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Effectual Energy Consumption and User Comfort Optimization Based on Dynamic User Set Parameters in Electric Vehicles

Muhammad Fayaz †, *Member, IEEE*, Junaid Khan†, and Muhammad Bilal, Senior *Member, IEEE*

***Abstract*— Efficient energy consumption minimization and comfort index maximization in electric vehicles have grasped the attention of many researchers in recent years. Several models have been proposed and developed for this purpose, but these models have limitations in one way or another; some provide good results in energy consumption minimization but compromise on comfort, and some are capable of maximizing the comfort level but also increasing the energy consumption. Hence, to tackle these problems, we have proposed a model based on optimization, machine learning, smoothing, and control algorithms. The purpose of the proposed model is two folds, first, to minimize energy consumption and second, to maximize user comfort. The suggested model comprises three main modules: the smoothing module, the optimization module, and the control module. In the smoothing module, the alpha-beta filter, the simplest and most effective filter, has been used to remove noise and smooth the data. The optimization module is further divided into two sub-modules: the FA-GA module and the support vector machine module. The purpose of the support vector machine in the optimization module is to make the system fully automatic and dynamic by setting the user parameters in the objective function of the FA-GA module. In the control module, Mamdani fuzzy logic has been used to provide the desired energy to corresponding actuators. The proposed method is compared with some well-known approaches, and the results indicate that the proposed method provides good results compared to counterpart algorithms.**

***Index Terms*— Energy; User Comfort, Optimization; Electric Vehicles, Control Algorithm, Smoothing Filters**

I. INTRODUCTION

ACCORDING to a 2014 report, energy consumption in the transportation sector accounts for roughly one-third (1/3), approximately 27% of the total consumption compared to the entire world [1]. Furthermore, the transportation sector is the second-largest source of greenhouse gas emissions, responsible for 34% of the overall CO2 emissions. These emissions result from the combustion of fossil fuels, including heavy oils, jet fuel, diesel, and gasoline [2]. Presently, individual mobility heavily relies on petroleum, which is the primary energy source. Additionally, in 2014, the energy consumed in the transportation sector constituted 92% of petroleum consumption [1,3].

In 2020, energy consumption decreased by 4.5% due to the COVID-19 pandemic. However, in 2021, global energy consumption rebounded with a 5% growth rate, which continues to increase over time. This rebound is three times higher than the average annual growth rate of 2% from 2000 to 2019. Furthermore, in 2021, energy consumption surpassed the levels seen in 2019. The various sources of energy consumption include oil, which is the most significant source accounting for 29% of the total energy; coal, the second most extensive source consuming 27% of the total energy; gas, the third source consuming 24% of the total energy; and biomass and electricity, each consuming 10% [4].

The optimization of energy consumption and maximization of comfort levels in electric vehicles are critical research areas, and numerous researchers are actively working on them. The objective is to create a comfortable environment for passengers in electric vehicles while also saving energy. To achieve this, state-of-the-art HVAC systems need to be developed, which can provide passengers with a comfortable environment. This can be accomplished through the utilization of new control, optimization, and machine learning methods [5, 6]. In today's world, energy is indispensable for daily living. Every emerging smart technology requires a consistent power supply. The Center for Sustainable Statistics estimated that in 2019, the United States spent $1.2 trillion, equivalent to 5.7% of GDP, on energy [7].

Researchers have proposed numerous techniques for optimizing energy consumption and maximizing user comfort in various areas. The fuzzy logic and genetic algorithms [8] have been utilized to control environmental parameters. The proposed model consists of various modules, including prediction, where the Kalman filter is used to forecast energy. The optimization module employs genetic algorithms to minimize the disparity between environmental and user-defined factors. The controller module utilizes the Mamdani FIS. This technology aims to enhance the comfort index and decrease energy consumption.

The performance of genetic algorithms is generally superior to that of the PSO algorithm, although it does depend on the specific scenario [9]. An incorrect selection of the PID controller can lead to system problems, impacting both

Muhammad Fayaz is with the Department of Computer Science, School of Arts and Sciences, University of Central Asia, Kyrgyz Republic (e-mail: Muhammad.fayaz@ucentralasia.org).

Junaid Khan is with Department of Environmental & IT Engineering, Chungnam National University, Daejeon 34134, Republic of Korea. (e-mail: Junaidstopi1@gmail.com).

Muhammad Bilal is with the School of Computing and Communications, Lancaster University, Lancaster LA1 4WA, United Kingdom (e-mail: m.bilal@ieee.org).

reliability and stability. To address this issue, research should focus on adaptive controllers that can respond to optimal controller and parameter changes [10].

The algorithm for optimizing the ant colony poses certain theoretical challenges: determining the arbitrary order is difficult, there can be repetition in the probability distribution, experimental results may not align with theoretical changes, and convergence time remains uncertain. However, integration is assured. Optimizing the ant colony exhibits inherent parallelism, and positive feedback enables quick identification of suitable solutions for dynamic applications. During a detailed analysis, inconsistencies were observed in the comparison table results using the genetic algorithm. Wahid and colleagues conducted another experiment to reduce the comfort and energy consumption of residential buildings, employing the artificial bee colony algorithm and fuzzy logic [11]. They aimed to combine the fitness characteristics of the artificial bee colony with a user-friendly index and energy consumption. Three parameters were considered for energy optimization: temperature, lighting, and air quality. The artificial bee colony (ABC) algorithm proved to be relatively easy to implement and involved fewer parameters compared to other algorithms.

Our proposed model is based on smoothing, optimization, machine learning, and control algorithms. The purpose of the proposed model is two-fold: first, to minimize energy consumption, and second, to maximize user comfort. The proposed model consists of three main modules: the smoothing module, the optimization module, and the control module.

In the smoothing module, the alpha-beta filter, which is a simple yet effective filter, has been employed to eliminate noise and smoothen the data. The optimization module is further divided into two sub-modules: the FA-GA module and the support vector machine module. The support vector machine in the optimization module serves to make the module dynamic and incorporates user-set parameters in the comfort index formula using a machine learning algorithm. The control module utilizes Mamdani fuzzy logic to deliver the desired energy to corresponding actuators. To evaluate the proposed method, a comparison with well-known approaches has been conducted, and the results demonstrate that the proposed method yields favorable outcomes in comparison to counterpart algorithms. The primary objectives of the proposed work are as follows:

- To Increase the comfort index of users in electric vehicles
- Implementation of smoothing and optimization algorithms for energy consumption
- To decrease the usage of energy in electric vehicles for comfort
- To specify the user set parameters by using a best machine learning algorithm

The organization will be carried out as below: section 2 presents the related work, section 3 presents a comprehensive proposed methodology, the implementation, results, and comparative analysis is given in section 4, and the paper is concluded in section 5.

II. Related Work

The transportation system plays a crucial role in driving economic growth. However, the current system relies heavily on internal combustion engines fueled by petroleum, resulting in a dependence on the global oil market. This reliance also makes the transportation sector the primary contributor to greenhouse gas emissions [13]. Considering the imminent oil shortage and the urgent necessity to decrease emissions, there is a growing emphasis on developing a sustainable transportation system that tackles the challenges posed by climate change and reduces dependence on oil [14].

Electric vehicles can be divided into plug-in hybrid electric vehicles (PHEVs) and battery-electric vehicles (BEVs). PHEVs are equipped with a relatively small battery and a traditional gasoline engine, allowing most of the driving to be done using electricity while maintaining the range of a typical gasoline vehicle [15]. On the other hand, BEVs run solely on electricity and can potentially completely replace petroleum-powered vehicles for certain types of driving. Electric vehicles are considered by many as one of the innovative technologies that have the potential to achieve these goals by being more efficient, reducing oil dependence and lowering carbon emissions. Many researchers work on electric vehicle (EVs) energy consumption problems, e.g., Wu et al. [16] proposed an energy consumption estimation and measurement for electric vehicles. The data used for evaluation are vehicle driving data and EV data. So, EV performance is better than gasoline vehicles. Bank [17] discussed overcoming technical challenges related to battery technology and its limitations. Sweda and Klabjan [18] proposed a charging infrastructure for EVs using an agent-based decision support system. Ullah et al. [19] proposed an ML-based electric vehicle energy consumption prediction. The method used for Prediction was extreme gradient boosting and light gradient boosting, which outperform the traditional neural network. Desreveaux et al. [20] discussed the climate impact of electric vehicles' life.

Matthias [6] designed an algorithm for climate control energy efficiency in electric cars. The method was developed for electric cars by the MUTE project, which is done with the cooperation of 20 departments at TU München. A multiple-objective climatization controller for a car was developed; the design focuses on specific characteristics of electric cars. Fiori et al. [21] developed and validated an energy consumption model. The proposed model used the least square optimization method and was also used for a power-based electric vehicle. The model was beneficial in maximizing the EV distance and minimizing energy consumption. Miri et al. [22] proposed an energy consumption estimation and modelling in Electric vehicles. This method solves the problem of limited driver range in EVs. The model uses longitudinal vehicle dynamics and the vehicle powertrain system. The results from this were also promising. Bingham et al. [23] studied the impact of characteristics of driving and energy consumption in an electric vehicle, and the state-of-charge (SOC) usage and the range were also discussed. Wang et al. [24] proposed an Energy

Consumption model for Electric vehicles, and the Prediction was primarily based on Road Information.

Sweeting et al. [25] discussed factors affecting EVs' energy consumption and identified the energy required for EVs and their performance. The range and cost are also calculated for EVs. In 2008, one of the interesting meta-heuristic-based algorithms recently introduced is the Firefly algorithm (FA). This algorithm is based on swarm intelligence methods which are nature inspired and introduced by Yang [26]. The primary source of motivation leading to the formation of FA is the phenomenon of the emission of light by fireflies. The fireflies' emitted light has used the fireflies' charm to their prospective buddy. FA is one of the most vigorous, simple optimization approaches, easily implementable, and extensively appropriate for solving complex optimization problems.

The previous work on EV energy consumption has multiple drawbacks and needs to offer a suitable solution to effectively reduction on energy consumption. Additionally, there needs to be more research on combining energy efficiency in electric vehicles with maximizing comfort for the user.

The previously proposed optimization algorithms (OA) [27] have a few key limitations, which are applied to the management of energy optimization in residential apartments. First, most of the OA was used in their everyday working processes. This independent operational feature of most optimization models makes them uncertain in controlling the environment's and the user's limitations, leading to inefficient energy management and optimization processes. Second, the OA suffer from an imbalanced relationship between the exploration and exploitation capabilities of the solution search space, leading to their failure to get the most optimal solution to an optimization problem. Because of these characteristics, such proposed energy optimization methods cannot accomplish maximum user comfort with minimum power consumption. Finally, some OA has been used in their hybridization process (HP) or revised and improved with other OA. Their complications arise sufficiently due to their complex procedures in embedding different kinds of characteristics of algorithms and introducing modifications. To deal with such type of limitations, a simple, efficient, and novel model is proposed in this paper.

Our newly developed model is a hybrid of two optimization algorithms: FA and GA. The HP makes the model more potent in minimizing power consumption and maximizing user comfort than independent and conventional optimization techniques. A balanced relationship between the exploration and exploitation capabilities of the standard FA solution search space has been achieved by embedding rich operators of GA used for exploration and exploitation, making it powerful to get the minimum power consumption and maximum user comfort. Lastly, the proposed model is easy to implement because both the FA and GA are manageable in terms of integration, running, development and parameter tuning.

When compared to conventional Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) approaches, the newly designed Firefly Algorithm-Genetic Algorithm (FA-GA) performs better. The advantages of FA-GA are probably due to its inclusion of both the evolutionary operators of Genetic Algorithm and the light intensity-based convergence of Firefly Algorithm. This hybrid strategy probably strikes a compromise between exploitation and exploration, enabling faster convergence to ideal solutions. FA-GA works well for complicated, multimodal landscapes because of the light intensity mechanism's assistance in escaping local maxima and finding many optimal solutions. While parameter sensitivity is still a factor, FA-GA's ability to solve complex optimization problems, where standalone PSO or GA would falter, emphasizes its effectiveness. However, exhaustive testing on several issue sets is advised to fully validate these findings.

III. Proposed Methodology

A conceptual structure diagram of the proposed model is illustrated in Figure 1. The suggested model comprises three main modules: smoothing module, the optimization module, and the control module. In the smoothing module of the proposed model, different noise removal algorithms, such as alpha-beta filter [16], Kalman filter [17], particle filter [28], weighted average [29], etc. have been used to remove noise and missing values from the sensors' data. The best smoothing algorithm is then considered for further processing. In the optimization module, different optimization algorithms, such as the firefly algorithm, genetic algorithm, ant colony algorithms, hybrid algorithms, etc. have been used to optimize the environmental parameters and machine learning set parameters.

In the optimization module, the comfort index formula has been used, and to tune the user-set parameters in the comfort index formula have been set through machine learning algorithms. The basic purpose of the inclusion of machine learning algorithms is to make the system dynamic and completely automatic. In the control module, the Mamdani inference system [30] has been applied to provide desired energy for actuators to the agent, and the agent supplies the corresponding energy to the actuators.

In the prediction module, the alpha-beta has been used to remove unnecessary information from the environmental parameters. The output of predicted module is then fed to optimization module. In optimization module, two sub modules namely support vector machine and FA-GA algorithm have been used to set the parameters and optimized the parameters respectively. The support vector machine takes the smoothed parameters (temperature, illumination, and air quality) and provides the predicted parameters (temperature, illumination, and air quality) as outputs. The support vector machine is trained on historical data of users. The difference of smoothed environmental parameters (temperature, illumination, and air quality) and support vector machine predicted parameters are then given as inputs to optimization module, and this this difference is then used in comfort index formula in FA-GA module.

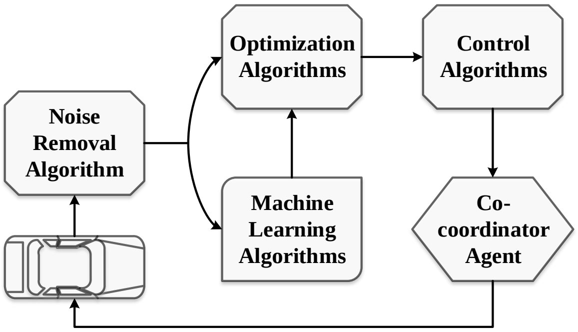

Fig 1. Conceptual Model of Proposed Work.

The comfort index is contrariwise related to the change in error. The difference in error (environmental parameters, and support vector machine set parameters) is related to power consumption. The smaller the error difference, the higher the comfort index, so this problem becomes a multifunctional optimization problem that minimizes power consumption and maximizes the comfort index. After calculating the comfort index, the next step is to control the state of the other actuators. Mamdani Fuzzy controller is used to provide the desired power to actuators. The fuzzy controller takes the error difference between smooth parameters (temperature, illumination, and air quality) and optimized parameters (temperature, illumination, and air quality). The output of the controller is the power required to control the actuator state (e.g., B. cooling/heating, lighting, ventilation, etc.). Then apply the current to the required coordinator agent. The coordinator agent checks the availability of the power supply and supplies power to all actuators based on the state of the purge controller. The fuzzy controller uses optimization algorithms optimized values and environmental boundaries (temperature, lighting, and air quality, etc.). The output value of the fuzzy controller depends on the difference between the environmental range (temperature, illuminance, air quality, etc.) and the optimization optimized value (temperature, illuminance, air quality).

The aim of the SVM is to make the system fully automatic. The purpose of the FA-GA module is to increase comfort index and decrease power usage. The power consumption can be decreased in one way if we decrease the gap between user preferences parameters and environmental parameters. The decreasing of the gap between environmental parameters and user set parameters ultimately decreases the power consumption. The learning to optimization module provides the optimized parameters. The learning to fuzzy logic module takes the optimized parameter values as inputs and provides the required energy to actuators. The coordinator's agent takes the output of the fuzzy controller as inputs and adjusts the actuators accordingly. Figure 2. shows the detailed structure diagram of the proposed approach.

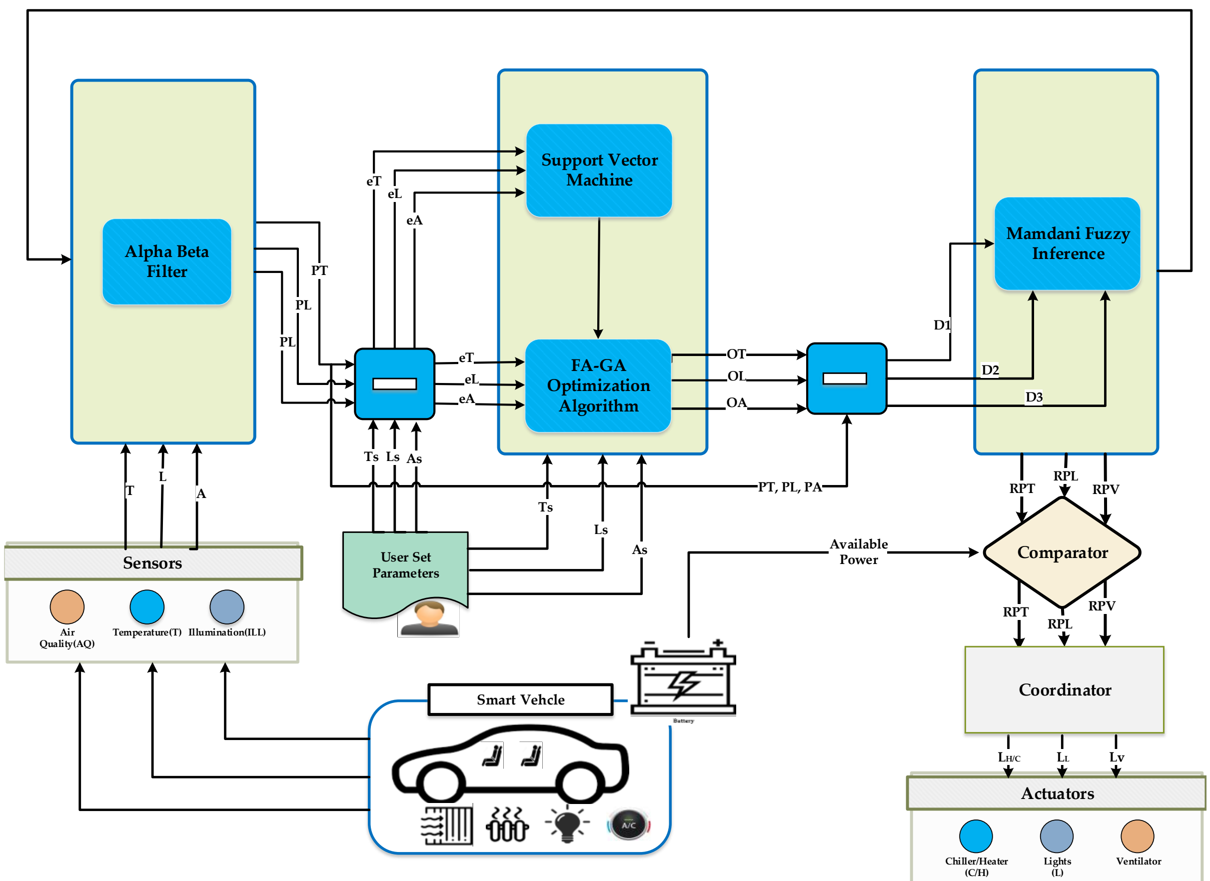

Fig 2. Detailed Structure Diagram of Proposed Approach.

A. *Alpha Beta Filter*

Alpha-beta filter [31,32] is one of the simplest filters used for estimation, control, and smoothness. The functionality of the alpha-beta filter is similar to linear filter algorithms. The main advantage of the alpha-beta filter is that it is very simple

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because it doesn't require any complex model to train it. It is the derived form of the Kalman filter [33]. In comparison to the Kalman filter, alpha beta filter needs a very small amount of space and computation power. Following are some mathematical formulas that are used to represent each step of the alpha beta filter. In the first step, initiation occurs as represented in Equations (1 and 2) [34-36]. The structure diagram of the alpha-beta filter is illustrated in Figure 3.

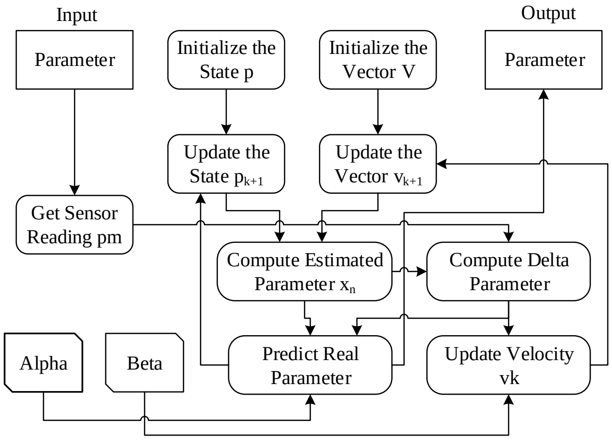

Fig 3. Structure Diagram of Alpha Beta Filter.

$$p_{k-1} = m_1 \quad (1)$$

$$v_{k-1} = c_2 \quad (2)$$

Equation (3) is for position updating, and Equation (4) is used to read data from the sensor.

$$p_k = x_{k-1} + v_{k-1}.\Delta t \quad (3)$$

$$p_m = Sensor() \quad (4)$$

To compute the difference, Equation (5) is used, and Equation (6) is used to compute the predicted position.

$$\Delta p_k = p_m - p_k \quad (5)$$

$$p_k = p_k + \alpha.\Delta p_k \quad (6)$$

Equation (7) is used to compute the predicted velocity, and Equations (8) are used to update the position and velocity for the next iteration.

$$p_{k-1} = p_k \quad (7)$$

$$p_{k-1} = v_k \quad (8)$$

B. Optimization Module

The optimization module is further divided into two parameters, namely the FA-GA module and the support vector machine module. The support vector machine is first trained by using the historical data of different users.

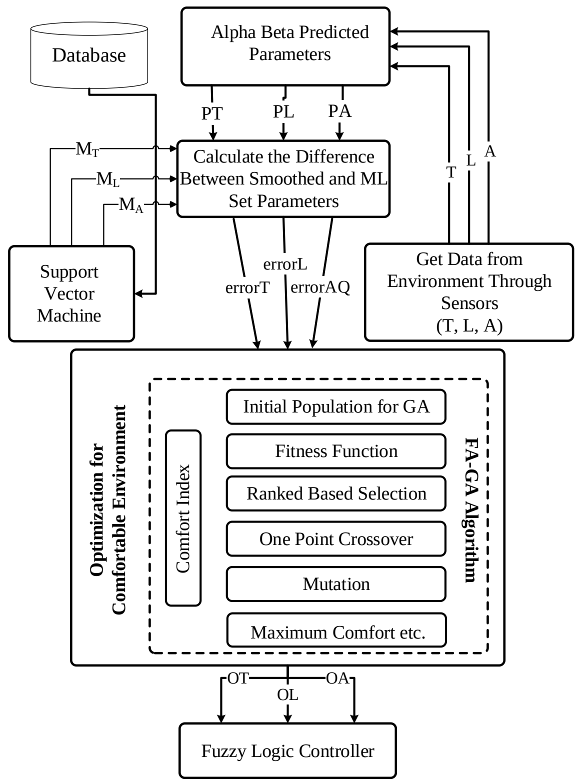

Fig. 4. Proposed optimization module with support vector machine learning algorithm.

It takes smooth parameters as inputs and provides user-set parameters as outputs. The FA-GA module takes the error difference between the support vector machine and smooth parameters, and these parameters are then used in the comfort index formula in the FA-GA algorithm. The schematic diagram of the optimization module is illustrated in Figure 4.

The database in Figure 4 represents our dataset, which includes three parameters: air quality, temperature, and illumination. At the first stage, the data in the database is populated by collecting and storing values for these parameters. These values can be obtained through various means, such as sensor measurements or data input from external sources. Once the data is collected, it is stored in the database, forming the initial dataset. This dataset serves as the input for subsequent stages of the process.

The comfort index formula is given in Equation (9).

$$Comfort\ Index = \omega_1\left[1-\left(\frac{error_T}{M_T}\right)^2\right] + \omega_2\left[1-\left(\frac{error_L}{M_L}\right)^2\right] + \omega_3\left[1-\left(\frac{error_A}{M_A}\right)^2\right] \quad (9)$$

In the formula ω_1, ω_2 and ω_3 indicate preferences. The overall satisfaction is between [0, 1], where the 0 indicates no satisfaction and 1 represents full satisfaction. The support vector machine factors in the comfort index formula are M_T, M_L, and M_A, these are support vector machine set parameters. User preferences parameters are represented by ω_1, ω_2, and ω_3, when we add all preferences, the sum is equal to 1 ($\omega_1 + \omega_2 + \omega_3 = 1$). In the comfort index formula $error_T$, $error_L$, and

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$error_A$ indicate difference: environmental temperature and temperature set by SVM, environmental illumination and illumination set by SVM, environmental air quality and air quality set by SVM respectively. The above comfort index formula can be generalized as given in Equation 10.

$$Comfort\ Index = \omega_1\left[1-\left(\frac{error_{p1}}{M_{p1}}\right)^2\right] + \omega_2\left[1-\left(\frac{error_{p2}}{M_{p2}}\right)^2\right] + \omega_3\left[1-\left(\frac{error_{p3}}{M_{p3}}\right)^2\right] + \ \ldots\ldots\ \omega_n\left[1-\left(\frac{error_{pn}}{M_{pn}}\right)^2\right] \quad (10)$$

Where $error_{p1}, error_{p2}, error_{p3}, \ldots error_{pn}$ indicate the difference between parameters set by the machine learning algorithm and smooth parameters. M_{p1}, M_{p1}, …. M_{pn} represent parameters set by the machine learning algorithm. ω_1, ω_2, ….. ω_n represent user set preferences. Hence, in future, if more parameters need to be encountered, then we can easily adjust them in the proposed system. The optimization module can be further divided into two main modules, namely the FA-GA module and the SVM module.

1. FA-GA module

Energy consumption reduction and minimization are one of the complex and tricky tasks of our proposed efficiency system for power management, which is also a multi-purpose optimization challenge to provide residents comfort maximization. The proposed model we are using is called FA-GA because it uses two powerful algorithms such as FA and GA. Both optimization algorithms are based on artificial intelligence (AI). While using the single algorithm, it is not possible to find the optimal parameters; for such kind of reasons, we combined these two algorithms to fast the entire optimization process and will be able to easily find the most optimal value of the problem and avoid any difficulty. Equation (10) shows the fitness and the objective functions used in this procedure and is linked with light intensity in equation (11). however, the comfort index parameters are correlated with the light intensity and also coupled with each firefly. For making a firefly, we used different input parameters such as air quality error differences, illumination, and temperature. We used these parameters as input for the generation of a randomly initial search space solution, and for the solution of each member, the initial population is computed, which characterizes the comfort index for every single combination. At the next phase in the FA, the algorithm uses equation (13), equation (14) and equation (15) for the firefly position switching phase and to update the solution generated in the initialization. The total numerical representation of the FA is defined in equations (11-15). While considering the rules of light in physics, equation 11 shows the intensity of the light secreted by the firefly, X (d), at distance d from the firefly.

$$X\,(r) = \frac{X_0}{d^2} \quad (11)$$

Where X_0 denotes the light intensity produced at the source of light, if α is the medium of absorption coefficient, then the intensity of light, X, at distance d is given by equation 12.

$$X = X_0\,exp(-\alpha d^2) \quad (12)$$

Where the distance between the light examination point and supply of light is denoted by d, the attraction between the fireflies in the FA is associated with light intensity, which is represented in equation 13.

$$A = A_0\,exp(-\alpha dk)\,, (k \geq 1) \quad (13)$$

Where A0 denotes the attractiveness at distance d = 0. pi and qi, is the Euclidean distance between two fireflies as shown in equation 14.

$$ij = |p_i - q_i| = \sqrt{\sum_{n=1}^{m}\left(p_{i,n} - q_{i,n}\right)^2} \quad (14)$$

In each production, the position of the firefly can be changed according to the following equation 5.

$$P_i = P_i + A_0 \exp(-\alpha P_i j^2)\,(p_i - q_i) + \beta_\varepsilon \quad (15)$$

Where randomization of a parameter is denoted by β, a gaussian distribution produces an arbitrary number which is represented by ε. While controlling the search space solution, random parameters were used. GA is applied for further optimization because FA runs on a limited number of iterations. A few technical steps are involved in the optimization process switching from FA to GA and vice versa. There are error differences for all parametric values to make the genes of GA, and the FA firefly turns into GA chromosomes. The search space solution produced by FA took to start by GA, reached its maximum number of iterations, and continued the process in the regular standard GA operational strides [37,38]. The following steps show further optimization by GA.With the help of ordinary FA population, we create an initial population for GA.

a. We calculate the fitness function for the user's comfort.
b. Ranked or tournament selection is commonly used; the finest individuals are preferred using the roulette wheel; in this paper, we used ranked-based selection.
c. For the selected individuals, one point crossover is performed.
d. After cross-over, off-springs are spawned.
e. We performed the mutation procedure.
f. All the steps from a-e are repeated for a particular number of iterations.
g. The finest-sized chromosomes are chosen when the termination condition is encountered.
h. The best chromosomes obtained represent the value of the maximum comfort index.

The use of GA in many applications has several reasons, Genetic algorithms (GA) are justified for use in near real-time applications despite their relatively slower speed due to several reasons. GA excels at exploring large solution spaces and handling non-differentiable or discontinuous functions, making it suitable for complex problem domains where traditional optimization techniques struggle. GA's ability to handle multiple objectives, robustness to noise and uncertainty, and potential to discover unexpected solutions further justify their use. Additionally, GA offers flexibility and adaptability, allowing customization for specific problem requirements. While GA may not be the best choice for all scenarios, its unique strengths make it valuable in many applications

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requiring complex, non-linear, and multi-objective optimization.

2. Support Vector Machine Module

A support vector machine is an important machine learning algorithm; it was first developed to solve binary classification problems [39]. This technique solves complicated classification and regression problems [40,41]. The kernel type is chosen based on the problem's nature and data size. The kernel selection is carried out from the pool of linear, polynomial, radial, etc. linear kernel has been used in the proposed work for prediction of user set parameters. The default model of SVM in MATLAB 2018a [42] with minimal sequential optimization (SMO) technique is used for optimization. The SVM algorithm is based on trial and error, and the best results are obtained after many experiments. The best-trained model is then trained for prediction. The SVM algorithm is trained based on previous data. In the proposed work, we have used a support vector machine to set the parameters in the comfort index formula. Previously, systems were static, and users performed these parameter settings, but our proposed system is fully automatic, and a support vector machine sets these parameters. The SVM is first trained on the historical data of different users and then predicted temperature, illumination, and air quality values are used as inputs to the SVM module, and the SVM module sets the temperature, illumination, and air quality values in the comfort index formula.

3. Fuzzy Logic Controller

In the proposed work, the fuzzy controller has been used to control the power. Nowadays, the application of fuzzy logic is everywhere, and fuzzy logic has grasped the attention of many researchers, and numerous researchers have used fuzzy logic in different fields. In the proposed work, the Mamdani fuzzy logic method has been used, which is one of the simplest and most effective fuzzy logic methods. Mamdani's fuzzy logic model consists of fuzzification, rule inference and defuzzification modules. The fuzzification module takes crisp values as inputs and applies input membership functions to convert the crisp inputs to fuzzy inputs [5]. The rule inference module uses input and output membership functions to construct rules. In the defuzzification module, the centroid method has been used to convert the fuzzy outputs are converted to fuzzy outputs by using the centroid method. The processing mechanism of mamdani fuzzy logic is depicted in Figure 5.

In this work, the triangular membership function has been used for the input/output membership function. The mathematical triangular membership function is represented in Equation (16).

$$F\,(m,l,u)=\begin{Bmatrix} 0 & x\leq 1 \\ \frac{x-1}{m-1} & x\leq l\leq m \\ \frac{u-x}{u-b} & m\leq x\leq u \\ 0 & u\leq x \end{Bmatrix} \tag{16}$$

Seven membership functions have been specified for the input variable Difference1 and output variable RPTemp. The labels for membership functions of input variable Difference1 are D11, D12, D13, D14, D15, D16, and D17, and the labels for output variable RPTemp are RPTemp1, RPTemp2, RPTemp3, RPTemp4, RPTemp5, RPTemp6, and RPTemp7. The second fuzzy controller also has two input and output variables. The input and output variables are named Difference2 and RPILL, respectively. The labels for membership functions of input variable Difference2 are D21, D22, D23, D24, D25, D26, D27, D28, D29, D210, D211, D212, D213, D214 and D215. The labels for membership functions of RPILL are RPILL1, RPILL2, RPILL3, RPILL4, RPILL5, RPILL6, RPILL7, RPILL8, RPILL9, RPILL10, RPILL11, RPILL12, RPILL13, RPILL14, and RPILL14 Third fuzzy controller also has two variables, one input and one output. The input and output variables are named Difference3 and RPAQ, respectively. The labels for membership functions of input variable Difference3 are D31, D32, D33, D34, D35, D36, D37, D38, and D39. The labels for membership functions of RPAQ are RPAQ1, RPAQ2, RPAQ3, RPAQ4, RPAQ5, RPAQ6, RPAQ7, RPAQ8, and RPAQ9. Fuzzy rules for all three fuzzy logic controllers are given in Table 1.

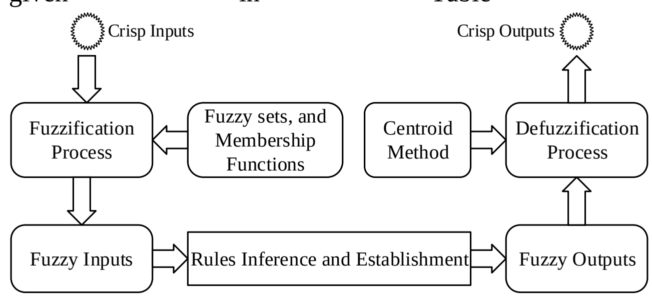

Fig 5. Mamdani Fuzzy Inference System.

We have added the power/energy models equation for better understanding of our proposed model results.

$$pkdc=\frac{td_w}{c_w} \tag{17}$$

$$pd=td_i\times 0.70 \tag{18}$$

$$abc=c_w\times ec \tag{19}$$

$$pwdc=c_w\times\frac{td}{c_w} \tag{20}$$

$$ac=c_w\times ec \tag{21}$$

Constrains

$$\frac{rabc\times pwdc}{rd}>1 \tag{22}$$

The coordinator agent plays a crucial role in the calculation of the remaining distance and battery capacity, as described in Equations (19-22). In this process, the agent determines whether the battery capacity exceeds the remaining distance. If this condition holds true, the coordinator agent initiates the provision of power to the actuators. This responsibility ensures efficient management of resources and enables the vehicle to continue its operation effectively.

TABLE 1. FUZZY RULES FOR TEMPERATURE, ILLUMINATION, AND AIR QUALITY FUZZY CONTROLLERS

Fuzzy Controller 1		Fuzzy Controller 2 Rules		Fuzzy Controller 3 Rules	
Difference$_1$	**RPTemp**	**Difference$_2$**	**RPILL**	**Difference$_3$**	**RPAQ**
D_{11}	RPTemp 1	D_{21}	$RPILL_1$	D_{31}	RPA_1
D_{12}	RPTemp 2	D_{22}	$RPILL_2$	D_{32}	RPA_2
D_{13}	RPTemp 3	D_{23}	$RPILL_3$	D_{33}	RPA_3
D_{14}	RPTemp 4	D_{24}	$RPILL_4$	D_{34}	RPA_4
D_{15}	RPTemp 5	D_{25}	$RPILL_5$	D_{35}	RPA_5
D_{16}	RPTemp 6	D_{26}	$RPILL_6$	D_{36}	RPA_6
D_{17}	RPTemp 7	D_{27}	$RPILL_7$	D_{37}	RPA_7
--	--	D_{28}	$RPILL_8$	D_{38}	RPA_8
--	--	D_{29}	$RPILL_9$	D_{39}	RPA_9
--	--	D_{210}	$RPILL_{10}$	--	--
--	--	D_{211}	$RPILL_{11}$	--	--
--	--	D_{212}	$RPILL_{12}$	--	--
--	--	D_{213}	$RPILL_{13}$	--	--
--	--	D_{214}	$RPILL_{14}$	--	--
--	--	D_{215}	$RPILL_{15}$	--	--

TABLE 2
FUZZY RULES FOR TEMPERATURE FUZZY CONTROLLER

Difference$_1$		RP_{Temp}	
Symbol	**Range**	**Symbol**	**Range**
D_{11}	(-25 -20 -15)	$RPTem_1$	(- 15 -10 -5)
D_{12}	(-20 -12.5 -5)	$RPTemp_2$	(- 8 - 7 - 6)
D_{13}	(-15 -7.5 0)	$RPTemp_3$	(-15 - 7.5 0)
D_{14}	(-7.5 -6.25 - 6)	$RPTemp_4$	(0 4 7.5)
D_{15}	(0 7.5 15)	$RPTemp_5$	(0 7.5 15)
D_{16}	(6 14 22)	$RPTemp_6$	(4 8 12)
D_{17}	(14 18.5 25)	$RPTemp_7$	(7 11 15)

Different kinds of fuzzy rules are presented in the below tables. Table 2. shows the fuzzy rules for the fuzzy temperature Controller, Table 3. shows the fuzzy rules for the fuzzy illumination controller, and Table 4. shows the fuzzy rules for the air quality fuzzy controller.

TABLE 3. FUZZY RULES FOR ILLUMINATION FUZZY CONTROLLER

Difference2		RPILL	
Symbol	**Range**	**Symbol**	**Range**
D_{21}	(-150 -135 120)	$RPILL_1$	(-10 -7.5 -7)
D_{22}	(-110 – 125 -90)	$RPILL_2$	(-9 - 8 -7)
D_{23}	(-100 – 85 -70)	$RPILL_3$	(-8 -7 -6)
D_{24}	(- 80 –65 -50)	$RPILL_4$	(-7 -6.5 -5)
D_{25}	- 60 - 45 -30)	$RPILL_5$	(-6 -4.5 -3)
D_{26}	(-40 – 25 - 10)	$RPILL_6$	(-4 -3 -2)
D_{27}	(- 20 –5 10)	$RPILL_7$	(-3 -2 -1)
D_{28}	(0 15 30)	$RPILL_8$	(-1 0 1)
D_{29}	(20 35 50)	$RPILL_9$	(1 1.5 2)
D_{210}	(40 55 70)	$RPILL_{10}$	(2 3 4)
D_{211}	(60 75 90)	$RPILL_{11}$	(2.5 3.5 4.5)
D_{212}	(80 95 110)	$RPILL_{12}$	(4 5 6)
D_{213}	(100 115 130)	$RPILL_{13}$	(6 7 8)
D_{214}	(120 85 150)	$RPILL_{14}$	(7 8 9)
D_{215}	(140 160 170)	$RPILL_{15}$	(9 9.5 10)

TABLE 4. FUZZY RULES FOR AIR QUALITY FUZZY CONTROLLER

Difference$_3$		RP_{AQ}	
Symbol	**Range (Lower, Mid,Upper)**	**Symbol**	**Range (Lower, Mid, Upper)**
D_{31}	(-175 -112 -50)	RPA_1	(0 0.6 1.1)
D_{32}	(-140 -120 -80)	RPA_2	(0.9 1.5 2.1)
D_{33}	(-90 -70 -50)	RPA_3	(1.8 2 2.2)
D_{34}	(-70 -40 -10)	RPA_4	(2.8 3.5 4.2)
D_{35}	(-30 0 30)	RPA_5	(4 5 6)
D_{36}	(10 40 60)	RPA_6	(5 6 7)
D_{37}	(40 60 100)	RPA_7	(6.5 7.25 8)
D_{28}	(70 100 130)	RPA_8	(7.75 8.75 9)
D_{29}	(120 150 175)	RPA_9	(8.8 9.4 10)

4. Coordinator Agent

The coordinator agent takes the fuzzy logic controller's outputs as inputs and sets the level of the heater or air condition, light and CO2 generator correspondingly. First, the remaining battery capacity and the distance that needs to be covered are measured. If the distance that needs to be covered is more than the remaining distance, then the corresponding power is provided to actuators, and the optimization process is continued. In vice versa, the optimization process is terminated. The structure diagram of the coordinator agent is illustrated in Figure 6.

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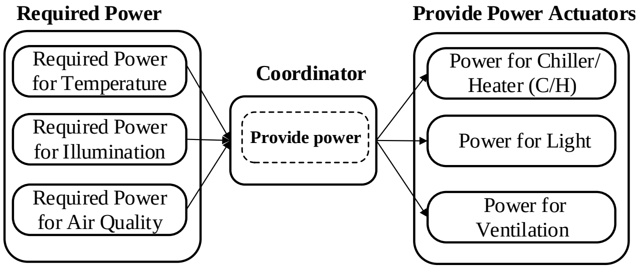

Fig 6. Structure diagram of Coordinator Agent.

5. Performance Evaluation

Many performance evaluators have been used to measure the performance of prediction algorithms. In the proposed work, (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) performance indices have been used to compare the actual values and the predicted values. The error minimization distribution is measured by using MSE. The MAPE evaluates the difference as a percentage of the target. The RMSE measures the error between the estimate and the target. The RMSE, MAE, and MAPE performance can be computed in Equations (23-25) respectively as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=0}^{n}(T_i - P_i)^2} \quad (23)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{n}|T_i - P_i| \quad (24)$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{n}\frac{|T_i - P_i|}{T_i} \times 100 \quad (25)$$

Where N signifies the total values, the target value is represented by T, and P indicates the estimated value.

IV. Implementation, Results, and Comparative Analysis

A. Implementation Setup

The proposed work is implemented on an Intel (R) Core (TM) i5-3570 CPU @ 3.40 GHz. Matlab 2018a has been used for implementing of the proposed model. The system confirmation for implementation and simulation analysis is given in Table 5.

TABLE 5. SIMULATION CONFIGURATION

Tool	Specification
CPU	Intel(R) Core (TM) i5-3570 CPU @ 3.40 GHz
RAM	16 GB
Graphics	NVIDA GeForce 9600 GT
Operating System	Window 10
Programing tool	Matlab 2018a

The data used in this work have been taken from reference [5]. The data consists of three factors: temperature, illumination, and air quality.

We have specified seven input and output rules for the temperature fuzzy logic controller's input variable D1 and output variable RPTemp, respectively. We have specified fifteen input and output rules for the illumination fuzzy logic controller's input variable D2 and output variable RPILL, respectively.

In air quality fuzzy logic controller, we have specified fifteen input and output rules for input variable D3 and output variable RPAQ, respectively.

In the proposed work alpha beta filter has been used to smooth sensor reading data and remove outliers from input sensor data. Figure 7 shows the actual temperature, sensor reading temperature, and predicted temperature. Similarly, in Figure 8, actual illumination, sensor illumination, and air quality illumination have been shown in detail. Figure 9 shows actual air quality, sensing air quality and predicted air quality values.

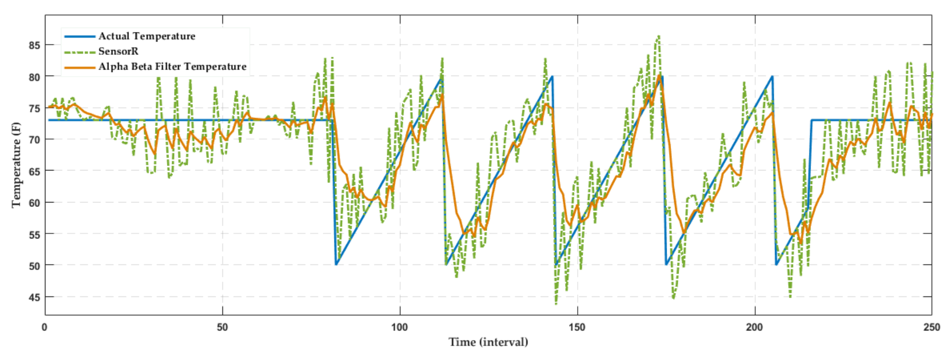

Fig 7. Actual temperature, sensing temperature, and predicted temperature.

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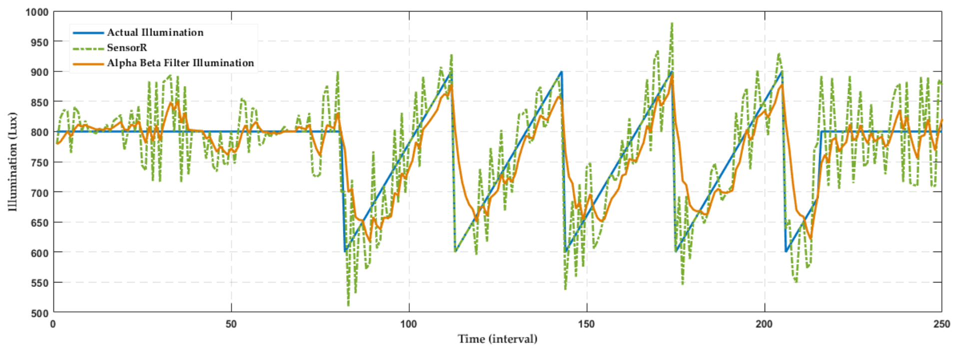

Fig 8. Actual illumination, sensing illumination, and predicted illumination

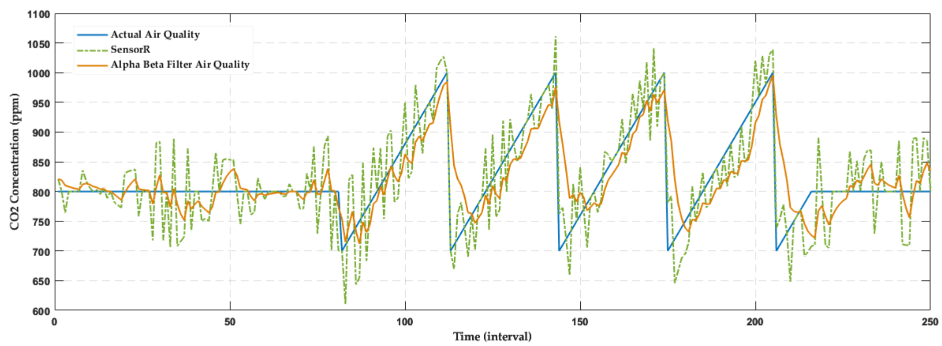

Fig 9. Actual air quality, sensing air quality, and predicted air quality.

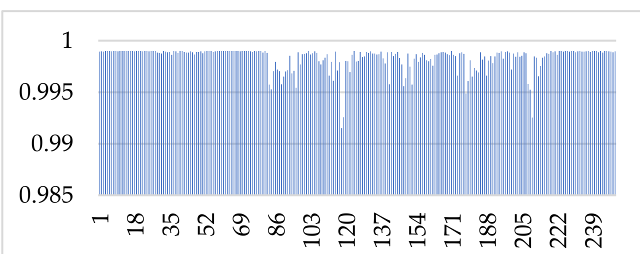

Fig. 10. Total Comfort Index without Optimization

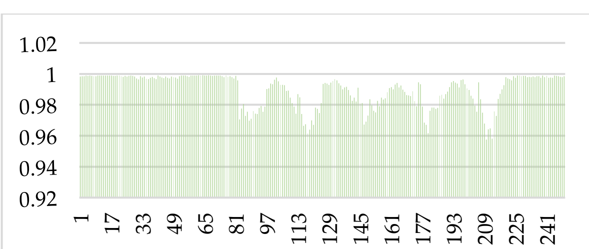

Fig. 11. Total Comfort Index with Optimization

In Figure 10, the comfort index values without optimization are given, as most of the values are far away; hence it indicates that the comfort index is low in a normal situation. Similarly, the comfort index values with optimization are exhibited in Figure 11 of the proposed approach, as most of the values are near 1, which indicates high comfort index. Hence, the proposed approach provides the best comfort index compared to the without-optimization approach.

The original and sensor error data have been used for the comparisons, as shown In Table 6. we also calculate the RMSE resulting from alpha-beta filter values and sensing data for temperature, illumination, and air quality. The resulting RMSE values of the Kalman filter are less than the sensing data RMSE values, which indicates that the alpha-beta filter [34] performance is good compared to the sensing data. Hence, we considered the alpha-beta filter values for further processing due to higher accuracy.

TABLE 6. TEMPERATURE, ILLUMINATION, AND AIR QUALITY DATA OF ALPHA-BETA FILTER SENSING DATA IN TERMS OF RMSE

Parameters	**Alpha-Beta Filter (RMSE)**	**Sensing Data (RMSE)**
Temperature	4.99	5.117
Illumination	45.34	53.33
Air Quality	48.14	51.317

The optimization algorithm performance measurement of temperature, illumination, and air quality representation is shown in figure 12. For calculating the optimization algorithm performance measurement, we have used different performance measures, such as root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) for temperature, illumination and air quality. The values of these performance measures indicate slight variations in the user set and optimized parameters. Table 7 represents the performance measurement of the optimization algorithm for temperature, illumination, and air quality.

TABLE 7. THE PERFORMANCE MEASUREMENT OF OPTIMIZATION ALGORITHM FOR TEMPERATURE, ILLUMINATION, AND AIR QUALITY

Parameter / Performance Maeasures	Temperaturen	Illumination	Air Quality
MAE	1.490	9.7222	8.0401
RMSE	2.543	16.5210	14.0310
MAPE	2.3123	1.2516	0.9849

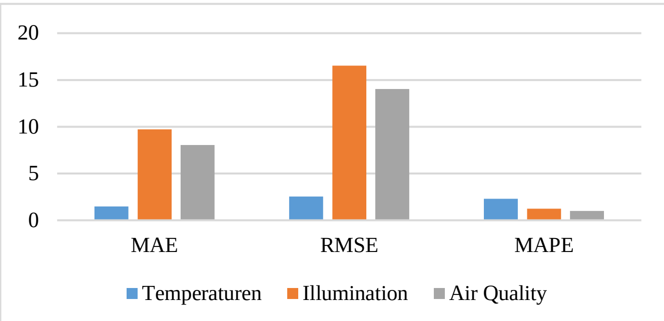

Fig 12. Representation of optimization algorithm performance measurement for temperature, illumination, and air quality.

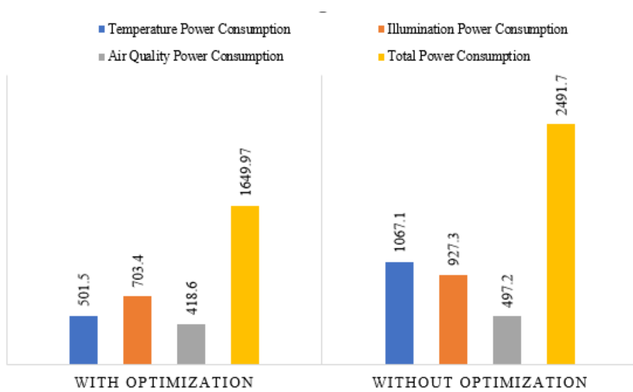

Fig 13. Energy Consumption with optimization and without optimization using fuzzy logic control

TABLE 8. ENERGY CONSUMPTION WITH OPTIMIZATION AND WITHOUT OPTIMIZATION USING FUZZY LOGIC CONTROL.

Parameters / Scheme	With Optimization	Without Optimization
Temperature Power Consumption	501.5	1067.1
Illumination Power Consumption	703.4	927.3
Air Quality Power Consumption	418.6	497.2
Total Power Consumption	1649.97	2491.7

Here, the power consumption with optimization using the fuzzy logic control [44] method and without optimization using the fuzzy logic control method is carried out. The results in Table 8 and Figure 13 represent the energy consumption with optimization and without optimization using fuzzy logic control. The parameters are air quality power control, illumination parameter, temperature parameter, and total power consumption, predicting that while using the fuzzy logic controller energy consumption optimization, the model performs better than without optimization.

The comparative analysis of the proposed approach is carried out with other well-known approaches in terms of energy consumption for individual parameters and total consumption, as illustrated in table 9 and Figure 14. The results show that the proposed approach's performance is better than other well-known energy consumption techniques.

TABLE 9. COMPARATIVE ANALYSIS OF PROPOSED APPROACH WITH OTHER APPROACHES

Parameters	**Algorithms**		
	GA [37]	**PSO [43]**	**Proposed Approach**
Temperature Power Consumption	440	522.63	601.32
Illumination Power Consumption	1475.16	1531.01	922.45
Air Quality Power Consumption	651.78	694.54	430.57
Total Power Consumption	2565.94	2747.29	1978.63

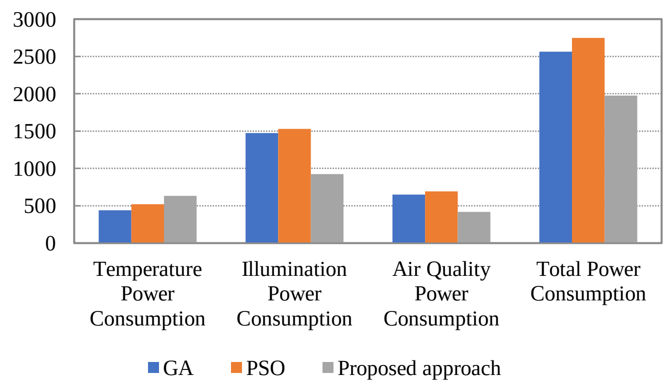

Fig 14. Comparative Analysis of Proposed Approach with other approaches.

IV. CONCLUSION

This paper proposes a novel model for energy consumption optimization and user comfort index maximization in electric vehicles. The proposed model comprised three main modules: prediction, optimization, and control. In the prediction stage of the proposed, we have used the alpha beta filter to remove noise from the data and make able the data for further processing. The optimization is divided into two sub-modules: the machine learning module and the optimization module. The optimization module aims to optimize the environmental parameters, and a machine learning algorithm is used to tune the user-set parameters in the comfort index formula. In the optimization module, a novel optimization technique called FA-GA and the support vector algorithm has been used in the machine learning module. In the previous similar models, the user set was set by the user manually. However, we have made the proposed model dynamic, and the user-set parameters are tuned through a machine-learning algorithm. The difference between environmental and optimized parameters is then fed as inputs to the control module. The Mamandi fuzzy logic method has been used in the control module, which is one of the simplest fuzzy inference systems. The controller's output is the required power for temperature, illumination, and air quality. The comparators took the desired power for each parameter as input from the controller and compared it with available power. The coordinator provides the desired energy to corresponding actuators if the required energy is available. Experimental results show that the proposed approach consumes less energy and enhances the comfort index of the user better than conventional methods. These results make us confident to explore this approach further through experiments in natural environments.

The limitation of this work is that we have used this for three parameters, though the proposed approach can accumulate more parameters. We have only utilized the indoor parameters in the proposed approach, and no external ones are used. However, the comfort index and energy consumption also depend on external parameters.

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