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Optimization of energy consumption in smart homes using firefly algorithm and deep neural networks

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Abstract

Electronic gadget advancements have increased the demand for IoT-based smart homes as the number of connected devices grows rapidly. The most prevalent connected electronic devices are smart environments in houses, grids, structures, and metropolises. Smart grid technology advancements have enabled smart structures to cover every nanosecond of energy use. The problem with smart, intelligent operations is that they use a lot more energy than traditional ones. Because of the growing growth of smart cities and houses, there is an increasing demand for efficient resource management. Energy is a valuable resource with a high unit cost. Consequently, authors are endeavoring to decrease energy usage, specifically in smart urban areas, while simultaneously ensuring a consistent terrain. The objective of this study is to enhance energy efficiency in intelligent buildings for both homes and businesses. For the comfort indicator ("thermal, visual, and air quality"), three parameters are used: temperature, illumination, and CO2. A hybrid rule-based Deep Neural Network (DNN) and Fire Fly (FF) algorithm are used to read the sensor parameters and to operate the comfort indication, as well as optimize energy consumption, respectively. The anticipated user attributes contributed to the system's enhanced performance in terms of the ease of use of the smart system and its energy usage. When compared to traditional approaches in expressions of Multi View with 98.23%, convolutional neural network (CNN) with 99.17%, and traffic automatic vehicle (AV) with 98.14%, the activities of the contributed approach are negligibly commanding.

Keywords: Energy consumption, Firefly algorithm, Hybrid rule-based deep neural network, Smart homes, User preference parameters

1. Introduction

The utilization of information technology (IT) within smart home contexts has evolved over the last few decades. Smart home networks are projected to connect more devices in the future. The Internet of Things has altered people's lifestyles [1]. Smart cities are being developed, including facilities such as automated railways, smart autos, automated parking, and smart lighting [1],[2]. Concerns have been raised about privacy and the misuse of technology in smart homes [3]. Because smart homes are grid-compatible, electronic devices run on energy; additionally, smart grids are synchronized with internal power units [4]. In order to reduce the energy consumption of smart homes, the need and supply of electrical power must be synchronized. Since the development of smart cities, conventional grids have been replaced with smart grids, which generate electricity and monitor energy consumption [5],[6]. Prediction methods are typically used to anticipate energy in smart homes and smart grids, as well as day ahead (DA) energy pricing [7]. Controlling energy use has become necessary due to the annual loss of precious resources. Furthermore, the cost of producing electricity is rising by the day. The situation has changed as the IT industry has advanced and the Internet of Things (IoT) has been implemented. Researchers are working to optimize the benefits of IoT technology. People are interested in smart homes and smart cities because of their enhanced features and automation.

Prediction and optimization of energy usage are key issues in smart homes. According to new studies, the problem remains unaddressed, and significant quantities of energy are being wasted. The architectural blueprints, in accordance with environmentally sustainable energy criteria, will use less energy in the long term, but with optimization methodologies, we may optimize the energy-saving benefit [8]. Energy use in smart homes has been efficiently forecasted using several prediction algorithms [9]-[11]. The other key problem is selecting characteristics such as CO2, light, and temperature. Previous research has shown that when it comes to optimizing the energy utilization approach, the user settings remain constant. After the first setup, the system will continue to run with the same values, resulting in decreased energy use. In conventional houses, the process is identical, with the owner adjusting the settings by remote control or more conventional means. Real-time environments have varying parameters, and the resident's preferred settings will fall within a certain range [11]-[13].

Because of the previously mentioned concerns, as well as the failure to keep smart home gadgets up to date with changes in weather conditions, energy consumption is significant. The comfort level of inhabitants is influenced by static parameters as a result of a system operating at static settings while taking into account user preferences and external weather conditions. Furthermore, this scenario creates issues for people with children and the disabled who are unable to properly use the systems; typically, current models are not user-friendly for specific groups of people. Many optimization algorithms [14],[15] are now used for energy minimization, including BAT Algorithms (BA)[16], FIREFLY (FF) [17], Grey Wolf Optimization (GWO) [18], and others. There are some controversies in energy minimization studies [19],[20]. Problems such as energy consumption reduction and an increased comfort index are addressed here. The created model will improve the system's performance by recognizing the needs of special people, such as youngsters and the disabled.

The following are the significant contributions of the full paper.

- To create the idea of using the FF+ Hybrid DNN algorithm to solve the energy reduction problem.
- To introduce Firefly Deep Neural Network (FF-DNN), a new method for optimizing energy usage and forecasting the parameters "air quality, temperature, and illumination."
- To maximize the user's level of comfort while minimizing energy use.

The exploration paper's association is designed in the following order: The literature review is depicted in Section II. Section III depicts the armature of stoner choice parameters as well as the optimization of energy usage. Section IV discusses the outcomes and discussions on the optimization of energy usage and stoner preference factors. Section V also leads to the conclusion of the entire study.

2. Literature review

In 2020, Shah et al. [21] concentrated on optimizing energy consumption in smart homes. Three major parameters similar to CO2 (ppm), temperature (°F), and illumination (lx) were used for the comfort indicator, like air, thermal, and visual quality. In the earlier workshop, the major challenge was stationary stoner parameters. These parameters were distributed at first and weren't changed. Also, the nascent beta sludge was employed to reduce the noise from the data and predict the air quality, inner temperature, and illumination. For validating the stoner parameters, a Deep Extreme Learning Machine (DELM) system was enforced. Fuzzy logic and BA techniques were utilized in order to enhance the management of comfort index and improve energy usage. The overall performance of the system was enhanced using the predicted user parameters, considering the utilization of comfort index management, smart systems, and energy consumption. Once the optimization was done, the comfort index was approximately 1, which shows the system's performance. The power usage also decreased after optimization.

In 2012, Corno and Razzak [22] introduced a result for energy conservation on the basis of unequivocal high-position modeling of stoner studies and verified the device control automatically from the result and a constrained Boolean satisfiability optimization problem. Therefore, the developed fashion was incorporated with a smart terrain frame and handled the stylish issues.

In their study conducted in 2019, Molla et al. [23] proposed a framework for the Home Energy Management System (HEMS) designed specifically for residential users in a smart grid setting. The authors introduced novel limitations and employed a multi-restricted scheduling technique to enhance the system's efficiency and effectiveness. The preamble of the optimization issue was implemented with the Time of Use Pricing (TUP) model. The utilization of a novel meta-heuristic algorithm called GWO was employed for the purpose of optimization, and its efficacy was compared to that of particle swarm optimization (PSO). In order to demonstrate the efficacy of the appliances, an integrated rooftop photovoltaic (PV) system was implemented within the system. A total of eight scripts, each exhibiting vibrant colors, were carefully selected for study. These scripts were subjected to examination using distinct time scheduling models.

In their 2018 study, Errapotu et al. [24] proposed a homomorphic encryption-based approach using the Alternating Direction Method of Multipliers (ADMM) for optimizing operation scheduling in a distributed manner while preserving the privacy of home operations. A comprehensive simulation was conducted by utilizing real-world facts, and the Scheduling for Flexible and Effective Energy Consumption (SAFE) model was implemented to achieve a reduction in electricity costs through the secure storage of pharmaceuticals.

In 2017, Joo and Choi [25] offered a distributed optimization system to record the power operation of numerous smart homes with dispersed energy coffers. For home energy operation, the optimization issue was resolved into a two-position optimization issue similar to global HEMS (GHEMS) in the alternate position and local HEMS (LHEMS) in the first position. In GHEMS, the power trading and energy storehouse system was among the listed and the homes, whereas in LHEMS, the comfort position and cataloging the consumer’s favored appliances The developed distributed system has revealed good performance concerning client comfort, position, and price of electricity. The analysis of the influence of various network topologies was done on the developed model. This has shown that the optimal network configuration selection was In Coscn 2019, Huang et al. [26] have formulated joint optimization of energy consumption scheduling and microgrid configuration as a leader-follower Stackelberg game for modeling the coordination among energy consumption scheduling and microgrid configuration. For optimal installed counts of PV units, batteries, wind turbines, and microturbines, the decision of microgrid configuration as a leader was designed as an upper-level optimization issue. The formulation of a bi-level non-linear programming method was done for the Stackelberg game. This study focused on the creation and evaluation of four bi-level hierarchical approaches in conjunction with the Differential Evolution (DE) algorithms for the purpose of addressing optimization problems. The examination of the microgrid configuration within the smart structure case study was undertaken to establish the feasibility and advantages of the advanced game-theoretic system.

In 2019, Essiet et al. [27] have recommended an advanced DE model to develop the response to demand among consumers and aggregators. The suggested approach made use of a secondary population library that holds infelicitous results that were preliminarily excluded by the main library of the bettered DE algorithm. The secondary library initiated, relocated, and recombined campaigners to improve their fitness before sending them back to the primary library for the fashionable selection. Non-dominated sorting genetic algorithm III (NSGA-III) is a multi-objective evolutionary algorithm that was compared to DE in terms of corruption and dominance to determine the produced model's capabilities. This was accomplished through a capability test of the model for maximizing the set of objectives characterizing the smart, intelligent home with a demand response aggregator. The smart home took into account both loads, known as non-shiftable and shiftable, to fake the energy consumption profile of a typical household.

In 2020, Dibavar et al. [28] have introduced a mongrel robust stochastic optimization system for managing power in smart homes in real time (RT) and DA energy requests. Misgivings of cost and generation of PV were anatomized in the advanced system. A control parameter was used to alter the quantum of traditionalism in the robust optimization approach (ROA), producing results with colorful traditionalism situations. Also, with the help of stochastic programming (SP), the suggested model assumed the associated misgivings and considered the RT energy request. To estimate the unknown features of PV generation and energy costs, probable scripts were employed at this stage. In addition, when the comfort of occupants was taken into account, loads were controlled. The advantages of the suggested mongrel fashion were demonstrated from the results analysis, which assured decision-makers about the profitability of energy operations.

The advantages and disadvantages of energy optimization and dynamic user preference parameter selection for smart homes are shown in Table 1.

3. Proposed architecture

3.1. Proposed methodology

Static user settings, comfort index management, and the optimization of energy utilization are all topics that are addressed in this article through the presentation of a generic approach. There are three steps that make up the model, and each of these stages has its own predetermined criteria. Before anything else, readings of "air quality, temperature, and illumination" are accomplished. During the course of a total of four weeks, continuous hourly observations were carried out, commencing at 7.30 in the morning and concluding at 5.30 in the evening, during the course of typical working hours. A module for making predictions based on raw data is included in the second layer of the proposed design. Additionally, the alpha-beta filter is applied to the data that has been acquired in this layer in an effort to eliminate any stray signals that may have been picked up by the sensors. The primary advantage of the alpha-beta filter is that it has the potential to immediately adapt to new circumstances and enhance system performance without the requirement of a comprehensive structure model. "air quality, temperature, and illumination" are the three things that are delivered by the alpha-beta filter. A phrase known as "indoor environmental" modules is used to refer to the predicted values. Furthermore, these projections are utilized as inputs by the optimization and prediction layer of the system that is being presented. Along with the user parameters, the initial anticipated values of "air quality, temperature, and illumination" are provided as inputs to the hybrid DNN and optimization algorithm that was built and given the name FF. The collected data comprise the amount of energy used by appliances in watt-hours, the amount of energy used by light elements in the rooms in watt-hours, the temperature in two rooms, the humidity in two rooms, the temperature outside in Celsius, the air quality in air quality index (AQI), the pressure in millimeters of mercury, the humidity outside in percent, and the wind speed in meters per second. With regard to the input to the layered architecture that has been specified for the proposed system, the three primary characteristics that are taken into consideration are air quality, temperature, and illumination. For each of the input parameters, a total of 330 data readings were gathered and collected. Eighty percent of these collected datasets, or 264 dataset collections for each parameter, are designated for training purposes. The remaining twenty percent, or 66 dataset collections, are, on the other hand, employed for testing and validation reasons.

Table 1. Merits and demerits of energy optimization and dynamic user preference parameters selection for smart homes

Author	Methodology	Features	Challenges
Shahet al. [21]	BAT	• It is utilized to enhance comfort index management and optimize energy consumption. • It has high convergence rate for large scale optimization problems under right conditions.	• For many applications, the best values are not clear. • If the count of function evaluations is not high, then the accuracy is restricted.
Corno and Razzak [22]	Domotic Effect Modelling	• It has the ability to allow the users to convey their requirements easily. • These are defined by the users based on the determined operators for the environment.	• Need to perform better integration for attaining best performance.
Mollaet al. [23]	GWO	• It is utilized to reduce the PAR and energy billing without impacting the user's comfort level. • It is used to solve the problem effectively.	• It has slow convergence rate. • It doesn't have the local searching ability.
Errapotuet al. [24]	ADMM	• It is utilized for solving the optimization issues by considering the privacy problems in smart homes. • It has robust decomposability property of dual ascent and convergence properties.	• Convergence rate is poor.
Joo and Choi [25]	Distributed Algorithm	• It is used to decrease the computational complexity. • It attains best performance and the comfort level of each user is adjusted.	• Need to improve the performance.
Huanget al. [26]	Evolutionary algorithms	• It scales well to high dimension problems. • It attains best performance.	• It doesn't guarantee diversity among the solutions acquired.
Essiet et al. [27]	DE algorithm	• It is utilized to optimize need of home management models. • It reduces the energy costs and enhancing the consumer comfort.	• It can easily fall into local optima.
Dibavar et al. [28]	ROA	• It is to tackle with the suspicions of smart home's energy management. • It controls the insecurity of price in DA market.	• It has to lead a realistic estimate of feasibility of smart homes.

The training of a hybrid deep neural network (DNN) has been accomplished with the assistance of historical environmental characteristics and user preference data. Additionally, user-set parameters have been forecasted. There are numbers for the user parameter lighting, CO2, and temperature included in the historical data. Additionally, there are values for the temperature, CO2, and illumination levels inside the building. The FF algorithm is utilized in order to perform adjustments to environmental parameters with the intention of lowering the amount of energy that is consumed and increasing the comfort index. The objective of the FF algorithm is to produce a value that is optimized based on the preferences of the user in order to improve the user's level of comfort. Figure 1 is a diagrammatic representation of the energy optimization and user preference parameters that were produced for smart homes through the utilization of the FF algorithm and hybrid data-driven neural networks.

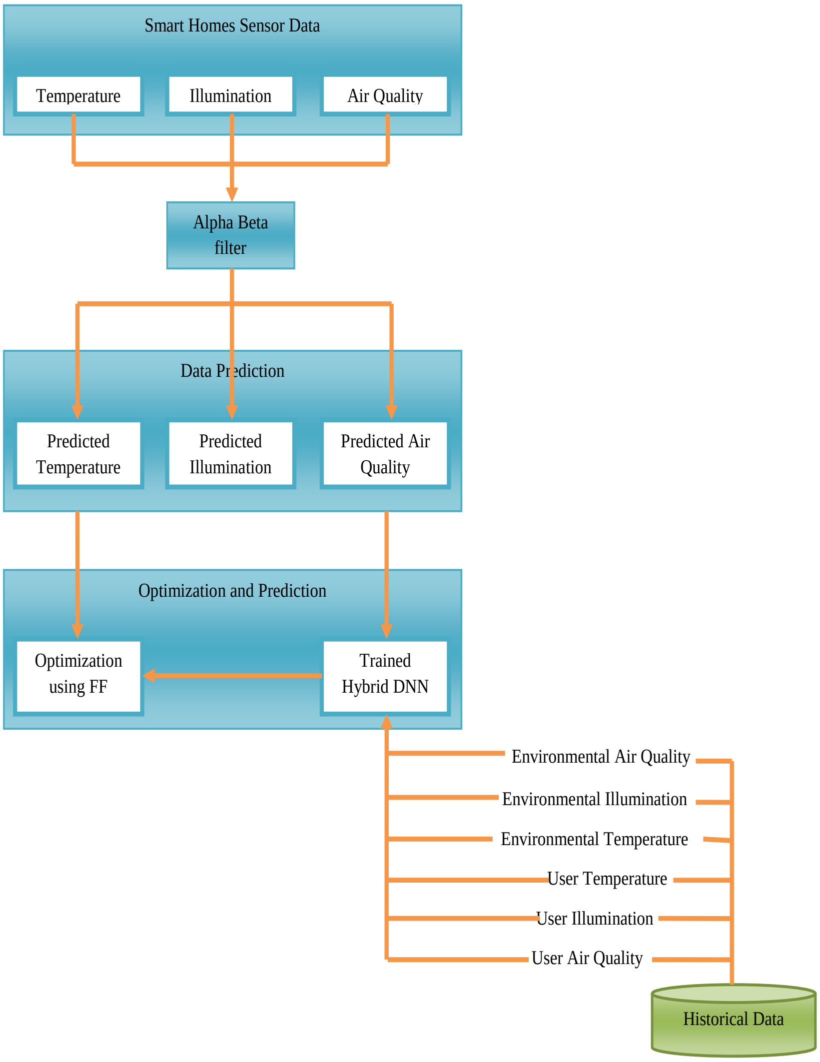

Figure 1. Proposed architecture of power consumption optimization & improved comfort index for smart homes

3.2. Hybrid rule-based deep neural network

The back propagation method is used to train Hybrid Rule-based DNN [29]. It tests if the present Neural Network (NN) parameters are appropriate for categorizing training samples on an individual basis. No changes occur when the predicted outcome for a given instance is identical to the actual label. The weight of NN is updated when the samples are misclassified. Moreover, the back propagation method operates in a hierarchical manner. After the output layer's weights have been refreshed, it moves on to the next shallow hidden layer. Each hidden neuron is then assigned a percentage of the error made by the corresponding output neuron. In general, a greater number of iterations is needed to alter the weights for the best results. In figure 2, the structure of DNN is given. As an activation function, Rectified Linear Units (ReLUs) are employed. Even more, it is a piecewise linear function that stands in for the missing gradients of the Tanh and sigmoid functions. The mathematical equation of ReLU is represented in (1).

$$\mathrm{Re}lu(X) = \begin{cases} X \;\; if \;\; X > 0 \\ 0 \;\; if \;\; X \leq 0 \end{cases} \tag{1}$$

Figure 2 is composed of three layers, specifically the input layer, output layer, and hidden layer. To extract the rules from a Deep Neural Network (DNN), a four-step process is employed. Firstly, the output of the neurons in the DNN's hidden layer is obtained. Secondly, a rule tree is constructed, connecting the DNN's hidden layer to its output layer. Thirdly, rule trees are created between each hidden layer and the input layer. Lastly, the rule trees generated in steps (a) and (b) are combined to form a singular rule tree, with the hidden layer acting as the join relation.

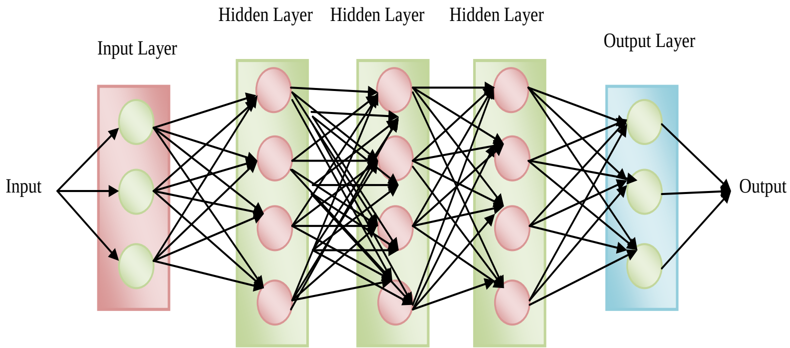

Figure 2. Structure of DNN

1. Extract Neuron Information: In the behalf of the output of each and every hidden layer neuron, one rule extraction approach is determined. The training of DNN with j hidden layers $hd_1, hd_2, \ldots, hd_j$ by considering a dataset $Dt = \{(P_1, Q_1), (P_2, Q_2), \ldots, (P_i, Q_i)\}$. In each hidden layer, there are k neurons, in which the k^{th} neuron in j^{th} hidden layer is given by hd_j^k. The neuron output is computed using (2). Here, the connection weight of c^{th} neuron and in $(j-1)^{th}$ hidden layer, there are d_{j-1} neurons. The threshold is given by θ, and the input from the c^{th} neuron is given by X_c. For the neurons present in j^{th} hidden layer, the mean value of the output is given by Op_{hd_j}, which is computed in (3).
$$No(hd_j^k) = \mathrm{Re}\,lu\left(\sum_{c=1}^{d_{j-1}} we_c X_c - \theta\right) \tag{2}$$
$$Op_{hd_j} = \frac{1}{d} \sum_{e=1}^{d_j} No(hd_j^e) \tag{3}$$
In (3), for every sample of data P, the collection $Op_i = \{Op_{hd_1}, Op_{hd_2}, \ldots, Op_{hd_j}\}$ is generated from the DNN when there are j hidden layers. Finally, the training dataset Dt is transformed into $Dt' = \{(Op_1, Q_1), (Op_2, Q_2), \ldots, (Op_i, Q_i)\}$ during the DNN, which is utilized to build a hidden-output tree.
2. Design a hidden-output tree: Decision tree algorithm is the core key component of the hidden-output tree. The calculation of the information entropy of the data Dt' is performed using equation (4), where the category of labels is represented by CA, and the proportion of category ca in the entire sample is designated as c_{ca}. It is required to discretize Dt', as Dt' is not discrete type. The Dichotomy approach is shown in (5). Here, the two adjacent values of Dt' sorted on Op_{hd_j} are given by $Op_{hd_j}^b$ and $Op_{hd_j}^{b+1}$, and the count of samples of Dt' is given by i. Later, Dt' is split into $Dt_t'^{+}$ and $Dt_t'^{-}$ on the basis of t computed in (5).
$$En(Dt') = -\sum_{ca \in CA} c_{ca} \log_2 c_{ca} \tag{4}$$
$$T_{Op_{hd_j}} = \left\{ \frac{Op_{hd_j}^b + Op_{hd_j}^{b+1}}{2} \middle| 1 \le b \le i \right\} \tag{5}$$
In (6), the computation of information gain is performed using the feature Op_{hd_j}. Subsequently, the decision tree selects the segmentation point t that yields the highest information gain, which serves as the branch

point. This selection process is technically denoted as equation (7). With the help of Op_{hd_j}, the vast gain of information is the more purity improvement.

$$Gain(Dt', Op_{hd_j}, t) = En(Dt') - \sum_{\lambda \in \{-,+\}} \frac{|Dt'^{\lambda}_t|}{|Dt'|} En(Dt'^{\lambda}_t) \tag{6}$$

$$Gain(Dt', Op_{hd_j}) = \max t \in T_{Op_{hd_j}} Gain(Dt', Op_{hd_j}, t) \tag{7}$$

3. Build input-hidden tree: The training data of DNN is considered as the input of input-hidden tree, whereas the output is a feature of the input of hidden-output tree. Assume that the input data for generating the input-hidden tree regarding the hd_j hidden layer is $Dt_{hd_j} = \{(P_1, Op^1_{hd_j}), (P_2, Op^2_{hd_j}), ..., (P_i, Op^i_{hd_j})\}$, in which the aim value of the sample is given by $Op^i_{hd_j}$, which is computed using (3). Moreover, the feature vector is denoted as $P_i = (X^1_i, X^2_i, ..., X^d_i)$. Two regions $Rg_1 = (k, X^k_i) = \{X \mid X^k \le X^k_i)$ and $Rg_2 = (k, X^k_i) = \{X \mid X^k > X^k_i)$ are defined using k^{th} feature variable X^k in Dt_{hd_j} and it's value X^k_i as the segmentation variable and segmentation point. In (8), the optimal k and X^k_i are acquired, in which ca_1 and ca_2 are the fixed outputs, which are computed in (9) and (10).

$$\min \left[\sum_{X_i \in Rg_{1(k,X^k_i)}} (Op^i_{hd_j} - ca_1)^2 + \sum_{X_i \in Rg_{2(k,X^k_i)}} (Op^i_{hd_j} - ca_2)^2 \right] \tag{8}$$

$$ca_1 = \frac{1}{d_1} \sum_{X_i \in Rg_{1(k,X^k_i)}} Op^i_{hd_j} \tag{9}$$

$$ca_2 = \frac{1}{d_2} \sum_{X_i \in Rg_{2(k,X^k_i)}} Op^i_{hd_j} \tag{10}$$

The equations provided above represent the distribution of samples in two regions based on a feature variable, denoted as k^{th}, and its corresponding value, denoted as X^k. The count of samples in the first region is represented by d_1, while the count of samples in the second region is represented by d_2.

4. Get the total tree: Since the output of the hidden layers is the union of the outputs and input of the input-hidden and hidden-output tree respectively, the data from the hidden layers may be used to combine the two trees into a single one. The output of the input-hidden tree is used as the input of the hidden-output tree to establish the connection between the two trees.
5. Rule tree-based detection: Whenever a novel unseen example is considered as the input for detection, the parallel input to the input-hidden trees is provided as an example. Subsequently, the use of two input-hidden trees yields the regression values of two hidden layers, denoted as Op_{hd_1} and Op_{hd_2}, respectively. Finally, the hidden-output tree yields the outcomes of detection.

3.3. Prediction process of DNN

Figure 3 depicts the DNN explanation process. Initially, the input Eigen vectors A are categorized as "Illumination, Temperature, and CO_2" using DNN. The input variables are then utilized to analyze the forecasting and discover useful data. The outcomes of this interpretation process demonstrate the significance of a characteristic in terms of prediction. The process commences with the retrieval of the hidden output derived from the DNN, followed by the acquisition of a substantial hidden layer from said hidden output. Once the most significant hidden layer is identified, it becomes possible to locate the input-hidden tree that is connected to it. Further, it is easy to determine which input feature is crucial to prediction.

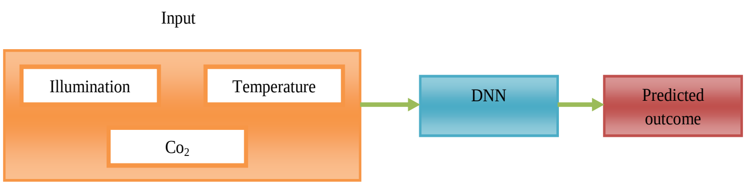

Figure 3. The explanation procedure of hybrid DNN

3.4. Conventional Firefly algorithm

To attract other fireflies and gain potential, fireflies utilize flash signals. These fireflies are classified as unisexual, and the intensity of their flash determines how attractive they are. Consequently, when faced with the decision between two firefly particles, the particle will be more captivated by the firefly exhibiting the highest degree of luminosity (illumination) and will proceed in the same direction. The firefly's route will be arbitrary in the absence of other fireflies in the area around it. A fitness function is associated with the brightness of the light. The light intensity of the inverse square law is specified in equation (11).

$$IL(d) = \frac{IL_{\partial}}{d^2} \tag{11}$$

In the above equation, the light intensity is given by $IL(d)$ the distance d as well as the intensity IL_{∂} at the source. The light intensity IL_{∂} varies with distance with distance d for the given medium with absorption coefficient λ is denoted in (12). Here, the original intensity is represented as IL_0. Since the firefly's attraction B is proportional to the light intensity noticed by neighboring flies, we may express this relationship mathematically as in (13).

$$IL = IL_0 \exp(-\lambda d^2) \tag{12}$$

$$\beta = \beta_0 \exp(-\lambda d^a)(a \geq 1) \tag{13}$$

In (13), the attractiveness β_0 is at $d = 0$. The term d is computed for two fireflies i_1 and j_1 at p_{i_1} and p_{j_1}, which is given in (14). In each of the iteration, the flies go near to the flies that have more brightness and it is shown in (15).

$$d_{ij} = \sqrt{\sum_{k=1}^{r} (p_{i_1,k} - p_{j_1,k})^2} = \lVert p_{i_1} - p_{j_1} \rVert \tag{14}$$

$$p_{i_1} = p_{i_1} + \beta_0 \exp(-\lambda d_{i_1 j_1}^2)(p_{i_1} - p_{j_1}) + \alpha\varepsilon \tag{15}$$

In the above equation from the Gaussian distribution, the vector of random numbers is taken, and it is given by ε and the randomization parameter is denoted as α. one of the most practical approaches to simulation optimization. One similar optimization algorithm is Firefly Algorithm. The announcing aurora of fireflies is astounding eyesight in the summer bliss in the extended and abstentious corridors. The arrangement of cautions is basically dissenting from a one firefly species to another. The announcing cockcrow is created by a bioluminescence subpoena, and the close capacities of similar signaling approaches are even more confusing. However, two introductory capacities of alike cautions are to attain cooperation (contact) and to attract a possible mark. The aurora ardency at a circumstantial difference from the light reference declines with the conversely commensurate of place of difference. Another confinement of this category of contact is that the charade absorbs aurora, which becomes handcuffed and handcuffed as it travels expanses. Obviously, fireflies attract towards further brilliance. The ardency of aurora is composed in such a lead that it's before long allied with the disinterested capacity to betide optimized, which makes it potential to breed current optimization algorithms, such as Firefly Algorithm. For the clarity of the Firefly Algorithm, following three idealized traditions is appreciated: all fireflies are androgynous, which means that one firefly will be drawn to other fireflies no matter how beautiful they are. So, the junior bright undefined will actuate towards the cloudless one for any two announcing fireflies. The beauteousness drop with contrast as the ardency again decreases. If there's no exploitable brilliantly firefly, it'll actuate anyhow; the brilliancy of a firefly is affected or decided by the chorography of the disinterested capacity. For an optimization question of maximizing a capacity, the brilliance is just commensurate to the merit of the disinterested capacity.

The basic reason tropical fireflies flash is because they think their bioluminescent messages will draw in possible mates and food. They may also serve as a protective alert system to warn off potential predators. The luminance of a firefly determines how attractive it is; if two fireflies are present, the brighter one will approach the lesser one. Fireflies lose appeal as they get farther away from the light source because of the inverse connection between light intensity and distance. A firefly will migrate at random if it cannot find another firefly that is brighter than it is. The luminance and, thus, the firefly's appeal are determined by the objective function with fitness value. According to our approach, a firefly's brilliance will increase with decreasing cost with respect to the fitness value.

Algorithm 1 shows the FF algorithm's step-by-step process.

Algorithm Pseudocode 1: FF [17]

Step 1: Initialize the number of fireflies

Step 2: Initialize iteration count as $i = i + 1$

Step 3: In each of the iteration, compute the fitness values of fireflies

Step 4: In each of the iteration, the fireflies are sorted by considering the best one based on the light intensity

Step 5: Adjust the light intensity of the remaining flies in accordance with the distance between them.

Step 6: Move the flies due to attraction that relies on the control parameters and light intensity

Step 7: In the event that the exit condition is not achieved, return to step 2. Otherwise, proceed to step 8.

Step 8: Give the results with FF particles that have a higher light intensity.

The diagrammatic representation of FF algorithm is shown in figure 4.

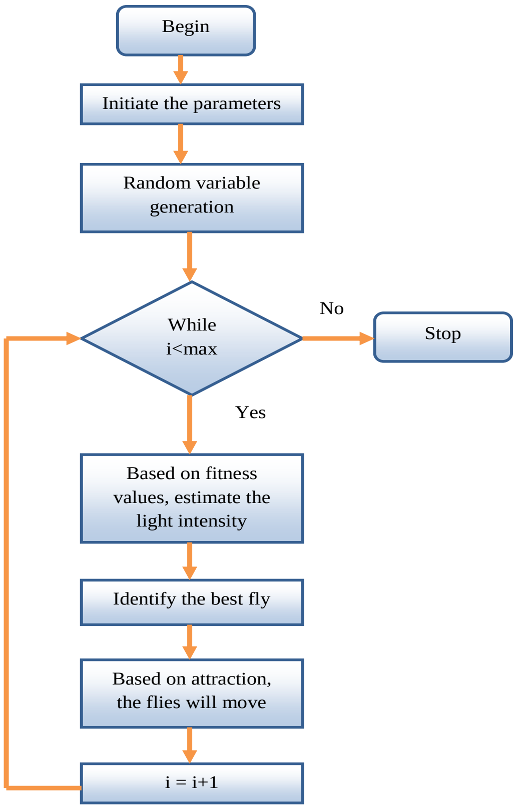

Figure 4. Flowchart representation of FF algorithm

4. Result and discussion

4.1. Experimental Setup

The complete mechanism was developed using MATLAB/Simulink software under "Air Quality, Temperature and Illumination". Various performance analyses were done. After obtaining the Alpha-Beta filter findings, the hybrid DNN and FF for the smart homes were evaluated for performance.

4.2. Analysis using conventional machine learning (ML) algorithms

We compare four well-known machine learning methods: Random Forest (RF), k-nearest neighbors algorithm (KNN) (K=5), Bagging, and Ada boost over the suggested model. To attain the best results, various parameters are adjusted for each algorithm. In Table 2, the outputs attained using these algorithms are depicted. The developed model acquires the best performance in relation of “precision, recall, F-Measure and also accuracy” when compared to other machine learning algorithms. From Table 2, the accuracy percentage of the suggested model is better than Bagging, KNN and RF is better than Ada Boost. Similarly, “recall, F-Measure and precision” is also attaining best performance in predicting the data.

Table 2. Analysis using conventional ML algorithms

Method	Accuracy (%)	Precision	Recall	F-Measure
RF	95.21%	0.9628	0.9625	0.9626
KNN(K=5)	93.31%	0.9431	0.9496	0.9474
Bagging	95.36%	0.9641	0.9649	0.9643
Ada Boost	87.52%	0.8887	0.8845	0.8852
Hybrid DNN	98.65%	0.9893	0.9927	0.9904

4.3. Analysis using conventional technologies

The analysis of the developed model and the conventional existing technologies is shown in Table 3. Here, the suggested approach is compared with the conventional Multi View, CNN. The outputs of the presented method are slightly high when compared over traditional methods in terms of Multi View, CNN, and Traffic AV. There are some benefits when compared over conventional models like it doesn’t require complex feature processing, fast detection in huge speed network environment and early packet detection. Thus, it is concluded that the suggested technique is superior to conventional techniques in predicting the optimization of energy usage and enhancing the comfort index values.

Table 3. Analysis using conventional technologies

Method	Accuracy (%)	Precision	Recall	F-Measure
Multi View	98.23%	0.9851	0.9805	0.9841
CNN	99.17%	0.9939	0.9946	0.9941
Traffic AV	98.14%	0.9822	0.9851	0.9823
Hybrid DNN	98.55%	0.9793	0.9827	0.9804

4.4. Absolute Mean Percentage Error (AMPE), Error based on Root Mean Square (ERMS), and Absolute Mean Error (AME) of Firefly Algorithm for ambient air quality, infrared temperature and luminosity

The outcome metrics of the "Ambient air quality, Infrared temperature, and Luminosity" are displayed in Table 4. The ERMS is a quadratic scoring rule that is employed to assess the mean magnitude of the error. The calculation of the ERMS involves determining the discrepancy between the observed values and the expected values. The specific equation for computing the ERMS is provided in (16). Additionally, the Absolute Mean Error (AME) quantifies the average magnitude of errors within a given group of forecasts, disregarding their respective directions. The metric assesses the precision of continuous variables. The mathematical expression for Mean Absolute Error (MAE) is denoted as (17). The Aggregate Mean Percentage Error (AMPE) is calculated by dividing the sum of the absolute errors by the demand for each period separately. This equation is represented as (18).

Table 4. AMPE, ERMS, and AME of FF algorithm for ambient air quality, infrared temperature and luminosity and air quality circulation for smart homes

The Performance Measurement System	Identifies the parameters		
	Ambient air quality	Infrared Temperature	Luminosity
AMPE	1.1956	2.919	1.696
ERMS	14.9860	2.676	14.98
AME	7.0901	1.5925	10.011

$$EMRS = \sqrt{\frac{1}{n}\sum_{e=0}^{N}(Ac - \Pr_f)^2} \tag{16}$$

$$AME = \frac{1}{n}\sum_{f=1}^{N}|Ac_f - \Pr_f| \tag{17}$$

$$AMPE = \frac{1}{n}\sum_{f=1}^{N}\frac{|Ac_f - \Pr_f|}{Ac_f}*100 \tag{18}$$

In the above equations, the actual and the predicted values are denoted as Ac_f and $\Pr_f$, respectively. The term n indicates the whole number of observations.

4.5. Total comfort index before and after optimization

It [30] is the significant factor each developed approach has attempted to enhance the user's comfort index within the smart homes as well as intelligent buildings. The mathematical equation of comfort index is given in (19) [31]. Here, the comfort index Ci values lie in between 0 and 1. The terms α_1, β_1, and γ_1 indicates the user set parameters of "temperature, illumination, and air quality", respectively. The sum of $\alpha_1 + \beta_1 + \gamma_1 = 1$, which should not exceed 1. Moreover, the terms e_T, e_I, and e_A denotes the environmental parameters of "Ambient air quality, Infrared temperature and Luminosity. It represents the error variances among optimized as well as the environmental values of the parameters α_1, β_1, and γ_1. The user set parameters of α_1, β_1, and γ_1 are given by dT_s, dI_s, and dA_s respectively.

$$Ci = \alpha_1\left[1 - \left(\frac{eT}{dT_s}\right)\right] + \beta_1\left[1 - \left(\frac{eT}{dI_s}\right)\right] + \gamma_1\left[1 - \left(\frac{eT}{dA_s}\right)\right] \tag{19}$$

Without optimization, the overall comfort index had numerous fluctuations, however after performing the optimization, it has smoothed down and persisted closer to 1 as shown in figure 5. It is concluded that the comfort index for smart homes has been closer to 1 or less than 1 but not more than 1. Initially, it is 1 later it got decreased and finally from 240s it is gradually increased to 1.

4.6. Energy consumption using FF and without using FF

In figure 6, the total energy utilized by "Ambient air quality, infrared temperature and Luminosity" optimization and without optimization is depicted. Here, without optimization, the total power consumption is more, and it is denoted in pink dotted lines. The aggregate power consumption attributed to the use of optimization techniques is depicted by the dark pink line, which exhibits a lower value in comparison to the scenario without optimization.

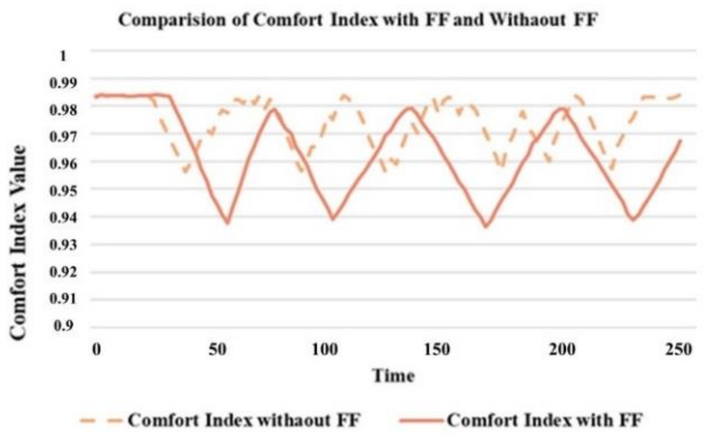

Figure 5. Total comfort index before and after optimization

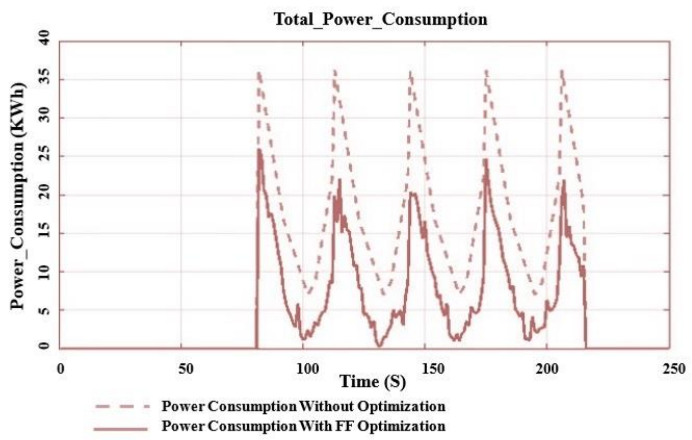

Figure 6. Energy consumption using FF and without using FF

4.7. Comparison of energy consumption using proposed method with traditional approaches

Table 5 compares the energy consumption of the proposed Hybrid DNN algorithm with PSO and genetic algorithms for ambient air quality, infrared temperature, and luminance. According to the table, the proposed algorithms have a greater energy consumption for infrared temperature management than the other two algorithms, while the energy consumption for ambient air quality and luminance from the proposed systems yielded better results than the other two techniques. The proposed system exhibits a lower total energy consumption in comparison to both the PSO and genetic algorithm.

Table 5. Comparison of energy consumption using proposed method with traditional approaches

"Method"	Energy Consumption			
	Infrared Temperature	Luminosity	Ambient Air Quality	Total
Particle Swarm Optimization	836.36	2454.31	1054.17	4344.83
Genetic Algorithm	704.04	2364.78	989.26	4058.08
Hybrid DNN (Proposed)	1641.10	1509.09	831.54	3981.73

5. Conclusion

Smart grid technology developments have made it possible for covering each and every nanosecond of energy use in smart structures. The conspiracy with smart intelligent operations is that they consume a large quantum of energy over conventional models. The demand for effective resource operation is adding day by day, due to the breakneck- fire accumulation of smart burgs and homes. Energy is a cherished finance with a commanding fate cost. As a solution, investigators are attempting to abate firepower consumption, especially in cosmopolitan burgs, while also maintaining a steady terrain. For comfort index management, three parameters such as “temperature, illumination, and CO2” were employed. The main issue in the earlier research with the state-of-the-art models was static user parameters and those parameters were not changed at first. The utilization of Alpha Beta filter was done for forecasting the indoor “Ambient air quality, Infrared temperature and Luminosity” to eradicate the noise from the data. For user parameters prediction, a hybrid rule based DNN was used. FF algorithm was utilized for comfort index management and the optimization of energy consumption. Finally, it was concluded that the energy consumption optimization was successful using the proposed algorithm. The commentary of the carved classic and the ceremonious breathing technologies is shown in Table 3. Then, the advanced form is equated with the ceremonious Multi View, CNN. The activities of the contributed approach are negligibly commanding when contrasted over traditional approaches in expressions of Multi View with 98.23%, CNN with 99.17%, and traffic AV with 98.14%. The proposed system exhibits a lower total energy consumption in comparison to both the PSO and genetic algorithm. Transportation and different means of communication are some of the major contributors to the changes in the current environment we are seeing. Around the world smart cities development strategies are under developing or in planning. So, in future work we can integrate the proposed systems with the machine learning IoT based adaptive traffic management system defined in [32] as well as other applications like wireless or mobile communications [33-35] to find out sustainability of the merged system in the development of smart cities. We will also like to collect huge amounts of data over long-time duration and will like to process proposed system on the huge amount of data.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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