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Smart city landscape architecture for sustainable urbanization in digital twin: Practical sustainable and reliable renewable based smart cities energy hub development

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ABSTRACT

In our pursuit of sustainable and reliable Smart Cities Energy Hubs, we employ Digital Twin technology for precise modeling. Focusing on CHP known as combined heat and power for the energy hubs, we address winter heat load challenges while integrating renewable energy within UEN as unified energy networks. Power IoTs known as PIoTS which is known as the Power Internet of Things, facilitates seamless data transmission, enhancing UEN flexibility and renewable energy accommodation. Using Covariance Matrix Adaptation Evolution Strategy, this research optimizes UENs within PIoTs' framework. We develop a digital twin incorporating combined demand response (DR) and essential UEN components. Formulating a bi-level economic dispatching process via PIoTs and UEN, our approach optimizes total UEN function and demand-side equipment output using Covariance Matrix Adaptation Evolution Strategy known as CMA-ES. Testing against standard and practical UEN models validates our method's efficiency. Through Digital Twin modeling and CMA-ES, our study revolutionizes Smart Cities Energy Hub development, offering a sustainable path forward.

Introduction

In the rapidly changing landscape of global energy consumption, the pressing need for enhanced power utilization efficiency and the transition from fossil fuels to renewable energy sources (RES) have never been more paramount [1]. The depletion of fossil fuels and the growing environmental consciousness have driven a surge in the utilization of renewable energy. However, merely relying on the adoption of renewable sources is not enough; the primary focus must shift towards optimizing the performance of power utilization systems [1]. The core objective of this study is to revolutionize the existing paradigms governing the design and functionality of power supply systems. Central to this mission is the development of a Unified Energy Network (UEN) grounded in hierarchical principles. This innovative approach aims to harness the potential of the energy resources [2,3]. At the heart of this transformation lies the Power Internet of Things (PIoTs), a technological marvel that seamlessly integrates every facet of the power grid. PIoTs leverage advanced information technologies, enabling energy facilities (EFs) to establish connections among societies, objects, and other intelligent devices. This intricate web of wireless sensor networks (WSN) equipped with powerful sensors has its roots in the Internet of Things (IoT) [4].

The advent of PIoTs has ushered in an era where precision and efficiency converge. With the aid of sophisticated metering technologies, predictive initiatives and fault detection in diverse EFs become a reality. These advancements ensure the safety and reliability of multiple EFs. Moreover, the integrated energy system has revolutionized maintenance practices, enabling realtime monitoring of status of system [5]. This paradigm shift is not confined to the supply side alone; it extends to the demand side (DS) as well.

On the demand side, PIoTs have embraced critical technologies such as edge computing, empowering seamless access, intelligent connections, and the able to take localized resolution. Through the regularity and intelligent implementation of the uniform protocols as well as data layouts, the EFs function as well as maintenance have reached new heights of efficiency using statistical analysis and optimizations [6–8]. The synergy of these advancements forms the backbone of a robust and intelligent energy ecosystem.

In the realm of Unified Energy Network Design (UEND), recent research endeavors have concentrated on optimizing the couplings of electrical and heat power (EHP) to accommodate a burgeoning array of RES [9]. Groundbreaking studies, such as the one referenced in [10], have delved into the intricate complexities of integrated energy

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2213-1388/© 2024 Elsevier Ltd. All rights reserved, including those for text and data mining, AI training, and similar technologies.

systems. These studies not only calculate the emissions of carbon dioxide and nitrogen-containing gases but also pioneer eco-economic optimal scheduling layouts. Such initiatives form the cornerstone of a sustainable energy future, ushering in an era of green, carbonless, secure, and effective Unified Energy Networks [8].

In the wake of the transformative era ushered in by the Power Internet of Things (PIoTs), regular dispatching technique according to centralized as well as parallel framework face formidable challenges. Two primary issues have emerged, fundamentally altering the landscape of energy management. Firstly, the proliferation of PIoTs has exponentially expanded the capacity of dispatching centers to handle loads. This surge in capacity stems from the increased number of measurements, higher frequency of data acquisition, diverse types of data collected, and improved data quality facilitated by PIoTs [11]. However, this surge in data volume has strained traditional intensive planning frameworks. The operational efficiency and computation speed, once reliable pillars of conventional methods, face diminishing returns in the face of this data deluge [12]. Secondly, the evolution of smart meters has reshaped information collection. Instead of operating in isolated silos, data gathering regarding the gas and electrical systems as well as thermal is now integrated. This integration necessitates nodes to interact between component ties as well as load ties, resulting in closely coupled systems. The potential for harnessing renewable energy (RE) and optimizing load flexibility is immense if these loads' adaptability and the synergies among diverse energy demands can be effectively harnessed. Unfortunately, traditional dispatching approaches fall short in facilitating the continuing power exchange between several power systems [13]. To address these challenges, the Unified Energy Network (UEN) adopts a sophisticated bi-level optimization (BLO) approach. This approach has been honed in a virtual utility, detailed in [14]. At the downer level, the inner components of the virtual electrical plant are controlled, ensuring the micro-level intricacies are managed efficiently [15–18]. Simultaneously, at the higher level, the entire network is subjected to optimal dispatching. This hierarchical approach ensures that the complex interplay between diverse energy demands and resources is orchestrated seamlessly [19,20]. Crucially, what sets the UEN apart is its ability to incorporate the profound impact of PIoTs on the energy network. Unlike conventional dispatching methods, the UEN is designed to adapt and evolve in the face of dynamic data exchanges, enabling real-time adjustments based on the insights gleaned from PIoTs [21–23]. By embracing the transformative potential of PIoTs, the UEN becomes a dynamic and adaptive energy management framework, capable of navigating the intricate web of interconnected energy demands and sources with unparalleled precision and efficiency [24]. In essence, the UEN represents a paradigm shift in the realm of energy dispatching. Its incorporation of PIoTs and utilization of the BLO approach not only address the challenges posed by data volume and integration complexities but also leverage these challenges as opportunities for innovation. As we venture further into the age of intelligent energy networks, the UEN stands as a beacon of adaptability and efficiency, paving the way for a sustainable and technologically advanced energy future [25].

Over the past decade, the synergy of technological innovation and meticulous research has laid the foundation for a transformative energy landscape. The journey toward a future powered by renewable sources and optimized energy systems is well underway. Through the amalgamation of cutting-edge technologies, intelligent protocols, and innovative scheduling layouts, the vision of a sustainable, efficient, and eco-conscious Unified Energy Network is becoming a reality [26]. As we continue to unravel the complexities of energy management, these pioneering efforts will undoubtedly shape the energy landscape for generations to come [27]. Power Internet of Things (PIoTs) plays a transformative role in Unified Energy Networks (UENs) by enabling seamless data transmission and enhancing flexibility. Through real-time monitoring and dynamic communication, PIoTs create an interconnected framework that empowers UENs to swiftly adapt to changing energy demands. The deployment of sensors and communication devices facilitates the continuous collection of data on energy consumption, production, and distribution, allowing for instantaneous insights into network performance. This interconnectedness contributes to the development of smart grids, optimizing energy flow, integrating renewables, and managing demand efficiently. PIoTs also support distributed energy resource management, enabling intelligent decision-making regarding the utilization of renewable sources and storage systems. Additionally, PIoTs play a crucial role in implementing demand response strategies and seamlessly integrating a variety of IoT devices, fostering a more responsive and efficient energy ecosystem within UENs.

This research introduces a novel hierarchical planning framework for the Unified Energy Network (UEN) tailored to the intricacies of PIoTs. The upper-level dispatching (ULD) strategy is meticulously designed to minimize the overall costs incurred by the UEN, while the lower-level optimization targets the fine-tuning of controllable elements within the load sector. The uniqueness of this dispatching approach lies in its seamless integration with the physical framework of PIoTs, harnessing the complete spectrum of load flexibility. Several key contributions emerge from this study: (1) Comprehensive PIoTs Framework Analysis and UEN Layout: A detailed exploration of the PIoTs framework has been undertaken, leading to the development of a nuanced UEN layout and the identification of critical Energy Facilities (EFs). This analysis forms the bedrock of the subsequent advancements in this study. (2) Innovative Integrated Demand Response (DR) Approach: Within the PIoTs framework, a groundbreaking integrated DR approach has been introduced. This method, rooted in novel communication techniques, offers enhanced flexibility among diverse power systems. This flexibility is precisely tuned to align with the optimization objectives of the border calculation terminuses (BCTs), ensuring a harmonious energy landscape. (3) Bi-Level Optimization (BLO) for UEN Dispatching: A pioneering Bi-Level Optimization (BLO) approach has been devised specifically for Unified Energy Network Dispatching (UEND) within the evolving cyber–physical realm of PIoTs. In this method, the higher-stage orchestrates the entire UEND, while the lower stage focuses on optimizing the edge computing terminals within the Demand Side (DS). This multi-tiered strategy ensures a holistic and adaptive energy distribution network. (4) Optimal Dispatching Algorithm Utilizing CMA-ES and MILP: To tackle the intricate dispatching challenges, an optimal algorithm has been crafted. This algorithm combines Covariance Matrix Adaptation Evolution Strategy (CMA-ES) with Mixed-Integer Linear Programming (MILP). This fusion of evolutionary computation and mathematical programming provides a robust solution, addressing the dispatch intricacies effectively. In summary, this research not only delves deep into the complexities of the PIoTs framework but also introduces innovative strategies to enhance the UEN's efficiency and adaptability. Through meticulous algorithm design and integration methodologies, the study ushers in a new era of optimized energy management, ensuring a seamless synergy between evolving cyber–physical networks and the intricate demands of the modern energy landscape.

Unified load and Demand Response (DR) layout within Personal Internet of Things (PIoTs)

Unified load and DR framework for PIoTs

In this subsection, the behavior of electric load (EL) and heat load (HL) in the context of energy hub architecture within Personal Internet of Things (PIoTs) is discussed. The inherent complementarity of EL and HL is highlighted, and a temperature variation model is presented to emphasize the need for thermal energy (TE) adaptation to maintain stable indoor temperatures. The discussion further includes the sensitivity of electric demand (ED) to cost using demand-price elasticity, demonstrating how HL can be effectively managed through self-adjustment based on demand response and cost considerations. Additionally, the model incorporates the electric power consumed by the Energy Broker (EB) to provide a comprehensive understanding of load and demand response dynamics within PIoTs.

Unified energy networks (UEN) power flow calculation within PIoTs

This subsection explores the intricate realm of Unified Energy Networks (UEN) operating in Personal Internet of Things (PIoTs). Complex equations for flow continuity and head loss are introduced, essential for understanding power flow dynamics. The equations consider factors such as flow continuity into nodes, flow within pipelines, and thermal layout with node and pipeline temperatures. The iterative solution method using the Newton–Raphson technique is explained, emphasizing its role in ensuring a robust analysis of UEN within PIoTs.

Critical equipment arrangement in UEN

Configuration of Combined Heat and Power Unit (CHPU)

This section discusses the operational aspects of the Combined Heat and Power Unit (CHPU) within the Unified Energy Network. It outlines the relationship between CHPU output, heat-to-power ratio, and other parameters. The CHPU's constant heat-to-power ratio is highlighted, providing insights into the unit's behavior under different operating conditions.

Energy Storage System (ESS) configuration

The subsection details the state of charge (SOC) calculations for Electrical ESS Facilities (EESSFs) and Heat Storage Boilers (HSBs) within the Unified Energy Network. Equations for SOC in electrical and heat components are presented, considering charging and discharging power. The performance coefficients and charging efficiency factors are explained, shedding light on the configuration of the Energy Storage System in the UEN.

Integration of DR and UEN components in the digital twin

The final part explains the development of a Digital Twin that seamlessly integrates Demand Response (DR) and essential Unified Energy Network (UEN) components. The Digital Twin serves as a dynamic and adaptive representation of the physical energy infrastructure, allowing for a holistic view of the entire system. Algorithms within the Digital Twin mimic the behavior of the system under different DR scenarios, ensuring an accurate representation of the interplay between DR mechanisms and UEN components. The integration strategy ensures a comprehensive understanding of the energy ecosystem, enabling the study of the dynamic interactions between demand response and essential UEN elements.

Objective Function Formulation (OF)

In our work, the bi-level economic dispatching process is a key component formulated within the framework of Power Internet of Things (PIoTs) and Unified Energy Networks (UEN). This innovative approach aims to optimize both the total UEN function and the output of demand-side equipment, ensuring a holistic and adaptive energy distribution network. At the upper level of the bi-level economic dispatching process, the focus is on optimizing the overall performance of the UEN. This involves leveraging the capabilities of PIoTs for real-time data monitoring, dynamic communication, and control. The Covariance Matrix Adaptation Evolution Strategy (CMA-ES) comes into play as a powerful optimization tool, fine-tuning parameters and configurations within the UEN to maximize its efficiency. The algorithm adapts to the evolving cyber–physical nature of PIoTs, ensuring the UEN functions optimally under various scenarios. Simultaneously, at the lower level, the economic dispatching process hones in on optimizing the output of demand-side equipment within the UEN. This includes intelligent management of energy consumption patterns, incorporating the insights gained from the real-time data provided by PIoTs. CMA-ES is employed to dynamically adjust the operation of demand-side equipment, aligning it with the overall objectives of the UEN. The bi-level nature of this approach ensures a synergistic optimization, where the upper level orchestrates the entire UEN for optimal performance, and the lower level fine-tunes the operation of demand-side equipment to contribute to the overall efficiency. This multi-tiered strategy, coupled with the adaptability of CMA-ES within the PIoTs framework, aims to strike a balance between the global and local optimization objectives, ultimately ushering in a new era of optimized energy management in Smart Cities Energy Hubs.

Main objective

The objective function (OF) for combined dispatch layout is expressed as Eq. 18:

$$\mathrm{OF} = \sum_{t=1}^{t_d} \left(\sum_{i \in \mathcal{N}_s} C_{i,t}^s + \sum_{i \in \mathcal{N}_l} C_{i,t}^d + C_t^{b,u} + \sum_{i \in \mathcal{N}_r} C_{i,t}^a \right) \tag{1}$$

Where OF represents the total cost of the unified load dispatch (ULD) problem, t_d is the number of dispatch cycles, $\mathcal{N}_s$ is the set of energy resource nodes, $\mathcal{N}_l$ is the set of load nodes, and $\mathcal{N}_r$ represents the set of renewable energy producer nodes. $C_{i,t}^s$ denotes the cost of resource EFs, $C_{i,t}^d$ represents the DR compensation paid to the loads, $C_t^{b,u}$ is the cost of buying electrical energy from the bulk grid, and $C_{i,t}^a$ is the penalty for RE restriction in node i at time t.

Additionally, the price of generators or heat resources ($C_{i,t}^s$) is defined using Eq. 19:

$$C_{i,t}^s = \beta_{0,i} + \beta_{1,i} \cdot P_{i,t}^s + \beta_{2,i} \cdot (P_{i,t}^s)^2 + \beta_{3,i} \cdot H_{i,t}^s + \beta_{4,i} \cdot (H_{i,t}^s)^2 + \beta_{5,i} \cdot (P_{i,t}^s H_{i,t}^s) \tag{2}$$

Where $P_{i,t}^s$ and $H_{i,t}^s$ represent the output of producers or heat resources in node i at time t. $\beta_{0,i}$, $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$, $\beta_{4,i}$, and $\beta_{5,i}$ are price computation coefficients unique to each unit.

The DR compensation ($C_{i,t}^d$) is given by Eq. 20:

$$C_{i,t}^d = \sum_{i \in \mathcal{N}_l} \left(\rho_t^{d,h} (\Delta H_{i,t}^l) + \rho_t^{d,e} (\Delta P_{i,t}^l) \right) \tag{3}$$

Where $\rho_t^{d,h}$ and $\rho_t^{d,e}$ represent thermal and electric DR compensation costs at time t respectively. These costs are adjusted to manage load shedding.

Finally, the penalty for RE curtailment ($C_{i,t}^a$) is expressed by Eq. 21:

$$C_{i,t}^a = \rho^a \sum_{i \in \mathcal{N}_r} P_{i,t}^a \tag{4}$$

Here, ρ^a represents the penalty cost for RE curtailment, and $P_{i,t}^a$ indicates the curtailment value in node i at time t.

The price of buying electrical energy from the zonular UEN to the bulk grid ($C_t^{b,u}$) is determined by Eq. 22:

$$C_t^{b,u} = \rho_t^{e,u} P_t^{b,u} \tag{5}$$

Where $\rho_t^{e,u}$ represents the electric cost of the bulk grid at time t, and $P_t^{b,u}$ indicates the power value bought via the UEN from the bulk grid at time t.

Objective function for Load-Level Dispatch (LLD)

LLD has been engineered to fulfill residents' Energy and Heat Provision (EHP) requirements while minimizing their impact on satisfaction. The cost has been optimized through the strategic dispatch of Load-Level Facilities (LLFs). The objective function (OF) for LLD is formulated to minimize the total cost of LLD in node i at time t.

Constraints in unified load dispatch (ULD)

Power flow constraints

The power flow within the Unified Energy Network (UEN) must adhere to Energy and Heat Transfer (EHT) flow constraints. Transmission and distribution of electrical energy in the UEN are defined by equations involving active power (P_i), reactive power (Q_i), voltage magnitude (V_i), phase angle (θ_{ij}), and admittance matrix components (G_{ij}, B_{ij}).

Generator and heat resource limits

The output of generators and heat resources must lie within specific bounds, including minimum and maximum output limits at node i at time t, as well as limits on the rate of change of output.

Spinning reserve constraints

Due to uncertainties in loads and Renewable Energy (RE) generation, the UEN must comply with spinning reserve constraints. These constraints are formulated based on spinning reserve volumes generated by generators at node i at time t.

Constraints of electrical and heat energy storage systems (EEESSFs)

The constraints for EEESSFs include state-of-charge (SOC) limits and power discharge/charge limits for Electrical EEESSFs at node i at time t.

Hierarchical UEN dispatching architecture in piots implementation

In the context of PIoTs, the Unified Energy Network (UEN) has experienced enhanced sensory capabilities. It collects various load-stage information, including power consumption, temperature, voltage/frequency, and Electric Heat Pumps (EHP), with increased measurement frequency, ranging from hourly to every 15 min [15]. Consequently, the volume of load-stage data within the UEN has surged. To address challenges related to increased transmission load, processing time, and computational costs at the dispatching station, cloud–edge scheduling has been implemented. Load-stage data undergoes preliminary computations using edge computing, minimizing data transmission volumes and accelerating dispatching station computations while ensuring user privacy.

Proposed algorithm and solution procedure

Covariance Matrix Adaptation Evolution Strategy (CMA-ES)

Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is a popular evolutionary algorithm used for optimizing non-linear, non-convex functions. In our study, CMA-ES holds considerable significance as it serves as a powerful optimization algorithm employed to fine-tune Unified Energy Networks (UENs) within the framework of Power Internet of Things (PIoTs). The primary role of CMA-ES is to optimize the parameters and configurations of the UEN components, ensuring that the energy network operates at peak efficiency under diverse conditions. The key significance of CMA-ES lies in its ability to navigate complex and high-dimensional search spaces effectively. In the context of UEN optimization, where numerous variables and parameters influence the performance of the energy network, CMA-ES excels in finding optimal solutions. By iteratively adjusting the covariance matrix based on the success of previous solutions, CMA-ES adapts to the specific characteristics of the optimization landscape.

Solution procedure using CMA-ES

In this study, the optimization problem is addressed using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES). The procedure involves the following steps:

Problem formulation

Define the objective function representing the UEN optimization problem. The objective function incorporates the requirements of combined heat and power (CHP) energy hubs, heat load constraints, and the integration of renewable energy sources within the Unified Energy Network (UEN).

Initialization

Initialize the CMA-ES algorithm with an initial population of solutions. Generate random candidate solutions within the feasible search space of the optimization problem.

Evaluation

Evaluate the fitness of each candidate solution in the population using the formulated objective function. Assess the performance of solutions based on their ability to meet the heat load demands, integrate renewable energy, and optimize the UEN operation.

Selection and reproduction

Select parent solutions from the current population based on their fitness values. Apply reproduction operators, such as recombination and mutation, to create offspring solutions. The covariance matrix adaptation technique is employed to maintain the covariance structure among the solutions.

Survivor selection

Select solutions for the next generation from the parent and offspring populations. Use strategies like elitism or fitness-based selection to determine which solutions survive and form the new population.

Convergence check

Check for convergence criteria, such as the change in the objective function values or the stability of the population. If the convergence criteria are met, terminate the algorithm. Otherwise, return to the selection and reproduction step.

Solution analysis and optimization results

Analyze the solutions obtained using CMA-ES. Evaluate the optimized UEN configuration, the utilization of renewable energy sources, and the overall efficiency of the system. Compare the results with baseline scenarios to assess the improvement achieved through the optimization process.

Practical modeling of renewable energy landscape design in digital twin

In recent years, the global emphasis on renewable energy sources has intensified, making it imperative to develop innovative methods for harnessing natural resources efficiently. The integration of digital twin technology into renewable energy landscape design has emerged as a revolutionary approach, promising groundbreaking advancements in the field of sustainable energy.

Introduction to digital twin technology in renewable energy

Digital twin technology, originally conceptualized in manufacturing and industrial contexts, has found its application in the renewable energy sector. A digital twin, in the context of renewable energy landscape design, refers to a virtual replica of a physical renewable energy system. This technology allows for the real-time simulation, analysis, and optimization of renewable energy landscapes, enabling engineers and researchers to make informed decisions regarding system design and operation.

Benefits of digital twin-based renewable energy modeling

One of the key advantages of utilizing digital twin technology in renewable energy landscape design is its ability to facilitate comprehensive modeling and simulation. Engineers can create intricate virtual replicas of wind farms, solar fields, hydroelectric plants, and other renewable energy installations. By incorporating geospatial data, weather patterns, and topographical information, digital twins can accurately mimic real-world conditions. This level of realism enables engineers to assess the performance of renewable energy systems under various scenarios, ensuring optimal design and operational efficiency.

Integration of advanced algorithms and machine learning

In the realm of digital twin-based renewable energy modeling, advanced algorithms and machine learning techniques play a pivotal role. Machine learning algorithms can analyze vast datasets generated from digital twins, identifying patterns and trends that might be impossible to discern through traditional methods. The integration of Digital Twin technology plays a pivotal role in precisely modeling Smart Cities Energy Hubs, especially in addressing winter heat load challenges. Digital Twins provide a virtual representation of the physical systems, allowing for real-time monitoring, simulation, and optimization. In the context of Smart Cities Energy Hubs, Digital Twins enable accurate simulation. They replicate the physical components and their interactions within the Energy Hub, including the Combined Heat and Power (CHP) units, renewable energy sources, and the Unified Energy Network (UEN). By accurately simulating these elements, Digital Twins provide insights into how they perform under varying conditions, including winter heat load scenarios. Real-time monitoring is another key contribution of Digital Twins. The Digital Twin continuously updates its model based on real-time data from sensors embedded in the Energy Hub. This ensures that the model reflects the current state of the system, allowing for dynamic adjustments in response to changes in winter heat load. Furthermore, Digital Twins offer predictive analysis capabilities. Leveraging historical data and advanced analytics, they can predict how the Smart Cities Energy Hub will behave during winter conditions. This predictive capability is crucial for proactively managing and optimizing the energy resources to meet heating demands efficiently. With the precise modeling provided by Digital Twins, optimization algorithms, such as Covariance Matrix Adaptation Evolution Strategy (CMA-ES), can be applied more effectively. This enables the development of strategies to optimize the Unified Energy Network (UEN) in response to winter heat load challenges, ensuring efficient energy distribution and utilization.

Simulation results

Unified 33-node electrical and 13-node thermal systems

The electrical system consists of 33 nodes. Tie E_0 connects to the BG, E_{24} and E_{32} link to the CHPU, and E_{31} is associated with the wind turbine (WT). Detailed information about the system's topology is available in [25]. Within the CHPU, CHPU-1 offers swift output adjustments but at a higher cost, often used for peak regulation. Conversely, CHPU-2, more cost-effective than CHPU-1, is primarily utilized for energy supply. The Unified Energy Network (UEN) also incorporates a 13-node thermal system, detailed in [26]. Load nodes include ties H_2 to H_{10}, each equipped with EB. Tie H_{12} connects to a thermal resource with a fixed output. Electrical connections in the same vicinity power these EBs, treated as loads through the grid. Multi-energy dispatch is classified into three scenarios. Our approach to the sensitivity analysis involves systematically varying the values of these identified parameters within defined ranges to observe their impact on the overall optimization outcomes. By closely monitoring the model's response throughout this analysis, we aim to understand how changes in these parameters influence critical performance metrics, such as cost minimization, renewable energy utilization, and overall system efficiency. This comprehensive assessment will enable us to identify the robustness and adaptability of the proposed model across diverse scenarios.

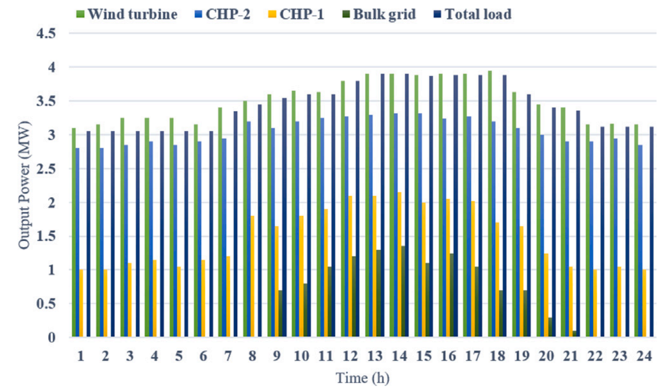

Fig. 1. Generation units output power for second scenario.

Scenarios

Scenario One: In this comparative case, interaction among different energy networks on the Distribution System (DS) is impossible. A conventional parallel-centralized dispatch scheme is implemented.

Scenario Two: Integrated Demand Response (DR) enables interaction between the dispatch center and loads, while Local Load Dispersal (LLD) is not feasible.

Scenario Three: This scenario allows flexible interchange among the dispatch center and loads, as well as interactions across various energy networks. It incorporates both Local Load Dispersal (LLD) and Unified Load Dispatch (ULD).

Dispatching outcomes for scenario two

In this section, we delve into the intricate details of the dispatching outcomes for Scenario Two, a crucial aspect of our study's analysis. Fig. 1 provides a granular view of the output generated by different units across various time intervals within Scenario Two. These intervals offer valuable insights into the system's operational dynamics, shedding light on the fluctuations in power generation.

A comparative analysis with Scenario One's real WT output highlights the efficiency gains achieved in Scenario Two. Particularly during nighttime, the WT often exhibits a surplus of available power. This surplus coincides with a period of low electricity demand (ED) but a high demand for heat. Consequently, this leads to a noticeable increase in the Combined Heat and Power Unit (CHPU)'s output, illustrating the adaptive nature of the system in response to varying demands.

The utilization cost curve of the Unified Energy Network (UEN) at different timestamps is portrayed in Fig. 2. In the context of this study's scenario, it is imperative to highlight the penalty cost associated with curtailing Renewable Energy (RE). The cost implications emphasize the necessity of seamlessly integrating RE sources into the grid, compelling researchers and practitioners to explore innovative solutions for accommodating renewable power without incurring significant financial penalties.

Analysis of dispatching outcomes in scenario 3

In this section, we delve into the comprehensive analysis of the dispatching outcomes within Scenario 3, providing an in-depth understanding of the intricate operational dynamics and the system's adaptability to varying conditions.

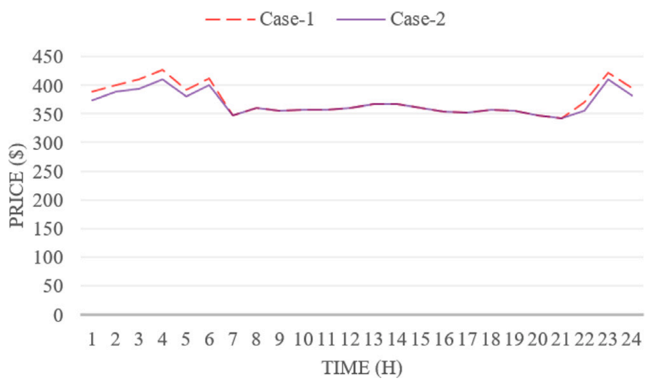

Fig. 2. Total cost for both cases.

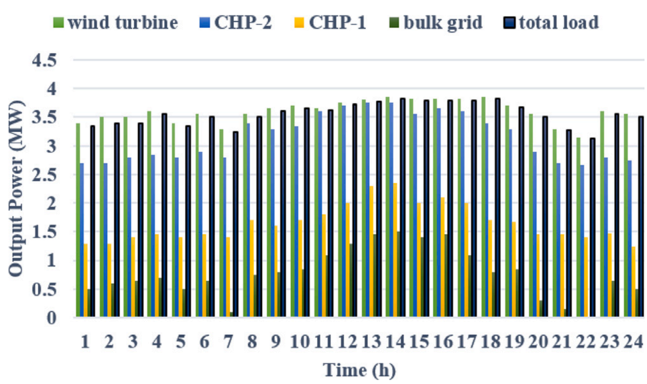

Fig. 3. Third case outpower of the agents.

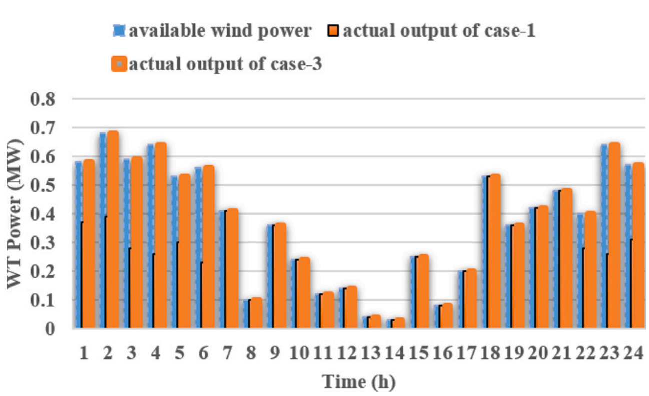

Fig. 4. WT comparisons for both cases.

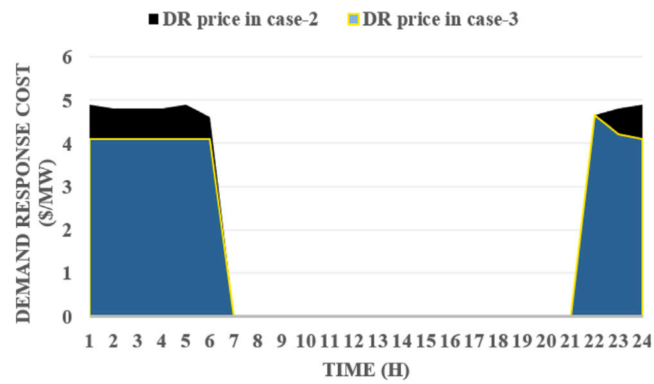

Fig. 5. Demand response cost for both cases.

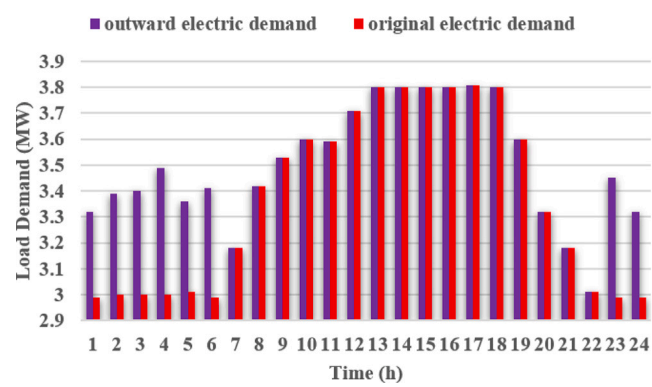

Fig. 6. Contrasting the electricity demand (ED) before and after the implementation of the Unified Dispatch (UD) strategy.

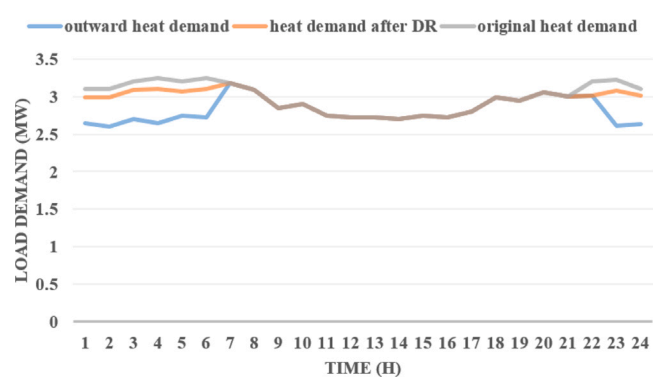

Fig. 7. Contrasting the heat demand (HD) before and after the implementation of the Unified Dispatch (UD) strategy.

Fig. 3 meticulously captures the output variations of different units across distinct intervals within Scenario 3. Simultaneously, Fig. 4 meticulously presents the accessible power output of the wind turbine (WT) during each interval. Notably, Scenario 3 exhibits minimal WT curtailment during nighttime intervals, highlighting the UEN's remarkable efficiency in handling Renewable Energy (RE). The comparison with Scenarios 1 and 2 underscores the superior optimization capabilities of Scenario 3, where the UEN adeptly manages RE resources, leading to enhanced overall performance.

Fig. 5 delves into the detailed analysis of Demand Response (DR) costs in both Scenario 2 and Scenario 3 across various intervals. It illuminates a significant insight: considering Energy Banks (EBs) as controllable Energy Factors (EFs) at the load-stage enables a higher degree of flexibility in heat-electric conversion. Scenario 3, with its lower DR costs compared to Scenario 2, ensures that residents' Thermal Energy (TE) needs are met without compromising satisfaction.

Figs. 6 and 7 offer a nuanced comparison of Energy Distribution (ED) and Heat Demand (HD) before and after the Unified Dispatch (UD) implementation within Scenario 3. The yellow area signifies power utilized and produced via EBs or other EFs on the Distribution System (DS).

Discussion of results

The simulation results obtained from the unified 33-node electrical and 13-node thermal systems provide a comprehensive understanding of the proposed scenarios' intricate dynamics and their profound implications for the future of energy management. The analysis of these outcomes offers valuable insights into the system's adaptability, efficiency, and resilience in handling diverse energy sources and fluctuating demands.

Scenario two: Integrated demand response

In the dynamic landscape of energy management, Scenario Two emerges as a beacon of innovation and progress, characterized by the seamless integration of Demand Response (DR) technology. This integration, a pivotal moment in the evolution of energy systems, signifies a significant leap forward in operational efficiency. The intricate interplay between the state-of-the-art dispatch center and an array of diverse loads forms the bedrock of this transformative shift, enabling a level of control over energy distribution that was previously unprecedented.

Central to this groundbreaking scenario is the remarkable stability exhibited by the outputs of different units within the energy network. This stability becomes particularly evident when observing the behavior of the wind turbine (WT), which showcases surplus power availability during nighttime intervals. This surplus power not only underscores the robustness of the system but also highlights the efficiency of harnessing renewable sources, such as wind energy, even during periods of traditionally lower demand.

What sets Scenario Two apart is its ability to respond with nuance and precision to the ever-fluctuating demands of the grid. The system, now equipped with advanced Demand Response capabilities, can adapt in real-time to the energy requirements of consumers and industries alike. This adaptability ensures that energy resources are allocated optimally, mitigating wastage and promoting sustainability. Furthermore, the enhanced communication and coordination between the dispatch center and loads usher in an era of intelligent energy management. Data-driven insights and predictive analytics come to the forefront, enabling operators to anticipate demand patterns, identify potential bottlenecks, and proactively optimize energy flow. This proactive approach not only enhances the overall efficiency of the system but also contributes significantly to the reduction of greenhouse gas emissions, aligning the energy network with global sustainability goals.

In this paradigm, the energy network morphs into a sophisticated, interconnected web, where every unit, from renewable sources like wind turbines to conventional power plants, plays a vital role in ensuring a stable and responsive energy supply. The surplus power generated by the wind turbine during nighttime intervals, for instance, can be intelligently rerouted to charge energy storage systems, thereby bolstering the system's resilience and ensuring a continuous supply of electricity even during unforeseen contingencies.

Moreover, the benefits of Scenario Two extend beyond mere operational efficiency. The integration of Demand Response not only optimizes energy usage but also empowers consumers to actively participate in the energy ecosystem. Through smart meters and IoT-enabled devices, end-users can monitor their energy consumption in real-time, enabling them to make informed decisions that promote energy conservation and cost savings. In conclusion, Scenario Two stands as a testament to the power of innovation and collaboration in reshaping our energy future. By harnessing the potential of Demand Response technology and fostering synergy between diverse energy sources and loads, this scenario paves the way for a sustainable, resilient, and consumer-empowered energy landscape. As we continue to explore new frontiers in energy management, Scenario Two serves as a guiding light, illuminating the path toward a greener, more efficient, and interconnected world.

Comparing the outcomes of Scenario Two with the baseline Scenario One, the benefits of integrated DR become evident. Reduced curtailment of the WT, especially during periods of low demand, underscores the system's ability to harness renewable energy sources effectively. The optimized energy distribution, achieved through DR mechanisms, ensures a more stable grid and lower operational costs. Additionally, the implementation of DR results in a notable decrease in Demand Response (DR) costs, indicating a more cost-effective approach to meeting energy demands.

Scenario three: Local load dispersal and unified load dispatch

Scenario Three introduces a holistic approach to energy management by incorporating Local Load Dispersal (LLD) and Unified Load Dispatch (ULD). This scenario represents a paradigm shift in energy optimization, emphasizing the importance of localized load management and unified energy distribution strategies. The outcomes from Scenario Three illuminate the system's adaptability to varied demands, demonstrating superior performance in handling Renewable Energy (RE) resources and minimizing waste.

The outputs from different units within Scenario Three showcase a harmonious balance between supply and demand. The wind turbine (WT) operates with minimal curtailment, maximizing its output potential during optimal conditions. Furthermore, the implementation of Local Load Dispersal (LLD) leads to a significant reduction in Heat Demand (HD) and Electricity Demand (ED) during specific intervals. This reduction, achieved without compromising user satisfaction, emphasizes the effectiveness of load displacement strategies in optimizing energy usage.

Unified Load Dispatch (ULD) ensures seamless coordination between diverse energy networks, resulting in efficient energy distribution across the grid. The utilization cost curve of the Unified Energy Network (UEN) under Scenario Three exemplifies its superior scheduling impact, highlighting its ability to minimize costs while maximizing energy utilization. The system's capacity to adapt to fluctuating demands and integrate renewable energy seamlessly underscores the viability of this approach in real-world applications.

Implications and future directions

The results obtained from the simulation scenarios not only validate the effectiveness of the proposed energy management strategies but also have far-reaching implications for the future of sustainable energy systems. The successful integration of Demand Response (DR), Local Load Dispersal (LLD), and Unified Load Dispatch (ULD) demonstrates a path towards creating smart and adaptive energy networks.

The findings from these scenarios provide valuable insights for policymakers, energy engineers, and researchers. Policymakers can use these results to formulate informed policies aimed at incentivizing the adoption of similar smart energy management practices. Energy engineers can leverage the lessons learned to design and implement efficient energy grids, ensuring a seamless transition towards renewable energy sources. Researchers, inspired by the successes observed, can delve deeper into refining algorithms, enhancing grid stability, and exploring innovative approaches to further optimize energy distribution.

As we look towards the future, the outcomes of these simulation scenarios pave the way for extensive research avenues. Further investigations can focus on exploring advanced machine learning techniques, artificial intelligence algorithms, and predictive analytics to create predictive models for energy demand and supply. Additionally, research can delve into the development of robust cybersecurity protocols to safeguard these intelligent energy grids from potential threats, ensuring the reliability and security of the future energy landscape.

In conclusion, the results obtained from the simulation scenarios exemplify the transformative potential of integrating advanced energy management strategies. As the world moves towards a sustainable future, these findings serve as a beacon, guiding the energy sector towards a greener, more efficient, and adaptive tomorrow.

Conclusion

In this comprehensive study, we introduce an innovative Unified Energy Network Design (UEND) layout specifically tailored for the intricate environments of Pervasive Internet of Things (PIoTs). Departing from traditional UEND configurations, our enhanced layout maximizes the intricate interplay between loads and resources while seamlessly integrating multiple energy sources within the Distribution System (DS). Furthermore, our research pioneers the implementation of a hierarchical dispatch architecture, strategically designed to alleviate the immense data transfer pressure inherent in PIoTs environments.

Within the context of different scenarios, our Unified Load Dispatch (ULD) framework optimizes the energy resource output of the Unified Energy Network (UEN). Leveraging the power of integrated Demand Response (DR), our approach dynamically adjusts multiple-energy demands, resulting in a harmonious balance between energy supply and demand. Importantly, this strategy significantly reduces the operational costs of the UEN, enhancing the network's overall efficiency and sustainability.

One of the key innovations of our approach lies in the application of Localized Load Dispatch (LLD). By implementing LLD, the multi-faceted energy requisitions of individual loads respond to upper-level cost curves without compromising user satisfaction. This strategic alignment between energy demand and cost signals ensures that users' comfort and convenience remain uncompromised while enabling a robust response to market dynamics and demand fluctuations.

As the energy market evolves and the PIoTs scheme becomes increasingly prevalent, our approach leverages the inherent flexibility of loads. Notably, loads can respond to cost signals by adapting their energy demands, further transforming multi-energy requirements into Electricity Demand (ED) through coupling Energy Factors (EFs). This not only minimizes the impact on user satisfaction but also leads to a decrease in the dispatch center's DR compensation price. Additionally, this enhanced flexibility augments the UEN's capacity to accommodate Renewable Energy (RE) sources, ushering in a new era of sustainable energy integration.

Crucially, our research recognizes the paramount importance of load-stage flexibility. By meticulously considering this factor, our proposed dispatch process provides invaluable guidelines for the optimal design and operation of UENDs within the expansive realm of PIoTs. Through this innovative approach, we pave the way for a future where energy networks seamlessly adapt to the complexities of PIoTs environments, ensuring efficiency, sustainability, and user satisfaction are at the forefront of energy management strategies.

CRediT authorship contribution statement

Xuefei Wang: Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Dawei Ma:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources.

Declaration of competing interest

I declare that there is no conflict of interest regarding the submission of our manuscript entitled "Sustainable and Reliable Smart Cities Energy Hub Development: Practical Modeling of Renewable Energy Landscape Design in Digital Twin" to the Sustainable Energy Technologies and Assessments Journal. All authors have read and understood the journal's policies and have no financial or personal relationships that could potentially bias or influence the work presented in this manuscript.

Data availability

No data was used for the research described in the article.

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