Forecasting Sectoral Energy Demand in Malaysia Using Artificial Intelligence Techniques : A Comparative Analysis

Muhammad Abqari Zulkifli[1], Suwannit Chareen Chit[2][0009-0007-5057-7915]
Jefri Marzal[3][0000-0003-0243-469X] Ahmad Hanis Mohd Shabli[4][0009-0007-2102-211X]

[1,2,4] Universiti Utara Malaysia, Sintok 06010, Kedah, Malaysia
[3] Universitas Jambi, Jambi 36361, Indonesia
chareen@uum.edu.my

Abstract. Forecasting energy demand remains crucial in the energy sector landscape to ensure reliable energy supply, resource allocation, and formulate future sustainable energy policy development. This study employs comparative analysis of forecasting methods to examine the efficacy of AI techniques for energy demand in Malaysia with the aim to provide insights for informed energy policy and planning. Using the datasets from the Malaysian Energy Commission spanning from 1978 to 2021, this study employs forecasting approaches such as prediction models, time-series models, and deep-learning models to predict energy consumption in key sectors across Malaysia. The results revealed that ANN showcased superior performance in capturing complex, non-linear patterns in energy demand data. Contrarily, SGD demonstrates significant stability in its prediction, thus offering reliable alternative to long-term forecasting. The findings provide insights to the growing body of AI-driven forecasting techniques while offering an enhanced understanding for policymakers in steering Malaysia's energy transition.

Keywords: Sectoral Energy Consumption, Energy Demand, Forecasting,

1 Introduction

The recent growth and advancement in manufacturing technology, residential sector, and electrification of vehicles have characterized increasing demand for electricity. The International Energy Agency (IEA) reported that global electricity demand will record an average growth of 3.4% annually through 2026 [1], and this accelerated growth is driven by several factors which include robust economic growth particularly in the Asian region. It is projected that by 2026, 85% of additional electricity demand will come from developing nations with China leading the charge. Another key factor for increased energy demand is electrification of key sectors particularly the adoption of electric vehicles in transportation, and electrification of residential sectors. Data centre expansions emerged as power-hungry sectors as artificial intelligence and cryptocurrency mining activities continue to expand thus impacting overall demand.

In Malaysia, the energy demand is expected to grow marginally at 0.2% annually from 95 million tonnes of oil equivalent (MTOE) in 2023 to 102 MTOE by 2025 [2]. The Malaysian Ministry of Economy in its National Energy Transition Roadmap (NETR) stated that the energy sector comprises several critical areas, including transportation, which heavily relies on fossil fuels but is inching toward more sustainable alternatives. Likewise, the industrial sector also significantly contributes to energy consumption.

In the recent years, concerns over climate changes and rising fuel costs have triggered a greater interest in Malaysia's national energy consumption, demand and policy. As a result, Tang et.al noted that there is an urgent need to examine the sectoral energy consumption and its interactions with economic growth, fuel prices, and technological advancements [3]. Tang et.al further suggested that asymmetric responses in energy consumption are relative to changes in macroeconomic variables whereby an increase in income raises energy consumption across all sectors, but a decrease in income does not trigger a similar reaction. The study also shows that advancements in technology has led to an increment in energy consumption, especially within the transportation sector.

To address the gaps highlighted in the literature, this study attempts to examine and employ comparative analysis to forecast sectoral energy demands in Malaysia. In this paper, this study will employ three forecasting approaches, namely prediction models, time-series models, and deep-learning models with the aim to provide insights for informed energy policy and planning, particularly in ensuring reliable energy supply, optimising resource allocation, and supporting present and future sustainable energy policy development.

The remainder of this paper is organised as follows: Section 2 provides a brief description of Malaysia's energy landscape, and the artificial intelligence (AI) techniques that will be used. Section 3 offers the ensemble forecasting framework and methods of this study. Section 4 discusses the results and findings, while Section 5 provides a brief implications of its key findings. The paper ends with conclusion and future directions of the study.

2 Literature Review

2.1 Energy Landscape in Malaysia

Malaysia is one of the fastest growing economies in the Asian region. Primarily an agrarian economy in the 1970's, Malaysia has diversified immensely to industrialisation and urbanisation in the recent years. In line with this, energy consumption was comparatively low back then but took a major boost in the 1980's until today. This is evident as shown in Figure 1 where in 1978, the industrial sector accounts to only a small fragment of the total energy consumption but growth in commercial, residential, and industrial sectors in the 1990's fuelled for huge demand for energy.

Malaysia's energy sector relies heavily on fossil fuels in particular petroleum, natural gas and coal. In 2022, according to Ember – a global energy think-tank, 81% of its energy is generated from fossil fuel, 17% from hydropower, and a meagre 2% of its energy share is generated by solar and wind power [4]. The IEA [1] and Malaysian Ministry of Economy [2] noted that five sectors are primary energy consumers in Malaysia. The industrial sector consumes the lion's share of energy, accounting to 49% of total final consumption of electricity. This industry includes manufacturing and energy intensive industries such as steel and cement production. The commercial sector also contributes significantly to the total final consumption of electricity in Malaysia. According to the IEA report, the commercial sector in Malaysia accounts for approximately 28% of the total electricity consumption, making it the second largest energy consumer. Another significant energy consumer is the residential sector. According to daud et.al., residential sectors in Malaysia accounts to 20.7% of total final consumption of electricity in Malaysia [5]. The increase in consumption from the residential sector can be attributed to behaviour and lifestyle changes in the residential sector which warrants for specific strategies for reducing consumption based on household characteristics.

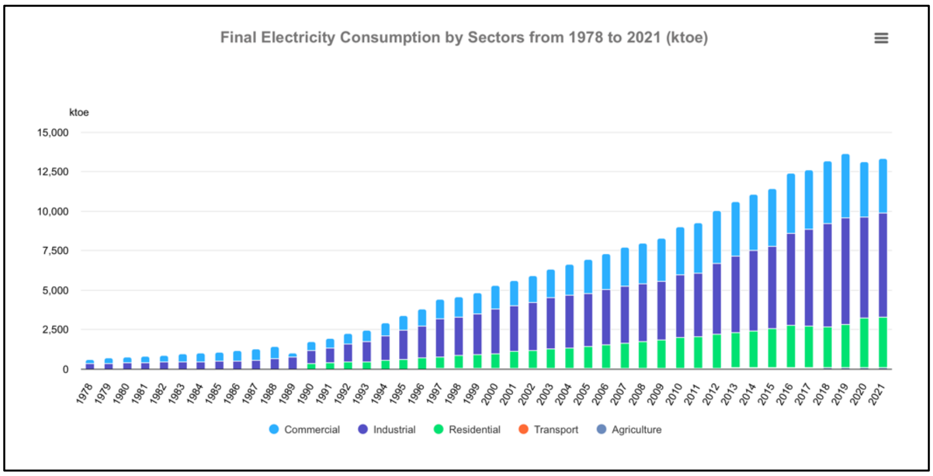

Fig. 1. Malaysia's Energy Demand by Sector 1978 – 2021. Source: MYenergySTats – Energy Commission of Malaysia.

2.2 Forecasting Techniques

The escalation of energy demand across all sectors observed in recent years underscores the imperative for rigorous scholarly investigation, particularly in the domain of energy demand forecasting. Numerous recent studies have been carried out to predict energy consumption, and these diverse approaches include prediction models, time-series models, and deep-learning models.

Prediction models are algorithms that analyse patterns in historical data to forecast future outcomes. The prediction model typically uses machine learning to forecast outcomes based on existing trends. In this study, three models are used to forecast sectoral energy demand in Malaysia namely Random Forest, Linear Regression, and Stochastic Gradient Descent.

Random forest is a widely used machine learning technique that combines the results of two or more decision trees to produce a unified outcome [6]. Random Forest algorithm is used today [7], [8] in a multitude of areas which includes computer vision, and data mining. Its popularity is attributed to its exceptional performance and efficient training process. Linear regression, on the other hand, models the conditional expectation of a dependent variable as a linear function of one or more independent variables. This technique relies on the assumption of a linear relationship between the predictors and the outcome, and provides a framework for predictive analysis [9]. Stochastic Gradient Descent (SGD) is an algorithm that teaches machine learning model by introducing randomness incrementally until it is capable of making predictions. SGD is a fast, scalable way to optimize models by making small, noisy updates to parameters based on individual data points. It's a cornerstone of modern machine learning, especially for deep learning [10].

A time-series model is a statistical or machine learning model designed to analyse and forecast future values based on past chronological events. These models take into account the sequential nature of data, capturing trends, seasonal patterns, and other temporal dynamics inherent in time-dependent data [11]. Two commonly used time-series models are Vector Autoregression (VAR) and Autoregressive Integrated Moving Average (ARIMA). VAR is a statistical model used to analyse and forecast multiple time series that influence each other. Contrarily, ARIMA assumes future values are dependent of previous values and therefore performs predictions that are in chronological manner [12].

Deep-learning is a specialized form of machine learning that uses artificial neural networks (ANN), particularly deep neural networks with many layers. This architecture allows deep-learning to capture complex patterns in large datasets. Deep-learning performs well with large amounts of high-dimensional data, such as images, audio, and text, and can automatically learn features without manual extraction. However, due to its complexity, deep-learning requires significant computational resources, especially for training deep networks that can have millions of parameters, necessitating GPUs or specialized hardware [13]. The strengths and drawbacks of each technique is presented in Table 1.

In this study, this paper will perform a comparative analysis on the different techniques to measure the techniques accuracy in forecasting sectoral energy demand in Malaysia. The study will employ datasets from the Malaysia Energy Commission from 1978 to 2021.

Table 1: AI Techniques – Strengths and Drawbacks

Technique	Strength	Drawback
Random Forest	• Handles non-linear relationships well • Robust to overfitting due to ensemble approach • Works with both classification and regression • Handles missing data effectively	• Computationally intensive • Less interpretable than simpler models • Requires tuning (e.g., number of trees, depth) • Poor extrapolation beyond training data
Linear Regression	• Simple and interpretable • Fast to train and predict • Works well with linear relationships • Provides statistical inference (e.g., p-values)	• Assumes linearity, independence, and normality • Sensitive to outliers • Poor performance with complex, non-linear data • Limited to continuous outcomes
Stochastic Gradient Descent	• Efficient for large datasets • Flexible (used in many models like SVMs, neural networks) • Adapts to online learning • Scales well with high-dimensional data	• Sensitive to learning rate tuning • Can get stuck in local minima • Noisy convergence • Requires feature scaling for optimal performance
Vector Autoregression (VAR)	• Models multiple time series simultaneously • Captures interdependencies between variables • Useful for forecasting and economic analysis • Relatively simple for multivariate time series	• Assumes stationarity of data • Requires careful lag selection • Computationally expensive with many variables • Sensitive to model misspecification
ARIMA	• Strong for univariate time series forecasting • Handles trends and seasonality (with SARIMA) • Well-established with statistical foundations • Interpretable parameters	• Assumes stationarity (or differencing needed) • Limited to linear relationships • Struggles with complex, non-linear patterns • Not suited for multivariate data
Artificial Neural Networks (ANN)	• Excels at modelling complex, non-linear relationships • Highly flexible • Scales with large datasets • Can handle diverse data types (images, text, etc.)	• Requires large amounts of data • Computationally intensive • Black-box (hard to interpret) • Prone to overfitting without regularization

3 Forecasting Framework & Methods

In this section, this paper discusses the framework and methods of sectoral energy forecast in Malaysia. First, the ensemble framework is presented, and by the forecasting model.

3.1 Ensemble Framework for Sectoral Energy Demand Forecast

The ensemble framework for the sectoral energy demand is diverged into four stages as shown in Figure 2. In the first stage, the study performs data collection where dataset is obtained from the Malaysian Energy Commission. The dataset gathered is from the year 1978 to 2021. In the next stage, this study perform data preprocessing. The forecasting model is then applied in the third stage. Finally, this study conducts its sectoral energy demand forecasting.

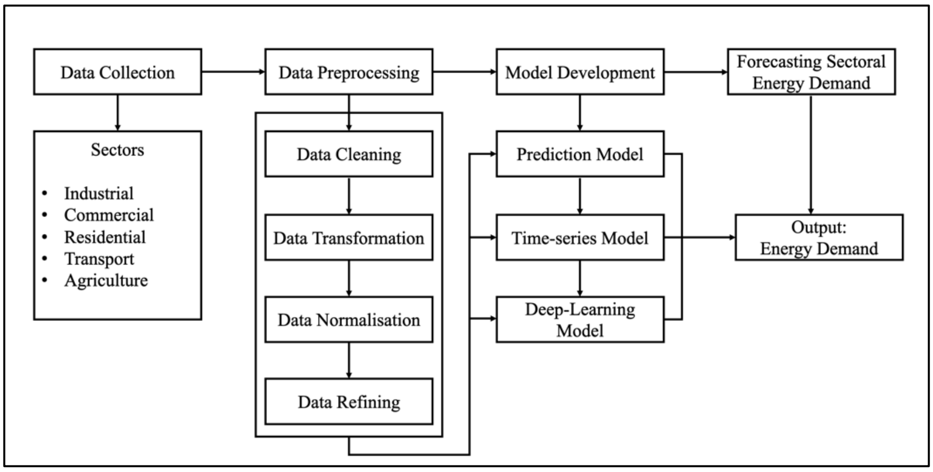

Fig 2: Ensemble Framework for Forecasting Sectoral Energy Demand in Malaysia

3.1.1 Data Collection

The data collection process for this study follows the systematic assembly of an extensive and multifaceted dataset, encompassing critical variables such as sectoral energy consumption, gross domestic product (GDP), and population statistics. These data were sourced from the Malaysian Energy Commission, covering a comprehensive temporal range from 1978 to 2021. The dataset encapsulated energy consumption metrics across five principal sectors—namely, industrial, transportation, agriculture, residential/commercial, and non-energy—offering a detailed breakdown of sectoral energy dynamics over the specified period.

To uphold the integrity of the dataset, a rigorous cross-verification process was employed, wherein the primary data were systematically compared with complementary public datasets. This step was instrumental in identifying and rectifying potential discrepancies, thereby enhancing the reliability of the information. In addition to energy-specific variables, the dataset was enriched with historical economic and demographic indicators, including both real and nominal GDP figures. These supplementary variables were integrated to facilitate a thorough evaluation of their influence on energy consumption patterns.

The collected data underwent an exhaustive validation procedure to address any instances of missing values, inconsistencies, or anomalies. This process involved detailed scrutiny and correction of entries to ensure alignment with observed long-term trends and sector-specific characteristics. By establishing a high standard of data quality, this validation phase laid a solid and dependable foundation for subsequent analytical efforts.

The resulting dataset enabled a nuanced exploration of the intricate interrelationships among the included variables. Its comprehensive nature rendered it particularly well-suited for advanced applications, such as predictive modelling and in-depth sectoral analysis, allowing for robust insights into energy consumption trends and their socioeconomic drivers over the 43-year span. This meticulous approach to data collection and preparation ensured that the study was grounded in a reliable and representative evidence base.

3.1.2 Data Preprocessing

The data preprocessing phase was meticulously designed to ensure that the dataset was thoroughly refined, consistent, and optimally prepared for analytical applications. The initial effort concentrated on resolving missing values, which constituted approximately 4.8% of the total dataset. To address these deficiencies, sophisticated imputation techniques were employed: numerical missing entries were replaced with the mean of their respective variables, while categorical missing entries were substituted with the mode, preserving the dataset's statistical properties.

To mitigate the potential adverse effects of outliers on model performance, a methodical approach was adopted. Outliers were first detected through a detailed visual examination of variable distributions, supplemented by statistical criteria where applicable. Once identified, these extreme values were managed by capping them at predetermined thresholds deemed acceptable within the context of the data's domain.

Normalization was subsequently applied to standardize the numerical features, ensuring that all variables were rescaled to a uniform range without compromising their inherent relationships. This standardization was critical for optimizing the performance of machine learning algorithms, particularly those dependent on distance-based metrics, such as clustering or regression models, where disparate scales could otherwise skew results.

For datasets containing categorical variables, an encoding process was implemented to transform these non-numerical attributes into a format compatible with machine learning frameworks. Techniques such as one-hot encoding or label encoding were selectively applied, depending on the variable's nature and the requirements of downstream models, ensuring seamless integration into the analytical pipeline.

3.2 Model Development

3.2.1 Prediction Model

The prediction workflow is designed to develop machine learning models that accurately forecast sectoral energy consumption using historical and socioeconomic data as shown in Figure 3. It commences with data preparation, structuring the dataset into key features—namely sectoral energy consumption, GDP, and population. Feature selection is then conducted to retain only the most influential variables, minimizing noise and enhancing model precision. The workflow utilizes algorithms such as Random Forest, Stochastic Gradient Descent (SGD), and Linear Regression to model energy demand across sectors. These models are trained on pre-processed data to delineate relationships between predictors and target outcomes, such as energy use in agriculture or industry. Model performance is assessed using metrics like Mean Squared Error (MSE) and R^2 to ensure accuracy and reliability. This methodical process yields robust insights into sectoral energy trends, supporting precise energy policy formulation.

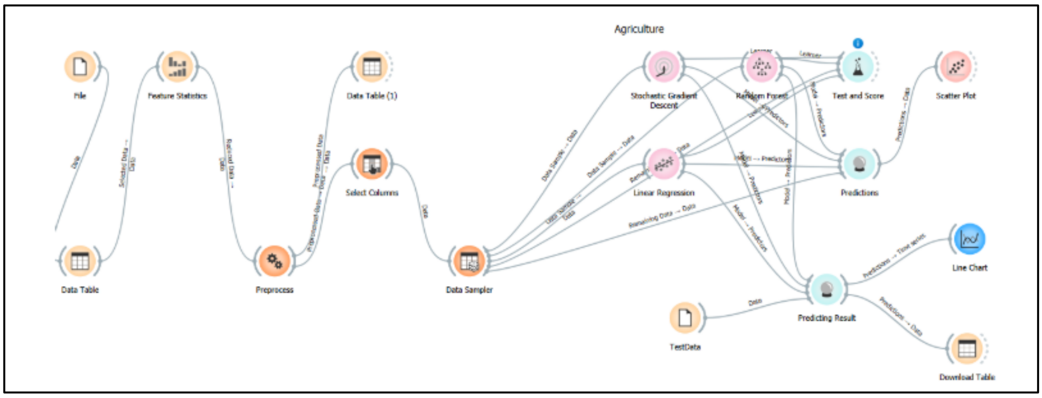

Fig. 3: Prediction Model for Forecasting Sectoral Energy Demand

3.2.2 Time-Series Model

Time series modelling focuses on detecting temporal trends and seasonal patterns in energy consumption data using Vector Autoregression (VAR) and Autoregressive Integrated Moving Average (ARIMA). Both technique are adept at handling time-dependent datasets. Preprocessing involves decomposing the data into trend and seasonality elements to boost prediction accuracy. Energy usage for each sector—namely residential, commercial and transportation—is modelled separately to reveal distinct patterns. Model complexity and parameter selection are evaluated with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). This temporal analysis delivers critical insights into long-term trends, aiding policymakers in strategic energy planning.

3.2.3 Deep-Learning Model

Deep learning models, notably Artificial Neural Networks (ANN), are employed through a structured process to identify complex, nonlinear relationships within sectoral energy consumption data.

This workflow shown in Figure 4, is modelled to address intricate patterns that simpler models might overlook, proving particularly effective for sectors such as transportation and agriculture where energy use is shaped by diverse influences.

The preprocessing phase involves specific steps: lagging the data and constructing sequences to enable time-series predictions. The ANN framework, consisting of input, hidden, and dense layers, is systematically designed to process extensive datasets with efficiency. The training process utilizes iterative optimization techniques to ensure the model captures essential energy usage patterns. Evaluation follows, with performance assessed using Mean Squared Error (MSE) and R^2 metrics to confirm robustness. This comprehensive deep learning process delivers exceptional flexibility and accuracy, serving as a foundation for sophisticated energy forecasting applications.

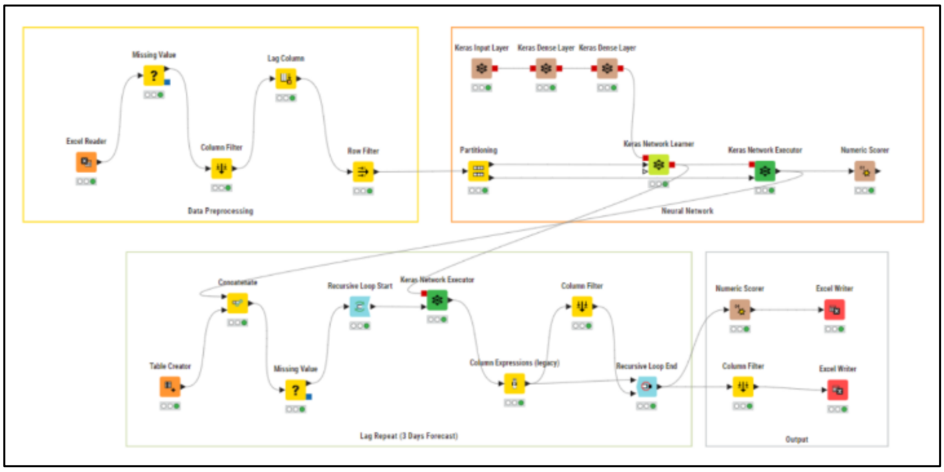

Fig. 4: Deep-Learning Model for Forecasting Sectoral Energy Demand

4 Results & Findings

This section presents the performance of various predictive models across five economic sectors namely Industrial, Transport, Non-Energy, Agriculture, and Residential & Commercial. The models evaluated include Linear Regression, Stochastic Gradient Descent (SGD), Random Forest, Vector Autoregression (VAR), ARIMA, and Artificial Neural Network (ANN). Key metrics for comparison are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Percentage of Correct Direction (POCID), and R^2.

4.1 Industrial Sector

Industrial energy consumption, closely correlated with economic activity, was most accurately forecasted by an Artificial Neural Network (ANN). The ANN's superior performance, evidenced by a low Mean Squared Error (MSE) of 30,528.616, Root Mean Squared Error (RMSE) of 174.724, and a high R^2 of 0.996, demonstrates its effectiveness in capturing the intricate, non-linear dynamics of industrial energy demand, surpassing both Random Forest and Linear Regression models. This underscores the industrial sector's reliance on models capable of adapting to complex and volatile trends.

Table 2: Forecast Results for Industrial Sector

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
LR	4084724.4	2021.07	1526.46	N/A	N/A	N/A	N/A	0.830
SGD	2334707.7	1527.97	1331.02	N/A	N/A	N/A	N/A	0.903
RF	3113481.2	1764.50	1282.09	N/A	N/A	N/A	N/A	0.871
VAR	N/A	802.7	470.5	0.062	71.4	51.3	52.0	0.977
ARIMA	N/A	891.2	417.5	0.064	62.8	706.6	711.9	0.973
ANN	73183.26	270.52	231.72	0.01341	N/A	N/A	N/A	0.9895

4.2 Transportation Sector

The transport sector's energy consumption, driven by urbanization, population growth, and economic activity, was most accurately modelled by an Artificial Neural Network (ANN) as shown in Table 3. The ANN's superior performance, evidenced by a Mean Squared Error (MSE) of 21,483.443, a Root Mean Squared Error (RMSE) of 146.572, and an R^2 of 0.998, demonstrates its robust predictive capability for the highly variable patterns characteristic of transportation energy demand. Its ability to incorporate seasonal trends and exogenous factors, including fuel prices and policy impacts, renders it particularly effective for forecasting within this sector.

Table 3: Forecast Results for Transportation Sector

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
LR	22802511.1	4775.19	3060.43	N/A	N/A	N/A	N/A	0.504
SGD	10901125.	3301.68	1954.37	N/A	N/A	N/A	N/A	0.763
RF	7948491.3	2819.30	2226.53	N/A	N/A	N/A	N/A	0.827
VAR	N/A	1109.9	523.7	0.065	78.6	51.4	52.1	0.977
ARIMA	N/A	1298.4	470.1	0.061	76.7	743.4	748.7	0.969
ANN	75331.69	274.46	269.16	0.013	N/A	N/A	N/A	0.9921

4.3 Non-Energy Sector

The Random Forest model demonstrated superior predictive capability within the non-energy sector (MSE: 785,672.163, RMSE: 886.381, R^2: 0.928). Its ensemble nature effectively modelled variable interactions and non-linearities, proving advantageous in a sector where energy consumption is weakly correlated with economic indicators.

Table 4: Forecast Results for Non-Energy Sector

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
LR	1306594.1	1143.06	699.254	N/A	N/A	N/A	N/A	0.881
SGD	870557.96	933.037	789.629	N/A	N/A	N/A	N/A	0.920
RF	785672.16	886.381	566.864	N/A	N/A	N/A	N/A	0.928
VAR	N/A	826.6	257.8	0.152	54.8	51.5	52.2	0.952
ARIMA	N/A	930.4	217.4	0.150	58.1	717.1	722.4	0.939
ANN	6349.828	79.685	67.165	0.009	N/A	N/A	N/A	0.99935

4.4 Agriculture Sector

For the agricultural sector, the Artificial Neural Network (ANN) demonstrated superior predictive efficacy. The model, characterized by a Mean Squared Error (MSE) of 8,756.838, a Root Mean Squared Error (RMSE) of 93.578, and a coefficient of determination (R^2) of 0.854, effectively modelled the seasonal and weather-dependent fluctuations in agricultural energy consumption. The robust performance of the ANN in this domain underscores its adaptability to temporal variability in energy demand.

Table 5: Forecast Results for Agriculture Sector

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
LR	128087.	357.89	309.88	N/A	N/A	N/A	N/A	0.161
SGD	129053	359.240	312.026	N/A	N/A	N/A	N/A	0.155
RF	127956	357.711	307.872	N/A	N/A	N/A	N/A	0.162
VAR	N/A	208.9	118.8	0.315	44.8	48.5	49.3	0.681

ARIMA	N/A	228.0	68.4	0.291	53.3	417.5	421.7	0.620
ANN	678.361	26.0453	24.2413	0.0275	N/A	N/A	N/A	0.98868

4.5 Residential & Commercial Sector

The residential and commercial sector, characterized by predictable energy consumption patterns, saw Stochastic Gradient Descent (SGD) outperform other models. SGD achieved an MSE of 77,249.620, RMSE of 277.938, and an R^2 value of 0.988. The iterative optimization approach of SGD enabled it to provide accurate and reliable predictions, particularly in a sector with stable growth trends influenced by population and urbanization.

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
LR	62423.436	249.847	209.697	N/A	N/A	N/A	N/A	0.990
SGD	77249.620	277.938	225.498	N/A	N/A	N/A	N/A	0.988
RF	125984.523	354.943	295.415	N/A	N/A	N/A	N/A	0.981
VAR	N/A	180.2	90.9	0.032	88.1	53.4	54.1	0.995
ARIMA	N/A	221.1	114.6	0.038	83.7	582.6	587.9	0.993
ANN	13873.718	117.78675	82.800659	0.0105637	N/A	N/A	N/A	0.949

5 Discussion

This study examines the effectiveness of various AI-driven forecasting models in predicting energy demand across Malaysia's key sectors It highlights the strong performance of these models (ANN and SGD) in capturing complex, sector-specific energy consumption patterns. The analysis further discusses how these forecasts can be used to inform and optimize energy efficiency strategies. More importantly, this study demonstrates that AI techniques are not merely tools for prediction but are essential for achieving effective energy management and sustainability through a dashboard that provides insights to researchers, policymakers, and businesses as shown in Figure 5 below.

This is essential as Malaysia steps into industrialisation, expanding residential and commercial sectors, and a shift toward electrification of the transportation sector. The major shift is inevitable and necessary policies and actions need to be in place to address the increasing need for energy, ensuring future supply for energy is secured, while at the same time transiting to green power to mitigate the effects of climate change.

With the exponential growth for energy demand, AI with precision forecasts allow for sector-specific, data-driven interventions. For example, predicting peak demand in the transport sector enables the strategic deployment of EV charging infrastructure. Similarly, predicting energy demand from residential sector (usage of air-conditioners, heaters etc.) necessitate for policymaking especially in building low-energy homes.

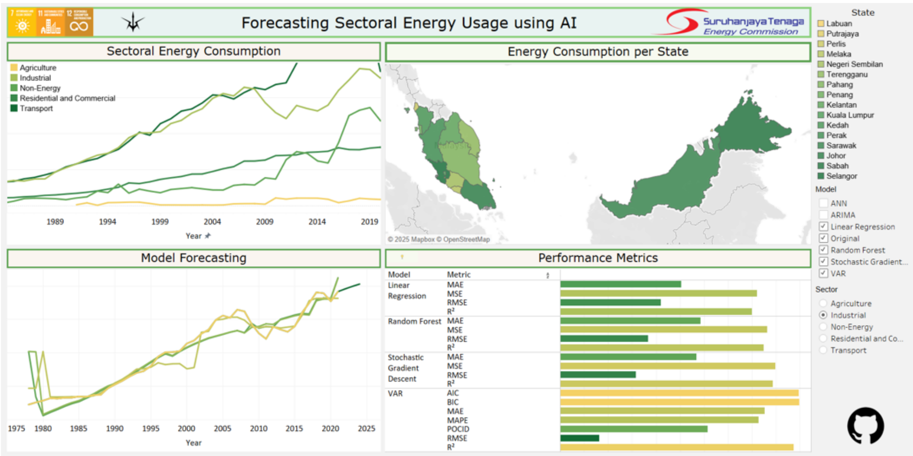

Fig. 5: AI-Powered Dashboard for Monitoring of Energy Consumption and Demand

It is without a doubt that with precise forecasting, continuous monitoring of energy demand trends, and awareness of energy usage will ensure reliable energy supply, optimising resource allocation, and supporting present and future sustainable energy policy development.

6 Conclusion & Future Research

This paper studies the efficacy of artificial intelligence (AI) models in forecasting sectoral energy consumption, thereby facilitating informed energy management and sustainability planning. Utilizing a comprehensive dataset spanning four decades (1978-2021) across industrial, transportation, residential/commercial, non-energy, and agricultural sectors within Malaysia, the study demonstrates the differential effectiveness of diverse AI methodologies in accommodating sector-specific energy consumption characteristics. Specifically, Artificial Neural Networks (ANNs) exhibited superior performance in modelling sectors characterized by complex, non-linear energy consumption patterns, such as the industrial and transportation sectors, achieving high predictive accuracy as evidenced by R^2 values exceeding 0.99. Conversely, simpler algorithms, such as Stochastic Gradient Descent (SGD), demonstrated utility in forecasting energy consumption within sectors exhibiting greater stability, such as the residential and commercial sectors.

The findings underscore the necessity of tailoring energy management strategies to the unique requirements of each sector. For instance, predictive analytics can enable industries to implement energy-efficient technologies, while transportation planning can prioritize electric vehicle adoption and renewable energy integration. The identification of state-level energy consumption disparities highlights opportunities for targeted interventions in regions with elevated demand. These AI-driven approaches not only optimize energy utilization but also contribute to Malaysia's attainment of sustainable development goals. In conclusion, this study elucidates the potential of AI-driven forecasting to support data-informed decision-making by governments, industries, and stakeholders. Future research should explore the development and evaluation of hybrid forecasting models, real-time forecasting methodologies, and the enhanced integration of socioeconomic and environmental variables to further refine the accuracy and applicability of energy demand predictions.

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