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RESEARCH ARTICLE

Efficient Energy Management Strategy for Fuel Cell Hybrid Electric Vehicles Using Classifier Fusion Technique

DEBASIS CHATTERJEE[1], PABITRA KUMAR BISWAS[1], (Senior Member, IEEE), CHIRANJIT SAIN[2], (Senior Member, IEEE), AMARJIT ROY[2], AND FURKAN AHMAD[3]
[1]National Institute of Technology Mizoram, Aizawl, Mizoram 796012, India
[2]Ghani Khan Choudhury Institute of Engineering and Technology, Malda, West Bengal 732141, India
[3]Division of Sustainable Development, College of Science and Engineering, Hamad Bin Khalifa University, Qatar Foundation, Doha, Qatar

Corresponding author: Furkan Ahmad (fuahmad@hbku.edu.qa)

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ABSTRACT This paper presents an efficient energy management strategy for Fuel Cell Hybrid Electric Vehicles (FCHEV) using a Machine Learning (ML) approach. Petroleum-based fuels are utilised in conventional cars to provide good performance and long-distance speed. There are certain disadvantages to using petrol or diesel, such as poor fuel economy and pollution-causing exhaust gas emissions. Furthermore, there are some limitations with existing available work, and the merger of these different optimisation techniques will be advantageous for achieving optimal performance. To address them, the purpose of this research is to create an efficient energy management approach by combining SVM, KNN, and the Naive Bayes technique. Additionally, by combining these classifier techniques better performing EMS is developed. Using the proposed features, the optimisation approach's performance accuracy is increased. Furthermore, these individual classifiers comprising of SVM, KNN & Naïve Bayes is giving accuracy percentage of 96%, 92% & 94% respectively. Finally, after combining these three classifiers we have achieved an accuracy percentage of 98%.

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

I. INTRODUCTION

In addition to having fuel cells as their primary power source, hybrid fuel cell vehicles often also contain batteries or ultra-capacitors as supplementary energy sources. The conditions for driving on the road are really difficult. They routinely cope with various large variations and unforeseen surges in the demand for power brought on by crises and changes. However, if fuel cells are used as the only source of energy, their longevity may be shortened by the production of extreme power swings. Therefore, the additional energy source is required for its intended use. Batteries and ultra-capacitors can both be useful parts of backup power sources. When there is a high demand for power from the load, the system simultaneously uses fuel cells and batteries to supply the energy. Environmental issues are currently receiving extensive attention throughout a number of nations, and the increasing use of fossil fuels is making them much worse. Fuel cells and hydrogen energy are two of the many energy sources and technologies being used to replace fossil fuels since they can produce zero emissions [1]. In many nations, the automobile industry is significant, and many people depend on their cars for daily transportation. Currently, a sizable portion of the market is still occupied

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by traditional fuel vehicles, which when driven, emit a lot of air pollution and greenhouse gases. Pollutant and greenhouse gas emissions can be significantly reduced by switching from fossil fuels to clean energy sources like electricity and hydrogen for vehicle propulsion [2].

There is also an article that suggests using machine learning to forecast, control, and manage energy in vehicles powered by hydrogen fuel cells [3]. Due to this hybridization, the system can be improved for better performance and fuel economy while still carrying some of the power demand provided by the batteries. An energy management approach that provides the load power necessary for efficient operation among the energy sources enables inclusion. Fuzzy control scheme optimization is employed in an energy management strategy with least square support vector machines for better optimal power consumption [4]. Fuel cells must be combined with cutting-edge energy reserving technologies, including Ni-Cad and Li-ion batteries, to boost the efficiency and power output of fuel cell hybrid technology. The EMS should be developed to achieve maximum fuel effectiveness while making sure that individual power source operates to its full potential. In addition to that, Ideally, the EMS should have less of an influence on every aspect of the life of the dual power system. The control findings are subpar due to the test operating conditions' lack of flexibility to various operating situations [5]. Among the most studied forms of energy management strategies are those that emphasise optimization.

FCHEVs often assemble power converters, auxiliary supplies, electric motors, and batteries. HEVs appear to be the most financially sensible option so far and are anticipated to stay that way for some time. The overall goal of creating this is to reduce fuel consumption and pollutants while maintaining the necessary power for drivers. To do this, researchers must first examine the most effective energy saving methods. Energy management aims to maximise power split while minimising emissions and fuel consumption in light of complex driving scenarios. It is generally acknowledged that HEVs' energy management strategies (EMSs) play a significant role in the increases in their fuel economy and the resulting reduction in emissions. Many fuel-cells in combination with different energy sources related power system energy management strategies covered in the survey. The literature on State machine control technique [6], [7] is a straightforward and effective rule-driven technique which is used in optimization fuel energy consumption. The Fuzzy based energy management technology is another popular approach and it distributes power using different membership functions and one Rule base is prepared which is created depending on the status of level of charge and fuel percentage of availability and a set of IF-THEN logic [8]. A cost function optimization technique is utilised to guarantee the fuel cell system is performing at its best for optimum fuel economy or greatest global efficiency [9]. There are few more approaches which proposes an effective energy management strategy are available.

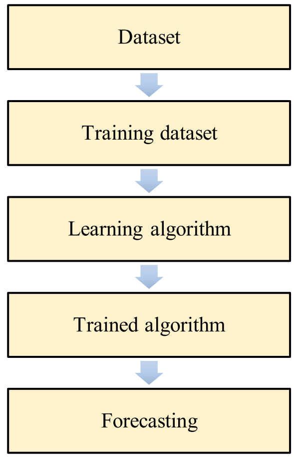

FIGURE 1. Main steps of machin learning.

A strategy based on ANN approaches and a wavelet denoising algorithm were applied to real data collected from the Bulgarian power system grid to produce short-term load predictions. The results suggest that the proposed strategy is effective in lowering the standard deviation between actual and anticipated data [10]. The HOMER software was used to assess the technical and economic viability of hybrid energy systems in Oman's Masirah Island power system. They used the DIgSILENT programme to examine various scenarios. According to the authors, a hybrid energy system comprised of diesel, photovoltaic, and wind turbines is a smart choice because it lowers operating costs [11]. A thorough investigation was conducted in order to anticipate the hourly energy output of a solar thermal collector system. Random forest (RF), extra trees (ET), decision trees, and support vector regression (SVR) were all used by the authors. The ability (stability), accuracy, and computational cost of these models were tested. The results showed that RF and ET function equally well and are more accurate than DT [12].

The Naive Bayes classifier was used to forecast the daily total energy generation of an installed solar system. The classifier was trained on a one-year historical dataset that included metrics such as daily average temperature, daily total sunshine duration, daily total global solar radiation, and daily total photovoltaic energy generation. The findings demonstrated that the Nave Bayes classifier is effective in predicting total energy generation, with an accuracy of 82.1917% [13]. In order to improve the performance of fuel cell hybrid electric vehicle, this paper proposes a fusion of classifier technique using SVM, KNN & Naïve Bayes by utilizing the feature vectors of the driving condition information for MPC controller. Which established the best optimized and stable EMS for this hybrid driving condition. EMS based on MPC and Fuzzy controller under different operating condition are optimized. We analysed how this intelligence can effectively use for optimum power utilization. The contribution of the paper is as follows:

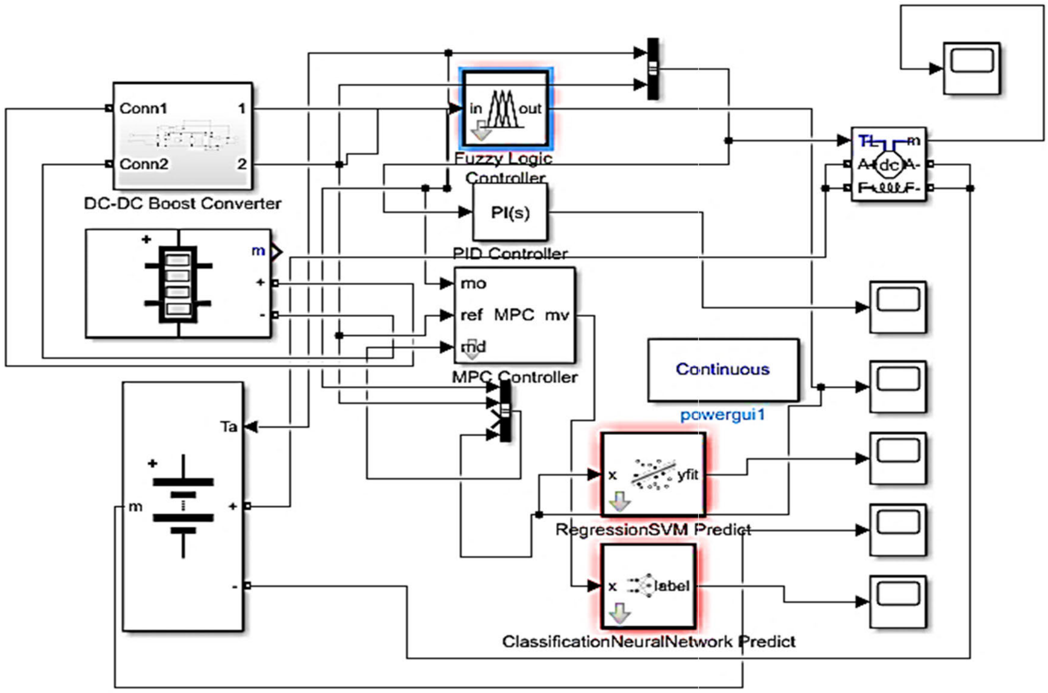

FIGURE 2. Mathematical model of fuel cell hybrid electric vehicle.

Machine learning is an artificial intelligence (AI) application. It is frequently employed in all aspects of life for people due to its potential to solve real-world problems. Figure 1 depicts the two main processes in developing machine learning (ML) systems. The dataset is separated into two unequal groups—training and testing datasets-to designate the training and testing stages. The dataset is utilised as input to the specified algorithm during the training stage.

In the testing stage, the trained selected algorithm is fed by testing the dataset to evaluate the selected algorithm performance. Machine learning challenges are classified into three types: supervised, unsupervised, and reinforcement learning. There is no one method that can address machine learning problems due to the simplicity and complexity of their classification, which occasionally necessitates the adoption of a unique algorithm [14].

The primary reason we chose the Support Vector Machine (SVM), Naive Bayes (NB), and K-Nearest Neighbour (KNN) algorithms is that they can handle the classification problem. Another factor is the quantity of data points and features that can be used by the algorithms to handle varied sized datasets. Furthermore, these techniques do not necessitate data normalisation. Furthermore, the algorithms are simple and straightforward to implement.

The proposed energy management strategy leverages a classifier fusion technique to enhance prediction accuracy and optimize power distribution. This section explains the concept of classifier fusion and how it can be applied to FCHEV energy management. Various types of classifiers suitable for this application are explored, such as artificial neural networks, support vector machines, and decision trees.

The contributions of this paper are as follows; Data Collection: Relevant data related to the FCHEV system, including the fuel cell, energy storage system, vehicle dynamics, and external factors (e.g., driving conditions, road gradients, traffic patterns), is collected. This data can be obtained from real-world driving tests, simulations, or experimental setups.

Data Preparation: The collected data is pre-processed and prepared for training. This may involve cleaning the data, removing outliers, normalizing or standardizing variables, and splitting the dataset into training and validation sets.

Feature Selection/Extraction: Depending on the specific energy management task, relevant features or variables are selected from the dataset. These features can include battery state of charge (SOC), current and voltage measurements, vehicle speed, power demand, and other relevant parameters.

Model Development: A machine learning model, such as a regression model, classification model, or reinforcement learning model, is selected or designed to learn from the labelled training data. The model's architecture, parameters, and hyperparameters are defined.

Training the Model: The prepared dataset is used to train the machine learning model. During training, the model learns the underlying patterns, relationships, and dependencies in the data. The model iteratively adjusts its internal parameters to minimize the difference between its predictions and the true labels provided in the training dataset.

Model Evaluation: The trained model is evaluated using the validation dataset to assess its performance, accuracy, and generalization ability. Various metrics, such as mean squared error (MSE), accuracy, or root mean squared error (RMSE), can be used to quantify the model's performance.

Model Optimization: If the model's performance is not satisfactory, adjustments are made to the model's architecture or hyper parameters. This process, known as model optimization or hyper parameter tuning, aims to improve the model's performance and generalizability.

Deployment and Testing: Once the model has been trained and optimized, it can be deployed for real-time energy management in FCHEVs. The model can take inputs such as current driving conditions, battery SOC, and power demand, and provide optimal control signals for energy distribution between the fuel cell and energy storage system.

Data training in machine learning for energy management of FCHEVs enables the development of accurate and efficient models that can optimize energy usage, enhance vehicle performance, and extend the range of the vehicle. It allows for adaptive and intelligent control strategies that can adapt to varying driving conditions and user requirements.

The remainder of this article is presented in the following manner: Section-II represents the proposed methodology, section-III describes the proposed system description, section-IV reflects the results and discussion, and the conclusion is provided in the section-V.

II. PROPOSED METHODOLOGY

The proposed methodology has been divided into two different part such as Energy management strategy followed by classifier fusion technique.

A. ENERGY MANAGEMENT STRATEGIES (EMS)

Fuel Cell Hybrid Electric Vehicles (FCHEVs) employ various energy management strategies to optimize the utilization of the fuel cell and energy storage system, ensuring efficient operation and extended driving range. Here are some common energy management strategies used in FCHEVs:

1) RULE-BASED STRATEGY

Description: This strategy utilizes predefined rules and thresholds to determine power distribution between the fuel cell and energy storage system.

EMS Approach: Power allocation decisions are based on predefined conditions such as battery state of charge (SoC), power demand, and other system parameters.

Key Contribution: Simple and intuitive control approach.

2) OPTIMIZATION-BASED STRATEGY

Description: This strategy formulates an optimization problem with constraints and objective functions to optimize power allocation and minimize fuel consumption or maximize efficiency.

EMS Approach: Mathematical optimization techniques, such as linear programming or dynamic programming, are used to find the optimal power split between the fuel cell and energy storage system.

Key Contribution: Provides optimal control solutions, but computationally intensive.

3) MODEL-BASED STRATEGY

Description: This strategy relies on system modelling to predict energy demand and optimize power allocation.

EMS Approach: Dynamic models, such as state-space models or equivalent circuit models, are used to estimate power demand and optimize energy flow.

Key Contribution: Balances optimality and real-time performance but requires accurate system modelling.

4) MACHINE LEARNING-BASED STRATEGY

Description: This strategy utilizes machine learning algorithms to learn patterns from historical driving data and make energy management decisions.

EMS Approach: Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), or other machine learning models are trained using historical data to predict power demand and optimize energy distribution.

Key Contribution: Adaptable to various driving conditions but requires sufficient training data.

5) REINFORCEMENT LEARNING-BASED STRATEGY

Description: This strategy employs reinforcement learning algorithms to learn optimal energy management policies through trial and error.

EMS Approach: Reinforcement learning techniques, such as Q-learning or Deep Q-Networks (DQNs), are used to learn and adapt energy management policies based on the system's state and rewards obtained from the environment.

Key Contribution: Achieves adaptability and learns optimal policies in real-time but requires extensive training.

These energy management strategies can be combined or further enhanced to develop advanced control algorithms that consider real-time driving conditions, vehicle performance, and user preferences. The selection of an appropriate energy management strategy depends on factors such as system complexity, computational resources, available data, and desired optimization objectives. The detailed comparative analysis of the various discussed energy management strategies is described in Table 1.

III. SYSTEM DESCRIPTION

The proposed Fuel Cell Hybrid Electric Vehicle (FCHEV) incorporates a Simulink model developed in MATLAB, as depicted in Fig. 2. This comprehensive model takes into account two primary power sources, namely a 2.4 kW, 48 Vdc Fuel Cell and a 5.4Ah Battery with an initial State of Charge (SoC) set at 100%. The Simulink model consists of various key components, including a DC/DC Boost Converter, a DC Motor serving as the load, 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

Controller, Model Predictive Controller (MPC), Support Vector Machine (SVM) Predictor, and a Neural Network Prediction System. To ensure the efficient operation of the DC/DC Boost Converter, specific specifications must be identified, such as the Input Voltage (Vin), Output Voltage (Vout), Inductance (L), Capacitance (C), and Switching Frequency (fs). Additionally, determining the duty cycle (D) of the converter is crucial. Through the integration of these components, the Simulink model allows for a comprehensive analysis of the FCHEV's performance, enabling valuable insights for the development of environmentally friendly and efficient hybrid electric vehicles.

In Simulink, use the building blocks to construct the boost converter circuit. One will need components such as a voltage source (representing the fuel cell), an inductor, a switch (controlled by the duty cycle), and a diode. Connect these components according to the boost converter topology.

Considering an ideal boost converter without losses, the dynamic Equation can be expressed in (1).

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

where, V_{in} is the input voltage from the fuel cell. V_{out} is the output voltage to the load. D is the duty cycle of the switch ($0 \leq D \leq 1$). L and C are the inductance and capacitance of the boost converter. R_{load} is the load resistance connected to the output.

The first term on the right side of the above Equation (1) represents the rate of change of the output voltage due to the inductor current and the duty cycle. It is derived from the energy balance equation of the boost converter.

To design a control algorithm to adjust the duty cycle based on the desired output voltage and the current system conditions. Configuring the simulation settings, such as the simulation time and solver options. Then, run the simulation to observe the behavior of the boost converter under different operating conditions. One can analyze the output voltage, current, and other relevant variables.

Battery: In a fuel cell hybrid electric vehicle (FCHEV) MATLAB model, the battery is typically used to provide additional power and energy storage to complement the fuel cell system. The battery helps in meeting the peak power demands and improving the overall efficiency of the vehicle. The characteristics and parameters of the battery we have taken [20]. These may include the nominal voltage, capacity, internal resistance, charge/discharge efficiency, and voltage limits. Develop control algorithms to manage the battery's state-of-charge (SoC) and handle charging and discharging operations. These strategies may include power flow control, SoC estimation, and protection mechanisms to prevent overcharging or deep discharging.

The SoC of a battery can be estimated using a dynamic equation that considers the charging and discharging currents over time. While there are various models and algorithms for estimating SoC, one commonly used equation is the Coulomb counting method. This method assumes that the battery's SoC can be determined by integrating the current flowing in and out of the battery over time.

The dynamic equation for battery SoC using the Coulomb counting method can be represented as follows:

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

where, $SoC(t)$ is the State of Charge at time t. $SoC(t-1)$ is the State of Charge at the previous time step $(t-1)$. $I(t)$

is the current flowing into or out of the battery at time t. Δt is the time step or sampling interval. C is the battery capacity.

In Equation (2), the current (I) can be positive when the battery is charging and negative when it is discharging. The battery capacity is typically specified in ampere-hours (Ah). By integrating the current multiplied by the time step and dividing by the battery capacity, the equation calculates the change in SoC over time.

Fuzzy Controller: A fuzzy controller is a type of control system that uses fuzzy logic to make decisions based on imprecise or uncertain inputs. In the context of an FCHEV, the fuzzy controller can be used to optimize the power flow between the fuel cell system and the energy storage system (such as batteries) to achieve optimal performance and efficiency. Fuzzy membership functions are used to quantify the degree of membership of a value to a particular linguistic term [21]. Determine the shape and range of membership functions for each input and output variable. The membership functions should capture the relevant linguistic terms, such as "low," "medium," and "high," based on the system requirements.

MPC Controller: MPC (Model Predictive Control) is a popular control strategy used in various applications, including FCHEVs (Fuel Cell Hybrid Electric Vehicles). MPC involves formulating an optimization problem based on a dynamic model of the system and solving it over a finite time horizon to determine the optimal control actions. In the case of an FCHEV, the objective of the MPC controller is typically to optimize power flow and energy management to achieve desired performance, efficiency, and battery SoC targets [6].

Let's consider a simplified example where the FCHEV system has two main state variables: the battery State of Charge (SoC) and the fuel cell current. The dynamic Equation can be represented as (3).

$$x(k+1) = Ax(k) + Bu(k) \tag{3}$$

where, $x(k+1)$ is the state vector at time step $(k+1)$. $x(k)$ is the state vector at time step (k). A is the state transition matrix that captures the system dynamics. B is the input matrix that relates the control inputs to the state variables. $u(k)$ is the control input vector at time step (k).

In the Equation (3), the state vector x(k) would be defined as [SoC(k), Fuel Cell Current(k)]. The control input vector u(k) represents the control actions that the MPC controller determines at each time step.

PI Controller: A PI (Proportional-Integral) controller is a common type of feedback control used in various applications, including FCHEVs (Fuel Cell Hybrid Electric Vehicles). The PI controller is designed to adjust control inputs based on the error between a desired setpoint and the measured system output. In the case of an FCHEV, a PI controller can be employed to regulate the power flow between the fuel cell system and the energy storage system (such as batteries) to achieve desired performance and efficiency [22], [23]. Here's how a PI controller is typically used in an FCHEV.

The control signal, which represents the adjustment to the power flow between the fuel cell and the battery, is calculated as the sum of the proportional and integral control actions, given in Equation (4).

$$u(t) = Kp * e(t) + Ki * \int e(t)dt \tag{4}$$

where, $u(t)$ is the control signal at time t. $e(t)$ is the error at time t. Kp and Ki are proportional and integral gains. $\int e(t)dt$ dt represents the integral of the error over time.

BLDC Motor: To model and simulate a BLDC (Brushless DC) motor used in an FCHEV (Fuel Cell Hybrid Electric Vehicle) in MATLAB. Start by defining the motor parameters such as motor constants (Kt, Ke), motor inductance (L), motor resistance (R), rotor moment of inertia (J), and the number of motor poles. Define the control strategy for the BLDC motor in the FCHEV. This can include speed control, torque control, or position control based on the desired motor performance. Implement the control algorithm in MATLAB, considering the motor model and the control objectives. Integrate the BLDC motor model into a comprehensive FCHEV model that includes other components such as fuel cells, energy storage systems, and power electronics. Use MATLAB's simulation capabilities to simulate the overall FCHEV system, considering the interactions and dynamics between the different components [24], [25].

A. CLASSIFIER FUSION TECHNIQUE

Machine learning has been incorporated with EMS to provide and predict better accuracy on Fuzzy and Model Predictive Control. The use of machine learning is that it can provide the accuracy of the system based on which it can be decided on which platform the system will work better. So, an automated approach has been designed with an exhaustive analysis.

The development of the proposed technique is based on the dataset available. The overall block diagram is shown in Fig. 3.

The system in this part has been divided into four different parts such as feature description, feature selection, training and testing.

1) FEATURES DESCRIPTION

EVs come with a variety of features designed to enhance their performance, efficiency, and user experience. Here is a description of some common features considered in this manuscript.

Battery Capacity and SoC: The amount of energy that is accessible in relation to the rating is indicated by a cell's state of charge (SoC). The SoC's value ranges from 0% to 100%. The battery is said to be completely charged if the SoC is 100%, however a SoC of 0% means the cell is totally exhausted. Since the SoC cannot rise above 50% in real-world

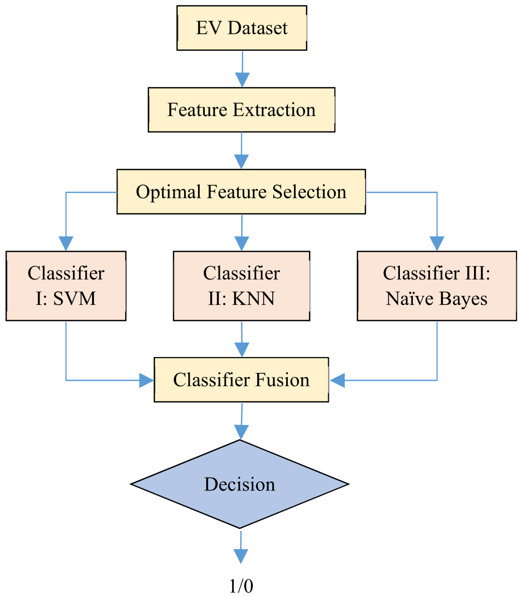

FIGURE 3. Block diagram of the proposed system.

applications, the cell is charged once the SoC hits that level. Similar to this, the maximal SoC starts to drop as a cell age. Accordingly, a 100% SoC for an old cell would be similar to a 75%–80% SoC for a young cell [26].

Battery Stress: Ions are transferred across the anode and cathode inside a battery that is rechargeable during operation, which can put the interior components under a lot of stress. The anode and cathode alternately expand and contract as a result of the movement and attraction of charge within the battery, which contributes to the malfunction of the battery. In order to recognize the warning signals of failure before the battery actually fails, researchers at the Nanostructures for Electrical Energy Storage (NEES) Energy Frontier Study Centre wanted to investigate how this compressive stress impacts the battery. To do this, they created a brand-new method known as pascalametry that enabled them to precisely construct and keep an eye on a micro battery under pressure [27].

Range EV Mode: Various important elements, including the dimensions and weight of the automobile, the power source size, and the electrical motor specifications, considerably affect the range of electric cars (EVs). A specific journey's physical location, driving style, and local climate are all factors to consider. With the appropriate knowledge of the factors that determine EV range, one will be able to conserve energy and increase the amount of distance one can go.

Fuel Tank Capacity: Hydrogen fuels fuel cell electric vehicles (FCEVs). Compared to conventional internal combustion engine vehicles, they are more efficient and only emit warm air and harmless water vapor through their tailpipes. The installation of FCEVs and the hydrogen infrastructure needed to fuel them is still in its early phases [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: Because battery cells are so considerably heavier than engines, electric vehicles can be hundreds to thousands of pounds heavier than comparable petrol vehicles.

Actual Fuel Economy: Over 77% of the electrical energy from the grid is converted by EVs into power for the wheels. Only roughly 12% to 30% of the energy stored in fuel is converted by conventional gasoline-powered vehicles into power for the wheels.

Aerodynamic Drag: The efficiency of a streamline aerodynamic body form in lowering the air resistance to a vehicle's forward motion is measured by the aerodynamic drag coefficient [29].

Slow Charge Max: A slow charger powers EV using AC (alternating current from the national grid), and it normally runs between 2.3 kW and 2.5 kW. The slow chargers often take the shape of 3-pin plug EV chargers and charge from standard wall outlets. The above-mentioned feature in Table 2 has been considered in this work.

2) SELECTION OF OPTIMAL FEATURE

Selection of optimal feature is one of the important tasks related to this work. There are so many techniques for determination of optimal feature such as incremental feature selection, anova1, Kruskal wallis test etc. In this work, anova1 test has been incorporated for determination of optimal feature. The statistically significant feature is decided based on the higher F value. The following Table 3 shows the ranking of feature with decreasing F value.

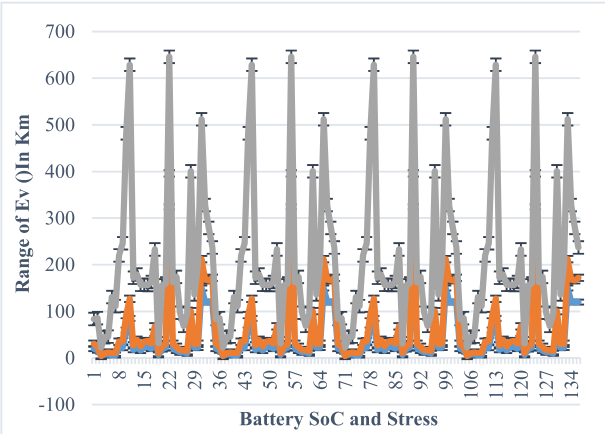

FIGURE 4. Graphical performance analysis of electric vehicle.

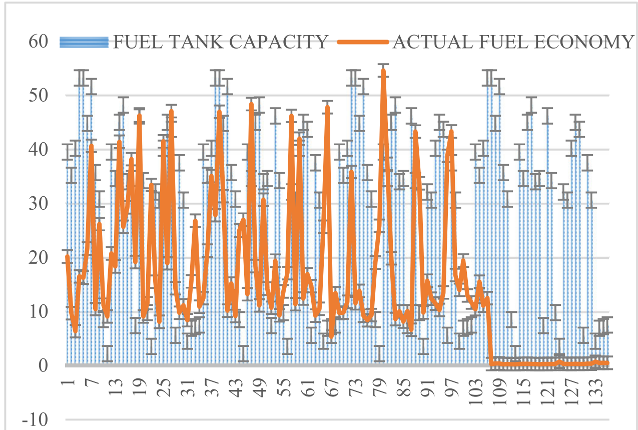

FIGURE 5. Fuel tank capacity Vs actual fuel economy.

After that, a different feature set has been prepared on the basis of ranking of feature. It can be observed that combination of Feature has been done to produce different feature vector set such as M, N, U, ..., Z. These are formed based on rank received from Anova1 analysis is depicted in Table 4.

3) TRAINING AND TESTING

In the training phase, the researchers utilized three distinct machine learning approaches. For the support vector machine (SVM) training, the feature vector set was handled according to the approach described in Equation (5).

$$D=\{(Feature\ Vector\ Set^1, y^1), \ldots, (Feature\ Vector\ Set^l, y^l\},\quad x \in R^n, y \in \{-1, 0\} \tag{5}$$

In a similar way, training has been done using k – Nearest Neighbor (k – NN) [14] algorithm. This is one of the non-parametric ways for solving classification problems. As this problem is going to solve for an even number of classes, odd numbered k values such as 1, 3, 5, 7 have been used in the training phase. Apart from these two classifiers, Naïve Bayes Classifier has also been incorporated in this proposed work. This Naïve Bayes Classifier incorporates the probabilistic concept for the formulation of classification.

Let's consider, the classified output from SVM, k-NN and Naïve Bayes are S_o, K_o *and* N_0 respectively. The corresponding output using classifier fusion will be as Equation (6).

$$Y_o = [(S_o\ OR\ K_o)\ OR\ N_0] \tag{6}$$

In Equation (6), *Yo* is the ultimate output that is achieved using Classifier Fusion. The utility of using classifier fusion is that even if there is any mismatch using other classifiers, that can be incorporated by Classifier Fusion.

IV. RESULT AND DISCUSSION

Performance analysis of an FCHEV (Fuel Cell Hybrid Electric Vehicle) shows below in Fig:4, which involves evaluating various aspects of its performance, including acceleration, top speed, range, fuel efficiency, and emissions.

The performance analysis of this Fuel Cell Hybrid Electric Vehicle is shown below. Here three major features of FCHEV is considered. The Battery State of Charge (SoC), Battery Stress and the range of Electric Vehicle is taken into consideration. The mentioned Fig: 4 shows that how with the distance covered (Range) by the vehicle varies with the batteries state of charge and accordingly the stress of the battery increases.

Fuel consumption is the inverse of fuel economy. It is the amount of fuel consumed in driving a given distance. It is measured in the United States in gallons per 100 miles, and in liters per 100 kilometers in Europe and elsewhere throughout the world. Fuel consumption is a fundamental engineering measure that is directly related to fuel consumed per 100 miles and is useful because it can be employed as a direct measure of volumetric fuel savings. It is actually fuel consumption. In the below Fig. 5 it is shown the capacity of the Fuel tank and 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

To simulate the performance of an FCHEV battery and fuel cell system in MATLAB, one would typically use a combination of mathematical models and numerical methods. Here's 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.

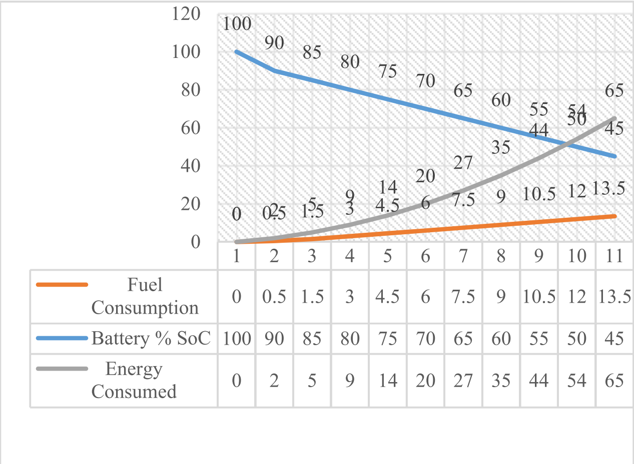

FIGURE 6. Graphical representation of fuel consumption, battery SoC & energy consumed.

After developing the mathematical model for the battery, fuel cell, and other relevant components of the FCHEV system. These models should capture the dynamic behaviour of the FCHEV energy management parameters. In an FCHEV, the fuel consumption, battery State of Charge (SoC), and energy consumed are interrelated. The fuel consumption represents the amount of fuel consumed by the fuel cell system, which powers the vehicle and charges the battery. The battery SoC indicates the energy level or capacity of the battery, while the energy consumed in Kilo Joules represents the total energy utilized by the FCHEV system. In the above representation in Fig 6 it is shown.

The relationship between these variables can be summarized as follows:

Fuel consumption and Energy consumed: Fuel consumption directly affects the energy consumed in an FCHEV. As the fuel cell system generates power, it provides energy to both propel the vehicle and charge the battery. The fuel consumption rate determines the rate at which energy is being supplied to the system.

Energy consumed and Battery SoC: The energy consumed by the FCHEV system influences the Battery SoC. As energy is drawn from the battery to power the vehicle's electrical systems, the Battery SoC decreases over time. Similarly, when energy is regenerated through processes such as regenerative braking, the Battery SoC increases.

Fuel consumption and Battery SoC: The fuel consumption indirectly affects the Battery SoC. As fuel is consumed by the fuel cell system, it replenishes the battery by charging it. The fuel consumption rate determines the rate at which the battery is being charged or discharged, thus impacting the Battery SoC. Here's a considered formula as expressed n Equation (7) to calculate fuel cost per mile.

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

The above plotting Fig:7 refers to the amount of fuel consumed by the vehicle per unit distance travelled. It is typically measured in miles per gallon (MPG) or litres per kilometre (L/km). This information can be obtained from the vehicle specifications or through experimental measurements. By representing fuel economy in terms of fuel cost per mile, one can easily compare the cost efficiency of different vehicles or track the cost savings achieved by improving the fuel economy of a specific vehicle.

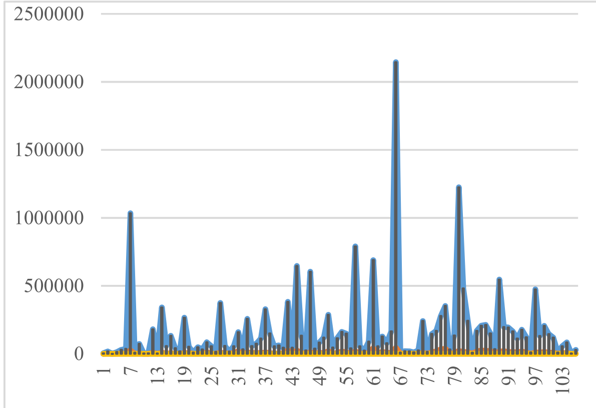

FIGURE 7. Representation of fuel economy with fuel cost per mile.

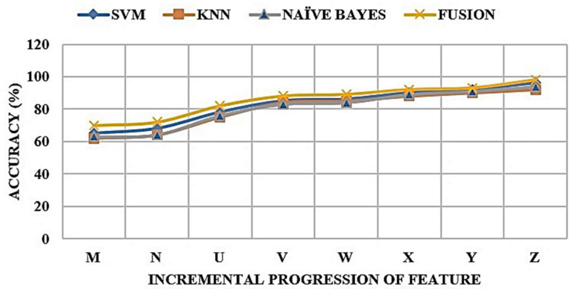

FIGURE 8. Accuracy with incremental feature set.

TABLE 6. Performance analysis using different kernel functions using SVM.

Kernels	Training			Testing		
	Sn	Sp	Acc	Sn	Sp	Acc
Linear	100	98.5	99	96	95	97.5
Polynomial	100	98.5	99.5	100	95	98

A. MACHINE LEARNING BASED PERFORMANCE ANALYSIS

Fig. 8 represents the incremental feature selection in terms of feature set M, N, U, V, W, Y, and Z. The experiment has been performed for all the classifiers considered in this work such as SVM, KNN, Naïve Bayes and Classifier Fusion Technique. It is observed that in most cases, accuracy has been increased along with increment of feature vector set.

A detailed performance analysis has been shown in Table 6, 7, and 8. In the first Table 6, performance has been presented using different kernel functions for both Training

TABLE 7. Performance analysis using different k values using k-NN.

k- values	Training			Testing		
	Sn	Sp	Acc	Sn	Sp	Acc
1	90	99	98	88	96	96
3	90	100	98	87	97	96.5
5	91	99	98.5	90	97	96.5

TABLE 8. Performance analysis using different distribution functions using naïve bayes classifier.

Distribution Functions	Training			Testing		
	Sn	Sp	Acc	Sn	Sp	Acc
Kernel	92	99	97	90	97	95
Normal	94	95	96	90	96	96

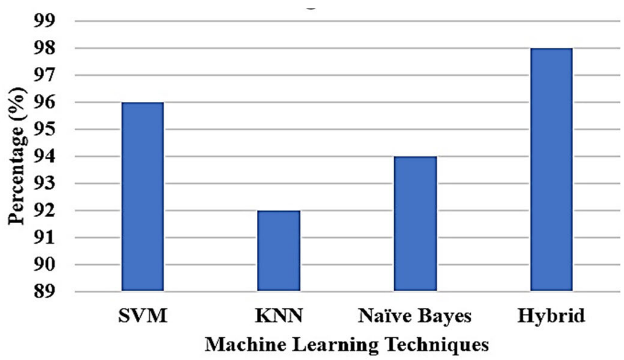

FIGURE 9. Performance comparison amongst classifiers.

and Testing. In these experiments, sensitivity, specificity along with accuracy have been presented to understand the feasibility of this system in context to the energy management system. It can be observed that a steady performance has been observed for polynomial kernel.

A similar performance has been done for the K-NN classifier using K values 1, 3, and 5. A significant performance has been seen using a K-value of 5. The improvement has been seen not only for sensitivity, but also for specificity and accuracy. Apart from that, performance using different distribution functions has been represented in Table 8 for Naïve Bayes. Normal distribution function provides better performance for sensitivity, specificity as well as accuracy too.

In Fig. 9, performance comparison amongst classifiers has been done. It is observed that Hybrid classifier provides better performance. So, it has been considered as the proposed classifier in this work.

V. CONCLUSION

EMS, which stands for Energy Management System, is a crucial component in hybrid vehicles, including Fuel Cell Hybrid Electric Vehicles (FCHEVs). Its primary function is to optimize the energy flow and utilization between the fuel cell system, battery pack, and other energy storage devices to achieve the most efficient operation of the vehicle. The energy management system optimizes the utilization of both the fuel cell system and the battery pack to achieve the desired driving range. During normal driving conditions, the EMS primarily relies on the fuel cell system for power generation. However, during high-power demand situations, such as rapid acceleration, the EMS can use power from both the fuel cell and the battery pack to provide additional power and meet the driver's demand. The application of SVM, KNN, and Naive Bayes algorithms for energy management strategies in Fuel Cell Hybrid Electric Vehicles (FCHEVs) was examined in this study. The purpose was to improve the performance, efficiency, and overall operation of FCHEVs by optimising the power flow between the fuel cell system and the energy storage system, such as batteries. As classification techniques, the SVM, KNN, and Naive Bayes algorithms were used to estimate the optimal power flow based on input data such as vehicle speed, battery state of charge (SoC), and other important parameters. The study's findings revealed that all three approaches, SVM, KNN, and Naive Bayes, exhibited promising capabilities in energy management for FCHEVs. In terms of accuracy, computing efficiency, and robustness, each technique demonstrated its strengths and limits. KNN, on the other hand, provided ease of use and computational efficiency. Power flow patterns were identified based on their proximity to similar instances in the training dataset. KNN demonstrated good accuracy, although it may struggle with high-dimensional datasets or imbalanced classes. The choice of technique should be based on specific requirements, dataset characteristics, and computational resources available. Further research can focus on exploring hybrid approaches or incorporating additional machine learning algorithms to improve the accuracy and efficiency of energy management systems in FCHEVs.

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DEBASIS CHATTERJEE received the B.Tech. degree in electrical engineering from the Maulana Abul Kalam Azad University of Technology, Kolkata, India, and the M.E. degree in power system from Jadavpur University, Kolkata. He is currently pursuing the Ph.D. degree in electrical engineering with the National Institute of Technology Mizoram, Mizoram, India. He is also an Assistant Professor with the Department of Electrical Engineering, NSHM Knowledge Campus-Group of Institution, Durgapur, India. His research interests include electrical machines, electrical circuit and networks, electric vehicles, and electrical machines design.

PABITRA KUMAR BISWAS (Senior Member, IEEE) received the B.Tech. degree from the West Bengal University of Technology, West Bengal, India, the M.E. degree in EE power electronics and drives from Bengal Engineering and Science University (IIEST), West Bengal, in 2007, and the Ph.D. degree in electrical engineering from the National Institute of Technology, Durgapur, India, in 2013. He is currently an Associate Professor in electrical engineering with the National Institute of Technology Mizoram, Mizoram, India. He was the HOD of the EEE Department, from February 2015 to August 2019. He is also an Associate Dean (R&C). He has published a numbers of research papers in national/international conferences and records/journals. He has a book and more than six book chapters and filed three patents. He has completed one DST-SERB Project. He has about 16 years of academic and research experience. He has guided seven Ph.D. students and more than ten M.Tech. students and ten more are pursuing their research at present. He has reviewed papers in reputed international conferences and journals. He is a member of International Association of Engineers. He is also a fellow of Institute of Engineers and Membership (FSASS) of SAS Society. He has received the Best Paper Award and Best Researcher Award (International Scientist Awards on Engineering, Science and Medicine). His research interests include electromagnetic levitation systems, active magnetic bearing, power electronics converters, PMSM and BLDC motor drives, electric vehicles, and renewable.

CHIRANJIT SAIN (Senior Member, IEEE) received the B.Tech. degree in electrical engineering from the Maulana Abul Kalam Azad University of Technology, West Bengal, the M.Tech. degree from the Electrical Engineering Department, National Institute of Technical Teachers Training and Research (NITTTR), Kolkata, India, and the Ph.D. degree in electrical engineering from the National Institute of Technology Meghalaya, India, in 2019. He is currently an Assistant Professor with the Electrical Engineering Department, Ghani Khan Choudhury Institute of Engineering and Technology (GKCIET), Malda, A Centrally Funded Technical Institute (CFTI) under Ministry of Education, Government of India. He was associated with the Siliguri Institute of Technology, Siliguri, India, from 2010 to 2021. He is a life-time member of the Institution of Engineers India Ltd. He has about 11 years of academic experience, six years of research experience, and one year of industrial experience. His current research interests include the senorless and vector control of permanent magnet motor drives, digital control in power electronics converters, electric vehicles, renewable energy systems, and the design and optimization of electrical machines. He has published several papers in national/international level journals/conferences/books/book-chapters in the relevant field. Additionally, he is guiding four Ph.D. scholars in joint collaboration with NIT Mizoram. He is also serving as a Reviewer in some reputed journals, such as IEEE Transactions on Circuits and Systems—II: Express Brief, IEEE Transactions on Industrial Electronics, IEEE Transactions on Energy Conversion, *Electric Power Components and Systems* (Taylor & Francis), and Inderscience publications.

AMARJIT ROY received the M.Tech. degree from the National Institute of Technology Silchar, in 2014, and the Ph.D. degree in electronics and communication engineering from NIT Silchar. After that, he joined as an Assistant Professor with BML Munjal University, in 2017. In July 2020, he joined as an Assistant Professor Sr. Grade 1 with VIT AP University. He is currently an Assistant Professor with the Ghani Khan Choudhury Institute of Engineering and Technology, Malda (A CFTI under MoE). His research interests include image noise removal, soft computing, and biomedical image processing. He has published many articles in journals, such as IEEE, Elsevier, and Springer.

FURKAN AHMAD received the Bachelor of Technology, Master of Technology, and Doctor of Philosophy degrees in electrical engineering from Aligarh Muslim University, India, in 2012, 2015, and 2019, respectively.

He is currently a Researcher with the Division of Sustainable Development, College of Science and Engineering, Hamad Bin Khalifa University, Qatar Foundation, Doha, Qatar. He was awarded the CSIR Junior and Senior Research Fellowship Award (2016–2019). Upon receiving his doctorate from AMU, he joined the Indian Institute of Technology Delhi (IIT Delhi) as a Postdoctoral Fellow. He has authored/coauthored more than 65 research articles. His research interests include microgrids, electric vehicles, charging infrastructure, grid integration, and energy management systems. He is also an Associate Editor of *Frontiers in Energy Research*, *International Journal on Smart Sensing and Intelligent Systems*, and *Frontiers in Future Transportation*.