Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A self-learning algorithm for coordinated control of rooftop units in smalland medium-sized commercial buildings



AppliedEnerg

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HIGHLIGHTS

- Proposed an indoor temperature prediction algorithm using coarse-grained thermostat data.
- Designed a software solution for RTU coordinated control during a DR event.
- Tested algorithm in a real-world office building, showing effective peak load reduction.

ARTICLE INFO

Keywords: Demand response (DR) Peak load management RTU coordination Thermal comfort IoT-based building energy management system

ABSTRACT

With the advent of the smart grid, demand response (DR) has been implemented in many electric utility control areas to reduce peak demand in buildings during grid stress conditions. However, small- and medium-sized commercial buildings typically do not deploy a building energy management (BEM) system due to high costs of commercially available solutions. Thus, their participation in DR events implies manual control and shutting down major building loads (e.g., air conditioning systems) without considering occupant comfort. With rapid development of Internet of Things (IoT) technologies, some cost-effective IoT-based BEM systems have become available. Based on such systems, this paper presents an algorithm to automatically coordinate the operation of rooftop units (RTUs) in small- and medium-sized commercial buildings, thereby meeting the specified power limit (kW) during a DR event while taking into account occupant comfort. The proposed algorithm has been designed to intelligently learn building thermal properties using coarse-grained indoor temperature data from thermostats, thus avoiding the deployment of sophisticated sensors network. A mixed-integer linear programming model has been utilized to determine an optimal RTU control strategy during a DR event. The peak load shedding performance of the proposed strategy has been tested in an office building in Blacksburg, VA, USA. The experimental result demonstrates that the building could achieve the required peak load reduction and the computation time required by the proposed algorithm is less than 5 min. This implies that with the proposed algorithm a building is capable of responding to a DR signal with a short notice, providing valuable demand-side resources for electricity capacity and ancillary markets.

1. Introduction

Buildings use around 40% of the total energy consumption worldwide [1] and consume over 70% of the total electricity usage in the U.S. [2]. As the major consumer of electricity, buildings have potential to provide energy savings and relieve stress on electric power grids during peak hours. Many studies have been conducted in recent years on this topic. Authors in [3,4] propose a multi-agent control platform that learns from occupant feedbacks to increase building energy efficiency while guaranteeing indoor comfort. A similar system is proposed in [5] using fuzzy control and a multi-objective genetic algorithm. Authors in

http://dx.doi.org/10.1016/j.apenergy.2017.08.093 Received 6 March 2017; Received in revised form 6 June 2017; Accepted 11 August 2017 Available online 20 August 2017

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[6] introduces a BEM system based on two-stage optimization capable of optimal scheduling of building appliances. A peak load reduction system based on model predictive control and real-time pricing is presented in [7]. Among various appliances in the buildings, HVAC systems usually consume over 30% of the total building electricity usage [8] and their reactive power usage is directly related to power grid voltage stability. Therefore, HVAC systems are the major loads in buildings to be controlled. Research in [9] quantifies energy savings based on different HVAC set points. A centralized heating system control approach to make building demand responsive is studied in [10]. Authors in [11] demonstrate peak cooling demand shifting with the



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help of building photovoltaic and thermal storage systems. Instead of using global set point adjustment, a computing tool is proposed in [12] to optimally control set points of each thermal zone during a peak-load reduction event. Authors in [13] propose a fast chiller control strategy to enable buildings to participate in electricity ancillary services [14] and providing a spinning reserve to the smart grid [15]. Another work targeting large commercial HVAC control for participating in fast demand response is presented in [16].

Not only in academia, electric utilities and third party demand aggregators show tremendous interest in the involvement of buildings in grid load balance. Many demand response (DR) programs have been introduced to encourage peak load reduction in buildings during critical times [17–20]. These incentive-based DR programs usually require a customer to sign a contract to maintain the building's power demand below a certain kilowatt (kW) limit during a DR event in exchange of financial benefits. However, by studying the non-domestic sector of the short term operating reserve (STOR) market in the U.K., authors in [21] point out that the challenges for involving more end users to participate in demand reduction are: (1) the short response time (as short as 5-10 min) to generate an effective response scheme and (2) the concern for compromising occupants' comfort. Because of these unresolved challenges, authors in [21] reveal that only a small portion of end users are willing to participate in the load reduction DR program. This implies that for a building to actively participate in a DR event, a control system that can response quickly and automatically and considering occupant comfort is required.

While large modern commercial buildings equipped with sophisticated building energy management (BEM) systems usually are able to achieve an automatic control, smaller buildings (less than 50,000 square feet), which constitute majority of buildings (i.e., more than 90% of commercial buildings in the U.S.), mostly do not have such automation systems [22]. The main reason is the prohibitive price for designing, programing and deploying an automatic energy management system. According to [23], a basic BEM is costly with an average price of \$2.50 (U.S. Dollar) per square foot and this number can be as high as \$7, not to mention a hefty annual maintenance expenditure of about 10-15% of the initial cost. The high cost of a traditional BEM system means return on investment is a challenge for all, but large buildings. To solve this problem, with fast development in the area of Internet of Things (IoT), many IoT-based BEMs enabled by IoT-based smart devices are emerging as cost-effective solutions to those building owners. Capable of providing controllability, system awareness and intelligent controls (see Fig. 1), they are gaining popularity for their low-cost, flexibility and scalability features among small- and mediumsized buildings. An example of such an IoT-based solution is the U.S. Department of Energy-sponsored Building Energy Management Open Source Software (BEMOSS) [24-26].

However, as of today, most of the IoT-based BEMs are focusing on controllability and monitoring, the intelligent applications are not welldeveloped, such as DR implementation. To implement DR, power consumption in buildings can be reduced by turning off unnecessary lightings and plug loads, but the control of HVAC systems is not straightforward and might need some decision making assistance. Since most small- and medium-sized buildings use rooftop units (RTUs), the coordination of multiple RTUs can be an effective approach for load reduction in such buildings.

Nevertheless, reducing HVAC power consumption in a building during critical periods, usually hot summer days, will inevitably impact occupants' thermal comfort. Thus, a good indoor temperature prediction will facilitate the HVAC control to minimize any occupants' thermal discomfort in a building. Time series and neural network methods are widely used in such predictions [27–33]. Authors in [27] predicts the thermal behavior of an open office using both linear parametric and neural network-based nonlinear autoregressive models. A similar study using an autoregressive model is discussed in [28]. Authors in [30] compare the performance of four different models to predict building thermal behaviors. However, existing work depends heavily on sensor inputs, which causes extra investment for building owners to establish the sensor network. For example, CO2 and occupancy sensors are needed to measure the building occupancy level, while door/window sensors are needed to examine the open/close status of windows and doors. To tackle this issue, authors in [31-33] propose approaches for multiple RTU coordination using minimal number of hardware. Authors in [33] specify a fixed number of RTUs that are allowed to operate at the same time. However, by limiting the number of operating RTUs, a building might not be able to fully utilize the allowable demand (kW) limit in case the rated power of various RTU is different from each other. Instead, a power limit should be used to cap the total RTU power demand to allow greater building operation efficiency and minimize occupant discomfort. Other studies in the literature use simulation data or sophisticated sensor data for indoor temperature prediction model training, which is not applicable with emerging IoT-based BEM systems. The reason lies in that the indoor temperature measurement comes from smart thermostats due to the absence of a sophisticated sensors network in IoT-based BEM systems, and the measurement granularity of many commercially available smart thermostats is large. (For example, RadioThermostat: 0.5 °F, Honeywell: 1 °F and ICM thermostat: 1 °F.) Thus, with such coarsegrained data, thermal properties that most time-series approaches trying to capture are lost, and new approach adaptive to these data is needed.

In all, the literature review shows that in the electric industry, involving more buildings in peak load reduction is highly beneficial, needed but not well-accomplished. Even though IoT-based BEMs provide an affordable solution for small- and medium-sized buildings, an intelligent DR implementation based on this platform is yet to come. Therefore, the originality of this work is the self-learning algorithm for coordinated control of multiple RTUs that can be used with the



Fig. 1. Utilities of the IoT-based BEM.

emerging IoT-based BEM system, thus facilitating rapid DR implementation in commercial buildings. The proposed self-learning algorithm automatically learns the thermal properties of zones to better consider occupants' thermal discomfort during a DR event. The value of this research is the development and validation of a practical and costeffective solution to allow more buildings to participate in DR. The proposed control method is validated by simulations as well as a realworld building control. The short response time (under 5 min) of the proposed approach enables rapid load reduction in buildings, providing valuable demand-side resources for electricity capacity and ancillary markets under power grid contingencies.

2. Research methodology and system design

To coordinate the RTUs' operation and meet the power limit (kW) while considering occupants' thermal comfort, it is essential to have a good knowledge of each zone's thermal behavior. A theoretical study [34] shows that given the RTU status, the indoor temperature variation rate can be expressed as a linear function of the indoor temperature at the previous time step:

$$\frac{dTemp_{t}}{dt} \approx \frac{Temp_{t} - Temp_{t-1}}{\Delta t} = k \cdot Temp_{t-1} + c \quad (\forall t > 1)$$
(1)

Where the value of k depends on building surface area, material heat resistance and other thermal properties; c is influenced by factors like outdoor temperature, instant solar radiation, RTU capacity and status. These influencing parameters usually are either not readily accessible to a building manager or additional sensors are required to capture such information (for real-time solar radiation). Thus, (1) cannot be easily configured and integrated to an indoor temperature prediction model.

Empirical observation also substantiates that during a short period, the indoor temperature variation rate can be considered constant. This is illustrated in Fig. 2, which shows the temperature measurements in a building under study vary linearly.

In a building, most of the influencing factors mentioned above, such as the ratio of area of wall and building heat resistance, typically remain constant. Therefore, their influences to indoor temperature variation are of a constant pattern and are reflected in the historical data of building operation. Based on the linear property in (1), an indoor temperature prediction model is proposed to study the historical data collected from smart thermostats, locate temperature raising and dropping periods and learn the temperature variation rate of the thermal zones. With the temperature variation rate as the representative of building thermal properties, a coordinated control algorithm utilizes this knowledge to coordinate RTU operation during a DR event. The RTU coordination strategy is generated using linear programming to guarantee the computational efficiency. As authors in [13] point out the sooner a building responds to a DR signal, the more value it provides to the electric utility.

Overall, the proposed RTU coordinated control is flexibly designed so that it can be a plug-in application to the BEM system. For small- and medium-sized buildings, a low cost IoT-based BEM solution can be deployed, such as the open sourced BEMOSS [24], which is the host of the proposed algorithm in this study. The proposed algorithm and its integration with the IoT-based BEM system is illustrated in Fig. 3. It comprises a learning process and optimization process, fulfilled by a learning agent and an optimization agent, respectively.

The learning agent utilizes smart thermostats' historical data provided by a BEM system to derive parameters for a polynomial regression model that captures thermal properties of different thermal zones in a building. The learning process can be carried out at night before potential DR/critical peak event day. During the DR day, when triggered by the signal, the optimization agent will start a linear programming and generate an optimal RTU control strategy which minimizes the overall cost from occupants' thermal discomfort and energy consumption while keeping the total RTUs' power consumption within a specified power limit. The control strategy will then be sent to BEM for execution.

The interface between BEM and the proposed algorithm is bilateral. That is, thermal information about a thermal zone from a BEM system, including indoor temperature and thermostat state, must be provided to the algorithm to allow learning of zones' thermal properties. On the other hand, the control strategy generated by the algorithm should be sent for execution by the BEM. In our implementation, the BEM used in this study, i.e., BEMOSS, saves historical data in a Cassandra database [35], which has granted open access to the algorithm. When the algorithm sends back control parameters, thermostat agents in BEMOSS execute corresponding commands.

3. Self-learning indoor temperature prediction model

In this section, a learning algorithm (implemented by the learning agent) based on a polynomial regression model is introduced for predicting indoor temperature variation rate, using coarse-grained temperature data from thermostats.

3.1. Influencing factors

Since indoor temperature is mainly influenced by heat gain from the outdoor environment and indoor activities, these two factors are discussed below.

3.1.1. Outdoor environment

Outdoor environment, such as temperature, humidity and solar radiation, have a direct impact on how fast a zone is cooled or how soon the zone's temperature rises due to heat gain. Temperature and

Fig. 2. Historical data of a thermostat in a building in Blacksburg, VA on July 7th, 2016.



Fig. 3. The integration of the proposed system and BEM.



Table 1 Categories of weather conditions from Weather Underground.

Category	Description	Weather Conditions from Weather Underground
Class 1	Will have direct sunlight into room during some time frame	Clear
Class 2	Might have direct sunlight into room during some time frame	Scattered Clouds, Partly Cloudy, Mostly Cloudy
Class 3	No direct sunlight	Overcast, Light Drizzle, Drizzle, Heavy Drizzle, Light Rain, Rain, Heavy Rain, Mist, Fog, Haze
Class 4	Invalid value	Unknown

humidity data are readily available via online sources. Determining the heat gain from solar radiation depends upon weather condition (sunny/ cloudy/rainy), time of the day and building orientation (i.e., a room facing west has direct sun radiance in a sunny afternoon). This study utilizes the historical and forecasted weather information from Weather Underground [36]. Some typical summer weather conditions used by this service are categorized in Table 1.

3.1.2. Indoor activity

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Occupant indoor activities contribute to internal heat gain which has a crucial impact on how fast the zone temperature drops or rises. Indoor activities can be inferred using information from occupancy sensors (e.g., occupancy status) and plug loads (e.g., appliance usage status). However, for a more general case where there exists neither occupancy sensor nor smart plug, indoor activities can be related to day of week and time of day in most cases.

Considering both outdoor and indoor environments, the indoor temperature variation rate can be expressed as:

$$\frac{dTemp_{room}}{dt} = f(Temp_{room}, Temp_{out}, time, dow, H_{out}, w)$$
(2)

 $Temp_{room}$ and $Temp_{out}$ represent indoor and outdoor temperatures respectively (unit in Fahrenheit for this study); *time* represents hour of day in 24 h format; *dow* represents day of week (1–7 meaning Monday to Sunday); H_{out} is outdoor humidity in percentage; and w is the weather class number (Class 1–4 as shown in Table 1).

3.1.3. Algorithm applicability

Using such parameters as day of week and time of day to estimate an indoor activity level is based on the assumption that the thermal zone has a regular operating schedule/occupancy level over days and weeks. Hence, the algorithm presented this paper focuses only on thermal zones that comply with this assumption. These are office buildings that have relatively constant number of employees and regular indoor activities on a particular time of the day and a particular day of the week. The performance test of the developed algorithm is validated in a real-world office building environment. Further studies will be required to determine the applicability of the developed algorithm (or adjustments needed) when considering other building types, such as clinics, public libraries and convenience stores. This is considered as future research.

3.2. Polynomial regression model

Since the impact of the aforementioned influencing factors on k and c in (1) is non-linear, their influence on the indoor temperature variation rate is also non-linear. In order to capture the non-linear relationship, while making it computationally feasible, the 3rd-order polynomial regression model is used for predicting the indoor temperature variation rate. Denote the influencing factors as x_1 to x_6 and the indoor temperature variation rate as y, the model can be written as:

$$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4 + \theta_5 x_5 + \theta_6 x_6 + \theta_7 x_1^2 + \theta_8 x_2^2 + \theta_9 x_3^2 + \theta_{10} x_4^2 + \theta_{11} x_5^2 + \theta_{12} x_6^2 + \theta_{13} x_1^3 + \theta_{14} x_2^3 + \theta_{15} x_3^3 + \theta_{16} x_4^3 + \theta_{17} x_5^3 + \theta_{18} x_6^3$$
(3)

Further assume $x_i^j = z_{(j-1)*6+i}$, and normalized each variables, the model becomes a linear regression:

$$y = \theta_0 \widetilde{z}_0 + \theta_1 \widetilde{z}_1 + \theta_2 \widetilde{z}_2 + \dots + \theta_{17} \widetilde{z}_{17} + \theta_{18} \widetilde{z}_{18} = \sum_{i=0}^{18} \theta_i \widetilde{z}_i = \Theta^T \widetilde{Z}$$
(4)

Providing historical data (y, \tilde{Z}) pairs for training, by utilizing the gradient descent method, an optimization problem can be solved to acquire the parameters Θ for the predicting model.

The cost function is mean square error for all predictions, namely the square of root mean square error (RMSE):

$$C(\Theta) = \frac{1}{2m} \sum_{i=1}^{m} (\Theta^{T} \widetilde{Z}^{(i)} - y^{(i)})^{2}$$
(5)

The total number of data points is m, and $\widetilde{Z}^{(i)}$, $y^{(i)}$ represents the preprocessed model input vectors and outputs respectively. Using gradient descent, the parameters can be iteratively solved by the formula below:

$$\theta_j \doteq \theta_j - \alpha \frac{\partial}{\partial \theta_j} C(\Theta) \tag{6}$$

 α is 0.02 in this study and iteration time is 6000.

4. Multiple RTU coordinated control

In this section, an optimization algorithm (implemented by the optimization agent) is discussed for the RTU coordinated control. The goal is to reduce peak load of all RTUs to a predefined limit while minimize the cost from occupants' thermal discomfort and energy consumption (if considered). In order to generate the control strategy efficiently, a linear optimization is applied.

4.1. Indoor temperature prediction model linearization

Given that in a short period of a DR event, five out of six variables of the indoor temperature prediction model typically do not change drastically, namely outdoor temperature, outdoor humidity, day of week (not change at all), hour (minor change during short time) and weather condition (usually clear or cloudy hot days when DR happens). This means the indoor temperature variation rate, either rising or dropping, can be expressed as a function of indoor temperature only.

$$\frac{dTemp}{dt} = f(Temp_{room}, \overline{Temp_{out}}, \overline{time}, \overline{dow}, \overline{H_{out}}, \overline{w}) = g(Temp_{room})$$
$$= k_1 Temp_{room}^3 + k_2 Temp_{room}^2 + k_3 Temp_{room}$$
$$+ c(\overline{Temp_{out}}, \overline{time}, \overline{dow}, \overline{H_{out}}, \overline{w})$$
(7)

According to (1), the temperature variation rate is linearly proportion to indoor temperature, which means (7) can be linearized around the short range of the normal indoor temperature. Thus, after linearization, the rate of temperature variation can be expressed as (8) and (9). μ_d , μ_r , ν_d and ν_r are provided by linearizing (7).

$$Rdrop = \mu_d Temp_{room} + \nu_d \tag{8}$$

$$Rrise = \mu_r Temp_{room} + \nu_r \tag{9}$$

4.2. Mixed integer linear programming model

The objective of the multiple RTU coordinated control is to minimize total cost derived from the occupants' thermal discomfort as well as energy consumption (optional, depending on the electricity tariff

 Table 2

 Variables in RTU coordinated control optimization problem.

rate the building has subscribed to) during DR events. Table 2 shows the definition of relevant variables, among which the status of RTUs at different time slots (S_t^h) are the control variables.

A study has shown that thermal discomfort will cause building occupants productivity loss [37]. To generalize, it is reasonable to assume that a building manager can quantify an equivalent economic loss caused by the productivity loss based on their understanding to the building's business. α_t^h is given as such indicators. In addition, depend on electric utilities, different buildings' DR programs vary with each other: some increase the electricity price drastically during a DR event while others have price protection under the buildings' capacity reserve (at the cost of capacity reserve charge). As a result, the facilities' managers might prefer or not prefer to consider the total energy consumption during a DR event, and ω represents the unit cost for the electricity. With both α_t^h and ω , the optimization model is trying to find the optimal tradeoff between occupants comfort and total energy consumption. Therefore, the objective function for the coordinated control is to minimize the overall cost from both aspects:

Minimize:
$$D = \sum_{h=1}^{H} \sum_{t=1}^{T} D_{HVAC}(Temp_t^h) + \omega \cdot \sum_{h=1}^{H} \sum_{t=1}^{T} P_{Normal}^h \cdot \frac{\Delta t}{60}$$
(10)

Where, the cost for the productivity loss is defined as:

$$D_{HVAC}(Temp_t^h) = \begin{cases} 0 & \text{if } Temp_t^h \leqslant T_{max}^h \\ \alpha_t^h(Temp_t^h - T_{max}^h) & \text{if } Temp_t^h > T_{max}^h \end{cases}$$
$$= \max[0, \alpha_t^h(Temp_t^h - T_{max}^h)]$$
(11)

The objective function is subject to the following constraints: **Inequality constraints:**

1. Room temperature should not be lower than a certain threshold:

$$Temp_t^h \ge T_{min}^h \quad (\forall h, \forall t)$$
(12)

2. Total power consumption of multiple RTUs should be under the DR RTU power limit P_t^{DR} at any time during a DR event:

$$P_t^{total} = \sum_{h=1}^{H} S_t^h \cdot P_{Normal}^h \leqslant P_t^{DR} \quad (\forall t)$$
(13)

The DR RTU power limit is determined by subtracting the total DR power limit, which is issued by an electric utility or a DR aggregator, by the amount of the base critical load predefined by the building manager.

Equality constraint:

Room temperature prediction at time t given the room temperature and RTU status at time t-1:

Variable	Definition	Variable	Definition
D	Total cost for occupant thermal discomfort and energy expenses.	Temp ^h	Indoor temperature of Zone h in Time slot t (°F)
ω	Cost of electricity per kWh, in currency unit. ($\omega = 0$ if do not consider energy conservation)	P_t^{total}	Total RTU power consumption in Time slot t (kW)
Н	Total number of thermal zones	Т	Total number of time slots
$D_{HVAC}(Temp_t^h)$	Cost for occupants' thermal discomfort under the indoor temperature of $Temp_l^h$	P ^h _{Normal}	Normal rate of RTU h (kW)
S_t^h	Status of RTU h in Time slot t (0, 1 stands for OFF/ON)	T_{max}^h	Maximum tolerable temperature (MTT) in Zone h (°F)
α_t^h	Monetary productivity loss caused by thermal discomfort of Zone h in Time slot t , reflecting zone priority	T^h_{min}	Minimum tolerable temperature in Zone h (°F)
P_t^{DR}	Demand response RTU power limit (kW)	Δt	Length of time slots (e.g., 5 min, 15 min)
β_t^h	New variable introduced to linearizing the problem	M	Big constant for solving the optimization problem

$$Temp_{t}^{h} = f \left(Temp_{t-1}^{h}, S_{t-1}^{h} \right)$$

$$= Temp_{t-1}^{h} + \Delta t \cdot Rdrop_{t-1}^{h} \cdot S_{t-1}^{h} + \Delta t \cdot Rrise_{t-1}^{h} \cdot (1 - S_{t-1}^{h}) \quad (\forall h, \forall t > 1)$$
(14)

Typically, there are $Rdrop_t^h < 0$ and $Rrise_t^h > 0$. Considering (8) and (9), (14) becomes:

$$Temp_{t}^{h} = Temp_{t-1}^{h} + \Delta t \cdot (\mu_{d}^{h} - \mu_{r}^{h}) \cdot S_{t-1}^{h} \cdot Temp_{t-1}^{h}$$
$$+ \Delta t \cdot (\nu_{d}^{h} - \nu_{r}^{h}) \cdot S_{t-1}^{h} + \Delta t \cdot \mu_{r}^{h} Temp_{t-1}^{h} + \nu_{r}^{h} \cdot \Delta t \quad (\forall h, \forall t > 1)$$
(15)

Therefore, this equality constraint introduces a quadratic element between control variable and state variable $(S_{t-1}^h \cdot Temp_{t-1}^h)$. To linearize the problem, assuming that:

$$\beta_{t-1}^h = S_{t-1}^h \cdot Temp_{t-1}^h \tag{16}$$

Thus, the following inequality constraints are added:

$$-M(1-S_{t-1}^{h}) \leq \beta_{t-1}^{h} - Temp_{t-1}^{h} \leq M(1-S_{t-1}^{h})$$
(17)

$$-M \cdot S_{t-1}^h \leqslant \beta_{t-1}^h \leqslant M \cdot S_{t-1}^h \tag{18}$$

where *M* is a constant. Since the indoor temperature is bound by *M* according to (17), M = 100 is sufficient and is used in this paper.

Although the optimization model above is designed for summer DR events, it can be easily modified (formula (11) and (14)) to be applicable for winter DR events, when RTUs are in heating mode.

5. Results and discussions

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In this section, first, the indoor temperature prediction model will be tested and evaluated using four months' collected thermostat data from an office suite; second, some simulations are compared between the proposed multiple RTU coordinated control and other commonly used control; third, a real-world building demonstration shows the feasibility of the proposed control in the real world; and finally, algorithm computation efficiency are analyzed.

5.1. Validation for indoor temperature prediction model

5.1.1. Training data

To train the indoor temperature prediction model, historical data including all influencing factors are required. Among them, meteorological data, such as outdoor temperature, outdoor humidity and weather condition, are from Weather Underground; while indoor temperature comes from smart thermostats. All data are retrieved from a corresponding BEM as needed by the learning agent.

The indoor temperature variation rate in F/s is calculated as the slope of blue (temperature dropping rate) and red (temperature rising rate) dash lines shown in Fig. 4.

For temperature dropping cases (e.g. T1–T2):

temperature dropping speed =
$$\frac{control \ deadband}{T2-T1}$$
 (19)

For temperature rising cases (e.g. T2–T3):

temperature rising speed =
$$\frac{\text{control deadband}}{T3-T2}$$
 (20)

Since most thermostats have a control dead-band of 1 $^{\circ}$ F, this implies that as for calculating the temperature variation rate, both thermostats with 1 $^{\circ}$ F granularity and 0.5 $^{\circ}$ F granularity have the same level of accuracy. Thermostats used in this research is Radio Thermostat CT-50 with 0.5 $^{\circ}$ F granularity and a control dead-band of 1 $^{\circ}$ F.

5.1.2. Model validation

According to Section 3.1.3, an office suite, named as Suite 1, in an office building on Virginia Tech campus in Blacksburg, VA, USA is studied to validate the proposed prediction model. Four groups of training data are from May, June, July and August in 2016. Once the model has been trained, the first 7-day data from June, July, August and September are used for validation respectively. Fig. 5(a)-(d) shows the validation results. X-axis represents temperature dropping or rising cases from the validation period (1st to 7th in each month) and Y-axis is the absolute value of indoor temperature variation rate (°F/s). In operation, the learning agent can use the past 30-day data for training the model.

To quantify the prediction error, the equation below is used to represent the error of a single prediction.

$$err_k = \frac{|S_{predict} - S_{actual}|}{\overline{S}}$$
(21)

 $S_{predict}$ is the predicted rate and S_{actual} is the actual rate, while \overline{S} is the average rate during these 7-day validation period. Ranking the error of all test cases in a descending order gives distributions as shown in Fig. 6.

According to Fig. 6, for both temperature rising and dropping speed prediction, around 90% of prediction have error less than 50%, around 70% of prediction have error less than 30% and around 30% of prediction have less than 10% error. The sources of error are manifold: (1) The measurement error from the coarse-grained thermostat temperature readings; (2) Lack of other sensors to observe the occupancy level, appliances' activities and the window open or close; (3) Error come from weather forecast result.

Considering the demand response duration is usually a few hours, the existence of a certain level of error on rate of temperature variation will not make a huge deviation between forecasted temperature and the reality. To substantiate this viewpoint, time-series experiments have been conducted and the results are shown below.

5.1.3. Time-series validation

Time-series experiments are conducted in Suite 1. Detailed meteorological and time information of the experiments are listed in Table 3. Fig. 7 shows the forecast result: the black solid line represents the predicted temperature change, acquired by initial temperature, RTU



Fig. 4. Schematic diagrams for calculating the indoor temperature variation rate.



Fig. 5. Validation of the proposed temperature prediction model using Suite 1's thermostat data in a building in Blacksburg, VA (May to August).



 Table 3

 Parameters needed for time-series control.

Case	Outdoor temperature (°F)	Outdoor humidity (%)	Weather category	Starting time	Duration (h)
a	80	55	2	15:44	2
b	84F	57	1	13:00	1.5

status and predicted temperature variation rate; the red solid line shows thermostat readings obtained later. It demonstrates that temperature readings on the thermostat follow the predicted values closely and are constantly within ± 1 °F error band, as shown in Fig. 7(a)-(b).

5.1.4. Control deviation caused by weather forecast error

Outdoor temperature and humidity are continuous variables changing constantly over time, however, most of the weather forecasts can only provide hourly prediction data. This means using the same outdoor temperature and humidity for the entire hour might introduce certain level of error. To quantify the impact, this section presents a sensitivity test among some typical environment settings. Fig. 8 shows the appearance time of the outdoor humidity when outdoor temperature is above 80 °F, when a DR event is more likely to happen. It reveals that the humidity is mostly around 50–70% during the scorchers.

Test cases are chosen from a Cartesian product of typical outdoor humidity and temperature:{50%, 60%, 70%} × {80 °F, 82 °F, 84 °F, 86 °F, 88 °F, 90 °F}. Next, small disturbances which are possible within an hour (\pm 1 °F and \pm 2 °F for temperature as well as \pm 5% and \pm 10% for humidity) are added to the test cases' base value pairs, then an indoor temperature variation rate prediction is conducted, given typical indoor temperature of 77 °F, a Class 2 weather, and time of 13:00. Absolute valued deviations are calculated and compared with the unbiased base value pairs in percentage form. For example, Fig. 9(A)



Fig. 7. Comparison between temperature prediction and actual temperature in Cases a and b.

shows the results for a test case of (60%, 86 °F) in temperature dropping rate prediction, the average deviation is 4.37% as shown in Fig. 9(B) together with average deviations of other test cases. Averaging all deviations of 18 test cases, Fig. 9(B) concludes an average deviation of all



Fig. 8. Humidity distribution when temperature is above 80 °F.

test cases for temperature dropping speed prediction: 4.33%. The same analysis can be applied to indoor temperature rising rate prediction for all 18 test cases, with an average deviation of 5.33%.

Considering the average temperature dropping rate in Suite 1, August 2016 is around 9.02×10^{-4} °F/s, a 4.33% deviation will cause a 0.04 °F difference after 20 min of cooling. Similarly, a 5.33% deviation will result in a 0.06°F difference after a 20-min non-cooling period. The magnitude of such differences demonstrates that these small control deviations caused by variation of outdoor temperature and humidity within an hour do not have serious impact on occupants' comfort.

5.2. Validation for multiple RTU coordinated control

In this section, the control algorithm proposed in Section 4 is implemented in Python code for case study. Comparisons between this algorithm and the most common practice of HVAC control in small- and medium-sized building during DR events, namely increasing thermostat set point, are made, as shown in Table 4.

Building information and operation data from four suites in a Virginia Tech building in Blacksburg, VA, USA are used as prototype to showcase the proposed algorithm. These four suites mainly consist of offices and laboratories. Each of them can be considered as a thermal zone and has its own thermostat and RTU. The electric power consumption from four RTUs are listed in Table 5, with the total RTU power of 32 kW.

The proposed algorithm is designed for RTU coordination during a DR event, which typically lasts for a few hours. For example, the length of DR in STOR, UK, can be as short as 2 h [38]. In addition, as authors in [21] point out, with a 'temporal' aggregation, the length of each end user's DR will be shorter. So in this section, it is reasonable to simulate a 90-min DR event, which happens in a Class 2 weather condition day during 13:00-14:30, with an outdoor temperature of 85 °F and

humidity of 49%. Initial temperature in Suite 1-4 before the DR event starts are 74.0 °F, 73.0 °F, 76.5 °F and 76.0 °F respectively. Two parameters need to be set before the operation of the control system: α_t^h and ω . In these simulations, α_t^h is set to be 1.25 reflecting the monetary productivity loss of 1.25 Dollars for every time slot (5 min) and every 1 °F increase above the MTT. ω is 0 when energy consumption is not considered or otherwise it is set to 1, representing the electricity price during a DR event is 1 Dollar per kWh. Other values of α_t^h and ω will be discussed later.

Eight scenarios with different requirements and control methods during the DR event are studied:

Scenario 1: Control using DBBC. Increasing the set point of all thermostats to 76 $^\circ \! F$ (Considering the dead-band of 1 $^\circ \! F$, the maximum temperature in each zone will be 77 °F).

Scenario 2: Control using DBBC-PL. Increasing the set point of all thermostats to 76 °F, meanwhile limiting the total power consumption under 13 kW.

Scenario 3: Control using DBBC-Pri. Increasing the set point of all thermostats to 76 °F. Starting from 13:30, change the set point of Suite 3 to 75.5 °F so that the temperature will be around 76 °F during a meeting from 13:45 to 14:30 in Suite 3. Total power consumption limited under 20 kW.

Scenario 4: Control using proposed coordinated control. Set occupants MTT as 77 °F and DR RTU power limit as 20 kW. Energy consumption is not considered, with $\omega = 0$.

Scenario 5: Control using proposed coordinated control. Set occupants MTT as 77 °F and DR RTU power limit as 13 kW. Energy consumption is not considered, with $\omega = 0$.

Scenario 6: Control using proposed coordinated control. Set occupants MTT as 77 °F and DR RTU power limit as 20 kW, total energy consumption is considered, with $\omega = 1$.

> Fig. 9. Deviation analysis under typical DR weather conditions.



Table 4

Control methods for demand response.

Control methods	Details
Dead-band based control (DBBC)	 Dead-band based control (DBBC): Most commonly, the control of RTUs rely on thermostats' dead-band control. Usually the temperature set point will be raised to make RTUs run less frequently during DR events Dead-band based control with power limit (DBBC-PL): Similar to the DBBC, but a RTU will not start if its start will cause the total power consumption exceed the predefined power limit, even though the zone temperature is over the upper bound of the dead-band Dead-band based control with priority (DBBC-Pri): Based on the DBBC-PL, however, some RTUs have higher priority to be operated even when power limit is reached. In such cases, running RTUs with low priority will be shut down to limit the total power
Proposed coordinated control	As stated in Section 5

Table 5

Information of testing thermal zones.

Suite	1	2	3	4
Main usage RTU power (kW) Approximate area (square feet) Approximate occupants number	Offices 8.5 3600 9	Laboratory 7.0 3150 10	Laboratory 12.0 5800 20	Offices 4.5 2400 5

Scenario 7: Control using proposed coordinated control. Set occupants MTT as 77 °F and DR RTU power limit as 20 kW. Temperature of Suite 3 should be around 76 °F same as in Scenario 3. Total energy consumption is considered, with $\omega = 1$.

Scenario 8: Control using proposed coordinated control. Set occupants MTT as 76.5 °F and DR RTU power limit as 13 kW. Energy consumption is not considered, with $\omega = 0$.

The simulations results are shown below: The temperature profiles and the total RTU power profiles from eight scenarios are shown in Fig. 10. Two kinds of average temperatures of all suites under 8 scenarios are compared in Fig. 11; and the productivity loss and total electricity consumed are summarized in Table 6.

Compared with the DBBC series, the proposed coordinated control shows three advantages on the following aspects:

(1) Peak load shaving effect. (Comparison between Scenario 1, 4 and 5)

Giving the same MTT, the maximum power consumption in Scenario 1 is 25 kW; while under the proposed control approach, consumptions in Scenario 4 and 5 are strictly limited under 20 kW and 13 kW respectively, both with zero occupants' discomfort. By reducing the maximum power, the building owners can reduce their capacity reserve charge during DR events.

(2) Indoor temperature control (Comparison between Scenarios 2 and 5)

Both with 13 kW power limit, in Scenario 2, the DBBC-PL method causes occupants discomfort which is equivalent to \$11.58 productivity

– Suite 1 – Suite 2 – Suite 3 – Suite 4

Demand Response RTU Power Limit

Thermostat control deadband

13:15



Time

Fig. 10. Temperature and total power profile of 8 demand response scenarios.



Fig. 10. (continued)

loss while in Scenario 5, no occupants discomfort at all.

(3) Zone priority management (Comparison between Scenarios 3 and 7)

Given the same power limit and temperature request in Suite 3, the coordinated control can save up to 80% of occupants' discomfort with similar energy consumption, compared with DBBC-Pri. In addition, discomfort is distributed among different suites in Scenario 7 while in Scenario 3 it is originated from a single suite's suffering.

To sum up, these advantages can be attributed to the load shifting feature of the coordinated control. Due to the lack of coordination, the ON/OFF status of each RTU is a random process when using DBBC. On
 Table 6

 Occupants discomfort, energy consumption and maximum power of 8 scenarios.

Scenario	Total monetary productivity loss from occupants discomfort (\$)	Energy consumed (kWh)	Maximum power (kW)
1	0.80	17.33	25
2	11.58	12.96	12
3	8.85	15.83	19
4	0	19.04	19
5	0	16.08	13
6	0.68	14	16.5
7	1.73	16	16.5
8	5.08	18.58	13



Fig. 11. Mean of four suites' temperatures under 8 scenarios.

Mean of four suites' average temperatures during the DK event
 Mean of four suites' maximum temperatures during the DR event



Fig. 12. Comparison of energy and thermal conditions under different monetary settings.

the other hand, the coordination eliminates the cases when multiple RTUs operating at the same time and causing undesirable high demand, as shown in Fig. 10(a) 13:40–13:45. Moreover, the coordination over a period of time will enable some RTUs to pre-cool when resource, namely the power capacity, is available. Thus, spread the demand over the temporal range. In all, the coordinated control results in a higher capacity factor, which enables taking most advantage of the power limit; and from the electric utility perspective, an increased load predictability is highly welcomed during DR events.

Besides the advantages mentioned above, the coordinated control also provides the following flexibilities.

 Jointly consider occupants discomfort and energy consumption, suitable for different DR programs

The values of α_t^h and ω are determined by the building manager, according to the building's business type and the DR program they participate in. Those two values will influence the tradeoff between user discomfort and total energy consumption, therefore, different settings of α_t^h and ω are provided and compared, as shown in Fig. 12. According to Fig. 12, two general rules can be concluded:

- (a) For the same α_t^h, more or equal amount of electricity will be consumed if the price is cheaper, meanwhile delivers a lower maximum average temperature (more comfortable).
- (b) For the same ω , usually more electricity will be consumed if the productivity quality is more valuable (larger α_t^h), also results in less occupants' discomfort.

In general, the building manager will set ω as the electricity price for their DR program if they want to consider energy consumption and set α_t^h according to their evaluation of occupants' productivity. Similar simulations as Fig. 12 can be run prior to the system configuration to give the building manager a better sense about how to set α_t^h .

(2) Flexible DR settings

A building manager can also determine the DR settings such as occupants MTT and power limit flexibly. From the scenarios above, there are two points worth noting:

a. In Scenario 4 and 5, the power limits are 20 kW and 13 kW respectively. Under both scenarios, the occupants do not suffer from thermal discomfort, however, if the power limit is 20 kW, the building manager needs to pay higher capacity reserve charge (\$/kW) during demand response. Thus, power limit of 13 kW is a better choice since it renders more monetary savings but not exacerbate occupants' discomfort. In addition, the 20 kW power limit in Scenario 4 may also cause higher energy consumption than the



Fig. 13. Schematic diagram for occupants' thermal comfort/discomfort. (A = the temperature set point during normal operation (without DR); B = the occupants' MTT; C and D = zero discomfort points).

13 kW limit in Scenario 5. As shown in Table 6, an extra 2.96 kWh of electricity is consumed in Scenario 4. This can be explained using Figs. 11 and 13.

In Fig. 13, since D has a smaller temperature difference from the normal set point than C, the operation point D thus yields higher comfort level. According to Fig. 11, since indoor temperature under Scenario 4 is lower than that of Scenario 5, it is reasonable to use C and D in Fig. 13 to represent Scenarios 5 and 4, respectively, and the comfort difference in the figure can explain the 2.96 kWh of extra electricity consumed in Scenario 4. Since energy consumption is not considered in these scenarios, the solver will provide an optimal solution among many, and this solution does not necessarily use less energy. In fact, the optimal control strategy might control the RTUs to use more energy to make occupants more comfortable.

In all, the building manager can determine the optimal power limit with the consideration of capacity reserve charge and the expected occupants' comfort level.

b. A building manager should set the MTT and power limit correspondingly. To be specific, a low power limit will not allow RTUs running frequently and as a result, might not be able to satisfy a low MTT. For instance, in Scenario 8 above, the power capacity factor is nearly 1 yet the temperature in each room can hardly be controlled below the MTT of 76.5 °F. This means the MTT of 76.5 °F is not very reasonable under the power limit of 13 kW.

Fig. 14. Schematic diagram of on-site system set-up in the building in Blacksburg, VA.



To find out an optimal power limit and a reasonable MTT-power limit pair, simulations can be run under some typical DR conditions, and based on simulation results, a building manager can decide the power limit and MTT to be implemented for each building.

5.3. Commercial building control and validation

To validate the feasibility of implementing the proposed system in a real-world environment, a building control experiment is conducted in an afternoon during 16:30–18:00, with Class 2 weather category. Four thermal zones in the building are the prototype for the simulation study in Section 5.2 and the suite information is provided in Table 5. On-site system set-up is illustrated in Fig. 14: with four smart thermostats installed and the BEMOSS running as the IoT-based BEM. The forecasted outdoor temperature and humidity during a DR event are 82 °F and 52%, respectively. The DR power limit and MTT are set to be 18 kW and 78 °F, respectively. Energy savings during DR is also considered in the optimization process with the electricity price of 1 Dollar per kWh ($\omega = 1$).

The initial temperature $Temp_0$ used by the optimization model complies with following rule:

Condition A: At the time of computation, the thermal zone's RTU is in off (not cooling) state.

Condition B: At the time of computation, the thermal zone's RTU is in cooling state.

$$Temp_{0} = \begin{cases} Temp_{dev} + \Delta T_{acc} & (if \ condition \ A) \\ Temp_{dev} & (if \ condition \ B) \end{cases}$$
(22)

In (22), $Temp_{dev}$ is the temperature reading from thermostat at that time; ΔT_{acc} is the accuracy granularity unit of the thermostat, adding this value to $Temp_{dev}$ under Condition A is a conservative measure.

Fig. 15 shows the control results, with the black line represents the predicted temperature variation under optimal control strategy generated from the proposed algorithm; and the red solid line shows the actual temperature reading later acquired from the smart thermostats.

The temperature profiles in all suites demonstrates a desirable control result. The temperature profiles in Suites 1, 2 and 4 stay closely with the predicted temperature (within \pm 1 °F error band). For Suite 3, around two third of the time, the temperature is within \pm 1 °F error band while the rest is slightly above this range. The reason is that Suite 3 is a research lab, with some large heat-generating pumps running randomly according to experiments schedule. Such a stochastic change in internal heat gain causes such control errors.

To study the peak load reduction effect, another non-DR event day with similar weather profile is found in historical data as a control group. The daytime outdoor temperature profiles of both days are shown in Fig. 16, implying that without a DR event, the DR event day should consume similar level of power of the non-DR event day.

As part of the research setting, some BACnet power meters are used to collect the power consumption data. After processing these data, the total RTU power consumption of the test day and the control group is shown in Fig. 17. The maximum power consumption decreases by almost 50% during the DR event (as compared with the non-DR event) in exchange with slight occupant discomfort according to Table 7.

The temperature in four suites during the DR event, which does not exceed MTT, is the indicator that the occupant discomfort has been minimized by the algorithm proposed.

It is worth noting that because the weak wireless signal in Suite 3, the smart thermostat missed the signal to turn on its RTU at 17:10 and thus caused an actual power ditch shown in Fig. 17. This problem can be avoided by providing a strong and reliable wireless network. In addition, the delay of turning RTU on may also contribute to the Suite 3's temperature deviation.

5.4. Assessment on algorithm efficiency

5.4.1. Measures to improve algorithm efficiency

Some types of rapid DR events require response within minutes to provide operating reserves to power system [13]. Therefore, the proposed algorithm should be able to respond quickly to meet such a requirement. While the learning process of the proposed approach is set to run at the night before a potential DR event day, the optimization process is run just before a DR event. Thus, only the efficiency of the optimization process is discussed. Generally speaking, the lower the DR power limit and the lower the MTT are, the longer it takes for the optimizer to reach the optimal solution. Two measures are taken to ensure the efficiency of the proposed algorithm.

- Offline testing This can be conducted given some typical DR event settings (e.g., temperature, time and weather) to determine reasonable DR RTU power limit and MTT. For example, Scenario 8 in Section 5.2 demonstrates that a 13 kW RTU power limit cannot satisfy the MTT of 76.5 °F. A reasonable setting will allow the optimization problem to be solved efficiently.
- Timeout option for the optimizer when the calculation time is more than five minutes and the precision is under a preset level, further computation will be terminated. This prevents the solver from spending unnecessary time searching for the absolute optimum.

Table 8 shows the computation time to obtain an optimal solution



Fig. 15. Temperature change in four suites during DR event.

using the proposed algorithm in Scenarios 4–8 from Section 5.2. The computation platform is a 2 GB RAM Linux virtual machine, which emulates the configuration of some embedded systems. The result implies the proposed algorithm can be solved quickly enough for real-time implementation:

5.4.2. Impact of the number of thermal zones on algorithm efficiency

To further study the impact of the number of thermal zones has on algorithm efficiency, additional scenarios are evaluated. For simplification, the settings from Suites 1–4 are doubled and tripled to create a group of eight and twelve thermal zones. The time it takes to solve the optimization problem is shown in Tables 9 and 10 for eight and twelve thermal zones, respectively. The timeout setting for the optimizer is 300 s in the study.

According to [22], around 72.1% of total commercial buildings in the U.S. have area less than 10,000 square feet. Assuming each thermal zone has 1000 square feet on average, total area of twelve thermal zones is up to 12,000 square feet, and thus the testing of up to twelve thermal zones is reasonable.

According to the testing results, it shows that most of the computation will reach an optimum or suboptimal solution and thus is capable of practical use.



6. Conclusion

In this paper, a peak load reduction algorithm based on IoT-based BEM is developed by optimally coordinating the operation of RTUs while minimizing occupant discomfort. The proposed approach comprises both the learning algorithm to capture building thermal parameters and the optimization algorithm to determine optimal RTU operation. Analyzing only the coarse-grained thermostat data, the learning algorithm is able to accurately capture the thermal properties of different zones. This will reduce investment on expensive sensor networks and free the building operator from complicated system configurations. The optimization algorithm used is mixed integer linear programming to enable fast response and guarantee computational efficiency. Tests on an office building show effective coordination between RTUs; the system maintains predefined occupant comfort level while keeping the total power consumption under the DR RTU limits. While the case study discussed here reflects the building in the U.S., the proposed algorithm can also be used in any commercial buildings in other countries that would like to limit electrical peak demand (kW) by coordinating the operation of multiple RTUs.

In all, the proposed peak load reduction algorithm can serve as an affordable software solution in small- and medium-sized commercial

Fig. 16. Weather profile of DR event and non-DR event day.



Indoor temperature of four suites during the DR event.

Suite	1	2	3	4
Non-DR event day set point (°F)	72	73	75	72
DR event day suites temperature (°F)	Around	77. See Fig	g. 15	

Table 8

Computation time for Scenario 4-8.

Scenario	4	5	6	7	8
Time (s)	0.09	0.08	1.95	2.43	2.24

Table 9

Algorithm efficier	cy test for 8	thermal zones	optimization	(total RTU load:	64 kW).
	2			-	

MTT	DR RTU power limit (kW)	$\omega = 1$		R RTU power limit (kW) $\omega = 1$ $\omega = 0$		
_		Time (s)	GAP	Time (s)	GAP	
79	26	0.23	Optimal	0.1	Optimal	
	30	0.22	Optimal	0.09	Optimal	
	34	0.22	Optimal	0.09	Optimal	
	38	0.22	Optimal	0.07	Optimal	
	42	0.2	Optimal	0.07	Optimal	
78	26	300	0.52%	0.1	Optimal	
	30	300	0.72%	0.12	Optimal	
	34	300	0.15%	0.09	Optimal	
	38	255.24	0.03%	0.09	Optimal	
	42	300	0.39%	0.09	Optimal	
77	26	300	1.77%	0.61	Optimal	
	30	300	1.72%	0.17	Optimal	
	34	300	1.46%	0.16	Optimal	
	38	300	1.53%	0.16	Optimal	
	42	300	1.48%	0.14	Optimal	
76	26	300	3.49%	300	4.99%	
	30	300	3.03%	300	7.69%	
	34	300	2.95%	300	28.02%	
	38	300	2.14%	300	2.95%	
	42	300	1.55%	1.02	Optimal	

buildings and can help mitigating the barrier of popularizing DR programs among these buildings. Future work may include a performance test of the proposed algorithm in small- and medium-sized commercial buildings other than office buildings and the improvement of the proposed algorithm to take into account multi-stage RTUs and part-load operation. Fig. 17. Power consumption during the DR event and non-DR event day.

 Table 10

 Algorithm efficiency test for 12 thermal zones optimization (total RTU load: 96 kW).

MTT	DR power limit (kW)	$\omega = 1$		$\omega = 0$	
		Time (s)	GAP	Time (s)	GAP
79	39	0.88	Optimal	0.13	Optimal
	45	0.86	Optimal	0.12	Optimal
	51	0.87	Optimal	0.1	Optimal
	57	0.88	Optimal	0.08	Optimal
	63	0.89	Optimal	0.1	Optimal
78	39	300	2.00%	0.15	Optimal
	45	300	2.16%	0.13	Optimal
	51	300	1.89%	0.12	Optimal
	57	300	1.85%	0.12	Optimal
	63	300	1.66%	0.12	Optimal
77	39	300	2.91%	0.78	Optimal
	45	300	2.71%	0.33	Optimal
	51	300	1.89%	0.24	Optimal
	57	300	2.00%	0.25	Optimal
	63	300	2.03%	0.2	Optimal
76	39	300	7.65%	300	13.05%
	45	300	6.54%	300	15.60%
	51	300	5.60%	300	81.20%
	57	300	2.83%	300	13.11%
	63	300	1.89%	0.67	Optimal

Acknowledgement

This work was supported in part by the U.S. Department of Energy under the Building-Grid Integration Research and Development Innovators Program (BIRD-IP). Grant No. AT-30264.

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