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Energy cost and consumption reduction of an office building by Chaotic Satin Bowerbird Optimization Algorithm with model predictive control and artificial neural network: A case study

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ABSTRACT

A large amount of energy consumed globally is done by buildings, also, buildings are responsible for a great portion of greenhouse gas emissions. With progress in smart sensors and devices, a new generation of smarter and more context-aware building controllers can be developed. Consequently, zone-level surrogate artificial neural networks are used herein, where indoor temperature, occupancy, and weather data are the inputs. A new metaheuristic optimization algorithm, called Chaotic Satin Bowerbird Optimization Algorithm (CSBOA) is employed for the minimization of energy consumption. 24-hour schedules of the heating setpoint of each zone are created for an office building located in Edinburgh, Scotland. Two modes of optimization including day-ahead and model predictive control are applied for each hour. The consumption of energy decreased by 26% during a test week in Feb in comparison to the base case approach of heating. By definition of a time-of-use tariff, the cost of energy consumption is decreased by around 28%.

1. Introduction

Today, the crises related to economics and energy are increasing, thus, the optimization of energy consumption is needed in constructing and designing buildings [1]. In general, construction engineering causes about 25% of greenhouse gas emissions and 40% of energy consumption globally [2,3]. The challenges concerning the energy sector are becoming more critical day-to-day. Novel techniques and energy efficiency actions are presently widely known and outspread, and the identification of the more reliable and efficient one over time is important [4–6]. Against this background, the "Internet of Things" (IoT), which is the wireless connection of common objects can be an opportunity to decrease energy consumption and enhance environment-related comfort in buildings [7]. Based on the studies, it can be observed that most of the present conventional systems of building automation and control (BAC) or building management systems (BMS) are not as responsive as energy-efficient systems. Moreover, problems such as overheating or overcooling that negatively impact indoor thermal environments have been observed in most buildings because of inappropriately designed BAC systems [8]. BMSs are getting more and more critical for sustainable building performance [9]. In addition, in many of the buildings, the temperature setpoint is controlled by a central thermostat all over the building. This causes great wastage of energy by heating the unoccupied zones even when it is not needed. Furthermore, the infrastructure of energy is experiencing significant changes. Decentralization of energy is widely spreading as the concept of smart grids and microgrids get stronger [10,11]. Since by application of stochastic renewable energy production the share of controllable generation is reduced, the system should regard demand and supply as partly controllable, i.e., through direct demand response (DR) controls or by the dynamic time-of-use tariffs (ToUT). Consequently, not only the features like predicted climatic conditions and occupation should be considered in the later generation of smart building controllers, but also it should be adequately adaptable for maximizing the application of on-site renewable resources, energy storage, and usage schedule in periods with lower energy cost [12]. The building controls' optimization is presently the main issue in the studies [13]. Based on the control strategy found in the literature studies, the best-known control approach is model Predictive Control (MPC) [14]. For thermal regulation of the building, MPC is an effective method, it

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also can be fairly used for the optimum management of local Renewable Energy Systems (RESs) [15]. The main challenges for the common application of model predictive control to buildings include a) an easy-to-use, precise, control-oriented, and computationally effective model of a building; b) a compatible communication interface and proper software and hardware infrastructure accessibility; C) MPC implementation that operates robustly and is plug-and-play; d) an automated system for designing, tuning, and deploying MPCs; e) Maintenance and commissioning of MPCs by trained personnel; f) Concerns about privacy and cybersecurity and the trust of users [16].

In [17], a review of management approaches for building energy management systems to enhance the energy efficiency of different types of buildings has been presented. In Ref. [18], an approach integrating thermal comfort in the design of an energy-effective building was proposed. An optimization technique and a sensitivity analysis have been used in a case study for the identification of the decision variables' value. The results showed 20% of heating energy savings in comparison to the baseline whilst considerably improving the thermal comfort of occupants. A method to resolve a critical problem in applying comprehensive building energy models in model predictive control computation-optimizations time by a studied case is proposed in Ref. [19]. In this work, three new major tasks are done including a reduction in the search space for the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) by application of the free oscillation curve; a reduction in time of convergence by using two associated steps; and a method for measuring, which couples the achieved solution's accuracy and the algorithm's temporal convergence. In Ref. [20], the authors focused on the reduction of electricity consumption using an optimization approach based on a new adaptive MPC algorithm and artificial neural networks (ANN). For reducing the electricity bill and achieving thermal comfort, a dual optimization method has been developed. It was based on mixed integer linear programming and a genetic algorithm (GA) for a two-step optimization. A smart Operation approach by MPC for the optimization of the operation of hydronic radiant floor systems in a real office building is presented in Ref. [21]. For the minimization of energy cost and usage whilst considering constraints of thermal comfort and equipment, dynamic predictions of zone temperatures and loads, models of the HVAC system, and climatic conditions were used. Cost savings of 34% in the cold season and a decrease of 16% in the consumption of energy in the hot season have resulted. In Ref. [22], a simulation-based model predictive control method was suggested, which includes operating cost optimization for thermal comfort and space conditioning through a multi-objective approach. The procedure was a combination of EnergyPlus and a genetic algorithm carried out in MATLAB®, aiming at the optimization of the hourly set point temperatures day-ahead planning. The inputs included the climatic conditions and profiles of occupancy considering a case study of a residential building in Naples, Italy. A typical day of the heating season has been considered. MPC reduced operating costs by up to 56% and improved thermal comfort compared to a standard control strategy. In Ref. [23], for decreasing the costs of computation, a process of optimization by coupling multiple-criteria evolutionary algorithms and surrogate models has been employed for energy consumption optimization and occupants' thermal comfort, concurrently. The results showed a reduction of 21.3% in yearly gas usage and 9.7% in electrical power consumption while maintaining thermal comfort in comparison to the base case building. In Ref. [24], a four-layer large data platform based on the IoT has been proposed for the day-ahead estimation of energy demands of the building using the hybrid predictive model based on machine learning. The results indicated 3% and 8% of Mean Absolute Percentage Error (MAPE) respectively in cases of training and testing, respectively.

According to the literature review, controllers of the building are required to be further context-dependent with the assumption of profiles of occupancy and forecasted climate conditions. In addition, predictive control requires a precise yet fairly simple model of prediction for deploying almost in real-time. Approaches of optimization can lead to considerable savings of energy when aimed at a room or zone level, making sure to use energy only when required. To satisfy these requirements, a zone level and setpoint schedules of heating are presented in this study to minimize the consumption of energy during the later 24 h with the maintenance of thermal comfort in the building. A new metaheuristic, which is the Chaotic Satin Bowerbird Optimization Algorithm (CSBOA) is used for the minimization of energy consumption. The main contributions of this paper are as follows.

- Implementation of a Zone-level artificial neural network for precise prediction of energy consumption and indoor temperature
- Using a new metaheuristic algorithm, called Chaotic Satin Bowerbird Optimization Algorithm
- Optimization of temperature set point for the minimization of energy consumption and cost
- Applying the control model to be adaptable to time-variant energy costs

2. Materials and methods

2.1. Case study description

An office building located in Edinburgh, Scotland is chosen to be studied in this section. The geometry of the building is created in DesignBuilder simulation software as represented in Fig. (1). Equipment details of electronics, lighting, construction, properties of the material, and profiles of occupancy (O), have been considered as the model inputs. The conditioned zones of the building include three office zones, i. e., the Downstairs office (D_{office}), a Ph.D. office ($Ph.D._{office}$), and the Researcher's office (R_{office}), and three more rooms including a meeting room (M), a kitchen (K), and a reception (R). Natural ventilation is assumed for cooling and ventilation. A model of an electrical heating system with heating control through a thermostat is considered. For all working days, a consistent occupancy schedule is taken into consideration in this study. The occupation time for the office spaces is between 08:00 a.m. to 7:00 p.m., for the kitchen between 12:00 a.m. to 2:00 p.m., and for room M between 10:00 a.m. to 11:00 a.m. Nonetheless, in real-world cases, the meeting room's occupation time can be obtained from the booking system.

As mentioned before the building is naturally ventilated and cooled, which can be highly efficient for decreasing the cooling and heating loads by increasing the heat exchange level between the interior and exterior of the building based on the temperature difference, with effective management. Considering a schedule defined by occupancy of the room, the natural ventilation rate is evaluated in steps of 0.1 (ac/h) between 0 and 5 (ac/h). The rate of infiltration is considered as the air leaking into the building from the outer environment by doors, open-

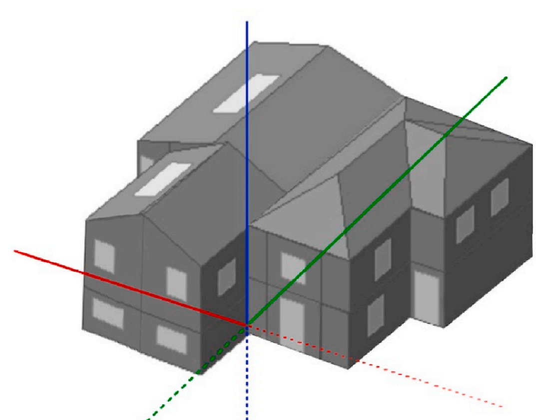


Fig. (1). The geometry of the building.

ings, and cracks. It is calculated in terms of air change per hour (ac/h). In this work, different infiltration rates ranging from 0.25 to 1.5 (ac/h) have been considered. For the lighting, the fluorescent lighting system has been utilized. The glazing system includes single-layer windows with 4 mm flat glass, aluminum frames, and a U-value of 3.1(W/m^2 K). We have assumed that the 3 office zones and the reception are occupied from 08:00 until 19:00. The kitchen is occupied from 12:00 until 14:00 and the meeting room from 10:00 to 11:00 although, in real-world applications, meeting room occupancy patterns will be available from electronic booking system used for this zone. In this paper, we have not considered day-by-day occupancy prediction and simply assume the same occupancy schedule for each working day as office building occupancy patterns are fairly consistent throughout the working week. The internal gains per space floor area, for the electric equipment, occupancy, and lighting are 7.32 W/ m^2, 0.05 people/ m^2, and 10.66 W/m^2, respectively.

The solar irradiance distribution and the outdoor temperature distribution for the investigated area are depicted in Fig. (2) [25,26]. Moreover, the hourly heating load distribution for one year is shown in Fig.(3). A schematic of the heating system is represented in Fig. (4).

2.2. Modeling using the artificial neural network (ANN)

In this study, the prediction of the hourly indoor temperature and the heating energy usage for all zones during the day is needed for the employed optimization. This calculation is required to be completed rapidly so that it can be integrated with the CSBOA approach, therefore, the complete simulation of energy cannot be applied as an assessment engine. Therefore, an artificial neural network surrogate model has been trained for each zone by simulation data generated using the energy model, thus it will precisely repeat it when optimizing the system in real time. For generating the dataset of training, 30 independent simulations have been performed for each day between Jan 1st to Mar 31st, with different setpoint schedules of heating in all zones in each simulation, some were typical, while some others changed randomly from 12 °C to 24 °C. For the prediction of the whole 24-h time period, it is required to define the inputs of an artificial neural network beforehand. In this paper, the inputted variables were related to the weather data including solar irradiance (SI), outdoor temperature (OT), and relative humidity (RH). The other variables are a binary occupation profile, the temperature setpoint (TS) (the design parameters), and the hours of the day. Moreover, since thermal inertia is an important factor in a building, the indoor temperature (IT) from the former three-time steps has been also assumed as inputs. Nevertheless, considering that the prediction of the later 24 h is needed, the indoor temperature prediction at time t has been applied to be inputted for the prediction at time $t+1$. The MATLAB artificial neural network toolbox has been used for training the artificial neural network and after being accomplished has been tested against a four-week duration simulation of DesignBuilder with inconstant TSs and different weather data. The achieved prediction model can be affected by several tunable variables when an artificial neural network has been configured, which include the function of training, the chosen inputs, the functions of transfer among layers, the hidden layers' number, and the hidden neurons' number of the hidden layers. No leading approach exists in the studied papers where these variables are optimized, thus, a method based on trial and error is used herein. The coefficient of variation of the root mean squared (CVRMSE) is used to measure the accuracy of the artificial neural network during the architecture trials of the artificial neural network based on the aforementioned four-week testing data. The chosen input is the factor with the highest effect on

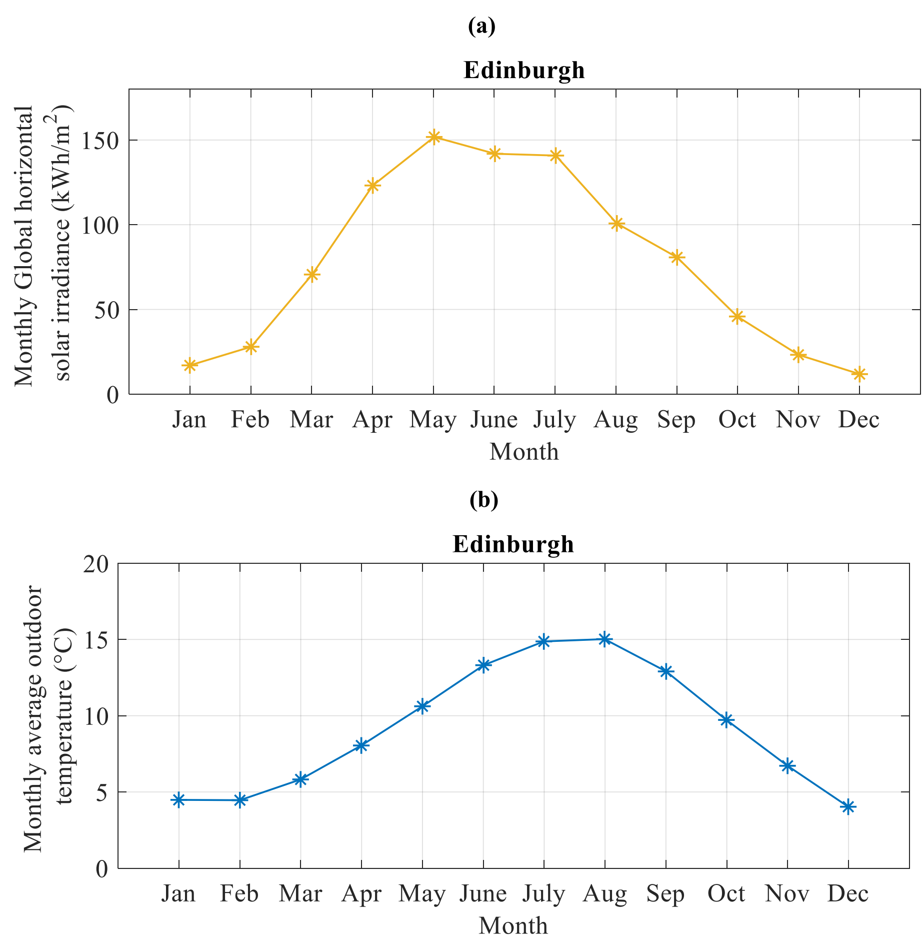


Fig. (2). The solar irradiance distribution (a) and the outdoor temperature distribution (b) for the investigated area.

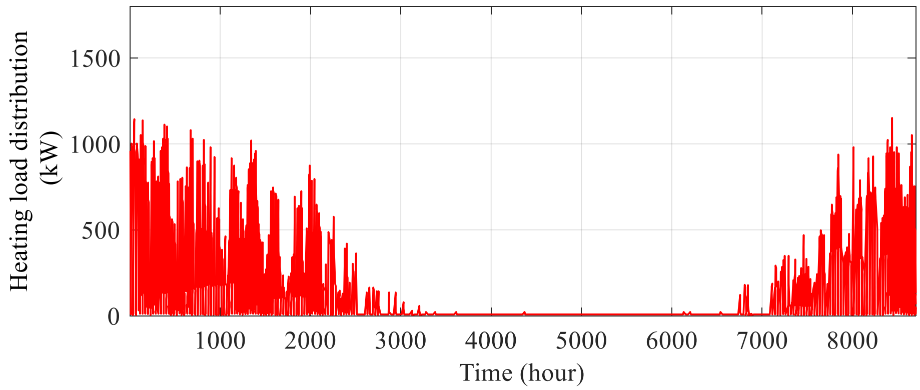


Fig. (3). The hourly heating load distribution for one year.

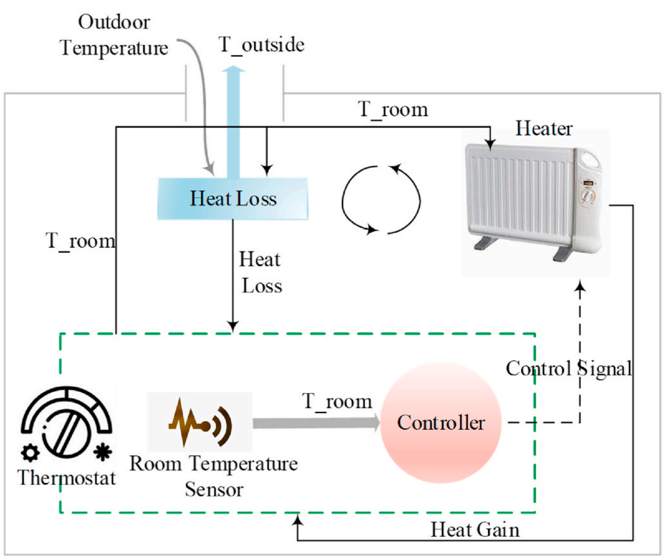


Fig. (4). The schematic of the heating system.

the accuracy of prediction. It appeared that the indoor temperature between hours *t-2* and *t-3* along with the relative humidity has caused poorer predicting accuracy of the artificial neural network, thus, they have been eliminated as potential inputs. These findings propose that the building zones' thermal lag is short and only the indoor temperature value of former hours is needed. Moreover, it is found that the accuracy is reduced by solar irradiance if inputted for zone one and zone six, thus, this has been eliminated from the artificial neural network of these zones. Changing other parameters of the artificial neural network leads to a significantly more limited impact given that 2 hidden layers have been applied and an acceptable neurons' number is kept by each layer. As depicted in Fig. (5), the final configuration of the artificial neural network for all zones (a-f) is 5–20-20-2 and for zones, b, c, d, and e are 6–20-20-2. The "Levenberg Marquardt (LM) based back propagation (BP)" is the chosen training algorithm, and "tansig" is the function of transfer between each layer. Pearson's correlation of input and output of the artificial neural network for all zones at the training and testing phases is reported in Table 1.

Based on the results of this table, a desirable prediction from the artificial neural network is achieved. The reliability of the results of prediction at the training and testing stages indicates no confirmation of overfitting, i.e., the general trends in the data were learned by the artificial neural network instead of only achieving the optimum fit to the dataset of training. Nevertheless, it should be noticed that at the testing stage, the previous indoor temperature is considered precisely predicted. In the optimization, it is reasonable that the accuracy of prediction can decline moderately during the 24-h time horizon because of errors of prediction in IT_{t-1}. The mean bias error (MBE) and CVRMSE for energy consumption and indoor temperature are reported in Table 2.

As observed in Table 2, for each zone, the MBE for the testing data is between +10% and −10% while CVRMSE is about 30%. In comparison to the prediction of indoor temperature (2%), the value CVRMSE is higher. Nevertheless, the worse statistical operation of energy consumption (EC) prediction is partly because of the data type. The energy consumption for heating has naturally considerably larger variations with rare high peaks but a totally low mean, which is substantially difficult to predict compared to the indoor temperature which has gradual change.

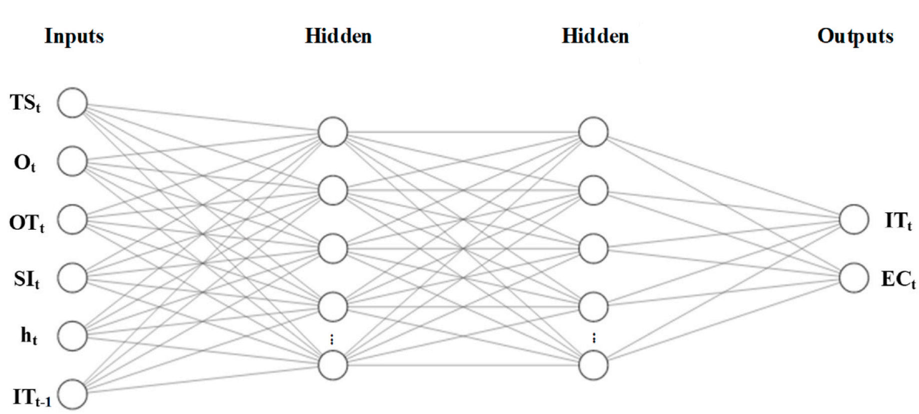


Fig. (5). The architecture of the artificial neural network used for zones b to e.

Table 1
The Pearson's correlation of input and output of artificial neural network for all zones.

Number		A	B	c	d	e	f
Name		D_{office}	$Ph.D._{office}$	R_{office}	M	R	K
r value	Training	0.99974	0.99915	0.99980	0.99991	0.99985	0.99993
	Testing	0.99970	0.99953	0.99975	0.99986	0.99990	0.99991

Table 2
The artificial neural network prediction's statistical values for energy consumption and indoor temperature.

Zone	Energy consumption		Indoor temperature	
	CVRMSE (%)	MBE (%)	CVRMSE (%)	MBE (%)
a	36.386	5.242	1.864	−0.187
b	26.333	−0.747	1.336	−0.180
c	36.554	0.844	0.969	0.046
d	28.007	−7.064	1.251	0.321
e	29.552	2.244	1.439	0.285
f	32.924	−6.439	1.480	0.431

2.3. Process of optimization

As aforementioned, a new metaheuristic optimization algorithm, which is the Chaotic Satin Bowerbird Optimization Algorithm (CSBOA) is employed for the optimization of temperature setpoint for each zone for the later 24 h. Further description of the optimization process of the proposed algorithm is presented in the following.

2.3.1. Chaotic satin bowerbird optimization algorithm (CSBOA)

Satin Bowerbird is a type of bird that lives in very nice nests made of decorative and precious stones with a shape of a bow. More beautiful nests made by male birds attract more female birds. The best nest can be selected by female birds after monitoring the construction process of nests and comparing them. The metaheuristic Satin Bowerbird optimization algorithm (SBOA) [27] is an inspiration by the behavior of the Satin Bowerbird.

Initialization; in the first phase of this algorithm, the initial place of the birds is determined randomly using population vectors with n-dimensions. In SBOA, the initial population can be defined as given below:

$$L_c = (l_1, l_2, \dots, l_k) \tag{1}$$

here, the c^{th} solution of the algorithm is denoted by L_c. The other solutions are defined by $(l_1, l_2, \dots, l_k)$. The function of fitness probability is used to specify the male birds' chance of being attracted by females, i.e., with the help of this feasibility females can select the best males. Finally, a male is defined and the female starts to follow it. This process is defined by the following equation:

$$Prob_i = \frac{fit_i}{\sum_{n=1}^{NC} fit_n} \tag{2}$$

$$fit_i = \begin{cases} \dfrac{1}{1+f(y_i)}, f(y_i) \geq 0 \\ 1 + |f(y_i)|, f(y_i) < 0 \end{cases} \tag{3}$$

Here, the cost function value for the location i is defined by $f(y_i)$.

Elitism; in this algorithm, this process is performed by the finest members. Based on which male birds make their specific bows, they have unique tastes and instincts. Mostly, the older males with more experience that can make better and more attractive nests, are attracted by females. Therefore, for males, attractiveness is directly associated with experience. In the SBOA, in each epoch, the nest with the best location is the elite. The places of the remaining nests are updated by the chosen elite.

Updating; the positions are renewed during the algorithm iterations based on the formula given below:

$$L_{cj}^{recent} = L_{cj}^{old} + \lambda_j \left(\frac{l_{ij} + l_{elite,j}}{2} \right) - l_{cj}^{old} \tag{4}$$

where, l_{elite} denotes the location of the elite. l_i refers to the selected solution in the current iteration and i is obtained using the roulette wheel technique, l_{cj} specifies the j^{th} component of l_c.

The equation below defines the attractiveness of a particular satin:

$$\gamma_j = \frac{\theta}{1 + \tau_i} \tag{5}$$

here, τ_i refers to the probability achieved by Eq. (2) and θ defines the solution's largest stage size.

Mutation; there is competition among male birds to attract females and it is likely to attack the other ones and ruin their nests, where the more experienced and stronger one can be successful. This behavior can be defined using the probability of l_{cj}; therefore, a normal distribution P assumed with the variance of σ^2 and mean value of l_{cj}^{old}.

$$L_{cj}^{recent} \sim P\left(l_{cj}^{old}, \sigma^2 \right) \tag{6}$$

$$P\left(l_{cj}^{old}, \sigma^2 \right) = l_{cj}^{old} + (\sigma \times P(0, 1)) \tag{7}$$

here, α defines the proportion of area width, and the equivalent formula is given below:

$$\alpha = x \times (Var_{max} - Var_{min}) \tag{8}$$

here, the proportion of the variance of the higher and lower bonds has been denoted by x, and Var_{min} and Var_{max} denote the lower and the upper bounds. The last population is made by locating and merging populations. When the final conditions are reached, the algorithm ends.

Chaotic theory-based SBOA; the SBOA algorithm has some shortcomings while it gives consistent results for optimization problems. One of these shortcomings is its low convergence rate which causes unsatisfactory solutions. To solve this problem, two approaches are suggested. One of them is the application of the pseudo-opposite learning technique to resolve the convergence flaw. In this process, a comparison of each individual in the population with their opposite amount is carried out. By consideration of a competitor y as a real number in the d dimensional search space in $[\lambda, \kappa]$, the process is implemented. This process is defined by the following formula:

$$\widetilde{y}_i = \lambda_i + \kappa_i - y_i \tag{9}$$

$$i = 1, 2, \dots, D \tag{10}$$

In the opposite learning technique, the quasi-opposite number is calculated as follows:

$$\widehat{y}_i = rand\left(\frac{\lambda_i + \kappa_i}{2}, \widetilde{y}_i \right) \tag{11}$$

This technique has been applied for generating a more proper population. The chaotic theory is the next approach to solving the problem of convergence. In this theory, the major system is nonlinear and complicated. Also, several techniques are random-based and the equation is defined by its quasi-random nature. The values of quasi-random have been applied in each generation to accelerate the theory of quasi-opposite. The second applied method for improvement is the Bernoulli shift map which is defined as follows:

$$\hat{y}_n^{q+1} = \begin{cases} \dfrac{\hat{y}_n^q}{1-\lambda} & 0 < \hat{y}_n^q \leq 1-\lambda \\ \dfrac{\hat{y}_n^q-(1-\lambda)}{\lambda} & 1-\lambda < \hat{y}_n^q \leq 1 \end{cases} \tag{12}$$

Here, λ equals 0.4.

The flowchart diagram of the proposed CSBOA is depicted in Fig (6).

Validation of the CSBOA; for better validation of the suggested algorithm, several standard benchmark functions are applied. These functions include Matyas, Bukin, Hybrid Composition, Schwefels, and Booth functions. The definitions of these functions are reported in Table 3.

For all functions except Hybrid Composition, the lowest amount is zero. The minimum value for the Hybrid Composition is 1. After applying the test functions to the suggested algorithm, the results were put in comparison with some of the latest optimization algorithms which are the elephant herding optimization algorithm (EHOA) [28], Firefly algorithm (FA) [29], Billiard-based Optimization Algorithm (BOA) [30], Multi-verse optimization algorithm (MVOA) [31], and the base SBOA [32]. The parameter set of the comparative optimizers is stated in Table 4.

For proper evaluation, the population size and the iterations' number are respectively 70 and 250. The mean value (MV) and the standard deviation (std) value are used to evaluate the efficiency of the suggested algorithm, which is independently run 30 times to achieve consistent results. The comparison results between the presented optimizer and the other latest optimizers are reported in Table 5.

According to the results of Table 3, it is observed that the proposed CSBOA algorithm with the lowest value of the mean, achieves more optimum accuracy in comparison to other algorithms. Moreover, the lower value of std of the suggested CSBOA compared to the rest of the algorithms indicates better reliability to obtain optimal results. In this study, a solution population of 24 temperature setpoints from 12 °C to 24 °C is included in CSBOA in which one value is represented for each hour. The optimization algorithms have been processed in MATLAB R2016b environment on a PC with Intel Core i5-2410 M @ 2.30 GHz CPU, and 8 GB of RAM, and thus, it can be easily coupled with the artificial neural network that has been also coded in MATLAB.

2.4. Objective function

In this paper, the aim of the optimization approach is the minimization of energy consumption and maintaining thermal comfort by choosing the optimum hourly schedule of temperature setpoint for all zones. The range of set points is from 20 °C to 24 °C when the building is occupied and 12 °C–24 °C when the building is unoccupied for maintenance of thermal comfort as demanded by occupants. While these ranges' settings constitute the main part of making sure thermal comfort (THC) is attained, a higher interior penalty method is also implemented. If the indoor temperature is higher than 24 °C or lower than 20 °C at the occupied time, the solution is excluded from the competition in the fitness evaluation because the value of energy consumption at that time is set at 100 kWh. This "penalty function" is most needed at the starting time of occupation during the day when the temperature setpoint of a zone is more likely higher than the lower limit of 20 °C, however, the indoor temperature can be below that at the time the zone gets warmer. Fig. (7) depicts the flowchart of the fitness evaluation.

To input the variables into the artificial neural network, they have been added into a matrix with a proper arrangement, in which, the former indoor temperature, outdoor temperature, occupation, temperature setpoint, solar irradiance, and hour of the day are included. The inputs were added to the zone artificial neural network after collecting for predicting the indoor temperature and consumption of energy for that time. Subsequently, the thermal comfort is checked to make sure that the indoor temperature is predicted to be higher than 20 °C and lower than 24 °C at the occupied time. Failing this, the consumption of energy for that period is altered to 100 kWh. The process is repeated for the later period using predicted indoor temperature from the former hour as the input until the process is done for all of the time-step of the day. The consumption of energy is considered during 24 h when all 24 h were accomplished and the achieved number is the fitness of solutions. By application of the explained process, the CSBOA is implemented in the six conditioned zones. Since the optimization of each zone is carried out independently, they can be carried out simultaneously to decrease the simulation time.

2.5. Model predictive control

The process of optimization will be performed at midnight and generate a timetable for the next day given that there exist 24 h of occupation and weather predictions, and starting zone temperatures. Nevertheless, the impact of performing this process as model predictive control (MPC) has also been evaluated in this work. Once performed 24 h before in the absence of model predictive control, errors in the temperature prediction at a former period will cause combined errors during the day. However, when the MPC is applied, the total setpoint schedule of heating could be performed irrespective of any unexpected variations in conditions. Nonetheless, when performed as model predictive control, the optimization could be implemented hourly for 24 h. This enables feedback on the indoor temperature building system enabling the controller to respond to any errors of prediction or obtain a further updated forecast of the weather. By implementing a model predictive control, the 24 h schedule of setpoints is up to date and changes hourly although only each initial hour of each optimization has been implemented. Considering that the case study is based on simulation, the real building has been replicated by a model of DesignBuilder simulation, therefore it is needed to apply a technique to link the MATLAB optimization method and DesignBuilder automatically. In this regard, MLE + as a middleware software has been employed. The interchange of data, after facilitating by MLE+, has been developed so that at the hour

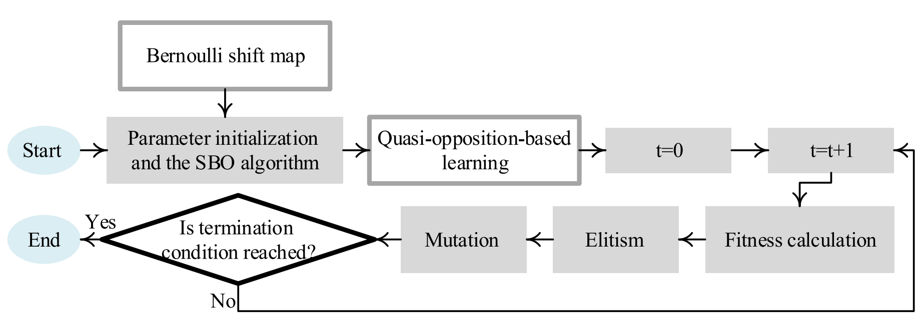


Fig (6). The flowchart of the presented CSBOA.

Table 3
Mathematical definition of the applied functions.

Function	Name	Dimension	Range
$F_1(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$	Booth	30	[10,10]
$F_2(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$	Matyas	30	[10,10]
$F_3(x) = 100\sqrt{(x_2 - 0.01x_1^2)} + 0.01\lvert x_1 + 10\rvert$	Bukin n. 6	30	[-5,15]
$F_4(x) = \left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}\right)^{-1}$	Hybrid Composition	2	[-65,65]
$F_5(x) = \frac{\pi}{n}\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)\ y_i = 1 + \frac{x_i + 1}{4}, u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 - a < x_i < a & \\ k(-x_i - a)^m & x_i < -a \end{cases}$	Schwefels Problem	30	[-50,50]

Table 4
The parameter set of the comparative optimizers.

Algorithm	Parameter	Value
BOA [30]	No. Of pockets	22
	w	0.7
	ES	0.3
FA [29]	α	0.2
	β	0.5
	γ	1
EHOA [28]	R	1000
	nClan	4
	A	0.25
	B	0.05
	Γ	0.02
MVOA [31]	Traveling distance rate	[0.6, 1]
	Wormhole existence probability	[0.2, 1]

Table 5
The comparison results between the presented optimizer and the other latest optimizers.

Algorithm Function	BOA [30]		FA [29]		EHOA [28]	
	MV	Std	MV	std	MV	std
F_1	8.90e-9	4.57e-9	6.20e-9	2.07e-9	13.99e-10	5.59e-10
F_2	10.21e-8	5.39e-8	9.21e-9	4.61e-9	6.19e-10	3.28e-10
F_3	14.59e-9	10.340e-9	12.28e-10	8.331e-10	13.40e-11	9.32e-11
F_4	0.985	0.753	0.323	0.141	0.0998	0.0720
F_5	5.020	2.122	3.201	1.549	1.037	0.790
Algorithm Function	MVOA [31]		SBOA [32]		CSBOA	
	MV	Std	MV	std	MV	std
F_1	9.17e-11	4.40e −11	4.71e −11	2.600E-11	1.529E-11	0.921E-11
F_2	8.20e −11	4.71e −11	12.69e −12	9.55E-12	5.78E-12	1.79E-12
F_3	15.10e −12	10.32 e −12	8.16e −13	6.25E-13	5.12E-13	1.80E-13
F_4	0.0530	0.0411	0.0505	0.0362	0.0408	0.0209
F_5	0.932	0.625	0.530	0.317	0.413	0.2989

h, each zone's indoor temperature has been recorded from the simulation model. The process of optimization can perform and create a 24-h schedule of setpoints for every zone that has been returned to MLE + to be carried out in the DesignBuilder model by application of these first amounts. With the initial values of the setpoint, the model of simulation will then carry on for the later hour. When this hour is completed the temperature is once again recorded by MLE+ and transferred to MATLAB, then the optimization is carried out once again with the up-to-date actual building temperatures. Thus, only the starting hour of the optimum schedule of setpoint is applied, however, the period of

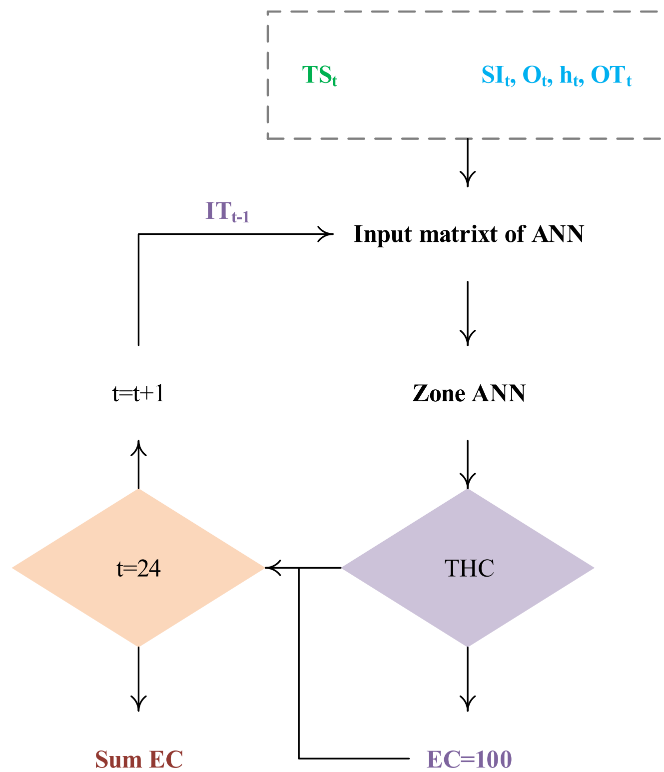


Fig. (7). The fitness evaluation procedure (SI: solar irradiance; OT: outdoor temperature; TS: temperature setpoint; IT: indoor temperature; THC: thermal comfort; EC: energy consumption; O: occupancy; h: hour).

optimization stays at 24 h to provide a prediction for planning beforehand and enable the probability of early shutting down or preheating. It should be noted that the process of optimization being implemented hourly is equal to that explained in section 3.2, but it takes place hourly instead of only once at the start of every day. In a real deployment, instead of employing the simulation model of DesignBuilder, the calculated indoor temperature in every zone can be easily recorded before performing the optimization. Fig. (8) depicts the diagram of the procedure.

3. Results of optimization

For this section, the CSBOA-ANN, level of zone, and setpoint of heating schedule can be used during a test week in Feb by real meteorological data of 2016 that have been inputted to DesignBuilder. A base case has been provided for the comparison, which applies the present set

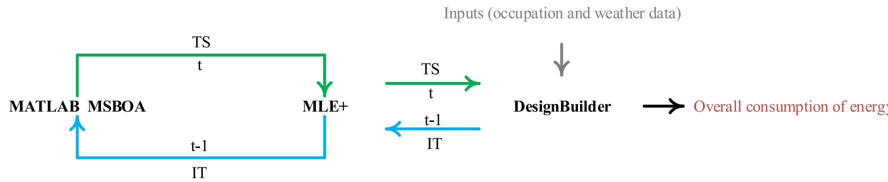


Fig. (8). The diagram of the model predictive control procedure by MLE+ (TS: temperature setpoint; IT: indoor temperature).

point of the heating approach. This equals 12 °C when the building is unoccupied and 21 °C at the time that the building is occupied for the 6 zones. The optimization starts with performing day-ahead scheduling and later as MPC with a 1-h step and 24-h control range. It is noticeable that for the validation of the results for the two cases, the achieved optimization schedules can be returned to DesignBuilder, which enables appropriate comparison with the base case given the fact that the model simulations are equal (containing climatic conditions) excluding the setpoint schedule of heating. Moreover, any impact of artificial neural network errors on prediction is eliminated and it might be needed to allow for a real assessment of the influence of the optimized approach of set point. Two scenarios of optimization have been performed: 1) standard energy tariff (SET), and 2) time-of-use tariff (ToUT). In scenario one, the objective of the optimization is the energy consumption minimization and consequently minimization of cost. The minimization of heating electrical power cost is the objective of optimization by ToU that will not consequently lower the consumption of energy. Minimum adjustment is needed for the optimization to perform this change of objective. The multiplication of hourly consumption of energy by the price per kWh has been easily carried out at that specific daytime that is equivalent to each working day. The prices of energy are that applied in subsection 4.2 and the variation of price has been stated in Table 6.

Between 23:00 and 06:00 energy is the cheapest, which costs £ 0.0496/kWh. The most expensive price of energy is £ 0.2495/kWh from 16:00 to 19:00. The price of energy for other times is £0.1194/kWh.

3.1. Standard energy tariff

The process of optimization has been performed every day between the 15th and 19th of Feb and the resulting schedules have been gathered seven-day schedule. Table 7 illustrate the comparison of energy consumption in all zone with both approaches of optimization.

According to Table 7, a very small difference between the MPC and the day-ahead optimization is seen. In fact, the day-ahead optimization performs a little better than the model predictive control with the major difference appearing in the R_{office}. The potentiality of 26% savings of energy in the course of mentioned test week for both optimizations is seen. To verify the obtained results for other envelope geometries as well, as air-conditioning plant systems and climatic contexts, a comparison of the proposed method with some other methods from the literature has been carried out. The results of the comparison are reported in Table 8.

As can be understood from Table 8, the proposed method gives better results and therefore the most accurate results compared to other methods. The major energy savings source is related to zones M and K, which are occasionally occupied but are heated the whole day in the baseline scenario. The R_{office} and R are the zones with the minimum savings of energy which are beside zone M. Thus, the lesser savings of energy of these rooms are not an optimization failure, it is because of the absence of the heat gain from zone M which is currently heated only for a limited time. In addition, the rooms like the D_{office} obtain savings of energy over the base case approach with identical hours of occupation (08:00 to 19:00). For more clarification, the consumption of energy, schedule of setpoint, and indoor temperature for the $D_{office,}$ on Feb 15th for the base case and optimum scenario is depicted in Fig. (9).

As observed in this figure, the optimum approach selects further gradual heating of the zone with heating from 07:00 to 08:00, therefore, it aims at a lower temperature just above the limit of 20 °C in the morning, which both lead to a substantially smaller peak in the morning. The optimum approach suggests heating the building from 12:00 to 15:00 with higher natural solar heating, to a warmer temperature to cause the peak of energy late in the afternoon, around 19:00, which is lower than that of the base case. In conclusion, considerable savings of energy have been shown by the defined modes of optimization, which can be achieved by giving freedom to a smart scheduler to change the set point temperatures in the range of the pre-determined limits and through actively taking account of outside climatic conditions and occupation. For occupants, this saving of energy does not affect thermal comfort since the temperatures stay higher than the 20 °C minimum limits. Nevertheless, it has not indicated the MPC's value for a simpler day-ahead scheduling strategy.

Table 6
Electrical power price on workdays.

Hours of the day	11:00 p.m. -06:00 a. m.	4:00 p.m.-7:00 p. m.	Other
Electrical power price (£/kWh)	0.0496	0.2495	0.1194

3.2. Time-of-use tariff (ToUT)

The optimizations including model predictive control and day-ahead have been performed again to take into account the time-of-use tariff and changed to lower the heating cost. The same week has been investigated with the same climatic conditions. If the same base case scenario is applied, there is no need for adjusting the new pricing system. Table 9 reports the results of the optimizations.

According to this table, using the ToUT optimization, the savings of energy are lower than the condition discussed in subsection 4.1, where the objective function of the optimization is associated with energy cost minimization in this case. Moreover, the savings in comparison to the base case are about 28%, and again a minimum difference is seen between the two applied approaches of optimization. An example of the strategy that the optimization provided for the time-of-use scenario is depicted in Fig. (10).

As observed in this figure, the optimization tries to preheat from 05:00 to 06:00 which is the latest period in which the price of the electrical power is minimum. In addition, lower consumption peaks of energy are seen at 13:00 and 15:00 to decrease the consumption of energy at the highest-price period from 16:00 to 19:00 which is effectively performed in comparison to the base case approach.

3.3. Discussion

The results achieved in subsections 4.1 and 4.2 show that using a smarter and more context-aware building controller will lead to improvement over the conventional static control. Considerable savings in cost and energy can be achieved by zone-level optimization compared to establishing a building-level approach. The Artificial Neural Network surrogate modeling approach provided here has proven to be

Table 7
The results of optimization by a standard energy tariff.

Zone		a	b	c	D	e	f	Total building
Name		D_{office}	Ph.D.$_{office}$	R_{office}	M	R	K	
Energy consumption/kWh	Base case	30.82	121.92	58.25	50.92	42.08	16.16	320.15
	MPC	27.17	102.08	63.73	7.39	39.14	1.79	241.31
	Day-ahead	27.05	101.31	57.93	7.66	39.84	1.84	235.63
Savings versus base case/%	MPC	11.84	16.27	−9.41	85.48	6.98	88.90	24.63
	Day-ahead	12.22	16.91	0.54	84.96	5.32	88.62	26.40

Table 8
The results of the comparison between the proposed method and some other methods.

Method	CSBOA	GA and MILP [20]	NSGA-II [19]	GA [22]
Energy savings	26%	21%	17%	23%

sufficiently precise to repeat the simulation model in the studied case. Nevertheless, for the conclusion validation, performing this control approach on a real building as the case study can be the objective of future work. It has been shown that the optimization approach is flexible to a variable environment of energy. The implementation of a ToUT is simple. More adjustments can be achieved to consider the local renewable sources or DR program as part of a district heating network which can benefit the energy supplier along with the user. Based on the achieved results, the difference between both optimizations (the MPC and the day-ahead) is minor based on both of the tariff scenarios, which is in conflict with the results reported in the latest studies on building control. Nevertheless, this can be because of the absence of uncertainty in the test scenarios provided in this work. The climatic conditions and occupation have been presumed to be previously determined and these predictions have been presumed to be 100% correct, which is not the case practically. Thus, the prediction uncertainty will be defined in future works, and the effect on both optimization cases will be evaluated. Based on the assumptions, the adjustment of model predictive control to these uncertainties will be more probable than day-ahead

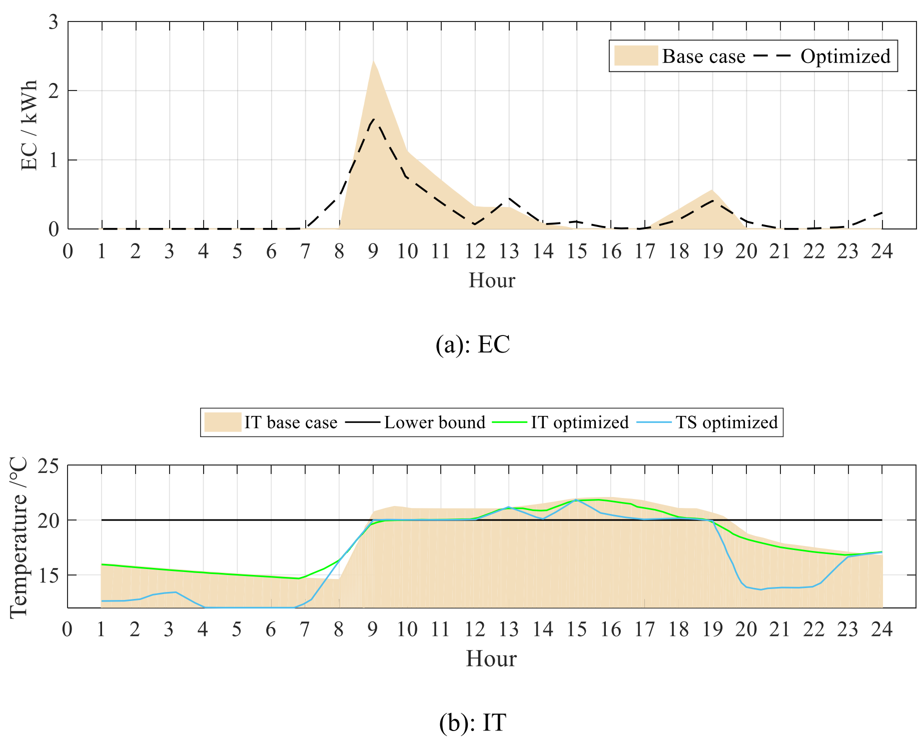
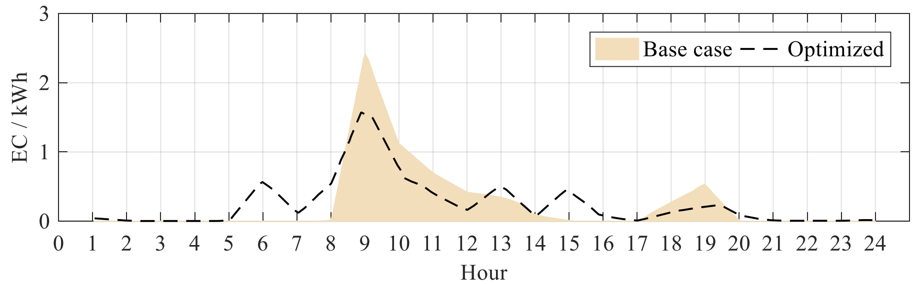


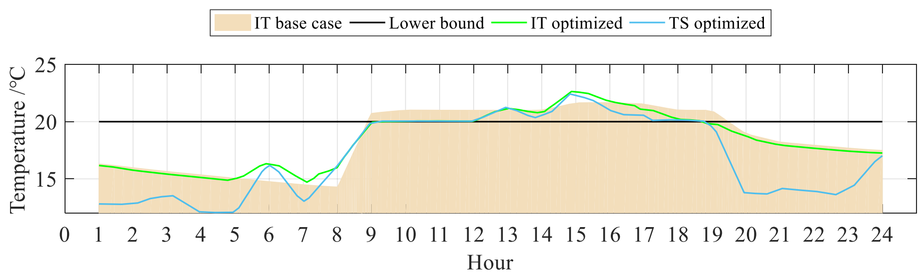
Fig. (9). Comparison of model predictive control optimization and the base case on the standard energy tariff in the D_{office} on the 15th of February, a: for energy consumption; b: for indoor temperature.

Table 9
The results of optimization by ToUT.

Zone		A	b	c	d	e	f	Total building
Name		D_{office}	Ph.D.$_{office}$	R_{office}	M	R	K	
Base case scenario	Energy/kWh	30.82	121.92	58.25	50.92	42.08	16.16	320.15
	Cost/£	4.330	18.288	8.377	7.399	5.995	2.439	46.828
Savings of energy/%	MPC	−5.13	14.73	−9.53	79.50	6.13	88.18	21.28
	Day-ahead	1.55	15.49	−6.96	83.46	5.44	90.01	23.31
Savings of cost/%	MPC	6.84	17.66	−0.04	86.60	10.18	91.11	27.26
	Day-ahead	9.87	19.16	−0.88	87.62	8.20	92.32	27.94



(a): EC



(b): IT

Fig. (10). Comparison of model predictive control optimization and the base case on the ToUT in the D_{office} on the 16th of February, a: for energy consumption; b: for indoor temperature.

forecasting. A further point of future work will target the design of a procedure whereby the optimization of each zone affects neighboring zones. In the current paper, the optimization of each zone has been carried out individually to decrease the overall time of optimization by parallel optimization of each zone. Despite the interaction absence among the optimizations of the zones, the suggested process could obtain considerable savings of energy without losing thermal comfort probably which is because the setpoint schedules do not considerably deviate day by day, the setpoints only changed slightly by the optimization. Thus, the exchange of the heat from one zone to another does not change enough to cause any effect and stop the optimization procedure. For the next work, we will try to pre-screen buildings as in the studied case to evaluate closely nearby zones and design a model where decisions taken in a zone are transferred to the other ones. For implementing this solution on a real building, a fairly small amount of supplementary hardware is needed. The process of optimization would need heating units' direct control and zone-level temperature sensors. Basically, all control systems have this capability already. Nowadays, a major increase in accessibility and interest in smart building devices controlled by a central Artificial Intelligence coordinator by a model of the internet of things is observed. Thus, it is possible and likely that most future buildings and some of the existing buildings (residential and commercial) will be able to control setpoints of the individual room and devices by a hybrid system. The suggested process of optimization can send and request related information including indoor temperatures and setpoints better than these physical systems, benefitting from the current network and physical infrastructure. It is expected to observe further applicability of this control model for commercial buildings firstly because the patterns of occupation are determined more precisely and are foreseeable in office buildings and the fact that the occupants do not assume that they can control the thermal system directly the systems of heating. The evolution of the surrogate designs for predicting indoor temperature and consumption of energy is the major important challenge in utilizing this control approach. The strategy that has been applied here was for training an artificial neural network defined by huge quantities of simulation data. Nevertheless, the accessibility to proper designs of simulation is not possible for the majority of buildings. Based on theories, it is expected that simulation models of a building will probably be more accessible at a future date, under governmental lawmaking to decrease the consumption of energy in buildings and enhance processes of retrofitting. This causes building information modeling to become more prevalent and incrementally consist of energy evaluation modules. The investigators are studying approaches to obtain information on the current building, converting it to a digital model, designing a model of energy simulation for the building, and model calibration by current documented data. For the studied case, if a considerable amount of data related to temperature and documented consumption of energy has been created, it will be possible to create machine learning models. It is needed to design a particular model of artificial neural network for each building if the studied timestep is 1 h or less because generic ANNs cannot capture the complexities of a single building.

4. Conclusions

In this study, a zone-level, Chaotic Satin Bowerbird Optimization Algorithm-Artificial Neural Network (CSBOA-ANN), setpoint scheduler of heating has been developed, where indoor temperature, occupancy, and weather data are the inputs. For artificial neural network training, a set of training data was generated by the model of simulation. A new metaheuristic, which is the Chaotic Satin Bowerbird Optimization Algorithm (CSBOA) is employed for the minimization of energy consumption, which is carried out in parallel to generate proper schedules of the setpoint for every zone, every day. Two modes of optimization including day-ahead and model predictive control that are repeated each hour have been applied. In the first mode, the optimization is performed once earlier in the day, while the second mode is repeated hourly. In addition, two optimization scenarios have been performed: 1) standard energy tariff (SET), and 2) time of use tariff (ToUT). Using a standard energy tariff, the consumption of energy was decreased by 26%, while ToUT decreased the cost by 28% for the two stages of optimization. The climatic conditions and occupation have been presumed to be previously determined and these predictions have been presumed to be 100% correct which is not true. Therefore, the prediction uncertainty will be defined in future work, and the effect on both optimization cases will be evaluated. Moreover, integration of a method of optimization similar to this in the context of a micro-grid setting or larger district will be the purpose of future work. Eventually, for validation of the achieved results, the control strategy will be performed on a real case-building when it is reliable enough.

Credit author statement

Xiao Chen: Conceptualization, Data curation, Writing – original draft, Writing - review & editing. **Benyi Cao:** Conceptualization, Data curation, Writing – original draft, Writing - review & editing. **Somayeh Pouramini:** Conceptualization, Data curation, Writing – original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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