A Case Study of Horizon Window in Receding Horizon Control for Renewable Energy Integration

Avijit Das and Zhen Ni
Electrical Engineering and Computer Science Department
South Dakota State University
Brookings, South Dakota 57006
Email: {avijit.das and zhen.ni}@sdstate.edu

***Abstract*—Integrating renewable energy sources (RESs) into power grid increases complexity and non-linearity in power system input profiles. Receding horizon control (RHC) approach has the potential to mitigate the complexity of power system optimization problems by reducing the future prediction effects. However, designing the horizon window size is being a classical issue of RHC optimization. In this paper, we study the effect of horizon size on an energy scheduling optimization problem with the integration of RESs. We conduct two different experiments and consider both single (only photovoltaic) and multiple (photovoltaic and wind) RESs, and show the performance of the RHC approach with different horizon windows. We validate the performance of the RHC approach with tuned horizon size comparing with our reference mixed integer programming approach. With increasing penetration of renewable energy resources, a longer horizon window may be needed to improve the optimization performance.**

***Index Terms*—Receding horizon control, horizon window size, renewable energy sources, real-time operation, and mixed integer linear programming.**

I. Introduction

Power share of renewable energy sources (RESs) in global electricity generation is increasing day by day due to their environmental and economical features [1], [2]. The integration of RESs, energy storage system, and other distributed energy resources (DERs) help the modern power system to spread the electricity all over the world specially in remote areas [3]. These RESs are intermittent in nature which requires special attention in terms of scheduling the generation units efficiently to guarantee a reliable and economic operation [4], [5]. In last decade, a significant improvement is observed in day-ahead optimization of the DERs using offline optimization techniques. Due to the uncertain behavior of the RESs and variable intra-day forecast data, real-time energy optimization of the DERs attracts serious attention in order to have a cost-effective solution of the power grid. Therefore, the real-time optimization with the presence of DERs is still a great challenge for the modern power system, especially in cases with the high penetration of RESs.

In the past decades, most of the energy optimization problems with the DERs are solved considering offline optimization approaches. In [6], a smart energy management system is developed using a matrix real-coded genetic algorithm (GA) to optimally coordinate the microgrid generation units so that the operational costs of microgrid can be minimized. In [7], a conditional value-at-risk optimization technique is proposed to solve an optimal energy storage management problem under risk consideration and transaction costs of trading energy with the power grid. A GA based methodology for optimal sizing and economic analysis of the energy storage system is proposed in [8]. In [9], a deterministic superstructure mixed integer linear programming (MILP) approach is proposed for distributed energy system planning in residential microgrid. A combined sizing and energy management methodology, formulated as a leader-follower problem are presented in [10]. The leader problem determines the optimal size of the microgrid components using a genetic algorithm and the follower problem solves the unit commitment problem using the MILP. These offline optimization techniques require the exact information of the entire optimization time frame and can not be applied for online/real-time optimization. In this case, the performance of the power grid operation may degrade if any expected things happen during the optimization time period.

Online optimization approaches are also proposed to investigate the real-time operation and optimization of the power grid. In [11], an energy optimization scheme is proposed where a multi-objective energy optimization problem is solved using a GA approach named NSGA-II to minimize the generation cost and to minimize the battery life loss. In [12], the authors proposed a decentralized, myopic, techno-economical, charging management method for electric vehicles connected to distribution grids. Myopic approach is also investigated for solving the real-time energy storage management problem in [13]. In the myopic approach, the optimization problems are solved based on current hour input information without considering the knowledge of future events which may fail to provide long-term cost-effective solution for the power grids.

Recent years, receding horizon control (RHC) based approaches are also proposed in the field of power system optimization and stability control which has the potential to reduce the effect of prediction errors during the optimization process [14], [15]. This approach is also commonly known as model predictive control (MPC) [16]. In [17], a two layer model predictive control method is proposed to minimize the running cost and to improve the robustness against uncertainties resulting from load demand and photovoltaic (PV) power in the islanded microgrid. An MPC based online optimal operation algorithm with a feedback correction to compensate for prediction error is proposed in [18]. A MPC-based home energy management system (HEMS) control strategy is proposed for a residential microgrid where a MPC-based framework is used to incorporate both forecasts and newly updated information for the HEMS [19]. The RHC based optimization techniques are also investigated in [20], [21]. The optimal horizon size of the RHC approach depends on the input profiles of the model. The RHC approach with a fixed horizon size may not suitable for all the non-linear input profiles and the performance of the RHC approach may degrade due to this issue.

Motivated by the above mentioned literature, in this paper, we investigate the effect of horizon size on the RHC approach for solving energy scheduling problem with the presence of RESs. We consider a microgrid model and formulate the energy optimization problem with the RHC principle. Through the experiments, we observe that the RHC approach with the fixed horizon window may not be suitable for all input patterns and the errors can be mitigated by tuning the horizon size. We also show the effect of increasing penetration of RESs on the horizon window size of the RHC technique. We conduct two different experiments with single and multiple RES environments, and validate the performance of the RHC technique for different horizon window sizes comparing with the reference MILP approach. The results show that the increasing penetration of RESs requires a longer horizon window, and the RHC approach can achieve the optimal performance if the horizon size can be tuned based on the input information.

The rest of this paper is structured as follows. In Section II, the model description and the mathematical formulations are discussed. In Section III, the RHC approach and the reference MILP technique are demonstrated. Simulation setup and results analysis are carried out in Section IV. Finally, the conclusions are drawn in Section V.

II. Model Description and Mathematical Formulations

In this paper, we consider a microgrid model with the DERs. In the microgrid model, the generation unit consists of RESs, grid level battery and the grid. A residential community load demand is considered as a demand of the microgrid. The microgrid controller receives real-time information of the generation units and load demand, and generates real-time microgrid operation policy considering the intra-day forecast based on the day-ahead forecasted profiles of the generation units and load demands. The goal of the controller is to schedule the generation units efficiently so that the microgrid daily operational cost can be minimized with satisfying the operational constraints.

At any time t, the real-time and intra-day forecast data of the microgrid exogenous information can be expressed as,

$$S_t = (R_t, I_t, \hat{I}_{t+1}, ..., \hat{I}_{t+H}). \tag{1}$$

where, R_t represents the available energy in the battery at time t. Here, I_t is a set of exogenous information as $I_t = (W_t, D_t, P_t)$, where W_t, D_t, and P_t represent the total available power from the RESs in kW, the load demand in kW, and the grid price in $cents/kWh$ at time t, respectively. In equation (1), $\hat{I}$ refers as the predicted future intra-day forecast information at time t. For scheduling the microgrid generation units smartly, the controller requires intra-day forecast data for a specific predictive horizon window ($\hat{I}_{t+1:t+H}$). Here, H represents the horizon window size.

The decision vector of the microgrid can be defined as,

$$a_t = \{a_t^{gd}, a_t^{rd}, a_t^{wd}, a_t^{wg}, a_t^{wr}, a_t^{gr}\}, a_t \geq 0. \tag{2}$$

where, the decision vector a_t contains the decision variables which represent the amount of power transferred from one unit to another unit at time t. In the decision vector, the superscripts g, r, w, and d represent the grid, battery, RESs and demand, respectively. For example, the decision variable a_t^{wd} indicates the total amount power allocated from the RESs to fulfill the demand by the controller.

The objective of this microgrid energy optimization problem is to minimize the daily operational cost of the microgrid considering the microgrid operational constraints. If the operational cost of the microgrid at time t can be defined as $C(t, S_t)$, then the objective function can be written as,

$$F = \min_{a_t} \mathbb{E}\Bigg[\sum_{t=1}^{T} C(t, S_t)\Bigg]. \tag{3}$$

where, T represents the final time step of the time frame $\{1, 2\Delta t, ..., T - \Delta t, T\}$ where $\Delta t = 1$. The cost function of the microgrid at time t can be defined as,

$$C(t) = P_t(a_t^{gr} + a_t^{gd}). \tag{4}$$

where, the battery charging cost and the cost of buying energy from the grid to fulfill the demand are considered.

The objective function subjects to the microgrid operational constraints as,

$$a_t^{gd} + a_t^{rd} + a_t^{wd} = D_t, \tag{5}$$

$$a_t^{wd} + a_t^{wg} + a_t^{wr} \leq W_t, \tag{6}$$

$$-1 \leq \frac{(a_t^{wr} + a_t^{gr})}{\theta} - \frac{a_t^{rd}}{\theta} \leq 1, \tag{7}$$

$$SOC_{min} \leq SOC_t \leq SOC_{max}, \tag{8}$$

where, the constraint (5) is defined to balance the microgrid generation side and load demand side. The constraint (6) limits the transferred power from the RES unit to other units within the generation of the RESs. The constraint (7) determines the battery mode of operation where θ represents the maximum charging/discharging limit of the battery in kW. The integer output of this constraints should be within the range as $\{-1, 0, 1\}$ which indicates the discharging, idle, and charging modes of the battery, respectively. The constraint (8) keeps the state of charge (SOC) of the battery within a certain range at any time t. In this paper, it is assumed that the battery charges/ discharges at its maximum charging/discharging limit.

The goal is to schedule the generation units efficiently at every time step considering the available future intra-day forecast information as

$$a_t(S_t) = \arg\min_{a_i} \sum_{i=t}^{t+H} C(i, S_t). \tag{9}$$

so that the total daily operational cost of the microgrid can be minimized.

The battery transition function can be formulated as,

$$SOC_{t+1} = \frac{1}{R_{cap}}(R_t + (a_t^{wr} + a_t^{gr}) - a_t^{rd}), \tag{10}$$

$$R_{t+1} = SOC_{t+1} R_{cap}, \tag{11}$$

where, R_{t+1} and R_{cap} represent the available battery energy at time $(t+1)$ and the capacity of the battery, respectively.

III. Receding Horizon Based Control Approach and Reference Technique

A. Receding Horizon Based Control Approach

The RHC is an online optimization approach which solves the optimization problem repeatedly over a sliding time horizon with the goal to achieve the optimization policy of the current time step considering the future outcome of the forecast errors, disturbances, and constraints [22]. The working principle of the RHC approach is illustrated in Figure 1.

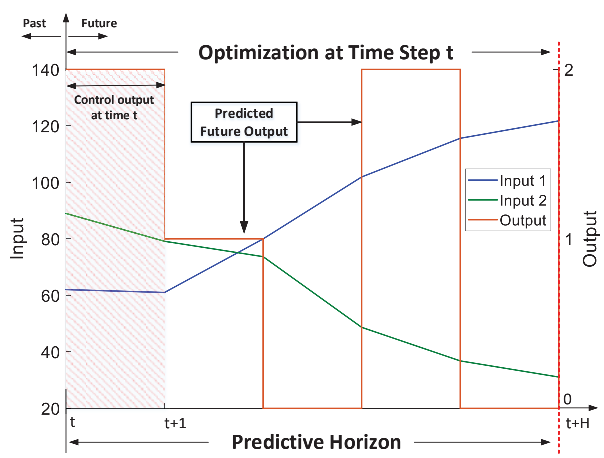

Figure 1. Real-time decision making process of the receding horizon based control approach.

In the figure, the x-axis represents the time scale. The left and right y-axis represent the input and the output, respectively. Here, it is assumed that the output is a control signal which is an integer number with the possible values 0, 1, and 2. According to the figure, at any time t, the RHC approach collects the real-time input information and the predicted future forecast information for the time frame $t+1 : t+H$. Note, the horizon size H plays an important role for solving the optimization problem with the RHC principle. Please refer to Section IV for the description of the tuning horizon size H. After receiving the real-time data and the forecasted data, the RHC approach solves the optimization problem (equation (9)) and outputs the optimization policy for the current time step. The RHC approach can also predict the future control outputs as shown in the figure with the brown stairs curve. However the RHC approach only execute the control output for the current time step, because the future predicted outputs are subjected to change based on the future predicted forecast. After solving the optimization problem for the current time step, the predictive horizon window shifts to next time step, collects the real-time and forecasted data similarly, and solves the optimization problem repeatedly for the whole time frame. This procedure continues until the time frame ends.

B. Reference Technique

In this paper, we use MILP approach as a reference approach to evaluate the performance of the RHC approach. The MILP approach is a linear optimization technique which can solve the constrained optimization problem with both integer and continuous variables [23]. The MILP approach is widely used in the existing literature for generating optimal solution through offline optimization process which requires the true input information over the optimization horizon. Note, the MILP approach is suitable for offline optimization problems and applying this approach online can not guarantee the optimality. For instance, to generate the optimal solution of our microgrid energy optimization problem using the MILP approach, we assume that the operator knows the future input profiles of the microgrid and generate the optimal solution of the problem. Simulation parameters and the experimental results are presented in Section IV.

IV. Simulation Setup and Results Analysis

In this section, we present the parameter settings of the microgrid and report the results analysis based on numerical experiments. We present two different experiences with single RES and multiple RESs, and provide the results to illustrate the effect on the optimization problem. All the experiments are conducted using the MATLAB $R2018b$ environment. We use MILP toolbox provided by the MATLAB software for solving the optimization problem using the MILP approach.

Table I
Battery Information

Battery	Lead-Acid
Capacity	200 kWh
Charging and discharging efficiency (α)	80%
Maximum charging and discharging rates (θ_{max})	50 kWh/Δt
Battery charging/discharging limit ($\theta = \alpha * \theta_{max}$)	40 kWh/Δt

The battery parameter settings of the microgrid is presented in Table I where the charging and discharging rate of the battery (θ) is determined using the charging and discharging efficiency (α) of the battery. The residential microgrid load demand and electricity price profiles are presented in Figure 2. The residential load profile of the city of Minneapolis in Minnesota are collected from [24]. The grid price profile in cents per kWh is taken from [25].

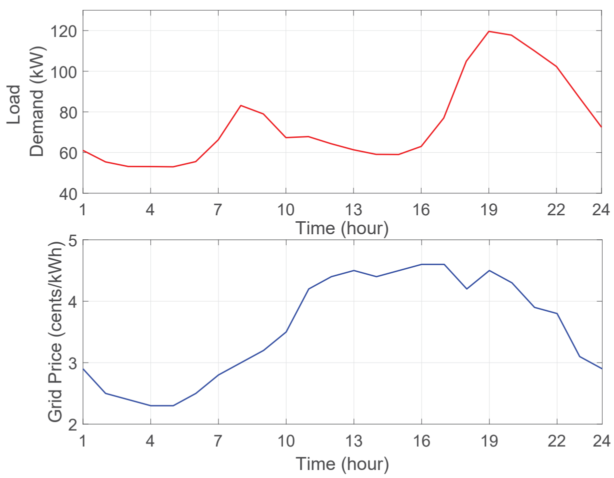

Figure 2. (A) Residential load-demand of the city of Minneapolis in Minnesota, (B) Grid electricity price.

The performance of the optimization techniques are evaluated using the optimization error (%) as,

$$Error = \frac{|F - F^{*}|}{F^{*}} \times 100\%. \tag{12}$$

where, F^{*} and F are the optimal total operational cost of the microgrid and the total operational cost of the microgrid obtained from a specific optimization approach, respectively. Note, the value of F^{*} obtained from the MILP approach.

A. Experiment 1: Integration of single RES

In this experiment, we use only photovoltaic (PV) system as a RES with the capacity of 100kW. The outputs of the PV system are collected from the system advisory model (SAM) by National Renewable Energy Laboratory for the city of Minneapolis, MN [26]. The PV power outputs are presented in Figure 3.

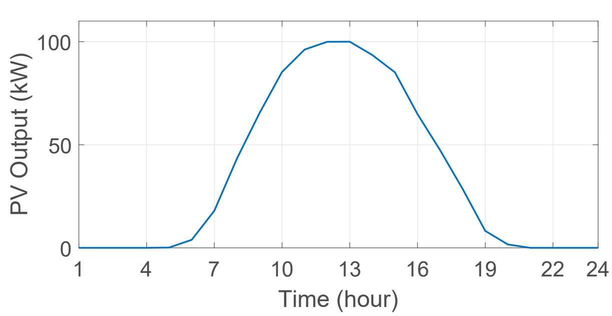

Figure 3. The PV output power where the maximum capacity of the PV output power is 100kW.

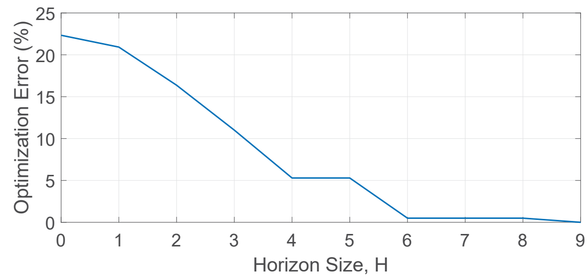

Figure 4. The effect of horizon size in terms of optimization errors.

With the given parameter settings, we analyse the effect of the horizon size in the RHC approach in terms of optimization error. The result of optimization error over the horizon size is presented in Figure 4. The result shows that tuning the horizon size, the performance of the RHC approach can be improved. According to Figure 4, the RHC approach incurs more than 20% of optimization error when the prediction window size is $H = 0$. The performance of the RHC approach improves with the increment of the horizon size, and the result shows that at $H = 9$, the RHC approach achieves the optimal solution. So, for this problem, the optimal horizon size is $H = 9$. It is better not to choose $H > 9$ because it may increase the computation time and also if any unexpected change happened in the intra-day forecast, the performance of the RHC approach may degrade.

Table II
PERFORMANCE COMPARISON OF THE OPTIMIZATION TECHNIQUES.

Approach	Operation Cost ($)	$Error$ (%)
MILP	28.34	-
RHC approach with horizon size H = 9	28.34	0
RHC approach with horizon size H = 5	29.84	5.29

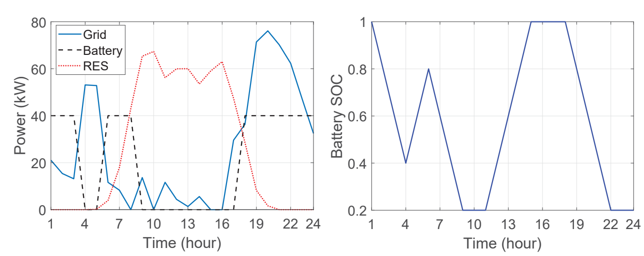

Figure 5. The operational profile of the microgrid to fulfill the demand and the battery SOC profile.

The results in terms of operational cost of the microgrid and optimization errors are presented in Table II. Note, we consider the result of the MILP approach as an optimal solution. The results show that the RHC approach can achieve the optimal solution with the horizon size $H = 9$. We also report the results of RHC approach with a fixed horizon size ($H = 5$)

where we observe the optimization error as 5.29%. According to the result analysis, we can observe that the RHC approach has the potential to achieve the optimal solution by tuning the horizon size with the help of intra-day future forecast information.

In addition, we also present the microgrid operational profile to fulfill the load demands and the battery SOC profile of the day. The results are illustrated in Figure 5. The results show that the load demands are fulfilled mostly by the battery and the grid at the beginning time steps of the day. At the middle time steps of the day, the microgrid utilizes the output power of the RES (PV) to fulfill the demand and to charge the battery so that in future time steps when the PV output power won't be available, the battery can supply the energy, and minimize the operational costs. The battery and the grid share the load demand mostly at the time steps of the end of the day because of low PV output powers. The battery SOC profile is also presented in Figure 5, where we can see that when the PV outputs are available in the microgrid, the microgrid charges the battery so that the battery energy can be utilized in future time steps to minimize the total operational cost of the microgrid.

B. Experiment 2: Integration of multiple RESs

In this case study, we consider multiple RESs in the RES unit where the output from the PV panels and wind turbines (WTs) are combined to represent the total power generation from the RES unit. The output power of the PV panels and WT are collected using the SAM software where the capacity of each RES is assumed as 50kW. The power output profiles of the RESs are presented in Figure 6.

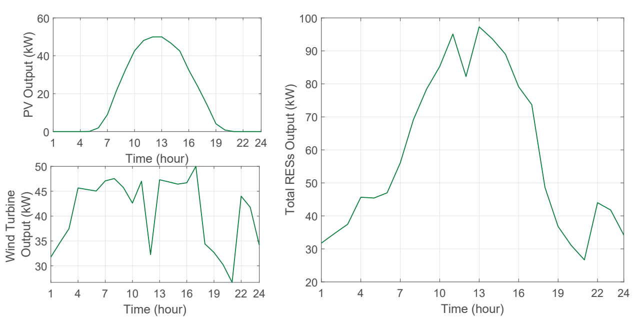

Figure 6. The total power output from the RESs where the maximum capacity of the output power is 100kW.

Due to the addition of WT output power, the non-linearity of the RES power output profile is increased which actually affects the horizon window size of the RHC approach in terms of percentage of optimization error. We observe that the RHC approach with horizon size $H = 9$ incurs optimization error as 4.74%. Therefore, the horizon size of the RHC approach needs to be tuned so that the RHC approach can achieve the optimal policy. The effect of horizon size in terms of optimization errors for multiple RESs is illustrated in Figure 7. The result shows that the horizon size of the RHC approach needs to be increased to get reach to the optimal solution. We observe that the RHC approach can achieve the optimal solution with the horizon size $H = 17$. So, the horizon size $H = 17$ is the optimal horizon size for this experiment.

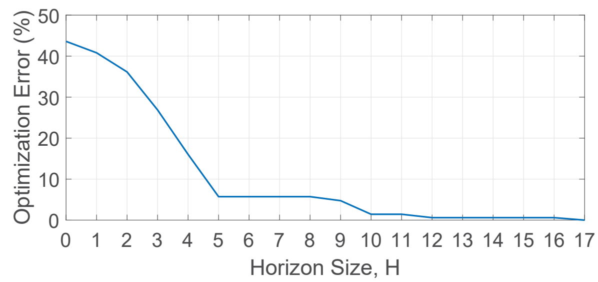

Figure 7. The effect of horizon size in terms of optimization errors for multiple RESs.

Table III
PERFORMANCE COMPARISON OF THE OPTIMIZATION TECHNIQUES

Approach	Operation Cost ($)	$Error$ (%)
MILP	13.28	-
RHC approach with horizon size H = 17	13.28	0
RHC approach with horizon size H = 12	13.36	0.60
RHC approach with horizon size H = 9	13.91	4.74

In this experiment, we also present the performance comparison which is summarized in Table III. The RHC approach with the horizon size $H = 17$ achieves the optimal solution where the RHC technique with the horizon size $H < 17$ incurs some errors.

Table IV
ALLOCATION OF MICROGRID ENERGY RESOURCES FOR FULFILLING THE LOAD DEMAND OF THE TOTAL TIME FRAME

Approach	Percentage Share		
	RESs	Battery	Grid
RHC approach with horizon size H = 17	51%	31%	18%
RHC approach with horizon size H = 9	57%	25%	18%
RHC approach with horizon size H = 12	49%	33%	18%

Moreover, the energy allocation of the microgrid generation units for fulfilling the demand using the RHC approach with different horizon window sizes are summarized in Table IV. The results show that all three approaches buy 18% of the total load demand of the day from the grid. The RHC approach with fixed horizon $H = 9$ allocates highest 57% of total load demand of the day to the RES unit. The RHC approach with fixed horizon $H = 12$ utilizes the battery energy to fulfill 33% of the total load demand of the day which is the highest battery utilization rate compared to other two approaches. The RHC approach with the horizon size $H = 17$ allocates 6%

less power to the RES unit to fulfill the demand compared to the RHC approach with fixed horizon $H = 9$, and utilizes this amount of energy to charge the battery so that the future cost of the energy can be minimized. In this experiment, the prediction horizon window size $H = 17$ helps to schedule the microgrid generation units efficiently considering the future outcome of the current operation decision and to minimize the total operational cost. According to the results, we can conclude that the RHC approach is a powerful optimization technique which can be strengthened by tuning the horizon size to achieve the optimal policy at every time step.

V. Conclusion

In this paper, we investigate the effect of horizon window size on the RHC technique for solving energy scheduling problem with the presence of RESs. We formulate the energy optimization problem of the microgrid with the RHC principle. We conduct two different experiments with single and multiple RESs in the microgrid RES unit. Through the numerical results, we show that the optimization performance of the RHC technique depends on the horizon window size, and the microgrid optimal operation can be achieved by tuning the horizon size. We also report the effect of increasing penetration of RESs on the horizon window size of the RHC technique. The performance of the RHC approach with different horizon sizes is validated comparing with the reference MILP approach. During the experiment, we observe that the horizon window size of the RHC approach needs to be updated with the addition of RESs in the microgrid to guarantee the optimal performance.

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