**A Novel Hybrid Modeling Method for Predicting Energy Use of Hydronic Radiant Slab Systems**

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# ABSTRACT

Accurately predicting the performance of radiant slab systems can be challenging due to the large thermal capacitance of the radiant slab and room temperature stratification. Current methods for predicting heating and cooling energy consumption of hydronic radiant slabs include detail first-principle-based (e.g, finite difference) and reduced-order (e.g, thermal resistor-capacitor (RC) network) models. Creating and calibrating detailed first-principle models, as well as RC network models for predicting the performance of radiant slabs requires substantial modeling efforts. To develop improved control, monitoring, and diagnostic methods, there is a need for simpler models that can be readily trained using in-situ measurements.

In this study, we explored a novel hybrid modeling method integrating a simple RC network model with an evolving learning-based algorithm growing Gaussian mixture regression (GGMR) modeling approach to predict the heating and cooling rates of a radiant slab system for a Living Laboratory office space. The RC network model provides heating or cooling load of the radiant slab system to the GGMR model as one of the inputs. The three modeling approaches have been compared with a case study for predicting the hourly radiant slab systems energy use of a Living Laboratory office space from January 15th to March 7th, 2022: 1) an RC network model; 2) a GGMR method; and 3) the proposed hybrid approach. The first two weeks of data were used for training, while the remaining data was used as a testing data set in all three modeling methods. The RC model has a normalized root mean square error (NRMSE) of 13.56%, a coefficient of variation of root means square error (CVRMSE) of 15.59%, a mean absolute error (MAE) of 5.76 kilowatts (kW), and a mean absolute percentage error (MAPE) of 108.53%. The GGMR model has NRMSE of 15.89%, CVRMSE of 17.76%, MAE of 6.40 kW, and MAPE of 27.68%. The hybrid approach has NRMSE of 8.77% (35% lower from RC, 45% lower from GGMR), CVRMSE of 9.95% (36% lower from RC, 44% lower from GGMR), MAE of 3.62 kW (37% lower from RC, 43% lower from GGMR), and MAPE of 19.31% (82% lower from RC, 30% lower from GGMR). And the hybrid approach outperforms the other two methods.

# 1. INTRODUCTION

Recently, hydronic radiant slab systems (HRSS) demonstrated significant benefits for thermal management of conditioned spaces, including increased thermal comfort and cost savings. Apart from these benefits, the large thermal storage capacity of HRSS has a few disadvantages. One disadvantage of the large thermal time constant is that it causes cooling output to be delayed when internal heat is increased and supply water is adjusted (Liu et al., 2011). Additionally, conventional control based on room temperature feedback may consume more primary energy than a conventional air system (Sourbron et al., 2009). Moreover, Hydronic Radiant Slab Systems frequently experience concurrent thermal disturbances caused by solar radiation, internal heat, and air systems (Koschenz et al.). As a result, conventional HRSS control frequently encounters overcooling or overheating issues. To address these issues, HRSS requires Model Predictive Control (MPC) with accurate load prediction, as stated in (Joe & Karava, 2019). In general, energy models for buildings fall into two categories: those that are physics-based and based on heat transfer and thermodynamics, and those that are data-driven, as summarized in ASHRAE's (Handbook, 1997) and Dong et al. - (Dong et al., 2016). The following sections will conduct a thorough review of physics-based and data-driven models, followed by a discussion of the current research gap and objective.

## 1.1 Physics-Based Model

Physics-based models comprises first-principle methods like the Finite Difference Method (FDM) and reduced-order models (such as the thermal resistor-capacitor (RC) network model). Traditional simulation programs such as TRNSYS and EnergyPlus are not suitable for the FDM because of its high computational costs (Rodrguez Jara et al., 2016). In comparison to FDM, the RC network model is considered of as a simplified model or as a collection of linear ordinary differential equations (ODEs). RC models are typically in the form of 2R1C, 3R2C, or lumped RC parameter models with associated self-adjusting methods (Rodrguez Jara et al., 2016). According to (O'Dwyer et al., 2016), when the resistance and capacitance values are positive, there is theoretically a guaranteed thermal passivity solution for RC models. As previously stated (A. Li et al., 2017), quantifying RC network parameters is advantageous for optimizing system control. As for the training of RC model, there is considerable research devoted to optimizing the trade-off between model accuracy and complexity (Ahn & Song, 2010; Goyal et al., 2011; Koschenz & Dorer, 1999). For instance, Liu et al. (Liu et al., 2011) proposed a method for defining the heat resistance and heat capacity of an assumed core layer by utilizing systematical geometric structure parameters.

There are some limitations in terms of the RC model application. Generally, the finer RC network of HRSS usually has more restriction for the onsite configuration, such as a start-type RC model proposed by Li et al.(A. Li et al., 2017) has aspect ratios limitation. According to Rodrguez Jara et al. (2016), the accuracy of lumped parameter methods, one type of RC model, is highly dependent on the values of their characteristic parameters. Although Rodrguez Jara et al. proposed self-adjusting methods for simplification of the RC model, the method is dependent on reasonable estimation of element properties (e.g. thermal diffusivity), element thickness, and special excitation for the training experimental setup. In practice, the accuracy of the RC model degrades when the slab is subjected to rapid thermal disturbances (Rhee & Kim, 2015). Additionally, according to Dong et al., the construction of RC models is typically dependent on a large amount of onsite input data that is not always available.

## 1.2 Data-Driven Model

There are a lot of data-driven model candidates for building energy modeling. Common data-driven methods, such as partial least squares (PLS) and principal component analysis (PCA), assume that the target model has an inherent single normal distribution (Karami & Wang, 2018). Other research indicates that PLS and PCA are typically used to describe non-Gaussian and linear relationships (D. Li & Song, 2020), which is not the case for complex dynamic systems such as HRSS. As summarized in Dong et al. (Dong et al., 2016), other conventional data-driven methods, such as artificial neural networks (ANN) and support vector machines (SVM), are incapable of performing spontaneous uncertainty analysis, which is critical for HRSS load prediction. Alternatively, Gaussian family models, such as gaussian process regression (GPR) and gaussian mixture models (GMM), have been used to develop data-driven system load prediction. The primary advantages of gaussian family methods are their nonlinearity, non-Gaussianity, inherent uncertainty formulation component, and multimode properties. As Guenther et al. (Guenther & Sawodny, 2019) demonstrate, GPR has been used to capture the complex and highly subjective relationships between room temperature and subjective thermal perception. The GMM is widely recognized for its ability to model multimode characteristics and deal with process uncertainty (D. Li & Song, 2020). Li et al. (D. Li & Song, 2020) asserted that GMR is appropriate for resolving nonlinear and non-Gaussian industry problems. As Srivastav et al. (Srivastav et al., 2013) demonstrated for baseline building energy modeling, the number of distinct building operational patterns can be identified using different Gaussians in GMR. Additionally, Wang et al. (2018) used GMR to forecast hourly energy consumption in buildings. On the other hand, the lack of an online adaptive mechanism makes GMR more difficult to address time-varying processes.

Considerable efforts have been made in the field of incremental learning, or growing GMR (GGMR), to develop a mechanism for GMR adaptation (Bouchachia & Vanaret, 2011; Cederborg et al., 2010; Karami & Wang, 2018; D. Li & Song, 2020). Generally, GGMR outperforms GMR from the following perspectives(D. Li & Song, 2020): avoiding the maintenance of all historical data through incremental learning; maintaining model compactness; and increasing model updating efficiency.

## 1.3 Research Gap and Objective

As summarized in (O'Dwyer et al., 2016), buildings' thermal responses are intrinsically complex and particularly susceptible to numerous disturbances (such as solar radiation, various miscellaneous electrical load and air systems load). However, RC model is usually restricted to many onsite buildings due to its reliance on lots of sensor inputs and the significant effort required to develop and calibrate. Additionally, uncertainty analysis is critical for predicting building energy consumption, which is not captured by the RC model. As for GGMR method, n, there are few studies exploring its application for HRSS load prediction.

To address the above research gap, we propose a hybrid approach, in which we use the outputs from a simpli1fied RC model as one of the inputs to a GGMR model. Additionally, the proposed Hybrid Model can inherit the benefits from the GGMR model and overcome the limitations of the RC model.

In the sequel, the methodology and performance metrics are detailed in Sec. 2. Section 3 presented model development and one real-world hybrid method case study for an existing office at Purdue University before a conclusion in Sec. 4.

# 2. METHODLOGY

This section discussed the methodology used to improve prediction performance, beginning with the development of RC network models and progressing to the GGMR approach, and finally to the Hybrid Modeling approach, which combines the RC and GGMR approaches. The final subsection describes the model prediction performance criteria metrics.



## 2.1 RC Network Model



Heat balance equations on each temperature or state variable are used to create a RC network model(Braun & Chaturvedi, 2002; Joe & Karava, 2017).

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

For a radiant slab system model, the output variable is the cooling and heating load. The state vector contains all the temperature nodes, which are surrounded by the estimated resistors and capacitors. The input vector contains all the driving conditions, such as the heated or chilled water temperature and its derivation along the sampling time within tubes, exterior air temperature, solar radiation, lighting, and occupancy schedule.

The discrete version of the above state-space model can be written in terms of a recursive formula as

|  |  |  |
| --- | --- | --- |
|  |  | () |
|  |  | () |

A typical objective function for RC network model is to minimize the root-mean-square error for the training duration, denoted as

|  |  |  |
| --- | --- | --- |
|  |  | () |















## 2.2 GGMR Method

Gaussian mixture regression (GMR)(Sung, n.d.) is a regression approach that models probability distributions rather than functions. Assume the data follow the join density

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

where , . The above Gaussian mixture probability function shown in Equation (5) can be portioned as

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

where

|  |  |  |
| --- | --- | --- |
|  |  | (7) |
|  |  | (8) | |

From Equation (6), the marginal density of X is

|  |  |  |
| --- | --- | --- |
|  |  | (9) |

The conditional probability density function of is

|  |  |  |
| --- | --- | --- |
|  |  | (10) |

with the mixing weight

|  |  |  |
| --- | --- | --- |
|  |  | (11) |















In the current study, we are interested in the expectation of y among all gaussian components:

|  |  |  |
| --- | --- | --- |
|  |  | () |

To control model complexity and allow to modeling time-varying processes, GGMR has been proposed by Bouchachia et al.(Bouchachia & Vanaret, 2011) with growing and shrinking mechanisms, to accommodate new data in an online setting. We utilized its updating gaussians algorithm in the present paper. More details can be seen in Bouchachia et al(Bouchachia & Vanaret, 2011). The best match Gaussian will be updated with the following formulas:

|  |  |  |
| --- | --- | --- |
|  |  | () |
|  |  | () |
|  |  | () |
|  |  | () |
|  |  | () |
|  |  | () |

in which is the match probability calculated with new input and best match Gaussian , is the expected posterior, is the sum of the expected posterior for best match Gaussian, is the weights of best match Gaussian, is the on-going learning rate for j-th Gaussian, is the converging learning rate.

## 2.3 Hybrid Approach

The basic idea of the Hybrid Model is to improve the forecasting accuracy for both RC model and GGMR model. In fact, it is evident that we should provide a close estimation as one of GGMR inputs to enhance its prediction power. In the present study, we have designed the Hybrid Model schema as shown in **Figure 1**, which illustrates the underlying structure of the hybrid approach. Enabled by the real time predicted system load from RC network model and incremental learning framework from the GGMR model, those trained gaussian components from Expectation Maximization (EM) will be updated accordingly as the update rules shown in Equation 11~ 16. Specifically, the RC network module will get the target time step index from GGMR and return the predicted RS system load back to GGMR module.

Diagram

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**Figure 1** Underlying Communication for Hybrid Approach



## 2.4 Model Performance Evaluation Criteria

Four indices, normalized root mean square error (NRMSE), coefficient of variation of root mean square error (CVRMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

|  |  |  |
| --- | --- | --- |
|  |  | (19) |
|  |  | (20) |
|  |  | (21) |
|  |  | (22) |
|  | = | (23) |

where n the number of observations, is the standard deviation of predictions, is the average of measured values.

# 3. CASE STUDY

This section presents a case study for all the three proposed methods, including RC network, GGMR and hybrid approach. It begins with a description of the test bed, then moved to the moved to the model development and selections, and concludes with a comparison of the performance of each modeling approach.

## 3.1 Test bed

The dataset included in-situ measurements for a living laboratory office space from January 15th to March 7th, 2022, with a 5-minute sampling rate. And further, we used the first two weeks data for training and the rest of data used for testing. The dataset can be divided into of two categories, onsite sensor data and estimated data. Onsite sensor data includes the followings: outdoor air temperature denoted by , Façade cavity space temperature denoted by , slab concrete temperature denoted by , flowing water temperature within slab pipe denoted by , solar radiation retrieved from a weather station denoted by (This public data is available on *www.ambientweather.net*), air handling unit consumed heating power . The estimated input values are determined using a predefined schedule in accordance with ASHRAE 90.1 (ANSI/ASHRAE/IES 90.1-2010, 2010), such as internal heating radiation denoted by , and lighting radiation .

## 3.2 RC Network Model Development

Considering model accuracy-complexity trade-off, the following is the overall design logic for RC network construction:

1. Improve the model’s accuracy. The RC model should capture the key and most thermal behaviors of targeted space to maintain model robustness under a variety of operating conditions.
2. Reduce the complexity of model. Reduce the number of input variables or training data to avoid creating an excessively complex model.

The major thermal components of the living laboratory office space (Joe & Karava, 2017) include external walls, roof/ceiling, internal wall, south-facing double façade system, conditioned air from air handling unit (AHU) system, and hydronic radiant floor system (as shown in Figure 2).

In the present study, we experimented different RC network design by considering model robustness and different levels of complexity or model orders. We designed three models, 4-states Model 1, 6-states Model 2 and 5-states Model 3, for RC networks as shown in Figure 3, in which represents temperature, capacitances, resistances, heat flux due to radiation and corresponding coefficients. As for the subscripts, , represent outdoor air, façade cavity, slab concrete, hot water or chilled water within tubes, insulation below tubes, envelope, room air, internal wall, solar radiation, internal heat, lighting, air handling unit, thermal heat flux load requirements, respectively.

All those three models consist of two parts: room part and concrete slab part. We chose the same room part network structure to well capture its thermal properties: two-node envelope, one-node internal wall, one node cavity for double façade system, and room air node to capture the provided disturbance heating or cooling from AHU system. It is worth noting that we used envelope node to represent external wall and roof/ceiling to maintain model complexity. As for radiant floor system, we have tried different model orders to capture its thermal behaviors. In Model 1, the detailed thermal structure of radiant floor has been neglected. We treated the entire slab as one node. Compared with Model 1, Model 3 has additional source node, which represents the water flowing through slab pipes. And Model 2 has one more sink node than Model 3 to represent the thermal insulation below concrete as shown in Figure 2.

Figure 4 shows the predicted and measured results during testing period (10892 sampling points for around 37 days). Compared with Model 2 and Model 3, the Model 1 has much higher error which can be attributed to the oversimplified floor representation. As for Model 2, it has lower CVRMSE than Model 3 which can be explained by the additional sink node. More detailed performance comparison can be view in Table 2. Model 2 has been chosen as the optimum model for the RC network method as it has better performance to capture the peaking load than Model 3.

The Model 2 can be represented by a state-space model with the following state, input, and output variables definitions:

|  |  |  |
| --- | --- | --- |
|  |  | (24) |
|  |  | (25) |
|  |  | (26) |

Thermal resistances, () and thermal capacity ( are evaluated using the following equations, the results of which are displayed in Table 1:

|  |  |  |
| --- | --- | --- |
|  |  | (27) |
|  |  | (28) |

As stated in Equation 4, the RC network model training is essentially an optimization problem. In the present paper, p

A picture containing chart

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Figure 2 Floor slab section view

**Table 1** Estimated values for Rs (K/W) and Cs (J/K)

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  |  |  |  |
| 3.6E-3 |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

Diagram, schematic

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**Figure 3** Structure of RC network. Left: Model 1 with 4 states; Middle: Model 2 with 6 states; Middle: Model 3 with 5 states.

Timeline

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**Figure 4** Testing results for Model 1, Model 2 and Model 3

**Table 2** Comparison of proposed RC models (5-mins interval)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Models** | **NRMSE (%)** | **CVRMSE (%)** | **MAE (kW)** | **MAPE (%)** |
| Model 1 | 156.96 | 117.52 | 5.76 | 87.88 |
| Model 2 | **16.15** | **21.31** | **0.84** | **26.10** |
| Model 3 | 27.60 | 31.37 | 1.28 | 35.89 |

## 3.2 GGMR Model Development

In this subsection, we mainly focus on the determination of input variables for GGMR model. As referred to Wang et al. (Wang et al., 2018), correlation coefficients has been used as a indicator of the strength and direction for of the linear relationship between inputs and model outputs. And the correlation coefficient is ranging from -1 to +1, where -1 represents the prefect negative linear correlation and +1 represents the prefect positive linear correlation. By referring the Table 3, we have experimented different inputs combinations for GGMR model as shown in Table 4. It is worth noting that strong linear correlation does not necessarily mean better GGMR prediction performance. has been selected as the GGMR Model inputs.

**Table 3** Correlation coefficients between Radiant Slab systems load and input variables

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |
| -0.06 | -0.08 | -0.16 | -0.89 | 0.35 | -0.16 | 1 |

**Table 4** Prediction performance comparison for different GGMR inputs

|  |  |
| --- | --- |
| **Inputs** | **CVRMSE (%)** |
|  | 107.42 % |
|  | 25.81 % |
|  | 26.93 % |

## 3.3 Hybrid Model Development

As mentioned in Sec. 2.4, the development of hybrid approach is mainly the determination of warming up steps for RC module, number of Gaussians and learning rate used in GGMR module. In the present study, the warming up period is statistically selected as shown in the left plot of Figure 5. And the ideal warming up steps for RC prediction has been selected as 15. Moreover, the best number of Gaussians and learning rate have been chosen as 15 and 8e-3 respectively as indicated from the middle and right plots of Figure 5. In addition, we investigated the impact of predicted water flow rate through pipes as shown in Table 3. And we finally selected as the Hybrid Model inputs.

Chart, line chart

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5hyperparameters for Hybrid Approach. Left: Warming up steps for RC model; Middle: Number of Gaussians for GGMR model; Right: Learning rate for GGMR Model.

**5**Hybrid Model

|  |  |
| --- | --- |
|  |  |
|  |  |
|  |  |

## 3.3 Performance Comparison for Proposed Models

As illustrated in Table 5, all the three proposed models met the requirement of ASHRAE Guideline 14(Landsberg et al., n.d.). This table indicates that Hybrid Model is the best model for predicting Radiant Slab system energy consumption. To furtherly analyze the prediction performance for those models, typical days has been selected and plotted in Figure 6. All of three models have a reasonably good prediction performance, although they cannot well capture the peak load (which occurs usually at 6:00 PM when the space is not occupied). Furthermore, GGMR Model tends to have to overshoot or oscillate a lot around the measured data, while RC Model lean for a undershoot prediction and smoothed the ups and downs. In addition, it is evident to observe that the Hybrid Model integrates the information from both RC model and GGMR model to make the best prediction for RS system load.

As shown in Table 5, the RC model has a normalized root mean square error (NRMSE) of 13.56%, a coefficient of variation of root means square error (CVRMSE) of 15.59%, a mean absolute error (MAE) of 5.76 kilowatts (kW), and a mean absolute percentage error (MAPE) of 108.53%. The GGMR model has NRMSE of 15.89%, CVRMSE of 17.76%, MAE of 6.40 kW, and MAPE of 27.68%. The hybrid approach has NRMSE of 8.77% (35% lower from RC, 45% lower from GGMR), CVRMSE of 9.95% (36% lower from RC, 44% lower from GGMR), MAE of 3.62 kW (37% lower from RC, 43% lower from GGMR), and MAPE of 19.31% (82% lower from RC, 30% lower from GGMR).

**Table 5** Performance comparison for hourly prediction of proposed models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Models** | **NRMSE (%)** | **CVRMSE (%)** | **MAE (kW)** | **MAPE (%)** |
| RC | 13.56 | 15.59 | 5.76 | 108.53 |
| GGMR | 15.89 | 17.67 | 6.40 | 27.68 |
| Hybrid | **8.77** | **9.95** | **3.62** | **19.31** |

Chart, histogram

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**Figure 6** Radiant slab load between RC model, GGMR model, Hybrid model and measured data.

# 4. Conclusion

In this paper, a novel Hybrid Model been proposed to predict the energy use of a hydronic radiant slab system, which integrate advantages of both RC model and GGMR model. The proposed method was tested with the real word radiant slab operation data, located at Purdue University. From the case study, the Hybrid Model has demonstrated the best prediction performance among all the three models, RC, GGMR and Hybrid Model. And the proposed Hybrid model has an hourly prediction CVRMSE as 9.95% (36% lower from RC, 44% lower from GGMR), which surely met the criteria for ASHRAE Guideline 14 (Landsberg et al., n.d.). Specifically, it has been proved that the RC model prediction can be used as input for a GGMR model to furtherly reduce the predictions for both RC model and GGMR model.

During the model development process for the input variables selection of GGMR model, we found that the stronger linear correlation does not necessarily mean better prediction performance. This observation indicates that there might be further potential to explore different input variables for both GGMR model and Hybrid model.

It is worth noting that the case study is limited to only one onsite dataset source. In the future, we need to do more case studies for various data source.

# NOMENCLATURE

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | area |  | *R* | resistors | K/W |
|  | capacitors | J/K |  | density | *kg/m3* |
|  | Specific heat | J/Kg/K | *T* | temperature | K |
|  | heat transfer coefficient |  | *t* | time | second |
| L | thickness | *m* |  |  |  |
|  | conductivity | *w/m/K* |  |  |  |
| Q | heating flux | *W* |  |  |  |
| **Subscript** |  |  |  |  |  |
| *adj* | adjacent |  | *intwall* | internal wall |  |
| *AHU* | air handling unit |  | *int* | internal heating |  |
| *cav* | cavity |  | *rad* | radiant heating flux |  |
| *env* | envelope |  |  |  |  |

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