FORECASTING SECTORAL ENERGY USAGE AND DEMAND USING AI (SENDA)

1. **INTRODUCTION** (Buat after done all)
    - Background of the Study
    - Problem Statement
    - Objectives

      On how to predict better on the consumption of the next year or in the future, align goal for SGD 7
    - Significance of the Study
2. **LITERATURE REVIEW** (all the ten and the best one from energies)
    - Review of Related Works
    - Research Gap Identification
3. **METHODOLOGY** (orange, knime)
    - Research Design
    - Data Collection Methods
    - Analysis Techniques (tell why other factor may affect others)
4. **RESULTS AND DISCUSSION**
    - Presentation of Findings (Include Tables and Figures)
    - Interpretation of Results
    - Discussion and Implications
5. **CONCLUSION**
    - Summary of Findings
    - Contributions to the Field
    - Limitations and Recommendations for Future Research

Acknowledgments (If Applicable)

- Acknowledge contributors, funding sources, or supporting institutions

References

Articles	Machine-Learning-Based Electric Power Forecasting[6]	Energy Demand Forecasting: Combining Cointegration Analysis and Artificial Intelligence Algorithm[7]	Electricity Demand Forecasting with Use of Artificial Intelligence: The Case of Gokceada Island[8]
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.

What features do I have?

	Name	Type	Role	Values
1	**Year**	**datetime**	**meta**	
2	Industrial	numeric	feature	
3	Transport	numeric	feature	
4	Agriculture	numeric	feature	
5	Non-Energy	numeric	feature	
6	Residential and Commercial	numeric	feature	
7	Population ('000 people)	numeric	feature	
8	GDP per Capita at 2015 Prices (RM)	numeric	feature	
9	GDP per Capita at Current Prices (RM)	numeric	feature	

Year	1978 - 2021
5 Sectoral energy Consumption	Ktoe
Population	1980 -2021
Real GDP and Nominal GDP	1980-2021 (RM million)

Dataset from st.gov.my
-Energy consumption
-Population

-GDP per Capita
-GDP per Capita at Current Prices

//We are doing the prediction, time series, and deep learning prediction
//we could learn whether the population and economy have effect or not on the energy consumption

3 types of models

Prediction model
- Random Forest
- Linear Regression
- Stochastic Gradient Descent

Time series model
- VAR model
- ARIMA model

Deep learning model
- ANN (Lots of paper do ANN)

Use Knime for better forecasting
ANN Model

Make box comparisons of all the values
Start from prediction

//All of the model will have a chapter 1.0 so that all of the model will have chances to explain itself.

//Presenting with Tableau

Literature Review

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

Author	Forecasting for	Method	Understanding
James Ogundiran, Ehsan Asadi,	Energy management and indoor environmental quality	Multi-layer perceptron(MLP) , convolutional	Use historical data and patterns to make predictions that help in optimizing building

Manuel Gameiro da Silva		neural network (CNN) , recurrent neural network (RNN)	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
Ghalehkhond	Energy Demand	They reviewed	It focuses on methods used to

abi, I., Ardjmand, E., Weckman, G. R., & Young, W. A.		traditional method (eg: econometric and time series models) and soft computing (eg: neural network and fuzzy logic)	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.

Author(s)	Forecasting for	Method	Variables
Abdulsalama and Babatundea	Electrical energy demand	ANN-RNN	Population, temperature, energy consumption, GDP
Kazemzadeh et al	Long-term electric peak load and demand	ANN-SVR-ARIMA-PSO	Load and energy data
Hao et al	Energy demand	Artificial Bee Colony Algorithm	GDP, industrial structure, urbanization rate, population, energy structure, CPI, and technological innovation
Bedi and Toshniwal	Electricity demand	ANN-RNN-SVR	Electricity consumption data set
Kaytez	Electricity consumption	LSSVM-ARIMA	Electricity imports and export, population, installed capacity, and gross electricity generation
Ramsami and King	Electricity demand	Adaptive network-based fuzzy inference system, ANN, RNN	Historical electricity data
Bendaoud et al.	Electrical energy demand	CNN	Load profile
Sen et al. [13]	Electricity consumption	ANN-SVM	Population, GDP, inflation rate, and unemployment rate
Tun et al.	Energy demand	RNN	Past energy usage data
Kolokas et al.	Energy demand and generation	Multi-step time series forecasting	Past energy data and weather forecasts
Al-Musaylh et al.	Electricity demand	Online sequential extreme learning	Climate variables\

		machine (OS-ELM)	
Moustris et al.	Load demand	ANN	Meteorological data, cooling power index (CP)
Bannor and Acheampong	Energy demand for Australia, China, France, India, and the USA	ANN, MLP optimization	Financial development, FDI, economic growth, industrialization, population, urbanization, energy price

RESULTS AND DISCUSSION

Findings

This study employed a combination of machine learning, time series, and deep learning models to forecast sectoral energy usage for Malaysia using a dataset spanning from 1978 to 2021. The analysis was conducted using KNIME and Orange, leveraging their powerful data processing and visualization capabilities. The models evaluated include **Random Forest**, **Linear Regression**, **Stochastic Gradient Descent (SGD)** for prediction tasks, **VAR** and **ARIMA** for time series forecasting, and **Artificial Neural Network (ANN)** for deep learning.

To ensure the reliability of the analysis, multiple performance metrics were applied, including **Mean Squared Error (MSE)**, **Root Mean Squared Error (RMSE)**, **Mean Absolute Error (MAE)**, **Mean Absolute Percentage Error (MAPE)**, **Percentage of Correct Direction (POCID)**, **Akaike Information Criterion (AIC)**, **Bayesian Information Criterion (BIC)**, and **R^2**. The results revealed that the performance of the models varied across sectors due to the distinct characteristics of energy consumption within each sector.

Evaluation Metrics

The performance of the models was evaluated using the following metrics, which were carefully selected to ensure a comprehensive assessment of accuracy, precision, and generalizability:

1. **Mean Squared Error (MSE):**

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

y_i: actual value (observed or true value).

$\hat{y}_i$: Predicted value (value predicted by the model).

n: Number of data points (total number of observations).

$\bar{y}$: Mean of actual values

This metric measures the average squared difference between the actual and predicted values. A lower MSE indicates a model with better performance, but it heavily penalizes larger errors due to the squared term, making it sensitive to outliers

2. **Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{MSE}$$

RMSE offers a more interpretable measure of model accuracy as it retains the same unit as the target variable. Lower RMSE reflects a model's ability to produce closer predictions to the actual values.

3. **Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

y_i: actual value (observed or true value).

$\hat{y}_i$: Predicted value (value predicted by the model).

n: Number of data points (total number of observations).

MAE measures the average magnitude of prediction errors, offering a straightforward interpretation of accuracy without considering the direction of errors.

4. **Mean Absolute Percentage Error (MAPE):**

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100$$

y_i: actual value (observed or true value).

$\hat{y}_i$: Predicted value (value predicted by the model).

n: Number of data points (total number of observations).

MAPE provides a percentage-based error measure, facilitating easier comparisons across models and sectors. However, it may be sensitive to small actual values.

5. **Percentage of Correct Direction (POCID):**

$$\text{POCID} = \frac{\text{Number of Correct Directions}}{n} \times 100$$

Number of Correct Directions = $(\hat{y}_i - y_{i-1}) \bullet (y_i - y_{i-1}) > 0$

This metric evaluates how well a model predicts the direction of change in the target variable, such as whether energy consumption increases or decreases. Higher POCID values indicate better performance in capturing trends.

6. **Akaike Information Criterion (AIC):**

$$\text{AIC} = 2k - 2\ln(L)$$

k**:** Number of model parameters (degrees of freedom in the model).

L: Maximum likelihood of the model (how well the model explains the observed data).

AIC balances the model's fit to the data against its complexity, penalizing models with a larger number of parameters. A lower AIC indicates a better model, striking a balance between simplicity and accuracy.

7. **Bayesian Information Criterion (BIC):**

$$\text{BIC} = k\ln(n) - 2\ln(L)$$

k**:** Number of model parameters (degrees of freedom in the model).

n: Number of observations.

L: Maximum likelihood of the model (how well the model explains the observed data).

BIC is similar to AIC but imposes a stricter penalty for model complexity, favoring simpler models, especially with larger datasets. A lower BIC indicates a model that performs well while remaining parsimonious.

8. **Coefficient of Determination (R²):**

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

y_i: actual value (observed or true value).

$\hat{y}_i$: Predicted value (value predicted by the model).

n: Number of data points (total number of observations).

$\bar{y}$: Mean of actual values

R^2 represents the proportion of variance in the dependent variable explained by the model. Values closer to 1 signify a better fit.

These metrics collectively provide a multidimensional evaluation of the models' accuracy, bias, and ability to generalize to unseen data. In this study, out-of-sample performance was prioritized, as it reflects the models' effectiveness in real-world applications.

Sectoral Analysis of Results

Industrial sector

For the industrial sector, energy consumption is strongly tied to economic growth and production output. Among the models tested, the Artificial Neural Network (ANN) achieved the best performance with an MSE of 30,528.616, RMSE of 174.724, and an R^2 value of 0.996. These metrics highlight ANN's ability to capture complex nonlinear relationships in the data, making it ideal for this sector. The model's high R^2 value indicates that it explains nearly all the variance in industrial energy demand. In contrast, Random Forest and Linear Regression models, while performing adequately, could not match the precision of ANN. This suggests that the industrial sector benefits from a model capable of adapting to dynamic and nonlinear trends.

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
Linear Regression	4084724.479	2021.070	1526.460	N/A	N/A	N/A	N/A	0.830
Stochastic Gradient Descent	2334707.778	1527.975	1331.028	N/A	N/A	N/A	N/A	0.903
Random Forest	3113481.295	1764.506	1282.092	N/A	N/A	N/A	N/A	0.871
VAR	N/A	2351.2	791.8	0.115	73.1	51.3	43.5	0.380
VAR (in-sample)	N/A	802.7	470.5	0.062	71.4	51.3	52.0	0.977
ARIMA (1,1,1)	N/A	1670.7	972.1	0.094	69.2	231.7	234.1	0.687
ARIMA (1,1,1) (in-sample)	N/A	891.2	417.5	0.064	62.8	706.6	711.9	0.973
ANN (Artificial Neural Network)	73183.26	270.5241	231.728	0.013418	N/A	N/A	N/A	0.989562

Transport sector

In the transport sector, energy usage is influenced by factors such as urbanization, population growth, and economic activities. The ANN again outperformed other models, achieving an MSE of 21,483.443, RMSE of 146.572, and an R^2 value of 0.998. These results underscore the model's robustness in predicting highly variable patterns in transportation energy demand. The ability of ANN to account for seasonal trends and external influences such as fuel prices and government policies makes it particularly suitable for forecasting in this sector.

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
Linear Regression	22802511.135	4775.197	3060.436	N/A	N/A	N/A	N/A	0.504
Stochastic Gradient Descent	10901125.347	3301.685	1954.373	N/A	N/A	N/A	N/A	0.763
Random Forest	7948491.337	2819.307	2226.535	N/A	N/A	N/A	N/A	0.827
VAR	N/A	3304.0	1346.8	0.112	64.7	44.6	45.3	0.189

VAR (in-sample)	N/A	1109.9	523.7	0.065	78.6	51.4	52.1	0.977
ARIMA (1,1,1)	N/A	2844.4	624.2	0.086	64.7	379.6	383.3	0.399
ARIMA (1,1,1) (in-sample)	N/A	1298.4	470.1	0.061	76.7	743.4	748.7	0.969
ANN (Artificial Neural Network)	75331.69	274.4662	269.1666	0.013056	N/A	N/A	N/A	0.992103

Non-Energy sector

For the non-energy sector, Random Forest demonstrated superior performance, with an MSE of 785,672.163, RMSE of 886.381, and an R^2 value of 0.928. The ensemble nature of Random Forest allowed it to effectively model interactions between variables and account for nonlinear effects, making it well-suited for this sector, where energy consumption patterns are less directly correlated with economic indicators.

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
Linear Regression	1306594.167	1143.064	699.254	N/A	N/A	N/A	N/A	0.881
Random Forest	785672.163	886.381	566.864	N/A	N/A	N/A	N/A	0.928
Stochastic Gradient Descent	870557.960	933.037	789.629	N/A	N/A	N/A	N/A	0.920
Hyper VAR	N/A	1947.2	752.6	0.195	58.8	46.2	47.0	0.752
Hyper VAR (in-sample)	N/A	826.6	257.8	0.152	54.8	51.5	52.2	0.952
Hyper ARIMA (1,1,1)	N/A	2195.5	1039.9	0.229	58.8	371.5	375.2	0.685
Hyper ARIMA (1,1,1) (in-sample)	N/A	930.4	217.4	0.150	58.1	717.1	722.4	0.939
ANN (Artificial Neural Network)	6349.828	79.68581	67.16513	0.009464	N/A	N/A	N/A	0.999356

Agriculture sector

In the agriculture sector, the ANN once again emerged as the most effective model. With an MSE of 8,756.838, RMSE of 93.578, and an R^2 value of 0.854, the model successfully captured the seasonal variability and weather-dependent nature of energy usage in agriculture. The high performance of ANN in this sector highlights its flexibility and ability to adapt to temporal fluctuations in energy demand.

Model	MSE	RMSE	MAE	MAPE	POCID	AIC	BIC	R^2
Linear Regression	128087.904	357.894	309.880	N/A	N/A	N/A	N/A	0.161
Random Forest	127956.843	357.711	307.872	N/A	N/A	N/A	N/A	0.162
Stochastic Gradient Descent	129053.328	359.240	312.026	N/A	N/A	N/A	N/A	0.155
Hyper VAR	N/A	213.1	215.7	0.198	50.0	46.0	46.7	-1.556
Hyper VAR (in-sample)	N/A	208.9	118.8	0.315	44.8	48.5	49.3	0.681
Hyper ARIMA (1,1,1)	N/A	231.2	158.6	0.192	50.0	349.6	353.3	-2.009
Hyper ARIMA (1,1,1) (in-sample)	N/A	228.0	68.4	0.291	53.3	417.5	421.7	0.620
ANN (Artificial Neural Network)	678.361457508712	26.04537305	24.2413263320923	0.027509257	N/A	N/A	N/A	0.988688108

Residential and 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

Random Forest	125984.523	354.943	295.415	N/A	N/A	N/A	N/A	0.981
Stochastic Gradient Descent	77249.620	277.938	225.498	N/A	N/A	N/A	N/A	0.988
Linear Regression	62423.436	249.847	209.697	N/A	N/A	N/A	N/A	0.990
Hyper VAR	N/A	336.0	206.8	0.039	82.4	49.6	50.4	0.894
Hyper VAR (in-sample)	N/A	180.2	90.9	0.032	88.1	53.4	54.1	0.995
Hyper ARIMA (1,1,1)	N/A	296.7	182.5	0.035	82.4	324.3	328.0	0.917
Hyper ARIMA (1,1,1) (in-sample)	N/A	221.1	114.6	0.038	83.7	582.6	587.9	0.993
ANN (Artificial Neural Network)	13873.71868	117.7867509	82.80065918	0.010563737	N/A	N/A	N/A	0.94924895

Discussion and Implication

The results indicate that the choice of the best model depends on the sector being analyzed and its specific energy consumption characteristics. ANN consistently demonstrated superior performance across sectors with complex and nonlinear relationships, such as industrial, transport, and agriculture. This underscores the value of deep learning models in energy forecasting applications where traditional models fall short. For sectors with more stable or linear patterns, such as non-energy and residential/commercial, simpler models like Random Forest and SGD performed effectively.

The inclusion of additional metrics such as AIC and BIC allowed for a nuanced evaluation of model complexity and fit, ensuring that the models selected are not only accurate but also generalizable. The high POCID values for the best-performing models in each sector further validate their capability to capture directional trends, which is crucial for policy formulation and energy resource management.

These findings provide a foundation for optimizing energy demand forecasting, supporting sustainable development goals such as SDG 7 (Affordable and Clean Energy). Future work should explore the integration of hybrid models to combine the strengths of multiple approaches, improving accuracy and robustness in energy forecasting applications.

Trash

Cara nak tgk prediction of ANN (2022 from -3) (2023 from -2) (2024 from -1)

Prediction model
- Random Forest
- Linear Regression
- Stochastic Gradient Descent

Industrial

Model	MSE	RMSE	MAE	R2
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Transport

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Agriculture

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Residential and commercial

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Stochastic Gradient Descent	77249.620	277.938	225.498	0.988
Linear Regression	62423.436	249.847	209.697	0.990

Time series model
- VAR model
- ARIMA model

Industrial

Model Evaluation - Orange

View Window Help

Evaluation Parameters

Number of folds: 9

Forecast steps: 2

Apply Automatically

	RMSE	MAE	MAPE	POCID	R^2	AIC	BIC
Hyper VAR	2510.0	1297.9	0.118	70.6	-0.379	45.3	46.0
Hyper VAR (in-sample)	802.7	470.5	0.062	71.4	0.977	51.3	52.0
Hyper ARIMA(1,1,1)	1623.6	954.9	0.085	70.6	0.423	374.3	377.9
Hyper ARIMA(1,1,1) (in-sample)	891.2	417.5	0.064	62.8	0.973	706.6	711.9

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Agriculture

Model Evaluation (1) - Orange

View Window Help

Evaluation Parameters

Number of folds: 5

Forecast steps: 1

Apply Automatically

	RMSE	MAE	MAPE	POCID	R^2	AIC	BIC
Hyper VAR	213.1	215.7	0.198	50.0	-1.556	46.0	46.7
Hyper VAR (in-sample)	208.9	118.8	0.315	44.8	0.681	48.5	49.3
Hyper ARIMA(1,1,1)	231.2	158.6	0.192	50.0	-2.009	349.6	353.3
Hyper ARIMA(1,1,1) (in-sample)	228.0	68.4	0.291	53.3	0.620	417.5	421.7

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Transport

Model Evaluation (2) - Orange

View Window Help

Evaluation Parameters

Number of folds: 9

Forecast steps: 2

Apply Automatically

	RMSE	MAE	MAPE	POCID	R^2	AIC	BIC
Hyper VAR	3304.0	1346.8	0.112	64.7	0.189	44.6	45.3
Hyper VAR (in-sample)	1109.9	523.7	0.065	78.6	0.977	51.4	52.1
Hyper ARIMA(1,1,1)	2844.4	624.2	0.086	64.7	0.399	379.6	383.3
Hyper ARIMA(1,1,1) (in-sample)	1298.4	470.1	0.061	76.7	0.969	743.4	748.7

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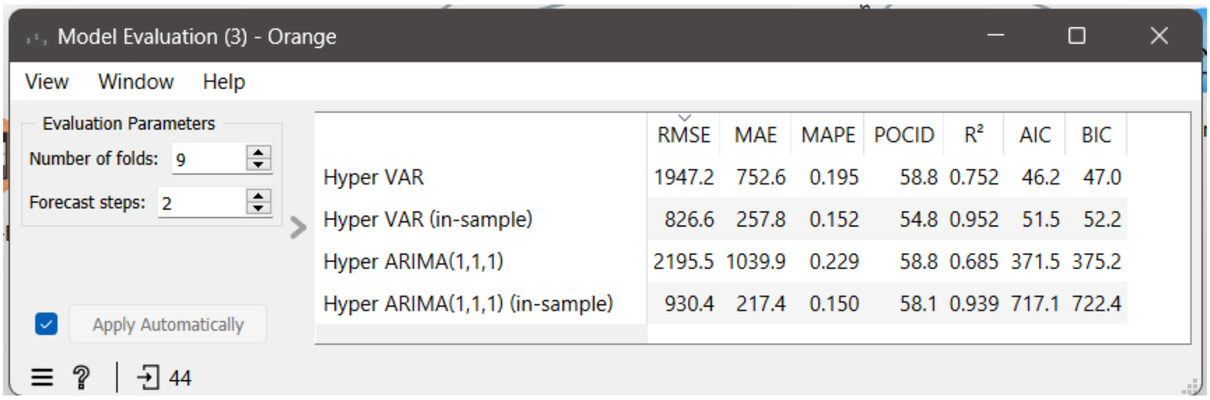
Non-Energy



	RMSE	MAE	MAPE	POCID	R^2	AIC	BIC
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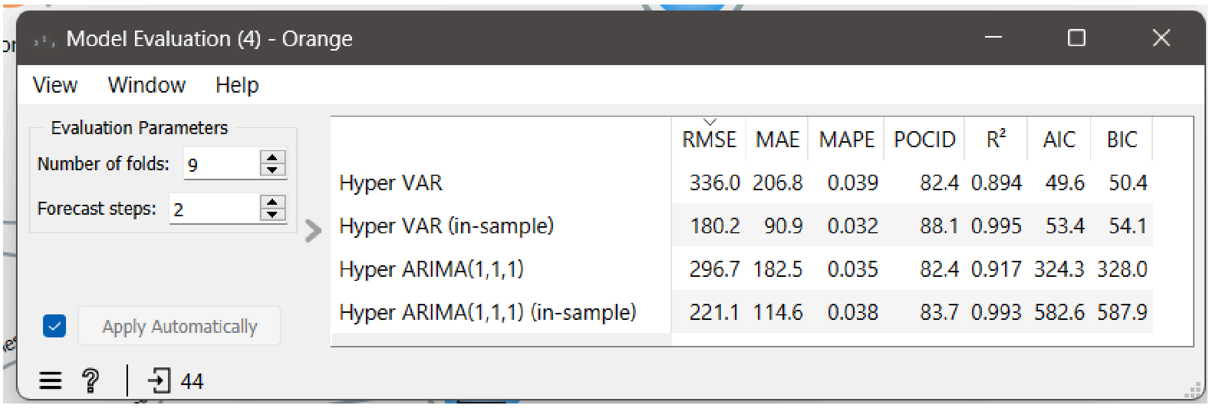
Residential and commercial

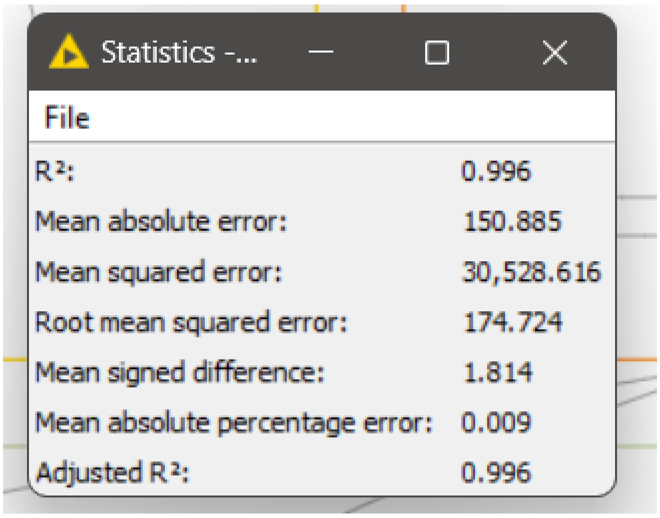


	RMSE	MAE	MAPE	POCID	R^2	AIC	BIC
Hyper VAR	336.0	206.8	0.039	82.4	0.894	49.6	50.4
Hyper VAR (in-sample)	180.2	90.9	0.032	88.1	0.995	53.4	54.1
Hyper ARIMA(1,1,1)	296.7	182.5	0.035	82.4	0.917	324.3	328.0
Hyper ARIMA(1,1,1) (in-sample)	221.1	114.6	0.038	83.7	0.993	582.6	587.9

Deep learning model

- ANN (Lots of paper do ANN)

  Industrial



R^2:	0.996
Mean absolute error:	150.885
Mean squared error:	30,528.616
Root mean squared error:	174.724
Mean signed difference:	1.814
Mean absolute percentage error:	0.009
Adjusted R^2:	0.996

  Transport

R^2:	0.998
Mean absolute error:	119.447
Mean squared error:	21,483.443
Root mean squared error:	146.572
Mean signed difference:	-119.447
Mean absolute percentage error:	0.005
Adjusted R^2:	0.998

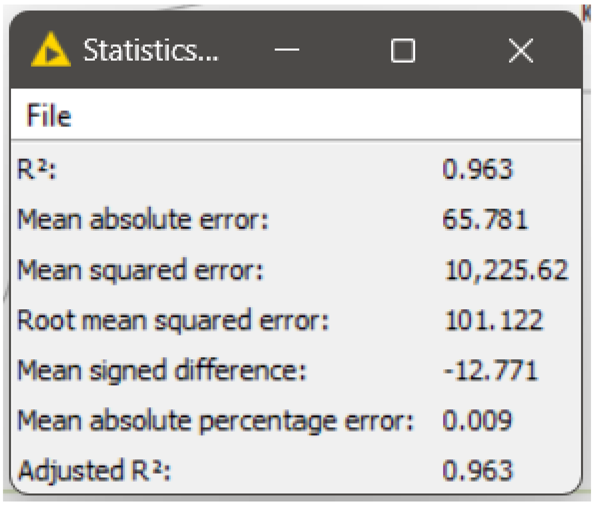
Non-Energy

R^2:	0.965
Mean absolute error:	476.533
Mean squared error:	346,008.323
Root mean squared error:	588.225
Mean signed difference:	-456.821
Mean absolute percentage error:	0.045
Adjusted R^2:	0.965

Agriculture

R^2:	0.854
Mean absolute error:	84.642
Mean squared error:	8,756.838
Root mean squared error:	93.578
Mean signed difference:	-76.152
Mean absolute percentage error:	0.099
Adjusted R^2:	0.854

Residential and commercial



Statistics...

File

R^2:	0.963
Mean absolute error:	65.781
Mean squared error:	10,225.62
Root mean squared error:	101.122
Mean signed difference:	-12.771
Mean absolute percentage error:	0.009
Adjusted R^2:	0.963

Which is more important?

- **Out-of-Sample (Not In-Sample) Performance** is more important for evaluating a model.
  - It tells you how well the model will perform on unseen, real-world data.
  - A model that performs very well on in-sample data but poorly on out-of-sample data is likely **overfitting** the training data. Overfitting means the model is too specialized to the training data and cannot generalize to new data.
- **In-Sample Performance** is still useful:
  - It helps you understand whether the model has learned the patterns in the training data.
  - Large discrepancies between in-sample and out-of-sample performance can indicate overfitting or underfitting:
    - **Overfitting**: Excellent in-sample performance but poor out-of-sample performance.
    - **Underfitting**: Poor performance on both in-sample and out-of-sample data.