BioGecko

Vol 12 Issue 03 2023
ISSN NO: 2230-5807

A School Based Optimization Real Time Data driven Approach For Minimizing Energy Consumption

Kalpana[1*] Dr. Pragya Nema[2]

[1*]Kalpana D. Vidhate Research Scholar, Oriental University, Indore
[2]Professor, Oriental University, Indore Department of Electrical engineering

Abstract.
Saving energy via changing people's habits may have a major impact. Yet, in order to minimise discomfort, careful evaluation based on actual facts is required when adopting energy-saving behavioural modifications. To fill this gap, this article suggests a data-driven approach to gauging the comfort and energy savings potential of occupant behaviour changes. Using residential data for model training and a School-Based Optimization approach for optimising the process and computing energy consumption and occupant comfort, the proposed approach has 3 components: (1) machine learning model for low energy consumption; (2) occupant behaviour models; and (3) occupant comfort models. The suggested strategy was put to the test using actual data gathered from neighbourhoods. The experimental findings indicated that behavioural energy savings were possible, with occupant comfort significantly
increased.

Keywords. Energy consumption, Rainfall optimization, Real time data, Testing and trainingmodel, Machine learning.

1. Introduction.

The construction industry is responsible for a significant portion of global warming [1, 2], using up 40% of all supplied energy and producing 30% of all CO2 emissions. More energy can be saved in this area than in transportation or manufacturing [3]. People spend the vast majority of their time inside buildings, making it difficult to reduce energy use without sacrificing comfort, health, or productivity [4]. It calls for in-depth knowledge of the relevant parameters and a comparison of various options. One of the most influential variables in a building's energy use is the actions of its occupants. Saving energy via changing people's habits may have a major impact. Parker et al. [5] provided evidence that the energy consumption of otherwisecomparable buildings may vary by as much as a factor of three due to variations in tenant behaviour. Hong and Lin [6] ran a simulation of three similar workplaces with varied occupant behaviours and found that frugality resulted in a 50% decrease in energy consumption compared to the baseline model, while wastefulness resulted in a 90% increase. Bonte et al. [7] used simulations to examine the effect of various occupant actions on building energy consumption and thermal perceptions, comparing the findings of the simulations to the standard French design method. The findings demonstrated that occupant behaviour has a considerable influence. Only residents' fixed schedules are considered. For instance, it presupposes that blinds remain completely open in the winter to maximise solar heat intake. Yet, occupants may use their blinds in a variety of ways, based on their own tastes and needs. So, the true heating energy demand is greater, or the thermal sense of the occupants is lower, in comparison to the French design approach because of the decreased solar heat gain. Yet, ensuring the comfort of the inhabitants is not compromised while implementing energy-saving. The goal of energysaving education is to change the ways in which residents behave by disseminating information about and guidance with implementing energy-saving measures [8]. Ouyang and Hokao [9] found that energy-saving education may reduce residential power usage by almost 10% on average. The goal of eco-feedback is to change people's behaviour for the better by showing them their energy use patterns over time and in real time. The quick effect of eco-feedback systems on energy savings has been shown in a number of studies (e.g., [10,11]). Residents may gauge their own consumption levels in relation to those of their friends and neighbours via these interactions. By sharing their own usage data, Gulbinas and Taylor [12] were able to significantly reduce energy costs for a whole office complex. Gamification is the use of games to motivate and educate people to adopt more energy-efficient lifestyles. Reeves et al. [13], for instance, created a game in which players reduced their energy use by making smarter decisions while renovating a digital house. In conclusion, building automation systems regulate structures in a manner that prioritises the convenience of the building's inhabitants while also reducing the facility's carbon footprint and operating costs [14]. Prediction models for a building's energy usage are a vital component of optimisation algorithms for evaluating alternative methods of reducing energy consumption. Several existing optimisation studies have relied on physical models to mimic alternative methods of conserving energy. Authors in [15]-[16] wanted to know what the optimum setpoint temperature would be in terms of both worker output and HVAC energy consumption. Ascione et al. [17] provided an optimisation technique based on a linkage between EnergyPlus and MATLAB. For a single-family house in a mild environment, [18] optimized thermal comfort and minimise life-cycle expenses. In order to minimise the amount of energy used for heating, cooling, and lighting as well as the number of uncomfortable hours spent inside conventional high-rise office buildings, Zhao and Du [19] suggested a multi-objective optimisation technique in collaboration with DesignBuilder. Nevertheless, getting reliable findings from physical models takes a lot of time [20]. The large number of iterations needed by optimisation algorithms to converge makes their employment impractical in several circumstances. For this reason, optimisation methods were combined [21-23]. Despite the importance of all these ef forts, there is a dearth of practical data-driven strategies to improve occupant behaviour. Data from physical model simulations is the only source for most of the current research on optimising occupant behaviour (e.g., [21,24, 25,26]). A growing number of physical models include occupant behaviour (e.g., [27]), although these models cannot fully capture the complexity and unpredictability of real occupant activities [28]. Using a data-driven strategy has two main advantages. Second, they may be tailored to a specific building and its occupants, providing a more precise depiction of the impact of human behaviour on in-house resources like energy and comfort. Two, the accuracy of these procedures has been shown to be higher than that of physical ones [30]. Thus, several other application domains have effectively leveraged data-driven and machine-learning techniques to encourage behavioural changes like eco-driving [31].

This work presents a genuine data-driven way to evaluate the potential of occupant behaviour in decreasing energy consumption and increasing comfort, filling a gap in the existing literature. The proposed approach is comprised of two main parts: (1) machine learning-based approach for building a training and testing model for residential data; (2) a SBO approach to optimize the entire process.

2. Proposed Algorithm

In the proposed approach we take real time data for energy minimization from Kaggle. The residential data is considered for training the model. We build a model by training it using the data and finally we test the model. The entire process is optimized by School Based Optimization approach.

2.1. School Based Optimization Algorithm.

Metaheuristic optimisation often involves generating a random population of candidate solutions and then systematically increasing the fitness of that population. This strategy is exemplified by algorithms like the eagle strategy and multiclass teaching-learning-based optimisation, which use multiple metaheuristics in order to search the entire search space (in the first stage) and zero in on the sub-region containing the most promising solutions (in the second stage) (MC-TLBO). Selecting and enacting the first stage termination criteria presents a difficulty in the use of two-stage algorithms. The complexity of the method rises because the termination criteria adds new, problem-specific tuning parameters. School-based optimisation (SBO), was presented to address this problem [32]. When applied to a school with many classrooms and more than one instructor, SBO, a multi-population metaheuristic algorithm, expands the pedagogical possibilities of the traditional one-teacher, one-classroom TLBO model. A group of instructors (one from each classroom) are pooled together at the conclusion of each iteration of the SBO algorithm after they have independently explored the search space using TLBO. Before each iteration, classroom instructors are shuffled to promote the sharing of lessons learned in different settings. On the basis of their fitness scores, instructors are randomly placed in classes using a roulette wheel. In addition, every new teacher placed in a classroom should be more physically fit than the incumbent. The best student (as determined by fitness) in each classroom c is chosen as the classroom's teacher, and all instructors are pooled together at the end of each iteration. Before each new iteration, each class uses a roulette wheel segmented by the instructors' fitness values to choose a new teacher from the pool. The SBO algorithm may take use of several teachers to direct the optimisation process thanks to the teacher assignment mechanism. As a consequence, the probability of the algorithm settling on a local optimum is diminished by this process. When one classroom reaches a local optimum, for instance, the teacher's performance will have a lesser chance of being taken into account when choosing a new teacher for other classes. In addition, by choosing a superior educator from among the available options, the local ideal classroom may be rescued from its current condition. As long as the optimal answer has not changed after a certain number of analyses, the parallel classrooms will continue to communicate collaboratively until the condition for termination is reached.

2.2. Training and Testing of data.

The dataset is collected from Kaggle. Eighty percent of each dataset was used for training, ten percent for validation, and ten percent for testing. All datasets were included in the test set in this way. To facilitate the creation of small batches, the data was divided into training samples of the same period. We settled on a runtime of 512 frames, or around 6.6 seconds, which is sufficient for one or two whole phrases. Some training samples, as a consequence of this set time, cover two distinct listening test circumstances. The samples' labels were calculated as an average of the SI measurements made under each of the two circumstances, with the relative importance of each condition being proportional to the number of frames from each condition included in the training set used to create the sample. The optimal batch size, considering GPU memory, training time, and final performance, was determined to be 32. Using the Adam optimizer [38] and the Mean Squared Error (MSE) loss function, we trained the network using chunks of the training dataset. An early stopping technique was implemented, where the training was terminated if the learning rate was not reduced by half after 25 epochs without a new global minimum in validation cost. A maximum of 300 training epochs were permitted.

3. Results and Discussion

The approach is implemented using python and Matlab. The proposed algorithm is compared with the actual value, ACO [32], and GA [33]. Energy-priority, thermal-comfort-priority, visual-comfort-priority, and balanced solutions were all taken into account throughout the optimisation process. Both energy-priority and comfort-priority approaches prioritise reducing energy usage and comfort, respectively. While any of these approaches may show how much money can be saved or how much more comfortable life can be, they do not boost all three goals in the same way. By combining the three goals into a single one using the weighted sum approach, which gives each goal an equal amount of emphasis, a balanced solution is reached. Fig. 1 displays the relationship between observed and predicted values of energy use. It is seen that the proposed approach makes the prediction which is closes to the actual value. ACO prediction diverts from that of the actual value, and GA has the worst performance. The performance gain of the proposed algorithm is due to better parameter optimization and convergence of SBO.

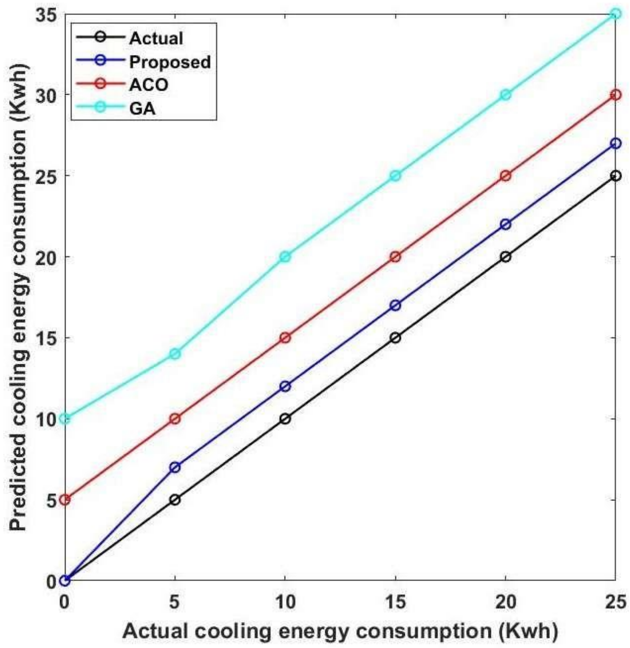

Fig. 1. Regression among predicted and actual cooling.

Fig. 2 shows the regression between the actual and predicted energy consumption values, for the proposed approach, ACO and GA. The predicted energy consumption values show a good agreement with the actual levels. It can be observed that the suggested method provides a forecast that is close to the actual number. The ACO forecast deviates from the actual value, and GA performs the worst. The suggested algorithm's improved performance is due to superior parameter optimisation and SBO convergence.

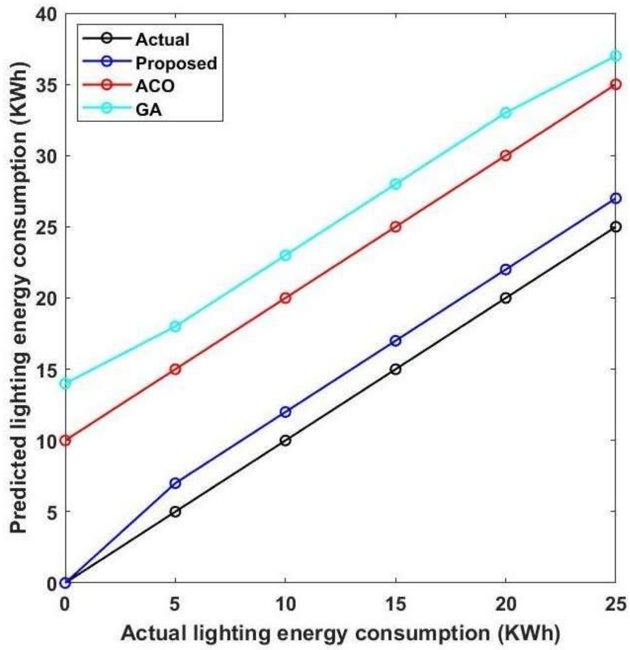

Fig. 2. Proposed approach compared with the existing ones in terms of actual lighting energyconsumption.

Figure 3 shows the total energy used together with the energy used by the three extreme and the moderate solutions. It can be observed that the suggested method predicts a value that is quite near to the actual value. The ACO model's forecast deviates from the true value, while the GA model performs the poorest. Improved parameter optimisation and convergence of SBO are responsible for the suggested algorithm's performance boost.

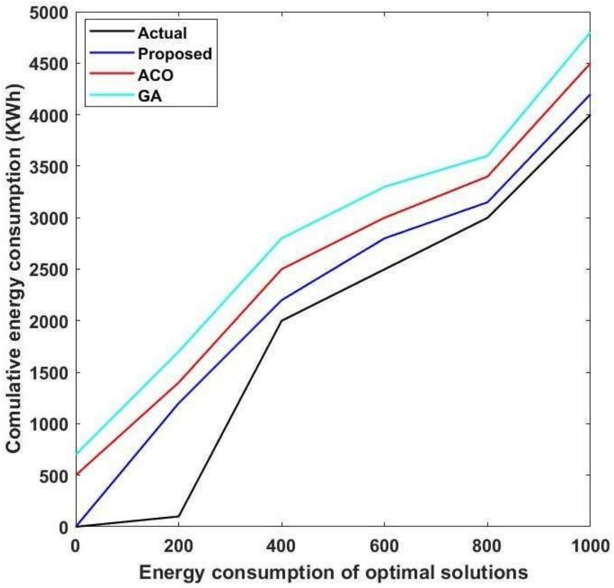

Fig. 3. Energy consumption comparison

The proposed approach is compared with ACO and GA in terms for convergence. It is evident from Fig. 4 that the SBO converges better and faster as compared to ACO and GA. Here the convergence is measured in terms of effectiveness of minimizing energy. Fig. 4 shows that the proposed approach is most effectives in energy minimization.

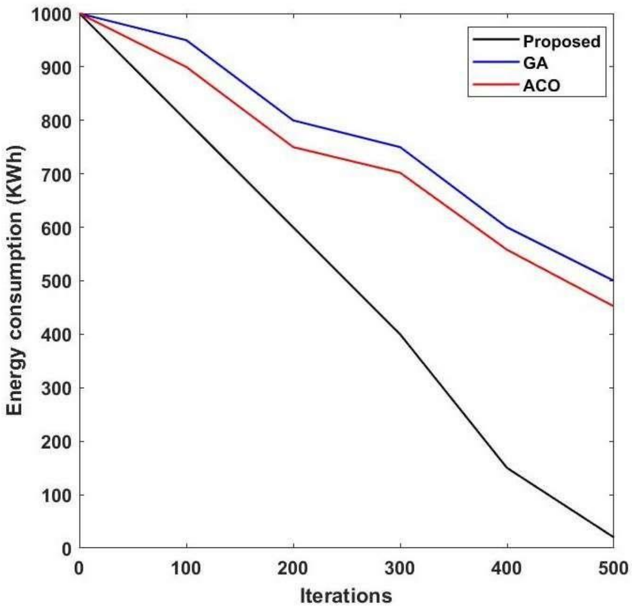

Fig. 4. Convergence performance of SBO

The proposed framework is compared with the existing approaches in terms of thermal comfort in Fig. 5. The suggested method is found to perform best, while GA performs the worst. Better convergence of SBO and parameter optimisation are to credit for the suggested algorithm's performance boost.

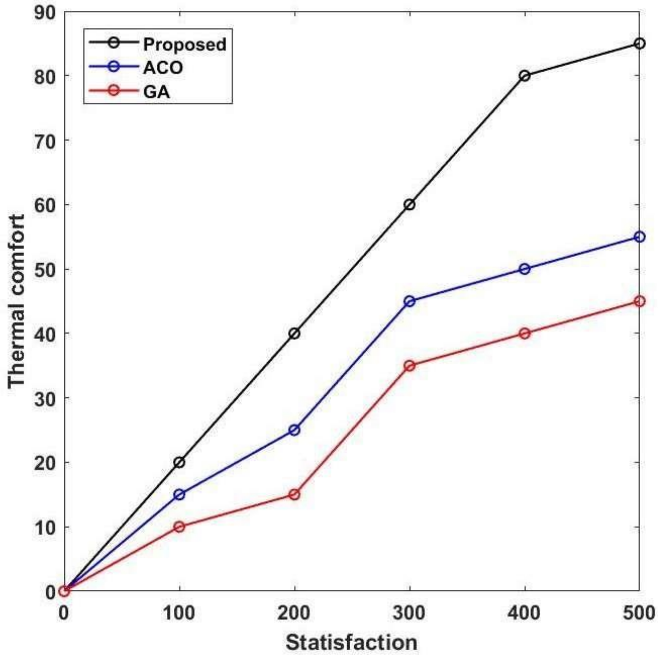

Fig. 5. Thermal comfort comparison

4. Conclusion.

This research offered a genuine data-driven approach to evaluating occupant behaviour's ability to accomplish these two goals (reduce energy consumption and improve comfort) in a single step. The suggested approach has two parts: a genetic algorithm-based optimisation model for optimising occupant behaviour, and a collection of machine learning-based occupant-behaviour-sensitive models for forecasting energy consumption and thermal and visual comfort. The suggested approach was put to the test and evaluated by instrumenting an office building and collecting data for around three months on energy usage, outside weather conditions, occupant behaviour, and occupant comfort. Models for data-driven prediction of cooling and lighting energy usage, thermal and visual occupant comfort, and other metrics were constructed using the gathered data and machine learning. The most reliable prediction models were then used to optimise occupant behaviour in the interest of lowering energy use and raising resident satisfaction. The models' results were compared to those of others that lacked occupant-behaviour variables to ensure that the behaviour features are really discriminatory.

The findings of this study add to existing information in two main ways. First, this study provides a real-data-driven method for hourly energy usage and comfort prediction that takes into account the actions of building occupants. The resultant models are able to better reflect the real-world complexity of occupant behaviour and its effect on occupant comfort and energy use because they have learned from actual building sensor data and genuine occupant input. This technology can more accurately estimate actual energy usage patterns and passenger comfort levels than can current data-driven machine-learning methods. Second, this study provides a quantitative method for incorporating occupant behaviour into the optimisation of a building's energy use. When prediction models are combined with optimisation, a potent tool is created for identifying the optimal adjustments in energy-use behaviour that lead to savings and improved comfort. Property owners, facility managers, tenants, and energy consultants may all benefit from its use in finding the most effective ways to reduce energy use via changes in behaviour. The suggested technique lays the way for behavioural energy efficiency and occupant engagement methods that use machine learning to motivate occupants to conserve energy without sacrificing their comfort or quality of life. Furthermore, we anticipate that such a real-data-driven strategy will become increasingly practical and desired with the rise of enhanced sensing and metering technologies and smart building systems.

References

1. Yang L, Yan H, Lam JC. Thermal comfort and building energy consumption implications – a review. Appl Energy 2014;115:164–73.

2. Ascione F, Bianco N, De Masi RF, Mauro GM, Vanoli GP. Resilience of robust cost optimal energy retrofit of buildings to global warming: A multi-stage, multi objective approach. Energy Build 2017;153:150–67.
3. Fan C, Xiao F, Zhao Y. A short-term building cooling load prediction method using deep learning algorithms. Appl Energy 2017;195:222–33.
4. Shaikh PH, Nor NBM, Nallagownden P, Elamvazuthi I, Ibrahim T. A review on optimized control systems for building energy and comfort management of smart sustainable buildings. Renew Sustain Energy Rev 2014;34:409–29.
5. Parker D, Mills E, Rainer L, Bourassa N, Homan G. Accuracy of the Home Energy Saver Energy Calculation Methodology. In: 2012 ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, California; 2012.
6. Hong T, Lin H-W. Occupant Behavior: Impact on Energy Use of Private Offices. In: ASim 2012 - 1st Asia Conference of International Building Performance Simulation Association, Shanghai, China; 2012.
7. Bonte M, Thellier F, Lartigue B. Impact of occupant's actions on energy building performance and thermal sensation. Energy Build 2014;76:219–27.
8. Yu Z, Haghighat F, Fung BCM, Morofsky E, Yoshino H. A methodology for identifying and improving occupant behavior in residential buildings. Energy 2011;36:6596–608.
9. Ouyang J, Hokao K. Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China. Energy Build 2009;41:711–20.
10. Peschiera G, Taylor JE. The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems. Energy Build 2012;49:584–90.
11. Vassileva I, Odlare M, Wallin F, Dahlquist E. The impact of consumers' feedback preferences on domestic electricity consumption. Appl Energy 2012;93:575–82.
12. Gulbinas R, Taylor JE. Effects of real-time eco-feedback and organizational network dynamics on energy efficient behavior in commercial buildings. Energy Build 2014;84:493–500.
13. Reeves B, Cummings JJ, Scarborough JK, Yeykelis L. Increasing Energy Efficiency With Entertainment Media: An Experimental and Field Test of the Influence of a Social Game on Performance of Energy Behaviors. Environ Behavior 2015;47: 102–15.
14. Paone A, Bacher J-P. The Impact of Building Occupant Behavior on Energy Efficiency and Methods to Influence It: A Review of the State of the Art. Energies 2018;11:953.
15. Papadopoulos S, Kontokosta CE, Vlachokostas A, Azar E. Rethinking HVAC temperature setpoints in commercial buildings: The potential for zero-cost energy savings and comfort improvement in different climates. Build Environ 2019;155: 350–

9.

16. Kim H, Hong T. Determining the optimal set-point temperature considering both labor productivity and energy saving in an office building. Appl Energy 2020;276: 115429.
17. Ascione F, Bianco N, De Masi RF, Mauro GM, Vanoli GP. Design of the Building Envelope: A Novel Multi-Objective Approach for the Optimization of Energy Performance and Thermal Comfort. Sustainability 2015;7:10809–36.
18. Grygierek K, Ferdyn-Grygierek J. Multi-Objective Optimization of the Envelope of Building with Natural Ventilation. Energies 2018;11:1383.
19. Zhao J, Du Y. Multi-objective optimization design for windows and shading configuration considering energy consumption and thermal comfort: A case study for office building in different climatic regions of China. Sol Energy 2020;206: 997–1017.
20. Chari A, Christodoulou S. Building energy performance prediction using neural networks. Energ Effi 2017;10:1315–27.
21. Reynolds J, Rezgui Y, Kwan A, Piriou S. A zone-level, building energy optimisation combining an artificial neural network, a genetic algorithm, and model predictive control. Energy 2018;151:729–39.
22. Yang S, Wan MP, Chen W, Ng BF, Dubey S. Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization. Appl Energy 2020;271:115147.
23. Bünning F, Huber B, Heer P, Aboudonia A, Lygeros J. Experimental demonstration of data predictive control for energy optimization and thermal comfort in buildings. Energy Build 2020;211:109792.

24. Asadi E, Silva MGd, Antunes CH, Dias L, Glicksman L. Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. Energy Build 2014;81:444–56.
25. Magalhaes ˜ SMC, Leal VMS, Horta IM. Modelling the relationship between heating energy use and indoor temperatures in residential buildings through Artificial Neural Networks considering occupant behavior. Energy Build 2017;151:332–43.
26. Ahmad M, Hippolyte J-L, Reynolds J, Mourshed M, Rezgui Y. Optimal scheduling strategy for enhancing IAQ, visual and thermal comfort using a genetic algorithm. In: ASHRAE IAQ 2016 Defining Indoor Air Quality: Policy, Standards and Best Practices, Alexandria, VA, USA; 2016.
27. Gaetani I, Hoes P-J, Hensen JLM. Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy. Energy Build 2016;121:188–204.
28. Amasyali K, El-Gohary N. Predicting Energy Consumption of Office Buildings: A Hybrid Machine Learning-Based Approach. In: Advances in Informatics and Computing in Civil and Construction Engineering. Cham: Springer International Publishing; 2019. p. 695–700.
29. Neto AH, Fiorelli FAS. Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. Energy Build 2008;40:2169–76.
30. Delnevo G, Di Lena P, Mirri S, Prandi C, Salomoni P. On combining Big Data and machine learning to support eco-driving behaviours. J Big Data 2019;6:64.
31. Farshchin, Mohammad, Mohsen Maniat, Charles V. Camp, and Shahram Pezeshk. "School based optimization algorithm for design of steel frames." Engineering Structures 171. 2018: 326-335.
32. Khan, F.A., Ullah, K., ur Rahman, A. and Anwar, S., Energy optimization in smart urban buildings using bio-inspired ant colony optimization. Soft Computing, 27(2), 2023. pp.973-989.
33. Amasyali, K. and El-Gohary, N.M., “Real data-driven occupant-behavior optimization for reduced energy consumption and improved comfort.” Applied Energy, 302, 2021. p.117276.