Building thermal dynamic RC model development using GA-based parameter identification

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***Abstract*—This study attempted to use Genetic algorithm for identifying building RC model parameters. An office building located in Berkeley was selected and two RC models $M1$ and $M2$ are proposed to compare the results in terms of different complexity. Thermal resistors (R) and capacitors (C) are identified using Genetic algorithm where the fitness function is constructed as mean absolute error between predicted zone temperature and GA predicted zone temperature. It was discovered that the $M2$ model, which differentiate external zones and internal zones in the RC model, has lower mean absolute error of $2°C$ over the entire month. The model can better capture different zone temperature patterns compared to $M1$ model. Based on the findings, future study should research more on GA fine-tuning techniques as well as more control-oriented RC modeling techniques for building thermal dynamics.**

***Index Terms*—Building RC modeling, Genetic algorithm, Thermal dynamics, Multi-zone analysis**

I. Introduction

Building industry is one of the most energy intensive sectors globally. It is estimated that 40% of energy is consumed by building space heating and cooling, ventilation, water pumping, lighting and so on. And 30% of carbon emissions are related to HVAC (Heating, ventilation, and air conditioning) equipment operation [1]. This has led to great concerns in terms of rapid climate change and more frequent power outage. Therefore, the whole industry is gradually shifting emphasize to more energy efficient and demand responsive management for the existing building stock. However, prior to implementing advanced control strategy such as model predictive control (MPC), it is essential to have a building thermal dynamics model that is both informative and computational efficient [2]. Models that are able to capture heat transfer physics normally can provide observable states such as temperature set points and air flow rates. Those models are preferred in real practice since building managers have less difficulty during implementation. Also, models with less computation requirements enable more rapid response to temperature changes or electricity rates for example.

As for modeling techniques, three different categories are commonly used: white box, black box and grey box techniques. White box is physics-based modeling which could result in solving hundreds of first principle equations. On the contrary, black box modeling does not require physical knowledge and is entirely data-driven. Therefore, current research is attempting to develop grey box models that combines both data-driven modeling and also physical interpretation. Therefore, this paper aims to study the possibility of using a Resistor-Capacitor (RC) circuit analogy to model building thermal dynamics. Similar to the electric circuit, R indicates thermal resistance of a building (such as walls and windows) while C indicates thermal capacitance of a building (such as indoor air and furniture). The general equation is indicated as:

$$C * \frac{dT}{dt} = \frac{T_o - T}{R} + Q_{HVAC} + Q_d \tag{1}$$

where T and T_o represent zone air temperature and outdoor air temperature respectively. Q_{HVAC}, and Q_d represent power input from HVAC equipment for heating or cooling and disturbances such as solar heat gain and additional load from occupancy. Depending on the configuration and number of building thermal zones in the model, the number of parameter R and C would vary. In this study, Genetic algorithm (GA) are used to identify those parameters. The algorithm is an analogy of biological evolution and starts with a population of randomly generated parameters as genes. A fitness function is constructed to select species with higher fitness values. During the process, elite genes would be kept for producing offspring through mutation and crossover. The iteration would be terminated either by limited number of generation or minimum deviations achieved from desired fitness.

II. Data description

The data used in this study is collected from an open source project by Lawrence Berkeley National Laboratory (LBNL) [3]. The curated data describes an office building in Berkeley, California shown in figure 1, and the dataset covers three-year whole building energy end-use, HVAC system operation conditions, indoor and outdoor environment measurements. For the scope of this study, only one month of data is used from April 1^{st} 2018, to April 30^{th}

For simplicity, only the first and second floor data on north side of the building is retrieved and is summarized in the following table I. Due to different resolution of the data collection, the time step Δt is determined to be 30 min.

III. Methodology

Various studies have demonstrated ways of constructing RC models from high complexity to simplified version. This paper also compares two models with different levels of complexity. The following two sections have detailed specification for the

Fig. 1. The office building used in this study from LBNL project [2].

TABLE I
SUMMARY OF USED DATA IN THE FOLLOWING RC MODEL PARAMETER IDENTIFICATION

Symbol	Description	Resolution
T_o	Average outdoor temperature	15 min
T_j	Average zone temperature at floor j	10 min
T_{je}	Average external zone temperature at floor j	1 min
T_{ji}	Average internal zone temperature at floor j	10 min
u	Average HVAC power input	15 min
P_d	Solar heat gain power input	15 min
SR	Solar radiation	15 min
$SHGC$	Solar heat gain coefficient	NA
SC	Shading coefficient	NA

proposed two models. Additionally, since the measurements are collected in discrete time, Euler discretization is applied to equation 1 and is shown below.

$$C * \frac{T(k+1) - T(k)}{\Delta t} = \frac{T_o(k) - T(k)}{R} + u(k) + P_d(k) \quad (2)$$

A. Simple Model ($M1$) construct

In the simple model $M1$, a $3R2C$ configuration is proposed and shown in the following figure 2.

Each floor is considered to be an aggregated zone using $1R1C$ and in-between zone connection is modeled using $1R$. In this case, the model is interpreted to have two paths of thermal dissipation (one through outdoor environment $R1$, $R3$, and the other through adjacent zone $R2$) and one integrated thermal mass for thermal capacitance ($C1$, $C2$). Therefore, the model is expressed as:

$$C_1 * \frac{T_2(k+1) - T_2(k)}{\Delta t} = \frac{T_o(k) - T_2(k)}{R_1} + \frac{T_1(k) - T_2(k)}{R_2} + u(k) + P_d(k) \quad (3)$$

$$C_2 * \frac{T_1(k+1) - T_1(k)}{\Delta t} = \frac{T_o(k) - T_1(k)}{R_3} + \frac{T_2(k) - T_1(k)}{R_2} + u(k) + P_d(k) \quad (4)$$

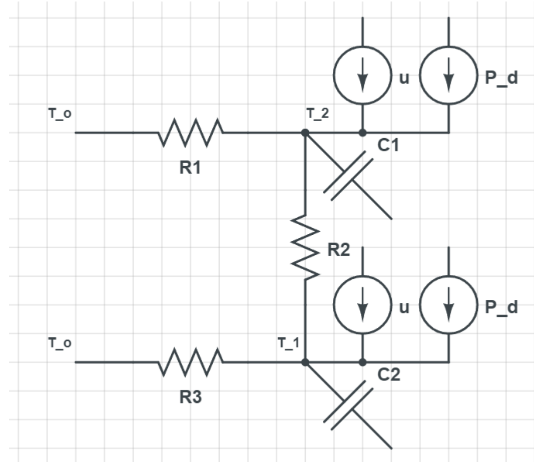

Fig. 2. Configuration of the simple model using $3R2C$.

As indicated in table I, the disturbance P_d is modeled as solar heat gain. Although the dataset includes solar radiation, other information such as glazing material, window area are not available. Therefore, it is assumed that for this case study office building, double glazing is used and $SHGC = 0.4$, floor to window ratio is around 15% and shading factor $SC = 0.75$. Thus solar heat gain is calculated as:

$$SHG = SR * A_{floor} * 15\% * SHGC * (1 - SC) \quad (5)$$

B. Complex Model ($M2$) construct

In the complex model $M2$, a $6R4C$ configuration is proposed and shown in the following figure 3.

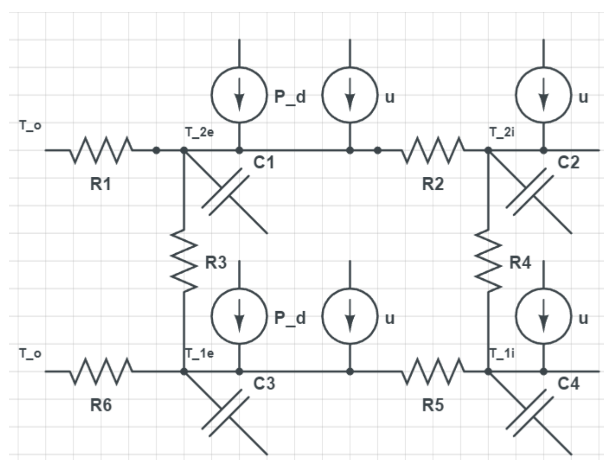

Fig. 3. Configuration of the complex model using $6R4C$.

Each floor consists of an external zone and an internal zone. Similarly to $M1$, both zones are modeled as $1R1C$ and in-between zone connection is modeled using $1R$. The interpretation is similar to $M1$, but with finer spacial resolution. In this case, the solar heat gain is only applied to external zones, which more accurately simulates the reality. Hence the model is expressed as:

$$C_1 * \frac{T_{2e}(k+1) - T_{2e}(k)}{\Delta t} = \frac{T_{1e}(k) - T_{2e}(k)}{R_3} + \frac{T_{2i}(k) - T_{2e}(k)}{R_2} + \frac{T_o(k) - T_{2e}(k)}{R_1} + u(k) + P_d(k) \quad (6)$$

$$C_2 * \frac{T_{2i}(k+1) - T_{2i}(k)}{\Delta t} = \frac{T_{2e}(k) - T_{2i}(k)}{R_2} + \frac{T_{1i}(k) - T_{2i}(k)}{R_4} + u(k) \quad (7)$$

$$C_3 * \frac{T_{1e}(k+1) - T_{1e}(k)}{\Delta t} = \frac{T_{2e}(k) - T_{1e}(k)}{R_3} + \frac{T_{1i}(k) - T_{1e}(k)}{R_5} + \frac{T_o(k) - T_{1e}(k)}{R_6} + u(k) + P_d(k) \quad (8)$$

$$C_4 * \frac{T_{1i}(k+1) - T_{1i}(k)}{\Delta t} = \frac{T_{1e}(k) - T_{1i}(k)}{R_5} + \frac{T_{2i}(k) - T_{1i}(k)}{R_4} + u(k) \quad (9)$$

C. Genetic Algorithm

The total number of evolution is determined to be 500 generations, and all parameters were initially set to be 5. Other research which studies RC modelling techniques shows that the parameters are normally between 0 and 20 [4]. The total DNA strands in one generation is set as 10 to avoid excessive computational time. In addition, the mutation rate is set to be relatively small due to limited variations of R and C found in the literature. The fitness function is defined as mean absolute error between predicted temperature $T(k+1)$ in the above equations and measured temperature from the dataset at each time step from $k = 1$ to $k = N$ at each zone j. Considering the computation time, only the first two days measurements (from April 1^{st} to April 2^{nd}) are used to train the algorithm.

$$Objective : min \frac{\sum_{k,j} |T_{GA,j}(k) - T_{measure,j}(k)|}{N} \quad (10)$$

IV. Result

A. $M1$ Results

The training results of $M1$ is shown in figure 4. The figure shows a more refined parameter search after an initial trial which are not included in the plot. This explains why the average error increases after the initiation of evolution, and most of the parameters remain stable.

As a result, the identified parameters with minimum value of fitness equation 10 are summarized in the following table II:

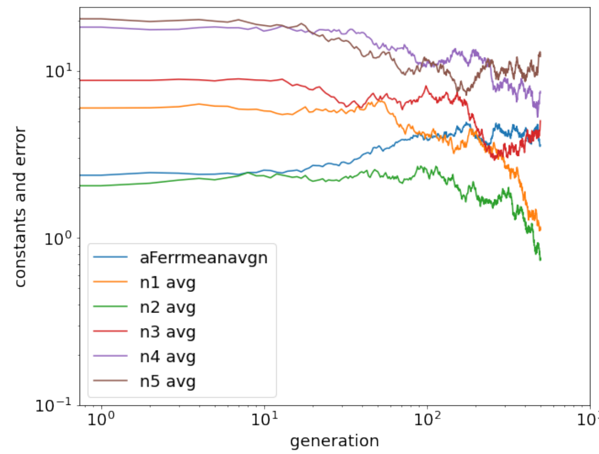

Fig. 4. $3R2C$ parameter and MAE average values during GA training over 500 generations.

TABLE II
SUMMARY OF USED DATA IN THE FOLLOWING RC MODEL PARAMETER IDENTIFICATION

Symbol	Description	Value
$n_{1,min}$	R_1	6.00
$n_{2,min}$	R_2	2.05
$n_{3,min}$	R_3	8.79
$n_{4,min}$	C_1	18.32
$n_{5,min}$	C_2	20.55

Figure 5 and figure 6 show the comparison of the identified RC model with real measurements over the training periods. For both floors, GA is able to make prediction on zone temperature with an overall mean absolute error of $3°C$. Despite the relatively low deviations from real temperature data, the GA trained RC model tends to overestimate the increase of zone temperature indicated as the two peaks in figure 5 and 6.

The overestimation is more obvious in figure 7 and 8 when extending the comparison over the entire month. The break in the time series plots simply indicate no data measurements.

B. $M2$ Results

Overestimation on the zone temperature could cause both energy waste and dissatisfied occupants. One possible explanation could be the oversimplification on the aggregated zone average temperature. For example, external zones and internal zones are aggregated in $M1$ which are normally separated in HVAC control. This is because external zones are more influenced by outdoor weather change such as outdoor temperature or solar heat gain while internal zones are generally more stable. Therefore, in $M2$, external zones and internal zones are separated as T_{je} and T_{ji} in table I and figure 3. The training results are shown in figure 9 and the identified parameters with minimum fitness value of equation 10 are shown in the following table III.

Figure 11 and figure 12 show the comparison of the identified RC model with real measurements over the training

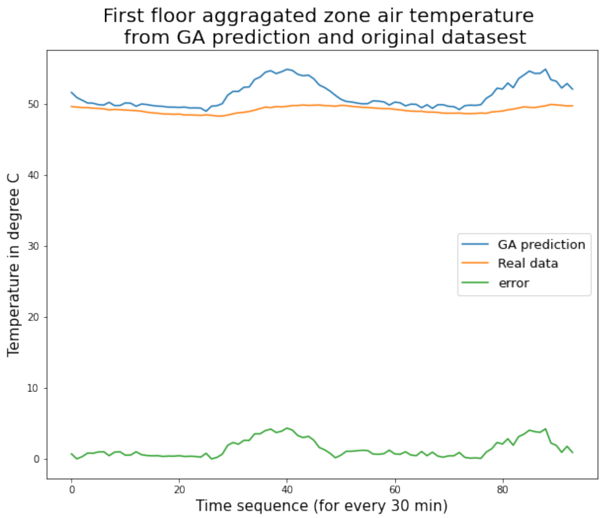

Fig. 5. Comparison between GA prediction on first floor zone temperature $T(k+1)$ and ground truth data from measurements over training period.

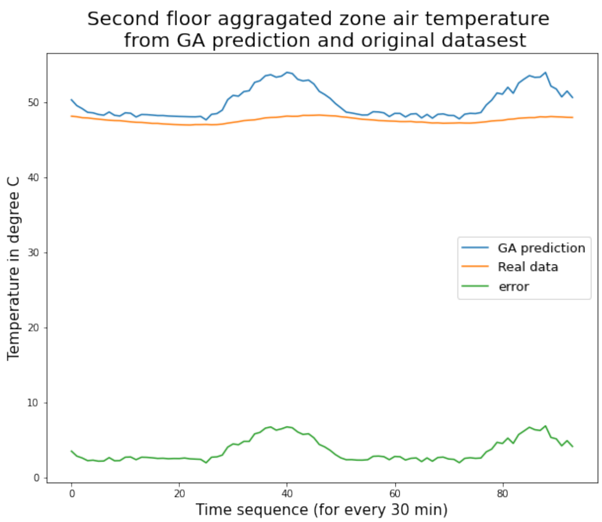

Fig. 6. Comparison between GA prediction on second floor zone temperature $T(k+1)$ and ground truth data from measurements over training period.

TABLE III
SUMMARY OF USED DATA IN THE FOLLOWING RC MODEL PARAMETER IDENTIFICATION

Symbol	Description	Value
$n_{1,min}$	R_1	9.37
$n_{2,min}$	R_2	3.06
$n_{3,min}$	R_3	7.61
$n_{4,min}$	R_4	10.59
$n_{5,min}$	R_5	3.20
$n_{6,min}$	R_6	4.13
$n_{7,min}$	C_1	27.10
$n_{8,min}$	C_2	15.66
$n_{9,min}$	C_3	25.30
$n_{10,min}$	C_4	19.85

periods. From the figures, the temperature differences between inter and external zones validate the reason of separation.

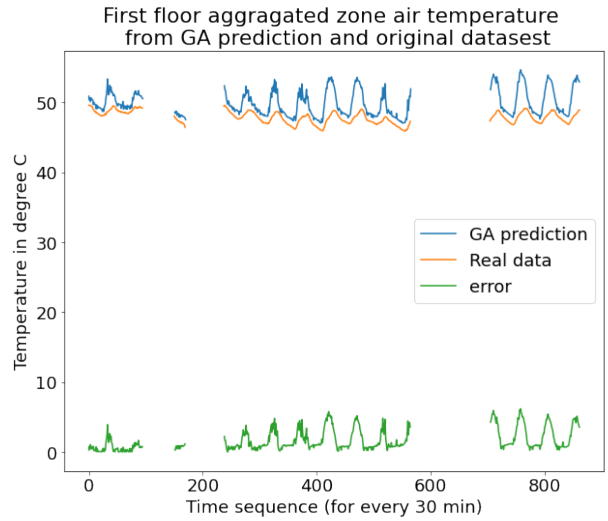

Fig. 7. Comparison between GA prediction on first floor zone temperature $T(k+1)$ and ground truth data from measurements over entire month.

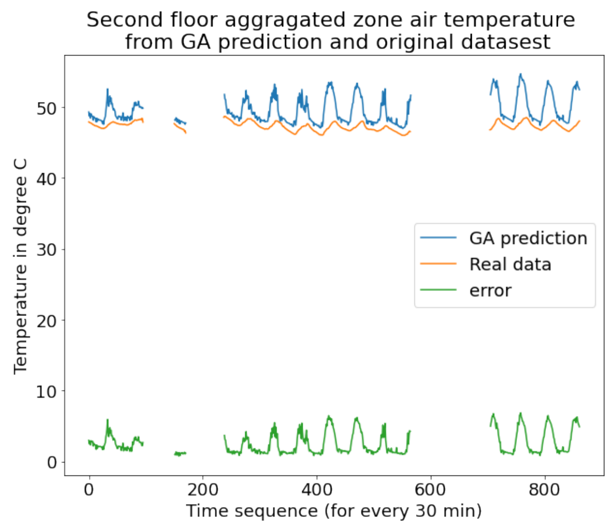

Fig. 8. Comparison between GA prediction on second floor zone temperature $T(k+1)$ and ground truth data from measurements over entire month.

In addition, the overestimation of temperature increase is mitigated in this model and thus, the mean absolute error in temperature prediction is further reduced shown in figure 10. For both floors, GA is able to make prediction on zone temperature with an overall mean absolute error of $1°C$.

The prediction results of the entire month are shown in figure 13 and 14 and the error is shown in figure 15. It can be found that the overestimation shown in $M1$ has been significantly mitigated for the extended period. And the temperature prediction deviation is mostly within $2°C$. As mentioned before, external zones and internal zones exhibit different patterns. After differentiating into two types of zones, parameters associated with external zones can better capture higher fluctuations of zone temperature due to outdoor weather influence.

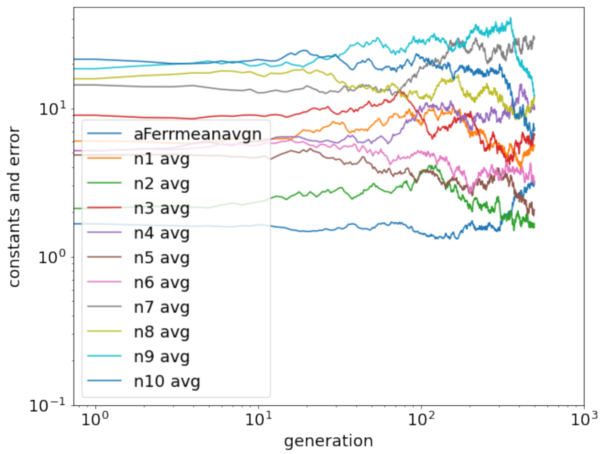

Fig. 9. $6R4C$ parameter and MAE average values during GA training over 500 generations.

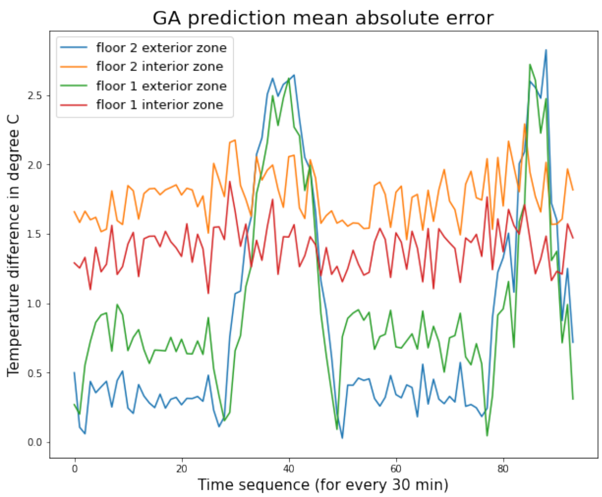

Fig. 10. Mean absolute error of GA zone temperature prediction in both external and internal zones over the training period.

V. Discussion

A. RC model

The overall performance of the two proposed RC models is comparable to other studies in the literature [4] in terms of number of parameters and error in temperature prediction. It still remains unclear how R and C should be initiated at the beginning. In this study, it has been demonstrated that $6R4C$ in $M2$ yields high prediction accuracy, but whether the configuration of $1R1C$ for each zone and $1R$ for in-between zone connection are reasonable for all types of buildings. Also, one of the intentions of designing grey box modeling techniques such as RC models is to facilitate more advanced control algorithms. For example, some research on Model Predictive Control (MPC) uses lumped parameter R and C in the model to reduce the order [5]. Hence, it is a trade-off between complexity and accuracy that needs to be considered.

Since the configuration of the HVAC system and orientation

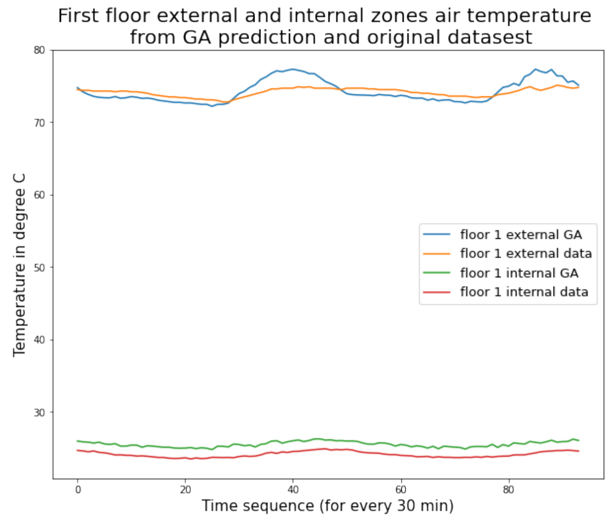

Fig. 11. Comparison between GA prediction on first floor zone temperature $T(k+1)$ and ground truth data from measurements over training period.

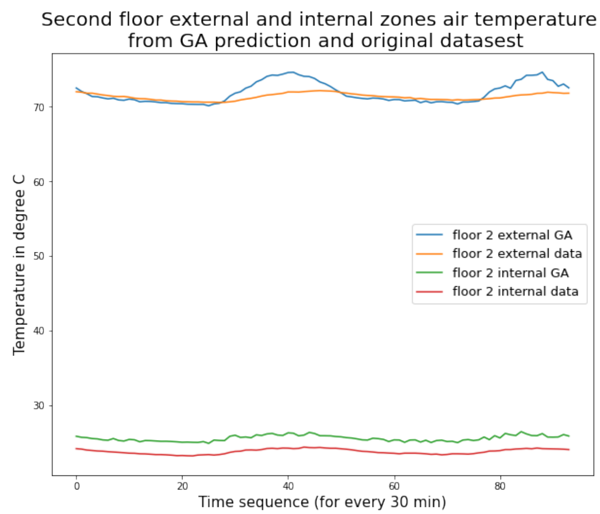

Fig. 12. Comparison between GA prediction on second floor zone temperature $T(k+1)$ and ground truth data from measurements over training period.

of the building are not available in the data. The solar heat gain SHC can only be estimated. Also, the heat gain from occupancy is not included but should be added to the disturbance P_d. Besides, the study only investigated the periods from April 1^{st} to April 30^{th}. Potential seasonal effect is excluded, which is considered as an limitation of the study.

B. Genetic algorithm

The algorithm is capable of parameter searching but generally has difficulty in converging to global minima, especially compared to gradient-based algorithms. The study uses MacBook Pro Apple M1 Chip, and the computation time for 500 generation is around 25 minutes. Although the more complex model $M2$ also takes 25 minutes, an initial search is operated as mentioned in figure 4 prior to the iteration. Therefore, the real computation time should be longer than

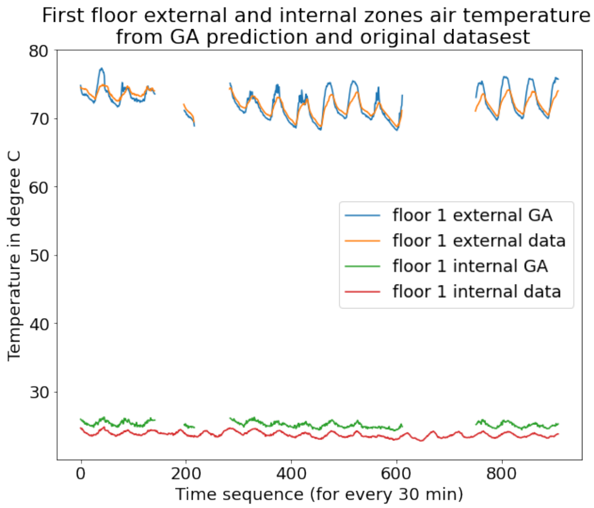

Fig. 13. Comparison between GA prediction on first floor zone temperature $T(k+1)$ and ground truth data from measurements over entire month.

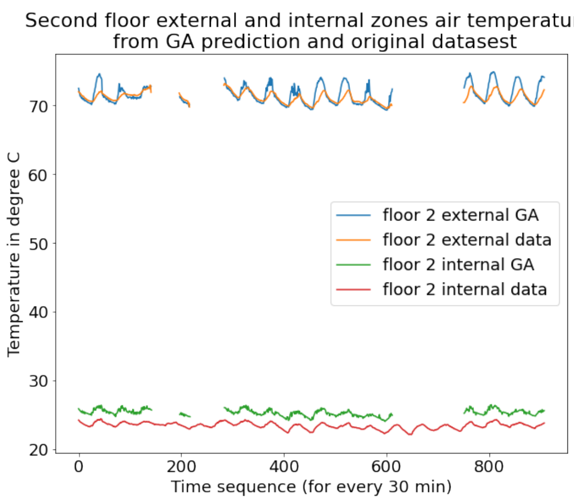

Fig. 14. Comparison between GA prediction on second floor zone temperature $T(k+1)$ and ground truth data from measurements over entire month.

25 minute. Future study could investigate how GA tuning, such as number of iteration and DNA strands, would influence computation time. Furthermore, the level of mutation and variation of DNA are deliberately reduced for the latter refined iteration. And hence for future improvements, the algorithm could introduce a varying mutation factor depending on the number of generation or convergence of mean absolute error.

VI. Conclusion

This study implemented a grey box modeling technique for building thermal dynamics. An office building located in Berkeley was selected and two RC models $M1$ and $M2$ are proposed for different complexity. Thermal resistors (R) and capacitors (C) are identified using Genetic algorithm where the fitness function is constructed as mean absolute error between predicted zone temperature and GA predicted zone

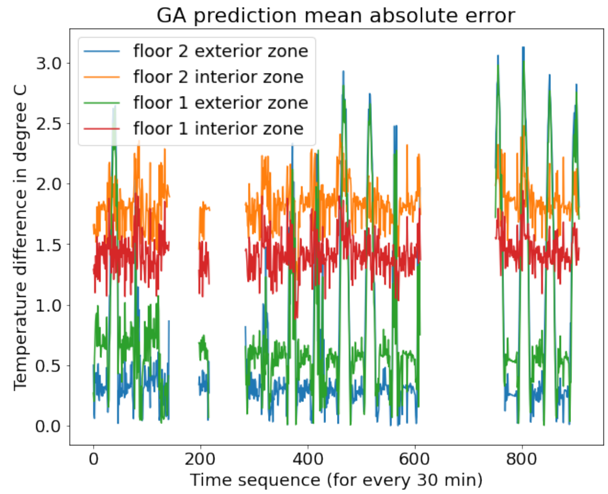

Fig. 15. Mean absolute error of GA zone temperature prediction in both external and internal zones over entire month.

temperature. It was discovered that with the differentiation of external zones and internal zones, $M2$ has lower mean absolute error of $2°C$ over the entire month and can better capture different zone temperature patterns. Based on the findings, future study should research more on GA fine-tuning and control-oriented RC modeling of building thermal dynamics.

VII. Appendix

The code is written in python language and attached below.

References

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