Artificial Intelligence Models in Power Generation for Energy Consumption Prediction

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Abstract—**The incorporation of artificial intelligence (AI) into power-related applications signifies a new and unexplored domain in machine learning for predicting power generation. This novel method utilizes prediction models, often used in different fields, to predict energy-related patterns, providing a unique and specialized viewpoint. The synergy of academicians, AI experts, and industry professionals in the energy sector has resulted in the creation of customized AI models to optimize operational efficiency. By customizing various AI models to suit the distinct attributes of energy scenarios and datasets, these models are positioned to transform energy management methods. This study examines the utilization of AI models to enhance energy efficiency in power generation in Malaysia. The project seeks to predict future power consumption in various sectors, analyze growth rates, and identify sectors with investment potential by developing a Linear Regression model. In addition, a thorough power plan is developed using the estimated energy usage. A comparative analysis is performed to determine the most appropriate model for this particular scenario, which will improve decision-making in the energy sector. The results of this study present promising opportunities for further investigation. By broadening the study's focus to encompass a broader array of AI models and their assessment of performance, it is possible to gain useful insights for predicting power generation. Furthermore, the integration of real-time data streams and the inclusion of feedback loops in the AI models could improve their ability to adapt and increase their accuracy as time progresses.**

Keywords—artificial intelligence, artificial neural network, linear regression, energy efficiency, power generation

I. INTRODUCTION

In the current changing world, Artificial Intelligence is now a prominent topic and study around the globe. As AI technology flourishes, it is now being deployed and utilized in many fields, such as healthcare, finance, natural language processing and most importantly, IT [1]. As a sub-category and one of the products of modern technology, AI is now deployed into various aspects in the IT field [2]. As for this project, we are going to explore the usage of AI models in power generation specifically on energy efficiency [3]. Energy efficiency in power generation refers to the optimization of the total energy generation according to demand, making sure that the demand is met and reducing waste to the minimum [4]. AI models are deployed to study the patterns of the energy consumption of different sectors, then utilizing their strong processing power and learning capabilities to create and deploy a highly efficient energy usage plan to achieve the above goal [5]. However, it is also important that current AIs still require human intervention to manually feed data to them, review and decide whether the created model is fully applicable to their case. In thisproject, we will be exploring creating an AI model to tackle the energy efficiency problem in power generation [6].

When it comes to using AI for power related usage, it is not a very new concept for AI in machine learning history. As prediction models are used to predict almost anything in the world, the idea where it is used to predict energy related topics is not unique and niche [7]. There are studies conducted by other scholars, AI engineers working with related personnel in the energy industry to create AI models which helps them in their work [8]. As such, with different nature of the scenario as well as the variety of datasets, different AI models are selected and developed to assist them intheir work. However, as different AI models have different characteristics, it is also natural that there are different use cases for every AI model [9]. Some AI models might perform well on certain scenarios which match their characteristics and perform worse when the nature of the dataset as well as the scenario completely avoids the strengths of the AI model.

As power plant owners are receiving a steady payment for their power plants even though the power is not utilized, it takes a toll on the other people and business as they are the ones indirectly paying the electricity tariff via paying their electricity bills. Even though having more electrical reserve

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margin could prove useful when desperate times come, it comes with the cost of depleting natural resources that will only replenish in thousands of years. Furthermore, it also will cause more carbon dioxide and harmful substance emission and pollute the environment. The main objective of this study is to develop AI model to predict the yearly growth rate of energy usage in Malaysia.

The following is the structure of the remaining parts of this research article: Section 2 discusses the literature review; Section 3 discusses the research methodology; Section 4 offers the findings and discussion, and Section 5 is the conclusion.

II. Review of Literature

Artificial intelligence, or AI is defined as a form of intelligence that has a thinking processand reasoning, resulting in making a decision based on that train of thought [10]. [11] mentioned that this field does not only include the ability to analyse and understand things, but it also includes on creating entities that possess the ability to make decisions in an "intelligent" way to ensure that the outcome is the best in its situation. This ever-growing field is raking in millions and millions of money as diverse types of AI models are created, trained, and deployed into a multitude of fields. According to a survey conducted by the Pew Research Centre, over half of the responses are leaning towards the idea of current human jobs being taken over by non-human counterparts [12]. Besides, a quarter of responses think that newer, higher-paying jobs would appear in conjunction with the above statement and close to a half of the responses are leaning towards the statement where society will flourish more swiftly only when technology replaces humans in their current jobs. These findings proved a few points: people are more aware of the improvement and capabilities of the growing AI sector and begin to believe that they are the future. However, from the other perspective there are also some negative effects brought by the rapid growth of AI. There are several cases involving AI that have issues with philosophical and ethical aspects in terms of the actions of the AI [13]. [13] mentioned that the "trolley problem", which was a philosophical idea in the 1970s, is widely used as the main debate in AI's ethical system. Even after a long discussion and debate, there is no conclusion. The philosophers simply could not find the correct answer for this idea. This brings us to the issue of deploying AI in autonomous systems where it could cause fatal damage to other living beings in any situation where their decisions and actions endanger humans.

When it comes to power generation, energy sources come in different forms. Some energy sources include coal, fossil fuel, wind, geothermal heat, nuclear fission, etc. Energy sources are divided into two types: renewable energy sources and non-renewable energy sources. Among all these various sources, coal is the most prominent type of energy source across the world. In the global primary energy demand, coal contributes to around a quarter of it as well as close to 40% in the production of electricity. Even though coal is the most prominent form of energy source used in the entire world, it is also a type of non-renewable energy source and there are several negative impacts of using coal for power generation. [14] mentioned that sulphur dioxide, nitrogen oxides and particles are the main contaminants from burning coal for power. Even though the government has restrictions in terms of acceptable levels of emission, it still slowly brings negative effects, such as acid rain and air pollution.

In utilizing AI algorithms for power prediction, the Particle Filter (PF) technique is used to predict the future power consumption for every single day up to a year [15, 16]. This technique could be described as a recursive Bayes filter, where probabilities of multiple current beliefs are considered and updates the final outcome. Particle Filters, which are Bayesian filters, are used for state estimation in dynamic systems. In the context of energy prediction, particle filters can be employed to estimate the current state of an energy system based on observations. Furthermore, ANNs are advantageous for capturing intricate non-linear relationships, while particle filters excel in handling uncertainties and non-linear dynamics in energy-related predictions [17, 18]. Both methods contribute significantly to enhancing the accuracy and robustness of energy forecasting models. The Artificial Neural Network (ANN)-based predictive algorithm which takes inspiration from the natural constitution of the human brain is used [18]. This technique requires a data input to train the AI model to identify the patterns within the data and predict the output when new data with a high similarity is fed to their inputs subsequently.

III. Methodology

A. Data Preparation

The dataset is obtained via the government website where all data is public and open. The link is as follows: https://meih.st.gov.my/statistics. After selecting the desired range and parameters for the dataset, a word document could be downloaded directly from the website. However, there are graphs as well as other tables as visualization other than the raw data. Therefore, the document is cleaned up, removing any irrelevant and unused data to preserve only the crucial data.

B. Model Type

Linear Regression: The first model will be linear regression. As the historical dataset shows a linear trend, it will be suitable to predict future values. Besides, linear regression is also a model which is easy to interpret and explain due to its simplicity. The dataset only has several simple variables, such as average annual growth rate of primary energy supply, average annual growth rate of final energy consumption, final energy consumption, etc. which contributes more to the reason linear regression is suitable.

The dataset is loaded into the model. The dataset is split into training and testing data used to construct the model with a ratio of 4:1. Linear regression is being used; therefore, a linear line function is used as the basis of the model line. In this case, the math function which is typically used to plot linear lines is used: $y = mx + c$. The cost and the calculation of its derivatives are also declared to show the training cost of the model when it is completed.

IV. Results and Discussion

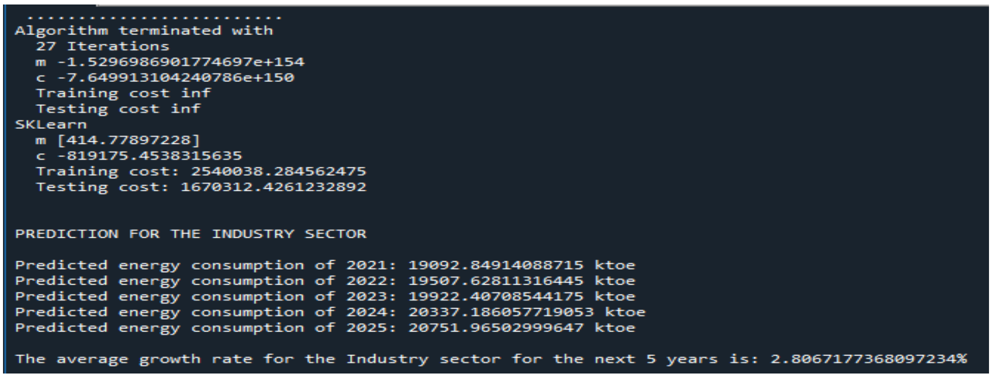
A. Single Run

The outputs for the predicted energy consumption for the industry sector, transport sector and agriculture sector are shown below in Fig. 1, Fig. 2 and Fig 3. As the result shows, it could predict the energy consumption for the future 5 years for each sector. Besides, the growth rate is also calculated for all five sectors and displayed together.

Fig. 1 shows the 5-year prediction for the industry sector and Fig. 2 shows the energy consumption in the industry sector. The result shows that the energy consumption as at year 1978 was 2273, and the highest so far was in 2018 with value of 19046 and the following year 2019 dropped to 18921. This is due to COVID-19 that made people stay at home on lockdown.

Fig. 3 shows the 5-year prediction for the transport sector and Fig. 4 shows the energy consumption in the transport sector. The result shows that the energy consumption as at year 1978 was 2135, and the highest so far was in 2019 with value of 25004 and the following year 2020 dropped to 18660. This is due to COVID-19 that made people stay at home on lockdown and therefore the rate of transportation reduced.

Fig. 5 shows the 5-year prediction for the agriculture sector and Fig. 6 shows the energy consumption in the agriculture sector. The result shows that the energy consumption as at year 1978 was 0, and in the year 2010, the value got to an high point of 1074, followed by the value of 1021 in 2018 and after that it dropped to the lowest low in 10 years which was 867 in 2020. This is due to COVID-19, which paused agriculture activities for a long time.



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...........................
Algorithm terminated with
  27 Iterations
  m -1.5296986901774697e+154
  c -7.649913104240786e+150
  Training cost inf
  Testing cost inf
SKLearn
  m [414.77897228]
  c -819175.4538315635
  Training cost: 2540038.284562475
  Testing cost: 1670312.4261232892


PREDICTION FOR THE INDUSTRY SECTOR

Predicted energy consumption of 2021: 19092.84914088715 ktoe
Predicted energy consumption of 2022: 19507.62811316445 ktoe
Predicted energy consumption of 2023: 19922.40708544175 ktoe
Predicted energy consumption of 2024: 20337.186057719053 ktoe
Predicted energy consumption of 2025: 20751.96502999647 ktoe

The average growth rate for the Industry sector for the next 5 years is: 2.8067177368097234%
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Fig. 1. Five Years Prediction for the Industry Sector

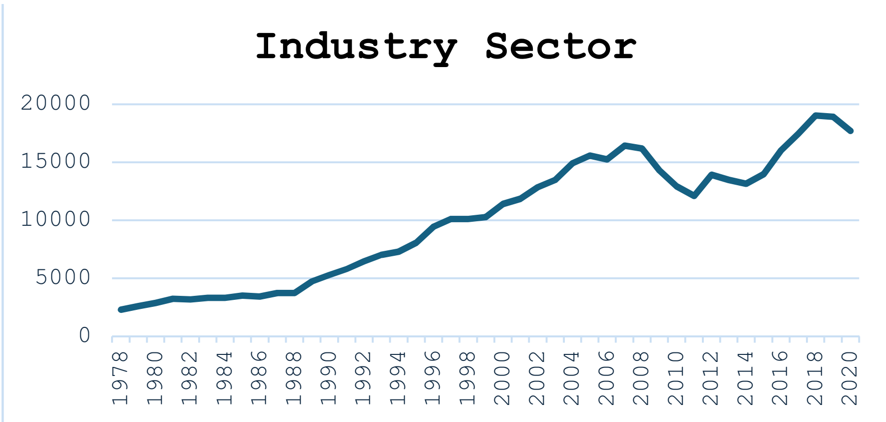
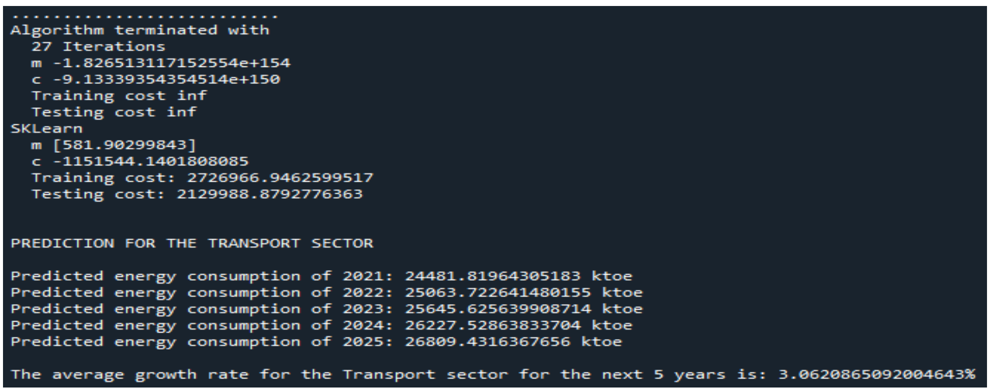


Fig. 2. Result for Energy Consumption for Industry Sector



```
...........................
Algorithm terminated with
  27 Iterations
  m -1.826513117152554e+154
  c -9.13339354354514e+150
  Training cost inf
  Testing cost inf
SKLearn
  m [581.90299843]
  c -1151544.1401808085
  Training cost: 2726966.9462599517
  Testing cost: 2129988.8792776363


PREDICTION FOR THE TRANSPORT SECTOR

Predicted energy consumption of 2021: 24481.81964305183 ktoe
Predicted energy consumption of 2022: 25063.722641480155 ktoe
Predicted energy consumption of 2023: 25645.625639908714 ktoe
Predicted energy consumption of 2024: 26227.52863833704 ktoe
Predicted energy consumption of 2025: 26809.4316367656 ktoe

The average growth rate for the Transport sector for the next 5 years is: 3.0620865092004643%
```

Fig. 3. Five Years Prediction for the Transport Sector

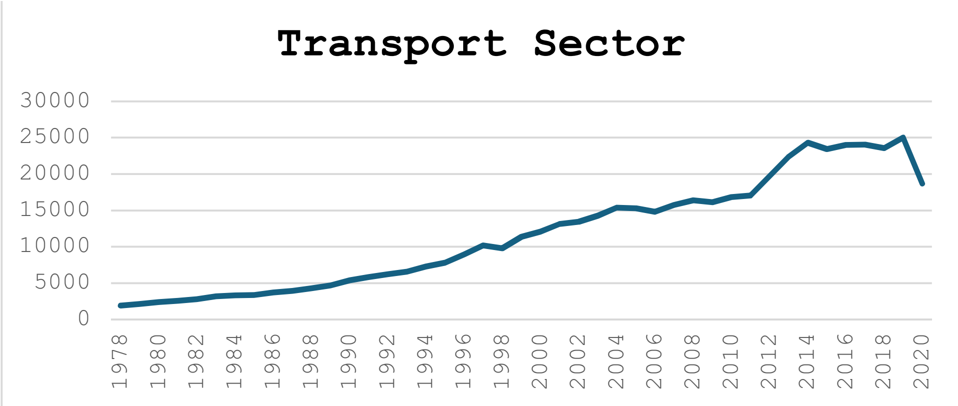
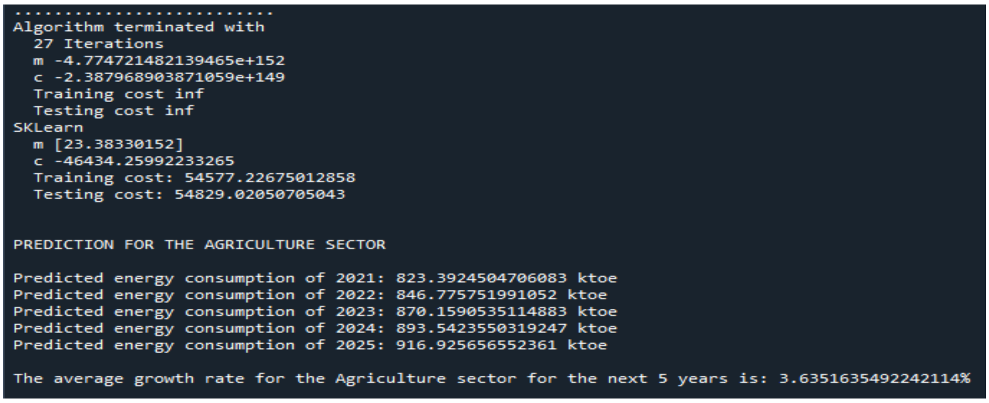


Fig. 4. Result for Energy Consumption for Transport Sector



```
..........................
Algorithm terminated with
  27 Iterations
  m -4.774721482139465e+152
  c -2.387968903871059e+149
  Training cost inf
  Testing cost inf
SKLearn
  m [23.38330152]
  c -46434.25992233265
  Training cost: 54577.22675012858
  Testing cost: 54829.02050705043


PREDICTION FOR THE AGRICULTURE SECTOR

Predicted energy consumption of 2021: 823.3924504706083 ktoe
Predicted energy consumption of 2022: 846.775751991052 ktoe
Predicted energy consumption of 2023: 870.1590535114883 ktoe
Predicted energy consumption of 2024: 893.5423550319247 ktoe
Predicted energy consumption of 2025: 916.925656552361 ktoe

The average growth rate for the Agriculture sector for the next 5 years is: 3.6351635492242114%
```

Fig. 5. Five Years Prediction for the Agriculture Sector

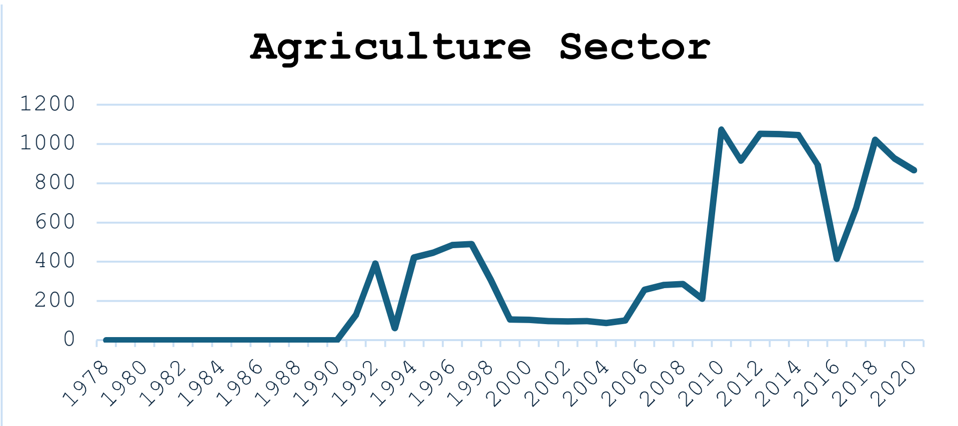


Fig. 6. Result for Energy Consumption for Agriculture Sector

The figures above are the outputs for the predicted energy consumption for three sectors. As the result shows, it could predict the energy consumption for the future 5 years for each sector. Besides, the growth rate is also calculated for three sectors and displayed together.

B. Multiple Runs

For testing purposes, another two more runs are done with similar settings. This is to determine the accuracy and stability of the training for predictions. The table below shows the results for the second and third run together with the first for comparison. The m values are taken from the regression line trained using the scikit-learn module, rounded to four significant digits for ease of comparison. This is also due to the variable "m" is the gradient of the regression line.

TABLE I. COMPARISON FOR VALUE OF "M"

	First run	Second run	Third run
Industry	414.7890	401.6458	398.8290
Transport	581.9030	603.9452	610.8696
Agriculture	23.3833	23.6716	24.4033

TABLE II. COMPARISON OF SUGGESTED TOTAL SUPPLY

	First run	Second run	Third run
2021	70956.80	71208.78	70706.95
2022	72638.68	72896.42	72391.91
2023	74320.57	74584.07	74076.87
2024	76002.45	76271.71	75761.83
2025	77684.33	77959.36	77446.79

As shown in Table I, the difference in the value of m is close to each other, the difference is just the scale of difference between runs for each sector. For example, the difference between the highest and lowest value for agriculture is 1.02, while the difference for transport sector is 28.9666. The average ratio difference for the m values between the transport sector and agriculture is 25.1437. However, there are also several factors to take account of, such as dataset, size of data, etc.

As gradient descent is the core of this methodology, the variance in m would be the best factor to determine the accuracy and stability of the model's performance. Overall, the model takes around 15 seconds for it to finish a complete run. The time can be further reduced if the output to display the changes in every iteration of the model is turned off, as generating the results will take extra time. However, having the results generated will allow the users to clearly view the difference in iterations as well as allowing easier projection of the model. In terms of accuracy and stability, the results shown in the previous sections contribute positively to these aspects. The variance in the difference between different variables throughout the three runs is exceedingly small, therefore could be categorized as the acceptable margin of variance.

V. CONCLUSION

In conclusion, an AI model using the linear regression model is trained to anticipate the total energy consumption of five Malaysian sectors from 1978 to 2020 during the next decade. The expected data allows it to determine the growth rate and average growth rate for all three sectors, as well as the highest and lowest growth rates and the best sector to invest in. Also, the model can aggregate all three sector predictions and build power plans based on them. Thus, the model achieves its three key goals. It can forecast energy consumption for the sectors highlighted, their growth rates, and a power plan to guarantee enough power is generated for daily usage and unforeseen events. This study provides the groundwork for studying artificial intelligence in Malaysian power generating. Future studies can incorporate other AI models, assimilate real data streams, and create a hybrid model that combines Linear Regression and Artificial Neural Networks. Further research might analyse how renewable energy and energy storage affect future power generation projections. These technologies will give Malaysian energy providers advanced forecasting skills, ensuring a reliable power grid.

ACKNOWLEDGMENT

This work is funded by the Internal Grant of Sunway University Malaysia with the grant code GRTIN-KSGS(02)-DCIS-08-2023.

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