A SMART ENERGY MANAGEMENT SYSTEM FOR RESIDENTIAL BUILDINGS USING IOT AND MACHINE LEARNING

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Abstract. The Smart Energy Management System (SEMS) for Residential Buildings using IOT-based back propagation with ANN is a novel approach to optimize energy consumption in buildings by leveraging data from internet of things (IOT) devices. This system collects data on energy consumption, weather conditions, occupancy patterns, and sensor data from IOT devices such as motion sensors, temperature sensors, and smart appliances. The collected data is then preprocessed and used to train an artificial neural network (ANN) using back propagation algorithm. The trained model can then predict future energy demands, leading to cost savings and reduced environmental impact by optimizing energy consumption in a residential building. The proposed algorithm can be used as a foundation for building an effective SEMS using IOT-based back propagation with ANN.

Keyword: Energy Management System, IoT, Back propagation, Artificial Neural Network;

1. Introduction

Smart Energy Management System for Residential Buildings using IoT and Machine Learning is an innovative approach to reduce energy consumption and improve energy efficiency in residential buildings[1-3]. This system combines the power of the Internet of Things (IoT) and machine learning to optimize energy usage by monitoring and controlling various electrical devices.

The main objective of this system is to minimize energy wastage by identifying patterns in energy usage, predicting future consumption, and optimizing energy consumption based on user preferences and energy demand[4][11]. This is achieved through the integration of smart sensors and devices that collect real-time data on energy consumption, weather

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conditions, and user behavior. Machine learning algorithms are then used to analyze this data and generate insights that enable the system to make smart energy decisions in real-time[5][18].

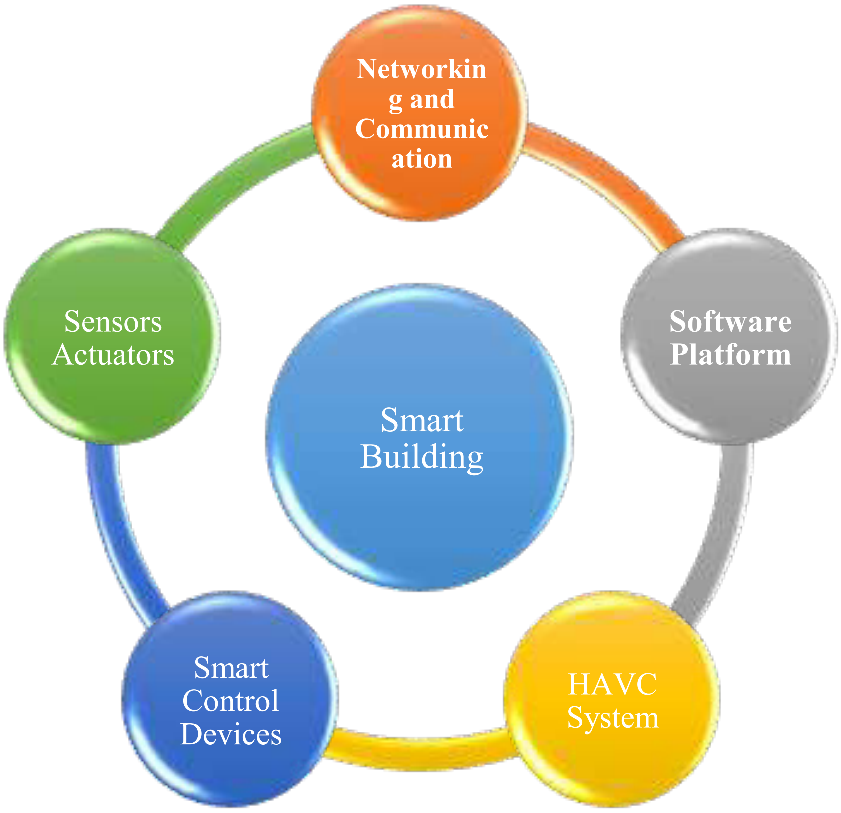


Figure1: Smart building and its Components

The Smart Energy Management System provides several benefits, including reducing energy bills, increasing energy efficiency, and reducing carbon footprint. The system also provides a user-friendly interface that allows users to control their energy consumption and make informed decisions about energy usage based on real-time data[6-8].

There are several reasons why a Smart Energy Management System for Residential Buildings using IoT and Machine Learning is important:

1.Cost savings: A significant amount of energy consumed in residential buildings is wasted due to inefficient energy usage. By optimizing energy consumption and reducing wastage, a smart energy management system can help homeowners save money on their energy bills[9][20].

2.Energy efficiency: Energy efficiency is crucial for reducing carbon emissions and combating climate change. A smart energy management system can help reduce energy consumption and promote sustainable living[10][19].

3.Convenience: A smart energy management system provides homeowners with a user-friendly interface that allows them to control their energy usage in real-time. This means that homeowners can adjust their energy consumption based on their preferences and needs, without compromising on comfort and convenience.

4. Real-time monitoring: A smart energy management system enables real-time monitoring of energy consumption and provides insights into energy usage patterns. This allows homeowners to identify energy-hungry appliances and make informed decisions about energy usage.

5.Smart decision-making: Machine learning algorithms enable the system to learn from historical data and make smart decisions about energy consumption in real-time[11][16]. This means that the system can automatically adjust energy consumption based on energy demand and user preferences.

Overall, Smart Energy Management System for Residential Buildings using IoT and Machine Learning is a promising solution that can help reduce energy consumption and improve energy efficiency in residential buildings. By optimizing energy usage, this system can help reduce energy costs and promote a sustainable future.

2. Related Work

An Artificial Neural Network (ANN) used to maintain for a Home Energy Management (HEM) arrangement base on Bluetooth low energy, called BluHEMS. The objective of infrastructure technology is to realize an extensive energy savings, in order to cut greenhouse gas emissions and to reach effectual ecological[2][17]. A smart grid is conceptualized as a gathering of underlay electrical network and super forces communication system. In this proposed system a profound examination for the pattern of the ANN in arrange to get the one that achieve the best presentation. This system supply widespread simulative assessment, perform all the way through the Network Simulator Version-2 (NS-2), in conditions of energy utilization and jitter for the wireless networks.

The residential representation of energy larger than Ethernet, IoT base solution transform the in-building connectivity of a huge swath of policy. A Building management System (BMS) is a complete platform that is working to observe and organize a building’s automatic and electrical apparatus. The technical junction is as it service of IP-based end tip strategy below the power of IoT[12-13]. The convergence of IoT, PoE, IP (IPv4 as well as IPv6) is unsurprising to work on the usefulness, capacity, power productivity, and value viability of building, influencing them up the computerization reach to a "smart building" position. The development of cloud-based posh examination will work with global streamlining and pertinent information pulling out, moving, and forecasting.

To expand the Neural Network (NN) base tidy demand estimator, practical data from a real power hub managing system is use for supervise preparation. The perception of central energy management system for micro grids, base on Unit Commitment (UC) and Optimal Power Flow (OPF) model, contain been report. The optimization trouble is tackle at independent time steps considering reorganized forecasted input with an advancing time possibility, with get most useful decision being single reasonable for the next moment step[3][15]. A NN based Housing Convenient Demand Profile Estimator (HCDPE) is ANN based Housing Convenient Demand Profile Estimator (HCDPE) is accessible, which is urbanized by purposeful and impersonation information starting around a real Energy Hub Management System (EHMS).

A survey about home energy management systems, where they discussed about the demand-side management, i.e. the collection of techniques applied to reduce energy costs on the consumption-side and improve energy efficiency. Furthermore, they discussed about dominant scheduling methodologies which are grouped into five categories[4][17].

Summarized research opportunities created by open issues in the field such as, block chain-enabled IoT platforms for distributed energy management, deep learning models to handle, use and evaluate big energy data, peer-to-peer energy trading and demand-side energy management, context-aware pervasive future computing, resilience-oriented energy management, forecasting models, user comfort and real-time feedback systems as well as, Internet of Energy (IoE)-based energy management[7][18].

3. Research Methodology

A Smart Energy Management System (SEMS) for Residential Buildings using IOT-based back propagation with ANN can be an effective way to optimize energy consumption in a building by utilizing data from sensors and devices connected to the internet of things (IOT). A Smart Energy Management System (SEMS) is a system that can optimize energy consumption in a building by utilizing data analytics and machine learning algorithms. One of the machine learning algorithms that can be used for this purpose is backpropagation with an Artificial Neural Network (ANN).

Backpropagation is a supervised learning algorithm that can be used to train ANNs. The algorithm works by iteratively adjusting the weights of the connections between the neurons in the network until the error between the predicted output and the actual output is minimized.

The SEMS using backpropagation with an ANN can be designed to control various energy-consuming devices in a residential building such as lighting, HVAC systems, and appliances. The system can analyze historical energy consumption data to learn the energy usage patterns of the building and predict future energy demands.

The system can also take into account external factors such as weather conditions and time of day to optimize energy usage. For example, the system can turn off unnecessary lights or adjust the temperature of the HVAC system based on the occupancy of the building and the weather conditions.

The backpropagation algorithm can be used to train the ANN to predict energy consumption based on various input parameters such as weather data, occupancy, and energy usage patterns. The system can then use this information to make intelligent decisions to optimize energy consumption.

The Backpropagation algorithm is a supervised learning method for multilayer feed-forward networks from the field of Artificial Neural Networks. The backpropagation learning algorithm can be isolated into two stages: Propagation and Weight update.

Algorithm 1Backpropagation Algorithm

```
1:  procedure BACKPROPAGATION
2:     initialization: initialize network weights(often small random values)
3:         whileany examples classified correctly or another stopping criterion not satisfied do
4:           for each training example named ex.
5:           prediction = neural-net-output(network, ex)
6:           actual =teacher - output(ex)
7:           compute error (prediction - actual) at the output units
8:           compute for all weights from hidden layer to output layer
9:           compute for all weights from input layer to hidden layer
10:          update network weights
11:     end while
12: end procedure
```

We proposed a modified ANN based algorithm to train the model where only the changed parameters get the right to be updated.

Algorithm 2 Artificial Neural Network Based Training Algorithm

```
procedure GET ACCURATE PARAMETERS
    Initialization: get a set of initial values of weight W.
    Get the predicted temperature T and collected real temperature R
    while the absolute error between T and R is bigger than the pre-set threshold, do
        for i from 1 to 5, do
            if The parameters changes from the last time slot then
                update the weight of this parameter using standard error correction method
            end if
            Calculate the uploaded prediction value
            Compare with the real value , update error value
    end for
end while
```

Here is an algorithm for building an IOT-based SEMS using back propagation with ANN:

Input: Energy consumption data, weather data, occupancy patterns, and sensor data from IOT devices Output: Predicted energy consumption

1. Collect data on energy consumption, weather conditions, occupancy patterns, and other relevant variables, as well as sensor data from IOT devices such as motion sensors, temperature sensors, and smart appliances.
2. Pre-process the data by cleaning, removing missing values, and normalizing the data.
3. Select the most relevant features that will be used to predict energy consumption.
4. Split the data into training and testing datasets.
5. Initialize the weights and biases of the ANN.
6. Train the ANN using backpropagation algorithm:

a. Forward propagation: Compute the output of the ANN given the input features and current weights and biases.

b. Compute the error between the predicted output and the actual output.

c. Backward propagation: Update the weights and biases of the ANN using the backpropagation formula:

$$\Delta w = -\eta * \partial E / \partial w$$

Where:

- Δw is the change in weight,
- η is the learning rate,
- E is the error function, and w is the weight.

d. Repeat steps a-c for a specified number of epochs or until convergence.

7. Test the trained model on the testing dataset by calculating the predicted energy consumption based on the input features and sensor data from IOT devices.
8. Evaluate the performance the model utilizing measurements like Mean Absolute Error (Mean Absolute Error), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).
9. Optimize the system by adjusting the parameters and repeating the training and testing process.
10. Use the trained model to make predictions on new data, incorporating real-time data from IOT devices.

Overall, this algorithm can be used to build an IOT-based SEMS using back propagation with ANN. The system can analyze sensor data from IOT devices to learn the energy usage patterns of the building and predict future energy demands. This can lead to cost savings and reduced environmental impact by optimizing energy consumption in a residential building.

4. Evaluation criteria

1. Mean Absolute Error

No of Datasets	ANN	Neural Networks (NN)	Proposed IoT based ANNBP
100	65	67	89
200	69	71	92
300	73	75	95
400	76	79	97
500	79	82	99

Table 1.Comparison table for Mean Absolute Error

The Comparison table 1 of Mean Square Error demonstrates the different values of existing ANN, Neural Networks (NN) and proposed IOT BASED ANNBP. While comparing the Existing algorithm and proposed IOT BASED ANNBP, provides the better results. The existing algorithm values start from 65 to 79, 67 to 82 and proposed IOT BASED ANNBP values starts from 89 to 99. The proposed method provides the great results.

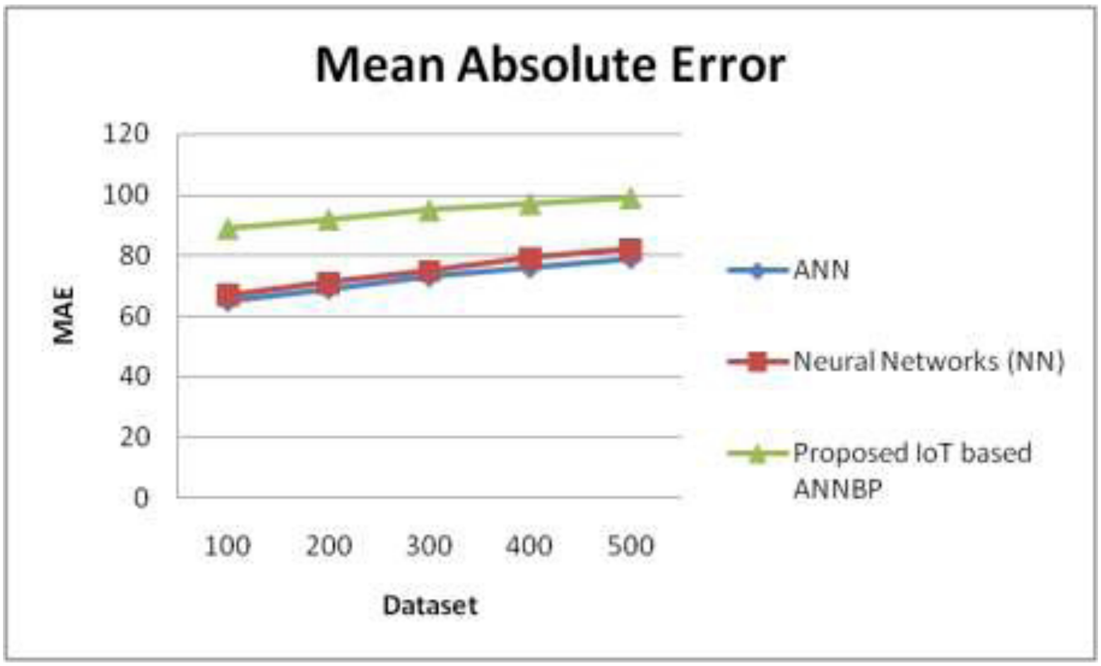


Figure 2.Comparison chart of Mean Square Error

The Figure 2 shows the comparison chart of Mean Square Error demonstrates the different values of existing ANN Neural Networks (NN) and proposed IOT based ANNBP. X axis denote the Dataset and y axis denotes the MAE. The existing algorithm values start from 65 to 79, 67 to 82 and proposed IOT BASED ANNBP values starts from 89 to 99. The proposed method provides the great results.

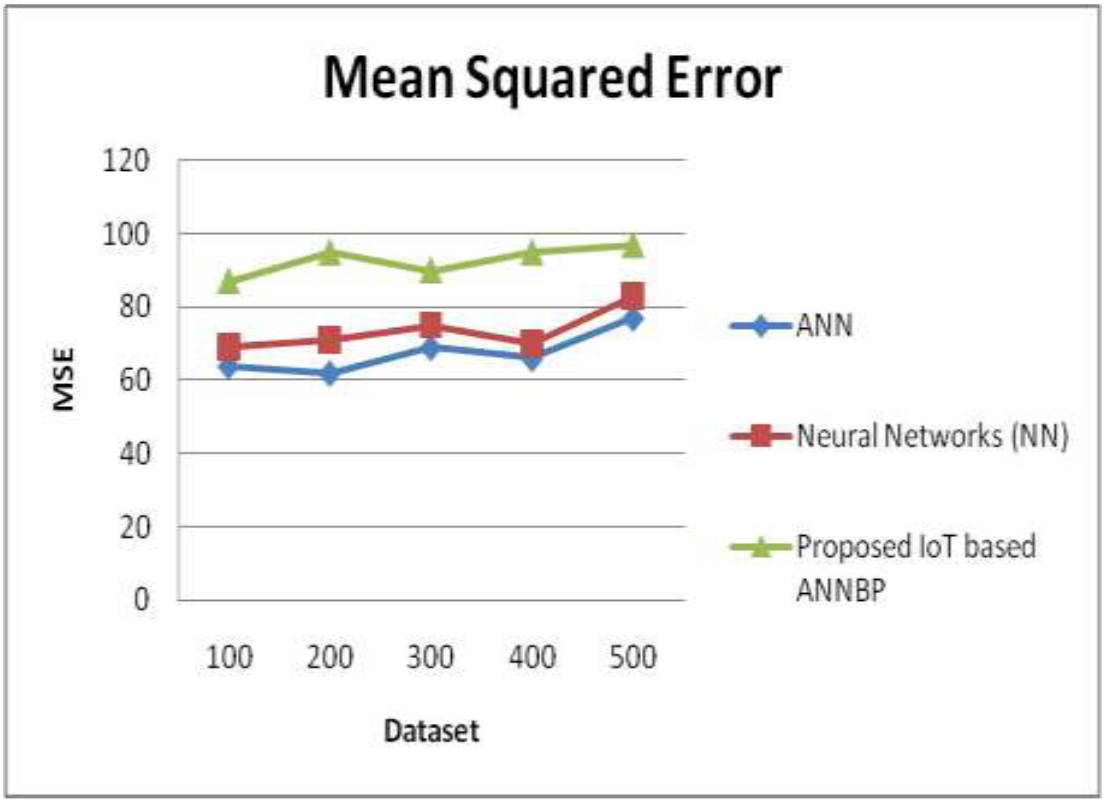
2. Mean Squared Error

No of Datasets	ANN	Neural Networks (NN)	Proposed IoT based ANNBP

100	64	69	87
200	62	71	95
300	69	75	90
400	66	70	95
500	77	83	97

Table 2.Comparison table for Mean Squared Error

The Comparison table 2 of Mean Squared Error demonstrates the different values of existing ANN, Neural Networks (NN) and proposed IOT BASED ANNBP. While comparing the Existing algorithm and proposed IOT BASED ANNBP, provides the better results. The existing algorithm values start from 64 to 77, 69 to 83 and proposed IOT BASED ANNBP values starts from 87 to 97. The proposed method provides the great results.



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3. Root Mean Squared Error

No of Datasets	ANN	Neural Networks (NN)	Proposed IoT based ANNBP
100	60	69	97
200	65	62	89
300	71	74	96

400	63	81	90
500	79	68	95

Table 3.Comparison table for Root Mean Squared Error

The Comparison table 3 of Root Mean Square Error demonstrates the different values of existing ANN, Neural Networks (NN) and proposed IOT BASED ANNBP. While comparing the Existing algorithm and proposed IOT BASED ANNBP, provides the better results. The existing algorithm values start from 60 to 79, 68 to 81 and proposed IOT BASED ANNBP values starts from 89 to 97. The proposed method provides the great results.

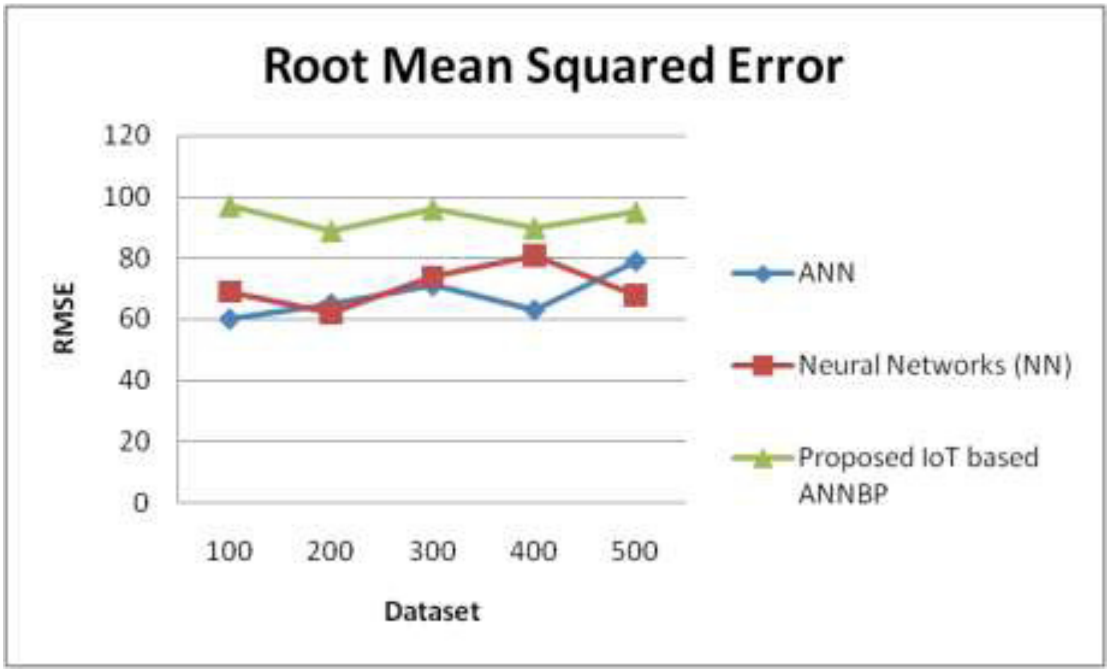

Figure 4.Comparison chart for Root Mean Squared Error

The Figure 4 shows the comparison chart of Root Mean Square Error demonstrates the different values of existing ANN, Neural Networks (NN) and proposed IOT BASED ANNBP. X axis denote the Dataset and y axis denotes the RMSE. The existing algorithm values start from 60 to 79, 68 to 81 and proposed IOT BASED ANNBP values starts from 89 to 97. The proposed method provides the great results.

5. Conclusion

Smart Energy Management System (SEMS) for Residential Buildings using IOT-based back propagation with ANN is an innovative solution for optimizing energy consumption in buildings. By leveraging data from internet of things (IOT) devices such as motion sensors, temperature sensors, and smart appliances, this system can collect and analyze data on energy consumption, weather conditions, and occupancy patterns to predict future energy demands. The collected data is then preprocessed and used to train an artificial neural network (ANN) using backpropagation algorithm. The trained model can then optimize energy consumption in a residential building, leading to cost savings and reduced environmental impact. The proposed algorithm provides a framework for building an effective SEMS using IOT-based back propagation with ANN, which has the potential to revolutionize the way we manage energy consumption in buildings. Overall, this system is an important step towards achieving sustainable and efficient energy management in residential buildings.

References

1. Ahmad, I., Ali, S., & Iqbal, S. (2020). J of Building Eng, 29, 101119.
2. Bhattacharya, T., Mukherjee, A., & Mishra, S. (2021). IOP Con Series: Materials Science and Eng, 1064(1), 012111.
3. Chen, Q., & Chen, X. (2019). Energy Procedia, 158, 1592-1597.
4. Ghatikar, G., & Ghatikar, S. (2020). Energy Reviews, 124, 109787.
5. Jia, H., Huang, B., Ma, C., Cao, Y., & Zhang, W. (2020). IEEE Tr on Industrial Informatics, 16(3), 1743-1752.
6. Khetan, A., & Kodali, R. K. (2020). 2020 IEEE 10th Annual Computing and Communication Workshop and Con (CCWC), 118-123.
7. Kothari, K., & Singh, P. (2019). 2019 IEEE 11th International Conon Advanced Computing (ICoAC), 1-5.
8. Liu, X., & Li, Y. (2019). 2019 IEEE International Con on Mechatronics and Automation (ICMA), 1976-1980.
9. Mishra, A., Gupta, N., & Singh, R. (2020). International J of Emerging Trends in Eng Research, 8(6), 4919-4924.
10. Kavitha, R.J., Thiagarajan, C., Priya, P.I., Anand, A.V., Al-Ammar, E.A., Santhamoorthy, M., Chandramohan, P.,(2022),Chemosphere,Vol.**309,**pp.-.doi:10.1016/j.chemosphere.2022.136525
11. Muñoz, E. L., & Ortiz, J. A. (2019). Procedia Computer Science, 162, 732-738.
12. Nair, S., & Nayak, S. K. (2019). 2019 3rd International Conon Inventive Systems and Control (ICISC), 1202-1205.
13. Thamba Meshach, W., Hemajothi, S., E A, M.A.,(2022),Computer Journal,Vol.**65**,no.4,pp.897-917.doi:10.1093/comjnl/bxaa125
14. Vijayan, D.S., Rose, A.L., Arvindan, S., Revathy, J., Amuthadevi, C.,(2020),Jof Ambient Intelligence and Humanized Computing,doi:10.1007/s12652-020-02666-9
15. Palacios-García, E. J., Aguilar-Lasserre, A. A., Rodríguez-Pérez, J. A., & Hernández-Luna, A. (2019).. Sustainability, 11(19), 5347.
16. Ashok, V., Geetha, N.B., Rajkumar, S., Pauline, T.,(2022),Energy Sources, Part A: Recovery, Utilization and Environmental Effects,Vol.**44**,no.2,pp.4165-4183.doi:10.1080/15567036.2021.1967517
17. Raza, S. M., & Ahmad, S. (2021).. In Artificial Intelligence for Smart Systems (pp. 177-193). Springer.
18. Packiaslacer, P., Rajam, P.P., Theresa, M., Jacob, J.J., Benila, A.,(2022),",AIP Conference Proceedings,Vol.**2393**,pp.-.doi:10.1063/5.0074220
19. Shah, S. A., Ali, M. A., & Ahmad, T. (2020). 2020 6th International Con on Advanced Computing (ADCO 2020), 15-19.
20. Yao, L., Cheng, X., & Xiao, J. (2020).