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A zone-level, building energy optimisation combining an artificial neural network, a genetic algorithm, and model predictive control

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A B S T R A C T

Buildings account for a substantial proportion of global energy consumption and global greenhouse gas emissions. Given the growth in smart devices and sensors there is an opportunity to develop a new generation of smarter, more context aware, building controllers. Therefore, in this work, surrogate, zone-level artificial neural networks that take weather, occupancy and indoor temperature as inputs, have been created. These are used as an evaluation engine by a genetic algorithm with the aim of minimising energy consumption. Bespoke 24-h, heating set point schedules are generated for each zone in a small office building in Cardiff, UK. The optimisation strategy can be deployed in two modes, day ahead optimisation or as model predictive control which re-optimises every hour. Over a February test week, the optimisation is shown to reduce energy consumption by around 25% compared to a baseline heating strategy. When a time of use tariff is introduced, the optimisation is altered to minimise cost rather than energy consumption. The optimisation strategy successfully shifts load to cheaper price periods and reduces energy cost by around 27% compared to the baseline strategy.

1. Introduction

Buildings account for a considerable proportion of global energy consumption and greenhouse gas emissions [1]. Therefore, improving energy efficiency in this sector is gaining increased focus from research and industry. The recent growth in popularity of the Internet of Things, IoT, means that future buildings will be equipped with a wealth of potential sensing devices. This additional information provides an exciting opportunity to reduce building energy consumption as it could be leveraged by a new generation of smart building controllers to manage building energy consumption in a more efficient way. It is estimated that buildings have the potential to reduce their energy consumption by 20–30% whilst using existing building components [2]. Dynamic information such as occupancy and outdoor weather conditions are not currently considered in the internal logic of traditional building management systems, BMS, which largely employ a reactive, rule based approach [3]. Furthermore, many older, smaller buildings have one central thermostat that controls the temperature set point throughout the entire building. This leads to large energy wastage as unoccupied zones are heated when they are not required to be.

Energy infrastructure is also undergoing substantial changes. Energy is becoming increasingly decentralised with the concept of microgrids and the smart grid gaining traction [4]. Large scale, centralised, fossil fuel power plants are giving way to more local renewable resources and smaller scale local generation. This substantially reduces energy transmission losses and allows generation to be far more efficient as waste heat from power generation can be utilised in local heating systems through cogeneration units. Energy is also no longer unidirectional, increased use of small scale, residential PV solar panels have given rise to the concept of the 'prosumer', one who both consumes and produces energy. Given that the share of controllable energy production is decreasing through use of stochastic renewable generation, the system must transition from a demand led network to one that considers both supply and demand as partially controllable. This could come in the form of direct demand response, DR, controls or through encouraging consumer behavioural change through dynamic time of use, TOU, tariffs. Therefore, the next generation of smart building controller must not only take into consideration aspects such as predicted occupancy and weather conditions, it must also be adaptable enough to maximise the use of local renewable resources, the use of energy storage, and schedule consumption around low energy price periods [5].

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To address these needs, this paper will demonstrate a zone-level, heating set point scheduler that minimises the energy consumption over the next 24 h whilst maintaining thermal comfort within the building. The remainder of this paper is organised as follows. Section 2 provides a review of related literature. Section 3 discusses the modelling of the case study building in a simulation environment, EnergyPlus, and as a series of Artificial Neural Networks, ANN. Section 4 outlines the optimisation strategy. Section 5 gives the results of the optimisation strategy, compares day ahead scheduling to hourly model predictive control for both a standard tariff scenario and a TOU tariff scenario. Section 6 provides the conclusion.

2. Related works

The optimisation of building controls is currently a popular topic in the literature. This is illustrated by a recent review paper [6] which assessed over 100 peer-reviewed papers. The review assesses the benefits of different control schemes, optimisation techniques and prediction model methods. It determines that the most popular control strategy found in the literature is Model Predictive Control, MPC. This is also confirmed by a further review [7]. MPC has proven to be valuable due to its ability to adapt to unforeseen disturbances or prediction errors, its ability to exploit a buildings' thermal mass, take account of variable energy pricing and be able to shift loads away from peaks. Whilst MPC appears to be the leading control scheme, there is still debate of the most appropriate modelling methods and optimisation techniques to deploy in conjunction with the MPC control scheme. A number of advanced computational methods exist that can be utilised for optimal building control and these are discussed in Ref. [8]. These include metaheuristic optimisations, multi agent systems, fuzzy logic controls and ANN. The paper also suggests the use of cloud computing to achieve the optimisation and relay results to be implemented by the existing Building Management Systems, BMS.

MPC strategies applied to building control optimise decision variables over a time horizon which usually ranges 8–24 h ahead of the current timestep. Only the first timestep, usually 15 min to an hour, of the optimal strategy is implemented before re-optimising with updated feedback from the relevant sensors [9]. Therefore, the controller must have an internal model of the process to be able to calculate the objective function over the complete time horizon. Li [10], reviews methods of building modelling for optimisation of building control, these include white, grey or black box modelling techniques. White box models include full energy simulations such as TRNSYS or EnergyPlus, these models are highly detailed but take a long time to accurately calibrate and run. Black box models have no understanding of the physical properties they are attempting to model, they are simply based on extensive amounts of training data that they are provided. This includes statistical models, ANN and Random Forest models. These can achieve good accuracy and very low calculation time but require a large amount of training data [11]. Grey box models are simplified physical models such as Resistor-Capacitance (RC) models, they also require some historical data to set their coefficients and also have a relatively low calculation time so they can be used for online optimisation.

In Ref. [12], the authors' coupled an EnergyPlus simulation with a MATLAB, MPC procedure using the middleware software BCVTB, Building Controls Virtual Test Bed, which is designed to facilitate data exchange between EnergyPlus and MATLAB. The MPC scheme controlled the extent of the pre-cooling with the objective of minimising energy cost. The various potential solutions were assessed in EnergyPlus and compared to typical control strategies. However, the case study building was very simplistic due to the simulation time involved in complex, realistic buildings. A 24 h scheduler utilising EnergyPlus was developed in Ref. [13] with the aim of simultaneously controlling the thermal comfort, visual comfort and indoor air quality whilst minimising the energy consumption. It used a genetic algorithm which used an EnergyPlus model as the evaluation engine to control window blinds, ventilation, and window opening operation for just a single zone. HVAC operational optimisation was addressed in Ref. [14]. An EnergyPlus model was combined with a MATLAB multi-objective GA to minimise annual energy consumption, thermal discomfort and productivity loss by setting the heating and cooling set point temperature. However, the same set point temperatures were used throughout the entire year failing to adjust to variable weather of occupancy conditions of each day. In both [15,16], Ascione has developed a multi-objective GA optimisation procedure to control indoor set point temperatures using an EnergyPlus model to evaluate potential solutions. Both case studies have demonstrated significant potential energy savings, however, the case study building was relatively simple, containing just three zones. Using the EnergyPlus model as an evaluation engine led to a computational time of 90 min to develop an optimal schedule for the next 24-h. Such a computational period would inhibit the use of sliding-window, MPC, which would have to re-optimise every hour.

In practice, using a detailed white box simulation in conjunction with an advanced metaheuristic optimisation strategy, such as a GA, is not possible in most scenarios targeting operational optimisation. This is due to the considerable number of evaluations required per iteration and the computational time required to complete an evaluation. The previously discussed works focus on very simple building energy models or just a single zone. To apply these methods to a realistically complex building would require significant computational power to reduce simulation times to acceptable limits (i.e. below 1 timestep). Thus, the focus must turn to creating surrogate, black or grey box, models which can accurately replicate the output of a white box model but can compute with minimal computation expense and time allowing their use in real time.

An example illustrating the use of surrogate models combined with optimisation can be found in both [17,18]. A TRNSYS model was run several times to produce a representative bank of data from which an ANN was trained. The developed ANN accurately predicted annual energy consumption and thermal comfort within the building based on retrofit design decisions as inputs. The ANN was combined with a multi-objective GA to minimise energy consumption, discomfort and retrofit costs. Both studies showed the benefits of deploying an ANN as opposed to a white box simulation model as the evaluation engine due to the dramatic decrease in reported computational time. This type of scheme was further enhanced in Ref. [19] which developed generic ANN that accurately replicated entire classes of buildings (e.g. an office built from 1920 to 70) rather than just a single building. Once combined with an optimisation procedure, the methodology recommended the most cost-effective building retrofit measures depending on budget. Magalhães [20], developed an ANN to forecast the annual energy consumption of a building based on readily available energy performance certificates, EPC, and specific user defined characteristics such as the length of the heating period and the percentage of area heated. The authors' argued that providing such information to occupants would allow more informed decisions in relation to energy saving measures.

Rather than address design or retrofit decisions, this paper aims to target operational optimisation of building energy consumption. The authors aim to emphasise the importance of optimisation every day to adjust to the specific conditions at hand. Thus, the building energy models required must have prediction granularity of an hour or less. Benedetti [21], developed a methodology to automate the generation a of sub-hourly building energy consumption ANN. In a Rome based case study, they found that a minimum of two months of historical data was required to accurately predict the next sixty days of electricity consumption. Three measures of accuracy were used and once all three measures fell below a predefined threshold the ANN was deemed inaccurate and retrained. Similarly [22], tests a sliding window approach or accumulative training of an ANN to predict sub-hourly electricity consumption. The sliding window approach retrains the ANN every day using the previous four weeks data. Accumulative training uses all the available data to train the ANN. Both models performed equally well with an average percentage error around 5%. Afram [23], developed a new algorithm for training ANN which was applied to modelling several HVAC components. The ANN were integrated into a MPC platform to control the ventilation rate, buffer tank set point temperature and indoor set point temperature. The control scheme showed aptitude for reducing the energy costs of the house by shifting the load to cheaper time periods. However, the building only has one set point temperature rather than zone level and occupancy was not considered in the MPC formulation.

Papantoniou [24], optimised the operation of fan coil units in a Greek hospital. An ANN predicted the outdoor temperature and the indoor temperature also taking the HVAC operation as an input. A genetic algorithm was used in conjunction with a fuzzy controller to minimise the cost of the energy consumption and ensure thermal comfort for the occupants. However, the optimisation time horizon was limited to only 8 h. Lee [25], used an ANN based MPC strategy to control a zone AHU. It aimed to calculate the optimal AHU cooling operation over the next 24 h to minimise the energy cost and maintain thermal comfort using Mixed Integer Non-Linear Programming, MINLP. The ANN an accurately predicted indoor temperature and energy consumption, but the application was limited to only a single zone within a building. An ANN based controller was also developed in Ref. [26]. The ANN predicts the change in indoor conditions including temperature, relative humidity and the Predicted Mean Vote, PMV. These predictions are subsequently used to control heating, cooling, humidifying and dehumidifying devices to minimise over or undershoots often found in non-predictive, conventional control. Whilst this approach provided better thermal comfort compared to conventional controllers, it did not consider the minimisation of energy consumption as an objective in its control scheme.

MPC using grey box modelling techniques were applied to a Czech university building in Refs. [27,28]. Blocks of the building were modelled using an RC model taking weather predictions as inputs. The optimisation was set up as a linear quadratic programming problem and the objective was to minimise energy consumption by controlling the supply water temperature set point. This strategy was implemented on the real building for over 2 months and was shown to reduce energy consumption by 15%–28%. Whilst this optimisation considers occupancy as a disturbance, it does not include predicted occupancy as a model input. Furthermore, only block level supply water temperature is controlled rather than the desired set point temperature in each zone. Oldewurtel [29], adapted traditional MPC to Stochastic MPC. Essentially this means the MPC strategy took into consideration uncertainties in forecasts when carrying out the optimisation. This resulted in a slightly more cautious optimisation that did not go so close to the comfort boundaries whilst still achieving good energy savings. Molina [30], produced an MPC strategy to control heating and cooling in a residential building using a state space model as an evaluation engine for a GA. However, this work considered unrealistically simplified ideal heating and cooling and the control strategy only considers a 1-h prediction horizon which is not long enough to be able to effectively utilise pre-heating or pre-cooling.

The importance of considering occupancy was shown in Ref. [31]. A distributed MPC strategy is developed where each room has an independent controller that can exchange data with neighbouring controllers to ensure heat gains from adjacent zones are considered. Pisello [32], reviewed the difference in building performance between the design stage assumptions and the actual post occupancy reality. By studying the real occupancy patterns throughout a large multipurpose building in New York, alterations can be made to controller schedules to achieve potential savings of up to 20.5%. Erickson [33], also developed a HVAC control strategy based on occupancy. A Markov Chain occupancy model is developed to allow the building control strategy to take advantage of sporadically occupied zones to save up to 20% on an EnergyPlus, simulation-based, case study.

From a review of the relevant literature it is clear building controllers need to become more context aware, considering both predicted weather conditions and occupancy profiles. Furthermore, predictive control needs an accurate yet simple enough prediction model to be able to deploy in (near) real time. Optimisation strategies could make significant energy savings if they are focussed at a zone or room level, ensuring that energy is only consumed when necessary. Therefore, the main contribution this paper makes is summarized as follows:

- Zone level ANN have been developed to accurately forecast the indoor temperature and energy consumption by considering variable weather, occupancy and temperature set points.
- This is combined with a genetic algorithm to optimise the temperature set point to minimise either energy consumption or energy cost within a computationally short period.
- The effect of deploying the optimisation as day-ahead optimisation or hourly, sliding window MPC was assessed.
- The control scheme was demonstrated to be adaptable to time varying energy prices.

3. Modelling methodology

The methodology involved a case study building, i.e. a small office building in Cardiff, UK. The building was scanned using a Faro 3D laser scanner to generate a point cloud of the building. From this an as-built representation was created in the BIM software Autodesk Revit. The relevant floor plans and building sections could then be exported and used to draw an accurate representation of the buildings' geometry in the energy simulation software Design Builder, the resulting model is shown in Fig. 1. Construction and material properties, occupancy profiles, lighting and electronic equipment specifications were inputted to the model based on a building survey. The building contains 6 conditioned zones including 3 office spaces, a reception, a kitchen and a meeting room. The building is naturally ventilated and cooled, and an electrical heating system was modelled with separate zone thermostat controls assumed. 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. We have assumed the 3 office zones and the reception occupied from 08:00 until 19:00. The kitchen occupied from 12:00 until 14:00 and the meeting room from 10:00 to 11:00 although if deployed in reality, meeting room occupancy patterns would be available from the electronic booking system used for this zone.

3.1. Modelling using and artificial neural network

For the optimisation utilised in this paper, it was necessary to be

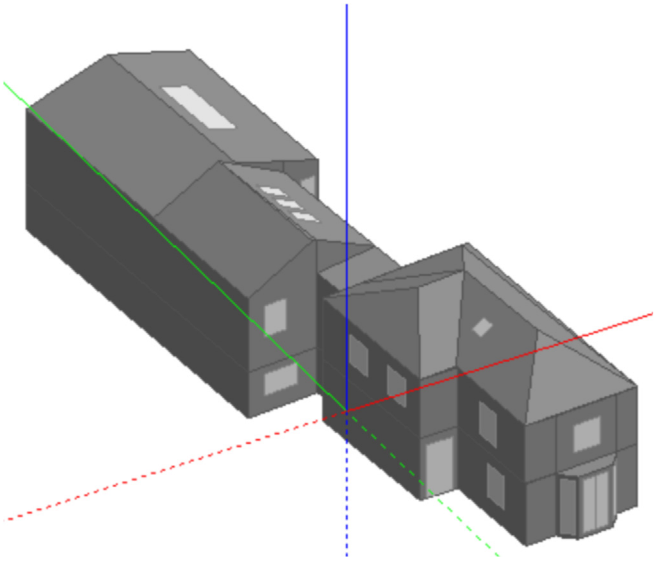

Fig. 1. Design Builder model of the case study building.

able to predict the heating energy consumption and the indoor temperature of each conditioned zone at each hour of the day for the entire 24-h, time horizon. This calculation needed to be completed quickly to be combined with a GA optimisation strategy, therefore the full energy simulation could not be used as an evaluation engine. Hence, an ANN surrogate model for each zone was trained using the simulation data produced by the energy model so it could accurately replicate it during the real-time optimisation. To produce the ANN training data set, 27 separate simulations were completed from the 1st of January to the 31st of March, each time with a different heating set point schedule in the 6 conditioned zones. Some of these training set point schedules were realistic, 'typical', schedules whilst others varied randomly between 12 °C and 24 °C. This was designed to generate 58237 h of diverse training data which would allow the ANN to produce reasonable accurate results throughout the entire range of possible set point schedules.

Inputs to the ANN needed to be known in advance to allow prediction for the entire 24-h time horizon. The variables considered as inputs in this study were weather variables including outdoor temperature, relative humidity and solar irradiance. These variables could reasonably be retrieved from local weather stations with good forecasting accuracy. Additional variables include the hour of the day, the set point temperature (the decision variable), and a binary occupancy profile. Furthermore, given that thermal inertia in a building is a considerable factor, the indoor temperature from the previous 3 timesteps was also considered to be an input. However, given that the requirement is to predict for the next 24 h, the prediction of indoor temperature at time *t* is used as the input to predict at time $t+1$. These predictions are rolled over until the full 24-h time horizon has been completed. For example, the prediction of energy consumption and indoor temperature at timestep 3 could use the predicted indoor temperature from timestep 1 and 2 as well as the initial measured temperature at the start of the optimisation.

The ANN were trained using the MATLAB ANN toolbox and once completed were tested against a 4-week long EnergyPlus simulation with variable set point temperatures and using an alternative weather file. When configuring an ANN, there are many tuneable parameters which can influence the quality of the resulting prediction model. These include the selected inputs, the number of hidden neurons in the hidden layers, the number of hidden layers, the training function and the transfer functions between layers. There is no leading method in the literature by which these parameters can be optimised therefore the authors have followed a largely trial and error based approach similar to the methodology outlined in Ref. [34]. Throughout the ANN architecture trials, the ANN accuracy was measured using the coefficient of variation of the root mean squared, CVRMSE, based on the 4-week testing data described above. The parameter with the largest influence on prediction accuracy was the selected inputs. It was found that including the indoor temperature from hour *t-2* and *t-3* as well as relative humidity made the accuracy of the ANN prediction worse, so these were removed as potential inputs. These results suggest that the thermal lag of the building zones is not long and only the previous hours' indoor temperature value is required. Furthermore, solar irradiance was found to decrease the accuracy when used as an input for zone 1 and 6, therefore this was removed from these zones' ANN. Varying the other ANN parameters had a much more limited effect provided two hidden layers were used and each layer held a reasonable number of neurons. The eventual architecture of the ANN for zone 1 and 6 was 5-20-20-2 and for zones 2 to 5 were 6-20-20-2 (shown in Fig. 2). The selected training algorithm was 'Levenberg-Marquardt backpropagation' and the transfer function between each layer was 'tansig'.

Table 1 displays the Pearson's' correlation between ANN output and target values during both the training and testing stage. The results display excellent prediction from the ANN. The consistency between the prediction results during the training phase and the testing phase shows no evidence of overfitting meaning the ANN has learned the general trends in the data rather than merely finding the best fit to the training data set. However, note that during the testing phase the previous indoor temperatures were assumed perfectly predicted. When deployed in the optimisation it is expected that prediction accuracy will decay slightly throughout the 24-h period due to prediction errors in Ti_{t-1}. The CVRMSE and the mean bias error (MBE) have also been reported graphically for both energy consumption (Fig 3) and indoor temperature (Fig 4). Fig 3 shows that the CVRMSE for the testing data is around 30% for each zone whilst the MBE remains within ±10%. This is higher than the comparative measures for the prediction of indoor temperature for which the ANN performs very well (CVRMSE around 2%). However, the poorer statistical performance of predicting energy

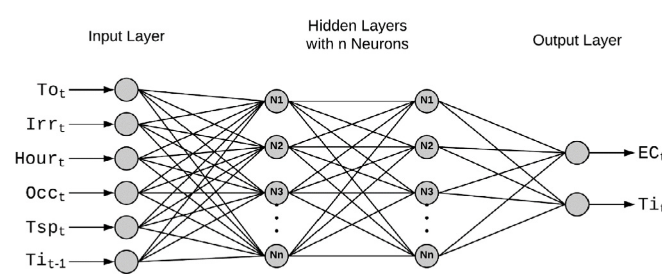

Fig. 2. ANN architecture for zone 2 to 5.

Table 1
Pearson correlation between input and output during training and testing.

Zone number	Zone name	r Value	
		Training	Testing
1	Downstairs Office	0.99964	0.99955
2	Kitchen	0.99987	0.99982
3	Reception	0.99980	0.99985
4	Meeting Room	0.99984	0.99981
5	PhD Office	0.99908	0.99941
6	Researchers Office	0.99971	0.99968

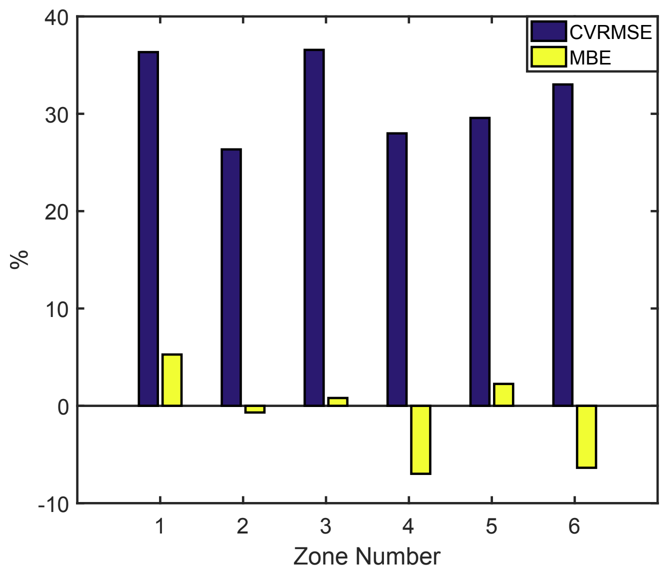

Fig. 3. Statistical measurements of ANN prediction for energy consumption.

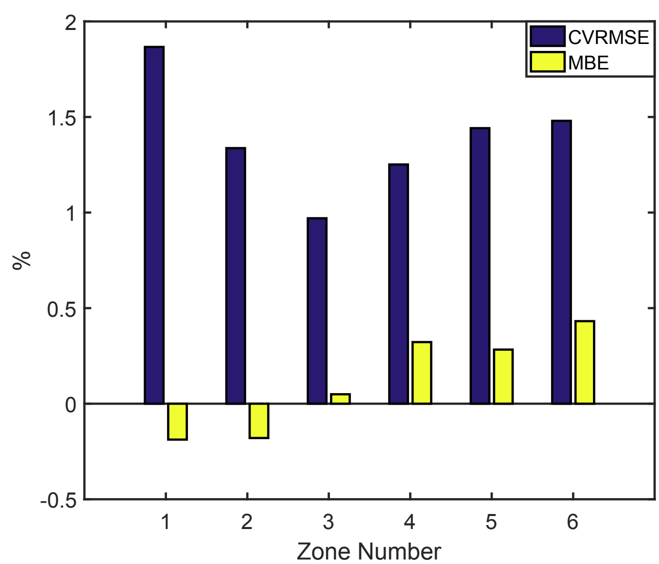

Fig. 4. Statistical measurements of ANN prediction for indoor temperature.

consumption is partly due to the nature of the data. Heating energy consumption is much more variable in nature with a few, large peaks but an overall low mean. This is significantly harder to predict than the gradual evolution of indoor temperature.

4. Optimisation strategy

As elaborated in the previous section, a GA is used to optimise each zone's set point temperature for the next 24 h. This section will provide finer detail of the optimisation process. A GA is a population based, meta-heuristic, searching algorithm inspired by the process of natural selection [35]. These have commonly been applied to building problems due to their ability to cope with non-linear characteristics often found within building control as well as their tendency to converge to the global optimal rather than local optimal solutions [36]. A GA contains a population of solutions, each individual solution contains 'genes', which in our case are 24 set point temperatures between 12 °C and 24 °C representing one value for each hour. Each individual solution is evaluated to assess its 'fitness' to the objective function. From this fitness, the individuals are ranked in order of preference and this determines their likeliness to 'crossover' with another individual to produce the next generation of solutions. Individual genes within a solution have an opportunity to 'mutate' to a random feasible solution and thus ensure that the optimisation does not get stuck in local minima. Some solutions are defined as 'elite' individuals, these represent the top percentage of solutions that pass to the next generation unchanged by crossover or mutation.

The process of producing new generations continues until a predefined stopping criterion has been met. This could relate to a maximum time, maximum number of generations, or related to the change in optimal solution over time. The MATLAB optimisation toolbox GA function was used in this paper, so it could be simply coupled with the ANN which were also developed in MATLAB. The exact parameters of the GA used in this paper is shown in Table 2. Note that the maximum number of generations is set to the MATLAB default of 100 multiplied by the number of decision variables which in this instance is relatively high. This allows the GA to exit in most cases by reaching the function tolerance which ensures that the GA has fully converged rather than forced to exit prematurely.

4.1. Objective function and fitness evaluation

The objective of this optimisation strategy is to minimise the energy consumption whilst maintaining thermal comfort by selecting the optimal temperature set point schedule, each hour, for each zone. The set point is free to vary between 12 °C and 24 °C during unoccupied periods and 20 °C–24 °C during occupied times as these were the temperature bounds requested by the occupants to maintain thermal comfort. Whilst the setting of these bounds forms a large part of ensuring thermal comfort is met a further internal penalty function is included. If the indoor temperature predicted by the ANN is below 20 °C or greater than 24 °C when the zone is occupied, then the energy consumption during that timestep is set at 100 kWh effectively excluding that solution from being competitive in the fitness evaluation and hence discarded. This penalty function is mainly necessary during the first occupied hour of the day where it is conceivable that the zone set point temperature would be above the lower bound of 20 °C but the indoor temperature would remain lower than this during the first hour while the zone warms up.

The fitness evaluation procedure developed in this paper is displayed in Fig. 5. The input variables are combined into one matrix with the appropriate structure to be inputted into the ANN. These include the outdoor temperature, solar irradiance, hour of the day, occupancy, temperature set point and previous indoor temperature. Once the inputs are collated, they are fed to the zone ANN which predicts energy consumption and indoor temperature for that timestep. Then follows the thermal comfort check to ensure

Table 2
Genetic algorithm parameter settings.

GA Parameter	Setting used
Number of Variables	24
Population Size	200
Creation Function	Uniform
Selection Function	Tournament
Crossover Function	Scattered
Elite Count	5%
Mutation Function	Uniform
Mutation Rate	0.1
Max Number of Generations	2400
Function Tolerance	1×10^{-5}

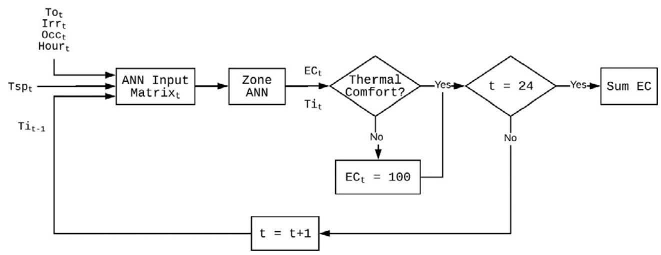

Fig. 5. Flowchart of the fitness evaluation procedure.

that during occupied hours the indoor temperature is predicted to be above 20 °C and below 24 °C. If this is not the case the energy consumption for that time step is changed to 100 kWh. Unless all 24 h have been calculated, the process loops around to repeat the calculation for the next timestep using the internal temperature prediction from the previous hour as an input. Once all 24 h have been completed, the energy consumption is summed over the 24 h and the resulting number is the solutions' fitness. A GA using the described procedure is completed for all 6 conditioned zones. This procedure can be accomplished in parallel to reduce optimisation time as each zone optimisation is independent and not reliant on inputs from other zones.

4.2. MPC adaptations

The optimisation procedure described in the previous subsection can be run once at midnight and produce a schedule for the following day provided it has 24-h weather and occupancy predictions and the initial zone temperatures. However, in this study, the effect of implementing this strategy as MPC will also be assessed. When implemented 24-h ahead without MPC, errors in temperature prediction at earlier timesteps can lead to compound errors later in the day. Once set, the entire heating set point schedule would be enacted regardless of any unforeseen changes in circumstances. However, if implemented as MPC, the optimisation would be run every hour, still with a 24-h time horizon. This would allow feedback from the building system of internal temperatures allowing the controller to react to any prediction errors or receive a more up-to-date weather forecast. Running as MPC means the 24-h set point schedule is updated and changed every hour but only the first hour of each optimisation is ever enacted.

As this is a simulation based case study, the 'real' building is replicated by an EnergyPlus simulation model thus a method of automatically linking the EnergyPlus model and the MATLAB optimisation procedure was required. The Building Controls Virtual Test Bed, BCVTB [37], middleware software was used to achieve this. The data interchange, facilitated by BCVTB, was set up so that on the hour the indoor temperatures of each zone are recorded from the simulation model. Using these initial values, the optimisation procedure could run and generate a 24-h set point schedule for each zone that was sent back to BCVTB to be implemented in the EnergyPlus model. The simulation model would then continue for the next hour with the first set point values. Once this hour was complete the temperature was again recorded by BCVTB, passed to MATLAB and the optimisation is run again with the updated, 'real', temperatures from the building. Therefore, only the first hour of the optimal set point schedule is ever implemented but the optimisation time horizon remains at 24-h to give it the foresight to plan ahead and allow the possibility of pre-heating or turning off early. Note that the optimisation procedure that takes place each hour is identical to that described in Section 4.1, however it occurs every hour rather than just once at the beginning of each day. If deployed in reality, instead of using the EnergyPlus simulation model, you would simply record the measured indoor temperature in each zone before carrying out the optimisation. The procedure is displayed in the diagram shown in Fig. 6.

5. Optimisation results

In this section the GA-ANN, zone level, heating set point scheduler will be applied during a test week in February using actual, 2016, weather data from a nearby weather station in Cardiff which was converted to an epw file for use in EnergyPlus. To provide a comparison, a baseline scenario has also been developed. This uses the current heating set point strategy of the building which is 21 °C during the occupied hours (08:00 to 19:00) and 12 °C during unoccupied hours in all 6 conditioned zones. First, the optimisation will be run as day ahead scheduling and then as MPC with a 1-h timestep and 24-h control horizon. Note that in both cases the schedules resulting from the optimisation will be put back into EnergyPlus to validate the results. This allows fair comparison with the baseline scenario as both simulation models are identical (including weather conditions) apart from the heating set point schedule of the zones. This also removes any influence ANN prediction errors may have to allow true evaluation of the effect of the optimised set point strategy.

Two optimisation scenarios were run, one where there is a standard, flat pricing tariff and one using a time of use, TOU, tariff. In the first scenario, the optimisation will aim to minimise energy consumption and hence cost will also be minimised. When the time of use tariff is used the optimisation will aim to minimise electricity cost for heating which will not necessarily minimise energy consumption. The optimisation requires minimal adjustment to achieve this objective change. Given that the energy consumption at each hour is already calculated during the optimisation, this is simply multiplied by the price per kWh at that particular time of day which is the same for every weekday. Whilst popular in continental Europe and parts of America, TOU tariffs have still yet to achieve significant penetration in the UK. However, this is predicted to change after a government backed roll-out of smart meters and the first widely available TOU tariff is now available from Green Energy UK, [38]. The energy prices from their TIDE tariff is that used in Section 5.2 and the price variation is shown in Fig. 7. Energy is cheapest, £0.0499/kWh, from 23:00 to 06:00 and has peak prices of £0.2499/kWh between 16:00 and 19:00, all other hours are an intermediate price of £0.1199/kWh.

5.1. Standard energy tariff

The optimisation strategy was run for each day from the 15th to the 19th of February and the subsequent schedules were compiled

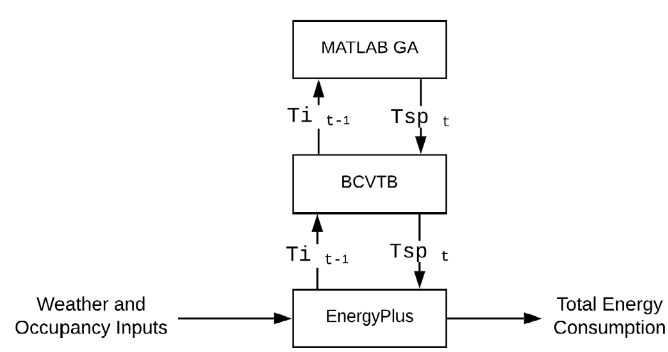

Fig. 6. MPC procedure using BCVTB.

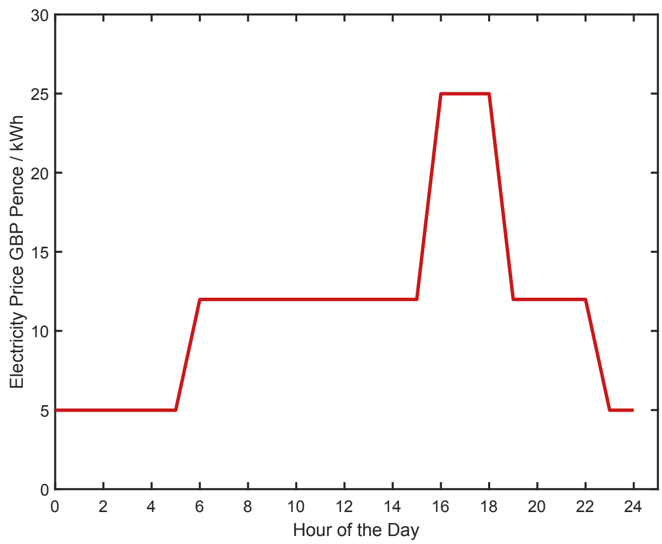

Fig. 7. TIDE tariff electricity price on weekdays.

Table 3
Optimisation results using a standard energy tariff.

Zone	Energy consumption/kWh			Savings vs baseline/%	
	Baseline	Day ahead	MPC	Day ahead	MPC
Downstairs Office	30.82	27.05	27.17	12.22	11.84
Kitchen	16.16	1.84	1.79	88.62	88.90
Reception	42.08	39.84	39.14	5.32	6.98
Meeting Room	50.92	7.66	7.39	84.96	85.48
PhD Office	121.92	101.31	102.08	16.91	16.27
Researcher Office	58.25	57.93	63.73	0.54	−9.41
Whole Building	320.15	235.63	241.31	26.40	24.63

into a week-long schedule (note the optimisation does not run on weekends). The energy consumption of each zone under both optimisation strategies is shown in Table 3. There is a very minor difference between the day ahead optimisation and the MPC. In fact, the day ahead optimisation slightly outperforms the MPC with the main difference coming in the researcher office. Both optimisations show the potential for around 25% energy savings over the course of this test week. The main source of the energy savings come from the kitchen and the meeting room which are sporadically occupied but are currently heated all day reflected in the baseline scenario. The zones that achieve the lowest energy savings, the reception and the researcher office, are directly adjacent to the meeting room. Therefore, the lower energy savings in these zones are not necessarily a failure of the optimisation but due to the lack of heat gain from the meeting room which is now only heated for a fraction of the time. Furthermore, zones such as the downstairs office achieve energy savings over the baseline strategy whilst still having the same 08:00–19:00 occupied hours. To understand these savings, Fig. 8 shows the set point schedule, indoor temperature and energy consumption for the downstairs office on the 15th of February for both the baseline and optimal scenario. As this figure shows, the optimal strategy chooses to more gradually heat the room with some heating between 07:00 and 08:00, it then targets a lower temperature just above the 20 °C bound during the morning, both of which result in a much lower morning peak. Between 12:00 and 15:00, when the solar gains are higher, the optimal strategy chooses to heat the building to a higher temperature to make the late afternoon energy peak, at around 19:00, lower than that of the baseline scenario. In summary, both optimisation modes have shown significant energy savings can be made by allowing a smart scheduler to have the freedom to vary set point temperatures between pre-defined bounds and by actively considering occupancy and external weather conditions. This energy saving comes with no impact on the thermal comfort for occupants as the temperatures remain above the 20 °C lower bound. However, it has not demonstrated the value of MPC over a simpler day ahead scheduling approach.

5.2. Time of use tariff

Both the day ahead optimisation and the MPC optimisation were run again to include the TIDE TOU tariff and altered to minimise cost of heating. The same week was studied using the same weather conditions. The same baseline scenario is used which does not make any attempt to adjust to the new pricing regime. The results of these optimisations are shown in Table 4. As is clear, under the TOU tariff optimisation the energy savings are lower compared to that shown in Section 5.1. This is because the optimisation objective function is now related to minimising the cost of energy, not the energy consumption itself. In terms of cost, the savings compared to the baseline are around 27% and once again there is very little difference (£0.32 over the week) between the MPC optimisation scheme and the day ahead control strategy. Fig. 9 is a representative example of the approach the optimisation tried to take during the TOU scenario. The figure shows that the optimisation attempts to pre-heat between 05:00 and 06:00 which is the last time period where the electricity price is at its lowest. Furthermore, there are smaller energy consumption spikes at 13:00 and 15:00 with the aim of reducing the energy consumption during the on peak price period of 16:00–19:00 which it successfully achieves when compared to the baseline strategy.

5.3. Discussion

The results shown in Section 5.1 and 5.2 clearly indicate that implementing a smarter, more context aware building controller can lead to improvements over traditional static control. Optimising at a zone level rather than setting a building level strategy can lead to significant energy and cost savings. The ANN surrogate models developed in this paper have been proven to be accurate enough to replicate the simulation model in this case study. However, future work will aim to implement this control strategy on a real case study building in the future to validate this conclusion. The optimisation strategy has proven to be flexible to a changing energy environment. It was simply adapted to take into account a TOU tariff. Further adjustments could simply be made to factor in local renewable resources or demand response events as part of a district heating network potentially benefitting the energy provider as well as the consumer.

Throughout both tariff scenarios, the results show negligible difference between the day ahead optimisation and the MPC optimisation. This contradicts results published in many other state of the art building control papers. However, this may be due to the lack of uncertainty in the testing scenarios presented in this paper. Both occupancy and weather conditions are assumed known in advance and these forecasts are assumed 100% accurate which would not be true in practice. Therefore, future work will introduce forecasting uncertainty and assess the impact on the two optimisation scenarios. The hypothesis being that the MPC optimisation will adjust to these uncertainties better than the day ahead prediction.

An additional point of future work will aim to create a mechanism by which each zones' optimisation can influence adjacent

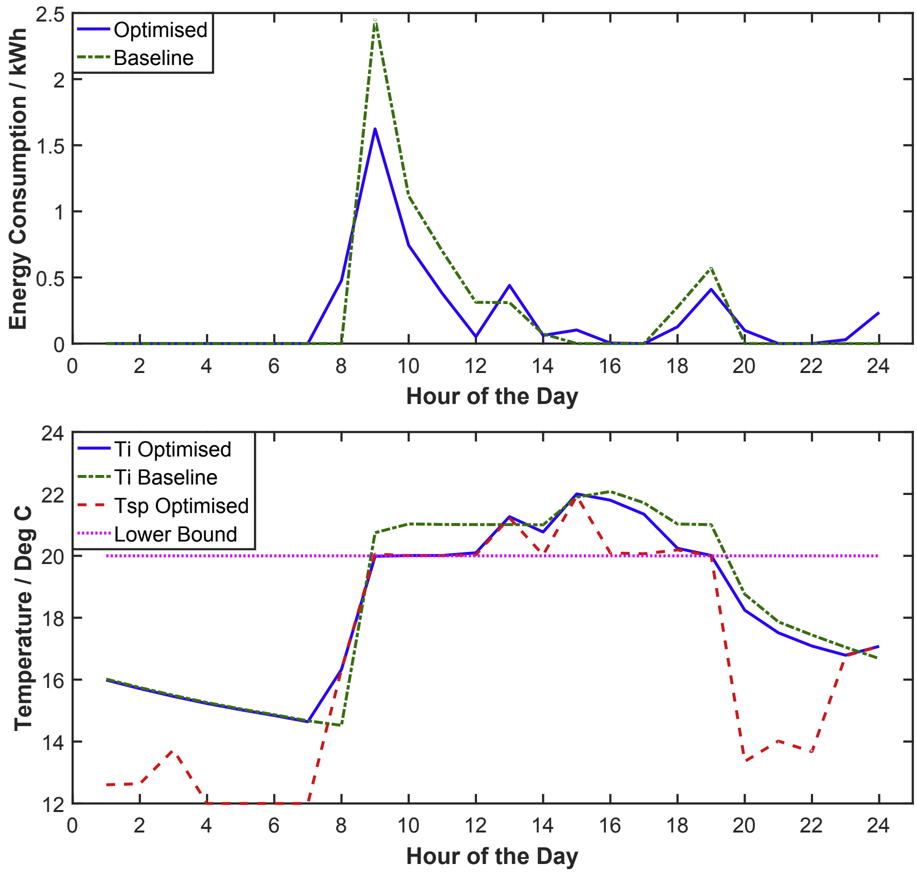

Fig. 8. Comparison between MPC optimisation and the baseline; for energy consumption (above) and indoor temperature (below) on the standard energy tariff, in the downstairs office (Feb 15th).

Table 4
Optimisation results using a TOU energy tariff.

Zone	Baseline scenario		Energy savings/%		Cost savings/%	
	Energy/kWh	Cost/£	Day ahead	MPC	Day ahead	MPC
Downstairs Office	30.82	4.335	1.55	−5.13	9.87	6.84
Kitchen	16.16	2.443	90.01	88.18	92.32	91.11
Reception	42.08	6.001	5.44	6.13	8.20	10.18
Meeting Room	50.92	7.409	83.46	79.50	87.62	86.60
PhD Office	121.92	18.296	15.49	14.73	19.16	17.66
Researcher Office	58.25	8.386	−6.96	−9.53	−0.88	−0.04
Whole Building	320.15	46.869	23.31	21.28	27.94	27.26

zones. In this study, each zone is optimised separately. This was a conscious decision to allow each zone optimisation to run in parallel, hence reducing the total optimisation time to the order of 10 min. Despite the lack of interaction between the zone optimisations the proposed procedure was able to achieve significant energy savings with no loss to thermal comfort. This was likely due to the set point schedules not deviating significantly day-to-day, the optimisation altered set points only somewhat. Therefore, the heat transfer from zone to zone did not vary enough to have a significant impact and prevent the optimisation working. Future work will aim to pre-screen case study buildings in order to assess closely coupled zones and develop a method by which decisions made in one zone are transmitted to the second.

To be able to practically deploy this solution to a real building would require a reasonably small amount of additional hardware. The optimisation procedure would require zone level temperature sensors and direct control of heating units. Currently, there is a significant surge in interest and availability of smart home devices controlled by a central AI coordinator using the paradigm of IoT. It is therefore feasible and indeed probable that most future (and some current) buildings, both commercial and residential, will have the capability to control individual room set points and devices through an integrated system. The proposed optimisation procedure would sit above these physical systems requesting and sending relevant information (set points and indoor temperatures) taking advantage of existing physical and network infrastructure. It is envisaged that this control scheme would be more applicable to commercial buildings initially. This is due to occupancy patterns being more clearly defined and predictable within office buildings and the fact that occupants do not necessarily expect to have direct control over the heating systems.

The most significant challenge in the application of this control

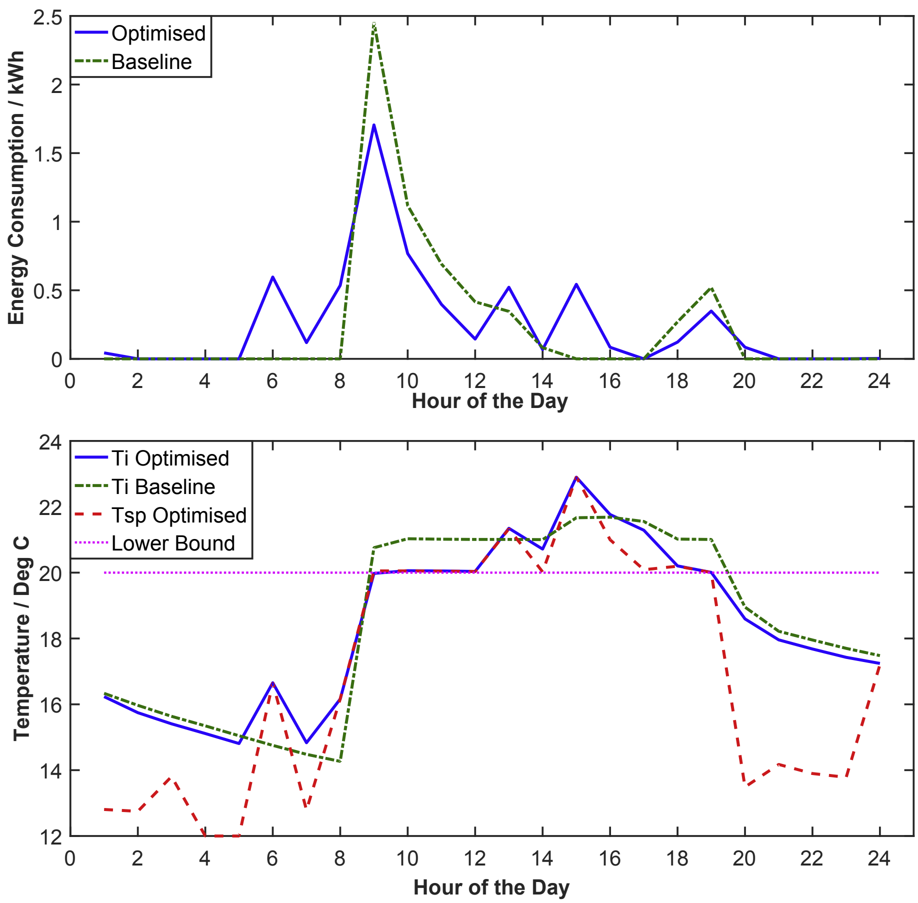

Fig. 9. Comparison between MPC optimisation and the baseline; for energy consumption (above) and indoor temperature (below) on the TOU energy tariff, in the downstairs office (Feb 16th).

strategy is the development of the surrogate models for the prediction of energy consumption and indoor temperature. The approach used in this study was to train an ANN based on large amounts of simulated data. However, accurate simulation models are not widely available for most buildings. It is theorised that building simulation models are likely to become more available in the future, driven by government legislation aiming at reducing energy consumption from buildings and improving retrofitting procedures. This is leading to increased prevalence of Building Information Modelling, BIM, which are increasingly including energy analysis modules. Researchers are working on methods to capture existing building information, convert to a digital representation, from which generate a building energy simulation model and calibrate the model based on existing historical data [39]. Alternatively, if the case study in question has developed a significant log of historical energy consumption and temperature data, machine learning models could be directly generated from this. To model at an hourly or sub hourly temporal scale the authors' believe that specific ANN would be required for each building as generic ANN based on broader building categories would not be able to capture the intricacies if an individual building.

The authors also argue that any such building energy optimisation strategies should be performed within a semantically enriched environment. A semantic model should encompass aspects relating to energy consumption and management both within the building and beyond to wider local energy networks. This method of linking data combined with the increased sensing capability that could be provided by the IoT could provide the basis for improved knowledge mining and feature extraction. For example, the system could assess wider environmental variables to investigate correlation between these and energy saving actions. It could also lead to more advanced reasoning to allow better prediction or measurement of building occupancy.

6. Conclusion

This paper has shown the development of a GA-ANN, zone level, heating set point scheduler. A simulation model produced a bank of training data from which zone level ANN could be trained. These took weather, occupancy, set point schedule, and previous indoor temperature as inputs to predict the energy consumption and indoor temperature at the next timestep. A GA then used the ANN as an evaluation engine to calculate the energy consumption over 24 h as the fitness function. GA optimisation of each zone took place in parallel to create bespoke set point schedules for each zone, each day.

The optimisation was run in two modes, day ahead optimisation and MPC. In day ahead mode, the optimisation was carried out once at the beginning of the day whereas the MPC strategy re-optimised every hour with updated information. Furthermore, two scenarios were considered, one using a standard flat pricing electricity tariff and the other using a TOU tariff. Using the standard tariff, the optimisation reduced energy consumption by around 25% in both modes. With the TOU tariff the objective was altered to minimise cost and the optimisation achieved a cost reduction of around 27% for both modes successfully shifting load to cheaper pricing periods.

Future work will introduce weather and occupancy forecasting uncertainties and assess how the two optimisation modes deal with this. Future work will also aim to integrate an optimisation strategy like this as part of a wider district or microgrid setting. Finally, once robust enough we aim to implement this control strategy on a real case study rather than a simulated building to validate the results in a real-world trial.

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Nomenclature

Abbreviation

IoT: Internet of Things

PV: Photovoltaics
DR: Demand Response
TOU: Time of Use
ANN: Artificial Neural Network
MPC: Model Predictive Control
BMS: Building Management System
BCVTB: Building Controls Virtual Test Bed
HVAC: Heating Ventilation and Air Conditioning
AHU: Air Handling Unit
MILNP: Mixed Integer Non-Linear Programming
PMV: Predicted Mean Vote
RC: Resistor Capacitance
GA: Genetic Algorithm
CVRMSE: Coefficient of Variation of Root Mean Squared Error
MBE: Mean Bias Error
BIM: Building Information Modelling

Optimisation

To: Outdoor Temperature
Irr: Solar Irradiance
Occ: Occupancy
Tsp: Temperature Set Point
Ti: Indoor Temperature
EC: `Energy Consumption
t: Current Timestep