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Towards Cost-Optimal Energy Procurement for Cooling as a Service: A Data-Driven Approach

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Abstract—Cooling as a Service (CaaS) is an emerging business that provides air conditioning services for buildings. With the rapid development of the business and the continuous increase of energy load, CaaS providers need cost-effective energy procurement to meet the service requirements. In this paper, we propose a data-driven approach for energy procurement for CaaS providers. First, we focus on two dominant variables of cooling energy cost, including outdoor temperature and electricity price. We predict their trends in the next day and accordingly, we estimate the energy usage and purchase the energy in the day-ahead energy market, one day before the actual usage. During the real-time operation, we can obtain the actual temperature and price, and we use this information to adjust the quality of service without violating the service standards. The adjustment serves as the demand response to the real-time energy market and can be cost beneficial. We conducted experimental studies to verify the performance of the proposed solution. The results show that our solution provides high-quality cooling services with minimal energy expenditure and helps improve the stability of the power grid.

Index Terms—thermal comfort, smart building, machine learning, energy procurement

I. INTRODUCTION

Buildings consume about 40 percent of the world's energy and 60 percent of electricity [1]. A large fraction of the building energy consumption is contributed by the heating, ventilation, and air conditioning (HVAC) system. The chief purpose of the HVAC system is to maintain comfortable thermal conditions for the building occupants. Thermal conditions, if not well maintained, can cause sick building syndrome, absenteeism, and degraded cognitive performance [2]. Besides, people nowadays spend around 90% of their time in buildings [3]. This further highlights the importance to create a thermally comfortable indoor environment with proper air conditioning.

Traditionally, air conditioning is managed by the building owners who normally own the HVAC system and are responsible for facility management like system maintenance.

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Unfortunately, such management often is a significant burden of the building owners, e.g., taking care of the system 24/7 and hiring a specialized team for the system. Recently, an emerging business called Cooling as a Service (CaaS) is introduced by some companies such as Keppel and Schneider to ease the burden of building owners. CaaS providers take care of the facilities and the related management tasks. The customers, or the building owners, just need to specify a preferred quality of service (QoS) like the comfortable temperature range and pay the corresponding service fee to the CaaS Providers.

One of the challenges of the CaaS provider is energy procurement, given the significant cooling energy load. The energy usage of an individual building is relatively small for the power grid. But the aggregated energy load of many buildings can be huge. Indeed, it can be even larger with the growing CaaS business. For energy procurement, two important markets are the day-ahead market (DAM) and real-time market (RTM). The former is for large-scale energy procurement one day before actual usage, and the latter is for balancing the power grid's generation and demand in real-time with small-scale energy trade. While small load customers like individual households normally do not need DAM procurement and can buy from retailers, such a large CaaS energy load drives the necessity of DAM energy procurement on a large scale. Besides, RTM controls the energy prices in real-time to incentivize customers to cooperate, or contribute to balancing the generation and demand. Real-time demand response thereby is also vital for expense minimization and comfort maximization for CaaS, e.g., increasing service quality with cheap energy and being relatively conservative when the energy is expensive.

Energy procurement is not unique for CaaS and it has received much research attention in recent years for different sectors, e.g., data centers [4], electrical vehicle charging [5], and cement production [6]. However, those works do not capture the unique requirements and preferences of CaaS and cannot be applied directly to the CaaS domain. While some other existing works like [7], [8] take both energy and comfort into consideration, the procurement is beyond the scope of those works. For example, a personalized comfort model for smart HVAC control is designed in [7] and the intermittent energy resources are considered in [8]. Overall, there is an urgent demand for CaaS energy procurement solutions.

In this paper, we propose the solutions for the energy procurement in both DAM and RTM for CaaS providers and we aim to improve the CaaS QoS with minimized energy expense. First, the next day's weather conditions and energy prices are predicted using a data-driven approach with long short-term memory (LSTM). The next day's energy usage can then be estimated accordingly as well as the DAM procurement amount, and the energy is procured from DAM one day before the actual usage. DAM procurement cannot be perfect due to the uncertainty of the real-time energy supply-demand dynamics. Therefore, we refer to the actual weather information and RTM prices available in real-time and perform demand response through service quality adjustment to gain cost-benefit. The main contributions of this paper are as follows.

- We propose an optimal solution for DAM procurement in the offline setting where the future weather and price are known in advance.
- We propose a two-stage solution under a realistic setting that future weather and prices are unknown in advance for both DAM and RTM energy procurement.
- We conduct the experimental study and show that the proposed solution can achieve outstanding results regarding both energy expense and thermal comfort. Besides, the solution shows promising demand response in RTM and helps stabilize the power grid.

The rest of this paper is organized as follows. We present the system architecture and models in Section II. In Section III, an optimal offline energy procurement solution in DAM is proposed. Section IV presents a two-stage solution for both DAM and RTM procurement. The experimental study is conducted in Section V to evaluate the performance of the proposed solutions. Finally, Section VI concludes this paper.

II. SYSTEM MODELS AND PROBLEM FORMULATION

In this section, we first present the system architecture and system models. Accordingly, we formulate the problem.

A. System Architecture

The system architecture of CaaS is shown in Fig. 1. The CaaS provider offers cooling service to buildings by regulating air and maintaining a comfortable temperature. As a reward for the cooling service, a service fee is charged from the building customers. Different pricing schemes, e.g., a fixed monthly subscription fee, can be designed and adopted in our framework. However, this paper focuses on the service side and the pricing schemes will be studied in the future. Naturally, energy will be consumed for cooling the buildings and thus shall be procured from the energy market. The procurement expense depends on energy price as well as the amount of procured energy, which in turn determines the CaaS QoS. The objective of this work is to minimize the energy expenditure while meeting the cooling QoS.

Fig. 1. CaaS system architecture with the interaction among buildings, CaaS provider, and energy market. The CaaS provider procures energy from the energy market and use the procured energy to provide cooling services to the building customers. Energy procurement incurs cost and a service fee is charged from the CaaS customers.

B. System Models

In this part, the system models will be discussed from three major sectors, namely, occupant comfort, building energy, and the energy market. Let us introduce the models as follows.

1) *Occupant Comfort*: The key role of CaaS is to cool down the air from the ambient atmosphere to create a comfortable indoor environment for occupants. Here, we follow a common practice where the indoor air temperature is taken as the media for evaluating the comfort level of building occupants. Specifically, let an optimal temperature T^* be the most comfortable temperature, which can be user-defined. When the outdoor temperature T^o is higher than T^* , the cooling mode is on to maintain a low indoor temperature. We assume that the indoor temperature is equivalent to the HVAC setpoint T^s , which is controllable and no smaller than T^* to avoid much cooling energy usage. Setpoint close to T^* indicates good comfort, e.g., not too hot in a cooling scenario. Otherwise, the outdoor air is cool enough and no cooling service is needed. Overall, the thermal discomfort $D(\cdot)$ is defined as follows.

$$D(T^s) = \begin{cases} |T^s - T^*|, & \text{if } T^s \leq T^o \\ 0, & \text{otherwise} \end{cases}, \quad (1)$$

where the two cases mean the cooling mode is on and off, respectively, and note that the latter case may rarely occur in a tropical environment like Singapore.

2) *CaaS Energy Usage*: Thermal comfort comes with a cost, as cooling down the air consumes energy. The amount of such energy also scales up with cooling intensity. Given a specific building, the cooling energy depends on several factors, including building properties (e.g., facade material and floor area), outdoor temperature T^o , and HVAC setpoint T^s . We have $T^s \leq T^o$, as the indoor setpoint shall not be higher than the outdoor temperature in a cooling mode. Here, we focus on the controllable variable and model the cooling energy with setpoint T^s as follows.

$$E(T^s) = \alpha(T^o - T^s)^\kappa + \delta, \quad (2)$$

where α , κ , and δ are positive constants that can be fixed given a specific building and HVAC system. In Eq. (2), the first component means that cooling energy increases with high QoS or low indoor temperature. The last component indicates the base energy usage of the HVAC system. Let us assume $\kappa > 1$ to indicate the decreasing energy efficiency with increased

cooling demand. This is true because of two facts. First, the HVAC efficiency degrades with increased cooling load [9]. Second, the fan power for distributing the cooling air scales exponentially with increased airflow [10].

3) *Energy Market and Cost*: Energy cost is not solely determined by energy usage. It is also affected by the energy prices published and determined by the energy markets, e.g., DAM and RTM. DAM is the main arena for energy trading. Everyday around the noontime, e.g., 12PM for Nord Pool [11], DAM determines its next day's hourly prices $p_1^{da}, \dots, p_{24}^{da}$ from 12AM to 11PM based on the bidding between the energy generators and consumers.

Inevitably the scheduled energy generation and consumption in DAM do not match with actual figures due to the unpredictability of the next day system circumstances. So, RTM is introduced for balancing the actual generation and consumption, e.g., high price for the unmet generation or the exceeded consumption to discourage excessive energy usage. Unlike DAM, the RTM decides its hourly prices $p_1^{rt}, \dots, p_{24}^{rt}$ in nearly real-time, e.g., the hourly price for 7AM is fixed at 6:45AM.

CaaS provider estimates the next day's hourly energy usage and performs energy procurement in the DAM one day before the actual usage. In real-time, the provider cools the buildings and may either incur RTM expense with insufficient procured energy from DAM or get refunded by RTM for unused procured energy based on the prevalent RTM price. Let $b_1, \dots, b_{24}$ be the positive hourly energy procurement amount in the DAM bid and let $l_1, \dots, l_{24}$ be the actual hourly energy load. Given a controllable setpoint T_h^s in the cooling mode, we have $l_h = E(T_h^s)$ at hour h according to Eq. (2). Thus, the CaaS provider's monetary cost at hour h is as follows.

$$P(b_h, T_h^s) = p_h^{da} b_h + p_h^{rt} (l_h - b_h) \\ = (p_h^{da} - p_h^{rt}) b_h + p_h^{rt} \alpha (T_h^o - T_h^s)^\kappa + p_h^{rt} \delta, \quad (3)$$

where the second term in the first line can be either positive or negative, corresponding to the RTM procurement and refund cases, respectively. Worth noting that the second component offers space for real-time demand response by optimizing the setpoint temperature with cost benefit.

C. Problem Formulation

The objective of this work is to optimize the energy procurement and monetary expense for the CaaS provider with satisfied QoS for thermal comfort. Outdoor temperature and energy prices are not controllable by the provider. Thus, two considerations for the CaaS provider are the amount of energy to be procured in DAM one day before the actual usage and the hourly HVAC setpoint to be configured in real-time. Here, a cost minimization problem is formulated as follows.

$$\begin{aligned} \underset{T_h^s \leq T_h^o}{\text{minimize}} \quad & C(\mathbf{b}, \mathbf{T}^s) = \sum_{h=1}^{24} P(b_h, T_h^s) + \lambda D(T_h^s), \\ \text{s.t.} \quad & T_h^s \leq T^{\max} \end{aligned} \quad (4)$$

where λ is a constant parameter to control the importance of QoS, modeled by the discomfort function $D(\cdot)$. Large λ

indicates high requirement on QoS from the building side and naturally more expensive CaaS service. Note that the DAM energy procurement $b_1, \dots, b_{24}$ must be predetermined one day before the usage and the setpoint can be dynamically adjusted in runtime. One more QoS consideration is the maximum acceptable temperature $T^{\max}$, and the indoor temperature must not exceed it. Here, CaaS provider and clients shall agree with λ and $T^{\max}$ before the commencement of the service.

Intuitively, the setpoint should not be too high beyond the optimal temperature T^* since the penalty for discomfort will scale up; however, energy load and expense will grow if the setpoint is always close to the most comfortable T^* . So there is a tradeoff between the monetary expense and discomfort. However, it is not trivial to determine the optimal DAM procurement amount under the uncertainty of the price and weather. Real-time demand response in RTM reacts to such a difficulty by setpoint control, which has a cost impact as shown in Eq. (4).

III. OPTIMAL OFFLINE PROCUREMENT IN DAM

In this section, an optimal offline solution for DAM energy procurement for the problem in Eq. (4) will be presented, where the next day's DAM prices and outdoor temperatures are assumed to be known in advance.

Only DAM is considered here assuming the equivalence between the bidding energy and actual energy, or $b_h = l_h$ for any hour h . RTM is not considered due to the following reasons. First, when RTM has a higher price than DAM, it is cost-optimal to make DAM procurement for all the actual load to avoid the higher RTM price. Second, when RTM price is lower, although cost-wise the optimal action is to procure all in RTM, the action leads to power grid instability which could be punished by the grid operator for this market manipulation behavior. After all, DAM is the main procurement venue and RTM is mostly for balancing.

The optimal hourly DAM energy procurement is shown in the following theorem.¹

Theorem 1. *Given the outdoor temperature $T_1^o, \dots, T_{24}^o$ and DAM prices $p_1^{da}, \dots, p_{24}^{da}$ in advance and let $b_h = l_h$ for any h , the optimal hourly energy bid in DAM is,*

$$b_h^* = \begin{cases} \delta, & \text{if } T_h^o < T^* \\ \alpha(T_h^o - T^*)^\kappa + \delta, & \text{else if } \lambda > \varphi_h^{da} \\ \alpha(T_h^o - T^{\max})^\kappa + \delta, & \text{else if } T^{\max} < T_h^{da} \\ \alpha^{\frac{1}{\kappa-1}} (\lambda/p_h^{da} \kappa)^{\frac{\kappa}{\kappa-1}} + \delta, & \text{otherwise} \end{cases} \quad (5)$$

where $\varphi_h^{da} = p_h^{da} \alpha \kappa (T_h^o - T^*)^{\kappa-1}$ and $T_h^{da} = T_h^o - (\lambda/p_h^{da} \alpha \kappa)^{\frac{1}{\kappa-1}}$.

As shown in Theorem 1, the energy bid is high to produce a comfortable indoor environment for large λ , low price, and large α . The reason is that large λ implies a strong emphasis on thermal comfort. During periods with low prices, it also makes sense to improve thermal comfort without costing too

¹Due to lack of space, we defer the proofs of the theorems in this paper to the full version of the paper.

Algorithm 1 TOSA: Stage 1 – DAM Procurement

Require: predicted $\hat{p}_1^{da}, \dots, \hat{p}_{24}^{da}$ and $\hat{T}_1^o, \dots, \hat{T}_{24}^o$

```
1: for  $1 \leq h \leq 24$  do
2:    $p_h^{da} \leftarrow \hat{p}_h^{da}$ 
3:    $T_h^o \leftarrow \hat{T}_h^o$ 
4:    $\hat{b}_h \leftarrow$  using Eq. (5) with  $p_h^{da}$  and  $T_h^o$ 
5: end for
6: return: DAM procurement amount  $\hat{b}_1, \dots, \hat{b}_{24}$ 
```

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much on energy. Small α indicates good energy efficiency, so the importance of thermal comfort grows relatively in Eq. (4).

IV. TOSA: A TWO-STAGE ALGORITHM FOR DAM AND RTM ENERGY PROCUREMENT

In the above section, we consider an offline setting where DAM prices and outdoor temperatures are known in advance before the bidding. In this section, a realistic setting will be investigated where the DAM prices are only known after the DAM bidding and outdoor temperatures are only knowable at runtime.

One day before the actual energy usage, the CaaS provider estimates the hourly load in the next day based on the prediction of the next day's prices and temperatures. The estimated amounts are derived based on the optimal offline scheme in Theorem 1 with the predicted values as input. Then, the provider performs energy procurement from DAM. At runtime, the provider responds to the current RTM price and outdoor temperature through setpoint adjustment to optimize the cost in Eq. (4). For example, consider an hour with very expensive RTM energy. The CaaS provider may loosen the comfort requirement to some extent and level up the setpoint, so as to reduce the cooling load and cut the energy bill.

Here, let us show a two-stage algorithm denoted as TOSA given the predicted next day's outdoor temperature $\hat{T}_1^o, \dots, \hat{T}_{24}^o$ and DAM prices $\hat{p}_1^{da}, \dots, \hat{p}_{24}^{da}$. The prediction algorithm can be flexible with different available solutions and the solution used in this research will be introduced in the following section.

The first stage of TOSA is shown in Algorithm 1. The algorithm aims to determine the energy procurement in DAM and takes the predicted hourly DAM price and outdoor temperature as inputs. Then the algorithm follows the conclusion in Theorem 1 for DAM procurement and computes the energy amount $\hat{b}_h$ for every hour h in the next day using Eq. (5).

Soon after the DAM bidding, the actual DAM prices $p_1^{da}, \dots, p_{24}^{da}$ will be determined and published by the DAM operator. However, despite the determined DAM prices, there are still several uncertainties such as RTM prices and outdoor temperature unknown in advance and only available in real-time. Here, we perform demand response in RTM and derive the HVAC setpoint based on the following theorem.

Theorem 2. *At runtime in RTM where the actual RTM price and outdoor temperature are known, the optimal setpoint at*

Algorithm 2 TOSA: Stage 2 – RTM Demand Response

Require: DAM procurement amount $\hat{b}_1, \dots, \hat{b}_{24}$

```
1: for  $1 \leq h \leq 24$  do
2:   get the current  $p_h^{rt}$  and  $T_h^o$ 
3:    $\hat{T}_h^s \leftarrow$  using Eq. (6) with  $p_h^{rt}$  and  $T_h^o$ 
4:    $\hat{l}_h \leftarrow$  using Eq. (7) with  $p_h^{rt}$ 
5:   if  $\hat{l}_h > \hat{b}_h$  then
6:     procure  $\hat{l}_h - \hat{b}_h > 0$  amount of energy from RTM
7:   else
8:     free up  $\hat{b}_h - \hat{l}_h \geq 0$  amount of energy into RTM
9:   end if
10: end for
```

---

hour h is,

$$\hat{T}_h^s = \begin{cases} T_h^o, & \text{if } T_h^o < T^* \\ T^*, & \text{else if } \lambda > \varphi_h^{rt} \\ T^{\max}, & \text{else if } T^{\max} < T_h^{rt} \\ T_h^{rt}, & \text{otherwise} \end{cases}, \quad (6)$$

where $\varphi_h^{rt} = p_h^{rt} \alpha \kappa (T_h^o - T^*)^{\kappa-1}$ and $T_h^{rt} = T_h^o - (\lambda / p_h^{rt} \alpha \kappa)^{\frac{1}{\kappa-1}}$. Accordingly, the total energy amount in RTM is $\hat{l}_h - \hat{b}_h$, where $\hat{l}_h$ is given by,

$$\hat{l}_h = \begin{cases} \delta, & \text{if } T_h^o < T^* \\ \alpha (T_h^o - T^*)^\kappa + \delta, & \text{else if } \lambda > \varphi_h^{rt} \\ \alpha (T_h^o - T^{\max})^\kappa + \delta, & \text{else if } T^{\max} < T_h^{rt} \\ \alpha^{\frac{1}{\kappa-1}} (\lambda / p_h^{rt} \kappa)^{\frac{\kappa}{\kappa-1}} + \delta, & \text{otherwise} \end{cases} \quad (7)$$

Based on the conclusions in Theorem 2, the second stage of TOSA is presented in Algorithm 2. Algorithm 2 executes at real-time. For each hour h , the current RTM price and outdoor temperature are obtained. Accordingly, the optimal setpoint is computed using Eq. (6) in Theorem 2. The corresponding total load from both DAM and RTM is computed using Eq. (7). Suppose the computed load exceeds the procured amount in DAM, or $\hat{l}_h > \hat{b}_h$, the additional amount of energy must be procured from RTM. Otherwise, there will be a surplus of the procured DAM energy of the amount $\hat{b}_h - \hat{l}_h$, and such surplus can be monetarily compensated by the RTM.

V. EXPERIMENTAL STUDY

In this section, we conduct the experimental study to validate the performance of the proposed solution.

A. Experiment Setup

Our objective is to minimize the formulated cost in Eq. (4) in terms of both energy expense and thermal comfort. Here, we use all of the 31 days in July 2020 for testing. For each day, we predict both outdoor temperature and DAM price based on the historical data in the past years, and run our proposed solution based on the prediction. In the following part, we present the experimental setup detail for the dataset, prediction algorithm, and energy model.

1) *Dataset*: Publicly available datasets of Philadelphia, the largest city of Pennsylvania in the United States, are used in this study. The hourly outdoor temperature data is collected by the Pennsylvania State Climatologist and the energy price data is published by PJM, the largest electricity provider in the region. Both datasets span over ten years period between 2010 and 2020.

2) *LSTM-based Prediction*: The two-stage algorithm for energy procurement takes both the predicted DAM prices and outdoor temperature as inputs as shown in Algorithm 1. In this study, the LSTM network is used to make such predictions. The prediction must be performed before bidding. Let us assume a popular setting where the bidding happens at 12PM. The LSTM network needs to predict the hourly outdoor temperatures in the next 36 hours, where 12 for the remaining hours in the current day and 24 for the next day. Thus, 36 neurons are configured in the output layer for temperature, where each neuron corresponds to one hour. To match with the prediction timespan, the 36 consecutive hours of outdoor temperature prior to the bidding time are taken as the inputs of the LSTM network.

The network setup for DAM prices is similar to the setup for temperatures as shown above. While the outdoor temperatures for the next half-day are unknown upon the bidding, the whole DAM prices for the current day were published the previous day. So, the network takes the 24 hours available DAM prices in the current day as inputs and predicts the following 24 hourly prices in the next day, indicating 24 neurons in the output layer.

Both networks adopt the `mae` loss function and `adam` optimizer. The max number of epochs is 500 and the training stops when the model is not improved for 10 consecutive iterations. Ten years of historical data is used for training a prediction model. We tested various network topologies and adopt the best-performed ones, i.e., three LSTM layers each with 30 cells for temperature and one layer with 110 cells for the price.

3) *Energy Model*: A realistic energy model for cooling in [12] is used in the experiments, where $\alpha = 0.06$, $\kappa = 2$, and $\delta = 0.6$. The optimal temperature is fixed to 23°C , a widely used setpoint [13]. The experimental tests are implemented using Python and the average performance is reported.

B. Energy Expense and Discomfort Performance

Two key performance criteria of CaaS are energy expense and thermal comfort. In this part, the criteria are evaluated with different values of the control parameters λ and the maximum acceptable temperature $T^{\max}$. The results are shown in Fig. 2.

1) *Impact of λ* : As seen from Fig. 2(a), the energy expense and discomfort show inverse change patterns, where the former increases with λ and the latter decreases. The importance of the two factors can be controlled by λ . Larger λ means more emphasis on thermal comfort but less on energy expense, and vice versa. When λ is large enough, e.g., over 80, the discomfort is almost zero, which means that the indoor temperature is close to the optimal temperature. Indeed, comfort comes with

Fig. 2. The performance of the proposed solution with different control parameter values. Fig. 2(a) shows the results with λ varies between 0 and 100 and $T^{\max} = 26^\circ\text{C}$. Fig. 2(b) shows the results with $T^{\max}$ varies between 23 and 28°C and $\lambda = 10$. Low expense and discomfort mean good performance.

a cost. The results also show a diminishing return on thermal comfort with the growing expense. For example, by increasing the expense from 48 to 58 by 10, the discomfort improves from 2.5 to 0.4 by 2.1. But triple the expense increase to 78, the discomfort only further decreases by around 0.3, only one-seventh of the above improvement. Thus, a reasonable value of λ not too large can be chosen to achieve acceptable thermal comfort and high energy efficiency.

2) *Impact of $T^{\max}$* : With different maximum setpoint $T^{\max}$, the inverse change pattern of expense and discomfort still exists as shown in Fig. 2(b). Specifically, energy expense decreases in $T^{\max}$ and discomfort increases. The reason is that with a higher setpoint ceiling, our solution can gain more freedom to compromise comfort by a certain amount with a high setpoint when the energy price is too high. Thus, the overall discomfort tends to increase with large $T^{\max}$, but the good impact is that the energy bill can be cut down significantly, e.g., around 20% bill cut from $T^{\max} = 23$ to 24°C by relaxing the average discomfort requirement by merely 0.5°C . Note that $T^{\max}$ is agreed by CaaS clients and the setpoint adjustment between the optimal temperature and $T^{\max}$ does not violate the CaaS QoS agreement.

C. Demand Response to RTM

The purpose of DAM bidding is to stabilize the power grid by matching the power generation and demand as much as possible in advance. RTM is normally not designed to deal with the large energy trade as DAM does and it is mainly used for balancing and fine-tuning the generation and demand in real-time. Thus, as an energy consumer, the CaaS provider should try to perform accurate energy procurement in DAM and cooperate with the RTM incentives for power grid stabilization. To investigate the impact of CaaS on RTM load, the RTM prices are divided into two categories, cheap (the lowest 25% prices) and expensive (the highest 25% prices). The RTM load of the two categories is shown in Fig. 3.

As seen from the figure, our solution incurs less RTM energy usage for high RTM price, which normally indicates that the power grid demand surpasses generation. For the negative RTM load, consuming less than the bidden amount

Fig. 3. The CDF of RTM load with different RTM prices and outdoor temperature within $25 \pm 2^\circ\text{C}$. Negative value means the bidden DAM energy is not fully consumed, and positive value means RTM energy is consumed. More RTM energy is procured when it is cheaper, and vice versa.

Fig. 4. Performance comparison of the proposed solution and two comparison solutions regarding expense and comfort. Fig. 4(a) shows the results based on the DAM and RTM prices, and the price distribution is shown in Fig. 4(b).

from DAM when RTM price is high could be beneficial for both the CaaS provider and the power grid. As such, the former gets a high rebate from RTM and the latter is stabilized by lowering down the demand. Even for positive RTM load when the CaaS has to meet the minimum QoS of thermal comfort, consuming less brings the same benefit to the grid and CaaS provider can avoid the surging payment in RTM to some extent. On the contrary, more energy is consumed with a high RTM load when the RTM price is cheap, indicating over-generation or under-demand. In this case, using more energy makes the grid stabilized. Meanwhile, the comfort can be improved without much energy expenditure.

D. Comparison Analysis

In this part, the proposed solution is compared with two comparison solutions regarding expense and comfort. The first comparison solution denoted as FDR follows a popular setting with a fixed setpoint and conducts energy procurement in both DAM and RTM. The second solution is a variant of the first one with fixed setpoint but only RTM procurement, denoted as FR. The results are shown in Fig. 4.

As seen from Fig. 4(a), the proposed solution can always achieve less energy expense compared to the comparison solutions with the same comfort standard. For example, the proposed solution incurs 50 energy expense with average discomfort of around 1.0. To achieve the same comfort, the two comparison solutions have to spend 73 and 74 expense, respectively, which are 46% and 48% higher compared to

TOSA. The expense saving of the proposed solution comes from its intelligent demand response. When energy is cheap, more conditioning load is produced for better comfort without much energy expenditure. During the period with expensive energy, the solution allows a certain compromise on comfort to avoid surging energy bills. Without those intelligent demand responses, the comparison solutions require higher expense as they do not improve comfort when energy is cheap nor save cost when energy is expensive.

VI. CONCLUSION

In this paper, we propose an energy procurement solution for CaaS. The solution first predicts the next day's temperature and DAM price using an LSTM-based learning algorithm. The DAM procurement amount for each hour of the next day is determined based on the estimation and the DAM procurement is conducted one day before the usage. During the real-time operation of CaaS, the current temperature and RTM price are monitored, and demand response to the RTM is performed with cost-benefit. The experimental study is conducted and the results show that the proposed solution can deliver good cooling services with low energy expense. Also, the solution shows a positive impact on power grid stabilization.

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