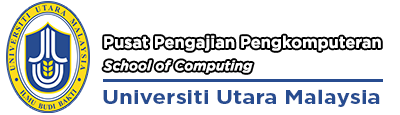
| SKIX 3113 Project Proposal |
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| SEMESTER | A232 |
| --- | --- |
| PROJECT TITLE | Forecasting Sectoral Energy Usage and Demand Using AI Approaches |
| STUDENT NAME | MUHAMMAD ABQARI BIN ZULKIFLI |
| MATRIC NUM. | 288492 |
| SUPERVISOR | Suwannit Chareen Chit a/l Sop Chit |
| PROJECT TRACK | Prototype / Experimental / Theoretical Computer Science |
| MAJOR | Cybersecurity / Human-Centred Computing |

| Prepared by |
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|  |  |  |
| --- | --- | --- |
| Student’s Signature |  | Date |

| Supervisor’s Approval |
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| Remarks: | | | |
| --- | --- | --- | --- |
| Please tick (√)   |  | Approve | | --- | --- | |  | Reject | |  |  |
| Project Supervisor’s Signature & Stamp |  | Date |

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# 1.0 Introduction

In a world without reliable access to energy, society would face daunting challenges, impacting everything from basic household functions to large-scale industrial operations[[1](https://www.mdpi.com/2071-1050/16/9/3627)]. The absence of consistent energy sources would disrupt essential services, communication networks, transportation systems, and healthcare facilities[[1](https://www.mdpi.com/2071-1050/16/9/3627)]. This scenario underscores the critical importance of efficient energy resource management, a challenge exacerbated by factors such as population growth, industrial expansion, and the looming threat of climate change[[2](https://link.springer.com/article/10.1007/s40684-023-00537-0)]. Addressing these challenges requires accurate forecasting of energy demand across various sectors[[2](https://link.springer.com/article/10.1007/s40684-023-00537-0)].At the same time, the negative consequences of climate change, such as extreme weather and rising sea levels, show the importance of turning to more sustainable energy sources.

While the immediate impact of a power outage highlights our dependence on electricity, the broader issue concerns the effective regulation and optimization of energy consumption amidst increasing demands and environmental concerns[[3](https://www.weforum.org/agenda/2021/09/this-is-how-ai-will-accelerate-the-energy-transition/)]. Fortunately, modern artificial intelligence (AI) technologies offer promising solutions to these complex problems[[4](https://deepai.org/publication/the-powerful-use-of-ai-in-the-energy-sector-intelligent-forecasting)]. By leveraging AI techniques, we can overcome traditional forecasting limitations and adapt to the dynamic nature of energy use trends[[4](https://deepai.org/publication/the-powerful-use-of-ai-in-the-energy-sector-intelligent-forecasting)]. These sophisticated algorithms enable us to integrate diverse datasets, identify intricate relationships, and forecast changes in demand with greater precision[[5](https://blog.greendatascience.ai/posts/ai-optimizing-renewable-energy-production)].

Indeed, studies have shown the potential of AI in enhancing energy forecasting accuracy and efficiency[[1](https://www.mdpi.com/2071-1050/16/9/3627)][[2](https://link.springer.com/article/10.1007/s40684-023-00537-0)]. By harnessing AI algorithms, we can better anticipate and manage energy demand fluctuations, paving the way for more resilient and sustainable energy management practices[[5](https://blog.greendatascience.ai/posts/ai-optimizing-renewable-energy-production)]. In conclusion, while the scenario of a power outage underscores the critical role of electricity in modern society, the broader challenge lies in effectively managing energy resources across the board[[3](https://www.weforum.org/agenda/2021/09/this-is-how-ai-will-accelerate-the-energy-transition/)].

By accurately forecasting energy demand and usage, we can provide mechanisms to reduce energy consumption while improving environmental impact.

Through the convergence of AI technology and energy forecasting approaches, we can illuminate pathways towards more sustainable and resilient energy management practices, mitigating risks and maximizing efficiency in an increasingly complex energy landscape[[4](https://deepai.org/publication/the-powerful-use-of-ai-in-the-energy-sector-intelligent-forecasting)][[5](https://blog.greendatascience.ai/posts/ai-optimizing-renewable-energy-production)].With these inventions, it gives us a glimpse of hope for reducing natural disasters caused by excessive energy use and contributing to the preservation of our planet.

# 2.0 Previous works

| **Articles** | Machine-Learning-Based Electric Power Forecasting[[6](https://www.mdpi.com/2071-1050/15/14/11299)] | Energy Demand Forecasting: Combining Cointegration Analysis and Artificial Intelligence Algorithm[[7](https://www.hindawi.com/journals/mpe/2018/5194810/)] | Electricity Demand Forecasting with Use of Artificial Intelligence: The Case of Gokceada Island[[8](https://www.mdpi.com/1996-1073/15/16/5950)] |
| --- | --- | --- | --- |
| Methodology | This study by Gang Chen et al. used a machine learning technique known as Support Vector Regression (SVR) to forecast regional electricity demand. The authors conducted extensive numerical experiments using an actual dataset from a large utility firm and other public data sources. They used SVR to capture the inherent complexities of the factors influencing the demand for electric power, such as fluctuations in business cycles, dynamic linkages among regional development, and climate change. | This research by Junbing Huang et al. presented a new energy demand forecasting framework. They used historical annual data of electricity usage from 1985 to 2015. The coefficients of linear and quadratic forms of the AI-based model were optimized by combining an adaptive genetic algorithm and a cointegration analysis. This combination allowed them to capture both the long-term equilibrium relationships and the short-term adjustments in the data. | This study by Mustafa Saglam et al. used Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), and Multi Linear Regression (MLR) to forecast electricity demand for Gokceada Island. They used imports, exports, car numbers, and tourist-passenger numbers as input values from 2014 to 2020, and estimated the electricity energy demands up to 2040 as an output value. The results obtained were analyzed using statistical error metrics such as R2, MSE, RMSE, and MAE. The correlation matrix was used to show the relationship between the actual value and method outputs and the relationship between independent and dependent variables |
| **Findings** | Socio-economic development was the major driver of growth in electricity demand, while weather variability was a key contributor to the seasonal fluctuations in electricity use. The SVR model showed high accuracy in predicting the demand. The proposed forecasting approach helped the regional electricity generation firms reduce a large amount of carbon dioxide emissions. | The prediction results of the proposed model indicated that the annual growth rate of electricity demand in China would slow down. However, China would continue to demand about 13 trillion kilowatt hours in 2030 because of population growth, economic growth, and urbanization. The model showed greater accuracy and reliability compared with other single optimization methods. | ANN yielded the highest confidence interval of 95% among the methods utilized, and the statistical error metrics had the highest correlation for ANN methods between electricity demand output and actual data. |

**Identified Gaps and Focus of Current Research**

While the studies mentioned have made significant contributions to energy demand forecasting, there are still gaps that need to be concerned about:

1. Sectoral Energy Demand Forecasting: Most of these studies focus on regional or national energy demand forecasting, with less emphasis on sectoral energy usage and demand. This leaves a gap in understanding how different sectors (like industrial, residential, commercial, etc.) consume energy and how their demands might change over time.

2. Use of Hybrid Models: Hybrid models, which combine different forecasting methods, have been shown to improve forecast accuracy in many domains, but their use in sectoral energy demand forecasting is not well-studied.

The current research will focus on addressing these gaps. It will aim to develop a sectoral energy usage and demand forecasting model using hybrid models. This could provide more accurate and robust forecasts, helping to optimize energy production and distribution.

**Limitations and Constraints**

The research will also need to consider several limitations and constraints:

1. Data Availability and Quality: The availability and quality of sectoral energy usage data could significantly affect the research. If the data is not available or if it’s of poor quality (e.g., missing values, errors, inconsistencies), it could limit the accuracy of the forecasts and the generalizability of the findings.

2. Model Complexity and Overfitting: While hybrid models can improve forecast accuracy, they are also more complex and can be more prone to overfitting compared to simpler models. Overfitting occurs when the model learns the training data too well and performs poorly on new, unseen data. Careful model design and validation will be needed to ensure the model generalizes well.

3. Model Interpretability: Hybrid models, due to their complexity, can sometimes be difficult to interpret. This could make it challenging to understand the underlying relationships in the data and the factors driving the forecasts.

These limitations and constraints will need to be carefully managed to ensure the success of the research. Despite these challenges, the potential benefits of more accurate and robust energy demand forecasts make this an important and worthwhile endeavor.

# 3.0 Problem statement

The growing need for energy, combined with environmental concerns and the need for efficient resource management, demands precise forecasting of energy demand across multiple industries. While past research have achieved substantial progress in energy demand forecasting utilizing artificial intelligence (AI) techniques, two major issues still exist:

1. Sectoral Energy Demand Forecasting: The importance of sectoral energy demand forecasting is highlighted in various studies. Energy is linked to industrial production, agricultural output, health, access to water, population, education, and quality of life[[9](https://www.mdpi.com/2071-1050/10/7/2348)]. Therefore, understanding how different sectors consume energy and how their demands might evolve over time is crucial for future economic planning and proper allocation of available resources[[10](https://link.springer.com/chapter/10.1007/978-1-4471-7468-4_5)][[11](https://link.springer.com/article/10.1007/s12667-016-0203-y)].

2. Use of Hybrid Models: Hybrid models, which combine different forecasting methods, have shown to improve forecast accuracy in many domains. For instance, a study by Dong & Wang[[12](https://link.springer.com/article/10.1007/s10651-023-00569-4)] proposed a hybrid electricity demand forecasting system based on sunflower optimization and a completely non-recursive decomposition strategy. Another research by Parizad et al.[[13](https://www.mdpi.com/2071-1050/16/6/2328)] developed a hybrid machine learning approach for forecasting home energy consumption. These studies highlight the potential of hybrid models in improving the accuracy and reliability of energy demand forecasts.

Addressing these problems is worth studying due to the critical role of energy in modern society and the potential of AI technologies in addressing complex forecasting challenges[[11](https://link.springer.com/article/10.1007/s12667-016-0203-y)]. Effective sectoral energy demand forecasting can lead to optimized energy production and distribution, contributing to more resilient and sustainable energy management practices[[9](https://www.mdpi.com/2071-1050/10/7/2348)]. Furthermore, the exploration of hybrid models could provide more accurate and robust forecasts, enhancing our ability to manage energy resources efficiently[[13](https://www.mdpi.com/2071-1050/16/6/2328)][[12](https://link.springer.com/article/10.1007/s10651-023-00569-4)]. Despite the challenges, addressing the identified problems holds significant promise for advancing our capabilities in energy demand forecasting and management[[14](https://link.springer.com/article/10.1007/s40747-024-01380-9)].

# 4.0 Objectives

1. **Develop a sectoral energy usage and demand forecasting model using hybrid models**: This involves creating a model that combines different forecasting methods to predict energy demand in various sectors. The hybrid model aims to leverage the strengths of multiple techniques to improve forecast accuracy.

2. **Evaluate the performance of the developed model**: After the model is developed, it will be tested using real-world data. The performance of the model will be evaluated based on its ability to accurately predict energy demand.

3. **Analyze the impact of various factors on sectoral energy demand**: This involves studying how different factors, such as economic growth, population growth, and climate change, affect energy demand in different sectors.

4. **Implement and evaluate energy-saving and environmental impact strategies**: Use the established model to devise methods for reducing energy use in various sectors. This includes detecting high-demand events and providing alternate solutions or modifications to reduce energy use. At the same time, analyze the environmental impact of these measures, with an emphasis on increasing sustainability and lowering carbon footprint.

# 5.0 Project Scope

This research will focus on energy demand forecasting using hybrid models. The problem is worth studying because accurate energy demand forecasting can lead to optimized energy production and distribution, contributing to more resilient and sustainable energy management practices. The research will utilize datasets from open-source platforms, the Department of Statistics Malaysia (DOSM)[[15](https://www.dosm.gov.my)], and Kementerian Peralihan Tenaga dan Transformasi Air(Petra)[[16](https://www.petra.gov.my)], which cover a wide range of sectors. This broad scope will allow for a comprehensive understanding of energy demand patterns across various sectors.

# 6.0 Project Significance

The research is significant because it can help optimize energy production and distribution, leading to more efficient use of resources and reduced environmental impact. By improving our understanding of energy demand, we can better plan for future energy needs and make more informed decisions about energy policy and infrastructure development.

# 7.0 Methodology

Our methodology for forecasting sectoral energy usage relies on a hybrid approach that combines machine learning algorithms with domain knowledge integration. This approach allows us to leverage the strengths of both data-driven techniques and expert insights, ensuring robust and interpretable forecasting models.

1. Data Collection: This involves gathering data on energy usage from reliable sources such as open-source platforms, DOSM, and petra.gov.my.

2. Model Development: This involves creating a hybrid model that combines different forecasting methods. The model will be trained using the collected data.

3. Model Evaluation: This involves testing the model’s performance using a separate set of data. The model’s predictions will be compared to actual energy demand to assess its accuracy.

4. Analysis: This involves studying the model’s predictions to understand how different factors affect energy demand.

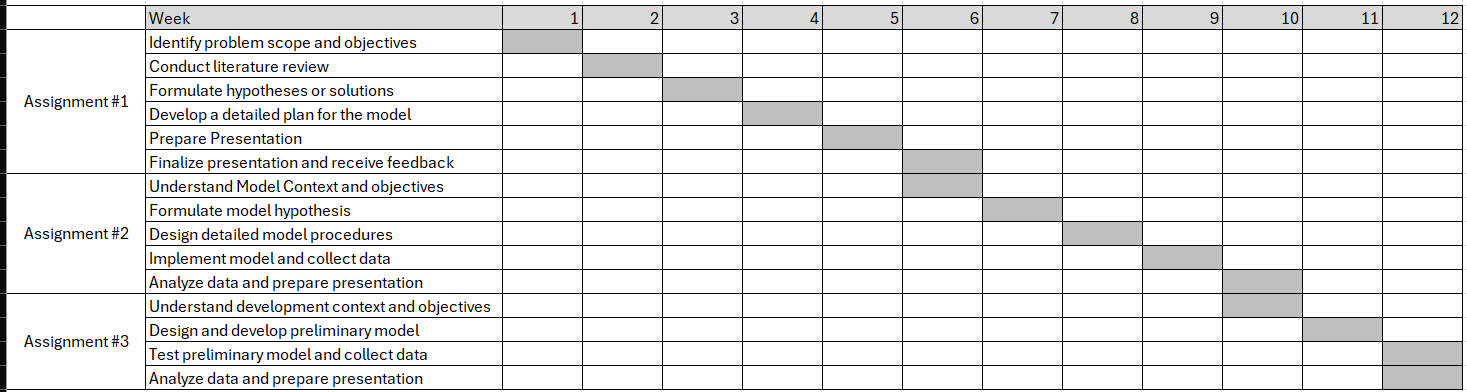
# 8.0 Potential Risks /challenges

1. Data Availability and Quality: The quality of the research depends on the availability and quality of data. If the data is incomplete, inaccurate, or not representative of the population, it could affect the accuracy of the forecasts.

2. Model Complexity and Overfitting: Hybrid models are more complex than single-method models, which can make them more prone to overfitting. Overfitting occurs when a model learns the training data too well and performs poorly on new, unseen data.

3. Model Interpretability: Due to their complexity, hybrid models can be difficult to interpret. This could make it challenging to understand the underlying relationships in the data and the factors driving the forecasts.

# 9.0 Project Timeline and milestones



# 10.0 Reference

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Table 1. Electricity demand and consumption forecasting studies in the literature.

| Author | Forecasting for | Method | Understanding |
| --- | --- | --- | --- |
| James Ogundiran, Ehsan Asadi, Manuel Gameiro da Silva | Energy management and indoor environmental quality | Multi-layer perceptron(MLP) , convolutional neural network (CNN) , recurrent neural network (RNN) | Use historical data and patterns to make predictions that help in optimizing building performance,reducing energy consumption, and ensuring occupant comfort |
| Wang, X., Wang, H., Bhandari, B., & Cheng, L. | Smart Energy Consumption | Machine Learning, Deep Learning, Reinforcement Learning | It provides an in-depth analysis of AI techniques for load forecasting, anomaly detection, and demand response in smart energy consumption. |
| Chen, G., Hu, Q., Wang, J., Xu, W., & Zhu, Y | Electric Power | Machine Learning | The authors propose a framework that integrates machine-learning techniques into regional electricity demand forecasting. They use a support vector regression model for forecasting and find that socio-economic development is the major factor of growth in electricity demand |
| Huang, J., Tang, Y., & Chen, S. | Energy Demand | Cointegration Analysis and AI Algorithm | The paper combines cointegration analysis and an AI algorithm for energy demand forecasting. It optimizes the coefficients of linear and quadratic forms of the AI-based model using an adaptive genetic algorithm and a cointegration analysis |
| Saglam, M., Spataru, C., & Karaman, Ö. A. | Electricity Demand Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), and Multi Linear Regression (MLR) | The authors use ANN, PSO, and MLR to forecast electricity demand for Gokceada Island. | They find that ANN yields the highest confidence interval of 95% among the methods utilized. |
| Ameyaw, B., & Yao, L. | Sectoral Energy Demand | Assumption-Free Data-Driven Technique | This paper proposes a high-accuracy assumption-free data-driven technique for sectorial energy demand forecasting. It utilizes zero traditional determinants as well as assumptions or scenarios |
| Ghalehkhondabi, I., Ardjmand, E., Weckman, G. R., & Young, W. A. | Energy Demand | They reviewed traditional method (eg: econometric and time series models) and soft computing (eg: neural network and fuzzy logic) | It focuses on methods used to predict energy consumption, including traditional techniques such as econometric and time series models, and soft computing methods such as neural networks and fuzzy logic |
| Dong, Y., & Wang, J. | Electricity Demand | Sunflower Optimization and Completely Non-Recursive Decomposition Strategy | Propose a hybrid electricity demand forecasting system based on a seasonal selection method, completely non-recursive decomposition strategy, and the sunflower optimization algorithm. The system is evaluated using actual electricity demand data from different seasons in various Australian states |
| Parizad, B., Ranjbarzadeh, H., Jamali, A., & Khayyam, H. | Home Energy Demand and Electricity Price | Hybrid Machine Learning model | develop a hybrid machine learning approach for forecasting home energy consumption and electricity prices. The approach combines price and energy demand forecasting and optimizes the machine learning method’s parameters using Particle Swarm Optimization |
| Oqaibi, H., & Bedi, J. | Electricity Load | Data Decomposition and Attention Mechanism | propose a hybrid approach that combines a data smoothing and decomposition strategy with deep neural models for improving electricity load forecasting results. An attention mechanism is integrated to capture relevant portions of the time series, thus achieving the ability to capture long-term dependencies among load demand observations. The performance assessment is carried out on a real-world dataset of five southern states of India. |