Operational Planning of a Residential Fuel Cell System for Minimizing Expected Operational Costs Based on a Surrogate Model

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ABSTRACT This study proposes a novel operational planning method for polymer electrolyte fuel cell cogeneration systems (PEFC-CGSs). PEFC-CGSs provide hot water by utilizing waste heat produced in the electricity generation process, and hot water is stored in an attached tank. Generating and storing hot water based on an optimal operational plan according to household demand leads to further energy saving; therefore, operational planning methods based on household demand prediction have received significant attention. However, the improvement in the demand prediction accuracy does not necessarily lead to efficient PEFC-CGS operation in terms of operational costs; in other words, the accuracy in the demand prediction does not directly indicate the resulting operational efficiency. In this study, the authors propose a novel approach based on a surrogate model for deriving an appropriate plan that minimizes the expected operational costs among the operational plan candidates. In the proposed scheme, the error between expected and actual operational costs explicitly represents the relevance of the operational plan, so that the optimal operational plan can be selected directly from the perspective of the resulting operational efficiency. The practicality of the proposed approach is evaluated with the existing demand prediction-based approach via numerical simulations using real-world measurements of multiple customers in Japan. The proposed method reveals 30% reduction of the excessive operational costs by avoiding the inefficient operation of the auxiliary gas-heater in the experiments and will further enhance the value of introducing highly efficient residential fuel cell system that contributes to a low-carbon society.

INDEX TERMS Cost minimization, machine learning, operational planning, polymer electrolyte fuel cell cogeneration systems, surrogate model.

I. INTRODUCTION

Recent efforts in the development of demand-side energy management are vital to reducing non-essential energy consumption and CO2 emissions. Polymer electrolyte fuel cell cogeneration systems (PEFC-CGSs) have received much attention for reducing energy consumption in the household sector. PEFC-CGSs generate electricity by chemically reacting with hydrogen from natural gas and oxygen in the air; CO2 is not produced in the generation process. These systems also provide hot water by using the waste heat emitted in the electricity generation process, and hot water is stored in an attached tank. Hence, their total energy efficiency is more than 90% [1]. The Agency for Natural Resources and Energy in Japan aims to increase the uptake of PEFC-CGSs to 5.3 million units (approximately 10% of all households) by 2030 [2].

In order to utilize PEFC-CGSs efficiently, not only improvement in the hardware systems but also an energy management system (EMS), which plans operational strategies to optimally control PEFC-CGSs is necessary. In this study, we focus on the EMS aimed at improving operational
performance of PEFC-CGSs in terms of operational cost, which is defined as the daily total household electricity and gas fee. The operational cost can be reduced by generating and storing hot water based on an appropriate operational plan according to household electricity and hot water demands.

Some studies have been conducted based on optimization by mathematical models [3]–[5]. Caliano et al. [3] proposed the economic optimization framework of a micro-combined heat and power (CHP) system producing electricity and heat during the cold season, for housing complexes in Italy. Dynamic programming was another popular scheme used to optimize the operation schedule of a CHP unit with a storage tank that supplies backup power to a Smart Grid [4]. Ou et al. developed real-time EMS for a polymer electrolyte membrane (PEM) fuel cell/battery hybrid operating system [5].

These basic studies aiming to derive an efficient operational plan of residential fuel cell and CHP system for predefined demand have evolved further to address the uncertainties in household energy demand caused by the variation of customer life styles. Many EMS studies for CGS operation, which challenge such demand uncertainty, have focused rather on the formulation of optimization problems under the possible future demand scenarios [6]–[15]. For example, Maeda et al. proposed an operational planning logic based on four operating modes derived by the predicted hot water demand [6]. Stochastic dynamic programming is popularly adopted for on/off scheduling [7] and operational modes between minimum output and power tracking [8]. Tanaka et al. have formulated the CGS scheduling problem as a stochastic programming problem involving recourse costs for the energy supply shortage and a chance constraint for excess of electric power contract [9]. The effectiveness of the stochastic programming has also been shown when other household energy appliances, e.g., photovoltaic [10] and battery [11] are combined; an implementation of two-stage stochastic programming [12] has also been discussed in the micro-grid context. A cost-risk tradeoff model [13] contributes to describe a relationship between economic operation and risk of the worst-case scenario to reduce the significant deterioration of the operation results when the realized demand is different from the expected behavior. Houwing et al. have proposed a model predictive control (MPC) scheme based on the mixed-integer linear programming [14], and Ziogou et al. have adopted on-line nonlinear MPC model [15]; these approaches aim to avoid the significant deterioration of the operation results by updating demand prediction results in the operation period while they require the computational cost for the frequent updates. All these existing approaches discuss the derivation of the operational plan based on the “forecast results of the expected demand sequence”, and therefore, estimation framework of the uncertain demand sequence plays an important role in obtaining an efficient operational plan.

State-of-the-arts of the prediction schemes for electricity and hot water demands are based on machine learning techniques; utilization of smart meters and other appliances makes it possible to obtain a significant amount of data from households for the prediction [16]–[20]. For example, neural network, support vector regression, and random forest are popularly utilized for this type of prediction scheme [16]–[18]. Sobrino et al. [19] aggregate several customers with similar characteristics by applying clustering techniques to identify a representative consumption pattern for accurate prediction. The literature [20] demonstrated the effects of input data and forecasting conditions on the accuracy of the day-ahead household load forecast under various forecasting techniques. Demand prediction results derived by these machine learning algorithms are utilized in operational planning of PEFC-CGSs [21]–[24]. Ogata et al. developed an operation scheme consists of three steps; prediction of household demand, operational planning based on optimization using the prediction results, and control of the PEFC-CGS by the operational plan [21]. Aki et al. discussed the EMSs for residential fuel cells using the bottom-up approach for hot water demand prediction [22], [23]. Fujimoto et al. have proposed a K-nearest neighbor-based multiple-scenario forecast scheme for operational planning of household energy system with the PEFC-CGS [24].

These approaches based on machine learning techniques improve prediction accuracy in terms of reducing the average error between predictions and the actual measurements at each time slice in the demand sequence. This improvement in the prediction error tends to contribute to the derivation of an efficient operational plan for fuel cells. However, demand prediction results with a small prediction error do not necessarily lead to efficient operational plans [25]. The difference between operational cost under the actual demand and that under the predicted demand does not simply reflect the impact of the general error between the predicted and actual demand sequences. In order to further increase the efficiency of operations, an operational plan should be derived from the perspective of the expected effect on operational costs, not the error generated by prediction.

In this study, we propose a novel operational planning method that estimates expected operational costs of operational plan candidates in order to derive an optimal plan by directly evaluating appropriateness of plans based on a surrogate model [26]. Here, the surrogate model is known to be a data-driven meta-model created by machine learning techniques in general to predict a phenomenon instead of performing a numerical simulation, which has been applied in various fields [28]–[32]. In the context of this study, the surrogate model derives expected operational costs of operational plans for controlling the PEFC-CGS on the following day under future uncertainty, and is utilized in the selection process for an appropriate plan. The impact of the prediction error in this scheme is significantly different from that in the demand prediction scheme; in this case, the error reduction

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1. The discussion provided in this manuscript is based on the conference paper presented at the 13th IEEE PES Power Tech Conference held at Milan, Italy, 2019 [27].
directly leads to the accurate evaluation for the appropriateness of operational plans. We evaluate the operational planning methods via numerical simulations using measured data collected from actual households, and show that the proposed method can achieve efficient operation in a stable manner.

The contributions of this paper are briefly described as follows: 1) it is revealed that the accuracy of the demand prediction which is emphasized in the existing operation approaches of PEFC-CGSs based on the demand forecast does not directly represent the efficiency of the operation, 2) a novel PEFC-CGS operation scheme aimed at directly minimizing the expected operational cost is provided from the viewpoint of surrogate modeling, 3) the effect of demand pattern and seasonality on the proposed method is clarified via numerical experiments targeting multiple households collected at various points in Japan, and 4) the validity of the proposed method is revealed by the comparison with the conventional operation approach based on the demand prediction scheme.

The remainder of this paper is organized as follows. In Section II, we describe the target residential energy system and an outline of the operation framework of PEFC-CGSs. In Section III, the conventional operational planning idea based on demand prediction is outlined. Section IV introduces our proposed method based on the surrogate model for minimizing expected operational costs. In Section V, the proposed approach is numerically evaluated via simulations. Section VI summarizes our findings and provides conclusions.

II. TARGET RESIDENTIAL ENERGY SYSTEM AND OPERATION FRAMEWORK OF THE PEFC-CGS

A. INTRODUCTION OF TARGET RESIDENTIAL ENERGY SYSTEM

This study assumes a detached household. Fig. 1 shows the equipment configuration and connections of the energy system of the household model. The system consists of a PEFC-CGS, a gas-fired water heater (GH), and an air conditioning (AC) system. The PEFC-CGS generates electrical and thermal output within the PEFC unit and stores hot water in the storage tank. Hot water demand is supplied from the storage tank of the PEFC-CGS. If the tank is empty, the GH meets the demand. We assume that the PEFC-CGS can be started/stopped only once a day and can operate continuously for up to 20 (h). The AC system is operated to minimize the electricity fee while maintaining a comfortable temperature range from the viewpoint of predicted mean vote (PMV) [33]. The setup of the system is the same as that utilized in [34]. The detailed formulation of the entire system is presented in the Appendix.

B. TARGET OPERATION FRAMEWORK OF THE PEFC-CGS

We next discuss the further efficient operational plan that is defined as the start/stop schedule for the next 24 (h) of the PEFC-CGS operation for this typical household. We evaluate operational performance in terms of operational cost, which is defined as the daily total household electricity fee while maintaining a comfortable temperature over up to 20 (h). The AC system is operated to minimize the electricity fee while maintaining a comfortable temperature range from the viewpoint of predicted mean vote (PMV) [33]. The setup of the system is the same as that utilized in [34]. The detailed formulation of the entire system is presented in the Appendix.

\[
C(\theta | e_{e}^{\text{dem}}, h_{e}^{\text{dem}}) = \sum_{t=1}^{T} \left[ C_{e}^e \left( e_{t}^{\text{grid}, e_{t}^{\text{dem}}, z_{t}} \right) + C_{e}^g \left( g_{t}^{\text{grid}, h_{t}^{\text{dem}}, z_{t}} \right) \right]. \tag{1}
\]

where \( e_{t}^{\text{grid}} \) and \( h_{t}^{\text{grid}} \) is the electricity and gas purchased at time slice \( t \) to meet the shortage demand or operate energy.
appliances under given operation $\theta$, and $C^e$ and $C^h$ are the energy unit prices. The detailed constraints of these variables are presented in the Appendix.

In order to reduce the operational cost, energy equipment should be controlled according to household demand. In particular, the \textit{ideal} operation $\theta^*$ of the PEFC-CGS for the demand sequences $\hat{e}_t^{\text{dem}}$ and $\hat{h}_t^{\text{dem}}$ can be obtained as the following minimizer:

$$
\theta^* = \arg\min_{\theta} C(\theta|e^{\text{dem}}, h^{\text{dem}}).
$$

Planning the efficient operation of the PEFC-CGS $\theta$ for future household demand can be an effective way to reduce the operational cost. In this study, we propose a method to produce an appropriate operational plan $\hat{\theta}$ of the PEFC-CGS for the next 24 (h).

### III. OPERATIONAL PLANNING APPROACH BASED ON HOUSEHOLD DEMAND PREDICTION

#### A. FRAMEWORK BASED ON DEMAND PREDICTION

For derivation of an efficient operational plan, one will try to predict demand sequences $e_t^{\text{dem}}$ and $h_t^{\text{dem}}$; future electricity and hot water demands considerably influence the operational cost, so that an operational plan based on the predicted household demand is expected to be effective. Ogata et al. [21] have discussed an operational planning framework based on demand prediction. Fig. 2 shows the conceptual diagram of the approach that consists of the following three steps:

1) Prediction step: The time series of expected electricity demand (kWh/15 min), i.e., $\hat{e}_t^{\text{dem}} = \begin{bmatrix} \hat{e}_1^{\text{dem}}; \hat{e}_2^{\text{dem}}; \ldots; \hat{e}_T^{\text{dem}} \end{bmatrix}$, and expected hot water demand (kWh/15 min), i.e., $\hat{h}_t^{\text{dem}} = \begin{bmatrix} \hat{h}_1^{\text{dem}}; \hat{h}_2^{\text{dem}}; \ldots; \hat{h}_T^{\text{dem}} \end{bmatrix}$, in the next 24 (h) with quarter-hourly temporal resolution are predicted with regression functions $\phi^e_t$ and $\phi^h_t$ as follows:

$$
\phi^e_t(x) \mapsto \hat{e}_t^{\text{dem}} \text{ for } t \in \{1, 2, \ldots, T\}, \quad (3)
$$

$$
\phi^h_t(x) \mapsto \hat{h}_t^{\text{dem}} \text{ for } t \in \{1, 2, \ldots, T\}, \quad (4)
$$

where $x$ is the actual measurement data (input for predictions) given on the day before the prediction target day. The regression functions $\phi^e_t$ and $\phi^h_t$ are constructed for each time slice $t$ respectively to minimize the expected errors of household demands.

2) Operational planning step: The operational schedule for the next 24 (h), i.e., $\hat{\theta} = [\hat{e}_1; \hat{e}_2; \ldots; \hat{e}_T]$, is determined. Energy demand sequences $e_t^{\text{dem}}$ and $h_t^{\text{dem}}$ predicted in the previous step are input as exogenous variables into a cost minimization operational planning problem, which is formulated as a mixed integer linear programming (MILP) problem. The objective function is given as follows:

$$
\hat{\theta} = \arg\min_{\theta} \sum_{t=1}^{T} \left\{ C^e_t \left( e_t^{\text{grid}}; e_t^{\text{dem}}, \hat{e}_t \right) + C^h_t \left( g_t^{\text{grid}}; \hat{h}_t^{\text{dem}}, \hat{h}_t \right) \right\}. \quad (5)
$$

The optimal start/stop schedule of the PEFC-CGS $\hat{\theta} = [\hat{e}_1; \hat{e}_2; \ldots; \hat{e}_T]$ is derived as a solution of (5).

3) Control step: The operational strategy $\hat{\theta}$ that was decided at the former step is applied towards the actual energy demands $e_t^{\text{dem}}$ and $h_t^{\text{dem}}$. The operational cost $C$ is calculated as (1).

One of the promising prediction approaches is based on the machine learning techniques that predict future behavior by statistically learning from past data [16]–[20]. The widespread use of residential sensing appliances, e.g., smart meters, leads to the collection of a significant amount of data from households to be used in machine learning techniques. Various algorithms have been applied to the demand prediction tasks [16]–[18]. In this paper, we explicitly focus on the

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**FIGURE 2.** Operational planning method based on demand prediction. Household demands are predicted using actual measurement data by regression functions to achieve low expected error with the next day’s actual demand. The operational plan is optimal in terms of the predicted demand. The operational cost is calculated by inputting the actual demand and the operational plan.
difference of the prediction targets utilized in the operational planning framework by utilizing popular prediction models that have achieved good predictions for various prediction tasks in general. The random forest [35] is one of the well-known nonlinear regression models which often yields small prediction errors in various prediction tasks.\textsuperscript{2} This algorithm adopts a kind of ensemble learning technique [36] which combines outputs of decision trees [37] using learning data obtained by the bootstrap method [38]. By the integrating framework and the bootstrap-based random resampling, the prediction results tend to avoid significant error and this algorithm realizes good generalization performance. In this study, we utilized regression models on the basis of random forest algorithm for implementation of a typical demand prediction-based operational planning approach.

\textbf{B. PROBLEM WITH DEMAND PREDICTION APPROACH}

Approaches that use machine learning techniques provide good predictions from the viewpoint of average errors defined as the difference between the actual demand sequence \( \{y_t; t \in \{1, 2, \ldots, T\} \} \) and the predicted sequence \( \{\hat{y}_t; t \in \{1, 2, \ldots, T\} \} \); a popular index used in construction of regression models is the root mean squared error (RMSE),

\[
\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (y_t - \hat{y}_t)^2}. \tag{6}
\]

This type of prediction error greatly affects the PEFC-CGS operation, e.g., the overestimation of hot water demand induces an excessive running time of the PEFC-CGS and lead to surplus hot water in the tank, whereas the underestimation results in inefficient operation of the backup gas heater because insufficient hot water is generated by the PEFC-CGS. The regression model is constructed to achieve the small expected average error of demand prediction as shown in Fig. 2, so that this framework is expected to lead to an efficient operational plan. However, the experimental results imply that the demand prediction result with a small prediction error does not lead to an efficient operational plan in some cases.
FIGURE 5. Operational planning method based on a surrogate model to minimize operational costs. The regression functions are constructed in order to appropriately predict expected operational costs of operational plans under the condition of future uncertainty. The optimal operational plan is selected using the predicted operational costs, and applied to the actual demand on the following day.

FIG. 3(a) shows an example of predicted hot water demand sequence, and Fig. 3(b) shows the corresponding operation derived by using the predicted demand. In this case, the RMSE of the demand prediction result is relatively low; however, the operation derived by using the predicted demand sequence leads to the lack of hot water, resulting in inefficient operation relying on the backup boiler. Figs. 4(a) and (b) show another example of predicted hot water demand sequence for the same day as shown in Fig. 3 and its corresponding operation. In this latter case, the RMSE of the predicted demand sequence is rather large, but the amount of hot water generated under the derived operation sufficiently meets the actual demand without using the backup boiler. These examples suggest that even when the errors in the demand prediction results are small, the derived operational plans can be inappropriate. In other words, in the operational planning scheme based on the demand prediction, there is a gap between the objective for constructing the model, i.e. the improvement of the prediction accuracy, and the objective of the essential task, i.e. the reduction of the operational cost.

IV. OPERATIONAL PLANNING APPROACH BASED ON A SURROGATE MODEL FOR MINIMIZING EXPECTED OPERATIONAL COSTS

We propose a novel approach that derives an operational plan aiming at optimization from the viewpoint of expected operational cost. Fig. 5 shows a schematic flow of the proposed approach. This approach explicitly estimates the expected operational cost which represents the predicted cost under the uncertain demand of the next 24 (h) for the possible operational plan candidates, and therefore, the reduction of prediction error directly leads to the accurate grasp of the expected operational cost under each operational plan candidate. The

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operational costs. The detailed construction process of the surrogate model in our proposed approach is described in the next subsection.

B. SURROGATE MODEL FOR OPERATIONAL PLANNING

We introduce the idea of surrogate model to derive the appropriate operational plan that minimizes the expected operational cost under the uncertainty in the future demand.

The proposed method consists of the following five steps:

1) Operational costs of possible operational plans under the various past demands are evaluated by simulations. Let $\Theta = \{\theta = \{z_1, z_2, \ldots, z_T\}\}$ be a set of possible operational plans and $x_d$ be actual measurement data observable before the date $d$. The operational cost $C^d_{\theta}$ under each operational plan $\theta \in \Theta$ is calculated for each past date $d \in \{1, 2, \ldots, D\}$ by using the actual demand of the date $d$. A set of triplets $\{(x_d, \theta, C^d_{\theta}) : d \in \{1, 2, \ldots, D\}, \theta \in \Theta\}$ constitutes the database for learning regression function.

2) The regression function $\psi_{\theta}$ is constructed using the database for each $\theta \in \Theta$; the model $\psi_{\theta}$ describes the relationship between the specific measurement $x_d$ which is observable before the date $d$ and the expected operational cost $\hat{C}^d_{\theta}$ under the operation $\theta$:

$$\psi_{\theta}(x_d) \mapsto \hat{C}^d_{\theta} \forall \theta \in \Theta.$$  (7)

3) The expected operational cost $\hat{C}^{D+1}_{\theta}$ for the target date $D + 1$ with the operational plan $\theta \in \Theta$ is predicted using the model $\psi_{\theta}$ and the current observation $x_{D+1}$:

$$\psi_{\theta}(x_{D+1}) \mapsto \hat{C}^{D+1}_{\theta} \forall \theta \in \Theta.$$  (8)

4) The operational plan $\hat{\theta}$ for the target date $D + 1$ is obtained by selecting the minimizer of expected operational costs $\hat{C}^{D+1}_{\theta}$ as follows:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \hat{C}^{D+1}_{\theta}. $$  (9)

5) The operational plan $\hat{\theta}$ derived in the former step is applied towards the actual energy demand of the target date $D + 1$.

In the first step, the dataset for construction of a surrogate model is collected. A set $\Theta$ indicates the possible operational plan candidates; the cardinality of this set, i.e., $|\Theta|$, indicates the number of candidates. In our implementation, $N$ possible operational plan candidates are derived using the intermittent operation count constraint of the PEFC-CGS and using the well-known fact that the cost-effective operation can be achieved by using the PEFC-CGS in the time periods when the electricity rate is high in the time-of-use tariff. The specific candidates used in our experiments are described in Section V.

Then, in the second step, the regression function, $\psi_{\theta}$, for derivation of the expected operational cost is learned by focusing on the relationships between the explanatory variables $x_d$ and the operational cost $C^d_{\theta}$ simulated under operational plan candidate $\theta \in \Theta$ derived on the basis of (1) using the actual demand sequences $e^{\text{dem}}_{\text{obs}}$ and $h^{\text{dem}}_{\text{obs}}$ at the corresponding dates. The data vector $x_d$ which is observable before the date $d$ is used as the explanatory that may affect the operational cost of the PEFC-CGS; e.g., the demand time-series subsequence on the previous day, the forecasted temperature and calendar information (weekday/holiday) of the target day are expected to be important components of the explanations. The regression function $\psi_{\theta}$ is constructed as (7) for each possible operational plan $\theta \in \Theta$, respectively; each model is trained to minimize the error between predicted cost $\hat{C}^d_{\theta}$ and the corresponding true cost $C^d_{\theta}$ for the entire learning period $\{1, 2, \ldots, d, \ldots, D\}$. Various types of machine learning techniques can be utilized as regression function $\psi_{\theta}$ for derivation of predicted cost $\hat{C}^d_{\theta}$. In this study, we utilize one of the well-known nonlinear regression algorithms, i.e. random forest [35], and evaluate the significance of the proposed surrogate model-based scheme by comparing with the traditional demand prediction-based scheme also constructed with the random forest. Note that Steps 1) and 2) can be pre-processed offline before performing the following steps.

In the third step, we derive expected operational cost $\hat{C}^{D+1}_{\theta}$ at the target date $D + 1$ by using the data vector $x_{D+1}$, which is observable before the date $D + 1$. The surrogate model, $\psi_{\theta}$, learned in the previous step is used for derivation of expected operational costs considering uncertainty in the demand behavior of the target date as shown in (8).

In the fourth step, the plausible operational plan $\hat{\theta}$ that minimizes the expected operational cost is selected from the candidates $\Theta$ as shown in (9) by evaluating expected costs for all the candidates. In our implementation, the number of candidates $N$ is not large, and therefore, $\hat{\theta}$ can be derived by the brute-force search. When multiple minimizers exist from the viewpoint of expected cost, we select the operational plan that achieves the longest PEFC-CGSs operation time and earliest operation start time, since overrunning of the PEFC-CGS (which could lead to leaving hot water in the tank) tends to have less negative impact on operational costs than the situation in which a house runs out of hot water.

Finally, in the fifth step, the operational plan $\hat{\theta}$ is applied under the actual energy demand sequences $e^{\text{dem}}_{\text{obs}}$ and $h^{\text{dem}}_{\text{obs}}$ of the target date $D + 1$. The actual operational cost $C^{D+1}_{\hat{\theta}}$ can be evaluated using (1).

The approach introduced in Section III and the one introduced in this section are very similar in terms of using regression functions, but there are significant differences in terms of prediction targets. The conventional method constructs the demand prediction model so as to reduce the expected error between the predicted and actual demand sequences (Fig. 2). In this case, the impact of error in demand prediction may not directly reflect the difference between cost under the actual demand and that under the predicted demand; therefore, the operational plan derived under the predicted demand does not necessarily lead to cost effective operation. Meanwhile, the model constructed in the proposed method predicts
expected operational costs of candidate plans (Fig. 5); in this case, the model is fitted to reduce the difference between the realized cost and the predicted cost. The reduction of this difference explicitly leads to the accurate estimation of the operational cost for the next 24 (h) of the operational plan candidates, i.e., the selected operational plan that minimizes the accurately-predicted operational costs directly represents the appropriate plan from the viewpoint of the essential operational planning target. Thus, the proposed approach is expected to contribute to the achievement of the operational plan with the low operational cost.

V. NUMERICAL EXPERIMENTS

In this section, we compare the operational plans derived by using the operation planning method based on household demand prediction (the conventional method) [27], and the method based on a surrogate model for minimizing expected operational costs (the proposed method). We evaluate the two methods utilizing real-world demand data.

A. SIMULATION SETUP

For our simulation, we refer to the case of the detached houses described in Section II. The demand data used in this simulation comprises real-world measurements of the electricity and hot water demands of twelve customers collected every 15 (min) [40]. The characteristics of the electricity and hot water demands for each household and each season are shown in Figs 6, 7, and 8. Fig. 6 shows the relationship between the average daily electricity and hot water demands. Each plot represents a household and is color-coded by the prefecture where the target households are located in Japan. The red line shows the case where the amount of electricity to hot water is equal. The electricity demand is higher than the hot water demand when the household is plotted below the red line; the opposite is true when it is plotted above the red line. As shown in Fig. 6, the demand patterns of each household considerably vary regardless of the region. Fig. 7 shows the average daily demand of all households in each season. Hot water demand is high in February and shows similar trends in May and November. Fig. 8 shows the average temperature at noon for each season in each prefecture. As shown in Fig. 8, February has the lowest temperature and August has the highest. The region named Hokkaido has the lowest temperatures.
The household demands and expected operational costs are predicted on the basis of random forest [35] by using the hourly demand data on the previous day, calendar information, and the temperature on the following day as explanatory variables, $x$. Note that calendar information indicates weekdays/holidays and days of the week of the target day, and the temperature on the following day is assumed to be known on the previous day.

Operational plan candidates $\theta \in \Theta$ are prepared under the following assumptions: the possible operational start time lies within the period 03:30-19:00 and the possible operational stop time lies within the period 03:30-22:15. Therefore, two thousand patterns of $\theta$ are used ($N = 2080$).

The prediction models used in these methods are learned by using the data collected in the previous 30 days for each target day ($D = 30$). We use the data collected in February, May, August, and November for our evaluation. We compare the operational costs for the actual demand on the target day under the operational plan derived by each method.

**B. COMPARISON OF PEFC–CGS OPERATIONS**

Figs. 9 and 10 show the examples of hot water demand prediction results and the derived operations. The RMSE of the example shown in Fig. 10(a) is about twice as large as that in Fig. 9(a) while the derived excessive operational cost in Fig. 9(b) is higher than that in Fig. 10(b) by 15 (JPY). These examples show the discrepancy between the reduction of demand prediction error and the improvement of operational performance of the PEFC-CGS.

Fig. 11 shows the monthly average excessive operational cost of the target households, defined as the difference between ideal operational cost and operational cost realized by the operational plan $\hat{\theta}$. The ideal operational cost is derived by $\theta^*$ solving the MILP under the actual demand for the target day.
day as (1) and (2). In the entirety period, the excessive operational cost is averagely reduced by 30 (%) of the conventional demand prediction-based method. In particular, the proposed method was most effective in February: the cost was reduced by 36 (%) of the conventional method. Fig. 11 suggests that the proposed method reduces the excessive operational cost steadily without severe negative effect by seasons. This is important for residential PEFC-CGSs because these systems are intended to be operated over a long-time period.

Fig. 12 shows the breakdown of the excessive operational costs in the entire evaluation period: 1) electricity fee purchased from the grid, 2) gas fee to operate the PEFC-CGS, and 3) gas fee to operate the GH. As shown in Fig. 12, the proposed method achieves lower cost for operating the GH by 37 (%) and purchasing electricity by 37 (%) while accepting a larger cost for operating the PEFC-CGS by 41 (%) than the conventional method: the total operational cost is reduced by 29 (%). The absolute values of all the elements of the proposed method are decreasing, so that the proposed method is close to the ideal operation. This result also implies that the inefficient operation of the GH and extra purchases of electricity can be avoided by utilizing the PEFC-CGS for longer time.

Fig. 13 shows the breakdown of the excessive operational costs in the entire evaluation period: 1) electricity fee purchased from the grid, 2) gas fee to operate the PEFC-CGS, and 3) gas fee to operate the GH. As shown in Fig. 12, the proposed method achieves lower cost for operating the GH by 37 (%) and purchasing electricity by 37 (%) while accepting a larger cost for operating the PEFC-CGS by 41 (%) than the conventional method: the total operational cost is reduced by 29 (%). The absolute values of all the elements of the proposed method are decreasing, so that the proposed method is close to the ideal operation. This result also implies that the inefficient operation of the GH and extra purchases of electricity can be avoided by utilizing the PEFC-CGS for longer time.

Table 1 shows the average excessive operational cost of all the target households for each season and the average relative cost rate that is defined as the excessive operational cost of entire evaluation period in the proposed method when the cost in the conventional method is regarded as 100 (%). The result indicates that the proposed method achieves lower operational cost than the conventional method for most households and seasons. The seasonal characteristics
shown in these results suggest the following two patterns when the operational costs tend to be high: 1) periods with high demand for hot water such as February and November, and 2) periods with low demand for hot water such as August. By the comparison with Fig. 6, the households with small average daily demands are assigned to the first pattern, and those with large demands are assigned to the second pattern. In the conventional demand prediction-based method, this tendency is remarkable; the increase in excessive operational costs is significant for these seasons. However, the proposed method tends to achieve the consistent cost reduction even when the conventional method does not work well. As a result, the proposed method reduced the excessive operational costs in 36 of the 48 total patterns of seasonal and household combinations, and the average relative cost rate for the entire evaluation period compared to the demand prediction-based method was reduced in 11 households.

Focusing on each households, for example, the average relative cost rate at Fukuoka-1 is decreased by about 50 (%). At Nigata-1 in February, the cost is also drastically reduced by 13.74 (JPY); this accounts for 5% of the average operational cost of the household in February. Fig. 14 shows the breakdown of the average operational costs of the household Nigata-1 in February. The result shows that the PEFC-CGS running time of the proposed method tends to be as long as that of ideal operation. Meanwhile, in the conventional method, the PEFC-CGS operation seems to be suppressed while the backup GH tends to be actively
operated. Fig. 15 shows the comparison of daily operational plans derived by each method at Nigata-1 in February. Comparison between Figs 15(a) and (b) suggests that the operational start time in the plans derived by the conventional method tends to be late which leads to a shortage of hot water. The result implies that the selection of appropriate operational plans according to the conventional demand prediction scheme is difficult. On the other hand, the results presented in Fig. 15(c) show that the proposed method derives rather similar operational plans to the ideal ones shown in Fig. 15(a); this suggests that the proposed scheme which evaluates the appropriateness of operational plans by directly estimating expected operational costs works well for derivation of effective operational plans.

Table 1 also indicates that the proposed method tends to reduce the excessive operational cost without significant negative effects. Even at Hokkaido-2 where no cost improvement has been seen in the entire evaluation period, the excessive operational cost is very low compared to the improvement in other households. Focusing on the cases with the highest operation cost in Table 1, the proposed method achieves the operation with 15.29 (JPY) at Osaka-1 in February, while the conventional method derives the operation with 23.07 (JPY) at Nigata-1 in February. The result also suggests that the proposed method stably keeps low operational costs even under various situations.

Numerical experiments show that the proposed method is effective in households with various demand patterns. The operational cost is reduced by efficient operation of the PEFC-CGS and shorter operation of the GH.

**VI. CONCLUDING REMARKS**

In this study, we examined the PEFC-CGS operational planning methods and proposed a novel approach based on a surrogate model for deriving an appropriate plan that minimizes the expected operational costs among the operational plan candidates. The proposed method resolves the gap between the improvement of the demand prediction accuracy and the reduction of the operational cost in the existing demand prediction-based operational planning scheme. The cost prediction model with the small error between the actual cost and the expected cost permits to select the appropriate operational plan directly from the viewpoint of operational cost reduction. The approach was evaluated via numerical simulations using actual demand data and comparing these with the conventional demand prediction-based method. The experimental results suggest that 30% of the excessive operational cost in the entire evaluation period can be reduced from the conventional method. The proposed method stably achieves low operational costs under various demand patterns, and its average relative cost rate shows about 50-90 (%) in most of the households.

The framework that uses a surrogate model for the evaluation of expected operational cost worked well for operational cost reduction even under the existence of uncertainty in the future demand predictions. In this paper, we focused on the evaluation of the validity of the concept of surrogate model for derivation of expected operational costs by comparing with the conventional operational planning approach based on demand forecasting scheme. However, for efficient operation, the approach for constructing a surrogate model will be also important. Adoption of various technologies discussed in the machine learning community in recent years for construction of the surrogate model will be expected to contribute to further efficient operation. In addition, the EMS for PEFC-CGSs can be applied in other areas of research and development, for example, in the efficient utilization of photovoltaic power outputs [24] and reducing the primary energy consumption in households. Therefore, we will develop our proposed method by connecting PEFC-CGSs and other residential energy appliances to realize an increasingly efficient demand-side EMS.

**APPENDIX**

We describe detailed formulations of energy flow and each equipment introduced in Section II.

**A. LIST OF NOMENCLATURES**

| Symbol | Description |
|--------|-------------|
| $e_{dem}^t$ (kWh/15 min) | Household electricity demand |
| $e_{AX}^t$ (kWh/15 min) | PEFC-CGS electricity consumption of the auxiliary equipment |
| $e_{RD}^t$ (kWh/15 min) | Electricity consumption in radiator |
| $e_{in,t}^FC$ (kWh/15 min) | Electricity consumption during startup and shutdown the PEFC-CGS |
| $e_{GH}^t$ (kWh/15 min) | Gas heater electricity consumption |
| $e_{AC}^t$ (kWh/15 min) | Air-conditioner electricity consumption |
| $e_{grid}^t$ (kWh/15 min) | Purchased electricity from the grid |
| $e_{out,t}^{FC}$ (kWh/15 min) | PEFC-CGS electricity output |
| $h_{dem}^{in,t}$ (kWh/15 min) | Household hot water demand |
| $h_{ST}^{out,t}$ (kWh/15 min) | Thermal output of the ST |
| $h_{GH}^{out,t}$ (kWh/15 min) | Thermal output of the GH into demand |
| $g_{grid}^t$ (Nm$^3$/15 min) | Purchased gas from the grid |
| $g_{in,t}^{FC}$ (Nm$^3$/15 min) | PEFC-CGS gas consumption |
| $g_{GH}^{in,t}$ (Nm$^3$/15 min) | Gas consumption of the GH |
| $e_{FC}^t$ (kWh/15 min) | PEFC-CGS electricity output |
| $h_{FC}^{in,t}$ (kWh/15 min) | PEFC-CGS thermal output |
| $z_t$ | Calorific value of gas consumption |
| $H$ (kWh/Nm$^3$) | Lower calorific value of city gas |
| $e_{EH}^t$ (kWh/15 min) | Electricity consumption in the EH |
| $h_{EH}^t$ (kWh/15 min) | Thermal output of the EH |
For household energy flow, supply and demand must match at each time slice \( t \in \{1, 2, \ldots, T\} \). In this study, electricity and hot water are assumed to be the household energy demands. The electricity balance is expressed as follows:

\[
\epsilon_t^{\text{dem}} + \epsilon_t^{\text{AX}} + \epsilon_t^{\text{RD}} + \epsilon_t^{\text{FC}} + \epsilon_t^{\text{GH}} + \epsilon_t^{\text{AC}} = \epsilon_t^{\text{rise}} + \epsilon_t^{\text{out},t}. \tag{10}
\]

Equation (11) shows the hot water demand and supply balance.

\[
h_t^{\text{dem}} = h_{t\text{,out},t} + h_{t\text{,GH}}. \tag{11}
\]

The main fuel of hot water is city gas. The balance of city gas inflow and consumption is expressed as follows:

\[
g_t^{\text{grid}} = g_{t\text{,in},t} + g_{t\text{,out},t}. \tag{12}
\]

### C. PEFC-CGS

As shown in Fig. 1, PEFC-CGS consists of PEFC unit, storage tank (ST), electric heater (EH), auxiliary, and radiator.

1) **PEFC UNIT**

This is the main unit of the PEFC-CGS. Electricity is generated from city gas, and hot water is produced by waste heat. \( \epsilon_t^{\text{FC}} \) and \( h_t^{\text{FC}} \) are formulated by inputting \( h_{t\text{,in},t}^{\text{FC}} \) as follows:

\[
\epsilon_t^{\text{FC}} = A_t^{\text{FC}} h_{t\text{,in},t}^{\text{FC}} + B_t^{\text{FC}} z_t, \tag{13}
\]

\[
h_t^{\text{FC}} = A_t^{\text{FC}} h_{t\text{,in},t}^{\text{FC}} + B_t^{\text{FC}} z_t, \tag{14}
\]

where \( A_t^{\text{FC}} \) and \( B_t^{\text{FC}} \) are conversion factors (slopes) between PEFC-CGS output and gas consumption, \( B_t^{\text{FC}} \) and \( B_t^{\text{FC}} \) are intercepts. \( h_{t\text{,in},t}^{\text{FC}} \) is converted from city gas consumption as follows:

\[
h_{t\text{,in},t}^{\text{FC}} = H_{t\text{,in},t}^{\text{FC}}. \tag{15}
\]

\( \epsilon_t^{\text{FC}}, h_t^{\text{FC}}, \) and \( h_{t\text{,EH}}^{\text{FC}} \) are divided as follows:

\[
\epsilon_t^{\text{FC}} = \epsilon_t^{\text{out},t} + \epsilon_t^{\text{EH}}, \tag{16}
\]

\[
h_t^{\text{FC}} = h_{t\text{,EH}}^{\text{FC}} = h_{t\text{,FC}}^{\text{ST},t} + h_t^{\text{RD}}. \tag{17}
\]

Equations (18) and (19) show the electricity load-followability of the PEFC. It can follow the load up to \( \epsilon_t^{\text{rise}} (\text{W/min}) \) when the output increases and \( \epsilon_t^{\text{fall}} (\text{W/min}) \) when the output decreases.

\[
\epsilon_t^{\text{FC}} \leq \epsilon_t^{\text{FC}} + \epsilon_t^{\text{FC}} \cdot \Delta t, \tag{18}
\]

\[
\epsilon_t^{\text{FC}} \geq \epsilon_t^{\text{FC}} - \epsilon_t^{\text{FC}} \cdot \Delta t. \tag{19}
\]

2) **STORAGE TANK**

This is the attached tank to store hot water generated by the PEFC and the GH. \( h_{t\text{,ST}}^{\text{ST}} \) is shown as follows:

\[
\left\{ h_{t\text{,ST}}^{\text{ST}} - h_{t-1}^{\text{ST}} \cdot (1 - \eta_{\text{loss}}^{\text{ST}}) \right\}/\Delta t = h_{t\text{,ST},t}^{\text{FC}} + h_{t\text{,GH}}^{\text{ST}} - h_{t\text{,out},t}^{\text{ST}}. \tag{20}
\]

\( h_{t\text{,ST}}^{\text{max}} \) is the amount required to heat the entire amount of water in the \( \rho V \text{ST} (\text{kg}) \) from \( \omega_{\text{water}} (\text{C}) \) to \( \omega_{\text{FC}} (\text{C}) \) as in (21).

\[
h_{t\text{,max}}^{\text{ST}} = \rho V \text{ST} \cdot \omega_{\text{water}} \cdot (\omega_{\text{FC}} - \omega_{\text{water}}). \tag{21}
\]

\( h_{t\text{,min}}^{\text{ST}} \) is also defined as follows:

\[
h_{t\text{,min}}^{\text{ST}} = h_{t\text{,max}}^{\text{ST}} \cdot \gamma_{\text{min}}^{\text{ST}}. \tag{22}
\]

3) **ELECTRIC HEATER**

The EH is a device that converts the surplus electricity generated by the PEFC into heat and stores it in a storage tank. \( h_t^{\text{EH}} \) is expressed as follows:

\[
h_t^{\text{EH}} = \eta_{\text{EH}}^{\text{EH}} \tag{23}
\]

4) **AUXILIARY**

The auxiliary consists of controller and pump to operate the PEFC-CGS. The electricity consumption is expressed as follows:

\[
\epsilon_t^{\text{AX}} = \epsilon_t^{\text{AC}} = \epsilon_t^{\text{pump},t}. \tag{24}
\]

The controller electricity consumption \( \epsilon_t^{\text{AC}} \) is always in operation. \( \epsilon_t^{\text{pump},t} \) is defined by \( \epsilon_t^{\text{FC}} \) and \( M \) that is large enough number

\[
\epsilon_t^{\text{pump},t} = \epsilon_t^{\text{FC}}/M. \tag{25}
\]

5) **RADIATOR**

A radiator is a device that dissipates heat by consuming power when the amount of heat stored in the hot water tank reaches the maximum amount of heat stored. The power consumption in the radiator is expressed as follows:

\[
\epsilon_t^{\text{RD}} = \eta_{\text{RD}} \tag{26}
\]
TABLE 2. Specifications of the PEFC-CGS.

| Specification                  | Value       |
|-------------------------------|-------------|
| Maximum of electricity output | 0.750 (kW) |
| Minimum of electricity output  | 0.200 (kW) |
| Maximum of thermal output      | 1.080 (kW) |
| Minimum of thermal output      | 0.210 (kW) |
| Controller $e_c$               | 6.6 (Wh/15 min) |
| Pump $e_{pump}$                | 26 (Wh/15 min) |
| Efficiency of the FH $n_{FH}$  | 95 (%)      |
| Fan efficiency $n_{fan}$       | 10 (%)      |
| Volume of hot water tank $V_{ST}$ | 0.147 (m$^3$) |
| Coefficient of thermal loss $\eta_{loss}^{ST}$ | 1.47 (%) |
| Minimum ratio of thermal storage $y_{min}^{ST}$ | 10 (%) |
| Maximum time for continuous running | 20 (h) |
| PEFC tapping temperature $\alpha_{FC}$ | 65 ($^\circ$C) |
| Slope parameter for electricity output of the PEFC $A_{FC}^{h}$ | 0.417 |
| Slope parameter for thermal output of the PEFC $A_{FC}^{e}$ | 0.582 |
| Intercept parameter for electricity output of the PEFC $B_{FC}^{h}$ | -63.308 |
| Intercept parameter for thermal output of the PEFC $B_{FC}^{e}$ | -171.63 |
| Start-up time of the PEFC      | 45 (min)    |
| Power consumption at start-up  | 984.04 (Wh) |
| Input gas volume at start-up   | 0.125524 (Nm$^3$) |
| Stop time of the PEFC          | 90 (min)    |
| Power consumption at stop      | 391.984 (Wh) |
| Input gas volume at stop       | 0.0794484 (Nm$^3$) |
| Load follow-up late when output increases $e_{L_{FC}}$ | 48.6 (W/min) |
| Load follow-up late when output decreases $e_{L_{FC}}$ | 33000 (W/min) |

D. GAS HEATER

A GH is the device that produces hot water from the city gas. Output of the GH $h_{GH}^t$ is expressed by $\delta_{in,t}$, $H$, and thermal efficiency $\eta_{GH}^e$ as follows:

$$h_{GH}^t = H \eta_{GH}^e \delta_{in,t}.$$  (27)

$h_{GH}^t$ and $e_{GH}^t$ are divided as follows:

$$h_{GH}^t = h_{GH}^{out,t} + h_{ST,GH}.$$  (28)

$$e_{GH}^t = e_{GH}^{GH} h_{GH}^t.$$  (29)

E. SPECIFICATIONS FOR NUMERICAL SIMULATIONS

We assume the specifications of energy equipment as shown in Table 2 and 3. Other energy parameters are also shown in Table 4. We set these values from catalog and experimental data using actual machines [41], [42].

TABLE 3. Specifications of the GH.

| Specification                  | Value       |
|-------------------------------|-------------|
| Efficiency for hot water demand $\eta_{GH}^h$ | 92 (%)      |
| Efficiency for electricity consumption $\eta_{GH}^e$ | 0.125 (%)  |

F. OPERATIONAL COST

In this study, we focus on operational cost $C$, which is defined as the daily total household electricity and gas fee as follows:

$$C = \sum_{t=1}^{T} \left( C_{e}^{grid} + C_{g}^{grid} \right).$$  (30)

$C_{e}^{grid}$ and $C_{g}^{grid}$ are the energy unit prices and shown in Table 5. These parameters are based on prices actually provided by Tokyo Electric Power Company Holdings, Inc. [43] and Tokyo Gas Co., Ltd. [44].

REFERENCES

[1] Agency for Natural Resources and Energy in Japan. (2014). About the Residential Fuel Cells. (in Japanese). [Online]. Available: https://www.meti.go.jp/committee/kenkyukai/energy/suiso_nenryodenchi/suiso_nenryodenchi_wg/pdf/002_01_00.pdf

[2] Agency for Natural Resources and Energy in Japan. (2014). Hydrogen / Fuel Cell Strategy Roadmap. (in Japanese). [Online]. Available: http://www.meti.go.jp/committee/kenkyukai/energy/suiso_nenryodenchi/pdf/report01_03_00.pdf

[3] M. Caliano, N. Bianco, G. Graditi, and L. Mongibello, "Economic optimization of a residential micro-CHP system considering different operation strategies," Appl. Thermal Eng., vol. 101, pp. 592–600, May 2016.

[4] P. Wolfrum, M. Kautz, and J. Schäfer, "Optimal control of combined heat and power units under varying thermal loads," Control Eng. Pract., vol. 30, pp. 105–111, Sep. 2014.

[5] K. Ou, W.-W. Yuan, M. Choi, S. Yang, S. Jung, and Y.-B. Kim, "Optimized power management based on adaptive-PMP algorithm for a stationary PEM fuel cell/battery hybrid system," Int. J. Hydrogen Energy, vol. 43, no. 32, pp. 15433–15444, Aug. 2018.

[6] K. Maeda, K. Masumoto, and A. Hayano, "A study on energy saving in residential PEFC cogeneration systems," J. Power Sources, vol. 195, no. 12, pp. 3779–3784, Jun. 2010.

[7] H. Kuraishi, T. Hayashi, Y. Fujii, K. Yamaji, and A. Yokoyama, "Optimum operating method of a small scale cogeneration system for home use with stochastic dynamic programming," in Proc. Tech. Meeting PE, Jpn., Sep. 2004, pp. 51–56.

[8] A. Ozawa and Y. Yoshida, "A stochastic dynamic programming model for the optimum operation of residential fuel cell system," in Proc. 29th conf. Envr. Info. Sci., Jpn., Aug. 2015, pp. 165–170.

[9] Y. Tanaka and M. Fukushima, "Optimum operation of cogeneration systems by stochastic programming," IEEE Trans. Power Energy, vol. 129, no. 6, pp. 765–775, Jan. 2009.

[10] K. Hashimoto and K. Kawahara, "Optimal operation of fuel cell and electrolyzer in household hybrid system by stochastic programming," in Proc. IEEE Innov. Smart Grid Technol. Asia (ISGT-Asia), Dec. 2017, pp. 1–6.
[36] T. G. Dietterich, “Ensemble methods in machine learning,” in Proc. 1st Int. Workshop Multiple Classifier Syst., Cagliari, Italy, 2000, pp. 1–15.
[37] L. Breiman, “Random forests,” Mach. Learn., vol. 45, no. 1, p. 5–32, 2001.

[41] F. E. Rangel-Patino, J. E. Rayas-Sanchez, A. Viveros-Wacher, J. L. Chavez-Hurtado, E. A. Vega-Ochoa, and N. Hakim, “Post-silicon receiver equalization metamodeling by artificial neural networks,” IEEE Trans. Comput.-Aided Design Integr. Circuits Syst., vol. 38, no. 4, pp. 733–740, Apr. 2019.
[42] ISO Standard for Moderate Thermal Environments—Determination of the PMV and PPD Indices and Specification of the Conditions for Thermal Comfort, Standard ISO Std. 7730, 1994.

[43] Tokyo Electric Power Company Holdings, Inc. (2019). Charge Calculation Formula for Main Contract Types. (in Japanese). [Online]. Available: http://www.tepco.co.jp/ep/private/plan2/chargelist04.html
[44] Tokyo Gas Co., Ltd. (2019). Gas Price List. (in Japanese). [Online]. Available: https://e-com.tokyo-gas.co.jp/tokyoins/Default.aspx?tk=1

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