A Novel Fitted Rolling Horizon Control Approach for Real-Time Policy Making in Microgrid

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***Abstract*—In recent years, rolling horizon control (RHC) approaches have attracted growing attention due to its feature of reducing forecast errors for real-time/online operation and optimization. However, the performance of the existing RHC approach degrades if the intra-day forecast data is unavailable or missing due to Internet or cloud service provider outages, software/hardware failures, and many other factors. In this paper, we propose a new fitted-RHC approach to overcome this challenge. The proposed fitted-RHC framework is designed with a regression algorithm which utilizes the empirical knowledge to make the real-time decisions whenever the intra-day forecast data is unavailable. The regression algorithm utilizes a statistical relative probability method to calculate the relative probability for each decision vector, and output the proper optimization policy. In addition, we adopt a modified version of exogenous information transition function that is more suitable to conduct the simulations in a real-time environment. Simulation results in microgird show that the proposed fitted-RHC approach can achieve the optimal policy for the deterministic case even with the missing data, and perform efficiently with the uncertain environment in stochastic case study. In comparison, the proposed fitted-RHC approach outperforms several other optimization techniques.**

***Index Terms*—Rolling horizon control (RHC), regression algorithm, mixed integer linear programming (MILP), microgrid energy optimization, and renewable energy sources.**

I. Introduction

DATA-DRIVEN learning approaches attract a lot of researchers attention around the world due to the potential of these approaches to improve the power system operation and optimization [1]. Especially, microgrid real-time energy optimization attracts serious attention in order to guarantee a reliable and economic operation due to uncertain microgrid forecast data and variable intra-day input profiles. In recent works, microgrid real-time operation and optimization have been investigated [2]. The existing real-time energy optimization techniques are highly dependent on intra-day forecast data and the performance may degrade if the microgrid intra-day forecast data is unavailable/missing. Therefore, real-time optimization of microgrids is still a great challenge for the modern power system, especially in cases with high penetration of renewable energy sources (RESs).

In the past decade, most of the microgrid energy optimization frameworks are formulated based on deterministic microgrid operations [3]–[5]. In these works, the microgrid resource information (RESs, load demand, battery, etc.) are considered as deterministic variables (input variables) assuming an accurate forecast. In the real-world, the RESs are highly intermittent in nature, and the deterministic formulation may affect the microgrid real-time operation depending on the accuracy of the forecast information. Also, the offline optimization approaches with deterministic formulations may not be feasible or may be too conservative for solving microgrid optimization problems with unstable scenarios [6].

In recent years, data-driven stochastic optimization approaches have also been studied in the field of microgrid energy optimization, considering the uncertain nature of the RESs [7]–[11]. The optimization performance of these approaches mostly depend on the scenarios or samples that are generated using the historical or day-ahead datasets and the forecast errors. Sometimes, a large number of scenarios or samples need to be calculated to reach to the optimal point. The algorithm training processes of these works also require high computation. Some consider only the integers for the decision variables to reduce the size of the feasible action sets. Another drawback of these stochastic optimization approaches is to identify probability distribution functions (PDFs) accurately, otherwise, the practicability of the solution can not be guaranteed.

The rolling horizon control (RHC) approach has been proposed in the literature as a promising approach to reduce the effect of forecast errors on microgrid real-time/online operation and optimization [6], [12], [13]. This approach is also commonly known as model predictive control (MPC) in engineering and receding horizon control in operations research [14]. In [15], the MPC based framework is proposed to handle a two-layer energy management system (EMS) for microgrids with hybrid energy storage considering degradation cost models. In the two-layer EMS, the minimization of the operational cost is handled by the upper layer by scheduling the power generation units, and the minimization of the power fluctuations by the RES forecast errors is tackled by the lower layer. A RHC based framework is proposed to minimize the hybrid RES system operation cost as well as the investment cost in [16]. The RHC approach is applied to improve the reliability of the hybrid RES system in online operation optimization and the effect of prediction horizon length on

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optimal scheduling has also investigated. In [17], a convex MPC based framework is proposed for dynamic optimal power flow between the distributed battery energy systems in an ac microgrid. In [18], a RHC based EMS is proposed for an islanded PV-powered microgrid with a battery storage system. The proposed EMS is applied to predict the future state of charge of the battery, and determine the timing and energy deficit of an upcoming energy outage. In [19], a MPC based approach is proposed for islanded microgrids with the presence of uncertain energy sources where an economical and reliable microgrid operation is achieved by combining the advantages of stochastic mathematical formulations. A RHC based framework is proposed to develop a centralized energy management system for isolated microgrid in [20]. The RHC approach is also investigated for the economic and reliable operations of the microgrids in [21].

In summary, the performance of the existing RHC approaches is influenced by the accuracy of the intra-day forecast information of the microgrid exogenous information (load demands, RESs, etc.). So, the economic operation of the microgrid depends highly on the intra-day forecast information. In this case, the performance of the existing RHC approaches may degrade greatly if the microgrid intra-day forecast information is unavailable or if the operator of the microgrid fails to obtain the updated intra-day forecast information. The possible cause of information unavailability could be Internet or cloud service provider outages, natural disasters, software malicious attacks, physical attacks, accidental misconfiguration, network equipment hardware failures, etc. At present, a perfect information system is unobtainable because the threats and issues can not be completely prevented or their prevention can be economically unfeasible, which makes the information outages inevitable [22]. For the stochastic case study, the exogenous information transition function (EITF) is used to determine the next-hour exogenous information using the current hour exogenous information in [23], [24]. In these works, the forecasted exogenous information is not taken under consideration in the EITF model, and the output of the EITF model is determined based on the real-time information and defined noises which may not be true for all RESs (like outputs of photovoltaic panels). In real-time operation, the microgrid exogenous information follows a pattern and in this case the existing model may not be feasible/realistic. Therefore, an improved version of the RHC approach is required to overcome the above mentioned challenges for real-time microgrid operation. Also, a modified version of the EITF is needed to conduct the simulation in a more realistic environment.

In this paper, we propose a new fitted-RHC approach to address the aforementioned challenges of microgrid real-time/online operation. Our contributions can be summarized as:

- The proposed fitted-RHC approach is capable of reducing the dependency of intra-day forecast information on the real-time operation and optimization. We strengthen our proposed framework by incorporating a regression algorithm which estimates the decision vector when the intra-day forecast information is unavailable or missing. The regression algorithm is designed with a statistical probability method to calculate the relative probability for each possible combination of actions or decision vector, and to generate the optimization policy based on the highest relative probability in the decision vector set.
- We adopt a modified version of the EITF. In the model, instead of using previous-hour exogenous information with some noise, we use the forecasted exogenous information with the forecasted errors to determine the real-time exogenous information. This model is more suitable to conduct the simulation studies in a real-time environment.
- The performance of the proposed fitted-RHC approach is justified using both deterministic and stochastic case studies, and compared with the traditional online optimization approaches. We show that the proposed fitted-RHC approach can achieve the optimal performance for the real-time/online microgrid operation by tuning the horizon size. We also conduct simulation studies with missing intra-day forecast information and observe that the proposed fitted-RHC approach can still show competitive performance in a microgrid energy optimization problem. To further validate the performance of the proposed fitted-RHC approach, we utilize both uniform and normal probability distribution functions for the stochastic case study, and analyze the effect of missing or no predictions (described in Section V). In the stochastic case study, we also present the sensitivity analysis to validate the performance of the proposed fitted-RHC approach in the presence of variable forecast information size. The proposed fitted-RHC approach outperforms the other conventional online optimization techniques.

The rest of this paper is organized as follows. In Section II, the background of the existing optimization techniques are discussed. In Section III, the proposed fitted-RHC approach is demonstrated. The benchmark model description and problem formulation are presented in Section IV. Simulation setup and results analysis are carried out in Section V. Finally, the conclusions are provided in Section VI.

II. Background of Existing Optimization Techniques

A. RHC Approach

The RHC approach is an online/real-time optimization technique which solves a constrained optimization problem repeatedly, considering the predictions of future costs, disturbances, and constraints over a sliding time horizon to choose the optimal policy for the current time step [25]–[27]. The procedure of the RHC approach is illustrated in Figure 1. In the figure, the red dotted line indicates the current time step t. The shaded sliding/moving window represents the time frame of the optimization problem where H is the available predicted time horizon. The size of the prediction horizon H plays an important role in the RHC approach which can be determined by trial and error method as shown in Section V. At time t, the optimization problem needs to be solved for the time frame $t : t+H$ where the output is the optimization policy, and $\mathbf{I}_t$ is

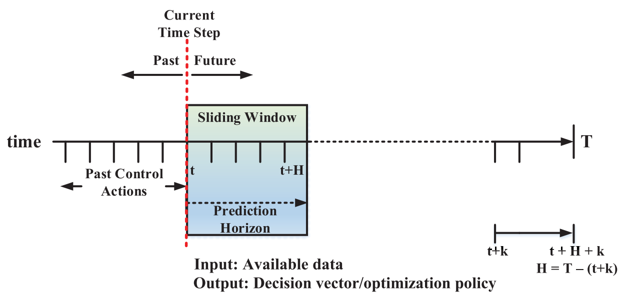

Fig. 1. The RHC approach with the sliding window and the prediction horizon.

the set of available information $\mathbf{I}_t = (\mathbf{E}_t, \hat{\mathbf{E}}_{t+1}, \ldots, \hat{\mathbf{E}}_{t+H})$. Here, $\mathbf{E}_t$ represents the current hour exogenous data (for example, in a microgrid, it could be the value of load demand, grid price, etc.) and $\hat{\mathbf{E}}$ represents the intra-day forecast data predicting from the time step t.

If the cost function for the available information $\mathbf{I}_t$ at time t can be defined as $C(t, \mathbf{I}_t)$, then the optimization policy/decision vector can be defined as,

$$a_t(\mathbf{I}_t) = \arg\min_{a_i} \sum_{i=t}^{t+H} C(i, \mathbf{I}_t). \tag{1}$$

where, a_t is the optimization policy/decision vector at time t. Note, the optimization problem could be subjected to the operational constraints of the system. According to the figure, the prediction horizon size needs to be adjusted if $t + H$ exceeds the final time period T. In this case, if the current time-step is $(t + k)$, then the prediction horizon size should be adjusted as $H = T - (t + k)$. Here, the value of k can be any number based on sampling rate of the time scale as $0 \le k < T$. For example, if the sampling rate of the time scale is 1 then the value of k should be an integer. According to the figure, if the values are $t = 6$, $k = 15$ and $T = 24$, then at time step $t + k = 6 + 15 = 21$, the horizon size H needs to be adjusted as $H = 24 - 21 = 3$.

B. Other Conventional Approaches

In this paper, for the optimal solution, we use mixed integer linear programming (MILP). The MILP is a mixed integer programming based approach which is suitable for solving linear optimization problems with both integer and continuous variables [28]. The MILP approach is usually used in an offline optimization process to get the optimal solution for a certain period of time, which requires the exact information over the optimization horizon. In the MILP approach, the objective function of the problem, which was described in last section, can be written as,

$$\min_{a_t} \sum_{t=1}^{T} C(t, \mathbf{I}_t). \tag{2}$$

Through the optimization process, the action set can also be obtained for each time step. To compare with the online optimization approaches, most of the existing publications considered the result of this approach as a reference and tried to reach the optimal solution by tuning their parameters. For example, to get the optimal operation of the microgrid using the MILP approach, it should be assumed that the system operator can "see" the future information of the microgrid, or the optimization problem should have to be solved at the end of the day when all the exogenous information is available.

Additionally, we investigate the myopic optimization approach. The myopic approach is an optimization technique where the decisions need to be made in an online manner, without knowledge of future events [14]. In the myopic approach, the objective function of the optimization problem can be presented as,

$$\min_{a_t} C(t, \mathbf{I}_t). \tag{3}$$

This approach optimizes the objective function based on the current environment information with the consideration of the operational constraints.

Furthermore, we also investigate the SBSP technique for the stochastic case study where the scenarios are generated using a Monte Carlo simulation technique. In the SBSP approach, the optimization problem is solved for each of the scenarios where the random scenarios are generated using the stochastic variables, and the final result is obtained using statistical methods (like statistical mean operation) [23], [29], [30].

III. Proposed Fitted-RHC Approach

The performance of the RHC approach degrades if the available intra-day forecast information size (S_I^f) is less than the prediction horizon size H or if $S_I^f = 0$ (no intra-day forecast information). In this paper, a fitted-RHC approach is proposed which fits the RHC algorithm using the regression algorithm so that the proposed approach can perform efficiently even with missing information ($S_I^f < H$) or no information ($S_I^f = 0$). The proposed algorithm is presented in Algorithm 1.

The fitted-RHC algorithm initializes by defining the day-ahead exogenous forecast input data, control period T, and horizon size H. Then the time step begins by defining a condition. If the condition is $S_I^f \ge H$, then the algorithm generates the intra-day forecast data for horizon H and the available input information at time t becomes $\mathbf{I}_t = (\mathbf{E}_t, \hat{\mathbf{E}}_{t+1}, \ldots, \hat{\mathbf{E}}_{t+H})$. At step 6, the algorithm solves the optimization problem (linear/non-linear) for the optimization policy at time t subject to the operational constraints using the sliding horizon time frame $t : t + H$. After solving the optimization problem, the algorithm executes the optimization policy (action) for current time step t at step 7, updates the dependent information variables, and returns to step 2. If $0 \le S_I^f < H$, the proposed fitted-RHC algorithm uses the regression algorithm to determine the optimization policy a_t. The regression algorithm is presented in Algorithm 2.

The regression algorithm initializes with the day-ahead exogenous data for the time steps $t + k : t + H$. For example, if $S_I^f = 0$, the regression algorithm initializes with the day-ahead exogenous data for the time steps $t + 1 : t + H$. At step 2, the algorithm generates N number of data samples by a Monte Carlo method using the forecast errors and the defined

Algorithm 1 The Proposed Fitted-RHC Algorithm

1: **Initialization:**
Initialize day-ahead exogenous forecast input data, control period T, and horizon H
2: **for** time t = 1 : T **do**
3: **if** $S_I^f \geq H$ **then**
4: Generate the intra-day forecast data
5: Available information:
$\mathbf{I}_t = (\mathbf{E}_t, \hat{\mathbf{E}}_{t+1}, \ldots, \hat{\mathbf{E}}_{t+H})$
6: Solve the optimization problem (e.g., MILP)
$a_t(\mathbf{I}_t) = \arg\min_{a_i} \sum_{i=t}^{t+H} C(i, \mathbf{I}_t)$
subject to the operational constraints
7: Execute the action for current time step "t"
8: **else**
9: **input:** day-ahead exogenous information
Use the regression algorithm (**Algorithm 2**)
10: **output:** action set, a_t
11: Execute the action, a_t
12: **end if**
13: Use the transition function to update the exogenous information variables and go to step 2
14: **end for**

Algorithm 2 The Proposed Regression Algorithm

1: **Initialization:**
Initialize day-ahead exogenous data for $t + k{:}t + H$
2: Generate "N" number of data samples by Monte Carlo method using forecast errors and probability distribution functions
3: Available information $\mathbf{I}_t$
4: **for** sample n = 1 : N **do**
5: Input Information: $\mathbf{I}_t(n)$
6: Solve the optimization problem (e.g., MILP)
$a_t^n(\mathbf{I}_t(n)) = \arg\min_{a_i^n} \sum_{i=t}^{t+H} C(i, \mathbf{I}_t(n))$
subject to the operational constraints
7: Save the action set for current time step "t"
8: $n = n + 1$, and go to step 4
9: **end for**
10: Calculate the relative probability for each possible action set and select an action set which has highest relative probability [31]
11: Send the action information to the main algorithm

probability distribution function. An example of the available information matrix at step 3 in the algorithm is

$$\mathbf{I}_t = \begin{bmatrix} \mathbf{E}_t & \cdots & \hat{\mathbf{E}}_{t+k}^1 & \cdots & \hat{\mathbf{E}}_{t+H}^1 \\ \mathbf{E}_t & \cdots & \hat{\mathbf{E}}_{t+k}^2 & \cdots & \hat{\mathbf{E}}_{t+H}^2 \\ & \cdot & & & \\ & \cdot & & & \\ & \cdot & & & \\ \mathbf{E}_t & \cdots & \hat{\mathbf{E}}_{t+k}^N & \cdots & \hat{\mathbf{E}}_{t+H}^N \end{bmatrix} \tag{4}$$

where, the superscripts $1, 2, \ldots, N$ represent the number of data samples.

In the matrix, the first notation $\mathbf{E}_t$ is same for all the rows because it represents the exogenous input data for current time step t which is available in real-time. All other information varies because of random forecast errors within a defined range. Then the algorithm solves the optimization problem for each of the information sets as described in steps 4 to 9. Note, in this paper, the MILP toolbox from *MATLAB* is used for solving the optimization problem. For each input data sample, the algorithm stores the action set for current time step t, proceed to next sample input data, and continues the process until $n > N$. At step 10, the algorithm calculates the relative probability for each possible action set and select an action set which has the highest relative probability. At the end, the regression algorithm sends the action information set to the main fitted-RHC algorithm. Then, the fitted-RHC algorithm takes the action which is recommended by the regression algorithm, update the input information, and go to the next-time step. The process of the fitted-RHC approach continues until the time t reaches at time T. At the end of each time step t, the next-hour exogenous information variables can be determined using the EITF model as $\mathbf{E}_{t+1} = min\{max\{\hat{\mathbf{E}}_{t+1}+\varepsilon, E_{min}\}, E_{max}\}$, where, $\hat{\mathbf{E}}_{t+1}$ and ε represent the day-ahead forecast data and the forecast error, respectively. E_{max} and E_{min} represent the maximum and minimum limit of the exogenous information data. Note, in the EITF model, we use the day-ahead forecast data instead of immediate previous hour data in literature, so that the model can be applied for all exogenous information. The cost function is used to calculate the cost for the optimization policy and the total cost can be obtained at the end of the total time period. Later, the performance of the proposed fitted-RHC can be determined by comparing with other online and offline methods.

IV. Benchmark Problem: Microgrid Energy Optimization

In this paper, we have considered a grid-connected microgrid with different generation units: photovoltaic (PV) and wind turbine as the RESs, a grid level lead-acid battery as the energy storage system, and the grid. The proposed fitted-RHC approach is used to allocate the residential load demand to the microgrid generation units efficiently so that the total operational cost of the microgrid can be minimized without violating the operational constraints. The proposed fitted-RHC approach in the microgrid energy optimization benchmark problem is illustrated in Figure 2. In our proposed design, the proposed technique considers the day-ahead exogenous forecast data (RESs, load demand, and grid price) with the real-time information of the exogenous input variables and battery energy storage system, and takes the microgrid operation and optimization decision so that it can achieve the objective without violating the operational constraints.

We formulate our optimization problem using the receding horizon principle and consider the intra-day forecasted exogenous information. In this benchmark problem, the available information at time t can be written as,

$$\mathbf{I}_t = \left(B_t, \mathbf{E}_t, \hat{\mathbf{E}}_{t+1}, \ldots, \hat{\mathbf{E}}_{t+H}\right). \tag{5}$$

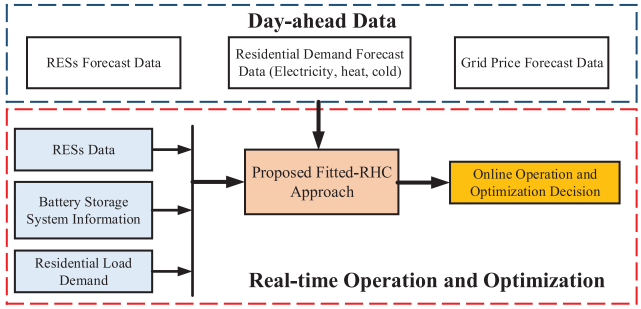

Fig. 2. The proposed fitted-RHC approach in the microgrid energy optimization benchmark problem.

where, B_t represents the available energy in the battery at time t. $\mathbf{E}_t$ can be defined as the set of exogenous information as $\mathbf{E}_t = (R_t, D_t, G_t)$ at time t. Here, R_t, D_t, and G_t represent the total available power from the renewable energy generation unit in kW, the total residential load demand in kW, and the grid price per kWh at time t, respectively. In this benchmark problem, we add B_t to the I_t set because B_t is not an independent variable and at time step t, we can only obtain the available energy in the battery from the battery unit. $\hat{\mathbf{E}}$ represents the intra-day future forecast information predicting at a specific time step. For example, for solving the optimization problem at time t using the RHC principal, we should have the intra-day future forecast information as $\hat{\mathbf{E}}_{t+1:t+H}$ so that the approach can achieve the optimal solution (deterministic case) or very closely approximated optimal solution (stochastic case).

In this problem, $\mathbf{a}_t$ represents the action set which contains the decision variables of the microgrid energy optimization problem, $\mathbf{a}_t \geq 0$, and $\mathbf{a}_t \epsilon \alpha_t$. Here, α_t represents the feasible action space. The action set $\mathbf{a}_t$ can be written as,

$$\mathbf{a}_t = \left\{P_t^{\text{grid},D}, P_t^{B,D}, P_t^{R,D}, P_t^{R,\text{grid}}, P_t^{R,B}, P_t^{\text{grid},B}\right\}. \tag{6}$$

where, each decision variable represents the amount of power flow transferred from one unit to another unit in the microgrid. For example, $P_t^{i,j}$ represents the amount of power transferring from unit i to j at time t. The superscripts *grid*, D, B, and R represent the grid, the load demand unit, the battery unit, and the RES unit, respectively.

The operational cost of the microgrid at time t can be written as,

$$C(t) = C_{\text{bat}}(t) + C_{\text{grid}}(t). \tag{7}$$

$$C_{\text{bat}}(t) = G_t P_t^{\text{grid},B}. \tag{8}$$

$$C_{\text{grid}}(t) = G_t P_t^{\text{grid},D}. \tag{9}$$

where, $C_{\text{bat}}(t)$ and $C_{\text{grid}}(t)$ represent the battery charging cost and the operational cost to buy energy from the grid to fulfill the load demand at time t, respectively.

The operational constraints of the microgrid can be defined as,

$$P_t^{\text{grid},D} + P_t^{B,D} + P_t^{R,D} = D_t, \tag{10}$$

$$P_t^{R,D} + P_t^{R,\text{grid}} + P_t^{R,B} \leq R_t, \tag{11}$$

$$-1 \leq \frac{\left(P_t^{R,B} + P_t^{\text{grid},B}\right)}{\psi} - \frac{P_t^{B,D}}{\psi} \leq 1, \tag{12}$$

$$SOC_{\min} \leq SOC_t \leq SOC_{\max}, \tag{13}$$

where, the constraint (10) maintains a balance between the microgrid generation and load demand. The constraint (11) distributes the available power from the RES unit to other units. The constraint (12) is used to keep the value of the battery decision variables within a certain range. Here, ψ represents the charging/discharging limit of the battery in kW. The constraint (13) is defined to keep the state of charge (SOC) of the battery within a certain range at any time t.

The transition function for the battery SOC and the available energy of the battery can be formulated as,

$$SOC_{t+1} = \frac{1}{B_{\text{cap}}}\left(B_t + \phi\left(P_t^{R,B} + P_t^{\text{grid},B}\right) - \frac{P_t^{B,D}}{\phi}\right), \tag{14}$$

$$B_{t+1} = SOC_{t+1} B_{\text{cap}}, \tag{15}$$

where, B_{cap} represents the battery capacity of the microgrid. B_{t+1} represents the next-hour available energy in the battery.

The overall objective of this microgrid energy optimization problem is to determine the optimization policy efficiently at every time step as equation (1) so that the total daily operational cost can be minimized as,

$$V = \min_{a_t} \mathbb{E}\left[\sum_{t=1}^{T} C(t, \mathbf{I}_t)\right]. \tag{16}$$

where, $\mathbb{E}[.]$ represents the expectation operator. The optimization problem is formulated for finite horizon of time as $\{1, \Delta t, 2\Delta t, \ldots, T\}$ where Δt indicates the time interval.

V. Simulation Setup and Results Analysis

In this section, the performance of the proposed fitted-RHC approach is determined by examining several experiments on a grid-connected microgrid system.

A. Simulation Setup

The grid-connected microgrid information parameters are summarized in Table I. In this paper, it is assumed that the battery efficiency and energy limit for the charging and discharging process are the same.

The residential microgrid load, RESs, and electricity price profiles with the forecast errors are illustrated in Figure 3. The residential load profile is collected for the city of Minneapolis in Minnesota from [33]. The RESs data are collected from the system advisory model (SAM) by National Renewable Energy Laboratory for the city of Minneapolis, MN [32]. We run the simulation with the given configuration in the SAM software, and the SAM provides the RESs output profile for one year. We select a RES output profile of a day from the summer time frame, which is presented in Figure 3. The grid price profile in cents per kWh is collected from [34]. The objective of the optimization problem is to minimize the daily operational cost of the microgrid over 24 hours with a time resolution of 1 hour. In this paper, we consider forecast error for the load demand as $\varepsilon_d = [-4, 4]$, for the RES

TABLE I
MICROGRID INFORMATION [32]

Photovoltaic	
System size	60 kWdc
Module type	Standard
DC to AC ratio	1.2
Rated inverter size	50 kWac
Wind Turbine	
Name	Endurance Wind E-3120
Rated output	50 kW
Rotor diameter	19.2 m
Hub height	20 m
Shear coefficient	0.14
Battery	
Type	2V/1000 Ah
Quantity and capacity	100 and 200 kWh
Charging and discharging efficiency (ϕ)	100%
Maximum charging and discharging rates (ψ)	40 kWh/Δt

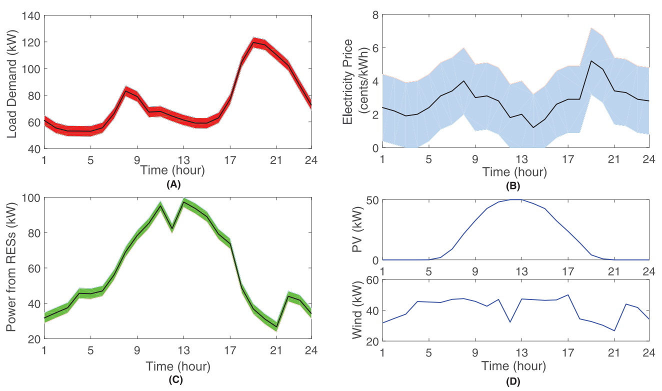

Fig. 3. (A) Residential load-demand with the forecast errors (red shaded region). (B) Electricity price with the forecast errors (blue shaded region). (C) Total power from the RESs with the forecast errors (green shaded region). (D) Original RES of PV and wind turbine forecast information.

unit as $\varepsilon_r = [-3, 3]$, and for the grid price as $\varepsilon_p = [-2, 2]$. Note, the forecast errors of the exogenous information can be determined by analyzing the historical exogenous information data. In this paper, we have analyzed the data, and observed the daily maximum and minimum changes/deviations in the input profiles. Later, we have obtained average maximum and minimum changes in values, and rounded up to the closest integers. For example, we have collected the day-ahead and real-time price profiles for a month from [34], and determined daily maximum and minimum changes/deviations of the input profiles. We have calculated average daily maximum and minimum changes/deviations, and used those numbers as forecast errors in the problem.

The EITF model is used to obtain the exogenous information variables as R_t, D_t, and G_t. This model is also used for determining the intra-day forecast information. For example, using the EITF model, the load demand at time t can be determined as $D_t = min\{max\{\hat{D}_t + \varepsilon_d, D_{\min}\}, D_{\max}\}$.

The optimality gap (%) is calculated as,

$$OG = \frac{|V - V^*|}{V^*} \times 100\%. \quad (17)$$

where, V is the total operational cost of the microgrid using a specific optimization approach and V^* is the optimal total operational cost of the microgrid. Note, the MILP approach is used to collect the optimal/reference value offline, and the optimal value can be obtained using this approach if and only if all the exogenous data can be provided as input with the operational constraints.

In this paper, we generate five hundred data samples by Monte Carlo simulation for the regression algorithm. We determine the sample number using the trial and error method. For deterministic cases, the competitive performances can be achieved with as low as a hundred samples. We have also tested with different large number of data samples (> 100) but did not observe any improvement. However, we observe that the stochastic cases require a large number of data samples for the regression algorithm to get close to the optimal solution. The sample number of the regression algorithm has an influence on the optimization result. Specifically, it depends on the forecast error bounds. A high forecast bound requires a large number of samples to reach the optimal solution. We use 200 data samples to train the regression algorithm for the stochastic case study. During our experiment, we have observed that our proposed approach takes on average 11.50 seconds for a single run to solve the optimization problem over the whole time frame, including the calculation of the regression algorithm. All the simulations are conducted in MATLAB $R2018b$ environment on a 7th generation Intel Core i7 − 7700K 4.2GHz Windows based PC with 32GB RAM. For the performance comparison, all other techniques are implemented in the same environment.

B. Results Analysis

1) Deterministic Case Study: Deterministic case study is usually used as an experiment to test the performance of the proposed approach in terms of percentage of optimality. In this case study, the day-ahead exogenous profiles are used as input at every time step. Note, the forecast errors of the exogenous input data are not considered in this case study.

First, the horizon size of the RHC approach is determined based on the performance of the RHC approach in terms of percentage of optimality gap. The horizon size of the RHC approach is dependent on the input profiles. The day-ahead input profiles can be used to determine the horizon size of the RHC approach for the next-day operation. In this paper, to determine the optimal horizon size H, we have used a trial and error method. The effect of the horizon size in terms of percentage of optimality gap is presented in Figure 4. The result shows that when the horizon size $H = 0$, then the RHC approach incurs more than 50% of optimality gap. The percentage of optimality gap drops with the increment of horizon size. According to the zoomed figure, we can observe that, at $H = 14$, the percentage of optimality gap becomes 0. During our experiments, we have observed that when $H \geq 14$, the optimal value can be achieved. According to the RHC theory, it is better not to use a large number for H because if any unexpected change occurred in the intra-day forecast, the performance of the RHC approach may degrade and also it may increase the computation time. Therefore, it can be concluded that the optimal horizon size of the RHC approach is 14 for the given exogenous input data.

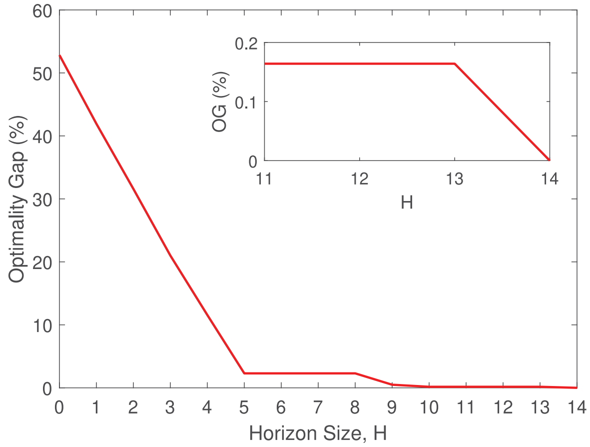

Fig. 4. Horizon size determination for deterministic case study in terms of percentage of optimality gap.

TABLE II
PERFORMANCE COMPARISON OF THE OPTIMIZATION TECHNIQUES FOR THE DETERMINISTIC CASE STUDY IN TERMS OF DAILY OPERATION COST AND OPTIMALITY GAP. MILP IS AN OFFLINE APPROACH AND USED AS A REFERENCE

Approach	Operation Cost ($)	Optimality Gap (%)
MILP (offline)	12.19	-
Proposed fitted-RHC	12.19	0
RHC with missing predictions	12.74	4.51
RHC with no predictions	14.97	22.81
Myopic approach	18.63	52.83

To show the effectiveness of the proposed fitted-RHC approach, the performance comparison of the optimization techniques for the deterministic case study are summarized in Table II. In the table, the *RHC approach with no prediction* indicates the RHC approach with $S_I^f = 0$. And, the *RHC approach with missing prediction* indicates the RHC approach with $S_I^f < H$. For both of these experiments, we assume that the intra-day forecast information at hours 12 and 15 are unavailable/missing. For the experimental setup of the RHC approach with missing predictions, we assume that 5 hours of intra-day forecast information is available where the size the intra-day forecast horizon should be $H = 14$ ($S_I^f < H$). The results show that the proposed fitted-RHC approach can achieve the optimal policy even with unavailable/missing intra-day forecast information which indicates the proposed technique reduces the dependency on the intra-day forecast information. The performance of the RHC approach degrades even if the intra-day forecast information are unavailable/missing only for two hours. The result shows that the RHC approach with no predictions and with missing predictions achieve 22.81% and 4.51% of optimality gap, respectively. Myopic optimization approach is also investigated, and the result shows that the fitted-RHC approach outperforms the myopic approach with a large margin.

In addition, the comparative performance analysis of the fitted-RHC approach with the RHC technique by varying the forecast information size at each time step is presented in

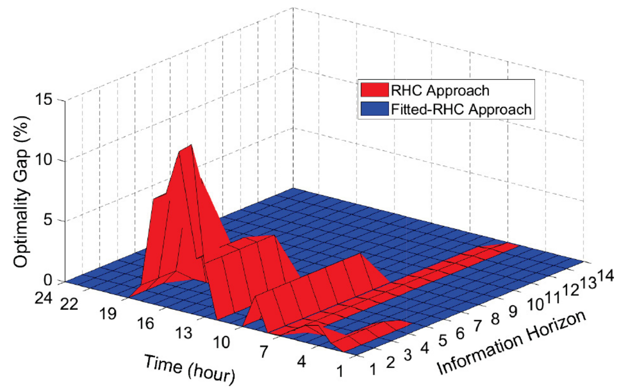

Fig. 5. The performance comparison of the fitted-RHC approach with the RHC technique by varying the forecast information size at each time step.

Figure 5. From this figure, we can see the time steps which are very much sensitive on the forecast information size in terms of the optimality gap. The blue surface represents the performance of the fitted-RHC approach. The red surface represents the optimality gap of the traditional RHC technique. All other places, the both approaches are overlapped and illustrated by the blue color. The available intra-day forecast information size (S_I^f) is varied from 1 to 14. In this experiment, at each run, the forecast information size is changed only for one time step and the forecast information size of all other time steps is kept the same as the optimal horizon size. For example, if any outage happens at time step 14 and the operator can only obtain data with the forecast information size $S_I^f = 1$, then the performance of the traditional RHC approach degrades with 14.06% of optimality gap. The result shows that for the deterministic case study with missing predictions, the fitted-RHC can achieve the optimal performance while the RHC approach shows some degraded performance.

2) Stochastic Case Study: Stochastic case study is an important experiment to measure the ability of the proposed technique in terms of uncertain environments which is more suitable for microgrid real-time/online energy optimization problem with uncertain generation units. To validate the performance of the proposed fitted-RHC approach, we define four stochastic test problems which are presented in Table III where U and N represent uniform and normal probability distribution functions [14]. For example, in stochastic test problem 2 in Table III, we use RESs noise as $U(-1, 1)$ which represents the value of forecast error ε in EITF equation should be within '-1' to '1' with the defined interval. In this paper, we use the interval as 1. For the load noise, we use normal probability distribution as $N(0, 3.0^2)$ where the mean value is as 0 and the variance is 3. A vector of discrete values between -4 to 4 is used with the interval of 1 for introducing noise into the system. The probability of each value in the vector is determined using the normal probability distribution function [23]. After obtaining the noise value, the load demand is calculated using the EITF model. Similarly, the stochastic price value can also be determined using the price noise and the EITF model.

In this case study, we generate random forecast errors based on the defined probability distribution functions and run each

TABLE III
STOCHASTIC TEST PROBLEMS

Problem NO.	RESs Noise	Load Noise	Price Noise
1	$U(-1,1)$	$U(-1,1)$	$U(-1,1)$
2	$U(-1,1)$	$N(0,3.0^2)$	$N(0,1.0^2)$
3	$N(0,1.0^2)$	$U(-1,1)$	$N(0,0.5^2)$
4	$N(0,2.0^2)$	$N(0,1.5^2)$	$U(-1,1)$

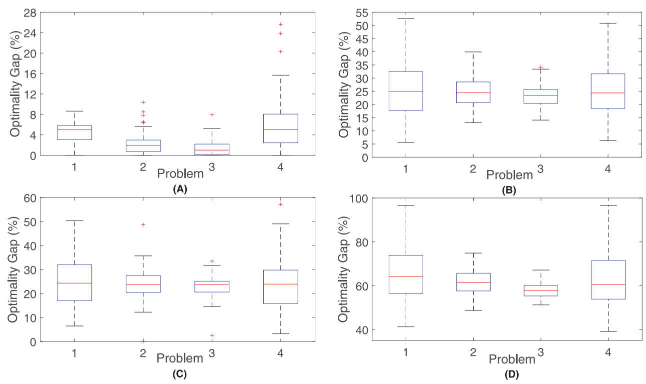

Fig. 6. Box plots for stochastic case study in terms optimality gaps: (A) proposed fitted-RHC approach, (B) RHC approach with no predictions at hours 12 and 15, (C) RHC approach with missing predictions at hours 12 and 15, and (D) myopic approach.

problem 500 times to study the effect of uncertainties in terms of optimality gap and how well our proposed approach can deal with the problems. At each time step, while solving the optimization problem using the given techniques, we save the real-time exogenous information so that at the end of each run we can calculate the optimal solution using the offline MILP technique and obtain the optimality gap. The results are presented in Figure 6. Note, in this experiment, the fitted-RHC approach performs considering with no predictions (intra-day forecast data) at hours 12 and 15. The results show that with the uncertainties, the proposed fitted-RHC approach incurs on average 5.07%, 1.87%, 1.01%, and 4.99% of optimality gaps for four different problems, respectively. On the other hand, the *RHC approach with no predictions at hours* 12 *and* 15 incurs on average 24.98%, 24.42%, 23.36%, and 24.38% of optimality gaps which are much higher than the proposed fitted-RHC approach. For the comparative study, we also report the performance of the *RHC approach with missing predictions at hours* 12 *and* 15, and the myopic approach. The results show that the proposed fitted-RHC approach outperforms both approaches. From this result analysis, we can claim that the proposed fitted-RHC approach can tackle the effect of missing or no predictions horizon window under the stochastic environment efficiently.

In addition, we validate the performance of the proposed fitted-RHC approach in a stochastic environment for the given input profile forecasts and forecast errors. The input profiles of this experiment is illustrated in Figure 7. The blue lines represent the forecast information of the input profiles and the brown lines indicate the input profiles that are realized in real-time. Here, the differences between forecast and real-time input profiles are causing due to the forecast errors. In the

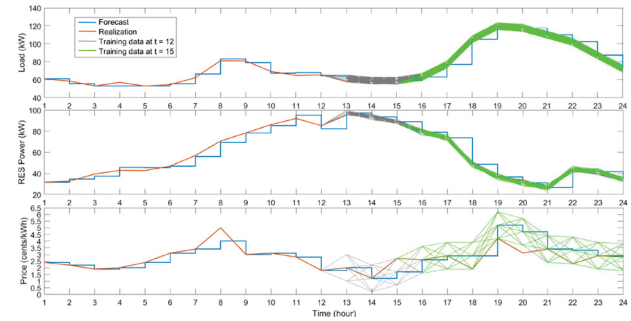

Fig. 7. Input profiles in a stochastic environment, where, the blue line represents forecast exogenous input data, the brown line represents the realized input profiles in real-time, and the grey and the green lines indicate the training profiles for the proposed fitted-RHC approach.

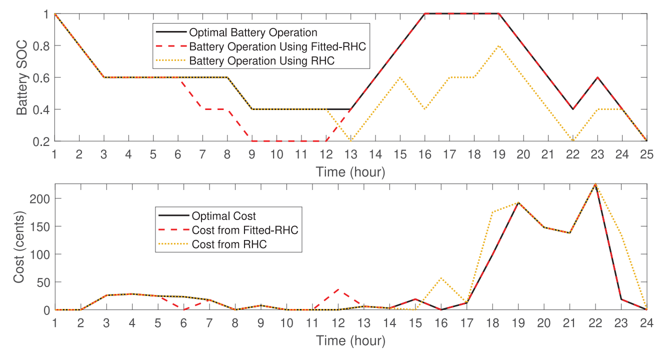

Fig. 8. Battery SOC and microgrid operation cost outputs for the stochastic case study.

figure, we also show the training input profiles for the fitted-RHC approach that we use in the regression algorithm to train the algorithm at hours 12 and 15 since we assume information outages at those hours. The outputs of this case study are presented in Figure 8. Note, in this case study, we also present results of the RHC approach considering no predictions at hours 12 and 15.

In Figure 8, the outputs are presented in terms of the battery SOC and microgrid operation cost. In our microgrid application, the charging and discharging cycle of the battery plays a very important role in terms of minimizing the operation cost. The charging and discharging cycle of the battery is highly dependent on the intra-day forecast input profiles. For example, if the intra-day price input forecast shows there is a chance of increasing the electricity price in the future hours, then the controller may charge the battery or save the battery energy at current hour so that the total operation cost can be minimized. The results show that at hours 12 and 15, the RHC approach discharges energy from the battery since no intra-day forecast information is available at those hours. On the other side, the fitted-RHC approach charges the battery considering the future outcome of the current taken decision. The total daily operation cost of the microgrid using the fitted-RHC and the RHC approach are obtained as \$10.03 and \$12.20, respectively where the optimal cost based on the realized input profile is \$9.90. Therefore, in this case, the optimization gaps of the fitted-RHC and the traditional RHC approaches are 1.31% and 23.23%, respectively, which depicts significant improvement in terms of scheduling operation decisions efficiently.

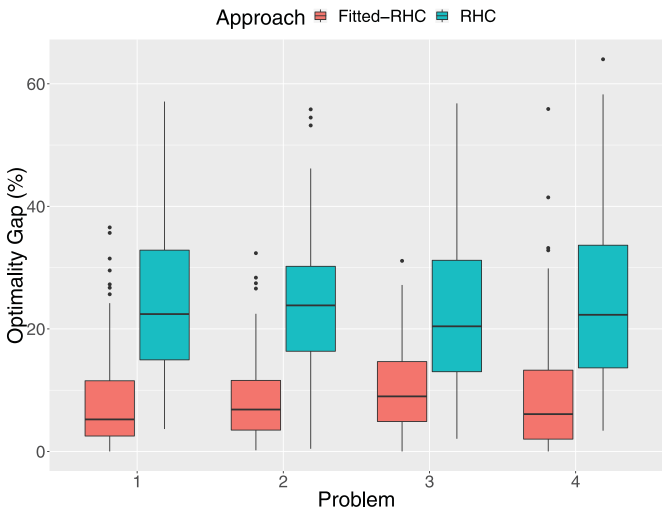

Fig. 9. Sensitivity analysis of the proposed fitted-RHC approach and the traditional RHC approach with variable predicted forecast information size in stochastic environment.

TABLE IV
COMPARATIVE STUDY FOR STOCHASTIC CASE STUDY

Approach	Average Total Cost ($)	Optimality Gap (%)
MILP	14.27	-
Proposed fitted-RHC	14.83	3.92
SBSP approach	20.63	44.57

In order to validate the performance of the proposed fitted-RHC approach further, we also analyze the sensitivity of the proposed technique in terms of the optimality gap with the variable forecast information size in a stochastic environment. The results are compared with the traditional RHC technique. We consider same four stochastic test problems and the results are reported after 500 runs. In this experiment, we randomly vary the predicted forecast information size as $S_I^f = 1 : 14$. The results are illustrated in Figure 9. During the experiment, we observe that the proposed fitted-RHC utilizes the proposed regression algorithm whenever the forecast information size (S_I^f) is less than the optimal (H), and generates the optimization policy based on its operational strategy. The results show that in a stochastic environment with the variable predicted forecast information size, the proposed fitted-RHC can perform efficiently with the optimality gap on average less than 10% in all four cases where the traditional RHC approach shows the optimality gap on average higher than 20%. According to this experiment, we can claim that the proposed fitted-RHC technique can be a powerful optimization tool to perform efficiently in a stochastic environment even with the missing predictions, and outperforms the traditional RHC technique.

Furthermore, we compare the performance of the proposed fitted-RHC approach with the SBSP approach. In this experiment, we conduct the simulations for 500 runs and report the average results in Table IV. The results are compared with the optimal results from the MILP approach, and the percentage of optimality gaps are calculated. The result show that the fitted-RHC approach obtains on average 3.92% of optimality gap and outperforms the existing SBSP technique. According to the result analysis, it can be concluded that the fitted-RHC can be a powerful tool for microgrid online/real-time optimization which can perform efficiently even with the uncertain environments.

VI. CONCLUSION

In this paper, we propose a new fitted-RHC algorithm for the online/real-time microgrid energy optimization. In the proposed fitted-RHC approach, the RHC approach is strengthened with a regression algorithm which overcomes the performance degradation effect of the existing RHC approach when the intra-day forecast data is missing or unavailable. To validate the performance of the proposed fitted-RHC approach, we conduct both deterministic and stochastic case studies. In the deterministic case study, we test the proposed algorithm with missing predictions or no predictions cases, and observe that the proposed fitted-RHC approach can achieve exactly the optimal performance without violating any constraints. To justify the performance of the proposed fitted-RHC approach, we conduct the stochastic case study with random intra-day forecast errors based on different probability distribution functions. In the stochastic case study, we present an example to show the performance degradation of the traditional RHC approach in terms of missing forecast data and how the proposed fitted-RHC approach overcomes this challenge. We also measure the sensitivity of the proposed fitted-RHC approach in terms of optimality gap with the variable prediction horizon size in the stochastic environment and compare with the traditional RHC technique. The results show that the proposed fitted-RHC approach can perform efficiently even with uncertain scenarios. For both cases, we observe that the proposed fitted-RHC approach has the strength to tackle the effect of prediction horizon size and make microgrid real-time decision efficiently.

In the future, we will investigate the proposed fitted-RHC approach for solving the power system optimization problems using different IEEE test cases considering the network constraints. We will also focus on analyzing the power system optimization problems over larger time frames (weekly and yearly).

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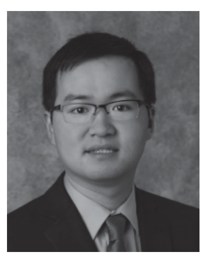

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