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# AN EFFICIENT HOUSE ENERGY MANAGEMENT SYSTEM FOR ENERGY SCHEDULING BASED ON AN OPTIMIZED ELMAN NETWORK

**ASHOK REDDYBOINA[1], SUBRAMANIAN RAMALINGAM[2],MANISH KUMAR[3]**
[1]Research Scholar, Department of Computer Science, Pondicherry University,Puducherry,India
[2]Professor, Department of Computer Science, Pondicherry University,Puducherry,India
[3]Research Scholar, Department of Computer Science, Pondicherry University,Puducherry,India
E-mail: [1]anshok0@gmail.com, [2]mailtokumarmanish92@gmail.com,[3]rsubramanian630@gmail.com

**ABSTRACT**

The development of new technology has created an energy distribution system with renewable sources and a storage system for energy cost reduction. However, the houses need the Home Energy Management System (HEMS) for controlling and scheduling each device's energy to optimize energy distribution. However, the past studies do not produce satisfying results for energy optimization; therefore presented a novel Aquila-based Elman management system (ABEMS) for the energy distribution scheduling. Initially, the IHEPC dataset was trained and initialized in the system. The dataset's unwanted noise and error values were removed through preprocessing function, and the time series data were analyzed. Subsequently, the energy needed for the home appliances is calculated through the fitness function of the Aquila. Further, the energy distribution is optimized to its desired level based on the calculated value. The proposed system was implemented in Python, and the efficiency metrics were validated. Additionally, a comparative analysis is done to evaluate the improvement score.

**Keywords:** *Energy Resources, Feature Extraction, Aquila Optimization, Household Appliances*

## 1. INTRODUCTION

The modern lifestyle of humans has raised the technologies and changed the world to a digital aspect [1]. The increased usage of electronic appliances in homes and industries increases energy usage and results from the energy in peak demand [2]. The deployment of efficient HEMS controls the resource demand side [3]. The system continuously examines the power utilized by the home appliances such as television, fan, air conditioner, refrigerator, etc., according to the user's desires for the change of the energy cost and energy utilization at the smart homes through the machine-human linkage [4, 5]. Among house appliances, equipment like a heater, ventilators, air conditioning, and refrigerator consumes much power at a non-schedulable rate [6]. In these issues, with the concern of users, the HEMS take a major role in monitoring, scheduling appliances and energy usage optimization to save both power and energy utilization costs [7]. The system saves energy and provides services for the distribution systems [8]. In the growing concern of global energy and environmental emissions, integrating the grid with renewable resources like hydro, wind turbine, solar panels etc., has been increased for better energy management [9].

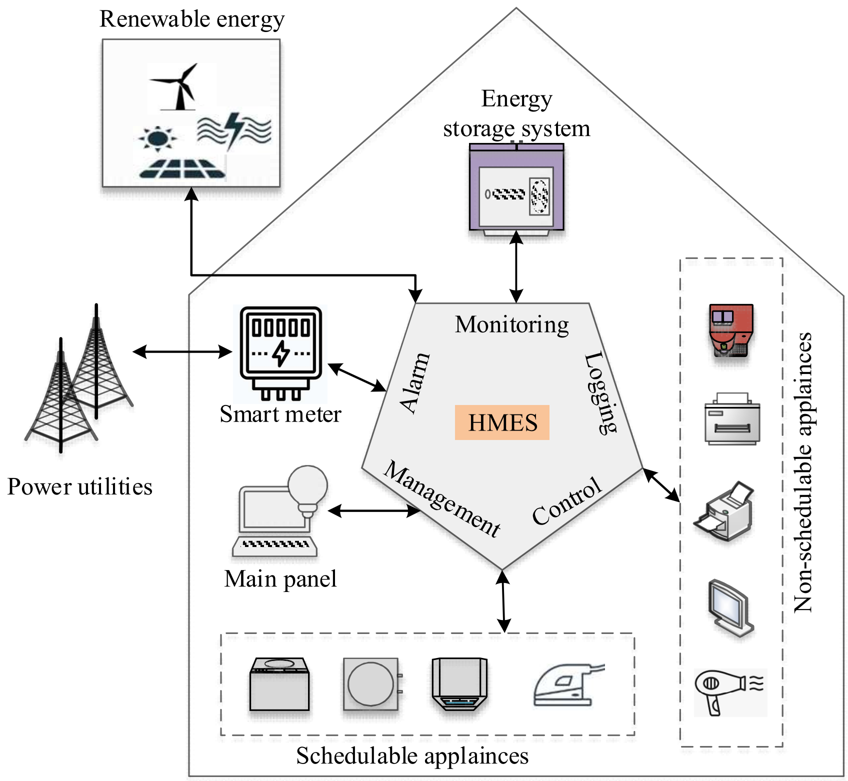


*Fig.1. Overall Structure Of HEMS*

The architecture of the HEMS is illustrated in Fig. 1. Recently, communication and information innovation gained greater attention in the energy sector [10]. More importantly, by wireless communication schemes such as house area networks [11, 12], it is possible to connect different smart appliances and estimate their power-consuming units to manage the operation in the most economical way [13]. At this nature, not only can the grid be managed in a secure, reliable and hazard-free way, but also the renewable sources can be hybrid. It enhanced the method of the management system at the user level [14]. The main expectation at the user level operation is low energy cost. Higher consumption is the main cause of the increased economic cost [15]. Large energy usage is continued as a major problem in a variety of sectors [16].

Therefore, an efficient energy management system is required to control excess energy use from available sources [17]. In the past, several strategies were developed for the HMES with stochastic modeling [18], taxonomy model and deep learning model [19] for energy management by scheduling the home appliances' energy. However, due to a large number of data, it needs more usage predictions and a larger computation time [20]. Hence, the present research designed a novel optimized energy utilization monitoring and management strategy.

The explanations of the presented framework are arranged as follows. Some recent literatures on energy management in house are discussed in section 2. The 3rd section elaborates on the problem statement. The proposed solution is described in section 4. The results of the suggested framework are discussed in section 5, and the sixth section has concluded the research validation.

## 2. RELATED WORKS

***Few recent works related to HMES are explained as follows,***

Huy et al. [21] introduced a unique HEMS architecture with renewable sources and a storage system. The system considered the energy utilization from the main grid and selling energy cost. This architecture builds the mathematical model for the energy cost and the peak ratio in the daytime. Here the energy cost and peak ratio was optimized by the hybrid

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optimizer. This system significantly dropped the house energy cost and achieved a better peak-to-average ratio rate. However, user comfort is not considered.

At a discrete-time, the decision process faces the problem of energy scheduling. To overcome this challenge, the data-informed model comprising the Q-learning and neural network has been developed by Xuxu et al. [22]. This hybrid function gained enhanced energy schedules for cost reduction. The model is implemented at the traditional house level with different appliances, storage systems, and solar panels. It reduced the electricity cost to the user's satisfaction rate. However, the temperature changes in the house environment affect the model's performance.

Masoud et al. [23] designed a novel multiple-objective optimizing model for effective scheduling in energy management for smart homes. The system is processed with kitchen appliances, photovoltaic panels and electric vehicles for scheduling. The system uses the techno-economic function and chooses the optimal schedule for the device's energy usage. The model gained the effective reduction of the energy cost and the peak demand. However, the scheduling is not accepted for residential users.

For the enhancement of energy management to rely on the complexity and difficulties of the end user, Yuankun et al. [24] presented a deep learning model for the energy scheduling of the house energy appliances to minimize the user's electricity bills. The minimization of the HMES cost is greater than the conventional Q-learning algorithm. It takes serious action in response to the dynamic environment. However, the enhanced conditions are not suitable for real-world implementation.

In the home electronic equipment, the resource energy usage must be estimated to control the energy usage. Therefore Zhuang et al. [25] explained a novel taxonomy technique for identifying higher energy-using applications. Additionally, the stochastic method manages the uncertainties at the loaded end users in the dual phase. This method shows efficient monitoring and the reduced energy cost of energy. However, the mapping model is complex to design.

The key contribution of the presented scheme is described as follows,

- Initially, a novel AbEMS is designed with optimizing and forecasting features and trained with the IHEPC dataset.
- Further, the time series data is analyzed through the feature extraction process.
- Next, the energy usage of each house application is calculated by the analyzed time series data.
- Furthermore, the energy distribution is optimized to the desired level and scheduled for each appliance.
- Moreover, the performance parameters were estimated for the proposed system.

## 3. SYSTEM MODEL AND PROBLEM STATEMENT

The HEMS can reduce the peak demand for energy. It also dealt with the problem of energy insufficiency and global warming. The energy control system decreases the emission of greenhouse gas. The applications used for household works need an efficient management system for monitoring, estimating energy usage and controlling the higher energy usage. The system analyzes the entire household applications and energy storage system data to learn the device characteristics and user preferences. The system model with the problem statement is explained in Fig. 2.

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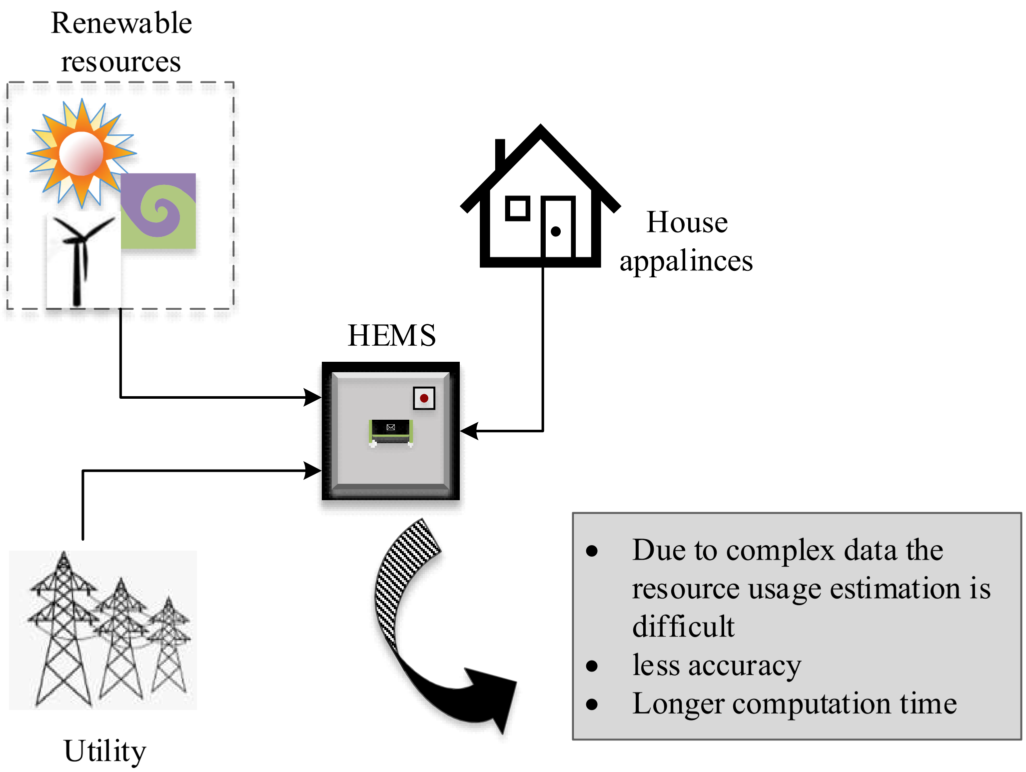


*Fig.2. System Model And Problem Statement*

However, for complex structured data, the data analysis process is difficult. Deep learning models can reduce these complexities. But still, the system shows poor accuracy in the resource usage prediction, less energy efficiency and larger computation time. To overcome these challenges, an optimized intelligent framework has been designed to optimize the house energy management system efficiently.

## 4. PROPOSED METHODOLOGY

A novel Aquila-based Elman Management System (AbEMS) has been designed to optimize excess energy usage in home appliances. Here, the solar panels receive the resource energy supplied to the appliances. Initially, the energy usage of applications deployed in the house has been estimated. The estimation of energy usage optimized the excess energy supply, and the required energy was supplied to the electrical appliances to reduce electricity bills. The process of the proposed management system is described in Fig. 3.

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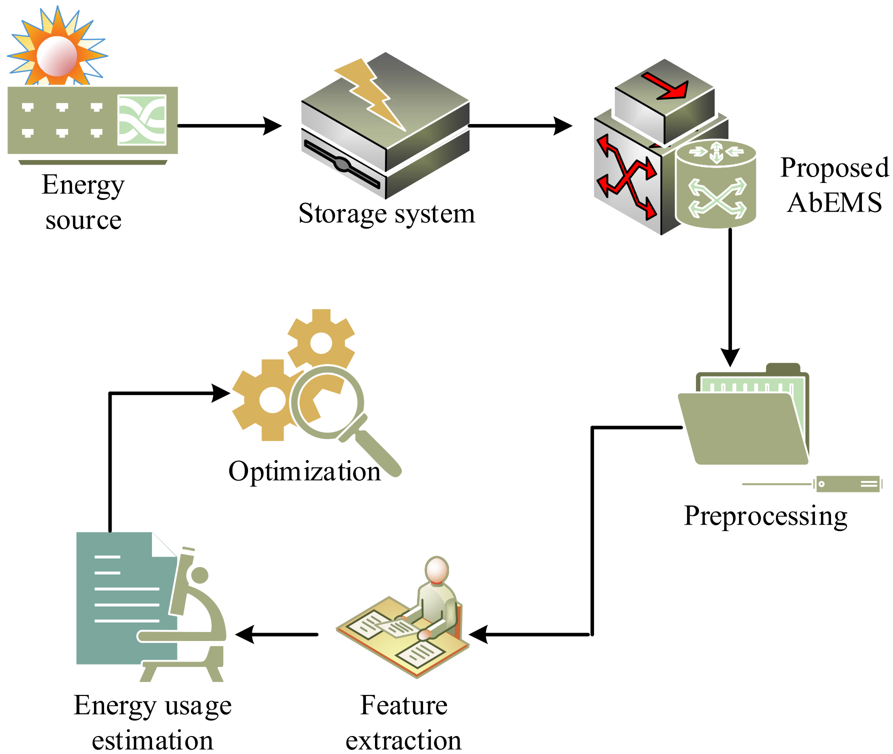


*Fig.3. Proposed Abems*

**a. Preprocessing**

The proposed system is worked on the hybrid function of the Elman neural network and Aquila optimization [36]. Initially, the energy usage data was collected from the Individual Household Electric Power Consumption (IHEPC) Dataset, and the preprocessing function was done to eliminate the unwanted noise features and the missing values present in the dataset. The preprocessing function has been described in the Eqn. (1).

$$P = \lambda(E_n - N^*), n = 1,2,3\ldots k \tag{1}$$

Here the preprocessing function is defined as $P$, $\lambda$ denotes the noise racking variable, $E_n$ represents the number of energy usage data collected from the dataset and the unwanted noise features and missing values are represented as $N^*$. The refined data is then entered into the feature extraction phase.

**b. Feature extraction**

In the feature extraction phase, the time series attributes of the electricity load for the residential house have been extracted. In the proposed AbEMS, the feature extraction was carried out by the expanded exploration function of the Aquila. The feature extraction function was described in Eqn. (2).

$$F = E_n + \sigma(t) \times [E_n - T_n] \tag{2}$$

Here $F$ represents the feature extraction function, $\sigma$ is the feature tracking variable, $t$ represents the number iteration, and $T_n$ indicates the time series data of the collected dataset.

**c. Estimation of energy resource**

The energy estimation was carried out for the eight household applications: dishwasher, microwave oven, washing machine, tumble dryer, lights, refrigerator, electric water heater and air conditioner. The energy consumption rate

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of household appliances can be estimated under three parameters: applications usage time, power rating of every appliance and number of applications. Here, the energy needed for each application was estimated through the fitness function of the Aquila optimizer. The energy estimation function has been expressed in Eqn. (3).

$$E_{ha} = s + \mu(m, p, a) \tag{3}$$

Here $E_{ha}$ denotes the energy estimation function for the entire household appliances, $s$ denotes the constant value fixed to 0.001, $\mu$ denotes the energy estimating variable, $m, p$ and $a$ denotes the energy estimation parameters such as usage time, power rating of every appliance and the number of applications.

**d. Energy optimization**

The extended energy distribution might increase the energy cost. Therefore, the higher energy consumption should be optimized. Using the Aquila's fitness function, each appliance's resource usage has been calculated and scheduled. The power optimization function has been expressed in Eqn. (4)

$$O_E = \min[E_d] * E_{ha} \tag{4}$$

Here $O_E$ represents the energy optimization function and $E_d$ denotes the energy distribution. Thus the proposed method continuously monitors the energy usage of each appliance and helps to minimize the energy cost by optimizing the energy distribution to its desired level for the house appliances deployed in the house based on the user demands.

***Algorithm1. DbENS***

***Start***

*{*

***Data initialization ()***

*{*

$E_n, n = 1,2,3....k$

*// electric power consumption dataset has been initialized*

*}*

***Preprocessing ()***

*{*

$\text{int } P, \lambda, N^*$

*//noise filtering variables are initialized*

$P \to (E_n - N^*)$

*//unwanted noise and missing values are eliminated*

*}*

***Feature Extraction ()***

*{*

$\text{int } F, \sigma, t, T_n$

*// feature analyzing terms are initialized*

$F \to \sigma(t) \times [E_n - T_n]$

*//The required features were extracted using the exploration function of Aquila*

*}*

***Energy usage estimation ()***

*{*

$\text{int } E_{ha}, s, m, p, a, \mu$

*//estimation variables are initialized*

$E_{ha} \to estimate(Energy\ usage)$

*//The energy usage of each appliance is calculated using the Aquila fitness function*

*}*

***Energy Optimization ()***

*{*

$\text{int } O_E$

*//optimizing variables are initialized*

$O_E \to Min(E_{ha})$

*//optimized the energy usage*

*}*

*}*

*End*

Furthermore, the working function of the designed model is structured in the algorithm format, which is described as an algorithm.1 and in Fig. 4. For this novel algorithm, python code was developed and tested with the selected dataset. Finally, the enhanced results have been earned for effective energy scheduling for house management.

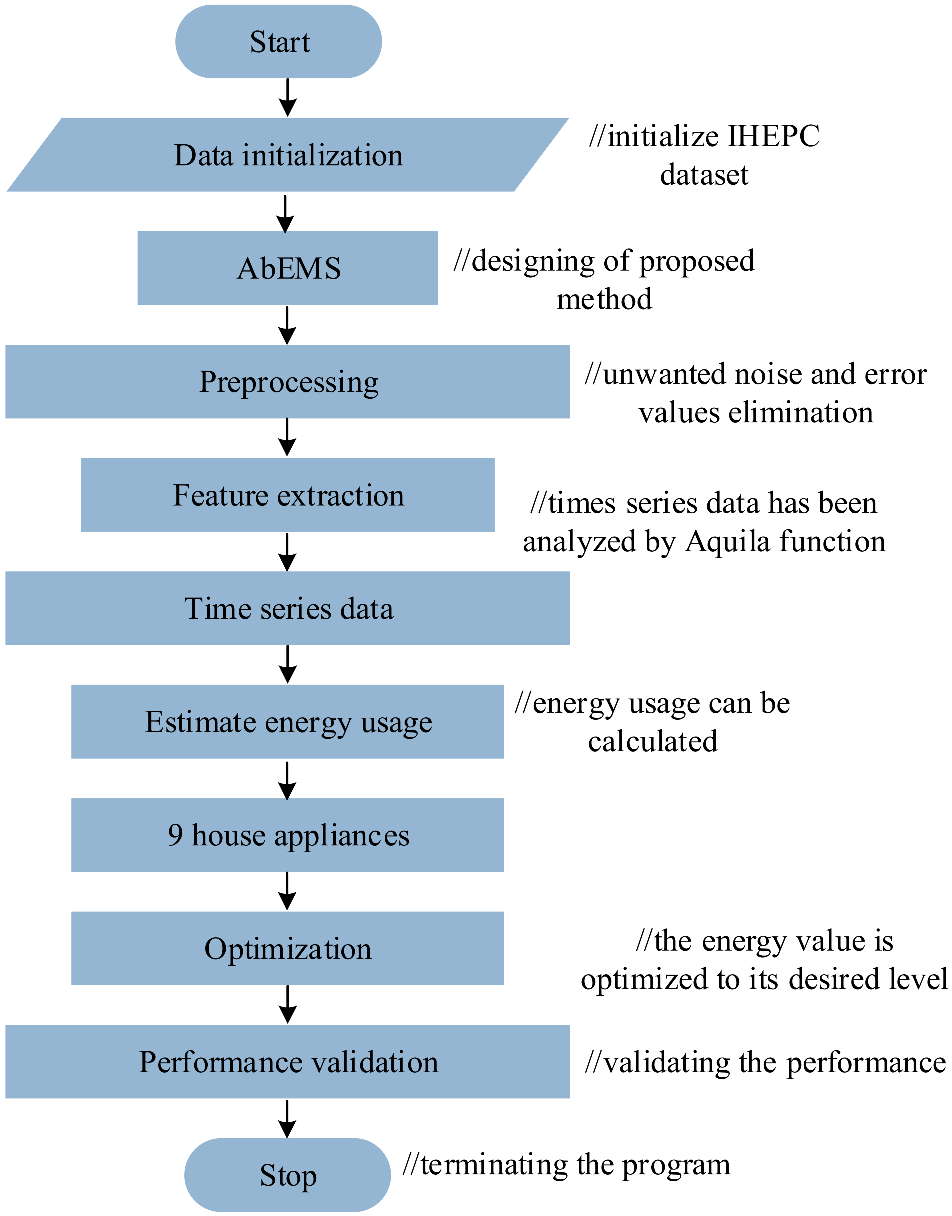


*Fig.4. Abems*

## 5. RESULTS AND DISCUSSIONS

The proposed AbEMS has been designed and executed in the Python environment. The proposed AbEMS continuously monitors the energy utilization of the different appliances in the house to optimize the energy distribution to its desired level to reduce energy costs. The important parameters required for designing and implementing the presented system are saved in table.1.

**Table.1. Execution parameters**

| Parameters | Description |
|---|---|
| OS | Windows 10 |
| Implementation tool | Python |
| Version | 3.7.14 |
| Input data | IHEPC dataset |
| Optimization | Aquila |

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### a. Dataset description

The IHEPC dataset consists of a total of 2,075,259 data values which are recorded from the house in France from December 2006 to November 2010. It includes the dataset for minute, hour, day and month. The applications included in the dataset are dishwashers, microwave ovens, washing machines, tumble dryers, lights, refrigerators, electric water heaters and air conditioners. For the testing of the designed system, it is trained and tested in a ratio of 80:20.

### b. Case study

In the presented research, a novel AbEMS model is created for measuring energy usage and optimizing the energy distribution level for the house energy management system. The system tested with the data collected from the IHEPC dataset. The noise and error values of the collected dataset are removed at the preprocessing stage, and the time series data is analyzed at the feature extraction phase. The extracted time series data calculated the energy usage of the trained appliances, and the optimization reduced the extended energy distribution to its required level. Additionally, the performance of the designed system was calculated through the metrics such as error, accuracy, computation time and power consumption. The number of appliances considered for testing the proposed AbEMS is categorized in table.2.

**Table.2.Schedulable and Non-schedulable appliances**

| S. No. | Schedulable appliances | Non-schedulable appliances |
|---|---|---|
| 1 | Dishwasher | Microwave oven |
| 2 | Washing machine | Refrigerator |
| 3 | Electric water heater | tumble dryer |
| 4 | Air conditioner | |
| 5 | lights | |

### c. Comparative analysis

The presented AbEMS is designed and executed in the Python software running on the Windows 10 OS, and the performance is validated by testing with the data from the IHEPC dataset. To validate the efficiency improvement of the designed AbEMS, it is compared with a few current techniques regarding error, accuracy, computation time and power consumption. The existing techniques considered for the comparison are Logistic Regression Method (LR) [26], Deep learning (DL) [27], Long Short Term Memory (LSTM) [28], Artificial Neural Model (ANM) [29], Event-based Optimization (EBO) [30], Harmony Search- Particle Search Optimization (HS-PSO) [31], Robust Energy forecasting (REF) [35], Q-learning based neural network [32], neural network (NN), random forest (RF), support vector model (SVM), predictive control model (PCM) [33] and reinforcement artificial neural system (RANS) [34].

#### i. Accuracy

The term accuracy is the measure of the ratio of correctly identified values to the defined values. The accuracy was determined in Eqn. (5)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

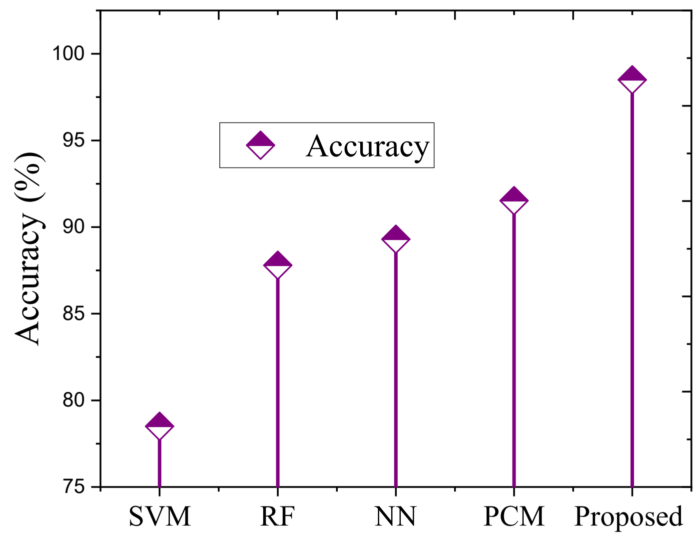


**Fig.5. Accuracy comparison**

The existing energy management framework, such as SVM, scored an accuracy of 78.5%, the RF scored 87.8%, NN gained 89.3% accuracy and the method PCM achieved 91.526% of accuracy. Besides, the presented framework gained an accuracy rate of 99.85%, higher than the other current framework. Thus the efficiency of the proposed system is increased. The comparison of the accuracy measure is given in Fig. 5.

**ii. Error**

The measure of incorrectly identified values is termed as error rate. The error of the proposed system is validated by the Eqn. (6).

$$Error\,rate = \frac{FN + FP}{TP + FP + TN + FN} \tag{6}$$

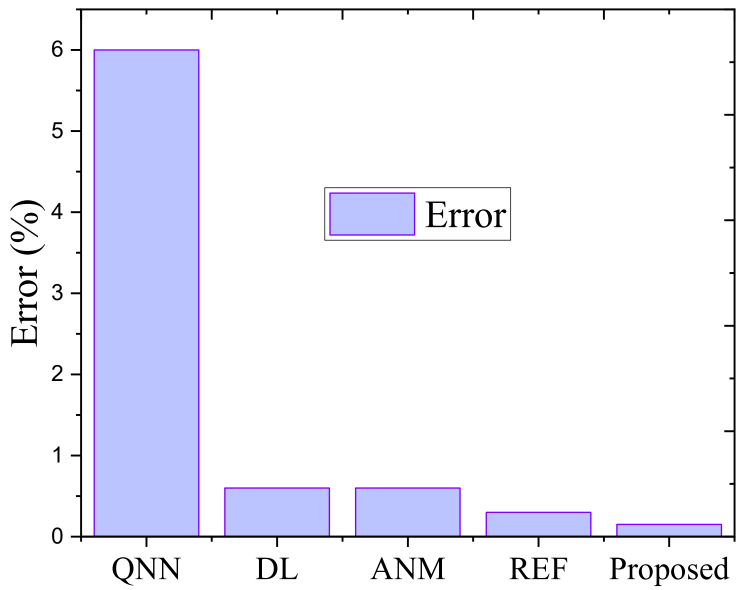


*Fig.6.Error Comparison*

The proposed AbEMS's error rate is compared with existing techniques such as QNN, DL, ANM and REF. The method QNN achieved an error rate of 8.82%, DL and ANN gained an error rate of 0.6%, and the model REF achieved an error rate of 0.3. Compared to this existing system, the proposed framework scored less error rate, which is 0.15%. The error rate comparison is shown in Fig. 6.

**iii. Power consumption**

Power consumption (PC) depends on energy consumption and required energy resources for distribution. The power consumption can be determined using Eqn. (7).

$$PC = \frac{E_{ha}}{t} \tag{7}$$

Here $EC$ represented as the energy consumption for household appliances and $t$ indicated as the running time of the appliances.

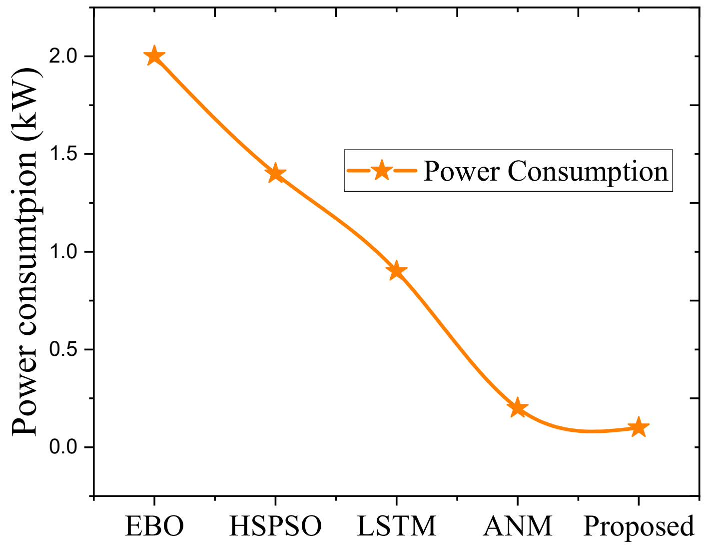


*Fig.7. Comparison Of Power Consumption*

The model EBO showed the power consumption rate as 2 kW, HSPSO scored 1.4 kW, the model LSTM scored the power consumption rate as 0.9 kW and the method ANM gained 0.2 kW. Compared to the existing schemes, the proposed model shows lower power consumption, 0.1 kW, which is lower than the other existing models. This result shows the effective optimization process of the proposed architecture. The comparison of power consumption rate is illustrated in Fig. 7.

**iv. Computation time**

The time the proposed system takes to estimate the energy value and the energy distribution optimization is measured as the computation time.

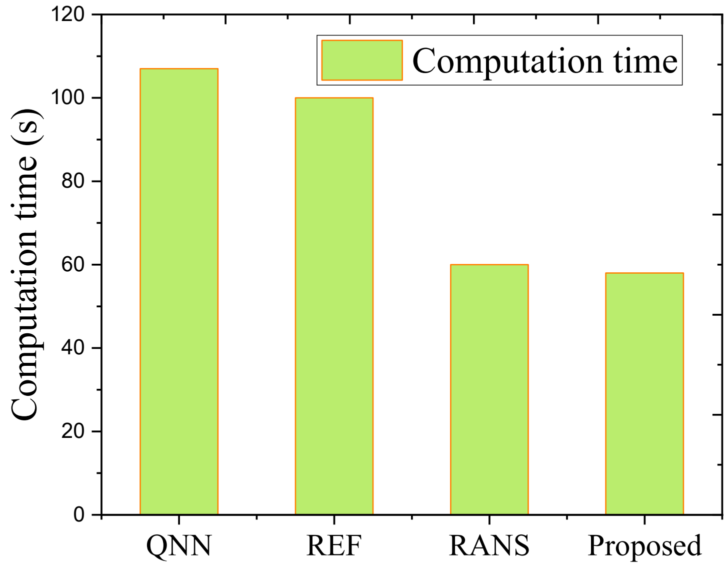


*Fig.8. Comparison Of Computation Time*

The computation time of the existing techniques, such as QNN, REF, and RANS scored the values of 107s, 100s and 60s. At the same time, the proposed architecture achieved a lower computation time of 58s. Adding the Aquila optimization at the Elman neural network increased the energy usage prediction accuracy and decreased the computation time. The computation time comparison is shown in Fig. 8.

**d. Discussion**

The presented AbEMS showed efficient results for all the metrics. The system estimated the energy needed for the nine household appliances used in the residential house with high prediction accuracy. The Aquila function carried out effective feature extraction and increased accuracy. Additionally, using the fitness function of the Aquila, the energy distribution level is optimized to its desired rate to reduce the energy cost. The overall performance results of the proposed system are recorded in table.3.

*Table.3 Performance Of The Proposed DGDBN*

| **Overall Performance statistics** | |
|---|---|
| Accuracy | 99.85% |
| Error rate | 0.15 |
| Power Consumption | 0.1kW |
| Energy demand | 1.0kW |
| Computation time | 58s |

## 6. CONCLUSION

This study deals with energy awareness about the smart, coordinated system for House management system. Initially, the process starts with preprocessing stage. The noise and the missing or error values were removed in this stage. Next, the feature extraction process helps extract the necessary feature for estimating the appliances' energy usage. Finally, optimize the energy, which would reduce the usage of energy distribution. Thus, the proposed AbEMS model reduced the energy usage for household

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appliances. The advantage of this framework is that it helps to improve the energy efficiency of the home management system. The proposed achieved a lower computation time of 58s and a higher accuracy of 99.85%. Thus the proposed system effectively monitors energy usage and optimizes the energy distribution.

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