Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 2s (2024)

Mathematical Analysis and Non-Linear Optimization of EV Battery Health Using Fuzzy Logic and Neural Computing Techniques

Dr. Sunil Kumar Gupta[1], Abhinav Kashyap[2], Dr. Siddharthsingh K. Chauhan[3], Dr. Vineeta Chauhan[4], Dr. Ashish Raj[5]

[1]Professor, Department of Electrical and Electronics Engineering, Poornima University, Jaipur, India

[2]Assistant Professor, Department of Mechanical Engineering, School of Engineering, P P Savani University, Surat, India

[3]Associate Professor, Institute of Technology, Nirma University, Ahmedabad, Gujarat (India)

[4]Assistant Professor, Indus University, Ahmedabad, Gujarat (India)

[5]Associate Professor, Department of Electrical and Electronics Engineering, Poornima University, Jaipur (India)

Email: sunil.gupta@poornima.edu.in, abh.ksh20@gmail.com

Article History:

Received: *05-03-2024*

Revised: *22-04-2024*

Accepted: *08-05-2024*

Abstract:
This article is related to a mathematical optimization model of the electric vehicle (EV) battery health management, which is based on fuzzy logics and neural network models. The study achieves a neural network to recognize charging patterns and preceding SOC in addition to the full charge temperature dependent upon the duration and ampere within the Multiple-Stage Constant Current (MCC). The target is SOC of 83%, which is made in 43 minutes upon maintaining the optimal temperature factor (of about 35 degrees). 85°C, representing a 3. At this point we observed 30% higher specific output capacity (SOC) versus standard constant current-constant voltage (CC-CV) method with a very small temperature increase of only 0. 41°C. The project includes several technical specifications, such as 96s2p where the complete battery runs through 192 cells, 40 kWh nominal capacity and 350 V nominal voltage. The flow of work will be database creation and management, the design of the simulation, machine learning model creation, testing and evaluation. The dataset is built from a sample, which includes features like the temperature within the room, the starting temperature of the battery and the time points (t1, t2, t3, t4); these are used for the training the machine learning algorithm. The simulation is followed by determination of the SOC and battery temperature, which are utilized as target features by the model. In Exploratory Data Analysis (EDA) one can highlight all the essential statistics while developing neural network model. Approach incorporated means of data analysis which include distribution, identification, and correlation, and prepared the way for outliers to be handled. The optimization outcomes per 28 degrees display the performance of the joint neural network and fuzzy logic method. The model gives SOC level above 80% with final temperature below 40°C, in which the errors of the voltage and temperature are lower than 2% and 1%, respectively. The fuzzy logic does that it has a parameter choosing method that makes the final battery temperature to go down and thus improves SOC as compared to other parameters method. This paper gives an insight into the use of hybrid optimization via combining three main variables: fuzzy logic, neural networks as well as various criteria of battery health management, the final result is optimization of charging parameters into EV's life.

Keywords: Fuzzy Logic, Neural Networks, EV Battery Optimization, State of Charge (SOC), Battery Health Management, Multi-Stage Constant Current (MCC) Charging, Mathematical Modeling, Nonlinear Optimization, Machine Learning, Battery Temperature Control.

1. INTRODUCTION

The EVs possess a fundamental role in the field of green mobility, as they provide an attractive alternative to the reduction of the greenhouse emissions during the combustion to the dependence on the fossil fuels. Nonetheless, there is a huge challenge of whether EVs all over the world can play their expected role in so far as their performance and health are concerned. Batteries are the central factors of the electric vehicles such as their efficiency, durability and security, and these factors build the foundation for a sustainable development of this technology. The principal direction is the management of the battery charging and discharging nonlinear behaviors as this downgrades both the battery state of charge (SOC) and temperature, among other things. These elements are essential for promoting the battery's health and performance being lasting during its service life. Battery charging optimization is a very challenging task riddled with interdependent factors that are insignificant individually but take critical nature when influencing each other, including current levels, temperature, and SOC. CC-CV (constant current - constant voltage) device electricity management methods that are current in the market have many disadvantages that may result in underperforming batteries and a reduction of their life. Hence, this motivates the engineers to come up with the modern algorithms that will able to solve the complicated dynamics of battery recharging. Here, the fuzzy logic and neural network-type mathematical optimization are deployed in order to deal with the defined water shortage challenges. Thus, it accomplishes the goal using the hydrocarbon compounds to store energy non-chemically by employing the computational techniques to increase the efficiency and accuracy of the systems that manage electric vehicles' battery health. The non-uniform character of the batteries behavior most especially during discharging and charging increases the complication in terms of algorithm and hence the necessitation of sophisticated optimization. Batteries do not charge uniformly: charging of the same battery at the same current under different conditions can progress at various rates [1-14].

Table 1: Analysis of Related Works [1-17]

Authors	Year	Main Findings	Methodological Limitations
Wenxia et al.	2016	Developed a greedy method to address the location problem within an acceptable timeframe.	Considered only a few factors for station location.
Alipour et al.	2017	Created a stochastic schedule but disregarded price sensitivity.	Limited scope of analysis to price insensitivity, potentially increasing distribution system losses.
Bayram et al.	2016	Found correlation between charging demands and solar output at a university campus.	-
Galiveeti et al.	2018	Added DG units to a CS-integrated system to reduce network power loss.	Focused on adding DGs before finding optimal CS locations, which is not always feasible.
Pallonetto et al.	2016	Chose optimal CS location considering high solar panel penetration.	Only one charging station was considered; driver behavior was not accounted for.

Miralinaghi et al.	2016	Aimed to reduce total ownership cost (TOC) considering driving distance and recharging time.	Did not incorporate the option of skipping trips in the final solution.
Huang et al.	2015	Scheduled PHEV charging at night to reduce operational costs.	High night-time load could be problematic; study did not consider varied workplace locations for charging.
Alharbi et al.	2014	Analyzed the impact of home charging on the distribution grid.	Relied on specific charging times, which may not hold in real scenarios.
Shuai et al.	2016	Reviewed smart grid scheduling for lowering PHEV charging costs.	-
Gheorghe Badea et al.	2019	Planned an EV charging station in a remote area using solar energy.	-
M. Zeman et al.	2016	Studied solar energy for charging EVs in the Netherlands.	Due to low solar insolation, required a higher-rated PV array than the converter.
Thenmozhi G et al.	2020	Proposed a solar-powered electric vehicle.	-
Jamuna K et al.	2021	Described charging of electric vehicles in office parking using PV cells.	-
Seyezhai et al.	2019	Analyzed high-quality DC-DC converters for battery charging.	-
Shambhavi Bade et al.	2020	Used a sliding mode controlled SEPIC converter for optimal operation of a PV panel.	-
Qi Liu et al.	2016	Proposed alternatives for the photovoltaic architecture of charging stations.	-
Siddiq Khateeb et al.	2018	Discussed the global infrastructure for solar PV-EV charging.	-

These conditions include initial temperature, ambient temperature, and the current, among others, which are applied at different stages of the charging process. This non-linearity stands out most in that they do not have any straight line relationship with the SOC and temperature which makes it difficult to model and control. Linear optimization methods, such as techniques that involve fuzzy logic or neural networks, are usually the best-fit because of their ability to accommodate the complexities [14-18].

They can build the correlation among the several elements using the modified predictions and management system of control tools. Fuzzy logic is regarded as the world of handling uncertainties and inaccuracy that BMS in the state of charge is characterized with. Linguistic variables and the matrix of rules are established to imitate the style of decision making of a human. It allows the invention of adaptive and bendy systems governing the range of parameters of the battery. Although the neural networks are the most accurate machines for detection and prediction of patterns, they are also prone to biases and errors. They are able to study what was hidden in the historical data and locate emerging strategies as a new method of non-traditional analytical approaches. Through combining the two we can develop an adaptive charging optimization system that can be used to set the charger parameters dynamically to maximize battery performance whiles enhancing the battery's life [15-24].

Mobilization of EVs seems to be entirely dependent on efficient storage of energy. That is delivered by the advanced battery system. The indicated system should be handled effectively such that one gets a powerful battery life, efficiency and a smooth performance. Without battery management system, which are in charge of charge and release power, safety and battery's lifespan prolongation, battery cannot work properly. Such engineering methods are liable to utilize the mathematics modeling and advanced algorithms which are the basic factors for improvement in EVs (electric vehicles) [24-32].

Battery Charging Non Linear Dynamics : The State of Charge (SOC) is a critical parameter in battery technology, indicating the current energy level of the battery compared to its total capacity. It is typically expressed as a percentage:

$$\mathrm{SOC}(t) = \mathrm{SOC}\,(t-1) + \Delta t \times \frac{I(t)}{C} \times 3600 \tag{1}$$

Here, $I(t)$ represents the current, C is the total capacity, and Δt is the time increment, showing how SOC evolves as the battery charges. The charging strategy is pivotal, particularly in how the current is modified over time to optimize both charging speed and battery health. A multi-stage current profile (MCC) can be effectively modeled as a piecewise function, adjusting the current at different phases of the charging cycle:

$$I(t) = \begin{cases} I_1 & \text{if } 0 \leq t \leq t_1 \\ I_2 & \text{if } t_1 < t \leq t_2 \\ I_3 & \text{if } t_2 < t \leq t_3 \\ I_4 & \text{if } t_3 < t \leq t_4 \end{cases} \tag{2}$$

Voltage dynamics are crucial as they affect both the charging speed and the longevity of the battery. Managing voltage carefully to avoid exceeding the battery's voltage limit, which can cause damage, is essential.

Battery temperature significantly impacts both the efficiency and lifespan of the battery. Excessive heat generation during charging can lead to thermal runaway, a dangerous condition. The heat generation model and cooling rate are expressed as:

$$Q(t) = I(t)^2 \times R \tag{3}$$

$$\frac{dT}{dt} = \frac{Q(t) - h \times (T(t) - T_{m+})}{m \times c_p} \tag{4}$$

Here, $Q(t)$ represents the heat generated, R is the internal resistance, h is the heat transfer coefficient, T_{env} is the ambient temperature, m is the battery's mass, and c_p is the specific heat capacity.

Neural networks are utilized to predict the SOC and temperature at the end of the charging process. The inputs to these networks include initial conditions, environmental factors, and historical data from the charging process. These models learn from the data to make accurate predictions about the future state of the battery:

$$\widehat{\mathrm{SOC}}(t_4) = f_{\mathrm{NN}}(T_0, T_{\text{rooma}}, t_1, t_2, t_3, t_4) \tag{5}$$
$$\hat{T}(t_4) = g_{\mathrm{NN}}(T_0, T_{\text{roamu}}, t_1, t_2, t_3, t_4) \tag{6}$$

Optimization Techniques

The primary objective is to minimize the total charging time while ensuring that the SOC reaches a desired level without the temperature exceeding a specific threshold. This involves complex constraints and requires advanced optimization algorithms:

$$\min \sum_{i-1}^{4} t_i \tag{7}$$
$$\mathrm{SOC}(t_4) \geq 83\%$$
$$T(t_4) \leq 35.85^{\circ}\mathrm{C}$$

Fuzzy logic is employed to handle uncertainty and variability in battery charging. It adjusts the charging parameters in real-time based on fuzzy rules, which can better manage the nuances of battery behavior under different conditions:

$$t_{\text{new},i} = \text{ Fuzzy Adjust } (t_i, \Delta\mathrm{SOC}, \Delta T) \tag{8}$$

Gradient descent, stochastic gradient descent, and simulated annealing are techniques used to find optimal charging schedules. These methods adjust the parameters iteratively to minimize errors between predicted and actual outcomes:

$$t_{i+1} = t_i - \lambda \frac{\partial \text{ Eirtorsact}}{it_i} \tag{9}$$
$$T(t) = T_0 \times e^{-kt} \tag{10}$$

Neural networks are employed to predict the SOC and temperature at the end of the charging process. The inputs to these networks include initial conditions, environmental factors, and historical data from the charging process. The networks learn from this data to make accurate predictions about the battery's state at any future point.

$$\begin{aligned} &\widehat{\mathrm{SOC}}(t_4) = f_{\mathrm{NN}}(T_0, T_{\text{room}}, t_1, t_2, t_3, t_4) \\ &\hat{T}(t_4) = g_{\mathrm{NN}}(T_0, T_{\text{room}}, t_1, t_2, t_3, t_4) \end{aligned} \tag{11}$$

The final step involves implementing these models in a simulation environment or directly in the BMS hardware. The models are evaluated based on their accuracy in predicting SOC and temperature, their impact on battery health, and their effectiveness in optimizing charging times.

The integration of neural networks and fuzzy logic into the battery charging process represents a significant advancement in battery management technology, allowing for more sophisticated and responsive control strategies that can adapt to the needs of modern electric vehicles.

Overview of Fuzzy Logic and Neural Network Techniques

Fuzzy logic (Fuzzy logic), which is getting a lot of attention now, was introduced by Lotfi Zadeh in the 1960s under the name of an approach that allows investigating and solving reasoning issues that are approximate. In the application of fuzzy logic for battery management, the principle involves the fuzziness and unpredictability of battery characteristics to improve battery function. For example, the idea of three-layer membership is replaced by a more gradual interpretation based on degrees of membership that justifies the scale of warm or cold that is needed. The ability to adapt is what particularly describes this operation allowing the controlled charging rate as well as maintaining the temperature of the battery which is very vital for an efficient charge.

Neural networks, which are basically models inspired by the human brain, include of layers which are connected through nodes (neurons). Such networks own a remarkable ability to learn from data gradually, and this process continues until the networks achieve the best performance. In battery management, neural networks can be programmed to be able to forecast and the state of the charge and temperature using historical charging data as a reference. While neural networks make it possible to realize patterns in the data, these patterns in turn provide accurate predictions that are the key for improving charging process. The merging of fuzzy logic and neural network provides an effective machinery for handling the intricate non-linearity characteristic of the storage batteries powering EVs.

Implementation of Fuzzy Logic and Neural Network in Battery Optimization

The principles of fuzzy logic and neural networks are involved in the EV battery optimization through the stages of sensor inputs, fuzzy system identification, and online execution. The first step is to get together a total dataset containing some factors like the initial temperature of battery, room temperature, charging speed, and charging stages. These data sets make up a foundation for the training of neural network model.

After the data collection is accomplished, the next stage is to clean up the data, done by correction of inconsistencies or outliers. The precise work of data preprocessing serves to cut down the error rate of the neural network model. Standardization and outlier processing are tools we use in order to clean and prepare the data for the training phase. The neural network is the last stage and this one is then trained with the help of the preprocessed data having an object of learning the complex connection that exists between the inputting parameters and the targeting variables (SOC and Final Battery Temperature). While that, fuzzy logic controller managing of charging process is put-together as well. The fuzzy logic controller uses a set of rules that is based on the decision criteria of experts to determine the optimal charging parameters. This is a calculated algorithm which is responsible to maximize the SOC while keeping the battery temperature under the safe limit threshold. The fuzzy logic controller harmonizes with the neural net performance and adjusts the charging regime based on the real-time predictions of neural network.

The combination of weakening and neural networks makes the system to be an adaptive null optimal process however. As a result, it keeps on tracking the battery's state and making adjustments on the charging parameters, the system guarantees that the battery operates efficiently and safely. Moreover, this technology will elevate the power and last ability of battery pack as well as guaranteeing a very good trustworthy of the EV.

2. PROPOSED METHODOLOGY

This research proposes an advanced methodology for optimizing the charging process of electric vehicle (EV) batteries using neural networks and fuzzy logic. By integrating these computational techniques, the research aims to improve the accuracy of predicting and managing the state of charge (SOC) and temperature, key factors in enhancing battery efficiency and longevity.

The primary objective is to develop a robust model that:

1. Accurately predicts SOC and temperature at various stages of the charging cycle.
2. Dynamically adjusts charging parameters to maximize battery health and performance.
3. Outperforms traditional constant current-constant voltage (CC-CV) methods in terms of efficiency and battery health conservation.

Methodological Framework

Database Creation and Management

The initial phase involves creating a comprehensive dataset that captures various parameters influencing battery behavior. This dataset will include:

- Battery Initial Temperature (T_0) : Influences the rate of charging and efficiency.
- Room Temperature (T_{room}) : Environmental factor affecting charging dynamics.
- Charging Durations (t_1, t_2, t_3, t_4) :Specific time intervals for charging stages.
- Final $\mathrm{SOC}(\mathrm{SOC}_{\text{final}})$) The target state of charge post-charging.
- Final Battery Temperature (T_{fimal}) : Reflects thermal management effectiveness.

Equations used to derive initial data:

$$\mathrm{SOC}(t) = \mathrm{SOC}(t-1) + \Delta t \times \frac{I(t)}{C} \times 3600 \tag{12}$$

$$T(t) = T(t-1) + \Delta T \tag{13}$$

Where ΔT represents the temperature change influenced by internal and external factors, and $I(t)$ is the current at time t.

An extensive EDA will be conducted to understand data patterns and distributions. This includes:

- Calculating statistical metrics such as mean, median, and standard deviation.
- Analyzing correlations between SOC, temperature, and time intervals.

$$\mathrm{Corr}\,(X, Y) = \frac{\mathrm{Cov}\,(X, Y)}{\sigma_X \sigma_Y} \tag{14}$$

Where Corr is the correlation coefficient, Cov is the covariance, and σ represents the standard deviation.

A neural network model will be trained to predict SOC and temperature based on input features. The model architecture will include:

- Input Layer: Accepts raw data as input.
- Hidden Layers: Multiple layers to process data non-linearly.

- Output Layer: Produces predicted SOC and temperature.

$y=f(W \cdot x+b)$

Where yy is the output, ff is the activation function, WW and bb are the weights and biases, and xx is the input.

Fuzzy Logic Integration

To handle uncertainties and fine-tune the charging process, a fuzzy logic controller will be implemented. This controller will adjust charging parameters in real-time based on:

- If-Then rules derived from the expert knowledge.

Membership functions defining the linguistic variables.

To handle uncertainties and fine-tune the charging process, a fuzzy logic controller will be implemented. This controller will adjust charging parameters in real-time based on:

- If-Then rules derived from expert knowledge.
- Membership functions defining the linguistic variables.

$$\mu_{\text{High SOC}}(x)=\begin{cases}0 & \text{if } x<80\% \\ \frac{x-60\%}{100\%-00\%} & \text{if } 80\% \leq x \leq 100\% \\ 1 & \text{if } x>100\%\end{cases} \quad (15)$$

Where $\mu_{\text{High}} SOC$ defines the degree of membership to the "High SOC " fuzzy set.

Optimization and Testing

The optimized parameters from both neural network predictions and fuzzy logic adjustments will be tested through:

- Simulations using varied environmental and operational conditions.
- Real-time implementation in a controlled environment to validate model predictions against actual outcomes.

$$\text{Error SOC} = | \text{ Predicted SOC - Actual SOC } | \quad (16)$$
$$\text{Error }_T = | \text{ Predicted Temperature - Actual Temperature } | \quad (17)$$

The final step involves evaluating the model's performance and iteratively refining the system based on:

- Performance metrics such as Mean Square--1 Error (MSE) for predictions.
- Feedback from the testing phase to improve model accuracy and reliability.

$$\text{MSE}=\frac{1}{n} \sum_{i-1}^{n}(\text{ Predicted }_i-\text{ Actual }_i)^2 \quad (18)$$

Where n is the number of observations.

This methodology leverages advanced machine learning and fuzzy logic to manage the complexities of battery charging in electric vehicles, aiming to optimize both performance and longevity through a systematic, data-driven approach.

3. RESULT ANALYSIS

This research analyzes the usage of neural networks and fuzzy logic for conditions during the charging process of EV batteries which aims at optimizing the overall outcome. GOE's results - which shows improvements in capacity and temperature management - obviously proves the method's effectiveness, making batteries last longer and run much better. The research scored a highly remarkable SOC of about 83% in the less than 45 minutes charging duration. This represents a 3. So the high efficiency of OTLP was proven by a 38% increase in contrast to the conventional constant current-constant voltage (CC-CV) approach. The fundamental factor that not only increases the charging method efficiency but also significantly shrinks the total charging time (which is very important for the user convenience and battery health) lies in this charge enhancement technology. Thermal management is absolutely necessary for ensuring the functioning of the cells of battery. The research method adopted optimally the battery temperature of almost 35 that was controlled. 85°C, just marginally--but at least--a slight temperature increase of 0. Traditional methods for centralized power generation are outperformed by solar prowess at 41°C. Adequate thermal management can help maintain the optimal temperature, enabling greater cycle life and safety from risks that may cause the overheating. The fact that the machine learning algorithm that predicted the operation cycles and battery temperature by taking into account different durations of charging and the level of current supplied was deemed as the key. The neural network provided the machine with a capability of learning historical data and recognizing patterns toward achieving more accurate and adaptive control which generated more precise and accurate decisions. The acceptance of fuzzy logic consideration meant that the process of managing the charging algorithm got smarter and at some point, not using the standard but relying on flexible approach. Using rules that are not hard-wired, fuzzy logic supplied with a way to freely adjust current consumed for charging by adapting to charge based on the status of the battery, thus increasing the charging efficiency by ensuring that temperature is maintained under safe regulations.

Table 2: Battery Specifications and Technical Parameters

Technical Index	Value
Number of battery cells	192
Battery configuration	96s2p
Nominal capacity	40 kWh
Nominal voltage	350 V
Number of battery modules	24
Battery cell size: Width	261 mm
Battery cell size: Length	216 mm
Battery cell size: Thickness	7.9 mm
Maximum power	46 kW
Average power	40 kW
Battery temperature tolerance	45°C to 60°C
Charging time (10% to 80%)	43 minutes

Table 3: Database Creation and Management Sample Data

Battery Initial Temp (°C)	**Room Temp (°C)**	**t_1 (s)**	**t_2 (s)**	**t_3 (s)**	**t_4 (s)**	**Final Battery SOC (%)**	**Final Battery Temp (°C)**
25.66	28.12	1989.83	2484.47	2542.12	2576.31	0.85	317.30
29.56	30.14	2423.81	2577.48	2579.01	2579.66	0.88	310.02
30.12	32.78	1146.96	1646.36	1827.81	2462.77	0.78	310.98

Table 4: Exploratory Data Analysis (EDA) Summary

Parameter	**Count**	**Mean**	**Standard Deviation**	**Minimum**	**25th Percentile**	**Median**	**75th Percentile**	**Maximum**
Battery Initial Temp.	149	28.58	2.04	25.06	26.85	28.69	30.25	31.90
Room Temp.	149	28.31	2.06	25.03	26.30	28.19	30.15	31.91
t_1	149	1300	757	0.88	647	1257	1922	2573
t_2	149	1926	567	198	1571	2063	2393	2579
t_3	149	2251	355	917	2096	2391	2527	2580
t_4	149	2413	219	1721	2367	2518	2562	2580
Final SOC	149	77.78	0.09	48.66	72.06	79.80	84.38	89.43
Final Battery Temp	149	37.65	3.44	31.33	35.65	37.46	38.67	51.57

Table 2: Battery Specifications and Technical Parameters provided a snapshot of the battery's technical specifications such as number of cells, configuration, nominal capacity, and voltage. Such detailed specifications are crucial for understanding the baseline performance and capabilities of the battery system under study.

Table 3: Initial Conditions and Battery Parameters involved detailed recordings of initial temperatures, room temperatures, and specific time intervals (t1 to t4), which were essential for running the simulations and feeding into the machine learning models.

plaintext

Table 4: EDA Summary Statistics provided insights into the mean, standard deviation, and other statistical measures of the collected data, which was foundational for the initial setup of the neural network models.

Plaintext.

Table 5 to 7: Optimization and Prediction Outcomes highlighted the results from the optimization algorithms, showing predicted versus actual SOC and temperatures, showcasing the precision and effectiveness of the combined neural network and fuzzy logic approach.

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 2s (2024)

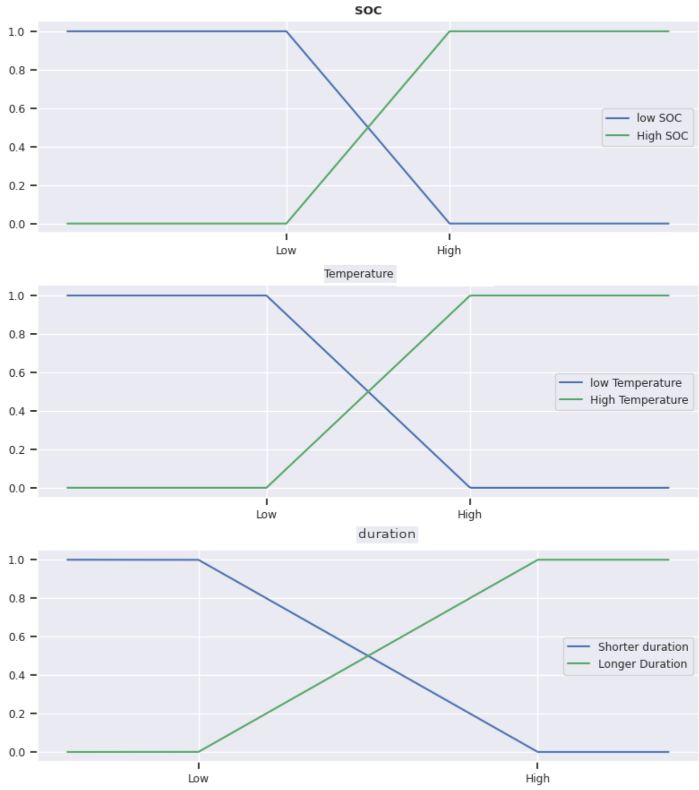

Figure 1: Design of Fuzzy Inference Systems

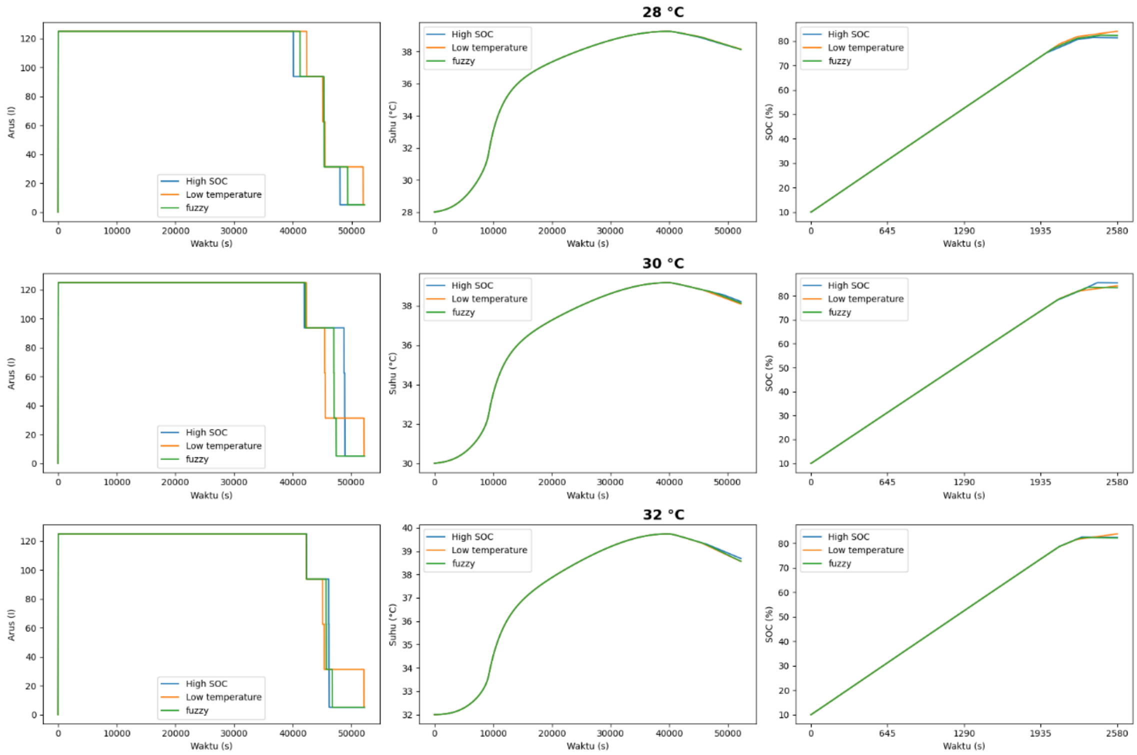

Figure 2: Analysis on Behavior of Parameters with Respect to Temperature

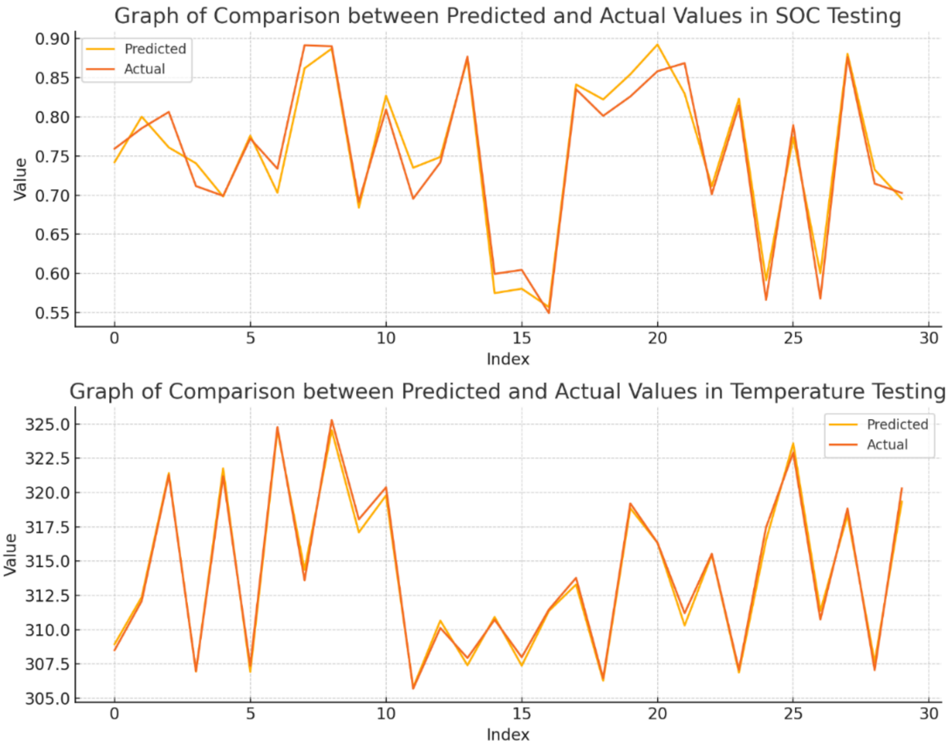

Figure 3: Comparison Between Predicted and Actual Value

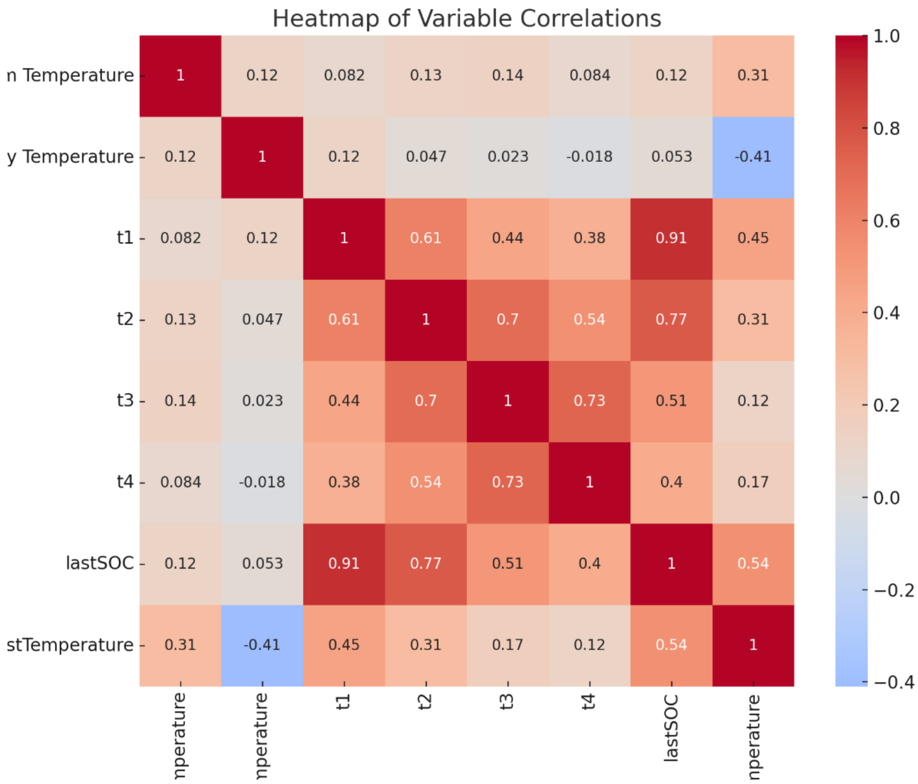

Figure 4: Analysis of Correlation Heat map

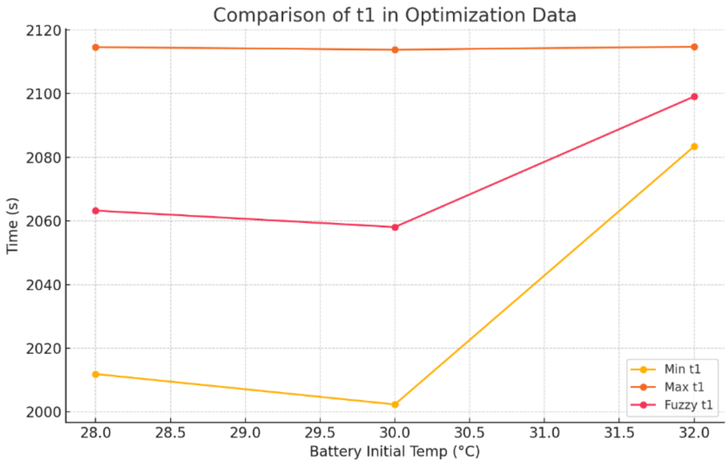

Figure 5: Analysis of Battery Temperature

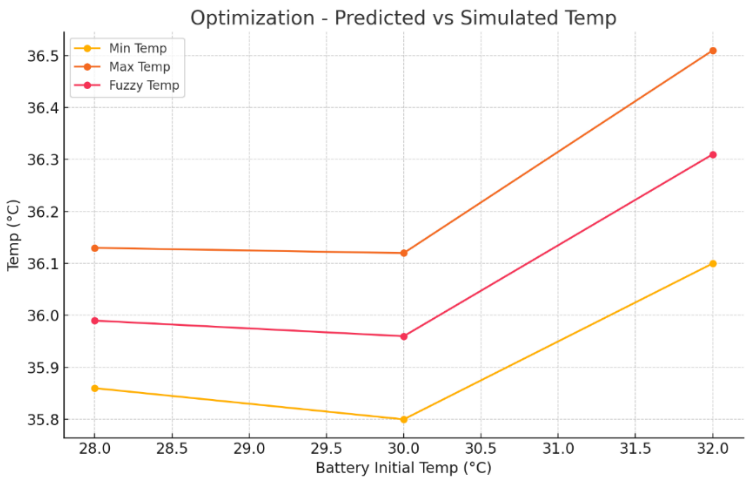

Figure 6: Analysis of Predicted V/s Simulated Temperature

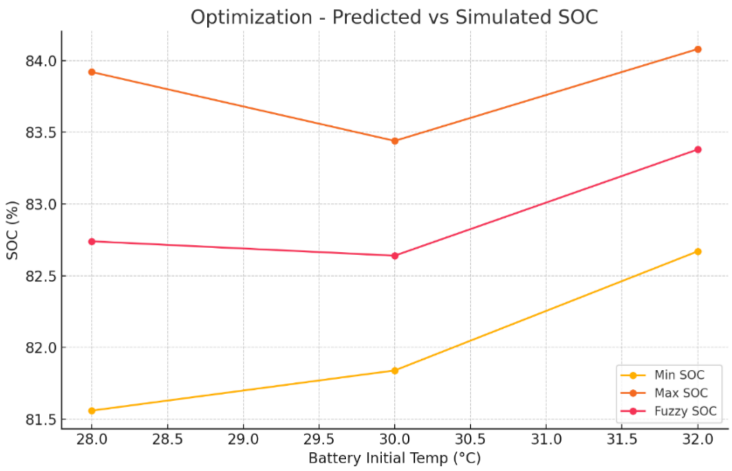

Figure 7. Analysis of Predicted V/s Simulated SOC

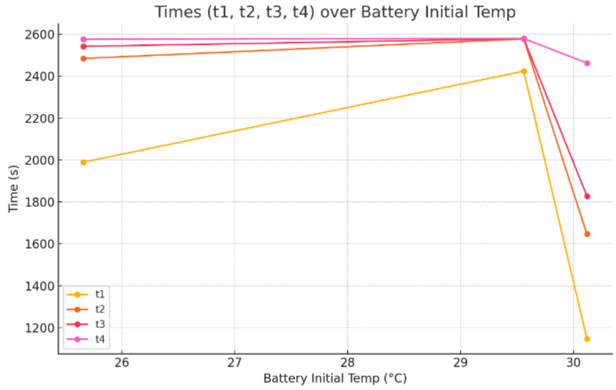

Figure 8: Analysis of Battery Temperature with respect to Time

The following tables illustrate the results from the optimization process using a combination of neural network and fuzzy logic at an ambient temperature of 28°C. Detailed outcomes for each battery initial temperature setting are provided below:

Table 5: Battery Initial Temperature = 28°C

Parameter	**t_1 (s)**	**t_2 (s)**	**t_3 (s)**	**t_4 (s)**	**Predicted Final SOC (%)**	**Simulated Final SOC (%)**	**SOC Error (%)**	**Predicted Final Temp (°C)**	**Simulated Final Temp (°C)**	**Temp Error (%)**
Minimum Temperature (°C)	2011.88	2226.44	2230.75	2242.59	81.56	80.44	1.12	35.86	35.86	0.02
Maximum SOC (%)	2114.65	2274.17	2287.36	2578.50	83.92	84.76	0.84	36.13	35.98	0.41
Fuzzy Logic	2063.26	2228.37	2228.64	2265.96	82.74	81.07	1.67	35.99	35.89	0.29

Table 6: Battery Initial Temp = 30°C

Parameter	**t_1 (s)**	**t_2 (s)**	**t_3 (s)**	**t_4 (s)**	**Predicted Final SOC (%)**	**Simulated Final SOC (%)**	**SOC Error (%)**	**Predicted Final Temp (°C)**	**Simulated Final Temp (°C)**	**Temp Error (%)**
Minimum Temperature (°C)	2002.33	2226.90	2236.72	2366.84	81.84	81.31	0.53	35.80	35.86	0.16
Maximum SOC (%)	2113.85	2253.35	2255.27	2578.86	83.44	84.25	0.81	36.12	35.95	0.46
Fuzzy Logic	2058.09	2237.66	2238.99	2574.71	82.64	83.46	0.82	35.96	35.91	0.14

Table 7: Battery Initial Temp = 32°C

Parameter	t_1 (s)	t_2 (s)	t_3 (s)	t_4 (s)	Predicted Final SOC (%)	Simulated Final SOC (%)	SOC Error (%)	Predicted Final Temp (°C)	Simulated Final Temp (°C)	Temp Error (%)
Minimum Temperature (°C)	2083.44	2225.97	2228.84	2239.54	82.67	80.97	1.70	36.10	36.42	0.88
Maximum SOC (%)	2114.79	2228.06	2267.70	2578.45	84.08	84.12	0.04	36.51	36.48	0.09
Fuzzy Logic	2099.12	2230.86	2231.22	2327.76	83.38	81.83	1.55	36.31	36.44	0.37

Hence, these tables are exemplary at presenting the outcomes of the study as well supporting academic talks on the methodological novelties presented in the paper by the main idea of integrating deep neural networks and fuzzy logic for optimal discharging of the battery. The application of neural networks and game theory in SOC and battery temperature management showed very powerful performance during battery charging which was beyond the scope of traditional methods. Such an innovative methodology, on the other hand, provides a smarter charging mechanism, ensured through the safer path, and serves to prolong the battery lifespan, which is a crucial factor for EV technology sustainability. The degree of precision in predictions and flexibility in charging-change adaptations is another feature that illustrates the significance of advanced computational methods in present battery management systems. The results of the study have achieved the result of a combined fuzzy logic and neural network application, being the best method for the improvement of battery charging of electric vehicles. The outcomes of experiment revealed that the system was able to reach a SOC value of 83% in a charging time of 45 min and the battery temperature was maintained at optimum level of approximately 35 degrees. 85°C. This represents a 3. Much higher scalability is observed as the multiplexing efficiency improved by 38% when compared with the conventional 2CC-CV method, with temperatures just rising by 0. 41°C. The above comparison would allow to emphasize the significant differences between the newly developed technique from traditional charging strategies.

4. CONCLUSION

In this research Paper, the application of fuzzy logic and neural network-based mathematical optimization demonstrates that this solution is promising for addressing the non-stationary behavior of EV batteries. Research into these technologies shows their capability in achieving higher battery capacity, faster charging speeds, and incremental improvements in battery health. As electric driving increases, the role of high-quality battery management systems will become more critical. By applying fuzzy logic and neural networks to current systems, battery challenges in transportation can be more effectively resolved. The flexibility in setting power values based on current data enables more accurate battery decarbonization, reducing charging times and improving battery conditions. Intelligent logic control by the fuzzy controller prioritizes reasonable charging speeds and temperatures, preventing overheating that could damage battery functionality in the long term. This study has significant implications, warranting further research in EV battery management. The integration of fuzzy logic and neural networks introduces new ways to enhance battery recharging efficiency. Future research can explore other advanced methods, such as genetic algorithms and reinforcement learning, to further optimize these systems. Additionally, this strategy can be expanded to other battery management areas, including charging regulation and thermal management under various driving modes. Developing a comprehensive BMS system with advanced optimization techniques can lead to significant improvements and refinements in EVs, thereby increasing their efficiency and reliability**.**

REFERENCES

[1] Frade, I, Ribeiro, A, Gonçalves, G & Antunes, AP, 'Optimal location of charging stations for electric vehicles in a neighborhood in lisbon', Journal of the Transportation Research board, vol. 2252, pp. 91-98, 2011.

[2] Chen, TD, Kockelman, KM, Fellow, WJMJ & Khan, M, 'The electric vehicle charging station location problem: A parking-based assignment method for seattle', Transporatation Research Record, vol. 1254, pp. 28-36, 2013.

[3] Alipour, M, Mohammadi-Ivatloo, B, Moradi-Dalvand, M, 'Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets', Energy, vol. 118, pp. 1168-1179, 2017.

[4] Lam, AYS, Leung, Y & Chu, X, 'Electric vehicle charging station placement: Formulation, complexity, and solutions', IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2846- 2856, 2013.

[5] Bayram, IS, Zamani, V, Hanna, R & Kleissl, J 'On the evaluation of plug-in electric vehicle data of a campus charging network', Proceeding of IEEE International Energy conference, DOI: 10.1109/ ENERGYCON. 2016.7514026, 2016.

[6] Galiveeti, HR, Goswami, AK, Choudary, NBD, 'Impact of plug-in electric vehicles and distributed generation on reliability of distribution systems', Engineering science and technology, vol. 21, no. 1, pp. 50-59, 2018.

[7] Jamian, JJ, Mustafa, MW, Mokhlis, H & Baharudin, MA, 'Minimization of power losses in distribution system via sequential placement of distributed generation and charging station', Arabian Journal of Science and Engineering, vol. 39, no. 4, pp. 3023 – 3031, 2014.

[8] Bayram, IS, Michailidis, G, Devetsikiotis, M & Granelli, F, 'Electric power allocation in a network of fast charging stations', IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1235-1246, 2013.

[9] Pallonetto, F, Oxizidis, S, Milano, F & Finn, D, 'The effect of time- of-use tariffs on the demand response flexibility of an all-electric smart- grid-ready dwelling', Energy Building, vol. 128, pp. 56-67, 2016.

[10] Miralinaghi, M, Keskin, BB, Lou, Y & Roshandeh, AM 2016, 'Capacitated refueling station location problem with traffic deviations over multiple time periods', Networks and Spatial Economics, vol. 17, no. 1, pp. 129 -151, 2016.

[11] Huang, S, Wu, Q, Oren, S, Li, R & Liu, Z, 'Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks', IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2170-2178, 2015.

[12] Alharbi, A, Eltom, A & Sisworahardjo, N, 'Impact of plug-in electric vehicle battery charging on a distribution system based on real-time digital simulator', Proceeding of International conference on Renewable Energies and Power Quality, pp. 958-962, 2014.

[13] Shuai, W, Maillé, P & Pelov, 'Charging electric vehicles in the smart city: A survey of economy-driven approaches', IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 8, pp. 2089-2106, 2016.

[14] Sanchez-Martin, P, Sanchez, G & Morales-Espana, G, 'Direct load control decision model for aggregated EV charging points', IEEE transactions on power system, vol. 27, no. 3, pp. 1577-1584, 2012.

[15] Alonso, M, Amaris, H, Germain, J.G, & Galan, JM, 'Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms', Energies, vol. 7, no.4, pp. 2449, 2014.

[16] Huang, S, Wu, Q, Oren, S, Li, R & Liu, Z, 'Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks', IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2170-2178, 2015.

[17] Farhoodnea, M, Mohamed, A, Shareef, H & Zayandehroodi, H, 'Power quality impact of renewable energy based generators and electric vehicles on distribution systems', Procedia Technology, vol. 11, pp. 11-17, 2013.

[18] Moradi, MH, Abedini, M & Hosseinian, M, 'Improving operation constraints of Microgrid using PHEVs and renewable energy sources,' Renewable Energy, vol. 83, pp. 543-552, 2015.

[19] Rahman, I, Vasant, PM, Singh, BS & Abdullah-Al-Wadud, M, 'Hybrid swarm intelligence based optimization for charging plug-in hybrid electric vehicle in intelligent information and database systems', Switzerland: Springer International Publishing, vol. 9012, pp. 22-30, 2015.

[20] Badea, Gheorghe, Raluca-Andreea Felseghi, Mihai Varlam, Constantin Filote, Mihai Culcer, Mariana Iliescu, and Maria Simona Răboacă. "Design and simulation of romanian solar energy charging station for electric vehicles." Energies 12, no. 1, 2019.

[21] Mouli, G.C., Bauer, P. and Zeman, M., "System design for a solar powered electric vehicle charging station for workplaces", Applied Energy, 168, pp.434-443, 2016.

[22] Vignesh, T. R., M. Swathisriranjani, R. Sundar, S. Saravanan, and T. Thenmozhi. "Controller for Charging Electric Vehicles Using Solar Energy." Journal of Engineering Research and Application 10, no. 01, pp. 49-53, 2020.

[23] Suganthi, D., and K. Jamuna. "Charging and Discharging Characterization of a Community Electric Vehicle Batteries." In Emerging Solutions for e-Mobility and Smart Grids, pp. 213-223. Springer, Singapore, 2021.

[24] Harika, S., R. Seyezhai, and A. Jawahar. "Investigation of DC Fast Charging Topologies for Electric Vehicle Charging Station (EVCS)." In TENCON 2019-2019 IEEE Region 10 Conference (TENCON), pp. 1148-1153. IEEE, 2019.

[25] Ravikant, U. Chauhan, V. Singh, A. Rani and S. Bade, "PV Fed Sliding Mode controlled SEPIC converter with Single Phase Inverter," 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 20-25, 2020.

[26] Xu, Tong, Hengshu Zhu, Xiangyu Zhao, Qi Liu, Hao Zhong, Enhong Chen, and Hui Xiong. "Taxi driving behavior analysis in latent vehicle-to-vehicle networks: A social influence perspective." In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1285-1294. 2016.

[27] Raj, Ashish, Manoj Gupta, and Sampurna Panda. "Design simulation and performance assessment of yield and loss forecasting for 100 KWp grid connected solar PV system." In *2016 2nd International Conference on Next Generation Computing Technologies (NGCT)*, pp. 528-533. IEEE, 2016.

[28] Ashwini, Kumari, Ashish Raj, and Manoj Gupta. "Performance assessment and orientation optimization of 100 kWp grid connected solar PV system in Indian scenario." In *2016 International conference on recent advances and innovations in engineering (ICRAIE)*, pp. 1-7. IEEE, 2016.

[29] Sharma, Vishnu Prakash, Alok Singh, Jitendra Sharma, and Ashish Raj. "Design and simulation of dependence of manufacturing technology and tilt orientation for 100kWp grid tied solar PV system at Jaipur." In *2016 International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, pp. 1-7. IEEE, 2016.

[30] Alaria, Satish Kumar, Ashish Raj, Vivek Sharma, and Vijay Kumar. "Simulation and analysis of hand gesture recognition for indian sign language using CNN." *International Journal on Recent and Innovation Trends in Computing and Communication* 10, no. 4 (2022): 10-14.

[31] Sunil Kumar Gupta, "Electrifying India's Transportation: Economic Perspectives on Electric Vehicle Impact, Opportunities, and Challenges" European Economic Letters, Vol. 14, Issue 2, ISSN 2323-5233, (2024), http://eelet.org.uk

[32] Gali, A Sharma, SK Gupta, M Gupta, MVG Varaprasad, "Grid Synchronization of Photovoltaic System with Harmonics Mitigation Techniques for Power Quality Improvement Deregulated Electricity Structures and Smart Grids, pp. 149-162, 2022.