Effective Energy Management Plan for Fuel Cell Hybrid Electric Vehicles Employing Classifier Fusion Method

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ABSTRACT: - This research uses machine learning (ML) to offer an effective energy management technique for fuel cell hybrid electric vehicles (FCHEV). Conventional cars use petroleum-based fuels to achieve high performance and long-distance speed. There are certain drawbacks to using petrol or diesel, such as low fuel efficiency and emissions of pollutants from exhaust gases. Moreover, the current body of work has certain limits. Therefore, combining these various optimisation strategies will be helpful in obtaining peak performance. The goal of this research is to combine SVM, KNN, and the Naive Bayes technique to produce an effective energy management system to address them. Additionally, better performing EMS is produced by merging these classifier algorithms. The performance accuracy of the optimising strategy is improved by utilising the suggested characteristics. Moreover, the accuracy percentages of the three classifiers—SVM, KNN, and Naïve Bayes—are 96%, 92%, and 94%, respectively. Ultimately, by merging these three classifiers, we obtain attained a 98% accuracy percentage.

INDEX TERMS: - Model predictive control (MPC), fuel cell hybrid electric vehicle (FCHEV), energy management system (EMS), K-nearest neighbour (KNN), support vector machine (SVM), and nanostructures for electrical energy storage (NEES).

I. INTRODUCTION

Hybrid fuel cell vehicles typically have batteries or ultra-capacitors as backup energy sources in addition to fuel cells as their main power source. The driving conditions are really challenging. They regularly handle a wide range of significant fluctuations and unanticipated spikes in the demand for power brought on by changes and emergencies. However, the generation of sharp power fluctuations may limit the lifespan of fuel cells if they are the sole energy source. For its intended use, therefore, the additional energy source is needed. Ultracapacitors and batteries can both be helpful components of backup power sources. When the load demands a lot of power, the system employs batteries and fuel cells at the same time to deliver the force. Numerous countries are currently giving environmental issues a lot of attention, and the use of fossil fuels is increasing the severity of these issues. Since they emit no pollutants, fuel cells and hydrogen energy are just two of the many energy sources and technologies being employed to replace fossil fuels [1]. The vehicle business is big in many countries, and a lot of people rely on their cars for daily transportation. Conventional fuel vehicles, which produce a lot of greenhouse gases and air pollution when driven, nonetheless make up a large share of the market. By changing, greenhouse gas and pollutant emissions can be greatly decreased for the propulsion of vehicles, from fossil fuels to sustainable energy sources like electricity and hydrogen [2].

Another article proposes the use of machine learning for energy forecasting, control, and management in hydrogen fuel cell vehicles [3]. Because of this hybridization, it is possible to enhance the system's efficiency and performance while retaining a portion of the batteries' power requirement. Inclusion is made possible by an energy management strategy that supplies the load power required for each energy source to operate efficiently. For more efficient power consumption, least square support vector machines are used in an energy management method that uses fuzzy control scheme optimisation [4]. The integration of fuel cells with advanced energy-reserving technologies, such as Li-ion and Ni-Cad batteries, is necessary to enhance the fuel cell hybrid technology's efficiency and power output. To maximise fuel efficiency, the EMS should be designed while ensuring that each power source uses its complete capability. Furthermore, the EMS should ideally have less of an impact on all facets of the dual power system's existence. The test operating circumstances' inability to adapt to different operating scenarios is the reason why the control findings are inadequate [5]. The energy management systems that prioritise optimisation are among the most researched.

Power converters, supplementary supplies, electric motors, and batteries are frequently assembled by FCHEVs. Up until now, HEVs have seemed like the most cost-effective choice, and they are expected to persist in that state for a while. This was made with the overall intention of lowering pollution and fuel consumption without sacrificing the power required for drivers. To accomplish this, scientists must first investigate the best energy-saving techniques. Considering complicated driving conditions, energy management seeks to maximise power split while limiting pollutants and fuel usage. Energy management systems (EMSs) on hybrid electric vehicles (HEVs) are widely recognised to be a major factor in the vehicles' increased fuel efficiency and thus lower emissions. The survey covers several fuel-cell combinations with various energy sources in relation to power system energy management strategies. The literature on state machine control methodology [6], [7] describes a simple and efficient rule-driven method for optimising fuel efficiency. Another well-liked method is fuzzy-based energy management technology, which divides power across several membership functions and creates a single rule base based on fuel % availability, charge level, and other factors as well as IF-THEN logic [8]. To ensure that the fuel cell system is operating at peak efficiency for maximum fuel economy or worldwide efficiency, a cost function optimisation technique is employed [9]. There are a few additional methods out there that suggest an efficient energy management plan.

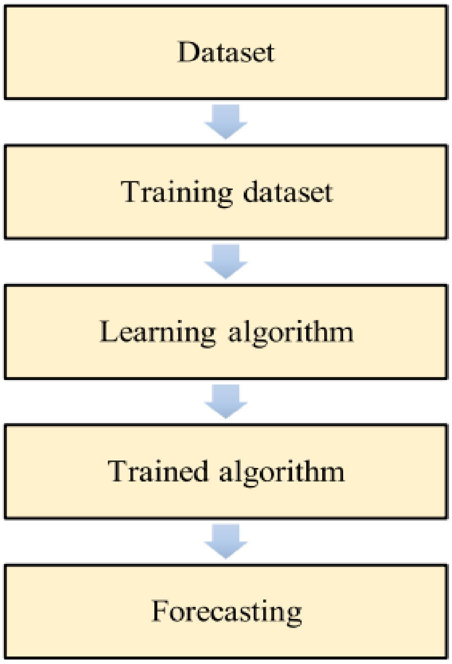

FIGURE 1. Main steps of machine learning.

Real data gathered from the Bulgarian power system grid was subjected to an ANN-based strategy and a wavelet denoising technique to generate short-term load forecasts. The outcomes imply that the suggested course of action is successful in reducing the standard deviation between the expected and actual data [10]. The Masinah Island power system in Oman underwent an evaluation of the hybrid energy systems' technical and financial feasibility using the HOMER programme. To investigate several scenarios, they employed the Dig SILENT software. The authors claim that because a hybrid energy system with diesel, photovoltaic, and wind turbines reduces operational costs, it is a wise decision [11]. To estimate a solar thermal collector system's hourly energy output, a comprehensive analysis was carried out. Decision trees, extra trees (ET), random forests (RF), and the authors employed support vector regression (SVR) in all cases. These models' accuracy, computational cost, and ability (stability) were evaluated. The findings demonstrated that RF and ET perform comparably to DT and are more accurate [12].

An installed solar system's daily total energy generation was predicted using the Naive Bayes classifier. The classifier was trained using a historical dataset spanning one year included data on average daily temperature, total amount of sunshine, total amount of solar radiation received worldwide, and total amount of photovoltaic energy generated daily. With an accuracy of 82.1917%, the results showed how successful the Nave Bayes classifier is at forecasting overall energy generation [13]. This research suggests a fusion of classifier technique using SVM, KNN & Naïve Bayes by leveraging the feature vectors of the driving condition information for MPC controller to improve the performance of fuel cell hybrid electric vehicles. which determined the most stable and optimised EMS for this hybrid driving scenario. Fuzzy controller and MPC-based EMS under various operational conditions have been optimised. We examined the most efficient way to employ this intelligence to maximise power usage. The following is the paper's contribution:

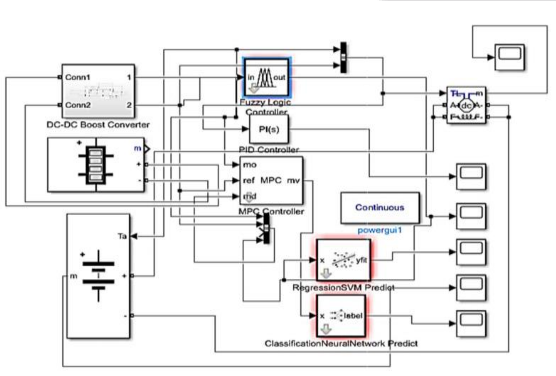

FIGURE 2. Mathematical model of fuel cell hybrid electric vehicle.

One application of artificial intelligence (AI) is machine learning. Its ability to address issues in the actual world has led to its widespread use in all facets of peoples' lives. Figure 1 shows the two primary development processes systems for machine learning (ML). To identify the training and testing stages, the dataset is divided into two unequal groups: the training and testing datasets. During the training phase, the dataset is used as input to the designated algorithm.

During the testing phase, the dataset is tested to feed the trained algorithm and assess its performance. Machine learning problems are divided into supervised, unsupervised, and reinforcement learning are the three categories. Because of the intricacy and simplicity of their classification, machine learning problems cannot be solved by a single technique, often requiring the use of a special algorithm [14].

The fact that the Support Vector Machine (SVM), Naive Bayes (NB), and K-Nearest Neighbour (KNN) algorithms can handle the classification problem is the main reason we selected them. The number of characteristics and data points that the algorithms can utilise to manage datasets of different sizes is another important consideration. Moreover, normalising data is not required for these methods. Moreover, the algorithms are easy to apply and understand.

A classifier fusion technique is used in the suggested energy management plan to improve prediction accuracy and optimise power distribution. This section provides an explanation of the application of the classifier fusion principle to FCHEV energy management. Different classifier types, including artificial neural networks, support vector machines, and decision trees, that are appropriate for this application are investigated.

The following are this paper's contributions: Information Gathering: pertinent information on the fuel cell, energy storage system, and vehicle for the FCHEV system dynamics and outside variables (such as traffic patterns, road slopes, and driving circumstances) are gathered. Simulations, experimental settings, or real-world driving tests can all provide this data.

Data Preparation: Before being used for training, the gathered data is pre-processed. This could entail dividing the dataset into training and validation sets, eliminating outliers from the data, normalising, or standardising variables, and cleaning the data.

Feature Selection/Extraction: Relevant features or variables are chosen from the dataset based on the energy management job at hand. These attributes may consist of state of charge (SOC) of the battery, measurements of the current and voltage, speed of the vehicle, power consumption, and other pertinent factors.

Model Development: Based on the labelled training data, a machine learning model—such as a regression, classification, or reinforcement learning model—is chosen or created. The architecture, parameters, and hyperparameters of the model are specified.

Model Training: The machine learning model is trained using the prepared dataset. The model gains knowledge of the underlying relationships, patterns, and dependencies inside the information. To reduce the discrepancy between its predictions and the true labels given in the training dataset, the model iteratively modifies its internal parameters.

Model Evaluation: The performance, accuracy, and generalizability of the trained model are assessed using the validation dataset. Numerous measures, including mean squared. The model's performance can be measured using error (MSE), accuracy, or root mean squared error (RMSE).

Model Optimisation: Modifications to the model's architecture or hyperparameters are made if its performance is deemed inadequate. The goal of this procedure, often referred to as hyperparameter tweaking or model optimisation, is to increase the generalizability and performance of the model.

Deployment and Testing: The model can be used for real-time energy management in FCHEVs after it has been trained and optimised. The inputs that the model can accept are the best control signals for energy distribution between the fuel cell and energy storage system are provided by considering the power demand, battery state of charge, and present driving conditions.

Machine learning data training for FCHEV energy management makes it possible to create precise and effective models that can maximise energy use, improve vehicle performance, and increase the vehicle's range. It makes it possible for clever and adaptive control schemes to adjust to changing road conditions and user demands.

The remaining portion of this article is organised as follows: The proposed methodology is shown in Section II, the proposed system is described in Section III, the results and discussion are shown in Section IV, and the conclusion is given in Section V.

II. PROPOSED METHODOLOGY

The suggested methodology is broken down into two distinct sections, such as the classifier fusion technique and the energy management strategy.

A. ENERGY MANAGEMENT STRATEGIES (EMS)

Fuel cell hybrid electric vehicles, or FCHEVs, use a variety of energy management techniques to maximise fuel cell and energy storage system utilisation, guaranteeing effective operation as well as a longer driving range. The following are some typical energy-management techniques applied in FCHEVs:

1) RULE-BASED STRATEGY

This method determines the power allocation between the fuel cell and energy storage system by using predetermined criteria and thresholds.

EMS Approach: Battery state of charge (SoC), power demand, and other system metrics are among the preset conditions that inform power allocation decisions.

Principal Contribution: Control strategy that is easy to understand and straightforward.

2) OPTIMIZATION-BASED STRATEGY

To optimise power allocation, reduce fuel consumption, or maximise efficiency, this technique formulates an optimisation problem with constraints and objective functions.

EMS Method: Techniques for mathematical optimisation, such dynamic or linear programming, are utilised to determine the ideal distribution of electricity between the energy storage system and fuel cell.

The main contribution is that it offers computationally intensive yet optimal control solutions.

3) MODEL-BASED STRATEGY

This approach uses system modelling to forecast energy use and maximise power distribution.

EMS Approach: State-space and other dynamic models or analogous circuit models, are employed in energy flow optimisation and power demand estimation.

Principal Contribution: strikes a balance between real-time performance and optimality, but precise system modelling is necessary.

4) MACHINE LEARNING-BASED STRATEGY

This approach makes use of machine learning algorithms to identify trends in past driving data and decide how best to manage energy.

Using Artificial Neural Networks (ANNs) in the EMS Approach Encouragement Utilising past data, machine learning models like as vector machines (SVMs) are built to forecast power consumption and optimise energy distribution.

Principal Contribution: Flexible enough to adjust to different driving situations, but needs enough training data.

5) REINFORCEMENT LEARNING-BASED STRATEGY

This tactic uses reinforcement learning algorithms to figure out the best energy management rules by making mistakes.

EMS Approach: Energy management rules are learned and adjusted based on the system's condition and rewards from the environment using reinforcement learning techniques like Q-learning or Deep Q-Networks (DQNs).

Principal Contribution: Adapts and learns the best policies in real time, but it needs a lot of training.

These energy management techniques can be combined or improved upon to create sophisticated control algorithms that take user preferences, vehicle performance, and real-time driving situations into account. The choice of an effective energy management plan is influenced by several variables, including the complexity of the system, the accessible data, the computational power, and the targeted optimisation goals. The numerous energy management techniques that have been addressed are thoroughly compared and explained in Table 1.

III. SYSTEM DESCRIPTION

As shown in Fig. 2, the proposed Fuel Cell Hybrid Electric Vehicle (FCHEV) uses a Simulink model created in MATLAB. This thorough model considers 2.4 kW, 48 Vdc Fuel Cell and 5.4 Ah Battery with initial State of Charge (SoC) set at 100% are the two main power sources to be considered. The main parts of the Simulink model are a DC/DC Boost Converter, a DC Motor acting as the load, and a Fuzzy Logic

TABLE 1. Shows online and offline methods and their comparison.

EMS	Reference	Modelling Technique	Key Contribution	Findings	EMS Approach
Rule-based Strategy	[15]	Rule-based control	Provides a simple and intuitive control approach	Effective in certain operating conditions, but lacks adaptability and optimality	Employs predefined rules to allocate power between the fuel cell and energy storage system based on predefined conditions and thresholds
Optimization-based Strategy	[16]	Mathematical optimization	Optimizes energy distribution to minimize fuel consumption or maximize efficiency	Offers optimal control solutions, but computationally intensive	Formulates an optimization problem with constraints and objective functions to determine the optimal power split between the fuel cell and energy storage system
Model-based Strategy	[17]	Dynamic models (e.g., state-space, equivalent circuit models)	Utilizes system models to predict energy demand and optimize power allocation	Balances optimality and real-time performance, but relies on accurate system modelling	Develops dynamic models of the FCHEV system and uses them to estimate power demand and optimize energy flow
Machine Learning-based Strategy	[18]	Artificial Neural Networks, Support Vector Machines, etc.	Learns patterns from historical data to make energy management decisions	Adaptable to various driving conditions, but requires sufficient training data	Trains machine learning models to predict power demand and optimize energy distribution based on historical driving data
Reinforcement Learning-based Strategy	[19]	Reinforcement Learning algorithms (e.g., Q-learning, Deep Q-Networks)	Learns optimal energy management policies through trial and error	Achieves adaptability and learns optimal policies in real-time, but requires extensive training	Utilizes reinforcement learning techniques to learn and adapt energy management policies based on the system's state and rewards obtained from the environment

Neural Network Prediction System, Support Vector Machine (SVM) Predictor, Controller, and Model Predictive Controller (MPC). To guarantee the effective functioning of the Certain parameters, such as the Input Voltage (Vin), Output Voltage (V out), Inductance (L), Capacitance (C), and Switching Frequency (fs), must be determined for the DC/DC Boost Converter. Determining the converter's duty cycle (D) is also essential. The Simulink model's integration of these elements enables a thorough examination of the FCHEV's performance, providing insightful knowledge for the creation of efficient and ecologically friendly hybrid electric vehicles.

Use the construction blocks in Simulink to create the circuit for the boost converter. Components like a voltage source (which stands in for the fuel cell), an inductor, and a switch are required. (Managed by the duty cycle), in addition to a diode. Assemble these parts in accordance with the boost converter topology.

The dynamic equation (1) can be used to represent the ideal boost converter with no losses.

$$\frac{d(Vout)}{dt} = (Vin - Vout) * \frac{D}{(L * C)} - (Vout / (Rload * C)) \quad (1)$$

wherein Vin is the fuel cell's input voltage. The output voltage to the load is known as V out. D represents the switch's duty cycle ($0 \leq D \leq 1$). The capacitance and inductance of L and C are the converter for boost. The load resistance attached to the output is denoted by R load.

The rate at which the output voltage changes because of the duty cycle and inductor current is represented by the first component on the right side of Equation (1) above. It comes from the boost converter's energy balance formula.

To create a control algorithm that will modify the duty cycle in accordance with the intended output voltage and the operating parameters of the system. Setting up the simulation's parameters, such the simulation duration and available solvers. Next, launch the simulation to see how the boost converter behaves in various operating scenarios. The output voltage, current, and other pertinent characteristics can all be examined.

Battery: Typically, the battery in a fuel cell hybrid electric vehicle (FCHEV) MATLAB model is utilised to supply extra power and energy storage to supplement the system using fuel cells. The battery increases the vehicle's overall efficiency and helps to meet peak power demands. The attributes and specifications of the battery that we have taken [20]. These could consist of the voltage restrictions, internal resistance, nominal voltage, capacity, and charge/discharge efficiency. Create control algorithms to regulate the battery's charging and discharging processes as well as its state of charge (SoC). Power flow control, SoC estimate, and protective systems against overcharging or deep discharging are a few examples of these tactics.

A dynamic equation that accounts for the charging and discharging currents over time can be used to determine the state of charge (SoC) of a battery. Although different models and techniques exist for the Coulomb counting method is a frequently used equation for determining SoC. This approach is predicated on the idea that the SoC of the battery may be ascertained by integrating the current that enters and exits the battery over time.

Using the Coulomb counting approach, the dynamic equation for battery SoC can be expressed as follows:

$$SoC(t) = SoC(t-1) + (I(t) * \Delta t)/C \quad (2)$$

where the State of Charge at time t is denoted by SoC(t). The State of Charge at the preceding time step (t − 1) is represented by SoC (t − 1). The current entering or leaving the battery at time t is represented by I(t). Time step, or sampling interval, is denoted by 1t. The battery is C ability.

When the battery is charging, the current (I) in Equation (2) might be positive, and when it is draining, it can be negative. Usually, the battery capacity is expressed in ampere-hours (Ah). The formula determines the change in SoC over time by integrating the current multiplied by the time step and dividing by the battery capacity.

Fuzzy Controller: A fuzzy controller is a kind of control system that bases decisions on imprecise or ambiguous inputs by applying fuzzy logic. When considering an FCHEV, to attain maximum performance and efficiency, the power flow between the fuel cell system and the energy storage system (such as batteries) can be optimised with the fuzzy controller. To measure a value's degree of belonging to a certain linguistic word, fuzzy membership functions are employed [21]. For every input and output variable, ascertain the membership functions' range and form. According to the system requirements, the membership functions shall record the pertinent linguistic phrases, such as "low," "medium," and "high."

MPC Controller: Fuel cell hybrid electric vehicles, or FCHEVs, use the well-liked control technique known as MPC (Model Predictive Control).

To find the best course of action for control, MPC formulates an optimisation problem based on a dynamic model of the system and solves it over a finite time horizon. The MPC controller's goal in an FCHEV is usually to optimise energy management and power flow to meet performance, efficiency, and battery SoC targets [6].

In this simple example, the battery State of Charge (SoC) and fuel cell current are the two primary state variables of the FCHEV system. The dynamic equation (3) can be used to express it.

$$x(k+1) = Ax(k) + Bu(k) \quad (3)$$

where the state vector at time step (k + 1) is denoted by x (k + 1). The state vector at time step (k) is denoted by x (k). The state transition matrix A represents the dynamics of the system. The input is B. Matrix that connects the state variables to the control inputs.

The control input vector at time step (k) is denoted by u (k).

The definition of the state vector x(k) in Equation (3) would be [SoC(k), Fuel Cell Current(k)]. The control actions that the MPC controller chooses to implement at each time step are represented by the control input vector u(k).
PI Controller: Fuel cell hybrid electric vehicles, or FCHEVs, use PI (Proportional-Integral) controllers as a typical kind of feedback control Automobiles). The error between a desired setpoint and the measured system output is used by the PI controller to modify control inputs. To achieve the required performance and efficiency in the case of an FCHEV, a PI controller can be used to control the power flow between the fuel cell system and the energy storage system (such as batteries) [22], [23]. This is the standard operation of a PI controller in an FCHEV.

The total of the proportional and integral control actions is the control signal, which indicates the modification to the power flow between the fuel cell and the battery.

$$u(t) = Kp * e(t) + Ki * \int e(t)dt \quad (4)$$

where the control signal at time t is denoted by u(t). Time t's mistake is denoted by e(t). Gains that are integral and proportionate are Kp and Ki. The error integral over time is represented by the formula ∫ e(t)dt dt.

Fuel Cell Hybrid Electric Vehicle (FCHEV): To model and simulate a Brushless DC (BLDC) motor in MATLAB. Define the motor parameters first such as the number of motor poles, rotor moment of inertia (J), motor resistance (R), motor inductance (L), motor constants (Kt, Ke), and motor resistance (R). Describe the FCHEV's BLDC motor control strategy. Depending on the required motor performance, this can involve torque, position, or speed control. Apply the control method in MATLAB while keeping the control objectives and the motor model in mind. Include fuel cells, energy storage devices, and power electronics in your comprehensive FCHEV model, together with the BLDC motor model. Utilise MATLAB's simulation features to model the entire FCHEV.

A. CLASSIFIER FUSION TECHNIQUE

To give and forecast higher accuracy on fuzzy and model predictive control, machine learning has been integrated with EMS. Machine learning is used because it can offer the system's accuracy, which is used to determine which platform the system will function best on. Thus, a thorough investigation was used to build an automated technique.

The given dataset served as the foundation for the development of the suggested approach. In Figure 3, the general block diagram is displayed.

This section's system is separated into four distinct sections, including feature selection, training, testing, and feature description.

1) FEATURES DESCRIPTION

Many features are included with EVs to improve their efficiency, performance, and overall user experience. Below is a summary of some typical elements considered in this manuscript.

Battery Capacity and SoC: A cell's state of charge (SoC) indicates how much energy is available in accordance to its rating. The value of the SoC spans from 0% to 100%. When the SoC is 100%, the battery is considered fully charged; when it is 0%, the cell is completely depleted. Given that the SoC in real life cannot climb above 50%.

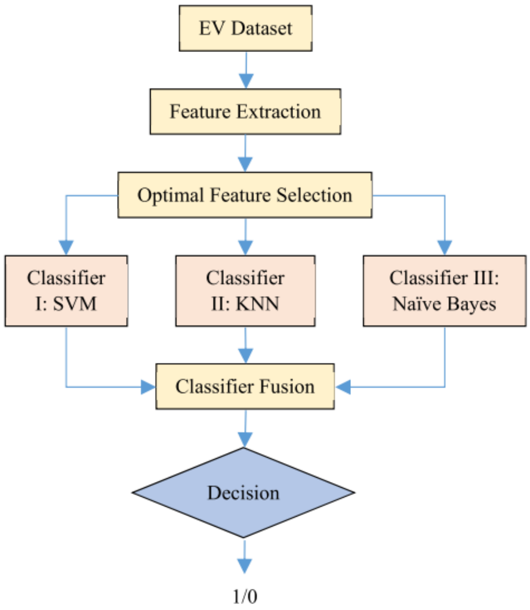

FIGURE 3. Block diagram of the proposed system.

applications, as soon as the SoC reaches that threshold, the battery is charged. In a manner like this, the maximal SoC decreases with cell age.

Thus, a 100% SoC for an aged cell would be comparable to a young cell's 75%–80% SoC [26].

Battery Stress: During operation, ions are exchanged between the anode and cathode of a rechargeable battery, which can result in significant stress on the internal components. The movement and attraction of charge within the battery causes the anode and cathode to alternately expand and contract, which adds to the battery's dysfunction. Researchers at the Nanostructures for Electrical Energy Storage (NEES) Energy Frontier Study Centre wanted to look at how this compressive stress affects the battery to identify the warning signs of failure before the battery fails. They achieved this by developing a novel technique called acclamatory, which allowed them to precisely build and monitor a tiny battery under pressure [27].

Range EV Mode: Several significant factors, such as the car's weight and dimensions, the size of the power source, and the characteristics of the electrical motor, have a significant impact on how far an electric vehicle (EV) can travel. A particular route's actual location, the driver's style, and the climate in the area are all important considerations. One can save energy and travel farther with an electric vehicle (EV) if they are aware of the variables that affect its range.

Capacity of Fuel Tank: Fuel cell electric vehicles (FCEVs) run on hydrogen. They are more efficient than cars with traditional internal combustion engines and only release safe, warm water vapour and air out of their tailpipes. We are still in the early stages of installing FCEVs and the hydrogen infrastructure required to fuel them [28].

TABLE 2. Feature used in the proposed work.

Name of feature	Symbol of feature
Battery Capacity (SoC)	f_1
Battery Stress	f_2
Range EV Mode	f_3
Fuel Tank Capacity	f_4
Mass	f_5
Actual Fuel Economy	f_6
Aerodynamic Drag	f_7
Slow Charge Max	f_8

TABLE 3. Ranking of feature based on decreasing F value.

Name of feature	Ranking of feature
Range EV Mode: f_3	*1*
Battery Stress: f_2	*2*
Battery Capacity (SoC): f_1	*3*
Actual Fuel Economy: f_6	*4*
Slow Charge Max: f_8	*5*
Fuel Tank Capacity: f_4	*6*
Aerodynamic Drag: f_7	*7*
Slow Charge Max: f_8	*8*

TABLE 4. Feature vector set.

Combination of Feature	Feature Vector Set
f_3	*M*
$f_2 + f_3$	*N*
$f_2 + f_3 + f_1$	*U*
$f_2 + f_3 + f_1 + f_6$	*V*
$f_2 + f_3 + f_1 + f_6 + f_8$	*W*
$f_2 + f_3 + f_1 + f_6 + f_8 + f_4$	*X*
$f_2 + f_3 + f_1 + f_6 + f_8 + f_4 + f_7$	*Y*
$f_2 + f_3 + f_1 + f_6 + f_8 + f_4 + f_7 + f_8$	*Z*

Mass: Compared to equivalent petrol vehicles, electric vehicles might weigh hundreds or even thousands of pounds more due to the significantly larger weight of battery cells.

Real Fuel Economy: EVs use more than 77% of the grid's electrical energy to power their wheels.

Conventional gasoline-powered vehicles only convert between 12% and 30% of the fuel's stored energy into power for the wheels.

Aerodynamic Drag: The aerodynamic drag coefficient [29] quantifies how well a streamline aerodynamic body form reduces air resistance to a vehicle's forward motion.

Slow Charge Max: A slow charger typically uses 2.3 to 2.5 kW of AC (alternating current from the national grid) to power electric vehicles (EVs). Often, the slow chargers resemble EV chargers with a 3-pin socket and be powered by regular wall outlets. In this work, the feature in Table 2 has been taken into consideration.

2) SELECTION OF OPTIMAL FEATURE

One of the crucial duties included in this process is choosing the best feature. Numerous methods exist for identifying the ideal feature, including incremental feature selection, Kruskal-Walli's test, anova1, etc. The anova1 test has been included in this work to determine the ideal feature. The greater F value determines which feature is statistically significant. The features are ranked with decreasing F value in the following Table 3.

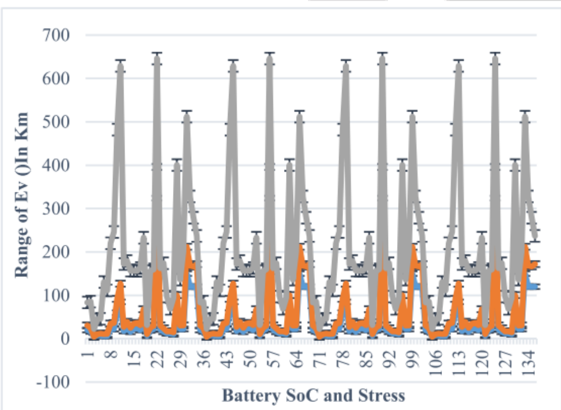

FIGURE 4. Graphical performance analysis of electric vehicle.

Subsequently, a distinct feature set was created based on feature ranking. It is evident that feature combinations have been made to yield various characteristic vector set, including M, N, U, Z. Table 4 shows how these are produced based on the rank obtained from the Anova1 analysis.

3) TRAINING AND TESTING

The researchers used three different machine learning techniques during the training phase. The feature vector set was treated in accordance with for the training of the support vector machine (SVM) to the methodology given in Equation (5).

$$D=\{(Feature\ Vector\ Set^1, y^1), \ldots, (Feature\ Vector\ Set^l, y^l\},$$

$$x \in R^n, y \in \{-1, 0\} \quad (5)$$

Like this, the k - Nearest Neighbour (k - NN) [14] algorithm has been used for training. This is among the nonparametric approaches to problem solution in classification. Given that this issue will be resolved for an even number of classes, odd. In the training phase, numbered k values such 1, 3, 5, and 7 have been employed. In addition to these two classifiers, this suggested study also includes the Naïve Bayes Classifier.

The probabilistic idea is incorporated into the Naïve Bayes Classifier's classification formula. Let us examine the classified output obtained from SVM, k-NN, and Naïve Bayes, which are So, Ko, and N0, in that order. Equation (6) represents the corresponding output obtained by employing classifier fusion.

$$Y_o = [(S_o\ OR\ K_o)\ OR\ N_0] \quad (6)$$

Yo is the result that Classifier Fusion produces in Equation (6). The benefit of classifier fusion is that, even in cases where there is a discrepancy when comparing various classifiers, that Classifier Fusion can integrate.

IV. SIMULTION RESULTS AND DISCUSSION

The performance study of a fuel cell hybrid electric vehicle, or FCHEV, is depicted in Fig. 4 below. This analysis includes a review of the vehicle's acceleration, top speed, range, fuel efficiency, and emissions. This fuel cell hybrid electric vehicle's performance analysis is displayed below. Three key FCHEV aspects are taken into consideration here. Considerations include the battery's State of Charge (SoC), battery stress, and electric vehicle range. The Fig. 4 illustrates how the vehicle's range, or the distance it travels, fluctuates with the batteries' state of charge and, in turn, raises the battery's stress.

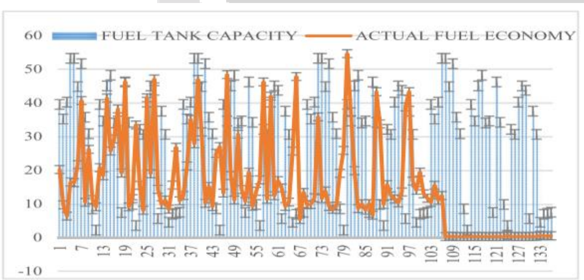

FIGURE 5. Fuel tank capacity Vs actual fuel economy.

TABLE 5. MATLAB simulation results of mathematical model.

Sl No.	Battery % SoC	Fuel Consumption (in Gm./Kwh)	Energy Consumed (in Kj)
1	100	0	0
2	90	0.5	2
3	85	1.5	5
4	80	3	9
5	75	4.5	14
6	70	6	20
7	65	7.5	27
8	60	9	35
9	55	10.5	44
10	50	12	54
11	45	13.5	65

Fuel economy is inversely correlated with fuel usage. It is the quantity of fuel used to travel a specific distance.

In the US, it is expressed in gallons per 100 miles and in litres per 100 kilometres outside of Europe in other parts of the globe. Fuel consumption is a basic engineering statistic that may be used to quantify volumetric fuel savings directly. It is directly correlated with the amount of fuel used per 100 miles. It is the usage of fuel. The gasoline tank's capacity and real fuel economy are displayed in Fig. 5 below.

To simulate an FCHEV battery and fuel cell system's performance in MATLAB, one would normally use mathematical models and numerical methods. Here is a general outline of the steps involved. The above results are shown in Table 5 is the MATLAB simulation results obtained from the mathematical model.

After the creation of the mathematical models for the fuel cell, battery, and other pertinent FCHEV system parts. The dynamic behaviour should be captured by these models of the energy management parameters of the FCHEV. The State of Charge (SoC) of the battery, gasoline usage, and energy consumption are all related in an FCHEV. The amount of fuel used by the fuel cell system, which powers the car and charges the battery, is represented by the fuel consumption.

The following summarises the relationship between these variables:
Fuel consumption and energy consumed: An FCHEV's fuel consumption has a direct impact on its energy consumption.

The energy produced by the fuel cell system powers the car and charges the battery at the same time. The energy source pace of energy delivery to the system is determined by the consumption rate.

Battery SoC and energy used: The Battery SoC is influenced by the amount of energy used by the FCHEV system. The Battery SoC gradually drops when power is extracted from the battery to run the car's electrical systems. In a similar vein, the Battery SoC rises with energy regeneration procedures like regenerative braking.

Fuel usage and battery SoC: The battery SoC is indirectly impacted by fuel use. The fuel cell system charges the battery as gasoline is used, replenishing it. The Fuel consumption rate affects the Battery SoC by dictating how quickly the battery is charged or discharged. Here is a formula for calculating gasoline cost per mile, as stated in Equation (7).

$$Fuel\ Cost/Mile = Fuel\ Cost/Distance\ Travelled \quad (7)$$

The fuel consumption of the vehicle per unit of travel is shown in the plotting of Fig. 7. Usually, it is expressed in litres per kilometre (L/km) or miles per gallon (MPG). You can get this information either from the vehicle's specifications or from measurements made during testing. Fuel cost per mile is a useful metric for comparing the cost-effectiveness of various cars and tracking the savings realised from increasing a particular vehicle's fuel efficiency.

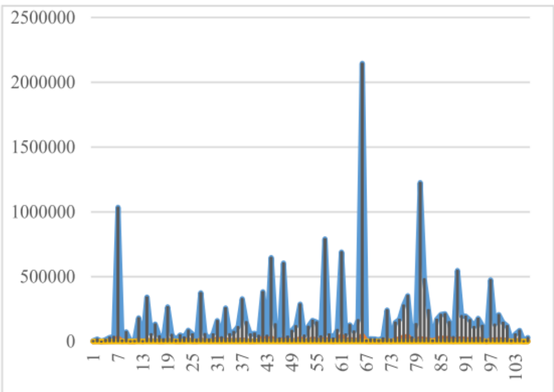

FIGURE 7. Representation of fuel economy with fuel cost per mile.

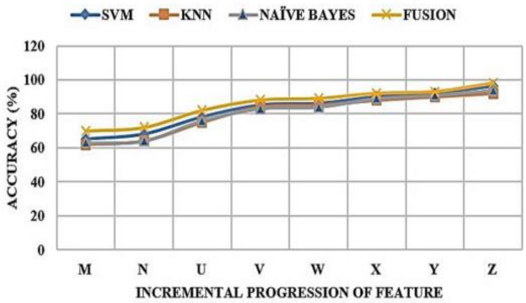

FIGURE 8. Accuracy with incremental feature set.

V. CONCLUSION

So, it has been considered as the proposed classifier in this work. An essential part of hybrid cars, such as Fuel Cell Hybrid Electric Vehicles (FCHEVs), is the Energy Management System, or EMS. Its main purpose is to achieve the most efficient operation of the vehicle by optimising the energy flow and utilisation between the battery pack, fuel cell system, and other energy storage devices. To attain the intended driving range, the energy management system maximises the use of the battery pack and the fuel cell system. When driving normally, the fuel cell system is the main source of power generation for the EMS. However, the EMS can employ both fuel cell and battery pack power to meet the driver's demand for additional power under high-power demand scenarios, including rapid acceleration. performance. So, it has been considered as the proposed classifier in this work. Fuel cell hybrid electric vehicles (FCHEVs) employ SVM, CNN, and Naive Bayes algorithms for energy management methods was investigated in this research. The goal was to maximise power flow between the fuel cell system and the energy storage system, such as batteries, to enhance the overall functionality, performance, and efficiency of FCHEVs. The best power flow was estimated using classification approaches such as SVM, KNN, and Naive Bayes, depending on input data such vehicle speed, battery state of charge (SoC), and other significant characteristics. The results of the study showed that the three methods—SVM, KNN, and Naive Bayes—all showed promise for managing energy for FCHEVs. Regarding precision, computational effectiveness, and resilience, every method shown its advantages. performance. So, it has been considered as the proposed classifier in this work. The identification of power flow patterns was done by comparing them to similar cases found in the training dataset. KNN displayed good precision, despite this, it might have trouble with imbalanced classes or high-dimensional datasets. The technique selected should consider the needs, properties of the dataset, and available processing power. To increase the precision and effectiveness of energy management systems in FCHEVs, more study can concentrate on investigating hybrid techniques or adding more machine learning algorithms.

REFERENCES

[1] S. A. Qadir, H. Al-Mutairi, F. Ahmad, and L. Al-Faghih, ‘‘A principal-agent approach for the effective design of a renewable energy incentive for a heavily subsidized residential sector: The case of Qatar,’’ IEEE Access, vol. 11, pp. 24238–24256, 2023, Doi: 10.1109/ACCESS.2023.3255105.

[2] X. Chang, T. Ma, and R. Wu, ‘‘Impact of urban development on residents’ public transportation travel energy consumption in China: An analysis of hydrogen fuel cell vehicles alternatives,’’ Int. J. Hydrogen Energy, vol. 44, no. 30, pp. 16015–16027, Jun. 2019.

[3] M. Khalid, F. Ahmad, B. K. Panigrahi, and H. Rahman, ‘‘A capacity efficient power distribution network supported by battery swapping station,’’ Int. J. Energy Res., vol. 46, no. 4, pp. 4879–4894, Mar. 2022, Doi: 10.1002/er.7482.

[4] Y. Zheng, F. He, X. Shen, and X. Jiang, ‘‘Energy control strategy of fuel cell hybrid electric vehicle based on working conditions identification by least square support vector machine,’’ Energies, vol. 13, no. 2, p. 426, Jan. 2020.

[5] F. Ahmad, L. Al-Faghih, S. A. Qadir, and M. Khalid, ‘‘EV charging station placement using nature-inspired optimisation algorithms,’’ in Proc. Int. Conf. Power, In strum., Energy Control (PIECON), Aligarh, India, Feb. 2023, pp. 1–6, Doi: 10.1109/PIECON56912.2023.10085885.

[6] D. Zhang, Y. Zhou, K.-P. Liu, and Q.-Q. Chen, "A study on fuzzy control of energy management system in hybrid electric vehicle," in Proc. Asia– Pacific Power Energy Eng. Conf., Mar. 2009, pp. 1–4.

[7] R. Pan, D. Yang, Y. Wang, and Z. Chen, "Performance degradation prediction of proton exchange membrane fuel cell using a hybrid prognostic approach," Int. J. Hydrogen Energy, vol. 45, no. 55, pp. 30994–31008, Nov. 2020.

[8] R. Pan, D. Yang, Y. Wang, and Z. Chen, "Health degradation assessment of proton exchange membrane fuel cell based on an analytical equivalent circuit model," Energy, vol. 207, Sep. 2020, Art. no. 118185.

[9] A. A. Makhathini, S. K. Rahimov, and S. L. Shabanov, "Optimal control strategies for CVT of the HEV during a regenerative process," in Proc. IEEE Conf. Electric Hybrid Vehicles, Dec. 2006, pp. 1–12.

[10] W.-S. Lin and C.-H. Zheng, "Energy management of a fuel cell/ultracapacitor hybrid power system using an adaptive optimal-control method," J. Power Sources, vol. 196, no. 6, pp. 3280–3289, Mar. 2011.

[11] H. M. Al Ghaithi, G. P. Fotis, and V. Vita, "Techno-economic assessment of hybrid energy off-grid system—A case study for Masinah Island in Oman," Int. J. Power Energy Res., vol. 1, no. 2, pp. 103–116, Jul. 2017.

[12] M. W. Ahmad, J. Reynolds, and Y. Rezgui, "Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees, and regression trees," J. Cleaner Prod., vol. 203, pp. 810–821, Dec. 2018.

[13] R. Balinder, M. Sailboat, M. Colak, and N. Genc, "A novel application of naive Bayes classifier in photovoltaic energy prediction," in Proc. 16th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA), Dec. 2017, pp. 523–527.

[14] P. Gupta, Introduction to Machine Learning in the Cloud with Python: Concepts and Practices. Berlin, Germany: Springer, 2021.

[15] S. Cau, W. Hank ache, M. Fadel, and D. Hessel, "On-line fuzzy energy management for hybrid fuel cell systems," Int. J. Hydrogen Energy, vol. 35, no. 5, pp. 2134–2143, Mar. 2010.

[16] J. Ke, R. Xeno, Y. Meng Xiong, and X. Min, "A hybrid fuel cell power system," IEEE Trans. Ind. Electron., vol. 56, no. 4, pp. 1212–1222, Apr. 2009.

[17] S. Yang, M. Li, B. Xu, B. Guo, and C. Zhu, "Optimization of fuzzy controller based on genetic algorithm," in Proc. Int. Conf. Intel. Syst. Design Eng. Appl., vol. 2, Oct. 2010, pp. 21–28.

[18] A. Biswas and A. Emadi, "Energy management systems for electrified powertrains: State-of-the-art review and future trends," IEEE Trans. Veh. Technol., vol. 68, no. 7, pp. 6453–6467, Jul. 2019.

[19] P. Garcia, L. M. Fernandez, C. A. Garcia, and F. Jurado, "Energy management system of fuel-cell-battery hybrid tramway," IEEE Trans. Ind. Electron., vol. 57, no. 12, pp. 4013–4023, Dec. 2010.

[20] C. Sain, A. Banerjee, P. K. Biswas, S. B. Thani Kanti, and C. B. Baladhanautham, "Sensor angle-based control strategy and dynamic analysis of a sinusoidal pulse width modulation-operated permanent magnet synchronous machine drive for electric propulsion unit," Int. Trans. Electra. Energy Syst., vol. 31, no. 12, Dec. 2021, Art. no. e13090.

[21] J. Moreno, M. E. Ortuzar, and J. W. Dixon, "Energy-management system for a hybrid electric vehicle, using ultracapacitors and neural networks," IEEE Trans. Ind. Electron., vol. 53, no. 2, pp. 614–623, Apr. 2006.

[22] P. Piso and G. Rizzoli, "A comparative study of supervisory control strategies for hybrid electric vehicles," IEEE Trans. Control Syst. Technol., vol. 15, no. 3, pp. 506–518, May 2007.

[23] A. Fadel and B. Zhou, "An experimental and analytical comparison study of power management methodologies of fuel cell-battery hybrid vehicles," J. Power Sources, vol. 196, no. 6, pp. 3271–3279, Mar. 2011.

[24] C. Sain, A. Banerjee, P. K. Biswas, T. S. Babu, and T. Dragicevic, "Updated PSO optimised fuzzy-PI controlled buck type multi-phase inverter-based PMSM drive with an over-current protection scheme," IET Electric Power Appl., vol. 14, no. 12, pp. 2331–2339, Dec. 2020, Doi: 10.1049/ietepa.2020.0165.

[25] E. Chamali, M. Preindl, P. Malysz, and A. Emadi, "Electrochemical and electrostatic energy storage and management systems for electric drive vehicles: State-of-the-art review and future trends," IEEE J. Emerg. Sel. Topics Power Electron., vol. 4, no. 3, pp. 1117–1134, Sep. 2016.

[26] S. Adhikary, P. K. Biswas, C. Sain, S. B. Thani Kanti, and N. I. Nula, “Bidirectional converter based on G2V and V2G operation with time of usage-based tariff analysis and monitoring of charging parameters using IoT,” Energy Rep., vol. 9, pp. 5404–5419, Dec. 2023.

[27] S. Adhikary, P. K. Biswas, and C. Sain, “Comprehensive review on charging solution of electric vehicle—An Internet of Things based approach,” Int. J. Electric Hybrid Vehicles, vol. 15, no. 1, pp. 40–66, 2023.

[28] C. Sain, A. Banerjee, and P. K. Biswas, “Modelling and comparative dynamic analysis due to demagnetization of a torque controlled permanent magnet synchronous motor drive for energy-efficient electric vehicle,” ISA Trans., vol. 97, pp. 384–400, Feb. 2020.

[29] C. Sain, P. K. Biswas, P. R. Sampath, T. S. Babu, and H. H. Achelous, “Self-controlled PMSM drive employed in light electric vehicle-dynamic strategy and performance optimization,” IEEE Access, vol. 9, pp. 57967–57975, 2021.