Optimised building energy and indoor microclimatic predictions using knowledge-based system identification in a historical art gallery

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Abstract

This paper presents a system identification (SID) model for an historical art gallery of great cultural significance. These buildings require tight indoor temperature and moisture controls that demand significant energy from air handling units. Complex dynamic building systems, stringent conservation restrictions, and lack of detailed monitoring make diagnosing and optimising their energy use difficult. Building simulation software programmes have proven to be effective, but have tended to rely on data generated by simulation models. This study shows how artificial neural network (ANN) models trained with historical real data can predict a building's energy use and the optimal indoor microclimate necessary for conservation. Four ANN target-data scenarios were designed for optimised model predictions, and 12 ANN training algorithms were tested with six architectural scenarios collecting daily and hourly data. The ANN models used a randomised 80% sample of the database, with the remainder (20%) validating the models. The model displayed a high coefficient of correlation (0.99), with the mean square error and mean absolute error less than 0.1% and 2%, respectively. This ANN-based SID tool efficiently represents a complex building system and could be an ideal method for investigating optimisation strategies prior to their implementation.

Keywords System identification · Artificial neural networks · Energy prediction model · Indoor microclimatic control · Optimisation · Historical art gallery building

Abbreviations

AHU	Air handling unit
ANN	Artificial neural network
BMS	Building management system
C1–C4	Case 1–Case 4
CAV	Constant air volume system
DC	Daily case
HC	Hourly case
HVAC	Heating ventilation and air conditioning
HWD	Hourly weights distribution
MAE	Mean absolute error
MSE	Mean square error
NGS	National galleries of Scotland
SID	System identification
TDb	Training database
PDb	Prediction database

List of symbols

A	Area (m ²)
C_p	Specific heat (kJ/kg K)
E	Electricity consumption (kW)
g	Moisture content (kg/kg dry air)
G	Gas consumption (kWh)
H_i	ANN hidden layer
I_n	ANN input layer
i, j, k	Hidden layer notations
$\dot{m}$	Mass flow rate (kg/s)
n	Outdoor air damper (%)
n_{HVAC}	HVAC's contribution in energy consumption
N_m	Number of days in month
N_{occ}	Number of occupants
R	Coefficient of correlation
RH	Relative humidity (%)
T	Temperature (°C)
T_a	ANN target layer
$\dot{v}$	Volumetric air flow rate (m ³ /s)
V	Volume (m ³)
W	ANN synapse weight
x	ANN neuron input

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X	Input variable
y	ANN neuron output
Δh_{vap}	Latent heat of vaporisation (kJ/kg)
φ	Sensible heat (kW)

Subscripts

b	Bias
D	Daily
h	Hourly
hh	Half-hourly
m	Mixed
M	Monthly
nth	Non-thursday weekday
o	Outdoor
occ	Occupants
R	Room
ret	Return
s	Supply
th	Thursday

1 Introduction

Buildings represent the largest energy-consuming sector in the economy with over one-third share of all the final energy use and half of the global electricity consumed [1]. In the EU alone, the building sector accounts for 40% of all the energy consumption and 36% of global CO₂ emissions [2]. More than one-third of the energy demand of industrialised countries is due to achieving acceptable conditions of thermal comfort and lighting in buildings [3]. In special purpose buildings such as museums and art galleries, most of which are housed in historical buildings, there is an added energy demand from the buildings' heating ventilation and air conditioning (HVAC) systems to maintain the indoor humidity and temperature at adequate levels specified by the conservation standards for preserving all the historical collections [4–7]. These set points are usually very tight and narrow, demanding considerable amount of HVAC energy investment [8, 9].

Driven by the pressure of cutting down the building energy consumption, the management of these special purpose buildings seek to several potential measures to induce energy savings from all the aspects of building design [8]. This is by no means an easy task. Firstly, designing and implementing an energy saving intervention measure are complex in nature [10]. Secondly, most of the special purpose historical buildings impose restrictions, forbidding any retrofit solutions to be implemented that may alter the original appearance and character of the building [11]. Thirdly, the strategy of using the building air handling unit (AHU) needs careful planning, satisfying a

balanced optimisation for both ensuring proper microclimatic controls as well as energy savings [12]. Hence, it is imperative for the building management to monitor, predict, and analyse the indoor environment and energy use to target adequate future energy saving and optimisation programs.

It is known that the first step for optimising energy use in buildings is to have a mean for adequate energy use prediction [1], not only for the building owners but also for urban planners and energy suppliers. With the potential of buildings to contribute towards the reduction in CO₂ emissions well recognised [2], urban planners seek to prediction of building energy systems to assess the impact of energy conservation measures [13]. It is also known that the building energy and indoor environmental prediction model form the core of a building's energy control and operation strategy design to induce energy savings including peak demand shaving [14, 15]. However, due to cost constraints, building energy systems are typically not well measured or monitored. Sensors are only installed when they are necessary for certain control actions. Sub-metering for building's energy sub-systems is also not commonly available in a building [15]. These problems lead to a lot of vital information not available to better understand the existing building system. A number of data model analyses, developed in recent years, cater to the need of obtaining building energy prediction and optimisation strategies while tackling the associated problems of system uncertainties and data availabilities. Building thermal and energy performance modelling is very complicated. It requires substantial and quality data input. The gap between design predicted and actual performances is common and mainly due to discrepancy of the two sets of data [16, 17]. For old buildings, a great amount of data is not available and the information for study is usually based on the best assumption, which further enlarges the gap [16, 17].

Some of the modelling approaches followed white-box modelling, involving detailed physics-based dynamic equations to model the building components [18–20]. A number of mature white-box software tools, such as EnergyPlus, ESP-r, IES, TAS, and TRNSYS, also exist, and they simplify the manual modelling process using this technique [21]. However, even though the tools are effective and accurate, these approaches bear the drawback of requiring detailed information and parameters pertaining to the buildings' energy systems, system components, and outside weather conditions, all of which are difficult to obtain or at times, unavailable [15]. Also, creating these models demand a lot of calculation time investment and expertise [10]. Some other approaches follow the grey-box Modelling strategy, such as resistance and capacitance model or lumped capacitance model, representing the

building elements in an analogue circuit [22, 23]. These approaches reduce the requisite amount of training dataset and calculation time. Model coefficients are identified based on operational data using statistics and parameter identification [24–26]. However, the parameter computation process is often computationally demanding and time-consuming, and developing the structure of the grey model requires expert knowledge [10, 15].

This is where black-box models, or purely data-driven models, are beneficial as they are easy to build and computationally efficient [15, 27–29], especially when a large amount of historical data is available to train the models. Multiple linear regression and self-regression methods were combined to predict building monthly energy consumption [30]. Fuzzy inferences system is also extensively used [31, 32]. Autoregressive with exogenous (ARX) model was developed to predict building load in [33]. An optimal trade-off between comfort and energy using a meta-model based on regression techniques was developed in [34]. Another simple and easy to implement building energy tool is the degree-day model [35]. However, linear models are obtained around a specific working condition and hence cannot guarantee a satisfactory approximation performance under varying working environments [36]. Artificial neural networks (ANN) have also been extensively used in the past 10 years for their outstanding approximation ability of nonlinear mapping along with online learning. The application of ANN models in building modelling sector has mostly been towards prediction and optimisation of building energy consumption [25, 37, 38], cooling loads [35, 39–41], temperature [10, 36, 42], and system identification [43–45]. System identification, which is the process for developing or improving a mathematical representation of a physical system using data collection, is widely used in engineering problems, but with limited use in building system modelling [46, 47].

In this study, the feasibility of using ANN to predict the indoor environmental conditions and energy consumption inside an art gallery housed in historical building is demonstrated by means of developing knowledge-based SID models using a set of real data collected from the building management system (BMS). The real data bring an added advantage over simulation model-generated database in terms of closeness in representing the actual world. The study comprises of two sub-categories. Firstly, a simplified ANN-based system identification program is developed and tested, which can model the building's energy system comprising of the HVAC system. Secondly, this model is used to predict future energy consumption and indoor microclimatic conditions in the building based on carefully selected set of inputs.

This paper is arranged as follows. While Sect. 2 describes the historical art gallery considered for this study, Sect. 3 outlines the research methods implemented for processing data, developing the ANN models and obtain the SI model after selecting the optimal ANN architecture. Section 4 describes the results obtained followed by a conclusion of key points of this study in Sect. 5.

2 The national galleries of Scotland

2.1 Building characterisation

Built in the mid-nineteenth century, this neoclassical building houses a number of important and highly valuable European masterpieces and Scottish works, currently with over 96,000 works in the permanent collection. Apart from the famous artworks, the building itself is classified by the Scottish Government as an 'A listed' building. This highlights its international importance, and the restrictions imposed to protect the character of the building (special architectural or historic interest) while allowing its continued use. The restrictions allow only non-invasive methods to monitor the building environment and nearly impossible to apply any retrofit solutions.

The building is stone-built with thick exterior walls of about 1 m in width. These walls are without fenestration, and all the natural lights in the building come from the skylights installed at the curved roof cupolas [8]. To ensure the good health of these delicate historical collections, it is a must to have a tight indoor microclimatic control.

The building consists of three levels—basement, ground, and first (Fig. 1). All the floors house a number of gallery rooms—B1–B15 at basement, 1–13 on ground floor and A1–A6 on the first floor. While the north and south gallery rooms above the basement have two levels, the central gallery rooms are double story in height, accommodating colossal paintings. In this study, one of these central gallery rooms, Gallery-11, is considered owing to historical data availability and management permission.

The building is open from 10:00 to 17:00 h every day except on Thursdays, in which case it is open till 19:00 h. An average of 280 visitors per hour is recorded by the building management.

2.2 HVAC system description and study data

All the gallery rooms are served by a set of four AHUs, to maintain the indoor microclimate as per the artwork conservation requirements. Table 1 describes all the AHUs and the rooms served by them. Gallery 11, the room considered in this study owing to data availability, is served by AHU-1 (Fig. 2). This AHU, similar to other units, provides

Fig. 1 NGS floor plan and levels

Table 1 Different zones served by AHUs at the NGS

AHU (zone)	Rooms served	Volume served (m ³)	Treated floor area (m ²)	Supply air flow rate (m ³ /s)
1	1–4, 10–12, A1	6984	919	3.96
2	5–9, A2–A6, store, mess room	4121	643	3.46
3	Basement galleries, print room	3090	1030	2.9
4	Basement offices, library	1324	480	2.9

Fig. 2 NGS HVAC system and AHU serving different rooms

a mixture of outdoor air and recirculated room air to the room after passing the mixture through filters, which is then cooled, heated, and humidified as and when required (Fig. 3). The treated air enters the gallery spaces through linear grilles located at high level and returns air at low level. Air flow to each gallery space is fixed by manual dampers in the duct, and the fans operate at constant speed (CAV). The plant is controlled by the building management system (BMS) with its current control philosophy set

to achieve the desired indoor environmental conditions as specified in Table 1.

BMS sensors are installed at various parts of the HVAC system to monitor the system functioning. However, the only measuring points or nodes where a comprehensive sequence of historical real data recordings available were the T and RH recordings for supplying air from a AHU and return air back to the AHU. Data for individual components of an AHU were not available for the requisite long periods

Fig. 3 NGS AHU system and four measurement nodes (outdoor, supply, room, return)

to train and test an ANN. Hence, the AHU is treated as a black box in this study and the ANN is trained with the only real data which was available—supply and return, along with room (Gallery-11) and outdoor T and RH.

3 Research methods

The concepts and corresponding functions of the case studies and ANN models are described. The scientific grounds of the developed approach are established.

3.1 HVAC system functioning

For any time instance, the room demands a certain investment of energy to maintain the indoor microclimate as per the conservation requirements. This energy demand, or the room load, comprises of a sensible component and a latent component. While the sensible component considers the load to maintain room air T, the latent component caters to the indoor moisture content. Equation (1) highlights the room load.

$$\text{Room load (kW)} = \dot{m}C_p(T_r - T_s) + \dot{m}\Delta h_{\text{vap}}(g_r - g_s) \quad (1)$$

where $\dot{m}$ is the mass flow rate of supply air (kg/s), C_p is the specific heat capacity of air (kJ/kg K), T_r is the room air temperature (°C), T_s is the supply air temperature (°C), Δh_{vap} is the latent heat of vaporisation of steam (kJ/kg), g_r is the absolute moisture content of room air (kg moisture per kg dry air), and g_s is the absolute moisture content of supply air (kg moisture per kg dry air).

The energy demand on the building's HVAC system to deliver this room load depends on the variations in outdoor air and the work done by the system to maintain the indoor T and RH as per the conservation requirements. The monitored parameter inside art gallery is RH, which is a representation of moisture content in air relative to the total

moisture holding capacity of air at that current air temperature. Equation (2) highlights the energy investment required on the AHU

$$\text{System load (kW)} = \dot{m}C_p(T_s - T_o) + \dot{m}\Delta h_{\text{vap}}(g_s - g_o) \quad (2)$$

where T_o is the temperature of outdoor air (°C) and g_o is the absolute moisture content of outdoor air (kg moisture per kg dry air).

However, as an energy saving measure, instead of feeding a full batch of fresh air into the AHU for treatment, a fraction of room air is recirculated back into the AHU as return air. The remaining fraction of outdoor air is mixed with return air to ensure optimal indoor microclimatic condition for occupants' health and safety. The system load then corresponds to the one described by Eq. (3)

$$\text{System load (kW)} = \dot{m}C_p(T_s - T_m) + \dot{m}\Delta h_{\text{vap}}(g_s - g_m) \quad (3)$$

where m corresponds to the mixture of return air and outdoor air. T_m is the temperature of the mixed air (°C) and g_m is the absolute moisture content of the mixed air (kg moisture per kg dry air). Assuming that the thermal capacity of returning air and outside air is identical, the T and g at this state is obtained using Eqs. (4, 5).

$$T_m = \frac{nT_o}{100} + \left(1 - \frac{n}{100}\right)T_{\text{ret}} \quad (4)$$

$$g_m = \frac{ng_o}{100} + \left(1 - \frac{n}{100}\right)g_{\text{ret}} \quad (5)$$

Since RH is a function of g and T , Eq. (5) leads to Eq. (6) as follows

$$\text{RH}_m = \frac{n\text{RH}_o}{100} + \left(1 - \frac{n}{100}\right)\text{RH}_{\text{ret}} \quad (6)$$

Occupants contribute transiently towards the indoor heat and moisture gains, and hence, the number of occupants is considered in the development of the hourly ANN model. The sensible and latent contribution from occupants

towards indoor environment is denoted by Eqs. (7, 8) [25, 37, 38],

$$\varphi_{\text{occ}} = (-4.46T_r + 176)N_{\text{occ}} \quad (7)$$

$$\dot{m}_{\text{occ}} = \frac{4.46T_r - 46}{\Delta h_{\text{vap}}} N_{\text{occ}} \quad (8)$$

where φ_{occ} is the sensible heat arising from N_{occ} number of occupants in a room at a time.

Apart from these, the indoor T and RH interacts with the outdoor air through the building fabric and infiltration. Moreover, there are several inter-zonal interactions and coupling effects which can affect the T and RH to vary in time. The high thermal mass of the building material and moisture buffering agents inside the building add a time lag to the response of indoor microclimate with the various variations causing sources. All these relations are nonlinear in nature, and hence, ANN models are implemented owing to their strength in modelling nonlinear systems effectively.

3.2 ANN model

3.2.1 ANN input and target: data-processing scenarios

Table 2 presents the input and target variables considered for the ANN models. It was observed that these parameters were not uniform in terms of their scope, for instance, the energy data available is that for the entire building block, whereas data pertaining to T and RH are limited to a particular room (Gallery-11) or zone (AHU-1). Moreover, the frequency of the data samples was non-uniform—the BMS

records T and RH at every 15-min intervals, while the data obtained for gas consumption was half-hourly and electricity consumption was on monthly basis. To achieve consistency in the available data, certain assumptions were made along with appropriate data processing by means of four case study scenarios. Finally, the case with the best performing ANN model and accuracy in terms of model predictions are chosen as the SID model representing the NGS indoor microclimate and energy consumption (Table 3).

The following assumptions were made for various data-processing scenarios

1. The density of air and flowrates is constant (Case 1–4).
2. The electricity consumption is same for each day of month (Case 1–4)
3. The indoor environmental conditions are represented by the ones measured in Gallery 11 and is uniformly distributed (Case 1, 3).
4. The zones have no boundaries (internal walls) between them. All the AHUs work collectively to maintain the Gallery 11 conditions in the entire space (Case 1, 3).
5. All the zones are bounded with perfect insulation for heat and mass transfer (Case 2, 4).
6. Gallery 11, which receives a fraction of the work output from AHU1, is isolated from the rest of the zone in terms of heat and mass transfer (Case 2, 4).
7. Each zone has separate indoor T and RH maintained by their corresponding AHUs and is uniformly distributed over the zonal volumes (Case 2, 4).

Table 2 ANN input and target layers after data processing for daily and hourly analyses

Input (I) parameters	Input analysis				Target (T) parameters	Target analysis			
	Hourly (H) analysis	Daily (D) analysis	Min	Max		Min (H)	Max (H)	Min (D)	Max (D)
Day	X	X	1	31	T_r (°C)	19	23	19	23
Month	X	X	1	12	RH_r (%)	45	55	45	55
Year	X	X			E_{C1} (kW)	50	183	1722	2751
Hour	X	–	1	23	G_{C1} (kW)	0	309	1108	4516
Occupants	X	X	1	1960	E_{C2} (kW)	1.5	5	52	82
$(1 - n) * T_{\text{ret}}$ (°C)	X	X	6.61	19.69	G_{C2} (kW)	0	16	60	244
$(1 - n) * RH_{\text{ret}}$ (%)	X	X	44.57	65.66	E_{C3} (kW)	63	166	1646	3408
T_s (°C)	X	X	13.28	35.09	G_{C3} (kW)	0	309	1108	4516
RH_s (%)	X	X	18.40	84.23	E_{C4} (kW)	2	5.47	54	112
$n * T_o$ (°C)	X	X	– 0.1	1.22	G_{C4} (kW)	0	9.83	35	143
$n * RH_o$ (%)	X	X	0.97	5.21					
T_o (°C)	X	–	– 2.06	24.26					
RH_o (%)	X	–	19.40	100					

Table 3 Data-processing case study variables (a) daily, (b) hourly

Inputs:	Gas (half-hourly)	Electricity (monthly)	
(a)			
Case 1	$G_D = \sum_1^{48} G_{hh}$	$E_D = E_M \div N_M$	(9)
Case 2	$G_{D,G11} = \sum_1^{48} G_{hh} \times \frac{V_{G11}}{V}$	$E_{D,G11} = \frac{E_M}{N_M} \times \frac{A_{G11}}{A}$	(10)
Case 3	$G_D = \sum_1^{48} G_{hh}$	$E_D = E_M \times \frac{n(H)_D}{n(H)_M}$	(11)
Case 4	$G_{D,G11} = \sum_1^{48} G_{hh} \times \frac{V_{G11}}{V}$	$E_D = E_{D,case3} \left[\left\{ \frac{V_{G11}}{V} \times n_{HVAC} \right\} + \left\{ \frac{A_{G11}}{A} \times (1 - n_{HVAC}) \right\} \right]$	(12)
(b)			
Case 1	$G_h = \sum_1^2 G_{hh}$	$E_{h,nth} = \begin{cases} a \times \frac{E_D}{24}, t \in (1000 \text{ h}, t) 1700 \text{ h} \\ b \times \frac{E_D}{24}, 1000 \text{ h} < t < 1700 \text{ h} \end{cases}$	(13)
		$E_{h,th} = \begin{cases} c \times \frac{E_D}{24}, t \in (1000 \text{ h}, t) 1900 \text{ h} \\ d \times \frac{E_D}{24}, 1000 \text{ h} < t < 1900 \text{ h} \end{cases}$	(14)
Case 2	$G_{h,G11} = \sum_1^2 G_{hh} \times \frac{V_{G11}}{V}$	$E_{h,G11} = E_{h,Case1} \times \frac{A_{G11}}{A}$	(15)
Case 3	$G_h = \sum_1^2 G_{hh}$	$E_h = \left[E_M \times \frac{n(H)_D}{24n(H)_M} \right] \times \text{HWD}_{Case1}$	(16)
Case 4	$G_{h,G11} = \sum_1^2 G_{hh} \times \frac{V_{G11}}{V}$	$E_h = E_{h,case3} \left[\left\{ \frac{V_{G11}}{V} \times n_{HVAC} \right\} + \left\{ \frac{A_{G11}}{A} \times (1 - n_{HVAC}) \right\} \right]$	(17)

The building opening hours were taken into account while distributing the daily electricity consumption amount over the 24 h. The constants, a , b , c , and d in Eqs. (13) and (14) are hourly weights assigned to distribute the daily electricity consumption over the 24 hourly intervals and pertain to the building-close and building-open hours for non-Thursday weekdays and the same for Thursdays, respectively. Total electricity use was split into HVAC applications (24-h requirement) and lighting, machineries (occupancy hours only), in the ratio of 3:1, obtained from the NGS building energy performance review report. Using this ratio along with the NGS opening hours, the values of the four constants are: $a = 0.919$, $b = 1.196$, $c = 0.89$, $d = 1.17$.

3.2.2 Randomisation, fragmentation, and data normalisation

The entire database (458 daily samples, 10,768 hourly samples) was randomised using Latin hypercube sampling (LHS) method. This method has proven to be more effective owing to the extra precision offered over the Monte Carlo sampling method [48]. Then, this randomised database was divided into two parts, i.e. 80% (366 daily, 8615 hourly samples) for training database (TDb) and 20% (92 daily, 2153 hourly samples) for prediction database (PDb),

to select the optimum ANN model on PDb results rather than TDb.

During the ANN model development in MATLAB environment, the TDb was further cross-validated into three subsets, in the ratio of 60:20:20 for training, validating, and testing (TVT). Through this division, the training set is used to adapt the weights of the ANN and the validation set is used for the early stopping to avoid the overfitting or underfitting, while the testing set is used to assess the prediction performance of ANN. However, the more complex K-fold cross-validation is out of scope of this work.

The normalisation of the parameters considered in the database has significant impact on the calibration and overall function of the ANN models, affecting their ability to provide accurate predictions. The normalisation process allows the conversion of the parameters considered into unitless (dimensionless) parameters. To avoid problems associated with low learning rates of the ANN, it is more effective to further normalise the values of the parameters between an appropriate upper and lower limit value. Furthermore, in order to compensate for the non-uniformity often characterising the purely experimental databases, it is considered more effective to normalise the values of the parameters considered between [0.1, 0.9] instead of [0, 1], through the use of Eq. (18).

Fig. 4 Flowchart of the optimal ANN model training program

$$X = \left(\frac{0.8}{x_{\max} - x_{\min}} \right) x + \left[0.9 - \left(\frac{0.8}{x_{\max} - x_{\min}} \right) x_{\max} \right] \quad (18)$$

3.2.3 ANN function and architecture

ANNs mimics their biological counterparts in the nervous system and the brains of animals and humans (Figs. 4, 5). Each ANN consists of a number of layers, and each layer

consists of a number of ‘neurons’, connected through synapses, which carries unique value of weights. The inputs get weighted and summed together along with a bias value for each neuron in the next layer. The learning and training algorithms guide and control how the weights should be adapted to improve the performance of the ANN. In this study, the sigmoid activation and tanh functions were used. Equations (19a) and (19b) describe the

Fig. 5 Functioning of an ANN neuron and distribution of neurons in hidden layers

mathematical form of sigmoid activation function and tanh activation functions, respectively.

$$f(y) = \frac{1}{1 + e^{-y}} \quad (19a)$$

$$f(y) = \tanh = \frac{e^y - e^{-y}}{e^y + e^{-y}} \quad (19b)$$

The way the weights and bias are adjusted depends on the training algorithm used. Different training algorithms are available in the MATLAB environment (Table 4). All of them have been considered in this study to identify the one most suited to the nature of the data and problem type.

Figure 6 illustrates the topology of the proposed ANN model considered in this study. Separate models are trained for hourly and daily analyses. The number of nodes in a hidden layer, or neurons, as well as the number of hidden layers depends on the nature of the modelling problem, and there does not exist any theoretical limit. In this study, three combinations pertaining to the number of hidden layer neurons, i.e. single layer (SL), double layer (DL), and triple layer (TL) were considered in the attempt to obtain the optimal ANN model architecture. Equal number of hidden neurons in each hidden layer(s) was used— $2 * N$ and $3 * N$, where N pertains to the number of input nodes.

3.2.4 ANN performance and convergence criterion

During the development of ANN, the learning cycle is iterated for all the different sets of input and target samples

until the one of the following convergence criteria is reached.

- The maximum number of epochs (iterations) is reached (set at 100). Figure 7 highlights the reasoning behind this: Good convergence is obtained after 23 and 36 epochs, respectively, for maximum epoch set at 100 and 1000.
- The model performance converges to the goal (set at 0.0001).
- The performance gradient falls below the set minimum gradient (set at 10^{-7}).
- The 'Mu' value exceeds the maximum set value (Set at 10^{10}).
- Validation performance has increased more than the maximum set failure time since the last time it decreased (Set at 20).

The performance of the ANN model is evaluated through the use of three criteria: Eqs. (20)–(22) describes the mathematical expression of the coefficient of correlation (R), mean squared error (MSE), and mean absolute error (MAE), respectively, for the predicted estimates values against their counterpart real values.

$$R = 1/(N-1) \sum_{i=1}^N \left[\frac{(Y_i - \bar{Y}_i)}{S_y} \frac{(X_i - \bar{X}_i)}{S_x} \right] \quad (20)$$

$$MSE = \frac{\sum_{i=1}^N |Y_i - X_i|^2}{N} \quad (21)$$

$$MAE = \frac{\sum_{i=1}^N |Y_i - X_i|}{N} \quad (22)$$

Table 4 Training algorithm selection—results of ANN model (a) hourly, (b) daily prediction accuracies and training time after training using the various available algorithms

MATLAB function	Description	Absolute error (hourly)	MATLAB function	Description	Absolute error (hourly)
(a)					
trainlm	Levenberg–Marquardt	0.018	Traincgf	Fletcher–Powell conjugate gradient	0.165
trainbr	Bayesian regulation back-propagation	0.018	Traincgp	Polak–Ribiere conjugate gradient	0.138
trainbfg	BFGS–Quasi-Newton	0.045	Trainoss	One step secant	0.113
trainrp	Resilient back-propagation	0.038	Trainidx	Variable learning rate back-propagation	0.043
trainscg	Scaled conjugate gradient	0.046	Traingdm	Gradient descent with momentum back-propagation	0.234
traincgb	Conjugate gradient with Powell/Beale restarts	0.280	Traingd	Gradient descent back-propagation	0.165
MATLAB function	Description	Absolute error (hourly/daily)	MATLAB function	Description	Absolute error (hourly/daily)
B					
trainlm	Levenberg–Marquardt	0.037	traincgf	Fletcher–Powell conjugate gradient	0.079
trainbr	Bayesian regulation back-propagation	0.038	traincgp	Polak–Ribiere conjugate gradient	0.044
Trainbfg	BFGS–Quasi-Newton	0.044	trainoss	One step secant	0.052
trainrp	Resilient back-propagation	0.038	trainidx	Variable learning rate back-propagation	0.045
Trainscg	Scaled conjugate gradient	0.041	traingdm	Gradient descent with momentum back-propagation	0.230
traincgb	Conjugate gradient with Powell/Beale restarts	0.043	traingd	Gradient descent back-propagation	0.079

where N = total number of samples, X_i = actual values, Y_i = predicted values, $\bar{X}_i = \sum_{i=1}^N \frac{(X_i)}{N}$ and $S_x = \sqrt{\frac{(X_i - \bar{X}_i)^2}{N-1}}$, same for the $\bar{Y}_i$ and S_y .

4 Results and discussion

4.1 Optimum ANN model and predictions

Table 4a, b describes the different learning algorithms available to train the ANN model for hourly and daily, all of which were considered in this study to identify the best algorithm after experimenting with the available dataset. It can be seen that the Levenberg–Marquardt (LM) training algorithm is the standout performer when it comes to ANN model prediction accuracies (lowest MSE, MAE).

After the best training algorithm was determined, ANN models were trained as a part of a comparative study in which a different combinations of hidden layers and hidden neurons in each layer was tried and tested for the four target-data case scenarios discussed in Sect. 3.2.4. Six different ANN architectures were considered for each case, and hence, a total of 24 neural network models were trained for each—daily and hourly analyses. All the ANN models showed high correlation between the chosen inputs and targets, in terms of R value varying between 0.96 and 0.98. The trained models were then used to make predictions for the PDb, which was removed from the ANN training dataset. Figure 8 represents the ANN performance results for all the 24 ANN models, in terms of the prediction accuracies (MSE, MAE, and R) as discussed in Sect. 3.2.4, along with the ANN model training time.

Fig. 6 Topology of the ANN models considered in this study

Fig. 7 Optimal epoch selection for the ANN model training considered in this study

From Fig. 8 (daily cases), it can be seen that for Case 1, the TL-2N ANN model is marginally better than the other five architectures in terms of the combination of prediction accuracies and model training time. Similarly, SL-2N, TL-2N, and TL-3N are observably the optimum ANN architectures for Cases 2, 3, and 4, respectively. Figure 9 (daily

cases) describes the performance of each of these four optimal ANN models in terms of the correlation of individual model-predicted target values with the actual recorded target values pertaining to the PDb. The electricity (Elec.) and gas graphs are further divided into two scales to accommodate the different data scales estimated

Fig. 8 ANN performance for six architectures designed for each of the four energy target-data cases: **a** daily analysis, **b** hourly analysis

by the four target-data case studies. Based on these two figures, it can be seen that of all the ANN models, TL-2N model for Case 3 is the best ANN model for daily scale analysis with the smallest error in prediction values ($MSE = 0.1\%$, $MAE = 2\%$), with the model trained and tested in MATLAB in only 8 s.

The same procedure was followed for the hourly analysis. From Fig. 8 (hourly cases), it can be observed that hourly cases also experienced uniformly high correlation (R between 0.97 and 0.99) between the ANN model predictions and the PDb targets. It is, however, clearly visible that the ANN models belonging to Cases 3 and 4 performed the poorest. TL-3N and DL-3N are the two ANN architectures with the best performances in these two cases. The optimal ANN architectures for Cases 1 and 2 were

identified to be TL-3N and DL-3N, respectively. Figure 9 (hourly cases) highlights the performance of the four optimal ANN models from the four cases based on correlation of each individual model-predicted output with their PDb counterpart from the same time period. The electricity and gas graphs are further divided into two, as done in the daily analysis. From the two figures, DL-3N of Case 2 is identified as the optimal hourly scale ANN model. This indicates that if the analysis is zoomed into hourly scale, then the owing to the complex nature of this scale of analysis, the ANN model, performs better with the NGS energy consumption scaled down to the possible energy requirements from Gallery-11 with the help of assumptions as discussed in Sect. 3.2.2.

Fig. 9 ANN prediction accuracies for each of the four identified targets representing indoor microclimatic conditions— T and RH, and NGS energy consumption—gas and electricity

4.2 System identification (SID) of the NGS building environment

The best ANN architecture from the most adequate data processing case study was selected as the optimal ANN-based SID model which identified the complex NGS building system in terms of the optimal indoor microclimatic conditions for artwork conservation (indoor air T , RH) and the NGS building energy consumption (gas, electricity). This step was performed on a daily scale and a

more detailed hourly scale involving the building opening hours and occupancy patterns, using separate ANN models as discussed in the previous section. The SID obtained from the optimal ANN model was validated by checking the correlation of the ANN model-generated target values with the actual recorded values of the same (real data from the BMS, corresponding to the same time period as the ANN predictions), which were not involved in the ANN training and testing cases (PDb). Figure 10 highlights this validation. Figure 10 (top) shows the comparison of the

Fig. 10 ANN-based SSID of the NGS building for **a** daily analyses, **b** hourly analyses

ANN-based SID estimates of indoor T, RH, and NGS gas and electricity consumption with the recorded real data from the same time period consumption on a daily scale. Figure 10 (bottom) highlights the same in a more detailed hourly case. To check the accuracy of the hourly prediction

ANN model in detail, three further sections of Fig. 10 (bottom) for three different ranges of samples, i.e. 340–440 (as described in Fig. 11), 940–1060 (as described in Fig. 12), and 1540–1660 (as in described Fig. 13).

Fig. 11 ANN-based SSID of the NGS building for hourly analyses for samples 340–460

Fig. 12 ANN-based SSID of the NGS building for hourly analyses for samples 940–1060

Fig. 13 ANN-based SSID of the NGS building for hourly analyses for samples 1540–1660

5 Conclusion

In this study, ANN has been utilised to predict the indoor microclimatic parameters critical for artwork conservation along with the building energy use in a historical art gallery building of great cultural significance. A set of four rough approximation-based case studies were designed and implemented to process the target data for improving the ANN performance. The ANN model development program in the study considered an experiment of six different combinations of hidden layers and number of hidden neurons, separately on two temporal scales—daily and hourly, for each case study. Different training algorithms were also considered in the experiment from which the Levenberg–Marquardt (LM) algorithm proved to be the best based on prediction accuracies.

The results of the developed ANN models were evaluated on statistical platform of error and performance metrics in comparison with a randomly separated fraction of the historical records excluded from the ANN training dataset. From the error analysis, the robust predicting ability of ANN models was demonstrated with the prediction data matching the actual data in terms of high overall accuracy with correlation coefficient (R) values ranging from 0.96 to 0.99. The MSE and MAE were observed to be within acceptable ranges of 0.1–0.3% and 2–4%, respectively, for daily scale analyses and of 0.05–0.18% and 1.8–2.7%, respectively, for hourly scale analyses. The two ANN-based system identification (SID) models for daily and hourly scales were TL-2N from target-data Case-3 and DL-3N from Case-2, respectively,

based on maximum performance of the models in their respective analysis data scales.

It is thus concluded that ANNs are able to work with limited amount of building system data (real data) readily available from the building management. Using this, it can emulate an otherwise complex and strongly coupled building system in terms of different zones, operating hours, occupancy, energy consumption, and optimal indoor environment for collections' care. Hence, the ANN model could be tailored into a module and built into a BMS system to improve forecasting and collecting data for evidence-based decision making to achieve real and effective optimisation for system operation. The study further reinstates that the ANN-based SI model can prove to be an ideal platform to investigate various optimisation strategies of the building operation in future, especially in the case of restrictive traditional building types where any retrofit solution needs a strong scientific backing of guaranteed success before practical implementation.

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