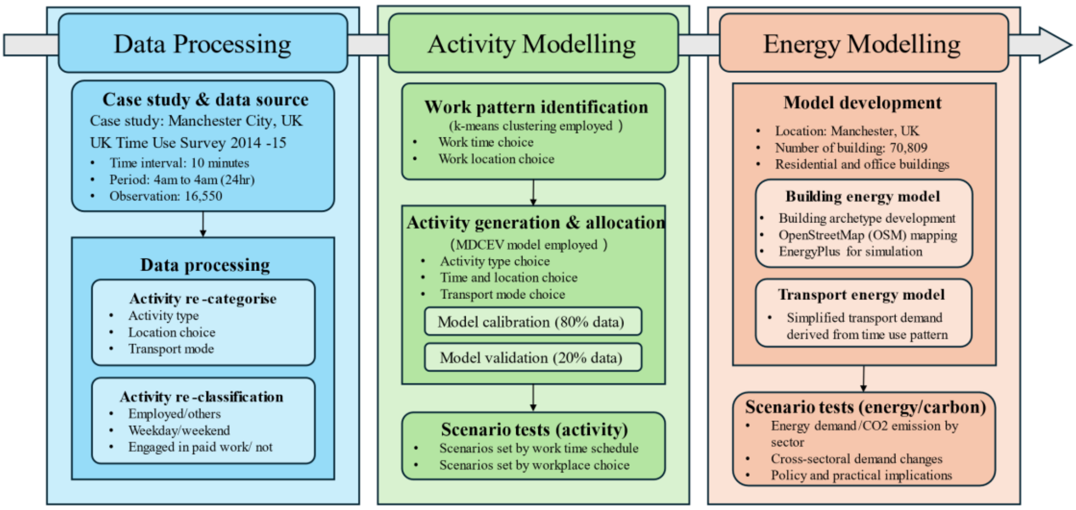


Figure 5.3 The Research Framework

Following the completion of the aforementioned steps, this study then identifies and selects eligible samples directly influenced by working patterns, in accordance with the research objectives, to develop the activity model. Data from employed respondents that are directly influenced by new working patterns are utilised for the calibration and validation of the activity model. Meanwhile, other samples are used to develop deterministic building occupancy and transport activity schedules for residents who are not directly affected by working patterns within the energy model.

Within the activity model, the study first employs the k-means clustering analysis to differentiate employment patterns among eligible individuals based on working hours and locations. Then, the study develops a utility-based activity model, implementing the MDCEV model to simulate residents' choices in activity generation and distribution processes, encompassing activity types, timing, locations, and transport modes for spatial transitions. For model calibration and validation, 80% of eligible data is randomly selected for calibration, with the remaining 20% reserved for validation. The study then adopts the calibrated model to test scenarios.

In the energy and carbon model, the study adopts different approaches to simulate energy demand across residential, office and transport sectors. For residential and office buildings, the research employs a bottom-up, engineering-based UBEM. The model development begins with the creation of building archetypes using building data from open sources (Open Street Map). Subsequently, local TMY (Typical Meteorological

Year) data is incorporated to capture accurate climate characteristics, including temperature, humidity, and solar radiation, which are key environmental inputs for calculating heating, cooling, and lighting energy demands. For the transport sector, the study adopts a simplified model based on travel time, average speed and energy consumption coefficients to estimate transport energy demand.

The results of the activity model serve as input for the energy and carbon models. For the building energy modelling, the occupancy schedules of the eligible employed population are endogenous and derived from the previously generated activity model. The occupancy schedules of non-employed population are deterministic. Similarly, for the transport sector, the transport activity schedules of the employed population are endogenous and the schedules of others are deterministic. The study then applies the energy models to scenario analyses to understand the variations in energy demand across different sectors and their derived carbon emissions under various working pattern scenarios.

5.3.2 UKTUS Data Processing

The UKTUS, conducted under the direction of the Office for National Statistics (ONS), has been extensively employed in economic and urban studies (Echeverría et al., 2022; Torriti & Yunusov, 2020; Chen and Wan, 2024) and is recognised as a reliable source for understanding time allocation patterns among British residents. This dataset has been employed for urban and building energy models in Dublin (Sood et al., 2023b) and London (Losa Rovira et al., 2022), providing building occupancy rates for energy demand forecasting and planning.

Following the guidelines of the Harmonised European Time Use Surveys (HETUS), the survey's core component is a time diary tool in which respondents record their daily activities. This diary captures activity data over a 24-hour period, starting from 04:00 AM and ending at 04:00 AM the following day, at 10-minute intervals (a total of 144 intervals). The dimensions of activity recorded include primary activities, secondary activities, activity location (and mode of transport), and level of enjoyment. A total of 11,860 sampled households resulted in 4,238 household interviews, with 10,208 eligible respondents, of whom 9,388 completed the individual interview. In the survey, all respondents were required to complete one weekday and one weekend activity record, while some of these were not entirely usable. Ultimately, the survey collects a total of 16,550 diary days.

The UKTUS 2014-15 data provides high-quality and multidimensional information. However, to build the activity model, this data requires further processing to avoid unnecessary model complexity due to its high degree of dispersion. During the data processing stage, the study first cleans the acquired UKTUS data. Subsequently, we re-categorise the activities and locations. Then, the study re-classifies the observations according to the research objectives. The data cleaning process of this study was based on the framework and methods of Losa Rovira et al. (2022), excluding a small number of observations with a significant amount of missing data, resulting in 16,541 valid diary days. To simplify the data, we define activities as primary activities (excluding any secondary activities) and adjust the time resolution to one hour (with each time point representing the respondent's time allocation for the subsequent 60 minutes). Subsequently, the study re-categorises residents' activities by type and location. In terms of activity type, the study simplifies the original 276 activity types from UKTUS into six categories: paid work, domestic work, leisure, personal care, sleep, and transport. For example, leisure activities include those initially categorised under social life and entertainment (codes 5000-5310), sports and outdoor activities (codes 6000-6312), hobbies, games and computing (codes 7000-7390), and mass media (codes 8000-8320) in the UKTUS questionnaire. The definitions and coverage of the re-categorises activity types are explained in Table 6.1. Also, in terms of location, the study simplifies the original 36 activity locations into five categories: residence, workplace, third places, outdoors, and transport. Furthermore, the transport category is divided into six modes: walk, bicycle, car, train, bus, and other transport modes. The definitions of these location categories and transport modes are presented in Table 5.2 and Table 5.3, respectively.

Table 5.1 Re-categorised location choices

Location Type	Definition	Coverage & Examples
Residence	A residence refers to a long-term, fixed location used by an individual for daily living and rest, excluding hotels.	Home, second home, or weekend house
Workplace	A residence refers to a fixed location used by an individual for paid work activities, but does not include a residence used for home office purposes.	Workplaces (e.g., offices)
Third places	Third places refer to indoor environments other than residences and workplaces.	Restaurants, cafés, pubs, others' homes, markets, shops, sports facility, arts or cultural centres,

		hotels, guesthouses.
Outdoors	Outdoors refers to all outdoor environments except those used for transport activities.	Parks, countryside, seaside, beach or coast
Transport	Transport refers to all outdoor environments and vehicles used for transport activities.	Bicycles, cars, trains, coaches, buses

Table 5.2 Re-categorised activity types

Activity Type	Definition	Coverage & Examples
Paid work	Paid work refers to activities directly related to remunerated employment, as well as any compulsory activities directly derived from them.	Working time in main job, working time in second job, any other specific activities related to employment.
Domestic work	Domestic work includes general unpaid household chores, voluntary or participatory activities.	Household and family care, volunteer work and meeting, studying, informal help to other households, shopping and services.
Leisure	Leisure includes all unpaid activities related to socialising, entertainment, relaxation, and hobbies.	Social life and entertainment, sport and outdoor activities, mass media, hobbies, games and computing.
Personal care	Personal care refers to activities and routines that individuals undertake to maintain their personal hygiene, health, and appearance, but does not include sleep.	Eating, bathing, dressing, grooming, and managing personal health needs.
Sleep	Sleep refers to sleep or the status of "in bed not asleep"	Sleep and in bed not asleep
Transport	Transport refers to the movements of individuals from one location to another using various modes of transportation	Travel by all purposes

Table 5.3 Re-categorised transport modes

Transport mode	Coverage & Examples
Walk	On foot
Bicycle	Bicycle
Car	Passenger car (as the driver, as a passenger, or driver status unspecified), or taxi
Train (and other rail transit)	Train, tram, or underground
Bus (and coach)	Bus or coach
Other	Travel by other transport modes (e.g., van, lorry or tractor, boat or ship, aeroplane, motorcycle, motorboat)

For the purpose of this study, we select samples in the UKTUS data for the activity model development according to the following criteria: (1) the respondent's employment status is employed (including full-time employed, part-time employed, and self-employed), and (2) the respondent's paid work activity time during the diary day is greater than zero. It is permissible for the same respondent to engage in paid work activities on both weekdays and weekends. Based on these selection criteria, we obtained 3,672 qualifying observations. 2,885 of them are on weekdays and 787 of them recorded activities at weekends (Saturdays and Sundays). Among the 3,672 selected observations, 24 individuals with multiple occupations were further excluded. The individuals with multiple occupations refer to those who, in addition to their primary employment, also engage in other regular paid employment activities. The reasons for excluding this group are: (1) multiple labour activities may result in more complex time allocation patterns, such as more flexible working location choices and the possibility of conducting different labour activities at the same location, and (2) the small size of this group may hinder the model's ability to accurately capture the impact of secondary occupations on their time utilisation patterns. The qualified samples that fulfil the above criteria are named as "selected samples".

5.3.3 Descriptive analysis

5.3.3.1 United Kingdom Population

Table 5.4 and Figure 5.4 illustrate the activity type selection patterns of UK residents during weekdays and weekends. Table 5.5 and Figure 5.5 show the location selection patterns for the same periods.

Apart from sleep, leisure time remains the highest for the UK population on both weekdays and weekends (273.52 minutes and 358.79 minutes, respectively). Compared to weekdays, the average time allocated to paid work by UK residents drops by 69.34% to 65.57 minutes on weekends. Additionally, paid work activities during weekdays are primarily concentrated during the daytime, whereas the time distribution for weekend paid work activities is more dispersed. Correspondingly, the time allocated to transport activities decreases on weekdays, likely due to reduced commuting demands. The reduction in time spent on paid work and transport activities on weekends allows residents to use more time for domestic work (i.e., +12.52%), leisure (i.e., +31.18%), personal care (i.e., +9.03%), and sleep (i.e., +7.58%). Furthermore, the time spent on paid work during weekdays and weekends is 213.87 minutes and 65.57 minutes, respectively, both higher than the time allocated to workplaces. This suggests that a significant proportion of paid work-related time may be utilised for homeworking or other new working patterns.

From the perspective of location selection, residence is the most time-consuming space for UK residents on both weekdays and weekends. On weekdays, UK residents spend an average of 16.22 hours (i.e., 973.40 minutes) at home, increasing to 17.58 hours (i.e., 1054.55 minutes) on weekends. On weekdays, workplaces receive more time allocation during daytime hours (8:00-17:00), peaking between 11:00-12:00 (22.19 minutes, accounting for 36.99%). This time allocation rapidly decreases outside of these hours. Conversely, on weekends, the average time allocated to workplaces decreases by 74.22% to 49.69 minutes, allowing British residents more daytime hours to visit other locations (such as shopping centres and cinemas) or explore the outdoor environment.

Table 5.4 Aggerated activity type choices of UK population

	Paid work	Domestic work	Leisure	Personal care	Sleep	Transport
Weekday	213.87	170.88	273.52	166.40	506.37	108.97
Weekend	65.57	192.27	358.79	181.43	544.76	97.18

Unit: minute

Table 5.5 Aggerated location choices of UK population

	Residence	Workplace	Third places	Outdoor	Transport
Weekday	973.40	192.77	32.18	132.69	108.97
Weekend	1,054.55	49.69	48.35	190.23	97.18

Unit: minute

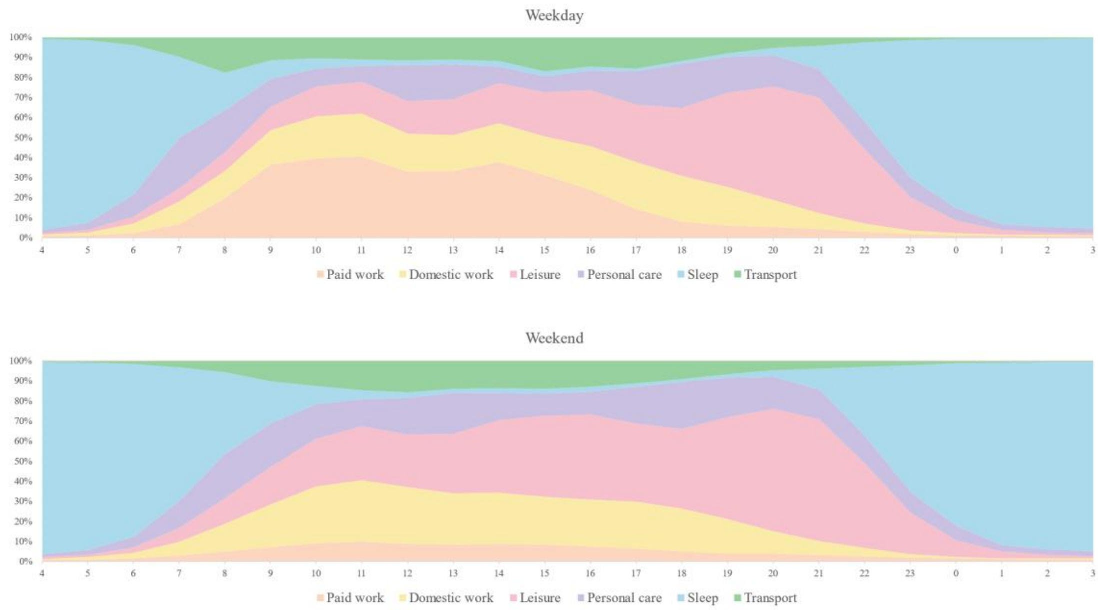


Figure 5.4 Aggregated activity type choices by weekend vs weekday

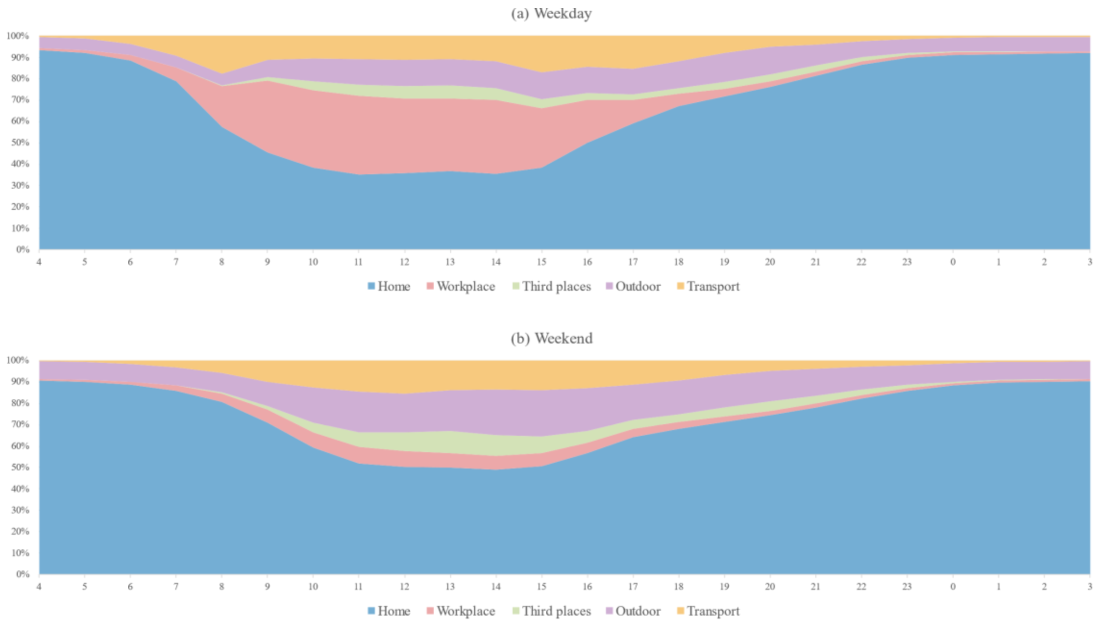
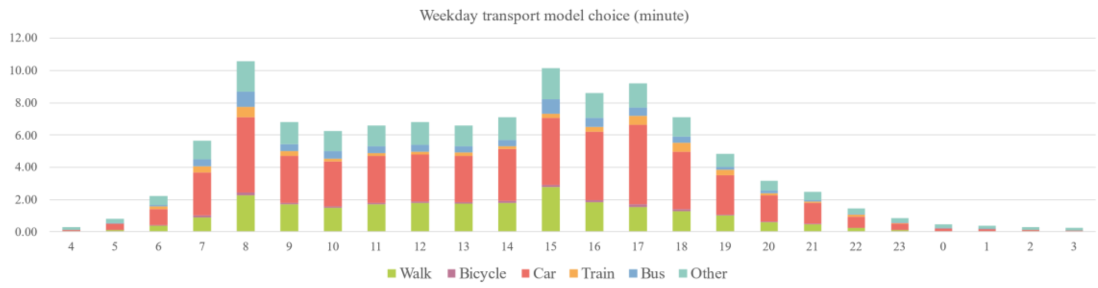


Figure 5.5 Aggregated location choices by weekend vs weekday (min)

Figure 5.6 presents the utilisation of time for transport activities and the selection of transport modes by UK residents on weekdays and weekends. On weekdays, transport activity demands peak between 8:00-9:00 (10.57 minutes) in the morning and 15:00-16:00 (10.14 minutes) in the afternoon. When focusing on road passenger transport (car and bus), the peaks occur between 8:00-9:00 (5.63 minutes) in the morning and 17:00-18:00 (5.48 minutes) in the evening. In contrast, weekends do not exhibit distinct morning and evening peaks. The highest demand for transport activities on weekends occurs at 12:00 noon, reaching 9.36 minutes. Regardless of weekdays or weekends, cars appear to be the most favoured transport mode among residents, with their proportion of transport time being higher on weekends compared to weekdays, in contrast to the trends for public transport modes such as trains and buses.



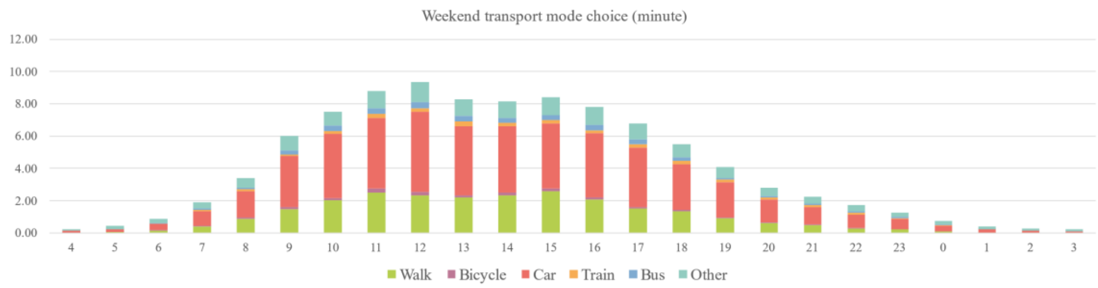


Figure 5.6 Aggregated travel mode choices by weekend vs weekday

5.3.3.2 The Selected Samples

The activity types, locations, and transport characteristics of the selected samples during weekdays and weekends are presented and compared in Table 5.6, Figure 5.7 Table 5.7, and Figure 5.8, respectively.

Compared to the population average, the selected samples have significantly higher working hours. Furthermore, the difference in average paid work duration between weekdays and weekends for these observations is considerably reduced (445.95 minutes and 439.30 minutes, respectively), compared to the population average (213.87 minutes and 65.57 minutes). Among these selected samples, those for the weekend spend more time on leisure, entertainment, and hobby-related activities (192.27 minutes) than those for the weekday (170.88 minutes)). Conversely, the time spent on transport by these residents (109.94 minutes) is less than that of the weekday observations (128.38 minutes), likely due to less pronounced congestion during weekend commuting.

Table 5.6 Aggerated activity type choices of selected samples in UKTUS

	Paid work	Domestic work	Leisure	Personal care	Sleep	Transport
Weekday	445.95	97.51	173.38	132.38	462.40	128.38
Weekend	439.30	88.48	194.54	137.56	470.19	109.94

Unit: minute

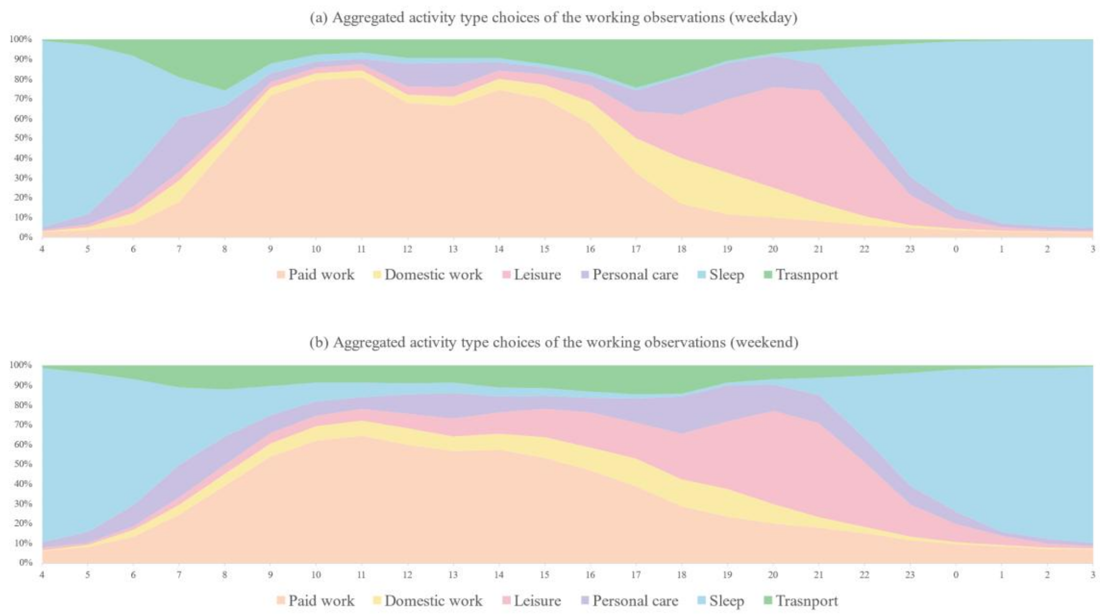


Figure 5.7 Aggregated activity choices of the working observations by weekend vs weekday

Compared to the population average, the selected samples allocate significantly less time to residences, with 796.10 minutes on weekdays and 788.03 minutes on weekends. Conversely, they spend more time in workplaces than the average. Notably, although the weekend samples have less time allocated to paid work-related activities compared to weekdays, they spend more time in workplaces (i.e., 416.06 minutes). Consistent with the choice of activity types, the time spent on paid work activities and in workplaces is more concentrated during weekdays (08:00-17:00), whereas the weekend samples display a more dispersed time distribution. These findings suggest that there may be differences in the proportion of employed residents engaging in new work modes on weekdays and weekends.

Table 5.7 Aggerated activity location choices of the working observations

	Residence	Workplace	Third places	Outdoor	Transport
Weekday	796.10	409.91	21.53	84.08	128.38
Weekend	788.03	416.06	28.89	97.08	109.94

Unit: minute

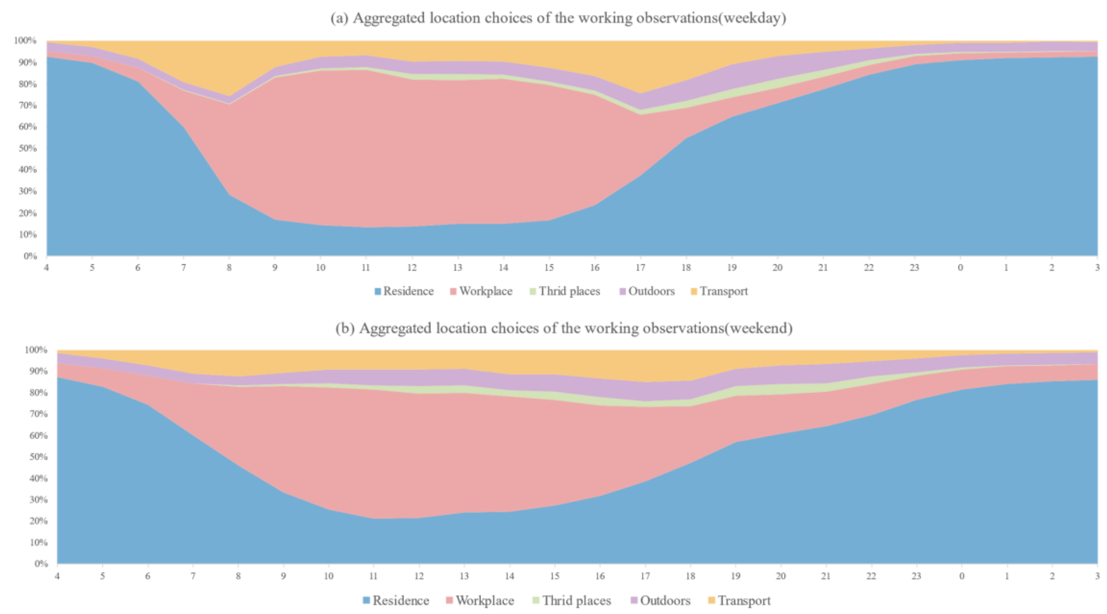


Figure 5.8 Aggregated location choices of the working observations by weekend vs weekday

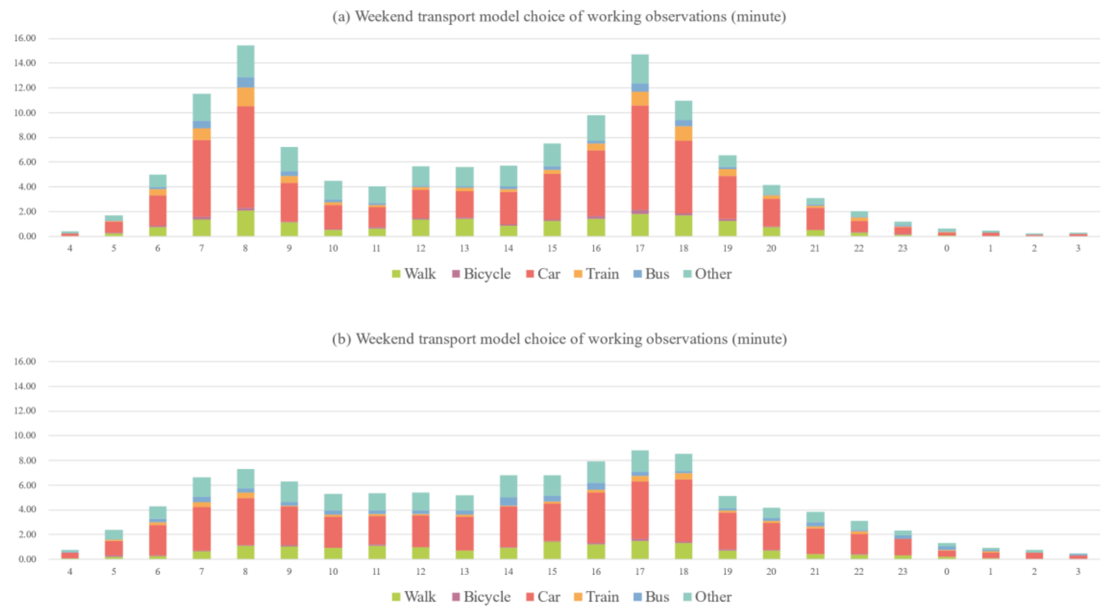


Figure 5.9 Aggregated transport mode choices of the working observations

On weekdays and weekends, the selected samples spend 128.38 minutes and 109.94 minutes on transport activities, respectively. As observed in Figure 5.9, the peaks for transport activities in both weekday and weekend samples occur between 8:00-9:00 in the morning and 17:00-18:00 in the afternoon. Apart from these peak periods, the differences in transport demand between weekday and weekend working observations are relatively minor. During the 8:00-9:00 period, weekday samples spend 15.45 minutes on transport, while weekend samples spend 7.32 minutes. Similarly, during the 17:00-18:00 period, weekend observations spent an average of 8.83 minutes on transport, a 39.97% reduction compared to the 14.71 minutes spent by weekday samples. This suggests that reduced traffic congestion on weekends benefits employed residents who engage in paid work activities.

5.3.4 The Activity Model

There are two critical steps in the activity model: (1) working pattern identification, and (2) activity pattern modelling. The identification of working patterns aims to determine the primary work mode categories of the employed population in the UK, considering two dimensions: the time and location choices of paid work activities. Activity pattern modelling, on the other hand, utilises a utility maximisation model to simulate residents' preferences in choosing activity types, times, locations, and transport modes, as well as the influence of different working patterns on these preferences.

This study employs k-means clustering to identify the work patterns of employed respondents. K-means clustering is a widely used unsupervised machine learning algorithm that partitions a dataset into k distinct clusters, where each data point belongs to the cluster with the nearest mean. The algorithm iteratively assigns data points to clusters and updates the cluster centroids until convergence is achieved, minimising the within-cluster variance. This method has been extensively applied in many urban research domains (Müller et al., 2021; Okereke et al., 2023). In this process, the study first preprocesses the dataset to ensure it is suitable for clustering by standardising the working time and working location variables. After that, the study employs the elbow method to determine the optimal number of clusters (k). It then initialises the cluster centroids and iteratively assigns each employed respondent to the nearest centroid based on their working time and location. This process continues until the centroids stabilise, indicating that the clusters have been formed. The resulting clusters can reveal distinct work patterns of employed respondents from both temporal and spatial perspectives.

In the second step, the MDCEV model (Bhat, 2005, 2008, 2018) is utilised for activity pattern modelling. The MDCEV model is a powerful econometric tool used to analyse and predict choices involving both discrete and continuous decisions. Unlike traditional discrete choice models, which are limited to binary or multinomial choices, the MDCEV model allows for the simultaneous selection of multiple alternatives, considering both the presence of multiple discrete choices and the continuous quantity of each choice. In addition, the MDCEV model accommodates scenarios where the time or resource allocation for some choices is zero. This feature makes it particularly useful in contexts where individuals allocate time or resources among multiple options. One of the key advantages of the MDCEV model is its ability to capture the richness and complexity of real-world decision-making processes, providing more accurate and detailed insights into consumer behaviour and preferences. Furthermore, the model's flexibility allows it to accommodate various forms of utility functions and interaction effects, making it highly adaptable to different contexts and datasets. Equation 5-1 presents the MDCEV utility function of time use pattern $\boldsymbol{x}$ that simultaneously considers activity types $\boldsymbol{j}$ and locations $\boldsymbol{k}$:

Max

$$U(x) = \frac{1}{\alpha_{11}}\psi_{11}x_{11}^{\alpha_{11}} + \sum_{j=1}^{J}\sum_{k=1}^{K}\frac{\gamma_{jk}}{\alpha_{jk}}\psi_{jk}\left\{\left(\frac{x_{jk}}{\gamma_{jk}}+1\right)^{\alpha_{jk}} - 1\right\}\left(1-\delta_{j1}\delta_{k1}\right) \quad (5-1)$$

$$\delta_{j1} = \begin{cases}1, & j=1\\ 0, & j\neq 1\end{cases} \quad \text{and} \quad \delta_{k1} = \begin{cases}1, & k=1\\ 0, & k\neq 1\end{cases}$$

S.T. $\sum_{j=1}^{J}\sum_{k=1}^{K}x_{jk}p_{jk} = T$

Where $U(x)$ is a quasi-concave, increasing, and continuously differentiable function. The vector x $(x \geq 0)$ represents the consumption quantity, where the elements x_{jk} refer to time allocated to activity type j at location k. The activity k=1 at the location j =1 is defined as the outside activity. ψ_{jk} $(\psi_{jk} > 0)$, α_{jk} $(\alpha_{jk} \leq 1)$ and γ_{jk} $(\gamma_{jk} > 0)$ are parameters associated with activity type j and location k. ψ_{jk} represents the baseline marginal utility associated with activity type j and location k. α_{jk} is an item to capture the satiation effect that the marginal utility of an activity decreases with time allocated to this specific activity. As α_{jk} moves downwards, the satiation effect for the activity type j at location k increases, and the satiation effect disappears when it equals 1. In addition to α_{jk}, γ_{jk} also serves the role of a satiation parameter. However, it also introduces the corner solutions, which means zero-time allocation to some specific activities at specific locations. There is no γ_{11} for the outside activity. $\boldsymbol{T}$ means the total time budget across all activity type j at location k. p_{jk} refers to the unit price of activity type j at location k, where p_{jk} for all activities and locations equal to 1 in this study.

According to the above explanations, both α_{jk} and γ_{jk} influence the satiation effect, albeit in entirely different ways: α_{jk} controls satiation by making the time consumption exponential, while γ_{jk} does so by transforming the amount of time consumed (Bhat, 2018). However, in practical applications, it is challenging to estimate both coefficients simultaneously, as it is difficult to reasonably allocate the satiation effect between these two factors. Bhat (2008) established two alternative versions of the utility function. The first is the γ-profile function, where α_{jk} approaches zero for all alternatives, and all γ_{jk} are estimated. The second is the α-profile function, where $\gamma_{jk} = 1$ is applied to all alternatives, and all α_{jk} are estimated. This study adopts the γ-profile function for several reasons: (1) in our case, there are numerous activity types where time utilisation may be zero (i.e., corner solutions), which requires capturing γ_{jk}, and (2) several previous studies report that the γ-profile is superior to the α-profile. Equation 5-2 presents the γ-profile utility function in our case:

Max

$$U(x) = \psi_{11} \ln x_{11} + \sum_{j=1}^{J} \sum_{k=1}^{K} \gamma_{jk} \psi_{jk} \ln\left(\frac{x_{jk}}{\gamma_{jk}} + 1\right)\left(1 - \delta_{j1}\delta_{k1}\right) \qquad (5-2)$$

$$\delta_{j1} = \begin{cases} 1, & j = 1 \\ 0, & j \neq 1 \end{cases} \quad \text{and} \quad \delta_{k1} = \begin{cases} 1, & k = 1 \\ 0, & k \neq 1 \end{cases}$$

S.T. $\sum_{j=1}^{J} \sum_{k=1}^{K} x_{jk} = T$

Consistent with the design of the UKTUS questionnaire, transport modes in the model are represented by specific location categories, including *transport_walk*, *transport_bicycle*, *transport_car*, *transport_train*, *transport_bus*, and *transport_others*. Therefore, the transport activity is neither represented as an activity type nor an activity location, The time allocated to transport activities is considered as the sum of the time distributed among these transport modes. This process is represented by Equation 5-3, where the vector $\boldsymbol{x}$ refers to the time allocation to a specific activity:

$$x_{Transport} = x_{walk} + x_{bicycle} + x_{car} + x_{train} + x_{bus} + x_{others} \quad (5-3)$$

Based on the above utility function, this study develops two MDCEV models to capture the time use preference of the employed population on weekdays and weekends, respectively. The MDCEV calibration is based on the Apollo (Hess & Palma, 2019), a developed package for discrete choice modelling in the R Studio environment.

5.3.5 The Energy and Carbon Model

The energy and emissions model consist of three main steps. The first step aims to generate building occupancy schedules, appliance and lighting system operation schedules, and transport demand schedules using deterministic data and time-use patterns produced by the activity model. These schedules serve as data inputs for the building energy model and the transport energy model. The second step involves constructing a bottom-up urban building model based on data from the study area. This model is developed to simulate aggregated energy demand in the residential and office sectors. This model also calculates the carbon emissions of each sector. The third step involves building a transport carbon emission model to predict transport carbon emission based on the time distribution of transport activities.

5.3.5.1 Building and Transport Schedule Development

Based on the deterministic data and the activity model, this study develops three schedules for the building energy modelling: (1) residential and office building occupancy schedule, (2) residential and office building lighting intensity schedule, (3) residential and office building appliance (electronic equipment) intensity schedule. In addition, the study also develops the transport demand schedule for the urban transport energy model. In our schedule development, third spaces, such as co-working centres, libraries, and cafés, were not incorporated as alternative workplaces. This omission is because the fact that the data were collected during 2014 to 2015, where third spaces had not yet been widely adopted in the UK and consequently featured only sparsely within our sample. As such, integrating these options into the model may reduce its predictive accuracy.

The study employs the residents' time allocated to residences and workplaces to generate the occupancy schedules for residential and office buildings. These schedules are divided into weekday and weekend categories and use relative occupancy density:

indicating the relative occupancy levels at different times rather than absolute numbers. The data used to construct building occupancy schedules comprise two parts. The first part is derived from the activity model outputs, primarily covering employed residents engaged in work activities. Using this data, the occupancy schedules can capture the population-level effects of variations in work patterns. The second part is based on deterministic UKTUS data, including unemployed residents, employed residents not engaged in paid labour (e.g., holidays and sick leave), and observations excluded from the activity model for various reasons. The study combines the building occupancy characteristics from these two data sources through weighted averaging to generate occupancy schedules for the entire population. The schedules use the maximum occupancy density reference value from the baseline scenario to calculate relative occupancy densities for all scenario time points, with a temporal resolution of one hour.

In addition to occupancy schedules, the study also provides appliance and lighting system intensity schedules for the residential and office energy models. These schedules reflect variations in the usage intensity of energy systems closely related to resident activities for each time unit. Similar to occupancy schedules, these intensity schedules use one-hour time steps and differentiate between weekdays and weekends. The schedules are generated using a weighted average of the activity model outputs and deterministic data.

However, in constructing the appliance and lighting system intensity schedules for residential buildings, resident occupancy is classified into active and inactive states (Richardson et al., 2010b). The inactive state specifically refers to residents sleeping, during which occupants tend to use less lighting and fewer appliances. Any activity other than sleeping at the residence is classified as active. When establishing the appliance usage intensity schedules for residential buildings, the study considers the direct impact of active occupancy variations and additionally sets a fixed 20% base load. This load accounts for electrical devices operating independently of resident activities, such as refrigerators and security systems.

Furthermore, residential lighting system usage is directly related to external daylight hours, based on local climate conditions in the City of Manchester. Based on the prEN16798-1 and ISO/FDIS 17772-1 Standards (Ahmed et al., 2017), we assume the average annual time for extensive indoor lighting is from 17:00 to 08:00. During this period, residential lighting system intensity is assumed to correlate directly with active occupancy, while outside these hours, only 20% of lighting is maintained for task and accent lighting. The office building lighting and equipment intensity, however, directly correlate with occupancy rates.

The transport demand schedule is an input for the transport model. This schedule reflects the time consumption for different modes of transport for each time step. The transport schedule is generated using a weighted average of the activity model outputs and deterministic UKTUS data. Similar to the building schedules, these transport schedules use one-hour time steps and distinguish between weekdays and weekends.

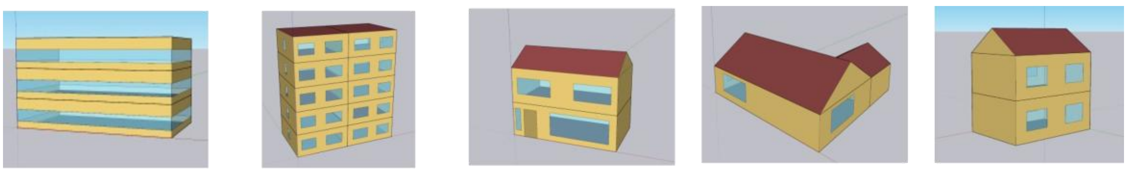
5.3.5.2 Urban Building Energy Model Development

To assess the effect of new work patterns on residents' activity patterns and their implications for urban energy consumption, a simplified UBEM was developed to analyse changes in energy demand under different working pattern scenarios. The method consists of three key steps: (1) developing building archetypes, (2) mapping OSM data to the predefined archetypes, and (3) implementing UBEM for energy simulation and validation.

The building archetype approach is a critical component of bottom-up engineering UBEM. Given the challenges associated with collecting detailed building data at the city scale, the archetype method allows for high accuracy with relatively low computational effort by summarising the typical characteristics of building types. In terms of building classification, the building stock can generally be divided into residential and non-residential buildings (Ali et al., 2019). Common residential building types include detached houses and apartments, while non-residential buildings comprise offices and commercial complexes (Ali et al., 2019). As this study examines the impact of new activity patterns on building energy consumption, the development of building archetypes is intended to provide a framework for assessing how these new activity patterns influence urban building energy consumption. Based on these categories, five building archetypes were developed for this study: office, apartment, semi-detached house, detached house and terraced. In terms of building envelope characteristics, the office prototype draws on the work of Korolija et al. (2013) to define the relevant parameters for the building envelope. For residential buildings, this study refers to the UK model within the TABULA project and the research by Ali et al. (2019), which outlines the energy characteristics of residential buildings in the UK. The schedule used in the building archetypes is based on the results of MDCEV modelling, which accounts for activity patterns. The weather data used is sourced from the EnergyPlus documentation, specifically from the meteorological station closest to the case, Aughton 033220. Table 5.8 provides the detailed characteristics of the building prototypes employed in this study and Figure 5.10 shows models of buildings.

Table 5.8 U Values and Input Parameters of Building Archetypes

Building Element	Office	Residential			
		Apartment	Semi-detached	Detached	Terraced
External wall	0.54	2.10	1.60	1.60	2.10
Roof	0.43	2.30	1.50	1.50	2.30
Ground floor	0.82	0.16	0.40	0.59	0.60
Windows	3.15	3.10	3.10	4.80	3.1
Occupancy rate		Derived from the activity model			
Occupant density, (People/Area)		Office: 0.09, Residential: 0.028			
Lighting power, W/m^2		Office: 12.0, Residential: 5.0			
Equipment, W/m^2		Office: 15.0, Residential: 6.7			



(a) Office (b) Apartment (c) Semi-detached (d) Detached (d) Terraced

Figure 5.10 Model Visualisation for Energy Simulation

In Step 2, this study initially used the Overpass API to extract building data for the study area from OpenStreetMap. The case city is Manchester, which has an urban area of approximately 45 square miles (116 km²). Consequently, data was extracted within a radius of 10.77 kilometres, centred on Manchester City Centre (53.479167°N, 2.244167°W), covering a total area of approximately 116 km². In total, data for 194,484 buildings was retrieved, while 71,153 buildings had missing labels or sufficient information to determine the building type. The extracted building data was subsequently mapped to align with the step 2 developed building archetypes, with the matching process based on building category. The classification results are as follows: 4,725 Offices, 10,982 Apartments, 14,969 Semi-detached houses, 2,187 Detached houses and 90160 terraced houses. These results provide a quantitative distribution of the various building types, offering valuable data support for the subsequent building energy analysis. Figure 5.11 shows the distribution of building types in the case area. The buildings outside the scope of residential and office were shown in grey.

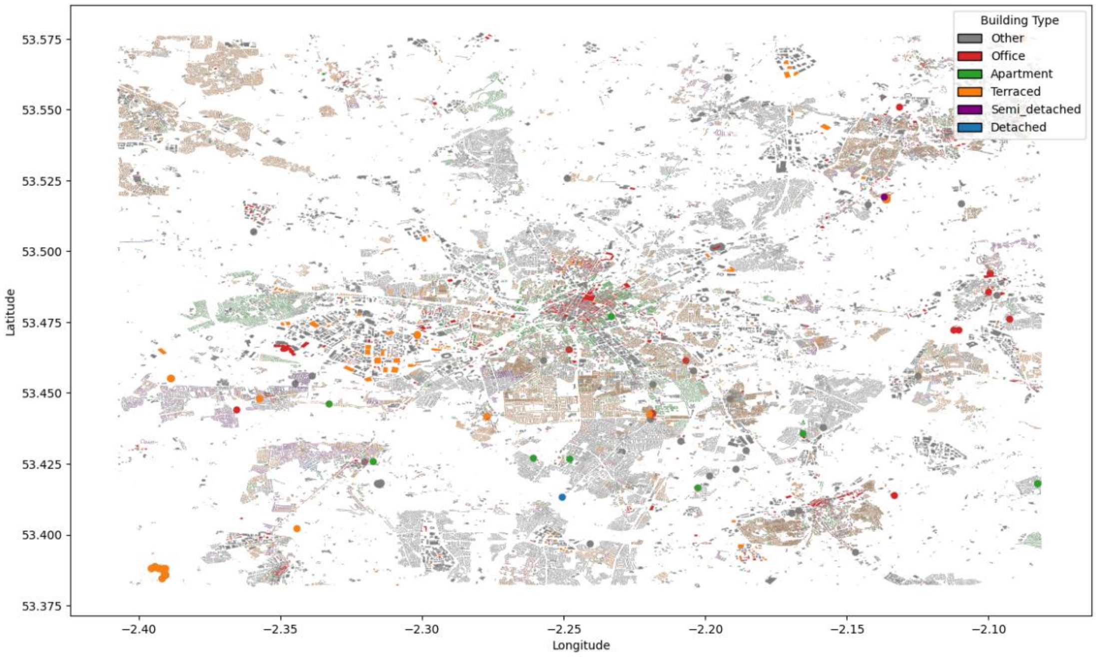


Figure 5.11 Building Distribution in the Case Area

Following the building archetype development and the preprocessing of the OpenStreetMap data, this step then involved the application of Python-based tools for UBEM, enabling the bulk simulation of building energy across the study area. This approach streamlined the modelling process, ensuring both efficiency and scalability in evaluating urban building energy consumption.

This study calculates the carbon emissions of the residential and office sectors based on building energy demand, using the following formula (5-4):

$$CE_{st} = \sum_{f} E_{fst} I_{ft} \qquad (5-4)$$

Where, CE_{st} refers to the total carbon emissions of sector ***s*** at time ***t***. E_{fst} denotes the demand for energy type ***f*** by sector ***s*** at time ***t***, where in this study, ***f*** =1 represents electricity, and ***f***=2 represents natural gas. I_{ft} stands for the emission factor of energy type ***f*** at time ***t***. According to the *Energy and Emissions Projections* data from the Department for Energy Security and Net Zero (2024), the carbon intensity of electricity employed in this study is 0.21 and the one of r natural gas is 0.18.

5.3.5.3 Transport Sector Model Development

This study employs a simplified model to estimate the carbon emission of the transport sector based on the time distribution of transport activities. The underlying principles can be referred to in formula (5-5):

$$CE_{Transport} = \sum_{m} F_m T_{mt} V_{mt} \quad (5-5)$$

Where, $CE_{Transport,t}$ refers to the total carbon emissions of the transport sector at time ***t***. T_{mt} refers to the total time allocated to the transport mode ***m*** at time ***t***, which is derived from the transport demand schedule. V_{mt} refers to the average speed of the transport mode ***m*** at time ***t***. F_m is the carbon intensity of transport mode ***m*** (usually in the unit of grams of carbon dioxide equivalent per kilometre).

In this study, the transport mode carbon intensity F_m is obtained from British Department for Energy Security and Net-Zero (2024). Table 5.9 details the carbon intensity values employed in the study.

Table 5.9 details the carbon intensity values employed in the study

Transport mode	Carbon intensity (gCO_2e/km)
On foot	0
Bicycle	0
Car	135.4.
Train	26.16
Bus	102.54
Other	135.4

5.4 The Activity Model Results

5.4.1 Time Use Pattern Identification

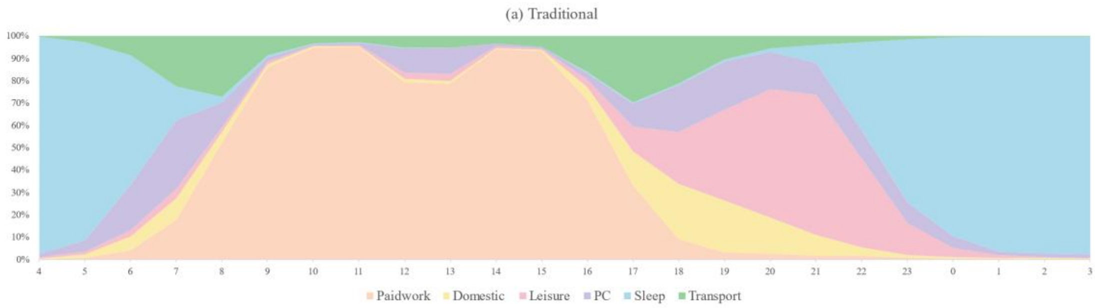
The first task of the activity model is to identify the work patterns of UK residents using k-means clustering method based on two dimensions: working time and working location. The study identified the optimal number of clusters as four for both dimensions using the elbow method. For working time choices, the cluster analysis identified four typical work time patterns: (1) the traditional (9-to-5) pattern, (2) the dispersed pattern, (3) the half-day pattern, and (4) the nighttime pattern. For working location choices, four typical patterns were identified: (1) commuters, (2) homeworkers,

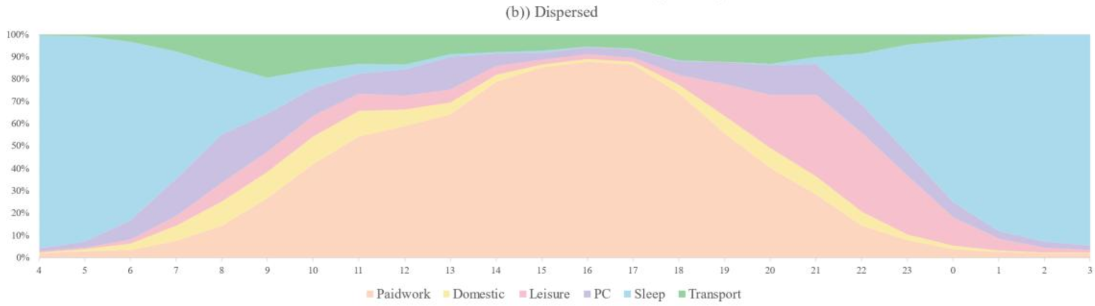
(3) outdoor workers, and (4) moving workers. Table 5.10 presents the sample size by cluster. In the work time dimension, the traditional (9-to-5) workers accounted for the largest proportion, totalling 2,046 (i.e., 56.09%). In the work location choice dimension, commuters were the most prevalent, comprising 2,632 (i.e.,72.15%). When considering both two dimensions together, the 9-to-5 commuters formed the largest group, with 1,528 individuals (i.e., 41.89%). These data indicate that while traditional work patterns continue to dominate in both dimensions, non-traditional work patterns are non-negligible in British society.

Table 5.10 Sample size by cluster (working pattern)

	Commuter	Homeworker	Outdoor workers	Moving workers
Traditional (9-to-5)	1528	74	430	14
Dispersed	337	31	123	3
Half-day	572	64	174	33
Nighttime	195	16	51	3

Unit: person





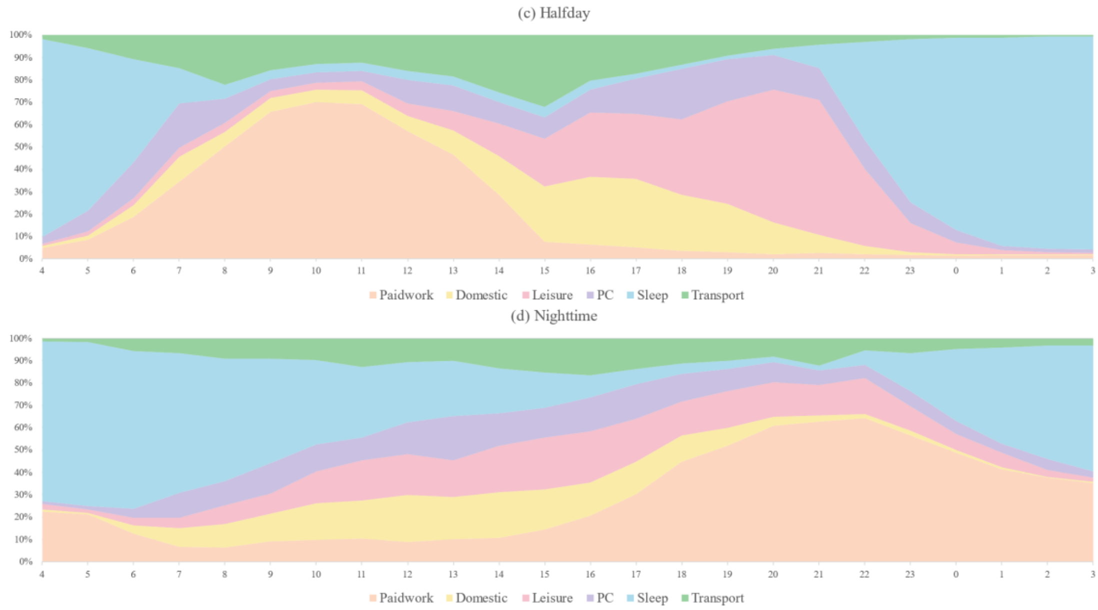


Figure 5.12 Activity Time Allocation by Working Time Type

Figure 5.12 compares the activity time allocation across four working-time clusters, with aggregate patterns summarised in Table 5.11. The traditional pattern, also known as the 9-to-5 pattern, is the most widely adopted work time pattern in contemporary society. Residents following this pattern exhibit a significant increase in time allocated to paid work starting at 08:00 (31.45 minutes, 52.41%), which dominates until 17:00. During this period, the proportion only decreases during lunchtime: the time spent on paid work from 12:00-13:00 and 13:00-14:00 is 47.67 minutes (79.43%) and 47.27 minutes (78.78%), respectively. After 18:00, the time dedicated to paid work drops rapidly, while leisure, domestic work, and personal care gain more time allocation. From 19:00 to 22:00, leisure activities occupy a more prominent position in the time allocation of traditional workers. Their transport activity concentrates between 08:00-09:00 and 17:00-18:00.

Table 5.11 Summary of Activity Time Allocation by Working Time Type

Pattern	Paid work	Domestic work	Leisure	Personal care	Sleep	Transport
Traditional	493.39	77.30	167.16	129.05	460.88	112.22
Dispersed	507.91	70.55	135.16	127.21	487.00	112.17
Half-day	296.03	144.57	231.87	146.95	459.50	161.08
Nighttime	419.21	126.60	172.83	135.28	462.53	123.55

Unit: minute

Dispersed workers adopt a more scattered work time allocation. These residents allocate a lower proportion of their daytime to paid work activities compared to traditional workers. They are more likely to dedicate their morning to sleep, leisure, and domestic work. Correspondingly, they continue working after 18:00, gradually reducing (rather than rapidly) the time allocated to paid work from 18:00 to 22:00. Dispersed workers allocate a total of 507.91 minutes to paid work throughout the day, exceeding the 493.39 minutes of traditional 9-to-5 workers. They enjoy longer sleep duration (i.e., 487.00 minutes), while their time allocated to leisure and domestic work is significantly lower than that of traditional workers. Their transport time (i.e., 112.17 minutes) is similar to that of 9-to-5 employees (i.e., 112.22 minutes), but their transport activity peaks (11.62 minutes) are lower and occur at 09:00.

Half-day workers have a shorter total time spent on paid work during workdays (296.03 minutes), which is concentrated in the early morning and afternoon. For this group, the dominant time for paid work begins earlier (06:00) compared to other types of workers. After 11:00, their time allocated to paid work activities gradually decreases. Post 15:00, they predominantly allocate their time to leisure, personal care, and domestic work. The time these residents allocate to these three activities is substantially higher than that of other employed residents. Compared to traditional 9-to-5 workers, half-day workers allocate an additional 67.27 minutes (87.02%) to domestic work, 64.71 minutes (38.71%) to leisure, and 17.90 minutes (13.87%) to personal care. Their sleep time (i.e., 459.50 minutes) is the shortest among the four work time patterns. Also, they have longer transport times (161.08 minutes), with transport activity peaks occurring from 08:00-09:00 and 15:00-16:00.

The last work time pattern is known as nighttime workers. This group concentrates their paid work activities at night, primarily from 18:00 to 03:00. Their occupations could be a part of the night economy, such as restaurant and bar operators, night patrol police, and night shift drivers. These residents allocate slightly less total time to paid work compared to traditional workers, but their time for sleep and personal care is very similar to traditional workers. Their transport activities are more dispersed, showing only gradual changes in transport activity proportions over 24 hours, with a peak at 16:00.

Figure 5.13 presents the hourly time allocation characteristics in different locations over a 24-hour period for the four work location patterns, summarised in Table 5.12. Among the four work location patterns, commuters are the most common. As shown in Figure 5.13 (a), commuters typically engage in paid work activities at fixed locations outside their residences. Residents following this pattern spend the most time in workplaces compared to other patterns, averaging 479.16 minutes. These individuals mainly visit third places and explore outdoor environments for non-transport purposes bet A distinctly different working pattern is that of homeworkers.

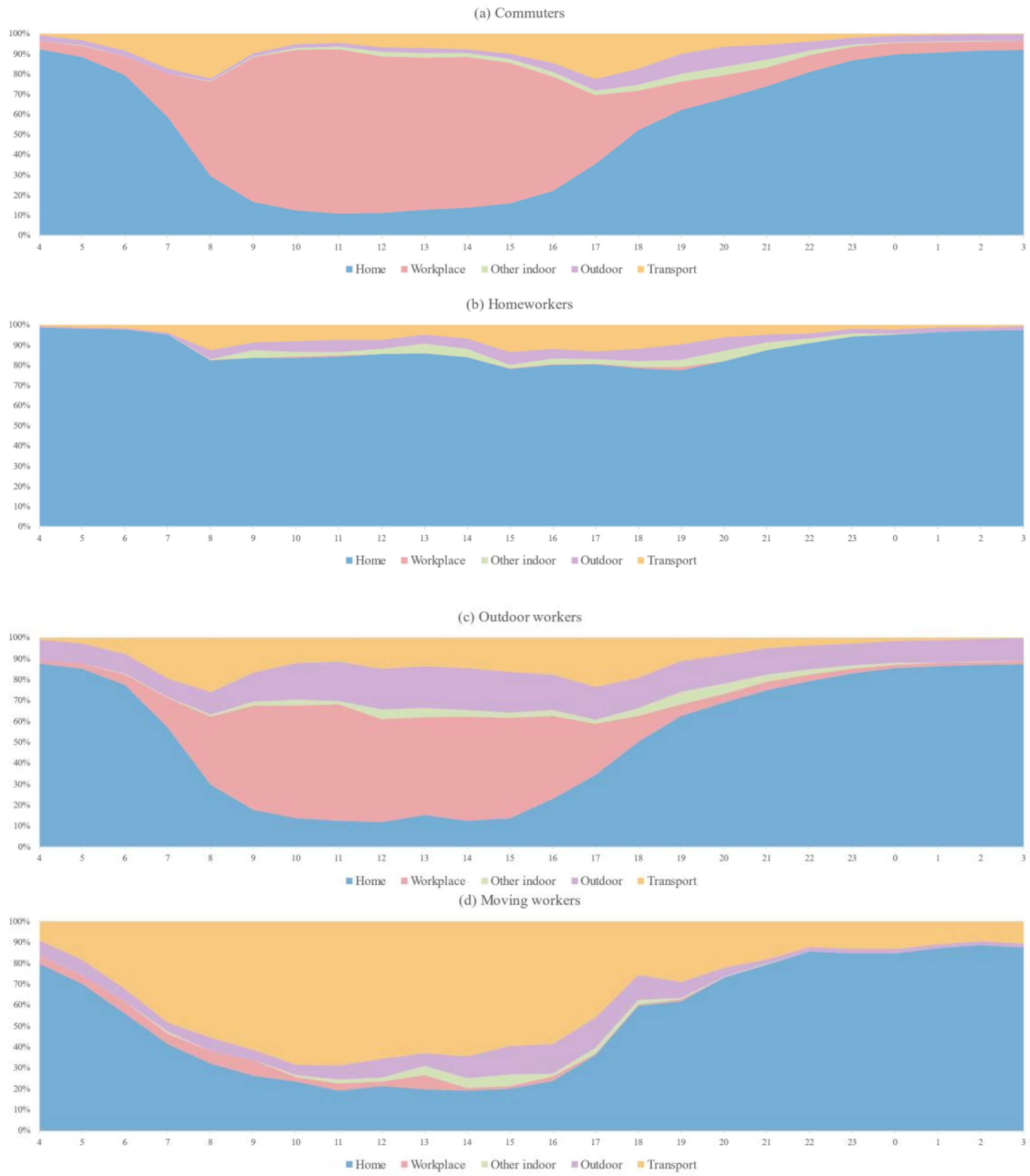


Figure 5.13 Activity Location Allocation by Working Location Type

Table 5.12 Summary of Activity Location Allocation by Working Location Type

Pattern	Residence	Workplace	Third places	Outdoors	Transport
Commuters	773.02	479.16	20.66	55.75	111.41
Homeworkers	1269.65	2.85	27.85	53.20	86.45
Outdoor workers	754.60	306.11	30.30	198.38	150.62
Moving workers	769.62	32.26	16.60	91.51	530.00

Unit: minute

Homeworkers primarily conduct paid work activities within their residences, with many possibly not having separate workplaces outside their homes. Homeworkers allocate less time at their out-of-home workplaces even if they have one: they spend only an average of 2.85 minutes per day at such locations. In contrast, they spend 1,269.65 minutes at home, exceeding the average time spent by commuters by 496.63 minutes (i.e., by 64.24%). This group has the lowest transport demand among the four types of employed residents, at only 86.45 minutes, likely due to reduced commuting demands.

The third pattern is named outdoor workers. These residents allocate time to paid work activities similarly to commuters but also conduct some paid work in outdoor environments. Examples of occupations following this pattern include those requiring field inspections or outdoor maintenance. While their total time in workplaces (i.e., 306.11 minutes) is lower than that of commuters (479.16 minutes), the nature of their work necessitates allocating part of their paid work time to outdoor environments. Moreover, the process of travelling to outdoor work locations results in significantly higher transport demand (i.e., 150.62 minutes) during their work hours compared to other patterns.

The final category is referred to as moving workers. Similar to homeworkers, moving workers spend minimal time conducting paid work activities at workplaces. However, their paid work activities primarily occur in transit. Examples of this pattern include bus and truck drivers, as well as flight crew members. These residents allocate 530 minutes per day to time spent in transit, far exceeding the average for the four categories. Conversely, they only spend 32.26 minutes at the workplace. Besides, they allocate more time to outdoor environments (91.51 minutes) compared to the average, while the time spent at residences (769.62 minutes) is comparable to that of commuters (773.02 minutes) and outdoor workers (754.62 minutes).

5.4.2 MDCEV Model Calibration and Validation

5.4.2.1 MDCEV Calibration

This study then employs the classified UKTUS data to calibrate the MDCEV model. During the modelling process, data from 53 moving workers were excluded for two reasons: (1) their time allocation to indoor environments at work locations is minimal, which may affect the accuracy of office building occupancy schedules, and (2) the nature of their work results in relatively stable work patterns that are unlikely to transition to other modes such as homeworking or outdoor working. Then, the dataset for modelling comprises 3,595 observations, including 2,827 weekday diary observations and 768 weekend observations. We randomly selected 80% of the data for model calibration, with the remaining 20% used for validation. For the weekday model, 2,262 observations were used for calibration and 565 for validation. For the weekend model, 614 observations were used for calibration and 154 for validation.

Among the results, gamma serves two critical functions within the model: firstly, it enables the possibility of corner solutions (i.e., zero time allocation), and secondly, it acts as a satiation parameter, capturing the effects of diminishing marginal utility as time allocation increases. The gamma parameter is inversely related to the satiation level for a given activity type and time period category. Thus, a lower gamma value indicates a higher satiation threshold for the given activity type and time period category, resulting in a larger proportion of time being allocated to that category. For instance, during weekday mornings between 08:00-09:00, the gamma values for paid work activities at residence, workplace, and third places are 119.07, 164.04, and 30.02, respectively. These values demonstrate that residents experience lower satiation levels for paid work activities at workplaces and residences during this time period compared to other indoor environments, leading to significantly higher time allocations for paid work activities at these two locations.

In addition, the betas represent the baseline preference constants and the influence of working patterns on these constants. Whilst baseline preference constants lack meaningful real-world interpretation, they reflect residents' relative preferences for certain activities at specific locations during the same time period. These baseline preference constants are calculated for each activity across different time periods, using the outside good (sleep activity at home during the respective time period) as the reference point. Consequently, most baseline preference constants are negative, indicating a lower preference for specific activities compared to the outside activity.

Furthermore, the impact of different working patterns on time allocation is reflected in the variations of preference constants. An increase in the preference constant suggests that under a particular working pattern, residents are more inclined to allocate time to specific locations or activities. However, if a working pattern's influence on the constant is negative, it indicates that adopting this working pattern leads to a reduced preference for the activity or location, subsequently negatively affecting residents' time allocation for these activities or locations. For example, during weekday nights between 23:00-00:00, the baseline preference constant for paid work at the workplace is -7.07, whilst the effect of nighttime working on this parameter is 6.46, demonstrating a significant preference for this activity among night-shift workers.

5.4.2.2 MDCEV Validation

This study employs a randomly selected 20% of the data for model validation. The estimated values from the calibrated MDCEV model are compared with the observed validation data using linear regression.

- *Activity Type Choices*

Figure 5.14 presents a regression analysis comparing the observed and estimated values of time allocation for all activities and locations. The R-squared value for the weekday model is 0.9876, while that for the weekend model is 0.9610. These high R-squared values indicate that the proposed MDCEV model demonstrates satisfactory predictive performance in activity patterns. However, the predictive ability of the weekend model is slightly lower than that of the weekday model. One possible reason is that the validation data for the weekend model are fewer (only 154 observations), making it more susceptible to the influence of outliers. Figure 5.15 illustrates the estimated and observed activity time allocation of the elected samples by activity type.

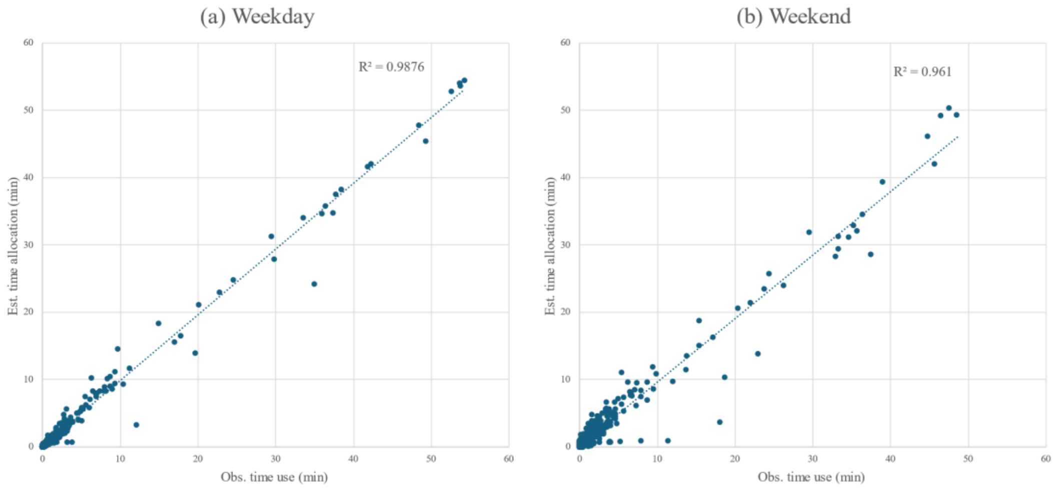
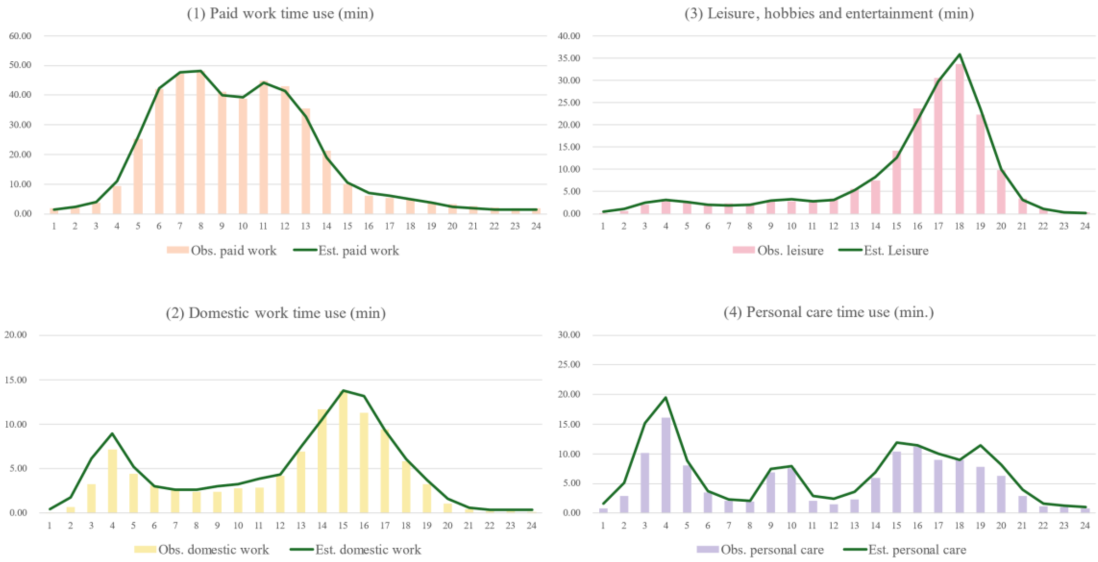
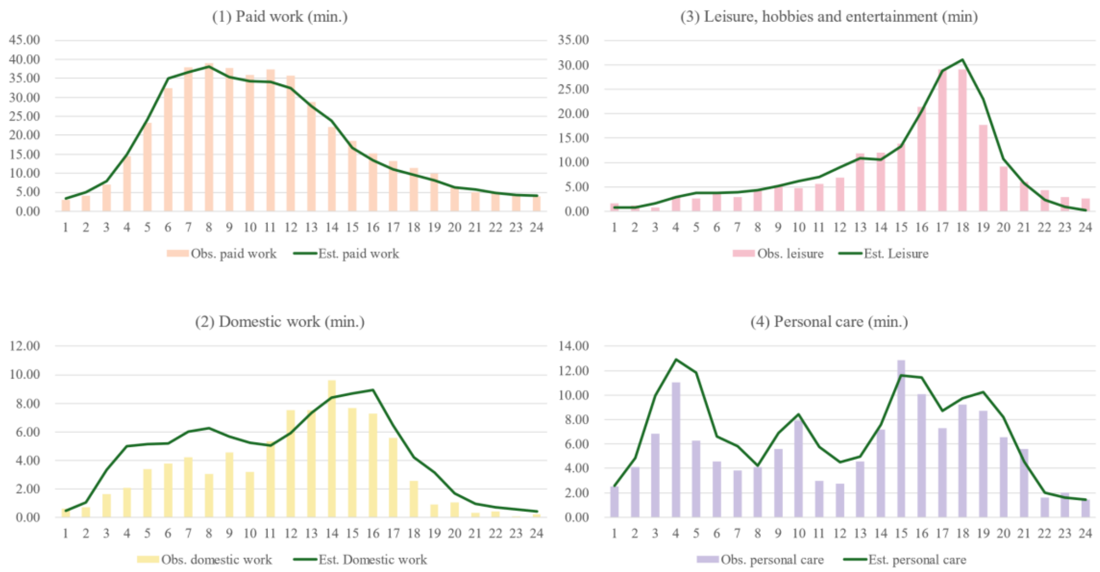


Figure 5.14 Estimated vs Observed Time Allocation to All Activity Types and Locations



(a) Estimated vs Observed Activity Time Allocation by Activity Type (Weekday)



(b) Estimated vs Observed Activity Time Allocation by Activity Type (Weekend)

Figure 5.15 Estimated vs Observed Time Allocation Time Allocation by Activity Type

- *Location Choices*

Figure 5.16 and Figure 5.17 further examine the predictive ability of the model in terms of time allocation to different locations. Figure 5.16 (a) and (b) represent the weekday and weekend models, respectively, with R-squared values of 0.9886 and 0.9843. Figure 5.17 illustrates the predicted hourly time allocation for four types of locations (residence, workplace, third places, outdoors) throughout the day.

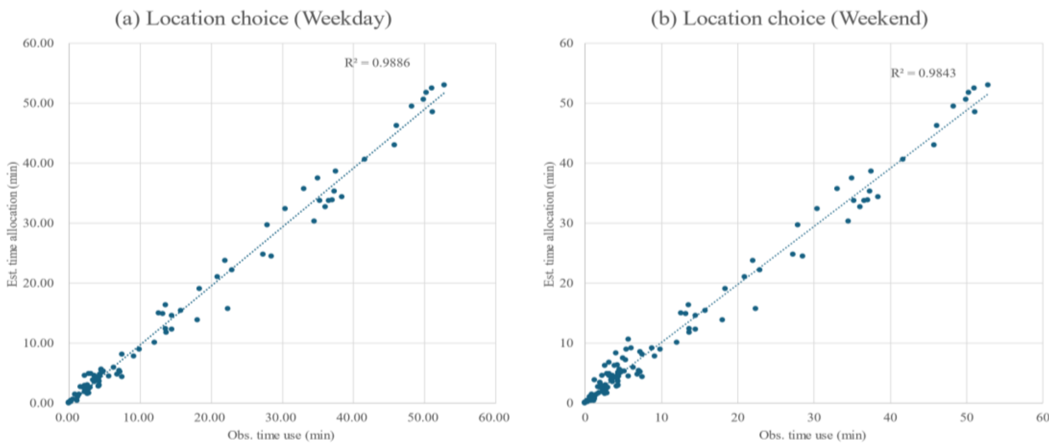
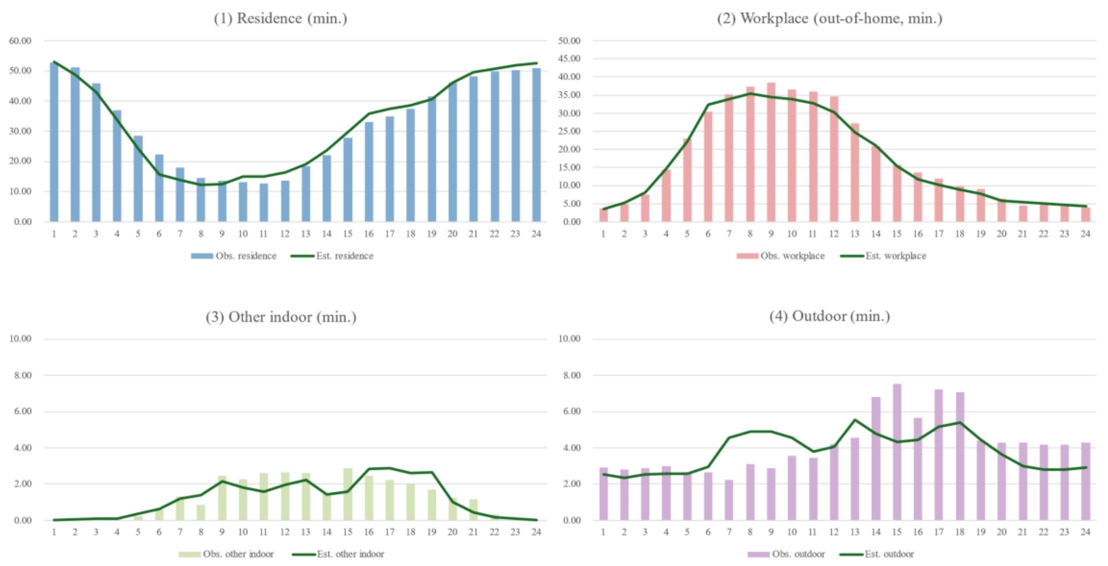
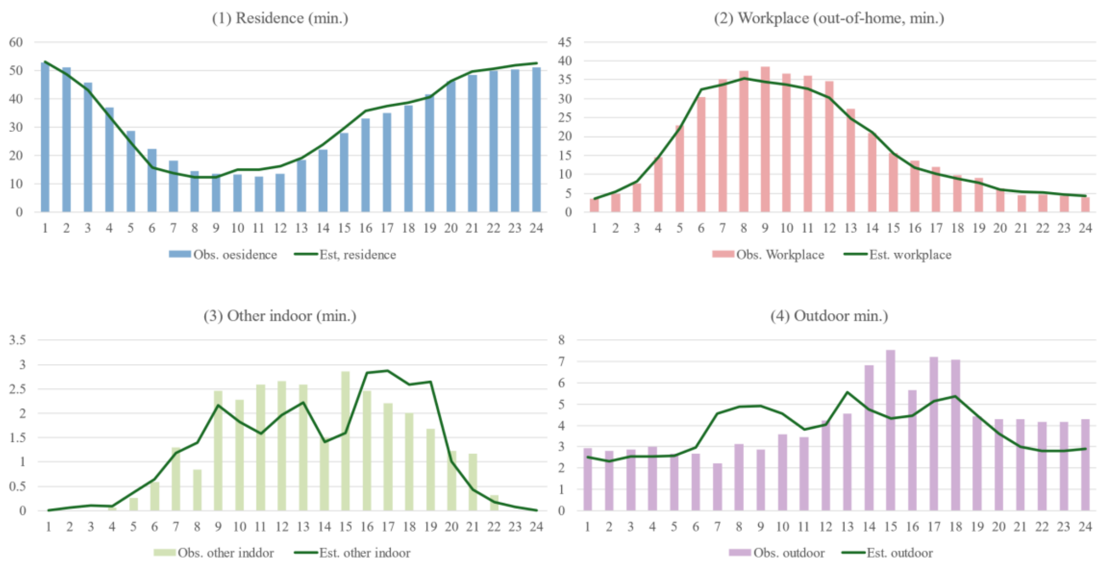


Figure 5.16 Estimated vs Observed Time Allocation to All Activity Locations



(a) Estimated vs Observed Time Allocation by Location (Weekday)



(b) Estimated vs Observed Time Allocation by Location (Weekend)

Figure 5.17 Estimated vs Observed Time Allocation by Location

- *Transport Mode Choices*

Figure 5.18, Figure 5.19 and Figure 5.20 present the predictive ability of the model regarding time allocation to all transport activities. Figure 5.18 presents a regression analysis comparing the observed and estimated time allocations for all transport activities by modes and types. Figure 5.18 (a) and (b) detail the weekday and weekend model results by hour, respectively. Figure 5.19 illustrates the predicted hourly time allocation for transport activities throughout the day. This figure indicates that the prediction bias in the weekend model is primarily due to an overestimation of transport demand during morning hours. Figure 5.20 compares the observed and predicted time allocations for different transport modes. Overall, these results demonstrate that the MDCEV model developed in this study exhibits satisfactory predictive performance in activity time allocation.

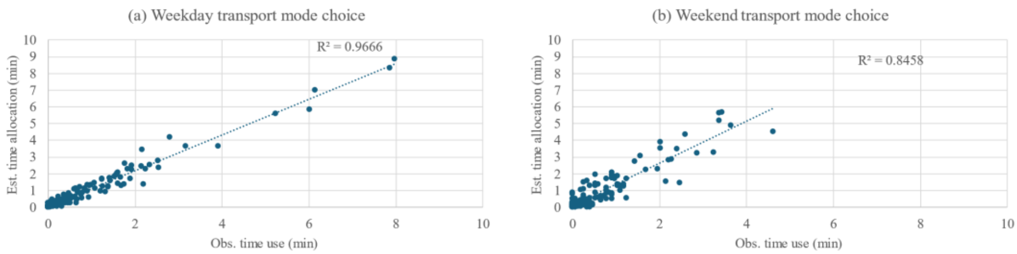


Figure 5.18 Estimated vs Observed Time Allocation to All Transport Modes

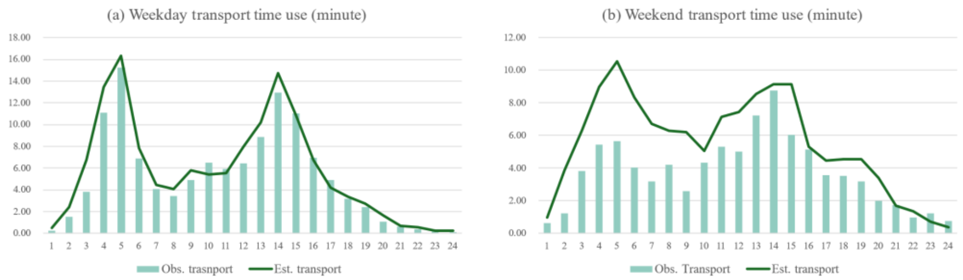


Figure 5.19 Estimated vs Observed Time Allocation to Transport Activity (By Hour)

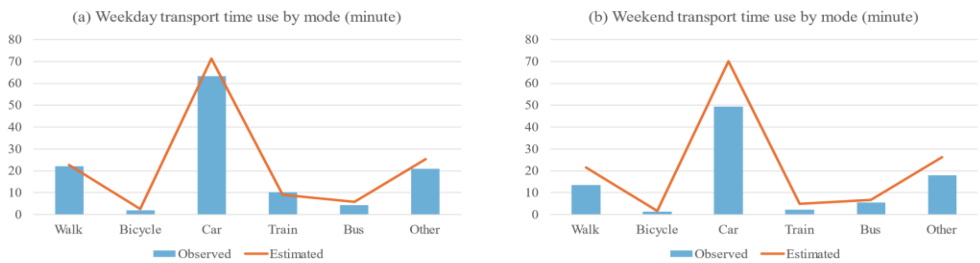


Figure 5.20 Estimated vs Observed Time Allocation by Transport Mode

5.4.3 Scenario Analysis

5.4.3.1 Scenario Setting

This research establishes a series of scenarios to better understand the impact of emerging work patterns on time allocation amongst urban population in the United Kingdom. The analytical results derived from these scenarios will serve as inputs for the energy modelling. The scenarios are categorised into three groups: the first group focuses exclusively on weekday work pattern changes (comprising eight scenarios: A1, A2, B1, B2, C1, C2, D, and E); the second group examines weekend work pattern changes (comprising five scenarios: F1, F2, F3, F4, and F5); whilst the third group encompasses whole-week work pattern alterations (comprising four scenarios: G, H, J, and K). Additionally, an independent scenario (Scenario L) has been incorporated to account for seasonal work pattern variations. Table 5.13, Table 5.14 and Table 5.15 present the settings for the weekday, weekend, as well as whole week and seasonal scenarios, as well as the baseline settings.

Table 5.13 The Weekday Scenario Settings

Scenario	Work location pattern	Work time pattern
Baseline	Commuter (72.23%) Homeworker (5.41%) Outdoor worker (22.36%)	Traditional (62.01%) Dispersed (11.71%) Half-day (20.73%) Nighttime (5.55%)
A1	40% commuters to homeworkers	
A2	50% commuters to homeworkers	
B1		20% traditional to dispersed workers
B2		50% traditional to dispersed workers
C1		20% traditional to half-day workers
C2		50% traditional to half-day workers
D	40% commuters to homeworkers	20% traditional to dispersed workers
E	40% commuters to homeworkers	20% traditional to half-day workers

Table 5.14 The Weekend Scenario Settings

Scenario	Work location pattern	Work time pattern
Baseline	Commuter (76.82%) Homeworker (4.17%) Outdoor worker (19.01%)	Traditional (36.33%) Dispersed (20.83%) Half-day (29.17%) Nighttime (13.67%)

F1	20% commuters to homeworkers	
F2		20% traditional to dispersed workers
F3		20% traditional to half-day workers
F4	20% commuters to homeworkers	20% traditional to dispersed workers
F5	20% commuters to homeworkers	20% traditional to half-day workers

Table 5.15 The Whole Week and Seasonal Scenario Settings

	Weekday		Weekend	
	Work location	Work time	Work location	Work time
Baseline	Commuter (72.23%) Homeworker (5.41%) Outdoor worker (22.36%)	Traditional (62.01%) Dispersed (11.71%) Half-day (20.73%) Nighttime (5.55%)	Commuter (76.82%) Homeworker (4.17%) Outdoor worker (19.01%)	Traditional (36.33%) Dispersed (20.83%) Half-day (29.17%) Nighttime (13.67%)
G	40% weekday commuters to homeworkers		20% weekend commuters to homeworkers	
H		20% weekday traditional to dispersed workers		20% weekend traditional to dispersed workers
J	40% weekday commuters to homeworkers	20% weekday traditional to weekday half-day workers	20% weekend commuters to homeworkers	20% weekday traditional to weekend half-day workers
K		20% weekday traditional to weekday half-day workers		20% weekend traditional to weekend half-day workers
L	40% commuters to homeworkers (Mar to Nov)			

Within these groupings, scenarios A1, A2, F1, and G emphasise the spatial flexibility of paid work activities, examining the implications of expanded homeworking during weekdays, weekends, and across the entire week, respectively. Similarly, scenarios B1, B2, F2, and H focus on temporal flexibility in work activities, investigating the effects of promoting dispersed working patterns. Scenarios C1, C2, F3, and K examine the impact of half-day working arrangements. Scenario J considers circumstances where residents adopting half-day working patterns on weekdays must continue this arrangement at weekends to fulfil sufficient working hours. Scenarios D, E, F4, and F5 explore the combined effects of novel work locations and temporal patterns. Scenario K, conversely, contemplates increased productivity enabling more residents to adopt both homeworking and half-day working patterns throughout both weekdays and weekends. Scenario L reflects the possibility of allowing spatial homeworking during non-heating seasons whilst requiring employees to return to primary workplaces during heating seasons to reduce residential heating loads. Due to the inherent nature of outdoor and night-time work, which typically imposes fixed requirements regarding work location and timing, these work patterns are treated as constant proportions across all scenarios.

5.4.3.2 Scenario Test Results

The study summarises the scenario test results from three dimensions: (1) location choice, (2) activity type choice, and (3) transport mode choice.

- *(1) Location Choice*

From the perspective of location choice, this study focuses on the time allocation between workplaces and homes, which directly affects the occupancy schedules of residential and office buildings. This section first presents the time use effects of three working patterns on weekdays (Scenario As, Bs, and Cs), then their combined effects on weekdays (Scenario D and E), and weekend scenarios (F1, F2, and F3).

Figure 5.21 The effects of Scenario A1, B1 and C1 on location choices

Figure 5.21 illustrates the impact of weekday homeworking, dispersed working, and half-day working scenarios on total time allocation between homes and workplaces. Figure 5.22 details the hourly changes (by duration and by proportion) of time allocated to workplaces and homes.

The analysis shows the direct and significant influence of homeworking on location choice. Figure 5.21 (a) shows that when 40% of commuters switch to homeworking, average homeworking time increases by 132.09 minutes. If this proportion increases by another 10%, the average time spent at home by employed residents would see a further increase of 33.12 minutes. According to Figure 5.22, there is a pronounced increase in at-home time during traditional working hours (08:00 to 16:00)., where at-home time in scenario A1 increases from baseline values of 8-16 minutes to 21-26 minutes, while workplace time during these hours dramatically reduces from baseline peaks of 39-44 minutes to 23-30 minutes. However, the increase in residence time exceeds the decrease in workplace time (Figure 5.21(a) vs Figure 5.21(b)) due to the reduction in commuting.

The results show that dispersed working has an insignificant impact on the total time allocation to residences and workplaces, but causes variations in the timing of activities at both homes and workplaces throughout the day. Based on Figure 5.22 (c) and (d), when 20% of 9-to-5 workers adopt dispersed working, the average time spent at home between 07:00 and 15:00 increases significantly, while from 16:00 to midnight, workers spend more time at workplaces. These changes may not be evident in aggregated time distribution but could significantly affect building occupancy schedules. For example, if workers visit workplaces in the evening instead of during the day, the energy demand for office buildings (e.g. lighting and ventilation) may increase substantially.

Compared to homeworking, half-day working results in a greater reduction in workplace time than the increase in residence time. When 20% of 9-to-5 employees switch to half-day working during weekdays, the time spent at home increases by 10.17 minutes, while the time spent at the workplace decreases by 20.99 minutes. This change can be attributed to the half-day working pattern allowing individuals to allocate more time to outdoor environments. Also, as shown in Figure 5.21, the impact of this work pattern is concentrated in the afternoon, peaking between 15:00 and 16:00.

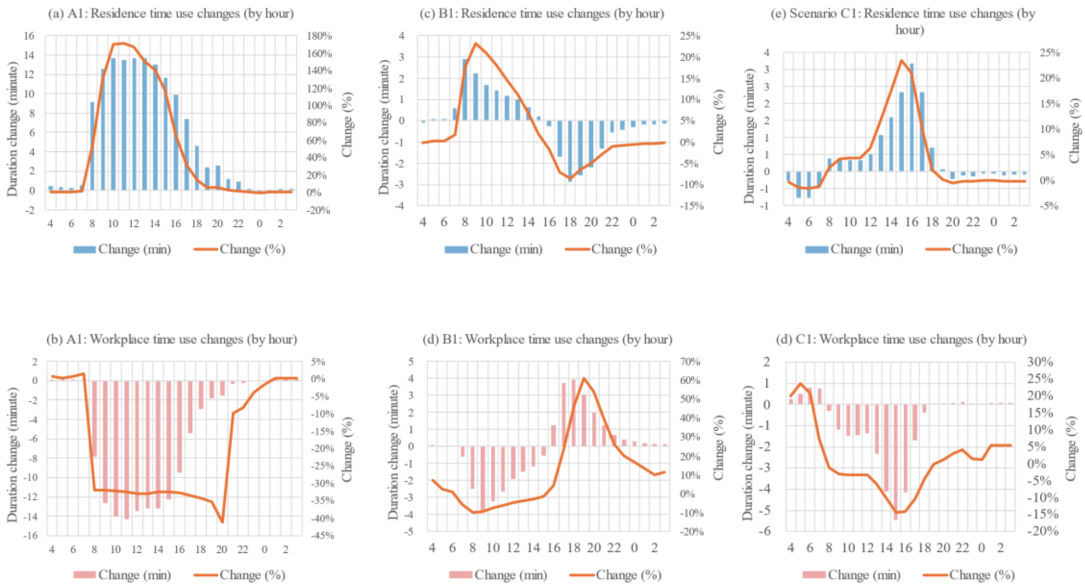


Figure 5.22 Hourly time allocation changes by location in Scenario A1, B1, and C1

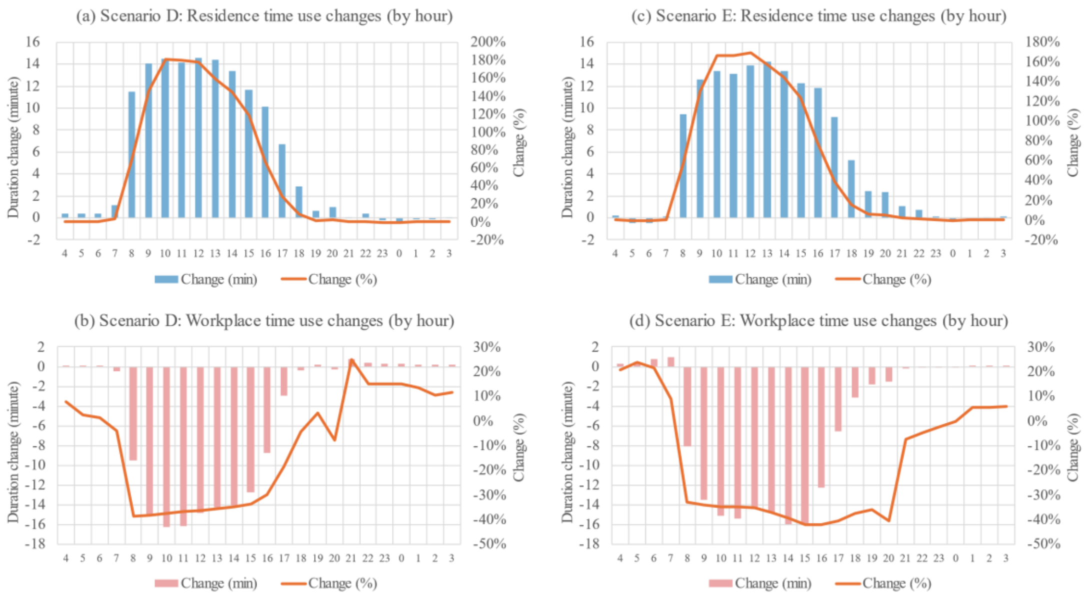


Figure 5.23 Hourly time allocation changes by location in Scenario D and F

Figure 5.23 illustrates the combined impact of new work patterns on weekday time allocation between residences and workplaces in Scenarios D and E, highlighting both total duration and proportional changes. Compared to pure homeworking scenarios (A1 and A2), Scenarios D and E reveal distinct redistributions of time allocation. In Scenario A1, workplace time is 282.48 minutes, whereas Scenario D's combined approach slightly reduces this to 282.08 minutes, indicating that dispersed working minimally affects the homeworking impact. By contrast, Scenario E, which combines homeworking with half-day working, significantly reduces workplace time to 269.23 minutes, demonstrating a more significant influence on conventional time use. Further analysis of temporal granularity uncovers finer distinctions. Scenarios A1 and A2 show relatively uniform increases in home time across working hours. In comparison, Scenario E exhibits a more focused redistribution of time, particularly during the afternoon and early evening (14:00–21:00). This indicates that half-day working fosters a more deliberate fragmentation of work time, potentially enabling greater flexibility in personal time management and energy consumption behaviours.

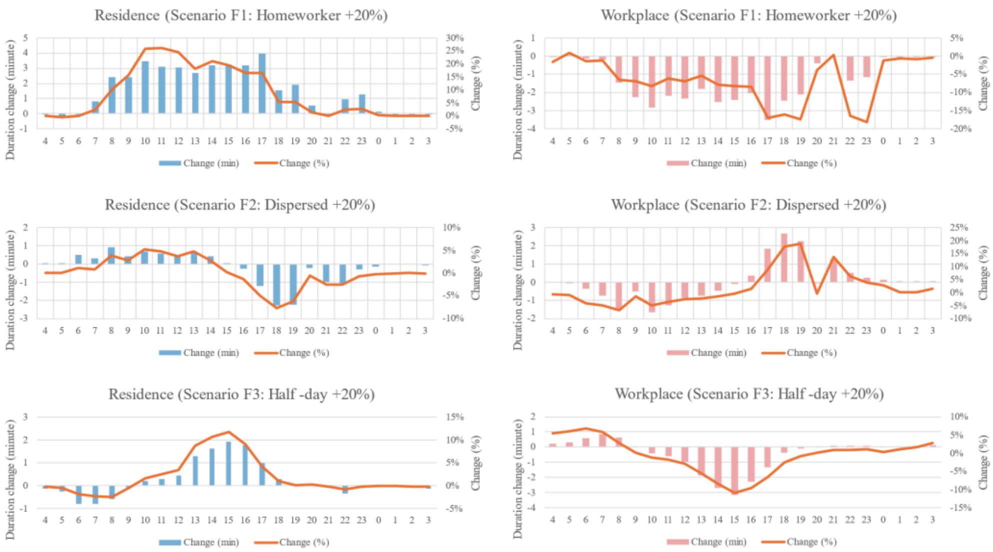


Figure 5.24 Hourly time allocation changes by location in Scenario F1, F2 and F3

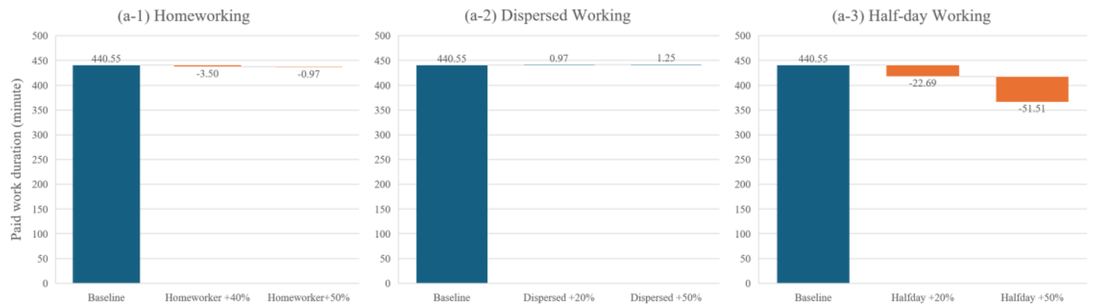
Figure 5.24 illustrates the hourly location choices for three scenarios focused on weekends, showing results comparable to those of weekday scenarios. In Scenario F1, where 20% of commuters transition to homeworking, home time increases by approximately 37.5 minutes across the day, particularly during the morning and afternoon hours. Correspondingly, weekend workplace time decreases by about 30 minutes. This suggests that the adoption of homeworking could reshape weekend energy consumption patterns of employed residents, potentially smoothing traditional energy demand peaks and troughs. In contrast, Scenario F2 reveals that the impact of dispersed working on residential activity time during the morning is significantly weaker compared to the weekday scenario (B1). As a result, the time allocated to residential activities decreases as the proportion of dispersed working increases in Scenario F2.

- *(2) Activity Type Choice*

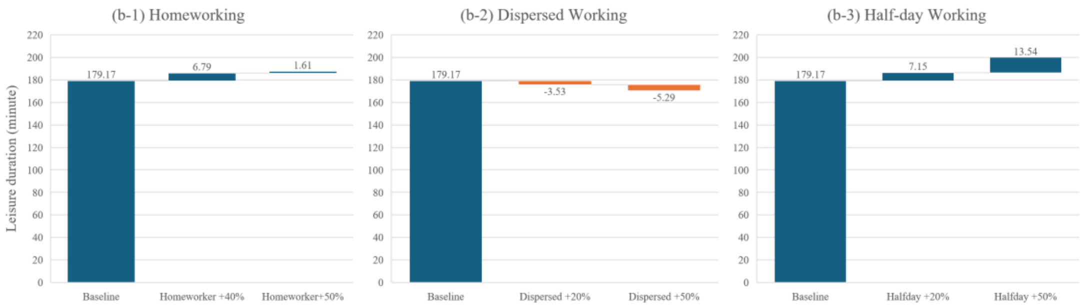
The section focuses on the effects of new working patterns on the preference to different activity types. We first present the scenario analysis results of the single patterns (Scenarios As, Bs, and Cs) and then discuss the combined effects (Scenario D and E).

Figure 5.25 compares three distinct working patterns (i.e., homeworking, dispersed working, and half-day working) and their respective influences on weekday activity choices. In particular, Figure 5.25(a) examines the variations in paid work duration associated with each working pattern, whereas Figures 5.25(b) and 5.25(c) delineate the effects on time allocated to leisure and domestic work, respectively. Furthermore, Figure 5.26 provides additional detail on the hourly distribution of these activity choices, thereby offering a comprehensive insight into how these working patterns modulate daily time allocation.

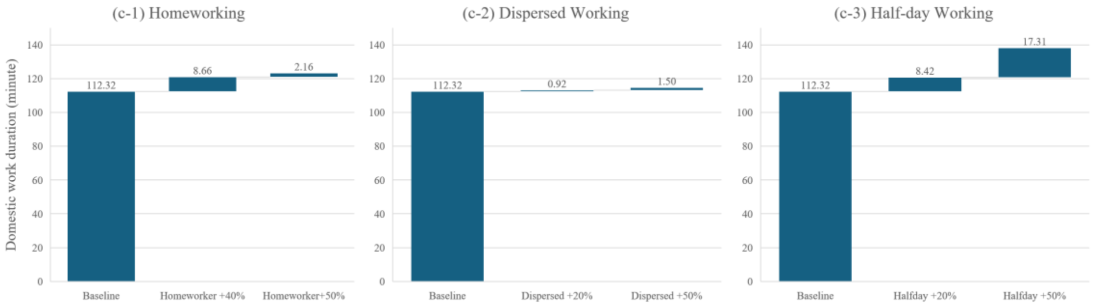
Figure 5.25 shows that during weekdays, the adoption of homeworking and dispersed working by more residents does not significantly alter the total duration of paid work activities. As illustrated in Figure 5.26, when a portion of previously commuting employees shift to homeworking, the urban population reallocates time originally dedicated to paid work in the morning (08:00-10:00) to leisure and domestic work activities. Conversely, in the evening (19:00-23:00), more time is allocated to paid work activities. When the dispersed working pattern is promoted, residents shift their paid work time from the morning and early afternoon (08:00-14:00) to the late afternoon (16:00-21:00), while evening leisure and domestic work activities may be moved to the morning. With the promotion of the half-day working pattern, the afternoon time previously spent on paid work is significantly reallocated to leisure and domestic activities.



(a) The effects on paid work duration (weekday)



(b) The effects on leisure duration (weekday)



(c) The effects on domestic work duration (weekday)

Figure 5.25 The effects of working patterns on weekday activity type choices

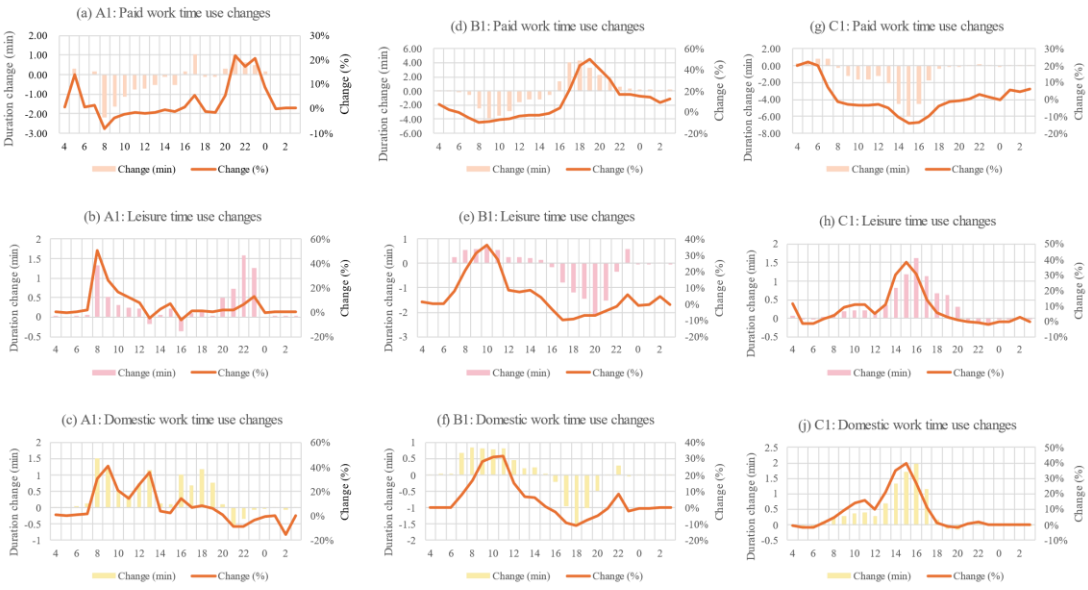


Figure 5.26 The effects of Scenario A1, B1, and C1 on activity type choices

In addition, Figure 5.27 compares the effects of two scenarios that focus on combined work patterns. In Scenario D, homeworking and dispersed working together intensify the reduction in paid work activity time during the morning and lead to a substantial increase in paid work activity time in the afternoon and evening. Homeworking mitigates the negative impact of dispersed working on leisure time between 18:00 and 21:00. These results are consistent with the changes in residence and workplace activity time under these scenarios.

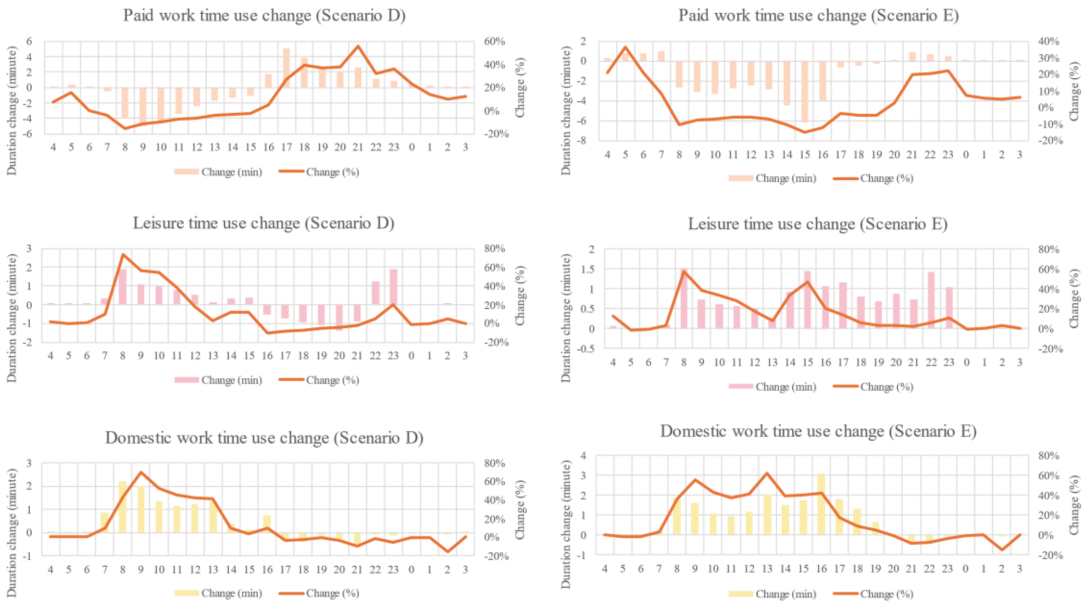


Figure 5.27 The effects of the weekday combined scenarios on activity type choices

- *(3) Transport Mode Choice*

This section introduces the effects of working patterns on transport activity and mode preference. Figure 5.28 and Figure 5.29 respectively illustrate the impact of the three working patterns on the overall weekday transport demand and on the hourly distribution of activity demand. Moreover, Figure 5.30 further delineates how these working patterns influence the time allocation among five modes of transport.

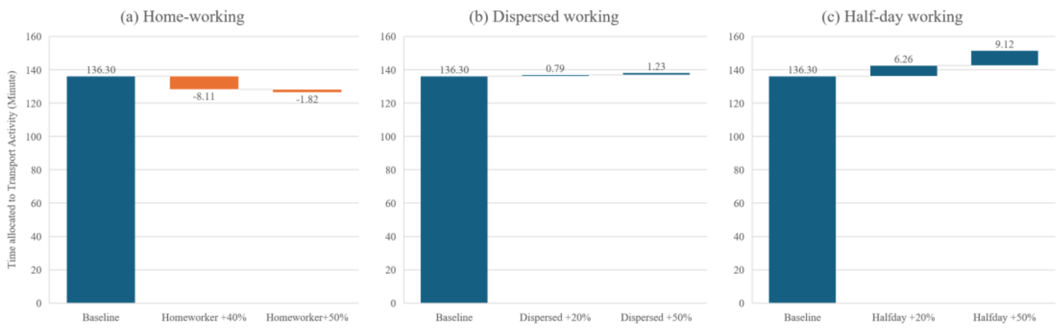


Figure 5.28 The effects of working patterns on weekday transport duration

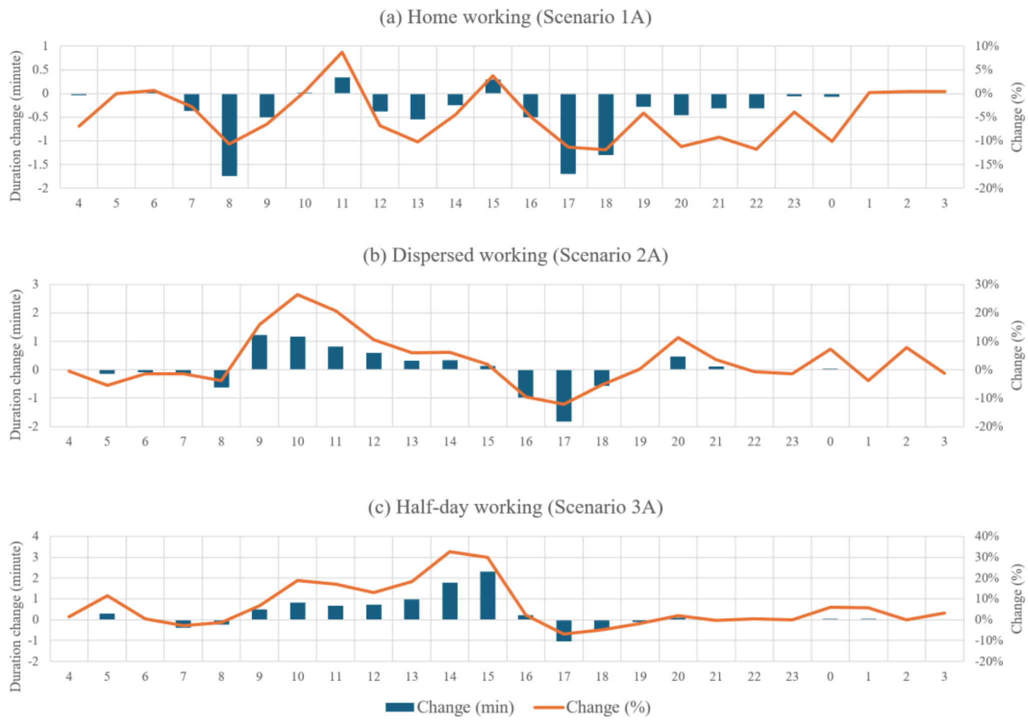
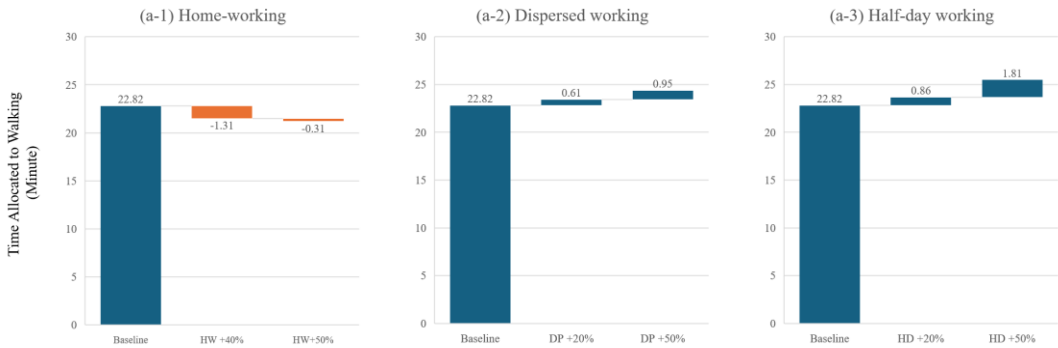
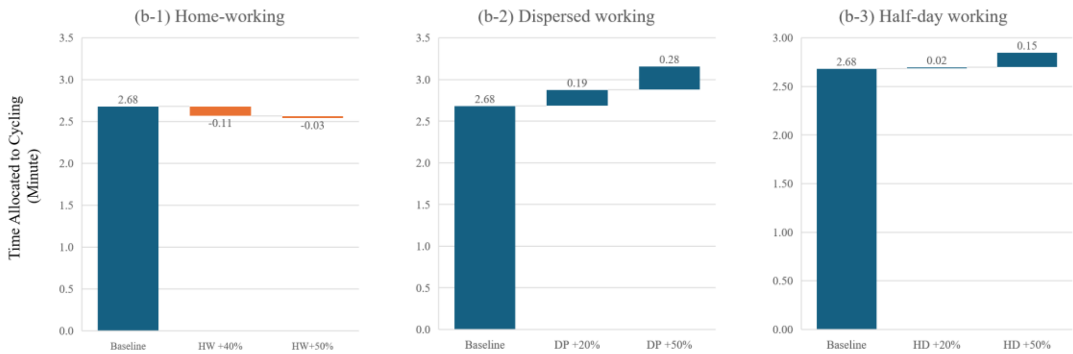


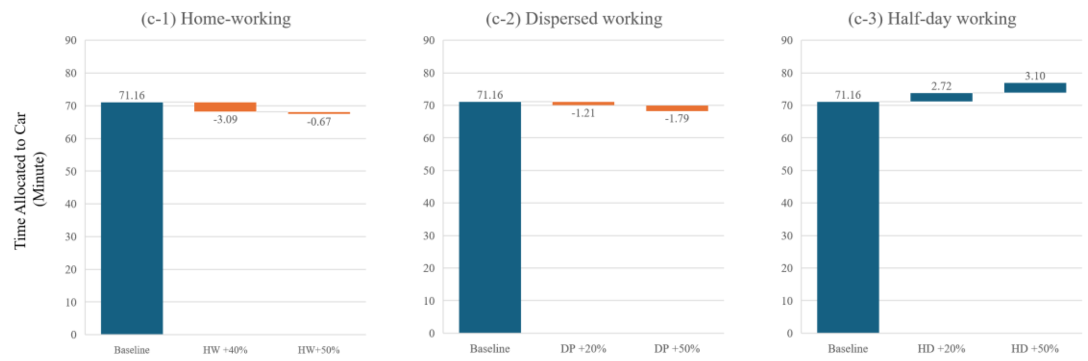
Figure 5.29 The effects of working patterns on weekday transport (by hour)



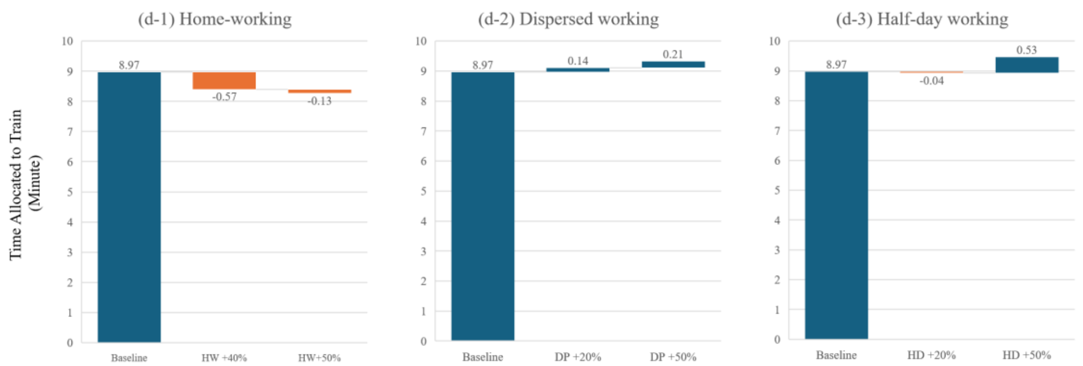
(a) The effects of working patterns on weekday transport (walking)



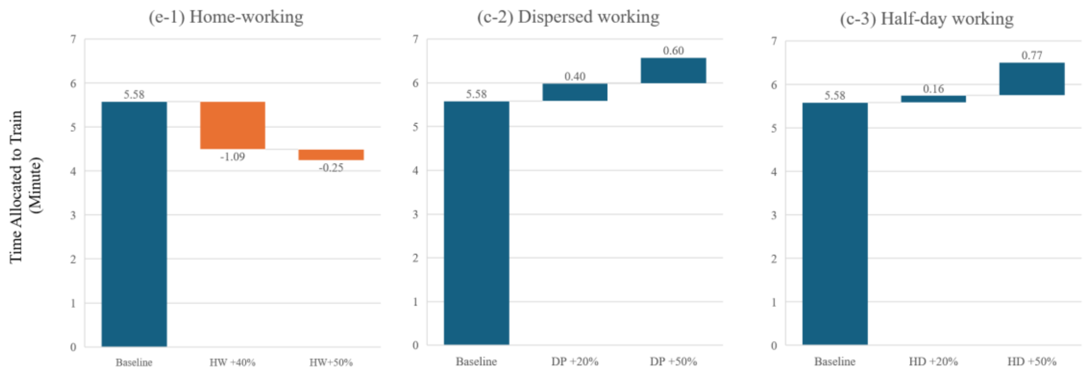
(b) The effects of working patterns on weekday transport (cycling)



(c) The effects of working patterns on weekday transport (car)



(d) The effects of working patterns on weekday transport (train)



(e) The effects of working patterns on weekday transport (others)

Figure 5.30 Weekday transport time use changes (by transport mode)

During weekdays, the promotion of homeworking results in a negative impact on transport demand across almost all time periods. This effect is particularly pronounced during the commuting peak hours of 08:00-09:00 and 17:00-19:00. Additionally, homeworking negatively affects the demand for all modes of transport, especially public transport modes such as trains and buses, which are mostly used for commuting purposes.

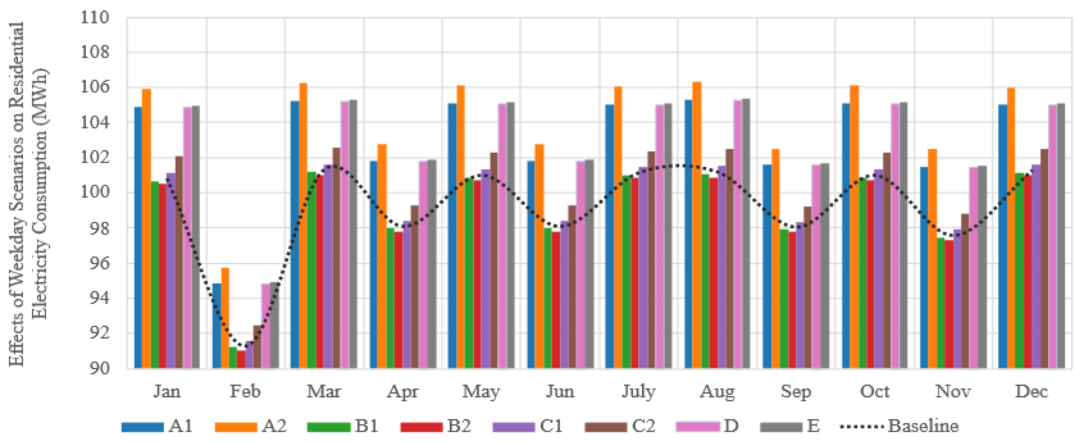
The analysis did not observe a significant effect of dispersed working on the total time residents spend on transport activities during weekdays. However, the transport activity time during traditional commuting peaks (08:00-09:00 and 17:00-19:00) decreases, while the transport activity time between 09:00 and 15:00 increases. On weekdays, dispersed working has a positive impact on the demand for environmentally friendly transport modes (such as walking and cycling) and public transport (trains and buses). This work pattern may negatively affect the demand for car travel during weekdays. Half-day working on weekdays may increase the total time spent on transport activities, with this increase primarily concentrated between 09:00 and 16:00. Unlike weekdays, dispersed working on weekends causes a slight increase in the total transport time.

5.5 The Energy and Carbon Model Results

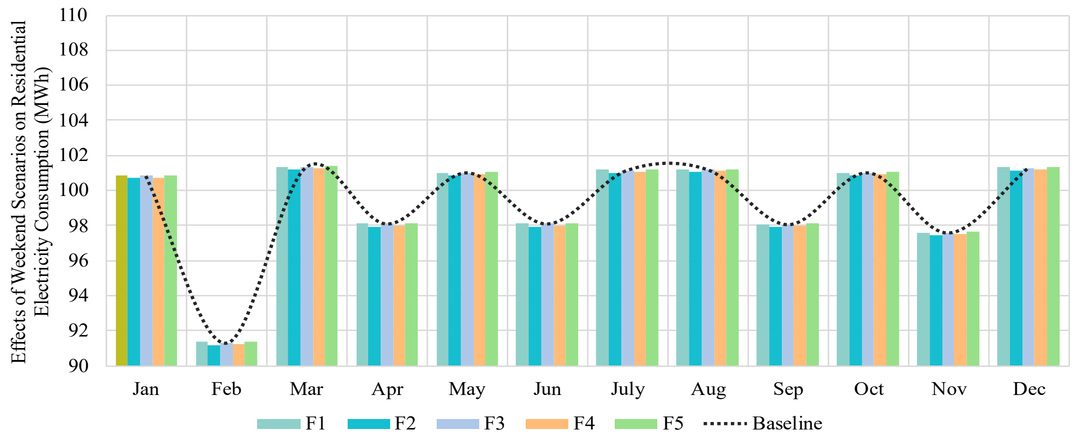
5.5.1 Building Sector Energy Demand and Carbon Emission

This section examines the changes in energy demand and carbon emissions within the building sector under different work mode scenarios. The analysis is based on scenario-specific time-use settings alongside the UBEM tool developed in this study. The occupancy and appliance use schedules are detailed in Appendix A (A1 to A12). Figure 5.31 compares residential electricity demand across scenarios, with Figures 5.31(a), 5.31(b), and 5.31(c) focusing on weekday (Scenario A1 to E), weekend (Scenario F1 to F5), and whole-week (Scenario J to L) scenarios, respectively. Furthermore, Figure 5.32, Figure 5.33, as well as Figure 5.34 provide detailed comparisons of residential natural gas demand, office electricity demand, and office natural gas demand under these scenarios. These figures share the same structure of Figure 5.31.

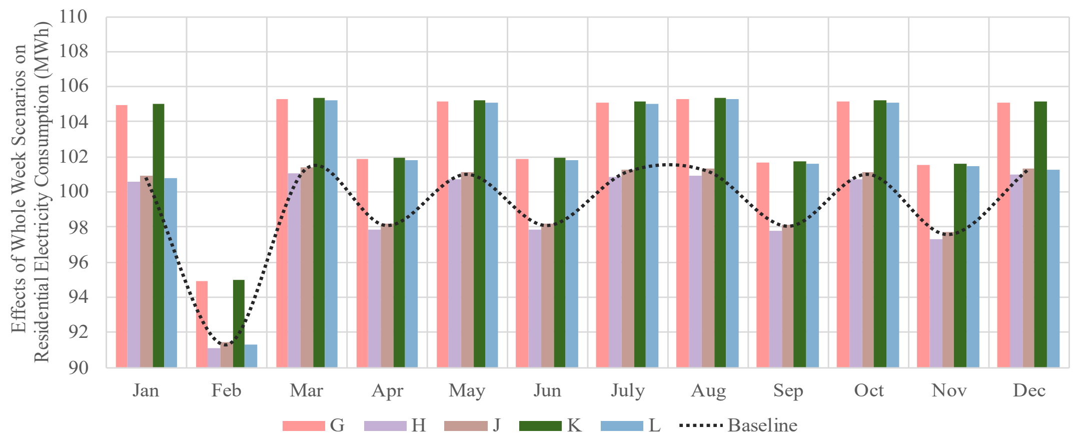
The analysis of residential building energy consumption reveals distinct patterns between electricity and natural gas usage. Electricity consumption remains notably stable throughout the annual cycle, showing minimal seasonal variation. In contrast, natural gas consumption demonstrates pronounced seasonal periodicity, characterised by peak consumption during the winter months (December to February) and manifesting as a distinctive U-shaped distribution. This pattern highlights the predominant role of natural gas in meeting winter heating demands.



(a) Effects of weekday scenarios on residential electricity demand

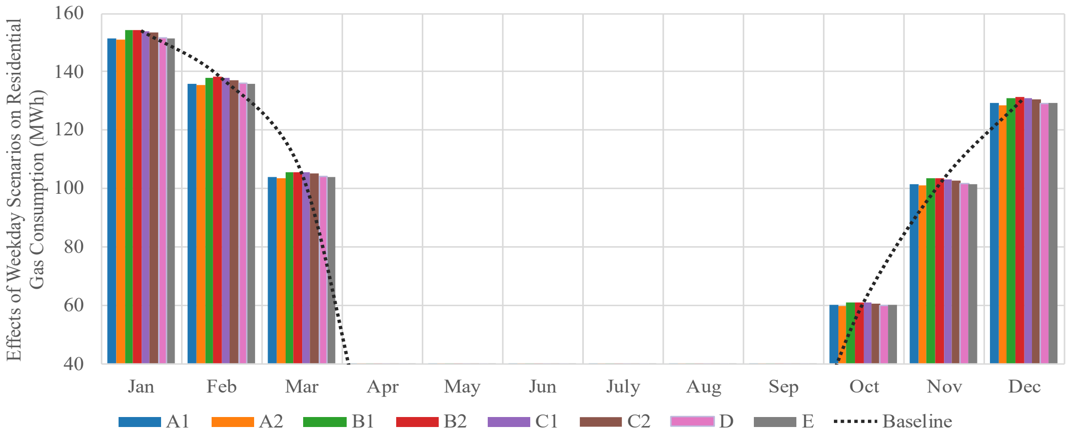


(b) Effects of weekend scenarios on residential electricity demand

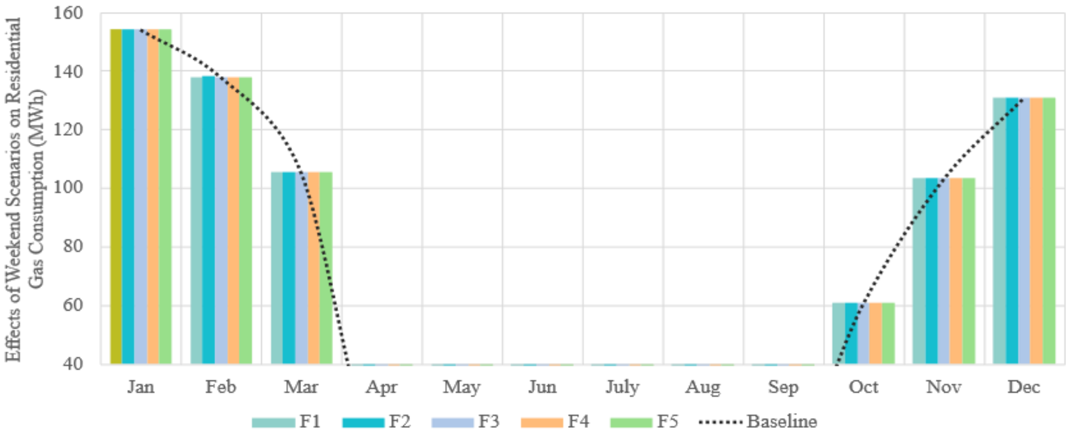


(c) Effects of whole-week scenarios on residential electricity demand

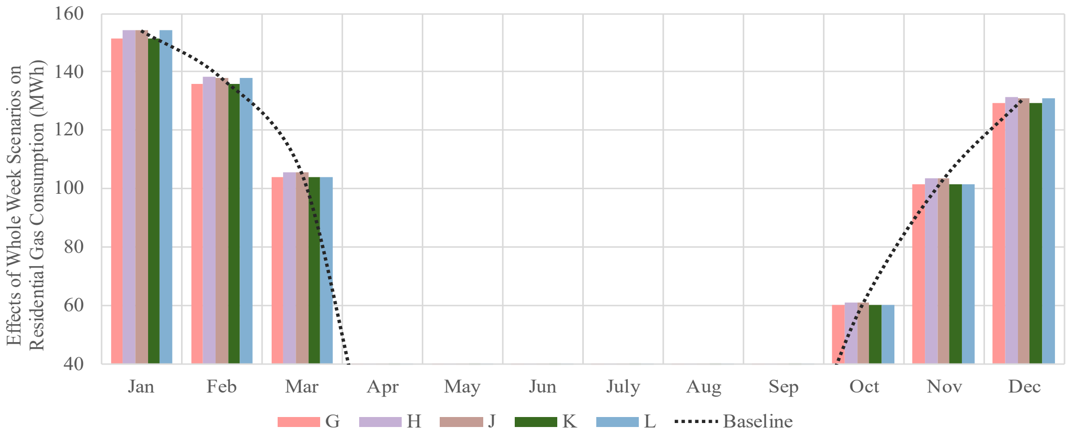
Figure 5.31 The residential electricity demand by scenario



(a) Effects of weekday scenarios on residential natural gas demand

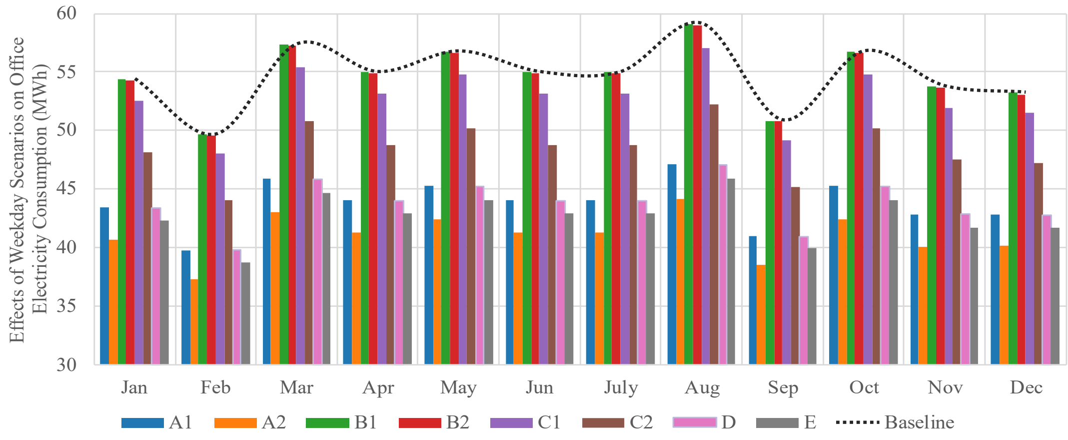


(b) Effects of weekend scenarios on residential natural gas demand

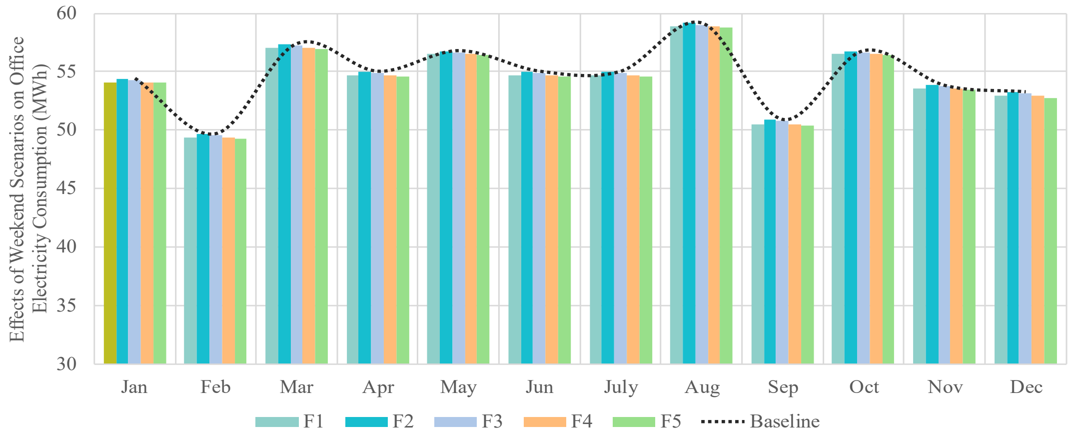


(c) Effects of whole-week scenarios on residential natural gas demand

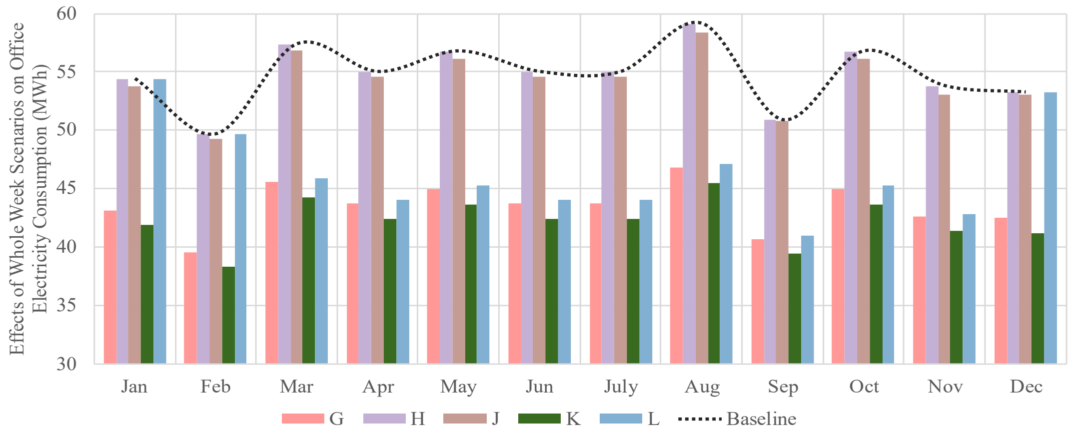
Figure 5.32 The residential natural gas demand by scenario



(a) Effects of weekday scenarios on office electricity demand

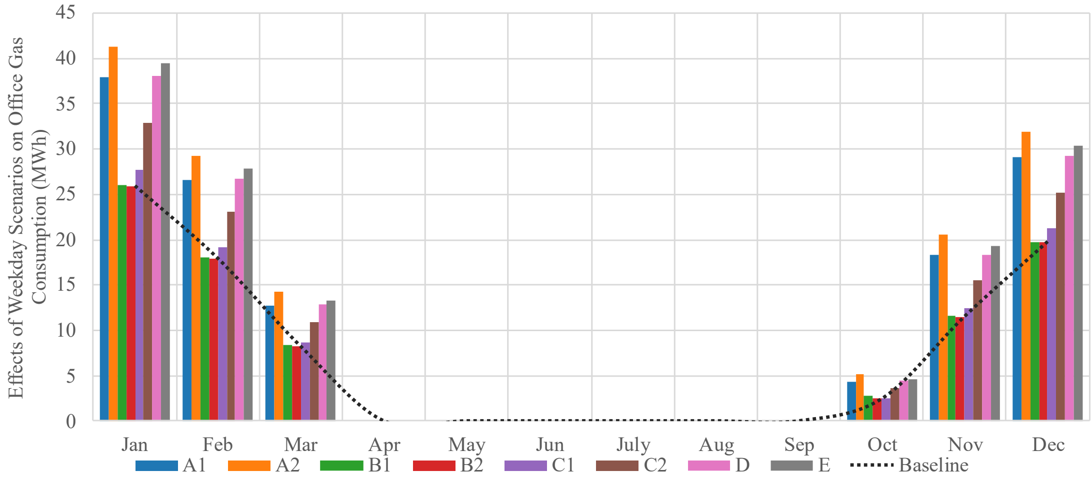


(b) Effects of weekend scenarios on office electricity demand

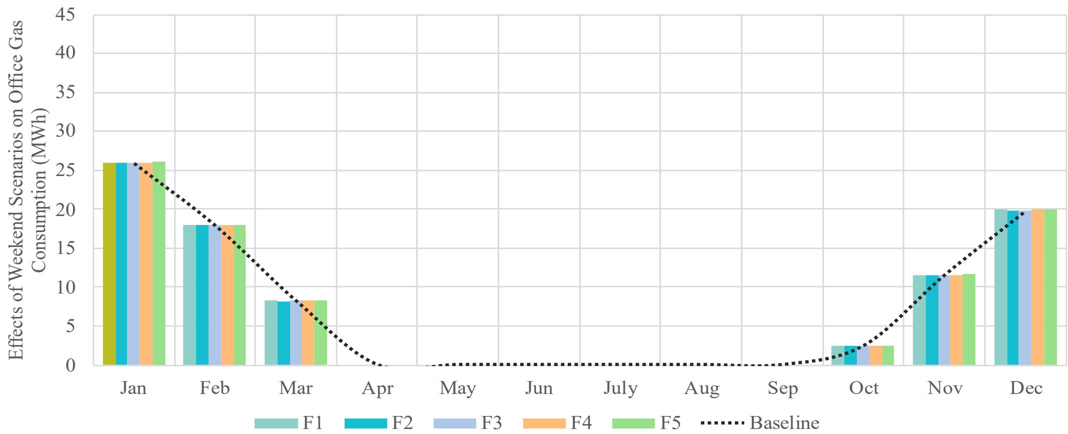


(c) Effects of whole-week scenarios on office electricity demand

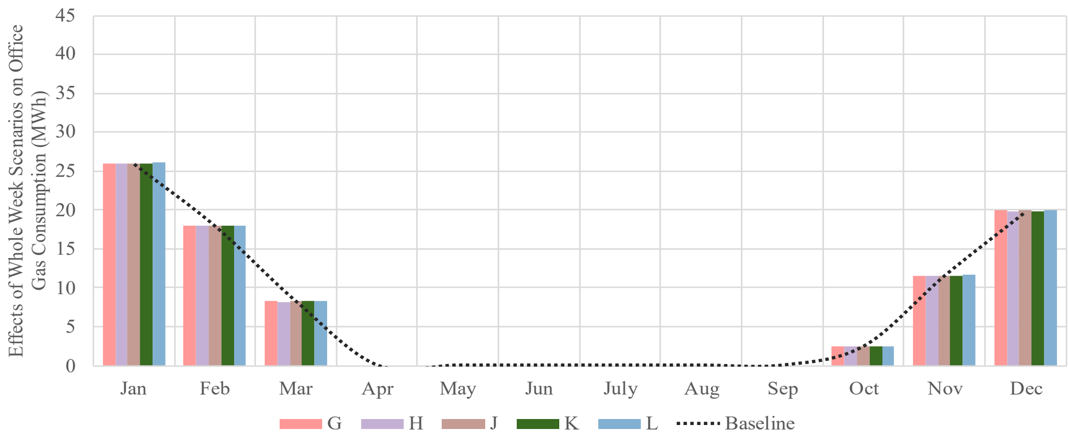
Figure 5.33 The office electricity demand by scenario



(a) Effects of weekday scenarios on office natural gas consumption



(b) Effects of weekend scenarios on office natural gas consumption



(c) Effects of whole-week scenarios on office natural gas demand

Figure 5.34 The office natural gas demand by scenario

The energy analysis results reveal distinct patterns in residential electricity consumption across different scenarios. When the new work pattern is applied on weekdays, scenarios B1 (1189.39 MWh) and B2 (1187.39 MWh) exhibit reduced residential electricity usage compared to the baseline, likely due to a greater proportion of dispersed workers spending more time at their workplaces rather than at home. In contrast, scenarios A1 (1237.32 MWh) and A2 (1248.90 MWh) show higher residential electricity demand, reflecting an increase in homeworking hours. Beyond homeworking, scenarios incorporating a half-day working pattern (i.e., scenarios C1 and C2) also contribute to increased residential electricity consumption, suggesting that this work arrangement leads to more time spent at home. On weekends, the adoption of the new work pattern results in only slight variations in residential electricity consumption compared to the baseline. When the new work pattern is applied throughout the entire week and across different seasons, residential electricity consumption generally increases in most scenarios relative to the baseline. For instance, scenarios G (1237.828 MWh), J (1192.105 MWh), K (1238.70 MWh), and L (1225.92 MWh) show increased consumption, whereas scenario J (1187.86 MWh) demonstrates a slight decline.

From the perspective of office buildings, various new work patterns contribute to reducing electricity demand. On weekdays, scenarios involving homeworking generally led to more significant energy savings. Notably, Scenarios A1 (525.64 MWh, a reduction of 20.01%), A2 (492.43 MWh, a reduction of 25.07%), D (a reduction of 20.09%), and E (a reduction of 22.18%) exhibit significantly lower electricity demand compared to the baseline. In these homeworking scenarios, a greater number of residents shift from workplaces to their homes, resulting in decreased office building occupancy. This analysis underscores the direct relationship between electricity demand and the spatial distribution of residents' activities. For new work patterns implemented only on weekends, office electricity consumption in Scenarios F1 to F5 shows a slight reduction compared to the baseline. In contrast, when applying new work patterns throughout the whole week or seasonally, various scenarios contribute to office electricity savings. In particular, Scenarios G, K, and L achieve reductions of 20.58%, 22.93%, and 15.25%, respectively.

However, from the perspective of office heating, the reduction in occupancy rates decreases the internal heat gain in office buildings. Given that office operating hours often remain fixed, this phenomenon may lead to a sustained increase in heat load during winter. This is reflected in the natural gas demand for heating in office buildings. For new work patterns implemented on weekdays, most scenarios, particularly A1 and A2, which focus on homeworking lead to higher natural gas consumption than the baseline, with increases of 50.30% and 66.06%, respectively. The half-day working scenario (C2) results in a 29.53% increase. Similarly, the combined working patterns in Scenarios D and E show increases of 50.90% and 56.93%, respectively. For new work patterns applied only on weekends, heating consumption remains close to the baseline. However, for work patterns implemented in the whole week and seasonally, most scenarios lead to increased heating demand compared to the baseline. Notably, Scenarios G and K exhibit substantial increases in heating consumption, rising by 50.90% and 57.70%, respectively.

Table 5.16 and Table 5.17 detail the carbon emissions resulting from electricity consumption and heating natural gas consumption in buildings, respectively. The variations in carbon emissions derived from electricity demand reflect not only the differences in the number of days per month but also the changes in lighting demand across different months. Overall, the carbon emissions from electricity consumption in residential and commercial buildings remain relatively stable throughout the year.

In contrast, the carbon emissions derived from natural gas demand display a pronounced seasonal periodicity, with commercial buildings generating significantly lower emissions than residential properties, despite following similar seasonal trends. Both sectors experience increased emissions during the colder months (November to February) and reduced emissions during the warmer periods.

Table 5.16 Carbon Emissions Generated from Building Electricity Consumption

Scenario		Month											
No	Type	1	2	3	4	5	6	7	8	9	10	11	12
0	R	20.87	18.91	20.98	20.31	20.91	20.31	20.94	20.95	20.30	20.91	20.20	20.97
	O	11.27	10.29	11.88	11.39	11.76	11.39	11.39	12.24	10.54	11.76	11.14	11.03
A1	R	21.72	19.65	21.79	21.09	21.76	21.09	21.75	21.80	21.04	21.76	21.02	21.75
	O	9.00	8.24	9.50	9.12	9.38	9.12	9.12	9.76	8.49	9.38	8.87	8.87
A2	R	21.93	19.83	22.00	21.28	21.97	21.28	21.96	22.01	21.22	21.97	21.22	21.94
	O	8.42	7.72	8.90	8.55	8.78	8.55	8.55	9.13	7.97	8.78	8.30	8.32
B1	R	20.85	18.89	20.95	20.29	20.89	20.29	20.92	20.92	20.28	20.89	20.18	20.95
	O	11.25	10.28	11.87	11.38	11.74	11.38	11.38	12.23	10.53	11.74	11.13	11.02
B2	R	20.81	18.85	20.92	20.25	20.85	20.25	20.88	20.89	20.25	20.85	20.15	20.91
	O	11.23	10.26	11.84	11.36	11.72	11.36	11.36	12.21	10.51	11.72	11.11	10.99

C1	R	20.95	18.97	21.05	20.38	20.98	20.38	21.01	21.02	20.36	20.98	20.27	21.04
	O	10.88	9.94	11.47	11.00	11.35	11.00	11.00	11.82	10.19	11.35	10.75	10.66
C2	R	21.15	19.14	21.24	20.56	21.18	20.56	21.20	21.22	20.54	21.18	20.46	21.22
	O	9.96	9.11	10.51	10.09	10.39	10.09	10.09	10.81	9.36	10.39	9.84	9.79
D	R	21.71	19.64	21.78	21.08	21.75	21.08	21.74	21.79	21.03	21.75	21.01	21.74
	O	8.99	8.23	9.50	9.12	9.37	9.11	9.12	9.75	8.48	9.37	8.86	8.86
E	R	21.73	19.66	21.80	21.10	21.77	21.10	21.76	21.81	21.05	21.77	21.03	21.76
	O	8.75	8.01	9.25	8.88	9.12	8.88	8.88	9.49	8.26	9.12	8.63	8.63
F1	R	20.88	18.92	20.99	20.32	20.92	20.32	20.95	20.96	20.31	20.92	20.21	20.98
	O	11.21	10.23	11.81	11.32	11.70	11.32	11.32	12.18	10.46	11.70	11.09	10.95
F2	R	20.85	18.88	20.95	20.28	20.89	20.28	20.91	20.93	20.27	20.89	20.18	20.94
	O	11.27	10.29	11.88	11.39	11.76	11.39	11.39	12.25	10.54	11.76	11.14	11.03
F3	R	20.88	18.91	20.98	20.32	20.92	20.32	20.95	20.95	20.31	20.92	20.21	20.98
	O	11.21	10.23	11.81	11.32	11.70	11.32	11.32	12.18	10.46	11.70	11.09	10.95
F4	R	20.86	18.89	20.96	20.30	20.90	20.30	20.93	20.94	20.29	20.90	20.19	20.96
	O	11.25	10.27	11.86	11.37	11.74	11.37	11.37	12.22	10.51	11.74	11.12	11.00
F5	R	20.89	18.92	20.99	20.32	20.92	20.32	20.95	20.96	20.32	20.92	20.22	20.99
	O	11.19	10.21	11.79	11.30	11.68	11.30	11.30	12.17	10.44	11.68	11.07	10.93
G	R	21.73	19.65	21.80	21.10	21.77	21.10	21.76	21.81	21.05	21.77	21.02	21.76
	O	8.94	8.18	9.44	9.05	9.32	9.05	9.05	9.70	8.41	9.32	8.82	8.79
H	R	20.83	18.86	20.93	20.26	20.86	20.26	20.89	20.90	20.25	20.86	20.16	20.92
	O	11.26	10.28	11.87	11.38	11.74	11.38	11.38	12.23	10.53	11.74	11.13	11.02
J	R	20.90	18.93	21.00	20.33	20.94	20.33	20.96	20.98	20.31	20.94	20.23	20.98
	O	11.14	10.20	11.77	11.30	11.61	11.30	11.30	12.08	10.52	11.61	10.98	10.99
K	R	21.74	19.67	21.82	21.11	21.78	21.11	21.78	21.82	21.07	21.78	21.04	21.77
	O	8.67	7.93	9.16	8.79	9.04	8.79	8.79	9.41	8.17	9.04	8.56	8.53
L	R	20.87	18.91	21.79	21.09	21.76	21.09	21.75	21.80	21.04	21.76	21.02	20.97
	O	11.27	10.29	9.50	9.12	9.38	9.12	9.12	9.76	8.49	9.38	8.87	11.03

Unit: 1000t CO_2e, R for residential buildings and O for Office buildings, Scenario 0 refers to the baseline.

Table 5.17 Carbon Emissions Generated from Natural Gas Consumption for Heating

Scenario		Month						
No	Type	1	2	3	4-9	10	11	12
0	R	27.77	24.85	19.00	NA	10.97	18.61	23.59
	O	4.67	3.23	1.48	NA	0.44	2.08	3.56
A1	R	27.29	24.48	18.73	NA	10.80	18.29	23.25
	O	6.82	4.79	2.29	NA	0.79	3.30	5.24
A2	R	27.17	24.39	18.66	NA	10.76	18.22	23.16
	O	7.44	5.27	2.58	NA	0.92	3.70	5.75
B1	R	27.78	24.86	19.00	NA	10.97	18.62	23.60

	O	4.66	3.23	1.47	NA	0.46	2.07	3.55
B2	R	27.79	24.87	19.01	NA	10.98	18.63	23.61
	O	4.68	3.25	1.50	NA	0.51	2.08	3.56
C1	R	27.73	24.83	18.99	NA	10.96	18.59	23.57
	O	4.99	3.45	1.57	NA	0.46	2.24	3.82
C2	R	27.59	24.71	18.90	NA	10.91	18.49	23.46
	O	5.91	4.14	1.97	NA	0.65	2.79	4.54
D	R	27.29	24.48	18.73	NA	10.80	18.30	23.25
	O	6.85	4.81	2.31	NA	0.80	3.29	5.26
E	R	27.29	24.48	18.73	NA	10.81	18.30	23.25
	O	7.09	5.01	2.40	NA	0.82	3.46	5.46
F1	R	27.76	24.84	18.99	NA	10.96	18.60	23.58
	O	4.69	3.24	1.49	NA	0.44	2.09	3.59
F2	R	27.78	24.86	19.00	NA	10.97	18.61	23.60
	O	4.67	3.23	1.48	NA	0.44	2.08	3.56
F3	R	27.76	24.84	18.99	NA	10.96	18.60	23.59
	O	4.69	3.24	1.49	NA	0.44	2.09	3.58
F4	R	27.77	24.85	19.00	NA	10.96	18.61	23.60
	O	4.68	3.23	1.48	NA	0.44	2.08	3.57
F5	R	27.76	24.84	18.99	NA	10.96	18.60	23.58
	O	4.69	3.25	1.49	NA	0.45	2.09	3.59
G	R	27.28	24.47	18.72	NA	10.79	18.29	23.24
	O	6.83	4.81	2.30	NA	0.80	3.31	5.27
H	R	27.79	24.87	19.01	NA	10.97	18.62	23.61
	O	4.66	3.23	1.47	NA	0.46	2.07	3.55
J	R	27.76	24.85	19.00	NA	10.96	18.60	23.60
	O	4.94	3.39	1.53	NA	0.44	2.19	3.73
K	R	27.28	24.47	18.72	NA	10.80	18.29	23.24
	O	7.12	5.03	2.41	NA	0.84	3.48	5.50
L	R	27.77	24.85	18.73	NA	10.80	18.29	23.59
	O	4.67	3.23	2.29	NA	0.79	3.30	3.56

Unit: 1000t CO_2e, R for residential buildings and O for Office buildings, Scenario 0 refers to the baseline.

Overall, the trends in electricity and natural gas demand often exhibit opposite patterns. This reflects the differences between the two types of energy demand driven by the spatial variations in activity demand: carbon emissions from electricity consumption are primarily derived directly from activity demand and are closely related to the location and intensity of activities. In contrast, carbon emissions from heating are associated with maintaining the comfort of the built environment, influenced not only by activity demand but also by external environmental factors.

Table 5.18 presents the total carbon emissions in the building sector by scenario. Despite the different emissions between residential and office buildings, emissions changes across the two building types tend to offset each other. Overall, the adoption of new work patterns is likely to lead to a net reduction in carbon emissions, though the magnitude of the reduction seems marginal across scenarios.

Table 5.18 Total Carbon Emissions from the Building Sector

Scenarios		Annual Carbon Emission by Sector	Total Annual Carbon Emission
0	R	371.35	522.89
	O	151.54	
A1	R	379.05	511.12
	O	132.07	
A2	R	380.98	508.62
	O	127.64	
B1	R	371.11	522.48
	O	151.37	
B2	R	370.77	522.00
	O	151.23	
C1	R	372.05	520.00
	O	147.94	
C2	R	373.72	514.16
	O	140.44	
D	R	378.95	511.03
	O	132.08	
E	R	379.20	509.35
	O	130.16	
F1	R	371.41	522.25
	O	150.84	
F2	R	371.10	522.65
	O	151.55	
F3	R	371.38	522.21
	O	150.83	
F4	R	371.21	522.51
	O	151.30	
F5	R	371.45	522.08
	O	150.63	
G	R	379.11	510.51
	O	131.39	
H	R	370.85	522.24
	O	151.38	
J	R	371.63	522.66

	O	151.03	
K	R	379.30	508.56
	O	129.26	
L	R	377.89	511.06
	O	133.17	

Unit: 1000t CO_2e, R for residential buildings and O for Office buildings, Scenario 0 refers to the baseline.

5.5.2 Transport Sector Carbon Emission

The study first generated transport demand schedules based on the activity model outputs (for employed residents) and deterministic data (for non-employed residents). These schedules include hourly time allocation to all modes of transport during weekdays and weekends. Detailed schedules can be found in Appendix B, with Appendices B-1 to B-6 presenting the weekday schedules for each transport mode.

Table 5.19 and

Table 5.20 illustrate the average transport carbon emissions per worker during weekdays and weekends across different scenarios. On weekdays, two peaks in energy demand are evident: between 08:00 and 09:00 (859.18 gCO_2e) and 17:00 to 18:00 (822.07 gCO_2e). In contrast, weekend peaks shift to 08:00 to 09:00 (564.26 gCO_2e) and 18:00 to 19:00 (522.48 gCO_2e).

During weekdays, carbon emissions during peak traffic periods (08:00–09:00 and 17:00–18:00) decrease across all scenarios. However, different working patterns exhibit varying impacts on off-peak hours. Similar to the peak periods, promoting homeworking (Scenarios A1 and A2) contributes minimally to increases in off-peak transport emissions. In contrast, the adoption of dispersed working (Scenarios B1 and B2) and half-day working (Scenarios C1 and C2) shifts traffic activity from traditional peak periods to other times, thereby significantly increasing traffic-related carbon emissions during off-peak hours. Notably, half-day working has a more pronounced effect, with emissions rising particularly between 14:00 and 16:00. Under Scenario C2, especially, where 50% of 9-to-5 workers transition to half-day schedules, the weekday afternoon peak shifts to 15:00–16:00, reaching 762.31 gCO_2e. While this remains below the baseline afternoon peak emissions of 822.07 gCO_2e, it highlights the impact of half-day working on temporal redistribution of emissions.

Weekend transport-related carbon emissions during peak periods are lower than those observed on weekdays; however, off-peak emissions are significantly higher on weekends. Unlike weekdays, an increased adoption of dispersed working patterns on weekends may positively contribute to morning peak emissions (08:00 to 09:00, 590.19 gCO_2e) while substantially reducing afternoon peak emissions (18:00 to 19:00, 469.43 gCO_2e). In contrast, the promotion of homeworking (scenario F1) results in a rise in emissions during the afternoon peak period to 581.70 gCO_2e. Similar to weekdays, weekend homeworking reduces emissions across most off-peak periods during daytime hours. Also, if 20% of employees previously engaged in weekday 9-to-5 roles shift to working half days on weekends (scenario J), the afternoon peak in transport-related carbon emissions by employed residents could be extended from 14:00 to 19:00. However, as the proportion of employed residents working on weekends generally remains below 10%, the overall impact of emerging work patterns on city-scale weekend transport emissions is substantially less pronounced compared to weekdays.

Table 5.19 Transport Carbon Emissions by Scenario (Weekdays, per worker)

Time	Scenario								
	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	33.37	30.89	30.10	33.30	33.23	33.12	33.23	30.84	30.67
5:00	137.51	137.33	137.31	127.32	112.30	159.40	112.30	127.18	159.18
6:00	354.23	356.47	357.04	347.65	338.00	358.10	338.00	349.85	360.29
7:00	718.96	690.16	683.68	680.20	620.93	686.39	620.93	648.02	656.74
8:00	859.18	772.70	752.92	820.38	763.42	855.23	763.42	726.43	766.96
9:00	393.21	381.18	381.57	452.15	541.16	420.14	541.16	419.28	403.33
10:00	243.63	253.28	257.64	303.36	392.73	292.61	365.20	303.92	307.20
11:00	202.13	217.35	222.84	246.36	312.39	236.73	289.05	255.86	256.17
12:00	285.33	274.86	274.28	317.85	366.57	330.64	397.98	298.58	316.47
13:00	255.17	242.56	240.98	268.34	289.27	308.48	388.86	250.14	286.84
14:00	294.38	298.41	300.73	308.08	329.43	391.44	536.90	308.94	386.77
15:00	427.82	443.68	448.87	432.23	439.56	561.47	762.31	445.04	561.93
16:00	567.79	542.06	536.56	506.53	415.66	585.33	611.18	481.41	550.26
17:00	822.07	725.47	699.15	718.73	563.14	766.88	682.05	635.97	674.70
18:00	574.68	515.59	499.41	539.85	487.33	550.95	515.36	491.14	494.23
19:00	353.68	342.23	337.80	350.77	346.07	351.42	347.93	346.58	340.61
20:00	218.83	185.79	177.33	238.79	268.35	226.39	238.12	204.13	192.07
21:00	189.63	172.09	167.75	196.42	206.12	190.24	190.97	177.59	172.99
22:00	138.25	121.42	117.09	134.75	129.53	139.05	140.28	118.51	122.15
23:00	88.77	85.31	84.55	86.89	83.99	89.09	89.59	83.34	85.68
0:00	35.95	30.93	29.99	38.12	41.30	37.94	41.30	32.21	32.60

1:00	34.37	34.42	34.43	32.87	30.79	36.84	30.79	32.92	36.89
2:00	15.62	15.68	15.70	16.93	18.29	15.60	18.29	17.01	15.66
3:00	14.27	14.33	14.33	14.23	14.19	15.01	14.19	14.29	15.07
Total	**7.2588**	**6.8842**	**6.8020**	**7.2121**	**7.1437**	**7.6385**	**8.0694**	**6.7992**	**7.2255**
		-5.16%	-6.29%	-0.64%	-1.59%	5.23%	11.17%	-6.33%	-0.46%

Note: The unit for per worker emissions is grams CO_2 equivalent (gCO_2e); the unit for total carbon emissions is kilograms CO_2 equivalent ($kgCO_2e$).

Table 5.20 Transport Carbon Emissions by Scenario (Weekends, per worker)

Time	Scenario					
	Baseline	F1	F2	F3	F4	F5	J
4:00	55.58	56.17	56.24	55.87	56.15	55.87	56.92
5:00	220.47	222.08	222.66	218.08	223.41	218.56	209.12
6:00	395.36	391.27	381.47	417.26	379.05	412.12	467.68
7:00	503.65	477.75	521.30	497.86	496.07	473.26	461.73
8:00	564.26	518.98	590.19	561.69	542.59	515.30	508.77
9:00	449.08	419.14	442.96	449.26	413.55	419.72	457.31
10:00	375.75	337.06	398.85	380.59	357.05	342.16	341.73
11:00	322.16	295.64	334.25	328.65	308.65	301.41	307.94
12:00	341.88	332.49	355.30	363.17	348.40	360.13	390.45
13:00	311.48	273.39	312.84	339.50	277.64	301.71	396.06
14:00	401.45	365.63	406.22	437.92	371.16	402.90	503.88
15:00	375.36	351.49	374.25	402.17	350.44	379.60	457.55
16:00	467.95	430.90	460.41	477.60	426.77	439.61	500.83
17:00	504.64	506.93	469.43	497.29	469.18	497.68	524.97
18:00	522.48	581.70	491.92	505.76	550.49	563.28	509.22
19:00	304.27	314.57	308.53	305.67	321.61	317.54	312.16
20:00	237.66	236.66	242.90	234.54	241.50	233.95	230.36
21:00	260.41	260.79	255.82	260.33	255.82	260.30	270.70
22:00	229.76	236.98	228.45	233.17	234.44	238.91	244.43
23:00	185.25	188.89	183.15	185.86	185.27	189.12	195.51
0:00	74.57	87.02	73.99	74.71	85.96	87.03	75.86
1:00	59.84	59.48	59.55	60.38	59.48	59.45	61.94
2:00	48.71	49.13	49.18	48.78	49.13	49.09	48.77
3:00	32.17	33.64	32.36	33.94	32.14	35.15	35.09
Total	7.2442	7.0278	7.2522	7.3700	7.0360	7.1539	7.5690
	N/A	-2.99%	0.11%	1.74%	-2.87%	-1.25%	4.48%

Note: The unit for per worker emissions is grams CO_2 equivalent (gCO_2e); the unit for total carbon emissions is kilograms CO_2 equivalent ($kgCO_2e$). The baselines for weekday scenarios and weekend scenarios are different.

Table 5.21 presents the changes in carbon emissions by mode of transport across scenarios, accounting for travel patterns of the entire population (including both employed and non-employed individuals). As the proportion of employed residents not engaged in paid work exceeds half of the weekday population, the impact of new work models on transport carbon emissions is less pronounced than observed in Table 5.19 and Table 5.20. Notably, activity model outputs represent only 9.5% of the weekend population, while Sunday travel arrangements influence merely 28.57% of the year. Therefore, the effect of weekend scenarios on annual transport carbon emissions is generally weaker than that of weekday scenarios. Amongst the emissions generated by residents' transport activities, approximately half originates from trips involving passenger cars, while rail transit and bus-related public transport together account for less than 20%. A significant portion of resident travel time is spent walking, but walking and cycling do not directly generate carbon emissions and therefore contribute nothing to the total urban transport emissions.

While increased adoption of dispersed working reduces carbon emissions from passenger car and bus travel, a rise in emissions from other modes of transport diminishes its overall impact on emission reductions. The implementation of half-day working on weekdays, however, may lead to a notable increase in transport-related carbon emissions due to heightened demand across all transport modes. For instance, under scenario C2, where 50% of traditional 9-to-5 employees transition to half-day schedules, annual emissions from residents' transport activities increase by 39,652.71 tCO_2e (a rise of 4.5%). Nevertheless, simultaneously promoting homeworking can mitigate the additional emissions caused by half-day working. Scenario E, for example, achieves a 0.18% reduction in annual transport emissions. Moreover, the analysis of scenario D reveals that combining homeworking with dispersed working leads to a more substantial reduction in emissions, amounting to 21,872.11 tCO_2e (i.e., -2.57%).

Adjusting work patterns solely on non-working days has a relatively minor effect on citywide transport-related carbon emissions. Promoting homeworking on weekends exhibits a marginal reduction in emissions (-0.09%), while the other two work models show slight increases in emissions (dispersed working by 0.02% and half-day working by 0.04%). However, more pronounced variations in energy demand can be revealed by accounting for changes in work patterns across both weekdays and weekends. For instance, under scenario J, where traditional 9-to-5 employees transition to working half-days throughout the week, transport-related carbon emissions increase by approximately 2.78%. Moreover, promoting dispersed working on weekends may counteract the emission reductions achieved by the widespread adoption of dispersed working during weekdays.

Table 5.21 Annual Aggregated Transport Carbon Emissions

Scenario	Walk/ Cycle	Car	Rail	Bus and couch	Other	Total (ppl)	Total (urban)
Unit	*$kgCO_2e$*						*$MtCO_2e$*
Baseline	0	804.31	20.42	276.40	500.45	1601.59	0.8807
A1	0	792.69	19.76	267.02	488.80	1568.27	0.8624
A2	0	790.16	19.61	264.98	486.21	1560.96	0.8584
B1	0	799.74	20.59	272.71	504.39	1597.44	0.8784
B2	0	793.02	20.84	267.28	510.22	1591.36	0.8751
C1	0	814.56	20.37	284.68	515.76	1635.37	0.8993
C2	0	826.21	20.99	294.10	532.40	1673.70	0.9204
D	0	787.12	19.90	262.52	491.17	1560.70	0.8582
E	0	801.94	19.64	274.49	502.56	1598.63	0.8791
F1	0	803.42	20.39	276.28	500.00	1600.08	0.8799
F2	0	804.21	20.49	276.54	500.65	1601.89	0.8809
F3	0	805.00	20.42	276.39	500.43	1602.24	0.8811
F4	0	803.35	20.44	276.40	500.14	1600.34	0.8800
F5	0	804.13	20.38	276.26	499.95	1600.72	0.8802
G	0	791.80	19.72	266.89	488.34	1566.76	0.8616
H	0	799.64	20.65	272.85	504.59	1597.73	0.8786
J	0	821.49	20.40	284.93	519.03	1645.85	0.9051
K	0	801.75	19.59	274.34	502.06	1597.75	0.8786
L	0	795.60	19.92	269.37	491.71	1576.60	0.8670

Table 5.22 summarises the annual carbon emissions changes by sector (i.e., residential, office, and transport) and by scenario. Our model captures the influence of typical time-use patterns among British residents on transport demand and its consequent carbon emissions. Analysis of baseline data indicates that the average per capita transport carbon emission is 1601.59 $kgCO_2e$, with car (including taxi) usage accounting for 804.31 $kgCO_2e$ (i.e., 50.2% of total emissions). In accordance with the *Official Statistics of Greenhouse Gas Emissions from Transport in 2023*, published by the Office for National Statistics (ONS, 2025), the domestic transport in the United Kingdom generates 111.8 $MtCO_2e$, which corresponds to an average per capita emission of 1635.69 $kgCO_2e$, where the contribution of car (and taxi) emissions is 54%. The results suggest that our simplified transport model achieves the expected explanatory power in

accounting for UK transport-related carbon emissions.

According to Table 5.22, an increase in the proportion of homeworking during weekdays is likely to result in higher energy demand in residential buildings. However, this is offset by a significant reduction in energy demand in the office sector. The net effect is a marginal decline in energy consumption and hence carbon emissions from the building sector (reductions of 2.24% and 2.73% under scenarios A1 and A2, respectively). In addition, promoting homeworking also contributes to carbon reduction in the transport sector.

Table 5.22 Annual Total Carbon Emissions by Sector

Scenarios	Residential	Office	Transport	Total
Baseline	0.3714	0.1515	0.8807	1.4036
A1	0.3791	0.1321	0.8624	1.3735
A2	0.3810	0.1276	0.8584	1.3670
B1	0.3711	0.1514	0.8784	1.4009
B2	0.3708	0.1512	0.8751	1.3971
C1	0.3721	0.1479	0.8993	1.4193
C2	0.3737	0.1404	0.9204	1.4346
D	0.3789	0.1321	0.8582	1.3692
E	0.3792	0.1302	0.8791	1.3885
F1	0.3714	0.1508	0.8799	1.4022
F2	0.3711	0.1516	0.8809	1.4035
F3	0.3714	0.1508	0.8811	1.4033
F4	0.3712	0.1513	0.8800	1.4025
F5	0.3715	0.1506	0.8802	1.4023
G	0.3791	0.1314	0.8616	1.3721
H	0.3709	0.1514	0.8786	1.4009
J	0.3716	0.1510	0.9051	1.4277
K	0.3793	0.1293	0.8786	1.3872
L	0.3779	0.1332	0.8670	1.3781

Unit: $MtCO_2e$

Increasing dispersed working primarily influences the temporal distribution of energy demand within the building and transport sectors rather than causing substantial changes in total energy use. Although the impact of dispersed working alone on energy demand is less significant compared to homeworking, combining the two work models (i.e., scenario D) achieves a more substantial reduction in total carbon emissions (-2.45%) compared to implementing homeworking alone (scenario A1).

The adoption of half-day working presents opportunities to reduce carbon emissions in the building sector. Similar to homeworking, half-day working increases energy demand in residential buildings. However, it also substantially reduces office energy use during the afternoon, resulting in an overall decrease in carbon emissions within the building sector. Nonetheless, commuting demand persists, and additional transport demand and hence emissions in the afternoon may offset these reductions. As a result, when transport emissions are considered, increasing half-day working may lead to an overall increase in carbon emissions. This trend is observed not only during weekdays (scenarios 3A and 3B) but also when a portion of the population transitions to half-day working on weekends (scenario J). Under this scenario, the marginal reduction in office emissions fails to compensate for a 2.77% increase in transport-related emissions, resulting in a net annual carbon emissions increase of 24,100 tCO_2e (1.72%).

The analysis further highlights the seasonal implications of working pattern changes. Scenario L suggests the conditions that conducting homeworking in other seasons but shifting to commuting in heating months (December to February). This seasonal shift can enhance the energy efficiency of office buildings by reducing heating loads during winter, thus lowering carbon emissions in offices. However, compared to the whole year homeworking scenario (e.g., A1), the growth in transport-related energy demand from increased commuting in winter may outweigh these savings. As such, the carbon reduction achieved under scenario L (-1.82%) is less substantial than the reductions observed when homeworking is promoted throughout the year on weekdays (scenario A1, -2.14%) or across both weekdays and weekends (scenario F1, -2.24%).

5.6 Policy Implications

(1) Home-working pattern can be a solution for urban energy demand management

In our case study, we found that home-working presents a significant carbon-reduction potential in both building and transport sectors. Therefore, it could be seen as an energy/carbon management solution in cities similar to Manchester in UK. In addition to home-working, other emerging working patterns may also play a positive role through integration with other energy management policies and practices.

The activity model employed in this study highlights the significant influence of three emerging work modes (e.g., homeworking, dispersed working, and half-day working) on the temporal and spatial distribution of residents' activities. Such influence, if leveraged through targeted policy interventions, can reshape the traditional temporal and spatial peaks of energy demand. For example, increasing dispersed working and half-day working during weekdays can transport demand from peak hours (08:00–09:00 and 17:00–18:00) to other times of the day. With the rising share of electric vehicles in urban passenger transport, these shifts are likely to affect the timing of peak energy demand for EV charging.

We emphasise that urban energy management based on working patterns requires a deep understanding of how these patterns affect residents' activities at different times. The widespread adoption of homeworking redistributes activities previously concentrated in offices (08:00–17:00) to residential buildings, redirecting energy demand from office to residential sectors. On a city scale, this reduces energy demand in central business districts during weekdays but poses challenges for energy supply in residential areas during these times. Similarly, promoting dispersed working redistributes evening residential activities to morning hours, altering residential energy consumption patterns. By transferring daytime office activities to the evening, dispersed working may also increase office energy demand at night while alleviating the peak electricity load in residential buildings. Energy demand management can utilise such insights to inform novel interventions for enhancing the sustainability and resilience of urban energy systems.

(2) An inter-sectoral, system-of-systems approach for decarbonisation

Flexible working policies have the potential to influence cross-sector carbon emissions in cities, thus playing a crucial coordinating role in linking the building and transport sectors. Our new modelling framework can capture complex cross-sector interactions in energy demand. A notable example is the homeworking scenario, where a strong trade-off exists between residential and office activities. As residents shift their activities from offices to homes, their energy demand changes accordingly.

Our study highlights that strategically encouraging changes in residents' working patterns can serve as an effective cross-sectoral energy management approach. In our case analysis, both temporally dispersed working and homeworking demonstrate potential for reducing net carbon emissions in the transport and building sectors, albeit through different mechanisms. The reductions associated with homeworking are primarily driven by decreased energy consumption in transport and office buildings. Conversely, temporally dispersed working achieves energy savings by redistributing activities from peak to off-peak periods, for example, shifting morning traffic (07:00–09:00) to mid-morning hours (09:00–12:00), or relocating weekday office operations (09:00–11:00) to evening hours (19:00–21:00). Such interventions may also unlock opportunities for enhancing urban energy flexibility and resilience, particularly as cities transition towards smart energy grids and decentralised renewable energy systems. For instance, dispersed working could facilitate dynamic load balancing, mitigating energy congestion and reducing the strain on electrical infrastructure during peak hours.

Also, the effectiveness of these approaches is contingent upon the urban environment. Homeworking appears more suitable for cities with high transport-related carbon emissions and moderate climates, whereas it may be less applicable in regions characterised by substantial building energy demands or extended seasons of extreme weather. Considering the cross-sectoral impacts of interventions not only enhances the efficacy of energy management strategies but also minimises adverse effects on urban economies and quality of life of population.

(3) Considering for seasonal variations in energy demand

Our analysis shows that the increase in residential energy demand during winter due to homeworking is lower than in summer. This asymmetry stems from different building energy intensities for maintaining comfortable indoor environments. Policymakers could consider implementing seasonally adjusted working patterns to exploit such variations. During cold winters, encouraging office work could optimise building energy use due to efficiency gains from central heating in offices. Higher office occupancy in winter can also increase internal heat gains, reducing heating loads, compared to home-based heating. Conversely, in warmer spring and summer months, where heating load is low, promoting homeworking could substantially lower transport-related emissions. For cities with longer, colder winters (e.g., Helsinki, Anchorage, Sapporo, and Moscow) or those requiring substantial cooling energy during summers (e.g., Dubai, Hong Kong, and Bangkok), targeted climate-specific work patterns may offer meaningful energy savings.

However, our case study suggests that such strategies (see scenario L), while effective in reducing building energy demand, could cause an increase in transport emissions caused by winter commuting.

However, such strategies may have different energy impacts on different urban sectors.

For example, in our case, although the seasonal work pattern strategy reduces carbon emissions throughout the year, the reduction of this strategy is lower than the impact of year-round homeworking. This is due to the strong positive contribution of winter commuting activities to greenhouse gas emissions in the transport sector. Therefore, this season-based strategy is context-sensitive and needs to take into account the local urban environment and climate characteristics before being applied to other cities and regions, and requires further sensitivity tests.

5.7 Limitations and Future Directions

We acknowledge that the study exists some limitations. First, due to data limitations, a simplified transport model was adopted, as our analysis is based on time-use survey data that does not capture detailed origin-destination or route information for residents' travel activities. This constraint poses significant challenges to the implementation of a comprehensive activity-based transport model within our framework. Moreover, clear variations in transport mode speeds and travel mode choices across different times of day further complicate the modelling process. Future research would benefit from integrating congestion effects and mode-shift dynamic considerations into the present framework.

Another important limitation is that the diversity of working locations is not fully considered in this study. The discussion of work locations focuses on two categories: office and residence. This is because the data used was collected in 2014 to 2015, when residents' work location choices were relatively limited. Only a small proportion of respondents reported working outside of their homes or primary offices, and many of these were engaged in outdoor or mobile work (e.g., maintenance, delivery, or driving). However, in the past decade, the flexibility of work locations has increased significantly, particularly with the rise of co-working spaces such as WeWork. This trend has accelerated further since the COVID-19 pandemic. Unfortunately, the data used in this study does not adequately capture this shift. Future research would benefit from using more recent datasets to reflect the growing diversity of work locations and to assess their energy implications more comprehensively.

The third limitation of the current study is the lack of a comprehensive assessment of net energy outcomes across sectors. While the shift to homeworking clearly reduces energy demand in office buildings, it simultaneously increases residential energy consumption, particularly for HVAC. The current model does not quantify whether these shifts result in a net increase or decrease in total energy use. Moreover, the potential role of renewable energy adoption (e.g., rooftop PVs) in offsetting increased residential demand remains unexplored. Future research should aim to integrate residential renewable energy generation into the modelling framework, and assess how such systems could mitigate the energy burden of flexible work arrangements. Additionally, the impacts of peak and off-peak electricity pricing, as well as grid flexibility mechanisms, should be considered to better understand the temporal dynamics of energy demand and their implications for energy system resilience.

While this study focuses primarily on energy demand and spatial patterns of activity, it does not address the broader economic and behavioural implications of flexible work arrangements. For instance, the productivity trade-offs associated with partial or half-day working schedules, particularly in relation to energy savings, remain underexplored. Future work could incorporate economic resilience metrics to evaluate how different working patterns affect not only energy use but also labour productivity and household well-being. Furthermore, as highlighted in our two case studies, scenario-based modelling could be extended to include the integration of renewable energy technologies in residential settings, particularly in the context of increased home occupancy. This would allow for a more holistic understanding of the synergies between urban energy planning, activity pattern change, and sustainability transitions.

5.8 Chapter Summary

This chapter applies the modelling framework established in Chapter 4 to the case of Manchester. It aims to quantify the cross-sectoral effect of emerging working modes on urban energy demand and associated emissions. Based on UKTUS 2014/2015 data, this chapter identifies new working patterns considering both temporal and spatial flexibility. Distinct time use patterns of the new working patterns are captured by a MDCEV model. By constructing a simplified bottom-up UBEM for the case area, the study quantifies how new working patterns affect different types of energy demand in building and transport sectors. Scenario analyses demonstrate that energy demands in residential and office buildings predominantly follow shifts in occupant activities. However, we highlight the importance of considering the roles of building services that introduce climate/environment-induced uncertainties into this dynamic. In addition, we illuminate how new working patterns fundamentally transform mobility and energy consumption trajectories. The spatial and temporal choices of working patterns directly modulate transport (commuting) demands as well as their temporal distribution, and, consequently, derived carbon emissions. Thus, the working pattern-based interventions could have potential to mitigate concentrated infrastructure demands across spatial and temporal dimensions. By elucidating the intricate relationships between emerging working patterns and urban energy dynamics, the study contributes to the growing body of knowledge on sustainable urban development and energy transition strategies. Also, the findings carry substantial policy implications for urban energy management. By demonstrating the potential of working patterns to alleviate energy congestion and reduce peak-period infrastructure pressures, the research provides valuable insights for policymakers and urban planners. The methodology and results are not only generalisable to similar urban contexts but also offer a strategic framework for energy management in rapidly developing regions.

Chapter 6 Conclusion and Reflections

6.1 Conclusion

This research aims to develop a new modelling framework for capturing the effects of emerging working patterns and lifestyles on the spatiotemporal characteristics of urban energy demand across different sectors. Traditional models typically pay more attention to the physical attributes of buildings and environmental conditions, thus overlooking the dynamics of activity chains driven by rapid changes in productivity and the social environment. The proposed modelling framework and its applications presented in this dissertation address several gaps in the existing literature:

First, to understand the distribution and characteristics of emerging working patterns. As work patterns evolve dramatically, residents could change their time allocation to activities and locations. Thus, a more in-depth exploration of the distribution of these new working patterns and their implications for time use patterns and energy demand is necessary.

Second, existing urban building energy models tend to reply on eterministic schedules to represent occupant behaviour, thereby neglecting the variability in activities performed both inside and outside of buildings. There is, therefore, a need to capture the energy impacts of occupant activities by exploring the relationship between the dynamic nature of occupant and fluctuations in building energy demand.

Third, a disciplinary and sectoral silo seems evident where buildings and transport are usually simulated as two separate systems in existing energy modelling studies. This contrasts with the inherent interdependences between the demand for floorspace and for travel. An inter-sectoral approach is thus required to integrate existing sectoral models for better consistency across sectors.

Fourth, the resurgence of new working patterns (e.g., home-based working) is expected to have profound implications for energy demand, which should be incorporated into city-scale energy management. Such a behavioural focus in urban energy modelling is crucial for developing effective policy interventions, as opposed to focusing solely on physical changes in building stock and transport infrastructure.

Based on the literature review presented in Chapters 2 and 3, this study has developed a novel modelling framework centred on residents' activity chains. In Chapters 4 and 5, we employ case studies to address the aforementioned research gaps and provide theoretical and methodological support for a more comprehensive prediction and management of urban energy demand. Through our analysis of a neighbourhood-scale case in Shanghai and an urban-scale case in Manchester, the study yields findings regarding both residents' time use and energy demand:

Firstly, we observes heterogeneity in how residents allocate their time and in their adoption of new working patterns, which are profoundly influenced by local economic culture, employment structures, and physical environments. For instance, based on UKTUS data, British residents demonstrate 16 distinct working patterns, with the traditional 9-to-5 pattern accounting for only 56% of cases, suggesting that over 40% of residents have embraced emerging working patterns. In contrast, in Shanghai, even following the COVID-19 pandemic, around 79% of the employed population continued to adhere to conventional pattern, reflecting a more conservative local stance towards other working patterns. This disparity not only reveals the unique characteristics of regional labour markets but also implies that the effects of different working patterns on overall time allocation vary geographically.

Second, the case studies analysed the impact of new working patterns on both working and transport times. In the UK case, when residents adopt home-working patterns, their average working hours remain stable while a substantial reduction in overall travel time was observed. By contrast, the model indicates that if 10% of Shanghai commuters were to switch to home-based or hybrid working, the average total working time would decrease by 4.83%, and under such flexible working conditions, the average transport activity time could increase by between 10% and 30%. This phenomenon could stem from two factors: (1) a reduction in commuting demand encourages some residents to opt for slower modes of travel, such as walking or cycling; (2) in high-density cities, flexible working provides residents with more opportunities to engage in activities across different areas, potentially increasing the overall travel demand.

Third, we discussed how activity patterns influence the energy demand (re-)distribution of the building sector. The energy analyses from both case studies indicate that the building energy demand is closely associated with activity patterns and derived building occupancy schedules. However, this redistribution does not simply replicate occupancy patterns; rather, it is affected by a combination of factors such as urban building geometry and climatic conditions. In our cases, under a home-based working scenario, the building energy demand in Manchester declined, whereas an opposite trend was observed in Shanghai. The primary reasons for this include: (1) Shanghai's long and hot summer, which shifts the cooling load originally concentrated in office spaces to the more widespread residential buildings; (2) differences in building geometries and residential typologies between the two locations, which lead to varied consumption patterns; and (3) the broader geographical scope of the Manchester case, which better captures the diversity of urban functions.

Fourth, the case studies examine the interactions between the building and transport sectors and their energy implications. In our UK case, the emerging working patterns can directly alter transport activities, for example, home-based working resulted in a pervasive reduction in overall travel demand. In addition, they can indirectly influenced the urban energy system by modifying the distribution of travel between peak and off-peak periods (e.g. through dispersed working and half-day working). In the context of Manchester, even if certain working patterns deliver energy savings at the building level, an associated rise in transportation activities could counteract or even reverse these savings (e.g. half-day working), thereby posing an increased risk of higher carbon emissions.

Based on the findings outlined above, the modelling framework proposed in this study addresses several limitations inherent in conventional models, particularly in representing dynamic residential behaviour, interdepartmental coordination, and the implications of flexible working arrangements. It also offers policy insights to support urban energy planning and management:

First, the framework explains the interconnectedness of residents' daily activities, evolving work patterns, and their substantial influence on both building and transport-related energy demand. These insights enable decision-makers to propose energy supply and demand-side management strategies in alignment with the socio-economic, cultural, and climatic contexts of regions. Thus, the resilience and cost-effectiveness of urban energy systems can be maintained during both peak and off-peak periods.

Second, the research highlights the imperative of cross-departmental collaboration in urban energy management. Considering energy demand within individual sectors in isolation may result in skewed policy outcomes. Improvements in one urban sector may be offset by unintended increases in energy use or carbon emissions in another. In response, this study advocates for an integrated and cross-sectoral approach, whereby policymakers employ multi-scenario simulation systems to assess the cumulative impacts of interactions across the building, transport, and other urban subsystems. Such an approach supports the formulation of effective intervention strategies.

In addition, the proposed framework lends to applications in regionally adaptive energy management. Recognising spatial variation in climate conditions, urban morphology, and behavioural patterns, the study highlights the necessity for differentiated strategies. For example, in cities in hot climate zones, increased remote working may lead to higher cooling loads in residential buildings. In temperate cities, flexible working patterns may contribute to overall energy savings. In cities with seasonal variation, adjusting work routines seasonally could contribute to reductions in carbon emissions. Through the application of this framework, urban planners can more accurately forecast future energy demand trends. This can provide an evidence base for infrastructure upgrading, energy efficiency improvements, and the development of smart cities, thereby advancing the strategic objective of low-carbon and sustainable urban development.

6.2 Limitations and Suggestions for Further Research

In terms of limitations, firstly, the two model applications assume that emerging working modes would influence the time and duration of office use, but the average energy intensity of office building usage remains constant. The recent churns in the office market, e.g the ‘flight to quality’ (Chilton et al. 2025) suggests that higher expectations from tenants in terms of building energy efficiency and social/welfare functions are changing the spatial arrangement and usage patterns of offices, which would in turn affect the energy intensity of building use. However, advancing research in this direction is hampered by the data gap between time-use data, occupant behaviour data and building occupancy data. These datasets often lack consistency in their collection and processing methods, making cross-dataset integration and analysis challenging. This highlights the crucial need for improved data integration regarding building occupants' behaviour and building operations in future research.

Secondly, the case studies in this research only consider the short-to-medium-term impacts of emerging working patterns on the time use of workers, while potential long-term impacts such as residential relocation and change of employment are not considered. Consequently, potential spatial shifts in energy demand incurred by relocations are not captured by our models. Additionally, the transition to emerging working modes is likely to influence the time use and location/travel choices of workers, but also other members of the same household/company. For instance, parent(s) switching to homeworking might alter their dependent children's daily routines and activity demands, affecting the energy consumption of the household as a whole. Future research is thus suggested to consider such within-household/company behavioural interactions.

This study acknowledges several inherent simplifications in the proposed framework. Specifically, two critical dimensions were constrained in the current analytical approach: (1) the geometric categorisation of urban architectural morphologies, and (2) the characterisation of urban climatic environments.

Future research could pursue the following advancements: (1) adopting granular geometric classifications to better reflect the heterogeneity of buildings, moving beyond oversimplified geometric and functional representations; (2) integrating the model with new urban microclimate models capable of dynamically capturing spatial and temporal variations in environmental parameters, such as the potential impacts of fluctuating urban population densities; (3) considering the roles of occupant behaviour, including energy-saving behaviour associated with environmental awareness and the complex influence of activity pattern changes on these behaviours; (4) developing computational frameworks that encompass a broader range of urban sectors, including the dynamics of public service buildings and energy infrastructures. These proposed directions aim not only to improve methodological precision but also to make a substantive contribution to cross-sectoral urban energy decision-making strategies. Moreover, future studies could benefit from dismantling disciplinary silos and adopting a more integrated, systems-oriented approach to investigating urban energy dynamics.

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Appendix A Building Occupancy and Appliance Use Schedules

This section lists the occupancy schedules, lighting intensity schedules, as well as appliance usage schedules for residential and office building energy modelling.

Appendix A-1 Residential Building Occupancy Schedule (Weekday)

	Baseline	1A	1B	2A	2B	3A	3B	4	5
4:00	1.000	1.003	1.003	0.999	0.999	0.998	0.999	1.002	1.001
5:00	0.980	0.982	0.983	0.981	0.981	0.976	0.981	0.983	0.978
6:00	0.936	0.937	0.938	0.936	0.936	0.931	0.936	0.938	0.933
7:00	0.828	0.831	0.832	0.831	0.837	0.825	0.837	0.835	0.828
8:00	0.613	0.669	0.683	0.631	0.657	0.615	0.657	0.683	0.670
9:00	0.485	0.562	0.582	0.499	0.520	0.488	0.520	0.571	0.562
10:00	0.408	0.491	0.513	0.418	0.434	0.410	0.413	0.496	0.489
11:00	0.376	0.458	0.479	0.384	0.398	0.378	0.381	0.462	0.456
12:00	0.386	0.470	0.491	0.393	0.405	0.389	0.394	0.475	0.471
13:00	0.394	0.478	0.499	0.401	0.410	0.401	0.411	0.482	0.481
14:00	0.383	0.462	0.483	0.387	0.393	0.393	0.408	0.464	0.465
15:00	0.412	0.483	0.501	0.413	0.415	0.426	0.448	0.484	0.487
16:00	0.540	0.600	0.615	0.538	0.536	0.559	0.588	0.602	0.612
17:00	0.638	0.683	0.693	0.628	0.612	0.652	0.674	0.679	0.694
18:00	0.725	0.753	0.759	0.707	0.680	0.729	0.735	0.742	0.757
19:00	0.771	0.785	0.788	0.755	0.731	0.771	0.772	0.775	0.786
20:00	0.819	0.835	0.838	0.806	0.786	0.818	0.816	0.825	0.834
21:00	0.868	0.876	0.877	0.860	0.848	0.868	0.867	0.869	0.875
22:00	0.921	0.927	0.928	0.918	0.913	0.921	0.919	0.924	0.926
23:00	0.959	0.960	0.961	0.957	0.953	0.959	0.958	0.958	0.960
0:00	0.975	0.975	0.975	0.974	0.971	0.975	0.971	0.973	0.975
1:00	0.980	0.981	0.981	0.979	0.978	0.980	0.978	0.980	0.980
2:00	0.983	0.984	0.984	0.982	0.981	0.983	0.981	0.983	0.984
3:00	0.986	0.987	0.988	0.985	0.984	0.986	0.984	0.986	0.987

Appendix A-2 Residential Building Occupancy Schedule (Weekend)

Residential	Baseline	6A	6B	6C
4:00	0.970	0.970	0.970	0.970
5:00	0.962	0.961	0.962	0.962
6:00	0.946	0.946	0.947	0.946
7:00	0.914	0.915	0.914	0.916
8:00	0.856	0.860	0.858	0.862
9:00	0.753	0.758	0.754	0.758
10:00	0.633	0.639	0.634	0.640
11:00	0.555	0.561	0.556	0.562
12:00	0.539	0.544	0.540	0.545
13:00	0.536	0.540	0.537	0.541
14:00	0.524	0.529	0.525	0.530
15:00	0.543	0.549	0.543	0.549
16:00	0.607	0.612	0.607	0.612
17:00	0.689	0.695	0.687	0.694
18:00	0.732	0.735	0.728	0.732
19:00	0.766	0.769	0.763	0.766
20:00	0.799	0.800	0.798	0.799
21:00	0.837	0.837	0.835	0.835
22:00	0.878	0.880	0.876	0.878
23:00	0.918	0.920	0.917	0.919
0:00	0.946	0.946	0.946	0.946
1:00	0.960	0.960	0.960	0.960
2:00	0.966	0.966	0.966	0.966
3:00	0.969	0.969	0.969	0.969

Appendix A-3 Office Building Occupancy Schedule (Weekday)

	Baseline	1A	1B	2A	2B	3A	3B	4	5
4:00	0.025	0.025	0.025	0.026	0.029	0.029	0.029	0.027	0.029
5:00	0.040	0.040	0.040	0.041	0.042	0.048	0.042	0.041	0.048
6:00	0.065	0.066	0.066	0.066	0.066	0.077	0.066	0.066	0.078
7:00	0.180	0.183	0.183	0.171	0.157	0.192	0.157	0.173	0.195
8:00	0.500	0.378	0.346	0.462	0.403	0.496	0.403	0.353	0.375
9:00	0.907	0.711	0.659	0.849	0.761	0.889	0.761	0.672	0.698
10:00	0.987	0.769	0.712	0.936	0.860	0.964	0.929	0.735	0.753
11:00	1.000	0.778	0.719	0.959	0.896	0.978	0.944	0.749	0.762
12:00	0.940	0.730	0.676	0.910	0.865	0.919	0.887	0.710	0.716
13:00	0.920	0.715	0.662	0.896	0.860	0.884	0.829	0.698	0.690
14:00	0.925	0.721	0.668	0.907	0.878	0.861	0.764	0.708	0.678
15:00	0.747	0.556	0.508	0.739	0.726	0.662	0.533	0.550	0.501
16:00	0.519	0.371	0.334	0.538	0.567	0.454	0.356	0.383	0.328
17:00	0.289	0.204	0.186	0.346	0.435	0.262	0.223	0.242	0.187
18:00	0.152	0.107	0.099	0.213	0.305	0.147	0.138	0.147	0.103
19:00	0.097	0.069	0.065	0.144	0.216	0.097	0.097	0.099	0.069
20:00	0.071	0.048	0.044	0.102	0.149	0.072	0.073	0.067	0.048
21:00	0.058	0.053	0.052	0.077	0.105	0.060	0.062	0.070	0.055
22:00	0.046	0.043	0.042	0.056	0.072	0.048	0.050	0.052	0.044
23:00	0.034	0.033	0.033	0.041	0.050	0.035	0.036	0.039	0.034
0:00	0.030	0.029	0.029	0.034	0.041	0.030	0.041	0.034	0.030
1:00	0.026	0.026	0.026	0.029	0.034	0.027	0.034	0.029	0.027
2:00	0.025	0.025	0.025	0.027	0.031	0.026	0.031	0.027	0.026
3:00	0.023	0.023	0.023	0.026	0.029	0.024	0.029	0.026	0.024

Appendix A-4 Office Building Occupancy Schedule (Weekend)

Office	Baseline	FA	FB	FD
4:00	0.020	0.020	0.020	0.020
5:00	0.028	0.028	0.028	0.028
6:00	0.042	0.041	0.040	0.040
7:00	0.070	0.069	0.067	0.066
8:00	0.111	0.105	0.105	0.099
9:00	0.170	0.160	0.167	0.158
10:00	0.187	0.175	0.180	0.169
11:00	0.198	0.189	0.193	0.184
12:00	0.193	0.183	0.190	0.179
13:00	0.183	0.176	0.180	0.173
14:00	0.177	0.166	0.174	0.163
15:00	0.159	0.148	0.158	0.148
16:00	0.127	0.118	0.129	0.119
17:00	0.106	0.091	0.114	0.098
18:00	0.081	0.070	0.092	0.080
19:00	0.065	0.056	0.075	0.064
20:00	0.056	0.054	0.056	0.054
21:00	0.049	0.049	0.054	0.054
22:00	0.044	0.039	0.047	0.041
23:00	0.035	0.030	0.036	0.031
0:00	0.029	0.029	0.030	0.029
1:00	0.026	0.026	0.026	0.026
2:00	0.024	0.024	0.024	0.024
3:00	0.022	0.021	0.022	0.022

Appendix A-5 Residential Building Appliance Usage Schedule (Weekday)

	Baseline	1A	1B	2A	2B	3A	3B	4	5
4:00	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236
5:00	0.281	0.283	0.283	0.281	0.281	0.280	0.281	0.283	0.282
6:00	0.441	0.442	0.442	0.441	0.441	0.438	0.441	0.442	0.439
7:00	0.681	0.684	0.685	0.683	0.687	0.678	0.687	0.687	0.681
8:00	0.660	0.718	0.732	0.678	0.705	0.663	0.705	0.732	0.719
9:00	0.613	0.692	0.712	0.627	0.648	0.616	0.648	0.701	0.692
10:00	0.576	0.661	0.683	0.586	0.602	0.578	0.581	0.666	0.659
11:00	0.557	0.641	0.663	0.566	0.580	0.560	0.563	0.646	0.639
12:00	0.575	0.660	0.682	0.582	0.594	0.578	0.583	0.666	0.661
13:00	0.583	0.668	0.689	0.589	0.599	0.590	0.600	0.673	0.672
14:00	0.568	0.649	0.670	0.572	0.578	0.578	0.593	0.651	0.651
15:00	0.600	0.672	0.690	0.601	0.603	0.614	0.637	0.673	0.676
16:00	0.733	0.794	0.809	0.731	0.729	0.752	0.782	0.796	0.806
17:00	0.836	0.882	0.893	0.826	0.809	0.851	0.873	0.878	0.893
18:00	0.927	0.956	0.962	0.909	0.882	0.932	0.938	0.945	0.960
19:00	0.971	0.986	0.989	0.955	0.931	0.972	0.973	0.976	0.987
20:00	1.000	1.016	1.019	0.986	0.966	0.999	0.997	1.006	1.015
21:00	0.987	0.995	0.997	0.979	0.967	0.986	0.985	0.988	0.994
22:00	0.774	0.788	0.791	0.772	0.771	0.772	0.770	0.786	0.786
23:00	0.494	0.503	0.505	0.495	0.498	0.493	0.491	0.505	0.502
0:00	0.329	0.330	0.331	0.329	0.329	0.329	0.329	0.330	0.330
1:00	0.249	0.249	0.249	0.249	0.249	0.249	0.249	0.249	0.249
2:00	0.238	0.238	0.237	0.238	0.238	0.238	0.238	0.238	0.237
3:00	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232

Appendix A-6 Residential Building Appliance Usage Schedule (Weekend)

Office	Baseline	FA	FB	FD
4:00	0.227	0.227	0.227	0.227
5:00	0.248	0.248	0.248	0.247
6:00	0.313	0.313	0.313	0.313
7:00	0.482	0.484	0.482	0.484
8:00	0.688	0.692	0.689	0.693
9:00	0.775	0.779	0.776	0.780
10:00	0.763	0.769	0.764	0.770
11:00	0.726	0.732	0.727	0.733
12:00	0.726	0.731	0.726	0.732
13:00	0.728	0.732	0.729	0.733
14:00	0.714	0.720	0.715	0.720
15:00	0.733	0.739	0.733	0.739
16:00	0.798	0.804	0.798	0.804
17:00	0.887	0.894	0.885	0.892
18:00	0.934	0.937	0.930	0.934
19:00	0.968	0.971	0.964	0.968
20:00	0.984	0.985	0.983	0.984
21:00	0.953	0.953	0.951	0.951
22:00	0.756	0.757	0.755	0.756
23:00	0.500	0.501	0.500	0.502
0:00	0.346	0.346	0.346	0.347
1:00	0.255	0.255	0.255	0.255
2:00	0.240	0.240	0.240	0.240
3:00	0.234	0.234	0.234	0.234

Appendix A-7 Office Building Appliance Usage Schedule (Weekday)

	Baseline	1A	1B	2A	2B	3A	3B	4	5
4:00	0.018	0.018	0.018	0.019	0.020	0.020	0.020	0.019	0.021
5:00	0.028	0.028	0.028	0.028	0.029	0.033	0.029	0.028	0.033
6:00	0.046	0.046	0.046	0.046	0.046	0.054	0.046	0.046	0.054
7:00	0.126	0.128	0.128	0.120	0.110	0.135	0.110	0.121	0.136
8:00	0.350	0.265	0.242	0.323	0.282	0.347	0.282	0.247	0.263
9:00	0.635	0.498	0.461	0.594	0.532	0.622	0.532	0.470	0.489
10:00	0.691	0.538	0.498	0.655	0.602	0.675	0.650	0.514	0.527
11:00	0.700	0.544	0.504	0.671	0.627	0.684	0.661	0.524	0.533
12:00	0.658	0.511	0.473	0.637	0.606	0.643	0.621	0.497	0.501
13:00	0.644	0.500	0.463	0.627	0.602	0.619	0.580	0.489	0.483
14:00	0.648	0.505	0.468	0.635	0.615	0.603	0.535	0.496	0.475
15:00	0.523	0.390	0.356	0.517	0.508	0.464	0.373	0.385	0.350
16:00	0.363	0.259	0.234	0.377	0.397	0.318	0.249	0.268	0.230
17:00	0.202	0.143	0.130	0.242	0.304	0.184	0.156	0.170	0.131
18:00	0.107	0.075	0.070	0.149	0.214	0.103	0.097	0.103	0.072
19:00	0.068	0.048	0.046	0.101	0.151	0.068	0.068	0.070	0.048
20:00	0.050	0.033	0.031	0.072	0.105	0.050	0.051	0.047	0.034
21:00	0.041	0.037	0.037	0.054	0.074	0.042	0.043	0.049	0.038
22:00	0.032	0.030	0.029	0.039	0.050	0.033	0.035	0.036	0.031
23:00	0.024	0.023	0.023	0.028	0.035	0.024	0.025	0.027	0.024
0:00	0.021	0.021	0.021	0.024	0.028	0.021	0.028	0.024	0.021
1:00	0.018	0.018	0.018	0.020	0.024	0.019	0.024	0.020	0.019
2:00	0.017	0.017	0.017	0.019	0.021	0.018	0.021	0.019	0.018
3:00	0.016	0.016	0.016	0.018	0.020	0.017	0.020	0.018	0.017

Appendix A-8 Office Building Appliance Usage Schedule (Weekend)

Office	Baseline	FA	FB	FD
4:00	0.014	0.014	0.014	0.014
5:00	0.020	0.020	0.019	0.019
6:00	0.029	0.029	0.028	0.028
7:00	0.049	0.048	0.047	0.046
8:00	0.078	0.074	0.073	0.069
9:00	0.119	0.112	0.117	0.111
10:00	0.131	0.123	0.126	0.118
11:00	0.139	0.132	0.135	0.128
12:00	0.135	0.128	0.133	0.126
13:00	0.128	0.123	0.126	0.121
14:00	0.124	0.116	0.122	0.114
15:00	0.111	0.104	0.111	0.104
16:00	0.089	0.083	0.090	0.084
17:00	0.074	0.064	0.080	0.068
18:00	0.057	0.049	0.065	0.056
19:00	0.046	0.039	0.052	0.045
20:00	0.039	0.038	0.039	0.038
21:00	0.034	0.035	0.038	0.038
22:00	0.031	0.027	0.033	0.029
23:00	0.025	0.021	0.025	0.022
0:00	0.020	0.020	0.021	0.021
1:00	0.018	0.018	0.018	0.018
2:00	0.017	0.017	0.017	0.017
3:00	0.015	0.015	0.015	0.015

Appendix A-9 Residential Building Lighting Intensity Schedule (Weekday)

	Baseline	1A	1B	2A	2B	3A	3B	4	5
4:00	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
5:00	0.101	0.103	0.104	0.101	0.101	0.100	0.101	0.103	0.102
6:00	0.301	0.302	0.302	0.301	0.302	0.298	0.302	0.302	0.299
7:00	0.601	0.605	0.606	0.604	0.609	0.598	0.609	0.608	0.602
8:00	0.115	0.129	0.133	0.119	0.126	0.116	0.126	0.133	0.130
9:00	0.103	0.123	0.128	0.107	0.112	0.104	0.112	0.125	0.123
10:00	0.094	0.115	0.121	0.096	0.100	0.094	0.095	0.116	0.115
11:00	0.089	0.110	0.116	0.092	0.095	0.090	0.091	0.111	0.110
12:00	0.094	0.115	0.121	0.096	0.098	0.094	0.096	0.116	0.115
13:00	0.096	0.117	0.122	0.097	0.100	0.097	0.100	0.118	0.118
14:00	0.092	0.112	0.117	0.093	0.094	0.095	0.098	0.113	0.113
15:00	0.100	0.118	0.123	0.100	0.101	0.104	0.109	0.118	0.119
16:00	0.133	0.149	0.152	0.133	0.132	0.138	0.146	0.149	0.152
17:00	0.795	0.853	0.866	0.782	0.762	0.813	0.841	0.848	0.866
18:00	0.909	0.945	0.953	0.887	0.852	0.915	0.923	0.931	0.950
19:00	0.964	0.983	0.987	0.944	0.914	0.965	0.966	0.970	0.983
20:00	1.000	1.020	1.024	0.983	0.958	0.998	0.996	1.008	1.019
21:00	0.984	0.994	0.996	0.974	0.958	0.983	0.982	0.985	0.993
22:00	0.717	0.735	0.739	0.715	0.713	0.715	0.713	0.733	0.733
23:00	0.367	0.379	0.382	0.369	0.373	0.366	0.364	0.381	0.377
0:00	0.162	0.163	0.163	0.161	0.161	0.161	0.161	0.162	0.163
1:00	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061
2:00	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047
3:00	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040

Appendix A-10 Residential Building Lighting Intensity Schedule (Weekend)

Office	Baseline	FA	FB	FD
4:00	0.034	0.034	0.034	0.034
5:00	0.060	0.059	0.060	0.059
6:00	0.141	0.141	0.141	0.141
7:00	0.353	0.355	0.352	0.355
8:00	0.122	0.123	0.122	0.123
9:00	0.144	0.145	0.144	0.145
10:00	0.141	0.142	0.141	0.143
11:00	0.132	0.133	0.132	0.133
12:00	0.131	0.133	0.132	0.133
13:00	0.132	0.133	0.132	0.133
14:00	0.129	0.130	0.129	0.130
15:00	0.133	0.135	0.133	0.135
16:00	0.150	0.151	0.149	0.151
17:00	0.859	0.867	0.856	0.865
18:00	0.918	0.921	0.913	0.917
19:00	0.960	0.964	0.956	0.960
20:00	0.980	0.981	0.979	0.981
21:00	0.941	0.941	0.939	0.939
22:00	0.695	0.696	0.693	0.695
23:00	0.375	0.377	0.375	0.377
0:00	0.182	0.183	0.183	0.183
1:00	0.068	0.068	0.068	0.068
2:00	0.050	0.050	0.050	0.050
3:00	0.042	0.043	0.042	0.043

Appendix A-11 Office Building Lighting Intensity Schedule (Weekday)

	Baseline	1A	1B	2A	2B	3A	3B	4	5
4:00	0.018	0.018	0.018	0.019	0.020	0.020	0.020	0.019	0.021
5:00	0.028	0.028	0.028	0.028	0.029	0.033	0.029	0.028	0.033
6:00	0.046	0.046	0.046	0.046	0.046	0.054	0.046	0.046	0.054
7:00	0.126	0.128	0.128	0.120	0.110	0.135	0.110	0.121	0.136
8:00	0.350	0.265	0.242	0.323	0.282	0.347	0.282	0.247	0.263
9:00	0.635	0.498	0.461	0.594	0.532	0.622	0.532	0.470	0.489
10:00	0.691	0.538	0.498	0.655	0.602	0.675	0.650	0.514	0.527
11:00	0.700	0.544	0.504	0.671	0.627	0.684	0.661	0.524	0.533
12:00	0.658	0.511	0.473	0.637	0.606	0.643	0.621	0.497	0.501
13:00	0.644	0.500	0.463	0.627	0.602	0.619	0.580	0.489	0.483
14:00	0.648	0.505	0.468	0.635	0.615	0.603	0.535	0.496	0.475
15:00	0.523	0.390	0.356	0.517	0.508	0.464	0.373	0.385	0.350
16:00	0.363	0.259	0.234	0.377	0.397	0.318	0.249	0.268	0.230
17:00	0.202	0.143	0.130	0.242	0.304	0.184	0.156	0.170	0.131
18:00	0.107	0.075	0.070	0.149	0.214	0.103	0.097	0.103	0.072
19:00	0.068	0.048	0.046	0.101	0.151	0.068	0.068	0.070	0.048
20:00	0.050	0.033	0.031	0.072	0.105	0.050	0.051	0.047	0.034
21:00	0.041	0.037	0.037	0.054	0.074	0.042	0.043	0.049	0.038
22:00	0.032	0.030	0.029	0.039	0.050	0.033	0.035	0.036	0.031
23:00	0.024	0.023	0.023	0.028	0.035	0.024	0.025	0.027	0.024
0:00	0.021	0.021	0.021	0.024	0.028	0.021	0.028	0.024	0.021
1:00	0.018	0.018	0.018	0.020	0.024	0.019	0.024	0.020	0.019
2:00	0.017	0.017	0.017	0.019	0.021	0.018	0.021	0.019	0.018
3:00	0.016	0.016	0.016	0.018	0.020	0.017	0.020	0.018	0.017

Appendix A-12 Office Building Lighting Intensity Schedule (Weekend)

Office	Baseline	FA	FB	FD
4:00	0.014	0.014	0.014	0.014
5:00	0.020	0.020	0.019	0.019
6:00	0.029	0.029	0.028	0.028
7:00	0.049	0.048	0.047	0.046
8:00	0.078	0.074	0.073	0.069
9:00	0.119	0.112	0.117	0.111
10:00	0.131	0.123	0.126	0.118
11:00	0.139	0.132	0.135	0.128
12:00	0.135	0.128	0.133	0.126
13:00	0.128	0.123	0.126	0.121
14:00	0.124	0.116	0.122	0.114
15:00	0.111	0.104	0.111	0.104
16:00	0.089	0.083	0.090	0.084
17:00	0.074	0.064	0.080	0.068
18:00	0.057	0.049	0.065	0.056
19:00	0.046	0.039	0.052	0.045
20:00	0.039	0.038	0.039	0.038
21:00	0.034	0.035	0.038	0.038
22:00	0.031	0.027	0.033	0.029
23:00	0.025	0.021	0.025	0.022
0:00	0.020	0.020	0.021	0.021
1:00	0.018	0.018	0.018	0.018
2:00	0.017	0.017	0.017	0.017
3:00	0.015	0.015	0.015	0.015

Appendix B Transport Demand Schedules

The section summarises the developed transport demand schedules for six transport modes. The schedules are generated based on the output of the activity model for employed and working population and a deterministic model for other people.

Appendix B-1 Weekday Transport Demand Schedule (Walk, Unit: Minute)

	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	0.033	0.033	0.033	0.032	0.031	0.037	0.031	0.032	0.037
5:00	0.169	0.169	0.169	0.169	0.169	0.167	0.169	0.169	0.167
6:00	0.467	0.469	0.470	0.467	0.468	0.462	0.468	0.469	0.464
7:00	1.078	1.089	1.092	1.128	1.201	1.085	1.201	1.141	1.097
8:00	2.462	2.466	2.471	2.456	2.446	2.462	2.446	2.434	2.462
9:00	1.797	1.753	1.745	1.864	1.968	1.829	1.968	1.794	1.778
10:00	1.518	1.509	1.508	1.574	1.660	1.537	1.567	1.553	1.528
11:00	1.771	1.819	1.831	1.805	1.858	1.812	1.873	1.848	1.870
12:00	1.815	1.756	1.742	1.829	1.850	1.821	1.829	1.757	1.756
13:00	1.758	1.674	1.656	1.767	1.786	1.790	1.844	1.673	1.691
14:00	1.836	1.762	1.745	1.875	1.936	1.926	2.066	1.791	1.828
15:00	2.815	2.839	2.844	2.852	2.907	2.927	3.096	2.873	2.931
16:00	1.904	1.876	1.868	1.882	1.850	1.913	1.928	1.853	1.877
17:00	1.634	1.577	1.562	1.573	1.478	1.606	1.562	1.522	1.548
18:00	1.312	1.211	1.184	1.290	1.258	1.294	1.266	1.199	1.196
19:00	1.010	0.970	0.959	1.004	0.999	1.000	0.985	0.972	0.962
20:00	0.641	0.634	0.631	0.666	0.704	0.642	0.644	0.664	0.636
21:00	0.470	0.454	0.449	0.470	0.469	0.471	0.472	0.454	0.455
22:00	0.314	0.297	0.292	0.309	0.303	0.315	0.316	0.293	0.298
23:00	0.173	0.170	0.169	0.176	0.179	0.170	0.166	0.172	0.168
0:00	0.058	0.058	0.058	0.056	0.053	0.062	0.053	0.055	0.062
1:00	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
2:00	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
3:00	0.026	0.026	0.026	0.025	0.023	0.025	0.023	0.025	0.025

Appendix B-2 Weekday Transport Demand Schedule (Bicycle)

	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5:00	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
6:00	0.091	0.092	0.092	0.091	0.092	0.090	0.092	0.092	0.090
7:00	0.131	0.132	0.132	0.139	0.152	0.132	0.152	0.141	0.134
8:00	0.178	0.147	0.139	0.172	0.163	0.168	0.163	0.143	0.141
9:00	0.093	0.082	0.080	0.095	0.097	0.089	0.097	0.083	0.080
10:00	0.108	0.097	0.095	0.120	0.136	0.115	0.124	0.105	0.102
11:00	0.088	0.079	0.078	0.103	0.127	0.091	0.096	0.089	0.081
12:00	0.085	0.075	0.073	0.102	0.124	0.090	0.097	0.087	0.079
13:00	0.092	0.096	0.097	0.110	0.140	0.100	0.112	0.112	0.103
14:00	0.116	0.138	0.143	0.119	0.123	0.129	0.148	0.141	0.153
15:00	0.132	0.181	0.193	0.127	0.121	0.147	0.171	0.170	0.199
16:00	0.151	0.130	0.124	0.137	0.118	0.137	0.118	0.121	0.121
17:00	0.142	0.113	0.105	0.126	0.103	0.133	0.121	0.103	0.108
18:00	0.113	0.094	0.090	0.116	0.120	0.113	0.114	0.095	0.094
19:00	0.085	0.100	0.103	0.086	0.087	0.077	0.064	0.104	0.090
20:00	0.048	0.060	0.062	0.057	0.070	0.045	0.042	0.076	0.056
21:00	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
22:00	0.017	0.015	0.015	0.035	0.061	0.017	0.017	0.031	0.015
23:00	0.022	0.021	0.021	0.021	0.021	0.022	0.022	0.020	0.021
0:00	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
1:00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2:00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3:00	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005

 # Unit: minute

Appendix B-3 Weekday Transport Demand Schedule (Car)

	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	0.147	0.149	0.149	0.147	0.147	0.147	0.147	0.149	0.148
5:00	0.528	0.528	0.528	0.491	0.436	0.599	0.436	0.491	0.598
6:00	1.321	1.329	1.331	1.323	1.325	1.300	1.325	1.330	1.307
7:00	2.955	2.990	2.999	2.719	2.363	2.800	2.363	2.752	2.833
8:00	4.899	4.588	4.515	4.761	4.557	4.861	4.557	4.422	4.544
9:00	3.089	3.024	3.021	3.280	3.569	3.146	3.569	3.145	3.063
10:00	2.854	2.885	2.900	3.047	3.337	2.993	3.200	3.048	3.040
11:00	2.932	2.982	3.001	3.078	3.297	3.018	3.150	3.113	3.082
12:00	3.038	2.971	2.962	3.132	3.274	3.167	3.358	3.037	3.082
13:00	2.938	2.976	2.992	2.974	3.031	3.091	3.321	2.994	3.113
14:00	3.270	3.345	3.368	3.307	3.364	3.567	4.011	3.372	3.629
15:00	4.328	4.413	4.438	4.339	4.358	4.762	5.416	4.412	4.801
16:00	4.359	4.266	4.245	4.131	3.792	4.401	4.463	4.041	4.277
17:00	4.964	4.593	4.491	4.576	3.993	4.751	4.428	4.261	4.401
18:00	3.608	3.413	3.359	3.478	3.282	3.528	3.406	3.322	3.340
19:00	2.520	2.485	2.470	2.499	2.467	2.506	2.485	2.492	2.474
20:00	1.628	1.528	1.503	1.685	1.769	1.648	1.679	1.586	1.546
21:00	1.410	1.346	1.330	1.410	1.407	1.413	1.417	1.344	1.351
22:00	0.772	0.727	0.716	0.762	0.745	0.775	0.778	0.718	0.729
23:00	0.483	0.472	0.469	0.476	0.467	0.484	0.485	0.465	0.473
0:00	0.178	0.157	0.153	0.195	0.221	0.184	0.221	0.170	0.161
1:00	0.173	0.173	0.173	0.170	0.166	0.185	0.166	0.171	0.185
2:00	0.111	0.111	0.111	0.111	0.110	0.111	0.110	0.111	0.111
3:00	0.087	0.087	0.087	0.087	0.086	0.087	0.086	0.087	0.087

 # Unit: minute

Appendix B-4 Weekday Transport Demand Schedule (Train)

	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5:00	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.026
6:00	0.220	0.222	0.222	0.221	0.221	0.216	0.221	0.222	0.217
7:00	0.421	0.428	0.429	0.451	0.496	0.426	0.496	0.459	0.433
8:00	0.566	0.460	0.436	0.533	0.485	0.515	0.485	0.432	0.421
9:00	0.262	0.239	0.234	0.305	0.371	0.272	0.371	0.270	0.246
10:00	0.190	0.197	0.199	0.210	0.239	0.206	0.229	0.216	0.217
11:00	0.212	0.221	0.223	0.229	0.251	0.228	0.250	0.237	0.240
12:00	0.174	0.159	0.156	0.196	0.230	0.200	0.239	0.176	0.179
13:00	0.200	0.170	0.163	0.217	0.242	0.239	0.295	0.180	0.195
14:00	0.164	0.142	0.137	0.168	0.174	0.191	0.232	0.145	0.161
15:00	0.243	0.224	0.218	0.239	0.234	0.268	0.306	0.221	0.243
16:00	0.324	0.328	0.330	0.303	0.274	0.318	0.311	0.307	0.320
17:00	0.519	0.514	0.512	0.463	0.378	0.472	0.401	0.459	0.466
18:00	0.487	0.495	0.497	0.450	0.394	0.446	0.385	0.461	0.453
19:00	0.302	0.305	0.304	0.312	0.325	0.287	0.264	0.320	0.290
20:00	0.141	0.145	0.145	0.170	0.215	0.136	0.127	0.176	0.140
21:00	0.100	0.093	0.092	0.110	0.124	0.090	0.077	0.102	0.085
22:00	0.131	0.122	0.120	0.129	0.126	0.131	0.132	0.120	0.122
23:00	0.055	0.053	0.053	0.054	0.054	0.055	0.055	0.053	0.053
0:00	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015
1:00	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
2:00	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
3:00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

 # Unit: minute

Appendix B-5 Weekday Transport Demand Schedule (Bus)

	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	0.010	0.010	0.010	0.010	0.009	0.010	0.009	0.010	0.010
5:00	0.048	0.047	0.047	0.048	0.048	0.047	0.048	0.047	0.047
6:00	0.112	0.113	0.113	0.113	0.113	0.111	0.113	0.113	0.112
7:00	0.493	0.498	0.499	0.512	0.541	0.496	0.541	0.518	0.501
8:00	0.972	0.885	0.863	0.976	0.981	0.963	0.981	0.887	0.878
9:00	0.458	0.413	0.403	0.498	0.559	0.466	0.559	0.440	0.419
10:00	0.450	0.426	0.422	0.488	0.543	0.463	0.481	0.452	0.435
11:00	0.417	0.419	0.420	0.430	0.449	0.429	0.446	0.430	0.432
12:00	0.426	0.421	0.420	0.429	0.435	0.433	0.445	0.424	0.427
13:00	0.388	0.375	0.372	0.392	0.397	0.402	0.422	0.378	0.385
14:00	0.418	0.394	0.389	0.422	0.427	0.447	0.489	0.397	0.415
15:00	0.886	0.859	0.852	0.884	0.881	0.912	0.950	0.857	0.877
16:00	0.560	0.552	0.551	0.558	0.555	0.560	0.562	0.550	0.552
17:00	0.541	0.491	0.478	0.510	0.460	0.512	0.467	0.467	0.469
18:00	0.358	0.302	0.289	0.373	0.395	0.343	0.321	0.311	0.292
19:00	0.192	0.172	0.168	0.207	0.233	0.191	0.191	0.183	0.172
20:00	0.137	0.124	0.122	0.145	0.157	0.136	0.134	0.130	0.124
21:00	0.106	0.102	0.100	0.106	0.106	0.107	0.107	0.102	0.102
22:00	0.050	0.048	0.047	0.049	0.048	0.050	0.050	0.047	0.048
23:00	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
0:00	0.012	0.012	0.012	0.022	0.036	0.012	0.036	0.022	0.012
1:00	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
2:00	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
3:00	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004

 # Unit: minute

Appendix B-6 Weekday Transport Demand Schedule (Others)

	Baseline	A1	A2	B1	B2	C1	C2	D	E
4:00	0.180	0.165	0.161	0.179	0.179	0.179	0.179	0.165	0.165
5:00	0.326	0.326	0.326	0.317	0.303	0.357	0.303	0.316	0.357
6:00	0.672	0.674	0.675	0.637	0.586	0.716	0.586	0.639	0.719
7:00	1.314	1.128	1.085	1.379	1.475	1.325	1.475	1.178	1.136
8:00	1.912	1.848	1.835	1.879	1.831	1.945	1.831	1.807	1.876
9:00	1.418	1.435	1.442	1.491	1.601	1.488	1.601	1.486	1.502
10:00	1.286	1.298	1.303	1.365	1.482	1.372	1.500	1.366	1.392
11:00	1.346	1.364	1.371	1.401	1.482	1.420	1.531	1.408	1.443
12:00	1.441	1.467	1.475	1.494	1.573	1.519	1.635	1.508	1.548
13:00	1.314	1.214	1.190	1.337	1.373	1.404	1.538	1.230	1.278
14:00	1.384	1.324	1.311	1.411	1.453	1.533	1.757	1.346	1.445
15:00	1.968	1.956	1.954	1.978	1.994	2.146	2.413	1.963	2.110
16:00	1.612	1.588	1.583	1.566	1.496	1.655	1.717	1.540	1.617
17:00	1.547	1.479	1.462	1.474	1.364	1.517	1.469	1.414	1.449
18:00	1.228	1.149	1.128	1.208	1.175	1.208	1.177	1.136	1.132
19:00	0.838	0.819	0.813	0.844	0.854	0.844	0.855	0.830	0.825
20:00	0.591	0.537	0.523	0.622	0.667	0.608	0.634	0.558	0.549
21:00	0.488	0.472	0.469	0.520	0.569	0.489	0.490	0.501	0.473
22:00	0.437	0.405	0.397	0.432	0.425	0.439	0.441	0.401	0.406
23:00	0.293	0.289	0.288	0.291	0.287	0.294	0.294	0.286	0.289
0:00	0.239	0.238	0.238	0.230	0.217	0.242	0.217	0.230	0.241
1:00	0.199	0.199	0.199	0.195	0.189	0.198	0.189	0.195	0.198
2:00	0.169	0.169	0.169	0.176	0.183	0.169	0.183	0.176	0.169
3:00	0.150	0.151	0.151	0.150	0.150	0.154	0.150	0.151	0.154

 # Unit: minute