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Simple and efficient machine learning model for optimizing control of radiant floor heating

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Abstract

Radiant-floor heating (RFH) is considered the prominent heating system for improving thermal comfort and advancing energy efficiency. However, due to the slow thermal response characteristic of RFH, the heating control issues arise in intermittently heated buildings. The optimal heating control for RFH involves predicting and operating at the appropriate start-stop times to ensure thermal comfort and efficient energy consumption. Despite numerous research studies suggesting optimal control in RFH based on MPC, they require a significant amount of computational time and parameter measurements. They are hard to apply in real-situated buildings. This study intends to predict the response time of the RFH system by indoor and outdoor environmental parameters to solve the problem of optimal start or stop of RFH. In this study, data collection was conducted in an intermittently heated building in Ansan, South Korea for a 2-month heating season, and all samples were taken from real building operations or occupancy. The method utilizes a decision tree algorithm to predict the response time based on the acquired historical data. The experimental results show that the time required for the RFH to reach the preset temperature can be predicted better using the proposed method, with an accuracy R2 of around 0.954 for the predicted time. This simple and adaptable control strategy provides a way to realize more sustainable and comfortable smart buildings.

Keywords : Radiant-floor Heating, Optimal Control Logic, Decision Tree, Machine Learning

1. Introduction

Radiant floor heating (RFH) are considered a prominent system for improving thermal comfort and advancing energy efficiency. Therefore, interest in RFH has emerged globally, especially in residential buildings. Nevertheless, RFH still presents challenges for intermittently heated buildings. Because RFH has a slow thermal response characteristic.

Unlike convective heaters, RFH systems employ a distinct heat transfer mechanism. Specifically, within a conditioned environment, heat transfer initiates with the embedded pipes within the concrete layer. Subsequently, heat permeates the pipe walls before accumulating within the concrete layer(1). Remarkably, the heat stored in the floor layer is not immediately released into the indoor air but remains within the floor layer for an extended period.

Consequently, heat gradually disperses through the floor surface. This stored heat profoundly impacts the startup phase, resulting in a gradual rise in indoor temperature following RFH system activation. During this phase, thermal comfort cannot be guaranteed because of lower indoor temperature than intended.

Conversely, upon system deactivation, the release of heat from the floor layer into the air impedes the decline in room temperature. The heating energy consumption is consumed inefficiently during this phase. Despite the indoor temperature does not need to meet the set-point temperature, it is being maintained for an extended period. Therefore, the issue of optimal control for RFH, accurately determining and operating at the appropriate startand stop moments, is very important.

Numerous scholars have explored and scrutinized methods for controlling RFH systems using diverse strategies to address the challenges posed by these systems. For example, Model Predictive Control (MPC) has emerged as an effective approach, utilizing demand prediction to directly manage RFH systems' start or stop. This dynamic MPC control method effectively addresses the challenge of starting or stopping RFH operations compared to predetermined temporal parameters, dynamically regulating the time problem of RFH. Cho et al. attained optimal control within a residential

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structure through the utilization of the MPC method on a centralized controller, based on the interplay among distinct thermal dynamics inherent to the RFH system and individual rooms. This approach resulted in energy conservation ranging from 14% to 46%[2]. However, the implementation of MPC involves solving optimization problems for each control step, potentially demanding extensive computational resources, and rendering it unsuitable for systems with stringent time constraints. Furthermore, its applicability to the enhancement and upgrade of existing RFH systems is limited. Additionally, the accurate tuning of the MPC controller necessitates specialized knowledge and typically involves adjusting various parameters, including prediction ranges, control ranges, and weighting factors. It indicates that the method becomes difficult to apply in real-situation building.

In response to the above challenges, this study proposes a simple and efficient model for optimal control of radiant floor heating systems. This study explores the impact of various indoor and outdoor environmental factors on the response time of RFH systems. The parameters pertaining to indoor and outdoor environments are initially subjected to screening and selection processes. This strategy, requiring fewer parameters, allows for the prediction of RFH system responses. Then it employs data-driven techniques to identify an optimized start/stop control strategy for RFH.

The methodology's significant contribution lies in its reliance on easily measurable, uncomplicated environmental parameters for input, highlighting its simplicity and applicability. Its seamless integration with the control system facilitates rapid adaptation to real-world scenarios. The results obtained serve as straightforward environmental state reference parameters for the subsequent stages of the control strategy, empowering advanced automatic control decision-making processes.

2. Methodology

2.1 Analysis methods and selection of research objects

2.1.1 Proposed method

One of the objectives is to predict the RFH system response time for optimizing the start-stop control by reducing the number of input variables without compromising their accuracy and significance, in the following five steps. (1) Constructing the dataset: Operational data are extracted for the entire heating-up or cooling-down phase and the environmental parameters at the current moment and the time required to reach the set temperature are calculated with a one-minute time resolution (Figure 1). (2) Reduce parameters: Use correlation analysis to remove less important and complex input variables and simplify future modeling. (3) Sort features: create strong links between the remaining relevant parameters and further sort among the highly relevant variables to optimize the inputs. (4) Create Machine Learning Models: Construct machine learning models to handle large datasets. (5) Integrate and Calculate RFH time: In the final stage, the identified variables are integrated with representative inputs and used in a decision tree model to accurately calculate the final response time.

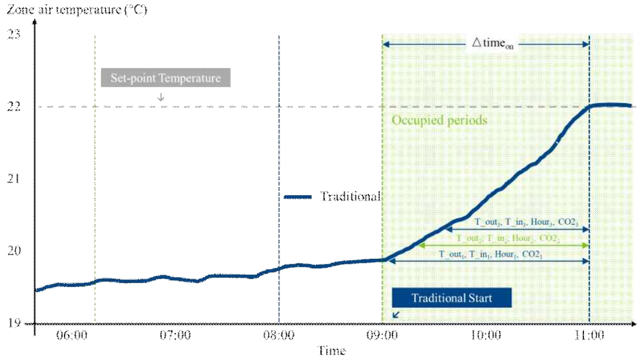


Figure 1. The process of creating a division of data for the training set (as an example of the start-up phase).

2.1.2 Theoretical analysis

Decision trees, widely employed in supervised learning for classification and regression tasks, construct a tree-like model wherein each internal node signifies a decision based on a feature, and each branch denotes the corresponding outcome[3]. The overarching objective is to classify or predict a target variable through a sequence of decision-based steps. The process begins with the entire dataset at the root node, subsequently splintering the data at internal nodes based on the optimal feature and value. This split aims to enhance the homogeneity of resulting subsets regarding the target variable. The determination of the best split depends on the problem type, utilizing metrics like Information Gain or Gini Impurity to minimize impurity in the branches. This recursive splitting continues until a predefined stopping criterion, such as achieving a certain level of purity or reaching a maximum tree depth. Terminal nodes, or leaves, represent the ultimate prediction for the target variable. In classification, this could be the dominant class within the subset, while in regression, it might be the average value. This structured approach provides transparency and interpretability, making decision trees a valuable tool in various data-driven applications. While there are different formulas depending on the task and splitting criteria, here's a common one used for classification problems called Information Gain (IG):

$$IG(S, A) = Entropy(S) - \Sigma |Si| / |S| * Entropy(Si)$$

where, S: The entire dataset at a particular node; A: A specific feature (attribute) being considered for splitting; Si: Subsets of S created by splitting on feature A (one for each possible value of A); Entropy(S): The initial "impuri-ty" of the dataset S, measured using entropy (measures the randomness or uncertainty); |Si| / |S|: Proportion of data points in subset Si compared to the entire dataset; Entro-py(Si): Entropy of each subset Si after the split.

2.2 Experiment

To determine the indoor environmental parameters and their correlation with the actual operational effectiveness of the RFH, we collected data from a public building located in Ansan City, Korea (37°20'19"N, 126°48'8"E) for a 2-month heating season. The three-story building is primarily used for kindergarten operations, with classrooms and offices on the first and second floors, and a kitchen-dining room and large activity space on the third floor. The radiant floor heating system is used as the main heating system in this building.

During the heating season operation, there is no mechanical ventilation inside the classrooms, but there is natural ventilation through the windows facing outside. These windows are usually opened during student meals at midday and remain closed both before members enter and after they leave. The collection points were mainly arranged in individual classrooms, and the collection of data on environmental parameters (indoor and outdoor temperature and humidity, CO2) and the operation of the RFH system was carried out with a 1-minute temporal resolution, with continuous measurements being maintained on both weekends and weekdays.

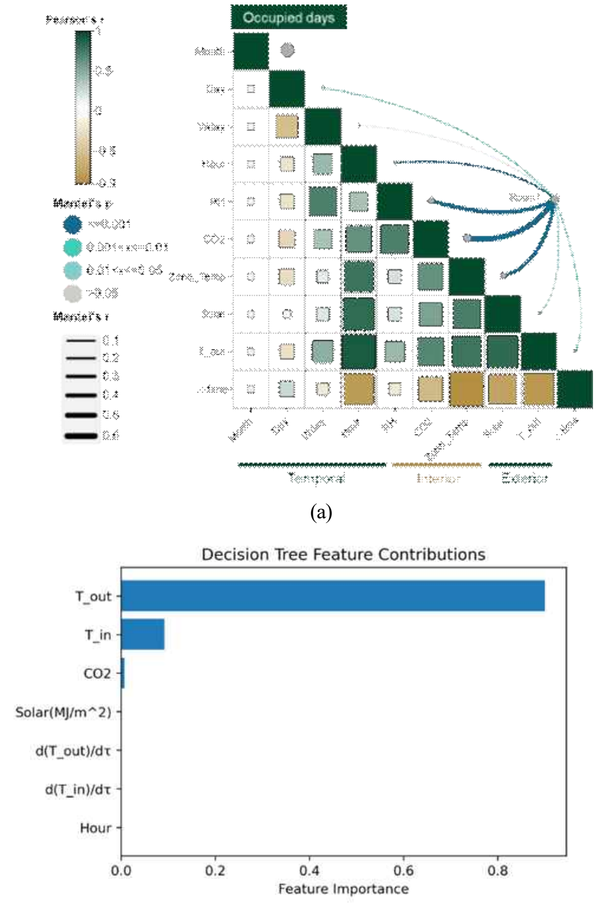
3. Results and discussion

3.1 Parameter selection

Figure 2(a) unveils a noteworthy association (Pearson correlation coefficient > 0.9) between the corresponding temporal aspects of Radiant Floor Heating (RFH) and outdoor air temperature. This observation signifies the impactful influence of outdoor temperature on the time of heating. Notably, the correlation coefficient for indoor temperature similarly exhibits positive correlation characteristics, with a coefficient of around 0.9. Furthermore, the correlation analysis involving solar radiation and system consumption time indicates a positive relationship. However, by calculating the GINI index in the decision tree, among the prioritization of features for the refined variables, it becomes evident that outdoor temperature encapsulates certain aspects of solar radiation information, in Figure 2(b). Consequently, the influence of solar radiation is overshadowed by the significance of the first two factors, resulting in a consequential reduction in the decision tree input variables.

3.2 Model development

The primary advantage of the decision tree algorithm lies in its graphical representation of decision trees, facilitating user comprehension. Moreover, users can directly derive classification rules from the decision tree generated by the algorithm, which can subsequently be converted into 'IF...THEN' format. The IF statement represents the diverse conditions and the THEN statement suggests the operation of the heating system depending on the conditions. Each traversal path from the root node to the leaf node within the decision tree corresponds to the derivation of a decision classification rule, wherein the test conditions along the path constitute the conjunctive terms of the rule's antecedents, and the class label assigned to the leaf node serves as the consequent of the rule.



(a)

(b)

Fig 2. (a): Correlation analysis of environmental parameters. (b):Ranking of importance of filtered variables.

During the construction of the decision tree model, the selected feature data include indoor and outdoor temperatures, timestamps, carbon dioxide concentration, and other relevant parameters. However, following algorithmic processing and model parameter adjustment, insignificant factors are disregarded, resulting in the identification of primary influencers on the response of the RFH system. Notably, outdoor temperature emerges as the predominant factor, followed by indoor temperature. While other factors have some influence but to a lesser extent.

For instance, the initial rule suggests that when the outdoor temperature falls below -3.05°C and the indoor temperature remains below 21.55°C, the system's activation and operational duration may exceed 147 minutes (See Figure 3). Furthermore, a comprehensive rule analysis reveals that variations in solar radiation rates, timing, and temperature changes per unit of time contribute marginally to the RFH system's response time. Consequently, building operators are advised to proactively monitor outdoor temperature fluctuations and appropriately guide RFH system operations to enhance indoor temperature response accuracy.

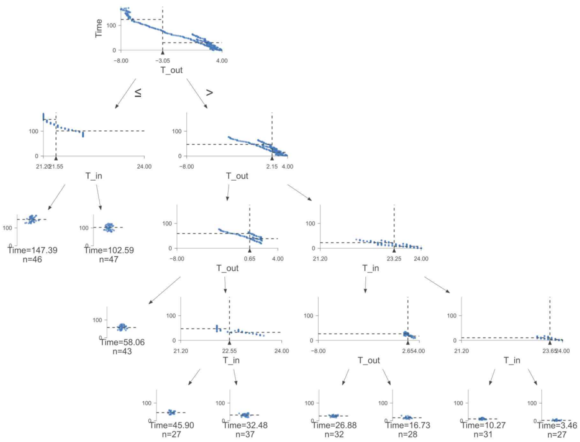


Fig. 3 Specific split points of the decision tree model.

3.3 Model validation

During startup, the fundamental input variables involve indoor and outdoor temperatures, selected for their significant influence on the Radiant Floor Heating (RFH) system's response time and their easy measurability. In this investigation, the machine learning approach adopts the decision tree algorithm. Decision trees offer clear prognostications by unraveling complex predicaments into a series of explicit decision rules[4], making them suitable for optimizing RFH control in various scenarios.

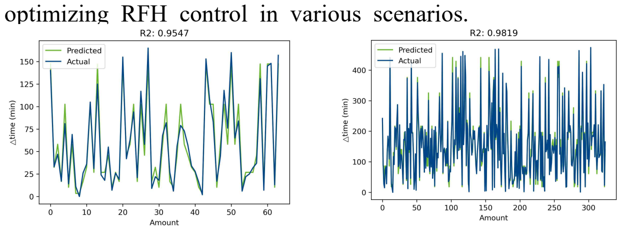


Fig. 4 Distribution of predicted and measured values during startup (a) and stopping (b) operation phases.

The expected RFH response time, illustrated in Figure 4, represents the minutes deduced from the methodology expounded in this study. A comparison with the actual elapsed time in the recorded dataset accentuates the effectiveness of the proposed strategy. Figure 4 presents the findings, revealing an R2 of 0.954 for the decision tree model during the initiation phase, indicating its adeptness in delineating the relationship between temperature and system response time. Moreover, the R2 for the projected time in the subsequent cessation phase is 0.981. The agreement between the anticipated and actual values is conspicuous in the figure, validating the accuracy of both results. The spatial configuration of data points in Figure 4 indicates a more uniform trajectory in the predicted response times computed by the advocated methodology.

4. Conclusion

Radiant Floor Heating is considered the prominent heating system for improving thermal comfort and advancing energy efficiency. However, the slow thermal response characteristics of RFH make it difficult to control as intended. Optimal heating control of RFH is considered the best solution assuring thermal comfort and efficient energy consumption.

In this paper, a simple and efficient optimal control method for RFH is proposed. The novelty of this research lies in the proposed model, which requires only simple parameters that can be easily collected, and it involves a small computational time. Therefore, this model is easily applicable in real buildings. the following conclusions were obtained through modeling and analysis:

(1) The proposed model for optimal control in RFH is characterized by applying simple parameters. It focuses solely on indoor and outdoor environmental factors to accurately predict optimal start and stop timing in RFH. Concurrently, the scrutiny disclosed that miscellaneous environmental parameters lack the significance attributed to indoor and outdoor air temperatures in influencing the RFH system's response time, showcasing correlation coefficients approximately settling at 0.9. Due to the novelty of the proposed method, optimal control for RFH can be easily implemented in real-situated buildings.

(2) The envisaged decision tree forecasting algorithm demonstrates commendable computational efficiency in delineating the intricate interplay between indoor and outdoor environmental variables and the response time dynamics of the RFH system. The refined onset R2 at the initial RFH system phase attains 0.95, while the prognostication R2 for the optimized cessation in the subsequent phase ascends to approximately 0.98.

(3) In practical scenarios, the advocated approach necessitates solely the measurement of indoor and outdoor air temperatures along with CO2 concentration, facilitating streamlined applicability for the optimized initiation and termination control of RFH. This approach seamlessly aligns with the overarching objectives of minimizing energy consumption while concurrently enhancing thermal comfort.

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