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Predictive Model for Electric Vehicle Reconfiguration in Malaysia

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Abstract

Electric vehicles (EVs) adoption in Malaysia was initially slow due to cheap gasoline and limited infrastructure. However, recent government efforts to promote sustainable transport have boosted EV sales, with 6,617 units sold in the first half of 2024. The government aims for net-zero emissions by 2050 and 1.5 million EVs on the road by 2040. Total Cost of Ownership (TCO) tools help fleet managers analyze vehicle expenses to choose cost-effective options, improve budgeting, track sustainability goals, and ensure compliance with environmental regulations. A locally customized tool is needed to account for unique factors like local prices, operational costs, government incentives, tax regulations, and customer financial behaviors. Machine learning is implemented using a predictive model to estimate the TCO based on those factors. The preliminary results of the predictive model will forecast cumulative costs, potential carbon emission reductions and recommend car models when transitioning from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) for the Malaysian market, providing accurate and reliable decision-making support.

Keywords
Electric vehicle, Automotive, Machine learning, Predictive model, Total Cost of Ownership.

1. Introduction

The electric vehicle (EV) market has grown quickly in recent years due to higher demand and policies to reduce emissions (Chakraborty et al. 2024). This growth is expected to continue with more investments in charging stations and better battery technology. Initially, the adoption of the EV landscape in Malaysia was slow due to low gasoline prices and limited infrastructure (Junid et al. 2023). However, recent years have seen a shift towards more proactive policies and initiatives to enhance the EV ecosystem by reducing carbon emissions and promoting sustainable transportation. The Malaysian Automotive Association (MAA) held a press conference to announce the sales of new motor vehicles in the first half of 2024. According to MAA's data, 6,617 full-electric vehicles (EVs) were sold in Malaysia during this period, representing a 112% increase—more than double the number sold in the same period last year (Samuel, 2024). Figure 1 shows the predicted battery electric vehicles sales for Malaysia market until 2029.

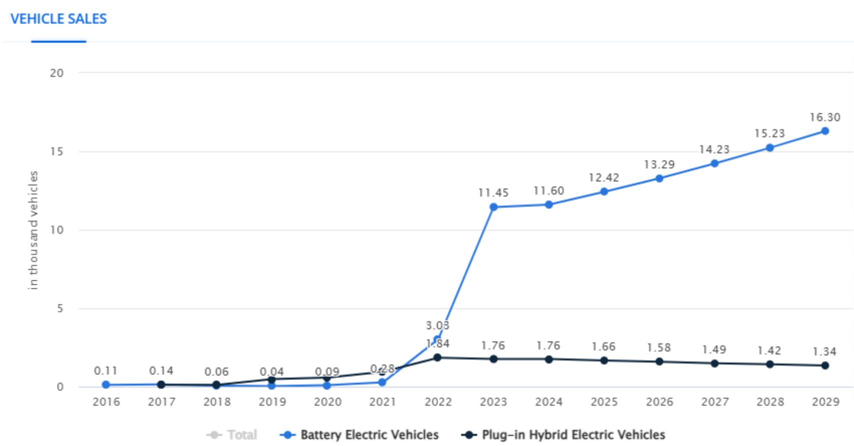

Figure 1. EV Unit Sales in Malaysia Market (Source: Statista Market Insights, 2025)

1.1 Objectives

The study aims to identify the key input parameters required for Total Cost of Ownership (TCO) conversion tools. By determining the essential TCO inputs, the research ensures the collection of relevant data, while the ANN model leverages machine learning to enhance the reliability of predictions. Finally, real-data validation will measure the model's effectiveness, ensuring its practical applicability in optimizing TCO calculations for vehicles in Malaysia.

2. Literature Review

a) Total Cost of Ownership (TCO)

The total cost of ownership (TCO) of vehicles is an important factor in deciding whether different energy options for passenger cars are affordable and sustainable (Cox et al. 2020). The evaluation of TCO for alternative fuel options involves a well-to-wheel analysis to assess both environmental and economic impacts (Langshaw et al. 2020). A study in France compared electric and diesel cars using a model that included costs like purchase price, maintenance, and energy use (Desreveaux et al. 2020). The study showed the financial aspects of owning an EV over time and gave a clear cost comparison with diesel cars. This helps decision-makers understand the long-term costs or savings of switching to EVs.

A researcher in India compared the total cost of ownership (TCO) for electric, petrol, diesel, and compressed natural gas (CNG) vehicles (Kumar et al. 2020). They found that EVs sometimes had a higher cost per kilometer due to factors like high upfront prices, limited charging stations, and energy costs. This shows that TCO comparisons need to consider local factors, as costs vary by region. Another study in France expanded this by analyzing Hybrid Electric Vehicles (HEVs), EVs, and Automated Electric Vehicles (AEVs). They looked at fuel use, maintenance, and depreciation to show how different vehicle types perform. Their research highlights the importance of including new technologies, as AEVs may have unique costs because of their self-driving features (Mitropoulos et al. 2021).

Jefferies et al. (2020) took a different approach by using discrete-event simulation to study the TCO of electric bus systems, factoring in not only vehicle costs but also infrastructure, energy demand, and staffing. This method emphasizes the complexity of public transportation systems and how the TCO is influenced by operational factors, particularly for large fleets where energy and labor costs are significant. Mohammadzadeh et al. (2021) participated in the discussion by examining pricing and complimentary periodic maintenance within an electric-and-fuel automotive supply chain. Their research emphasizes how service models, such as free maintenance, can substantially impact the total cost of ownership (TCO) for electric fuel hybrids, demonstrating that strategic pricing and service offerings can enhance the financial appeal of EVs over time.

Moreover, there was a study focused on how Vehicle-to-Grid (V2G) features in EVs affect total ownership costs (TCO). V2G lets EVs send energy back to the grid, offering owners ways to save or earn money. The research showed that these features can reduce TCO by allowing owners to use their vehicle's battery for energy market opportunities (Huber et al. 2021). The study from Hao et al. (2020) examined the cost-effectiveness of range for Plug-in EVs (PHEVs) based on different consumer behaviors. It showed that driving habits and charging preferences significantly impact total ownership costs (TCO), highlighting the importance of considering individual user scenarios when assessing the economic benefits of PHEVs.

Afraah et al. (2021) focused on electric motorcycles in Indonesia, comparing them to traditional motorcycles. Their TCO model included key factors like battery replacement costs, which are especially critical for smaller vehicles with shorter battery lifespans. This underscores the importance of battery durability in assessing the financial feasibility of EVs, particularly in emerging markets where consumers are highly cost-sensitive.

Another study analyzed California's plan to roll out five million Plug-in EVs, highlighting the challenges of large-scale EV adoption due to technological uncertainties and market changes. This research offers insights into the complexities of widespread electrification efforts and the role of TCO in policy and consumer choices (Chakraborty et al. 2021). In another analysis, researchers compared the TCO of gasoline, hybrid, and EVs across 14 U.S. cities. They found that location, energy prices, and driving habits significantly affect the cost-effectiveness of different vehicle types, showing that the TCO of EVs depends heavily on context. Table 1 below shows the parameters used in previous studies to evaluate the total cost of ownership (TCO) for electric vehicles.

Table 1. Summary of parameters for TCO calculation from the previous study

Author/s, Year	Research Objective	Place of Research	Parameter
Desreveaux, et al. 2020	Introduced a techno-economic model comparing electric and diesel vehicles	France	1. Purchase price 2. Maintenance 3. Energy costs
Kumar, P., & Chakrabarty, S., 2020	Created a model comparing the TCO of electric, petrol, diesel and compressed natural gas (CNG)	India	1. Upfront costs 2. Charging 3. Infrastructure 4. Energy prices
Mitropoulos et al. 2021	Studying Hybrid Electric Vehicles (HEVs), EVs, and Automated Electric Vehicles (AEVs)	France	1. Fuel consumption 2. Maintenance 3. Depreciation
Jefferies, D., & Göhlich, D., 2020	Emphasizes the complexity of public transportation systems and how the TCO is influenced by operational factors, particularly for large fleets where energy and labor costs are significant.	Germany	1. Vehicle costs 2. Infrastructure 3. Energy demand 4. Staffing
Mohammadzadeh et al. 2021	Exploring pricing and free periodic maintenance in an electric-and-fuel automotive supply chain.	Iran	1. Vehicle price 2. Maintenance
Huber et al. 2021	Focused on the Vehicle-to-Grid (V2G) capabilities of EVs and their impact on TCO.	Belgium	1. Vehicle's energy 2. Storage capabilities

Author/s, Year	Research Objective	Place of Research	Parameter
Hao et al. 2020	To compare the comprehensive TCO among ICEVs and different types of PEVs and to estimate the lowest-TCO PEV electric ranges in different cities in China	China	1. Cost-effectiveness for Plug-in EVs (PHEVs) 2. Consumer behaviors
Afraah et al. 2021	Comparing electric motorcycles with no conventional motorcycles in Indonesia	Indonesia	1. Battery replacement costs 2. Cost-sensitive consumers
Chakraborty et al. 2021	Detailed analysis of California's EV transition, focusing on the costs of deploying five million Plug-in EVs	California	1. Policy 2. Consumer behaviour
Woody et al. 2024	Compared with the TCO of gasoline, hybrid and EVs across 14 U.S cities	USA	1. Environmental factors 2. Regional energy prices 3. Driving habits

TCO assists the transition from ICEVs to EVs by evaluating financial and environmental benefits, improving budgeting and planning accuracy, tracking carbon emissions to meet sustainability goals, and improving operational efficiency. TCO is being used by organizations because it provides a comprehensive, data-driven analysis of all costs and benefits associated with various vehicle options, allowing fleet management to improve transparency and accountability, manage financial risks, ensure compliance with environmental regulations, and demonstrate cost savings and emissions reductions.

However, the available TCO tools are unsuitable for the Malaysian market because they are typically designed with general assumptions, data, and parameters relevant to other countries or regions, leading to irrelevant insights for local users. Aligning with digitalization, implementing a machine learning model in the tool will make it more adaptive. This is done by allowing it to learn data (local vehicle prices, vehicle specifications, component/spare part prices, fuel costs, electricity rates, government incentives, tax regulations, insurance costs, maintenance costs, charging station costs, driving behaviors, and other relevant data) from any automotive company. Once trained, the model will be able to forecast the total costs and carbon emission reductions over a period.

b) Carbon emissions

The combustion of fossil fuels releases carbon dioxide (CO_2), a major contributor to atmospheric changes and climate disruption. Growing concerns about environmental protection and the harmful impact of greenhouse gas emissions, especially within the automotive sector, have sparked increased interest in exploring creative and innovative solutions to reduce carbon dioxide (CO_2) emissions from various sources. Table 2 below shows the parameters used in previous studies to evaluate the carbon emission of various types of vehicles.

Table 2. Summary of parameters for Carbon emissions from previous researchers

Author/s, Year	Research Objective	Parameters
Udoh et al., 2024	Application of Machine Learning to Predict CO_2 Emissions in Light-Duty Vehicles	1. Engine power 2. fuel consumption comb (L/100 km) 3. target variable: CO_2 emissions (G/Km), 4. engine capacity (L) 5. manufacturer 6. model 7. transmission 8. fuel type 9. powertrain

Author/s, Year	Research Objective	Parameters
Al-Nefaie & Aldhyani, 2023	Predicting CO_2 Emissions from Traffic Vehicles for Sustainable and Smart Environment Using a Deep Learning Model	1. Model 2. vehicle class 3. engine size 4. cylinders 5. transmission 6. fuel type 7. fuel consumption city 8. fuel consumption highway 9. fuel consumption comb (L/100 km) 10. fuel consumption comb (mpg) 11. CO_2 emission(g/km)
Satpute et al., 2023	Predictive Modeling of Vehicle CO_2 Emissions Using Machine Learning Techniques: A Comprehensive Analysis of Automotive Attributes	1. Car make 2. car model 3. car class 4. engine size 5. cylinders 6. transmission 7. fuel type 8. fuel consumption measurements (measured in L/100 km) for both city and highway 9. fuel efficiency
Maino et al., 2021	A deep neural network-based model for the prediction of hybrid electric vehicles carbon dioxide emissions	1. Engine displacement 2. motor peak power 3. power-to-energy ratio 4. front final drive speed ratio 5. rear final drive speed ratio 6. motor generator speed ratio 7. discharge c-rate 8. charge c-rate
Safari et al., 2024	Advanced Predictive Modeling of Pollutant Gas Emissions in the Automotive Industry based on Machine Learning	1. Cylinders 2. fuel consumption city 3. fuel consumption highway 4. fuel consumption combined 5. fuel consumption combined 6. CO_2 emission 7. engine size
Dr. Ashok K & Palem Rithishbrahma (2024)	Prediction of Vehicle Carbon Emission using Machine Learning	1. Engine size 2. Cylinders 3. fuel consumption combination 4. CO_2 emission

Electric vehicles (EVs) have significantly lower carbon emissions compared to traditional vehicles, however, they are not entirely emission-free (Shao & Zheng, 2023). Carbon emissions can occur during electricity generation, depending on the energy sources used to charge the vehicles. EVs can contribute to carbon emissions, particularly during charging. Carbon emission can be calculated by identifying the specific activity (e.g., driving a car, using electricity, or manufacturing a product), and then apply the corresponding emission factor. This coefficient quantifies the emissions per unit of activity. Equation 1.1, taken from (World Resources Institute & World Business Council for Sustainable Development, 2004), is the standard formula in all major carbon accounting frameworks.

$$kg\ CO_2e = Activity\ Data \times Emission\ Factor(kg\ CO_2/unit) \tag{1.1}$$

c) Predictive model in automotive

Predictive modeling benefits the automotive industry in several ways, including estimating emissions and enhancing vehicle performance. By utilizing advanced machine learning methods, these models support better decision-making, enhance safety, and drive sustainability efforts. A review was conducted by Khurana et al. (2020) regarding the commonly used predictive model for forecasting engine emissions using machine learning starting from 2008 to 2020 as shown in Figure 2 below.

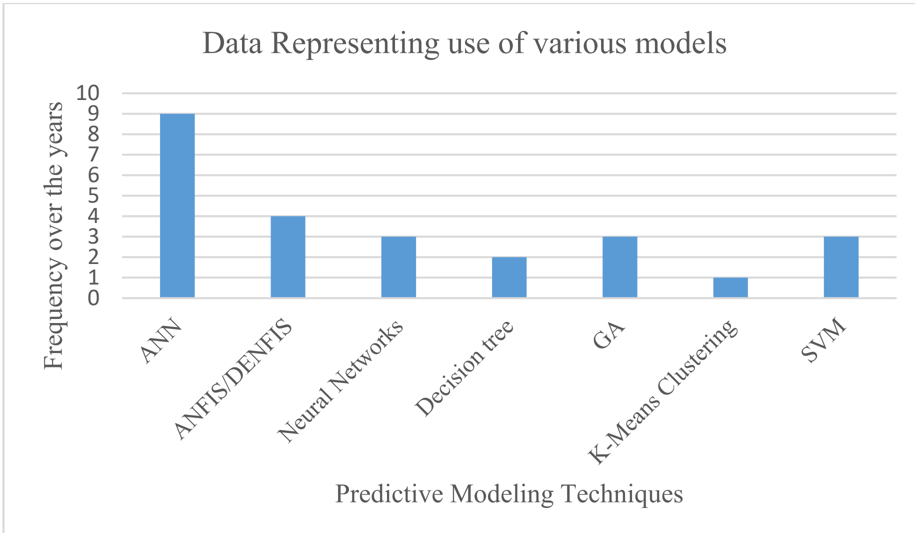

Figure 2. Predictive modeling techniques were commonly used from 2008 to 2020 (Khurana et al. 2020)

Machine learning models have been developed to predict CO_2 emissions from vehicles, utilizing features such as engine size and fuel consumption metrics. A study achieved an impressive R^2 of 0.991, indicating high accuracy in emissions forecasting (Safari et al. 2024). This predictive capability is crucial for informing policies that aim to reduce environmental impact and enhance fuel efficiency.

Predictive frameworks have been employed to forecast the adoption rates of Euro-compliant, battery-electric, and autonomous vehicles. The modified Gaussian model indicated rapid initial adoption, while the Logistic model suggested sustained growth over time (Alatawneh & Torok, 2024). These insights assist stakeholders in strategic planning and understanding market trends.

Another predictive model was developed using a federated unsupervised learning-based (FeduLPM), to control vehicle speed by analyzing local accident data, considering factors like weather and location, achieving 96.7% accuracy in preventing accidents in customizable automotive variants. This approach enhances road safety by providing tailored speed limits based on real-time conditions (Samsudeen & Kumar, 2023). This model exemplifies the potential of predictive analytics in accident prevention and driver assistance.

As electric vehicles grow in popularity, accurately predicting car prices has become crucial for buyers and businesses. This study uses machine learning, specifically linear regression, to predict car prices. It uses a detailed dataset with information like make, model, year, and mileage. The research includes data cleaning, feature engineering, and model tuning to improve accuracy. The model's performance is checked using R-squared and Mean Squared Error (MSE). The study also looks at ways to make predictions even more accurate with advanced methods (He, 2024). Table 3 below shows the predictive models used in previous studies and their evaluation metrics.

Table 3. Predictive model used in the previous study

(Authors, Year)	Algorithm	Evaluation Metric	Model Performance
(Safari et al. 2024)	Linear regression	R-squared	0.991
(Samsudeen & Kumar, 2023)	Random forest	Accuracy	96.7%
(He, 2024)	Linear regression and decision tree	Mean Squared Error (MSE) and R-squared	54.23 & 0.63, 26.40 & 0.82
(Udoh et al. 2024)	Decision tree	Mean Absolute Error (MAE)	2.20
(Maino et al. 2021)	cNN and rDNN	R-squared	0.918
(Al-Nefaie & Aldhyani, 2023)	Bidirectional LSTM (BiLSTM)	R-squared	0.9378
(Alam et al. 2025)	Multilayer perceptron (MLP)	R-squared	0.9938
(Satpute et al. 2023)	Linear regression, decision tree, random forest and support vector machine	MSE	30.00, 14.27, 12.32 and 406.86

3. Methods

Stage I: Identifying Parameters

The input parameters for Total Cost of Ownership (TCO) tools analysis are critical for accurately assessing the financial implications of conversion from ICEVs to BEVs. A tool tailored to the Malaysian market is required to account for unique factors such as local vehicle prices, vehicle specifications, component/spare part prices, fuel costs, electricity rates, government incentives, tax regulations, insurance costs, maintenance costs, charging station cost, and driving behaviors, all of which have a significant impact on the total cost and carbon emissions associated with owning and operating vehicles. A locally tailored tool proposed here would provide more accurate, reliable, and relevant insights for Malaysian vehicle fleet management, enabling them to make better decisions that align with regional economic, environmental, and regulatory contexts. Table 4 presents the parameters for the web application interface.

Table 4. Parameters for TCO tool.

Parameter	Definition
TCO Tool Inputs	Adjustable parameters in a TCO tool that allow users to modify inputs (e.g., fuel prices, interest rates, loan terms, vehicle costs) to see how changes impact the overall costs.
Upfront Costs	The initial expenses paid to acquire the vehicle, including the purchase price, taxes, and any other fees paid at the time of purchase. These costs are incurred once, at the start.
Annual Operating Costs	The recurring expenses are incurred each year to maintain and use the vehicle. This includes fuel costs, maintenance costs, insurance, registration fees, and any annual taxes. These costs vary depending on the vehicle's fuel efficiency, type of fuel used, and maintenance requirements.
Financing Conditions	The terms under which a vehicle is financed include down payment (initial amount paid upfront), interest rate (percentage charged on borrowed amount), and loan length (duration of repayment period).
Cumulative Cost	Referring to the total amount of money spent over a period, it combines all individual costs that have been incurred up to that point. It is calculated by adding the costs from each year (or period) to the total costs from all previous years.
Cumulative Cost Curve	A visual representation that shows the total accumulated costs of owning and operating a vehicle over time. This curve adds each year's costs to the previous years' costs to illustrate how total expenses evolve.

Parameter	Definition
Breakdown of TCO	Referring to the detailed analysis of all the costs associated with owning and operating a vehicle over a specific period. TCO includes all expenses beyond the initial purchase price to provide a comprehensive view of the total financial impact.
Subsidy	A financial incentive is provided by the government or another organization to reduce the cost of purchasing a vehicle. Subsidies lower the amount that needs to be borrowed, reducing the TCO.
Tax Reductions	Reductions or exemptions on taxes applied to the vehicle, which can decrease overall upfront and operating costs, making the vehicle more competitive in terms of TCO.
Carbon Emission Prediction	Estimation of the total amount of carbon dioxide (CO2) and other greenhouse gases a vehicle is expected to emit over a specific period or distance. Important for understanding environmental impact.

Stage II: Developing the model

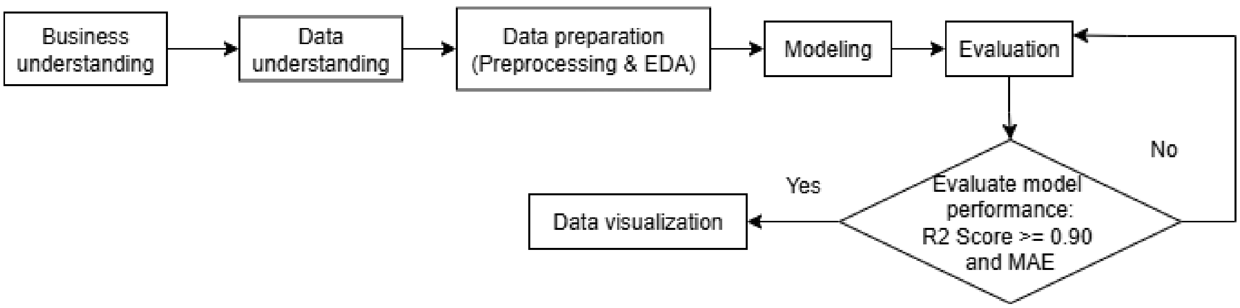

Figure 3. Predictive model process flow development

As shown in Figure 3, the model development consists of multiple stages, each of which is discussed in detail in the section below:

a) Business understanding

The first and foundational stage in any data project is to thoroughly understand the business objective. This involves engaging with stakeholders, defining the problem clearly, and identifying the goals of the project. A clear business understanding helps guide the data collection and modeling processes. It answers questions like: What decisions will the model influence? What are the key metrics for success? Who are the users of the model output? Without this clarity, technical work may miss the mark in addressing real business needs.

b) Data understanding

Once the business goal is clearly defined, the next step is to gather and understand the data. This stage focuses on collecting initial data, describing its characteristics, and identifying any issues that might impact model development. This stage is about transforming raw data into a format suitable for modeling.

c) Data preparation

A key part of this phase is Exploratory Data Analysis (EDA). EDA involves visualizing distributions, identifying missing or inconsistent values, and spotting patterns or anomalies in the data. Tools like histograms, boxplots, and correlation matrices are commonly used to gain insights. Often considered the most time-consuming step, data preparation includes tasks such as cleaning, feature engineering, encoding categorical variables, and splitting data into training and testing sets. This step ensures the model will learn from high-quality and representative inputs. Feature engineering is a creative and technical process where new variables are derived from existing ones to better capture patterns in the data. Normalization or standardization is often necessary for numerical features, especially if you're using algorithms sensitive to scale like k-nearest neighbors or neural networks.

d) Modeling

Modeling is the stage where machine learning algorithms are applied to the prepared data to find patterns and make predictions. In this process flow, the modeling process uses Python, a popular programming language for data science due to its rich ecosystem of libraries like scikit-learn, TensorFlow, and PyTorch. The choice of algorithm depends on the problem type and data characteristics. During this stage, various models are trained, compared, and tuned.

e) *Evaluation*
The final stage involves assessing the model's performance using various metrics. In the context of this project, the goal is to achieve a model accuracy with R^2 Score ≥ 0.90. However, accuracy is not the only metric to consider, other measures like mean absolute error (MAE) might be more appropriate to evaluate the model error. Model evaluation is performed on a separate test dataset that was not used during training. This gives an unbiased estimate of how the model will perform in real-world scenarios. It's also a chance to test the model under different scenarios or business conditions.

f) Visualization
This study aims to develop an intelligent web-based TCO tool that can help vehicle fleet management assess the TCO and carbon emission reductions when transitioning from an ICEV to an EV in Malaysia's settings.

4. Conclusion
While predictive modeling offers substantial benefits in the automotive sector, challenges remain, such as data privacy concerns and the need for robust algorithms that can adapt to rapidly changing technologies and consumer preferences. The project begins with an initial planning phase, where the primary focus is on identifying key input and output parameters. The objective was achieved as shown in Table 3. This step is critical, as it establishes the foundation for the entire workflow by defining the variables that will drive the analysis. Once the parameters are established, the project progresses to the model development phase. Various predictive modeling techniques are explored to determine the most effective approach for the given dataset. For future work on this project, based on the literature review, it seems like ANN is the commonly used predictive model. Thus, ANN algorithms will be implemented for this project, yet the selection of models depends on factors like data structure, problem complexity, and desired accuracy, ensuring a tailored solution. More trial and error should be conducted during training and testing of the predictive model. By the end of this phase, the most suitable predictive model is selected based on performance and scalability. The outcomes for this project inform further steps, such as deployment or integration into larger systems.

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Biographies

Nadia Adibah Rajab is currently pursuing her postgraduate studies as a master's degree candidate at Universiti Teknologi Malaysia (UTM), under the Department of Materials, Manufacturing, and Industrial Engineering. Her research project focuses on data analytics, where she applies computational and statistical techniques to extract meaningful insights from complex datasets, contributing to advancements in manufacturing and industrial optimization. With a strong academic foundation in Computer Science, having earned her bachelor's degree in software engineering from the same prestigious institution, she possesses a robust understanding of programming, algorithms, and system design that now integrate into her data-driven research. Before her postgraduate studies, she gained professional experience as a Process Validation Engineer at PharmEng Technology Sdn. Bhd., where she was involved in ensuring compliance with industry standards and regulatory requirements in pharmaceutical manufacturing.

Dr. Nor Asmaa Alyaa Nor Azlan is a senior lecturer at Universiti Teknologi Malaysia (UTM), specializing in Data Analytics, Data Science, and Industrial Engineering. She serves as the Deputy Head of the Industrial and Systems Engineering Research Group (ISERG). She is an Associate Research Fellow at the Automotive Development Centre (ADC), Institute for Vehicle Systems and Engineering. Previously, she worked as a Machine Learning Engineer at Intel Technology Sdn. Bhd. and as a Procurement Engineer at Honda Malaysia Sdn. Bhd. She holds a PhD in Operations Research (Manufacturing Engineering) from Universiti Teknikal Malaysia Melaka (UTeM), where she also earned her bachelor's degree in manufacturing engineering (Manufacturing Management) and a master's in industrial engineering. Her research focuses on academic-industry collaboration in predictive and prescriptive analytics, machine learning, and deep learning. She is also actively involved in consulting, offering expertise in data science, analytics, and programming language training.

Nur Liyana Mohd Aris is a dedicated research assistant who plays a crucial role in supporting this project with her expertise and skills. Having graduated with a bachelor's degree in computer science, specializing in Software Engineering from Universiti Teknologi Malaysia (UTM), she possesses a strong academic foundation in programming, software development, and system design. Her education has equipped her with technical knowledge in algorithms, data structures, and software development methodologies, making her an asset in research and project implementation. In addition to her academic background, she also works as a freelance UI/UX designer, where she combines her technical skills with creativity to design intuitive and visually appealing user interfaces.

Ir. Dr. Mohd Azman Abas is the Director of the Automotive Development Centre (ADC) at Universiti Teknologi Malaysia (UTM), Johor Bahru. With 12 years of automotive R&D experience at PROTON, he specialized in vehicle testing, validation, prototyping, and engine calibration. He joined UTM in 2016 as a senior lecturer and later became the Deputy Director of the Low Carbon Transport Centre (LoCARtic), focusing on research related to combustion engines. In 2020, he was appointed Director of ADC, overseeing automotive innovation and industry collaboration.

Dr. Izhari Izmi Mazali is a senior lecturer at Universiti Teknologi Malaysia (UTM) and is actively involved in teaching, research, and innovation. His expertise spans several critical areas in mechanical and automotive engineering, with a strong focus on vehicle powertrain, continuously variable transmission (CVT), renewable energy and electric vehicles (EVs).

Wan Muhammad Rifqi Wan Mohd Azmi is a dedicated Mechanical Engineering graduate with a focus on Industrial Engineering, with experience as a Facilities Engineer Trainee at Texas Instruments during his internship. In this role, he assists in designing and maintaining fire safety systems to ensure compliance with safety regulations and high reliability, conducting risk assessments, system tests, and fire drills to enhance workplace safety. Additionally, he contributes to optimizing ventilation systems, reducing energy consumption while improving efficiency, and collaborates with EHS and operations teams to minimize downtime and enhance system performance. He also maintains precise documentation to support audits and certifications. His academic project, "Develop Anomaly Alert System for Quality Department in an Automotive," shows his innovative problem-solving skills in quality control.

Assoc. Prof. Dr. Jafri Mohd Rohani is a highly experienced senior lecturer at Universiti Teknologi Malaysia (UTM), where he has been teaching Industrial Engineering courses for over 30 years, specializing in Quality Engineering, Operations Management, Reliability, and Safety. Beyond academia, he actively engages in industry collaborations, serving as a keynote speaker at international conferences, an editorial board member for two journals, and a technical committee member for multiple conferences. He is also a consultant for NIOSH and DOSH, contributing to Malaysia's OSH Master Plan 2021–2025 and leading OSH implementation projects in construction. At UTM, he plays a pivotal role in fostering partnerships, coordinating three MOUs (with NIOSH, SIRIM, and Universitas Sebelas Maret, Indonesia), and serving as a resource person for safety training, demonstrating his commitment to bridging academia and industry.

Assoc. Prof. Ir. Dr. Zool Hilmi Ismail is an Associate Professor and researcher at Malaysia-Japan International Institute of Technology (MJIIT) and Centre for Artificial Intelligence and Robotics (CAIRO), Universiti Teknologi Malaysia (UTM). He was honored with the SEARCA Regional Professorial Chair Grant (2021–2022) for his contributions to agricultural technology. He holds a B.Eng (2005) and M.Eng (2007) in Mechatronics Engineering from UTM and a PhD from Heriot-Watt University, UK. Starting as a tutor at UTM, he became a senior lecturer in

2011, balancing roles as an educator and researcher. His expertise focuses on autonomous systems control, robot motion planning, coordination algorithms, and applied combinatorial optimization.

Prof. Ts. Dr. Effendi Mohamad has been a lecturer at the Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka (UTeM), since 2005. Before joining academia, he held various engineering roles at NEC Semiconductors Sdn. Bhd., Perodua Sales Sdn. Bhd., and ST Microelectronics Sdn. Bhd., specializing in industrial and process engineering. He earned his Bachelor's degree in Manufacturing Engineering from the University of Malaya, Kuala Lumpur, and his Master's degree in Manufacturing Management from Coventry University, United Kingdom. He completed his PhD in Intelligent Structures and Mechanics Systems Engineering at the University of Tokushima, Japan. Prof. Effendi has also been a visiting professor and scholar at institutions such as Tokushima University, Japan, and Universitas Brawijaya, Indonesia. Currently, he is a professor at UTeM, actively engaged in research and consulting with various manufacturing organizations.