Model Predictive Control Energy Dispatch to Optimize Renewable Penetration for a Microgrid with Battery and Thermal Storage

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Abstract

As intermittent renewable energy becomes a larger fraction of the overall energy mix in the US, algorithms that efficiently utilize this energy are necessary. In this work, a model predictive control (MPC) method is developed to perform real-time optimization to maximize the power delivery from a renewable supply to a building. An isolated microgrid scenario is considered, consisting of a mixed-use residential and commercial building, renewable energy resource (RER), battery storage, hot water tank thermal storage, and a backup supply. The MPC strategy utilizes predictions of the building's electrical and hot water loads, on an hourly basis, along with predictions of the output from the renewable supply. At each time step, these predictions are used to create an optimized power dispatching strategy between the microgrid elements, to maximize renewable energy use. For a fixed size microgrid, the performance of this MPC approach is compared to the performance of a simple non-predictive dispatching strategy.

INTRODUCTION

Figure 1 is a block-diagram view of the MPC, where a process model predicts future outputs based on previous inputs/outputs and optimized future control signal. The optimization considers constraints, an objective function, and the difference between the reference trajectory and the predicted outputs. The performance of the MPC algorithm is highly dependent on the accuracy of the process model.

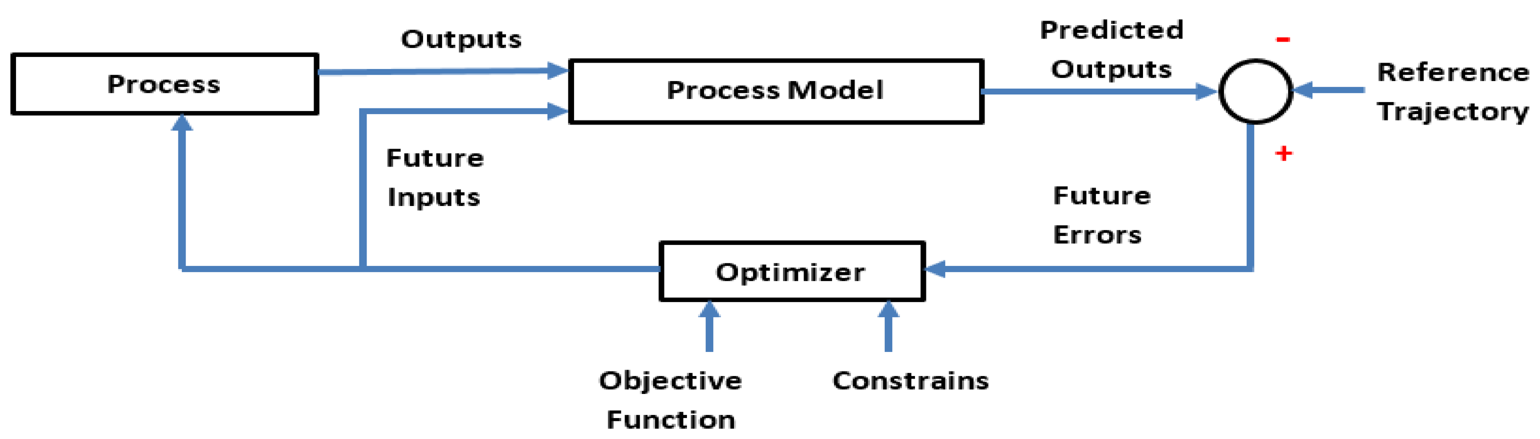

Fig. 1: General MPC control flow [1]

1- PROBLEM FORMULATION

Figure 2 contains a block diagram showing the elements of the microgrid, and the hourly energy flows between them. The mixed-use building load is divided into an electrical load which includes heating and cooling demand, and a domestic hot water load that is satisfied with stored energy or backup energy. Energy from a single renewable supply is sent directly to the electrical load (P_2), or it is transferred to the battery (P_3) or hot water tank (P_5). The goal of the MPC algorithm is to maximize the total transfer of energy from the renewable supply to the loads (P_2+P_4+P_6), while minimizing curtailed renewable energy and backup energy usage (P_{1E}+P_{1T}). Battery state of charge (SOC) and storage tank charge (SOC_{TH}) are maintained between specified limits.

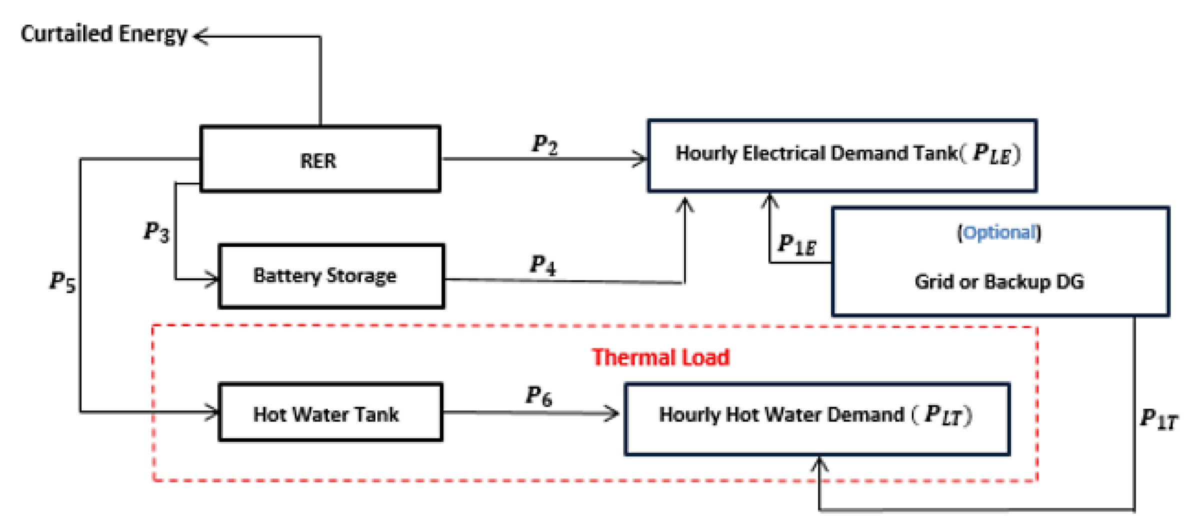

Fig. 2: Energy transfers between microgrid elements are simulated on an hourly basis, according to MPC algorithm that minimizes generator operation.

MPC Objective Function

The goal of the control system is to minimize backup energy usage and maximize the amount of renewable energy that is consumed directly by the load. Using battery or tank storage is necessary, but should also be minimized due to losses and the effect on storage system lifetime. The following expression represents an overall objective for the control system to minimize, and it is useful for developing the state-space representation.

$$J = \sum_{k=0}^{T}\{C_{1E}^2\, P_{1E}^2(k) + C_{1T}^2 P_{1T}^2(k) + C_2^2[P_3(k) + P_5(k) + P_4(k) + P_6(k)]^2 + C_3^2[P_{RER}(k) - P_2(k) + P_3(k) - P_5(k)]^2\}$$

The constantsC_{1E}, C_{1T}, C_2, and C_3 serve as weighting parameters that can modify the significance of the four terms. The first two terms penalize the usage of backup energy. The third term penalizes the usage of the battery and thermal storage systems. The last term assigns a cost to curtailed energy. The summation is done over a selected time interval ending at T.

Battery and Thermal Tank Storage

Using k to represent hourly time steps ($k = 1,2,3, \ldots$), the battery state of charge $SOC(k)$ and tank state of charge $SOC_{TH}(k)$, both in kWh, are combined into a single vector,

$$x_m(k) = \begin{bmatrix} SOC(k) \\ SOC_{TH}(k) \end{bmatrix}.$$

The following equation and definitions are used to recursively update these energy levels,

$$x_m(k) = x_m(k-1) + b_m u(k-1)\,,$$

$$u(k) = [P_2(k) \quad P_3(k) \quad P_4(k) \quad P_5(k) \quad P_6(k)]^T, b_m = \begin{bmatrix} 0 & \eta_c & -\eta_d & 0 & 0 \\ 0 & 0 & 0 & \eta_{TC} & -\eta_{TD} \end{bmatrix}$$

state-space model and Reference Trajectory

$$x(k+1) = Ax(k) + Bu(k)\,,$$

$$y(k) = Cx(k)\,,$$

$$A = \begin{bmatrix} I_{2\times2} & 0_{2\times4} \\ 0_{4\times2} & 0_{4\times4} \end{bmatrix}, B = \begin{bmatrix} 0 & \eta_c & -\eta_d & 0 & 0 \\ 0 & 0 & 0 & \eta_{TC} & -\eta_{TD} \\ C_{1e} & 0 & C_{1e} & 0 & 0 \\ 0 & 0 & 0 & 0 & C_{1T} \\ C_3 & C_3 & 0 & C_3 & 0 \\ 0 & C_2 & C_2 & C_2 & C_2 \end{bmatrix}, C = [0_{4\times2} \quad I_{4\times4}].$$

$$R = [C_{1E}P_{LE}(k), C_{1T}P_{LT}(k), C_3P_{RER}(k) \ldots C_{1E}\, P_{LE}(k+N_P|k), C_{1T}P_{LT}(k+N_P|k), C_3P_{RER}(k+N_P|k)].$$

2- Results

Figu re 4 illustrates average daily profiles of energy transfers on the electrical side of the microgrid for the non-predictive algorithm. In comparing Figures 3 and 4, it is clear that the MPC algorithm chooses to charge the batteries later in the afternoon than the non-predictive algorithm. Also, the MPC does not drain the battery as completely in the evening, saving stored energy for the morning peak in consumption. As a result, the MPC algorithm uses less backup energy in the morning than the non-predictive algorithm.

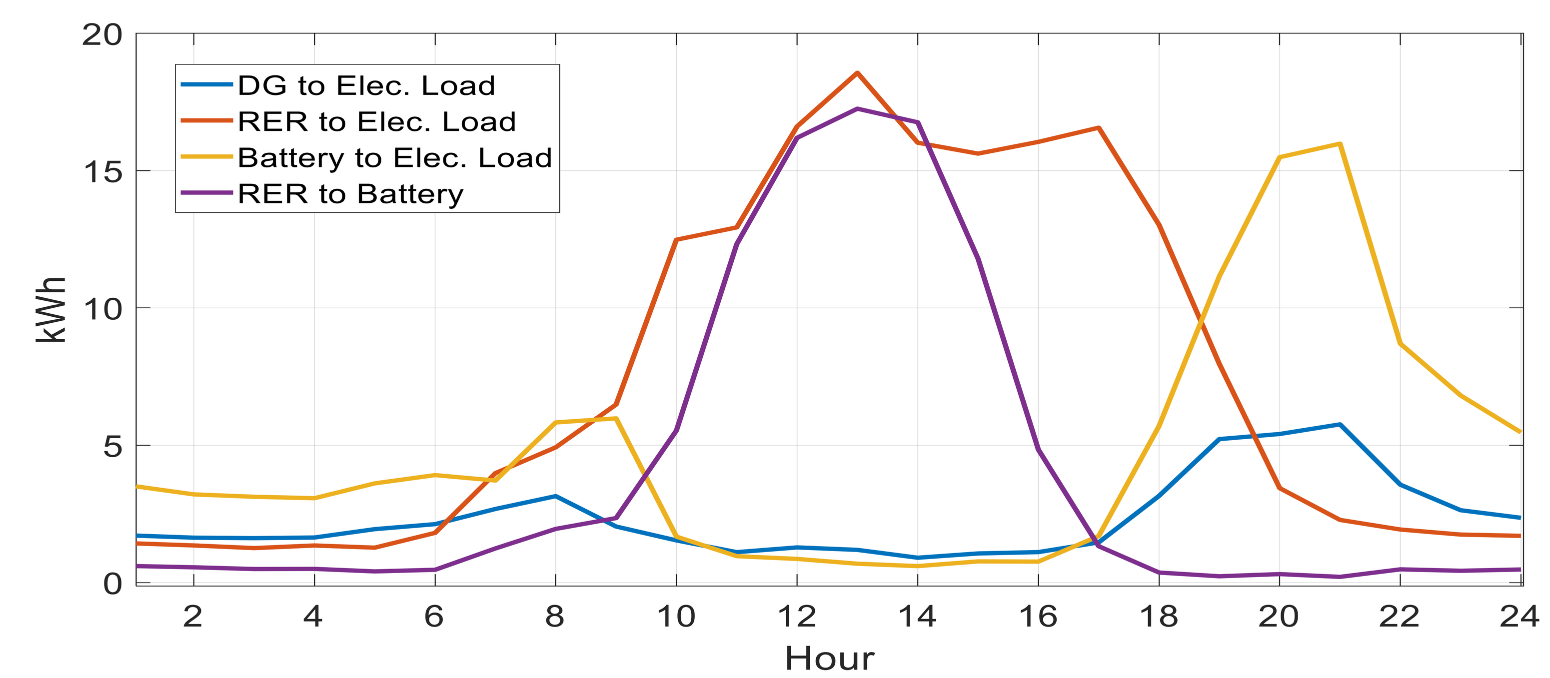

Fig. 3. MPC algorithm average daily electrical energy dispatching.

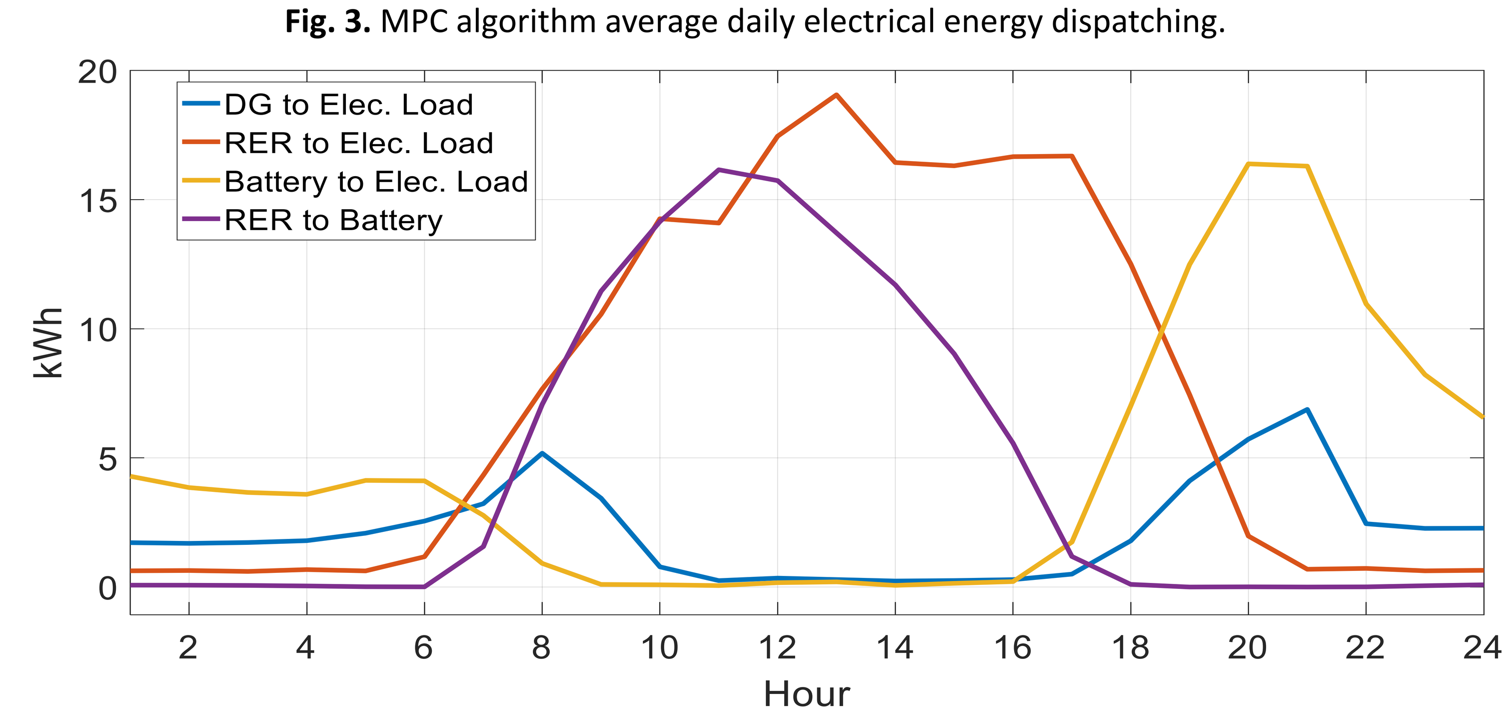

Fig. 4: Non-Predictive algorithm average daily electrical energy dispatching.

After operating both algorithms for a full year, it is possible to generate summary performance values such as renewable penetration and curtailment. A comparison for these quantities is shown in Table I between the MPC and non-predictive algorithms. The MPC dispatching increases RER penetration and decreases the curtailed power, illustrating the improvement over the non-predictive algorithm.

TABLE I. PERFORMANCE FOR BOTH CONTROL METHODS

	Non-Predictive	MPC
RER Penetration	88.60%	92.60%
Curtailed Power	38.40%	34.60%

The lower plot in Figure 5 shows an example of the daily demand and supply profiles, beginning at 12AM. The vertical line in the plot would indicate current time, with one day of values to the left, and one day of future forecasted values to the right. Actual future demand and supply (which would not be known in a real application) are shown next to the forecasts to illustrate forecasting error.

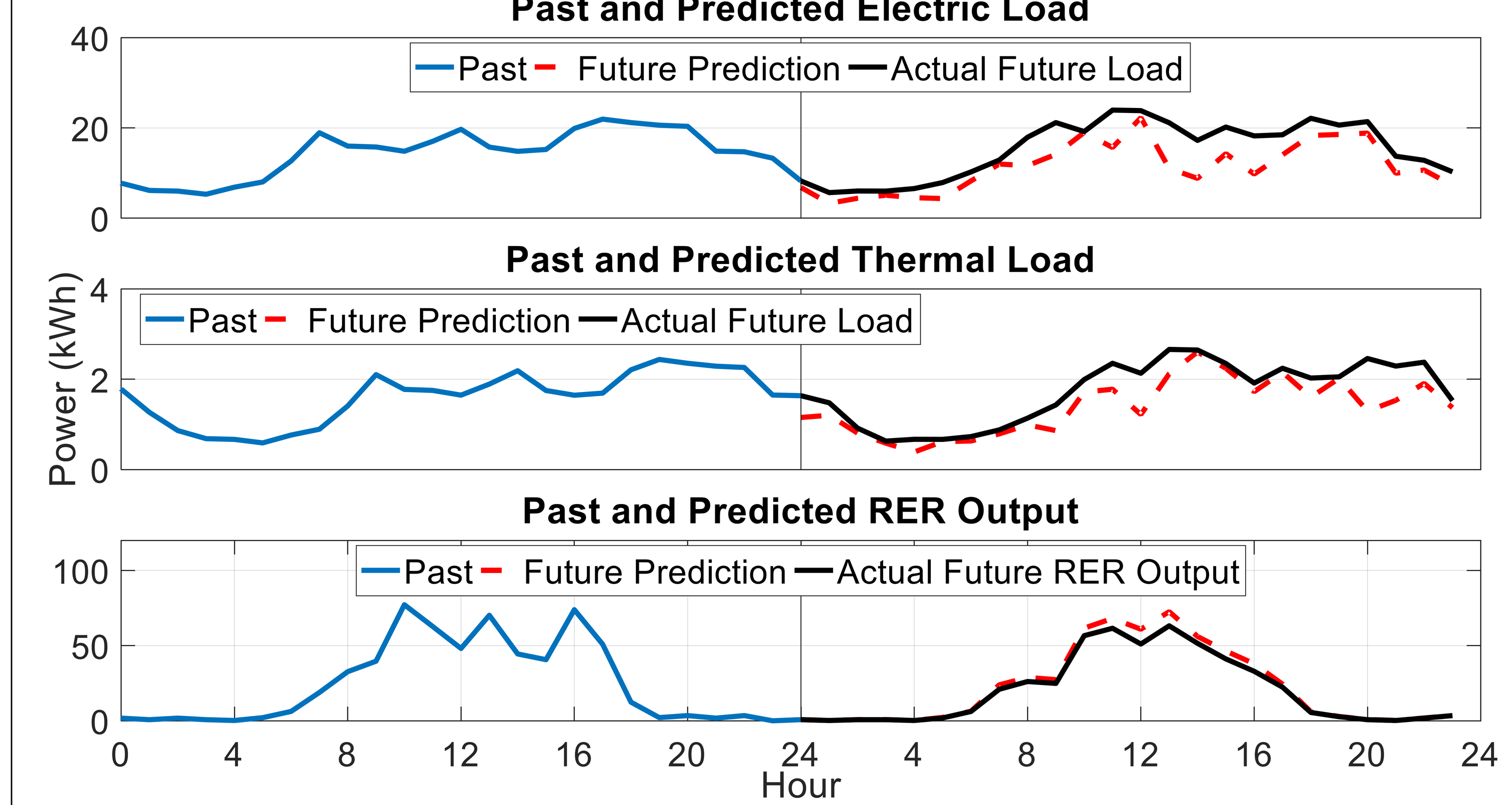

Fig. 5: Two days of demand and supply profiles used in simulation.

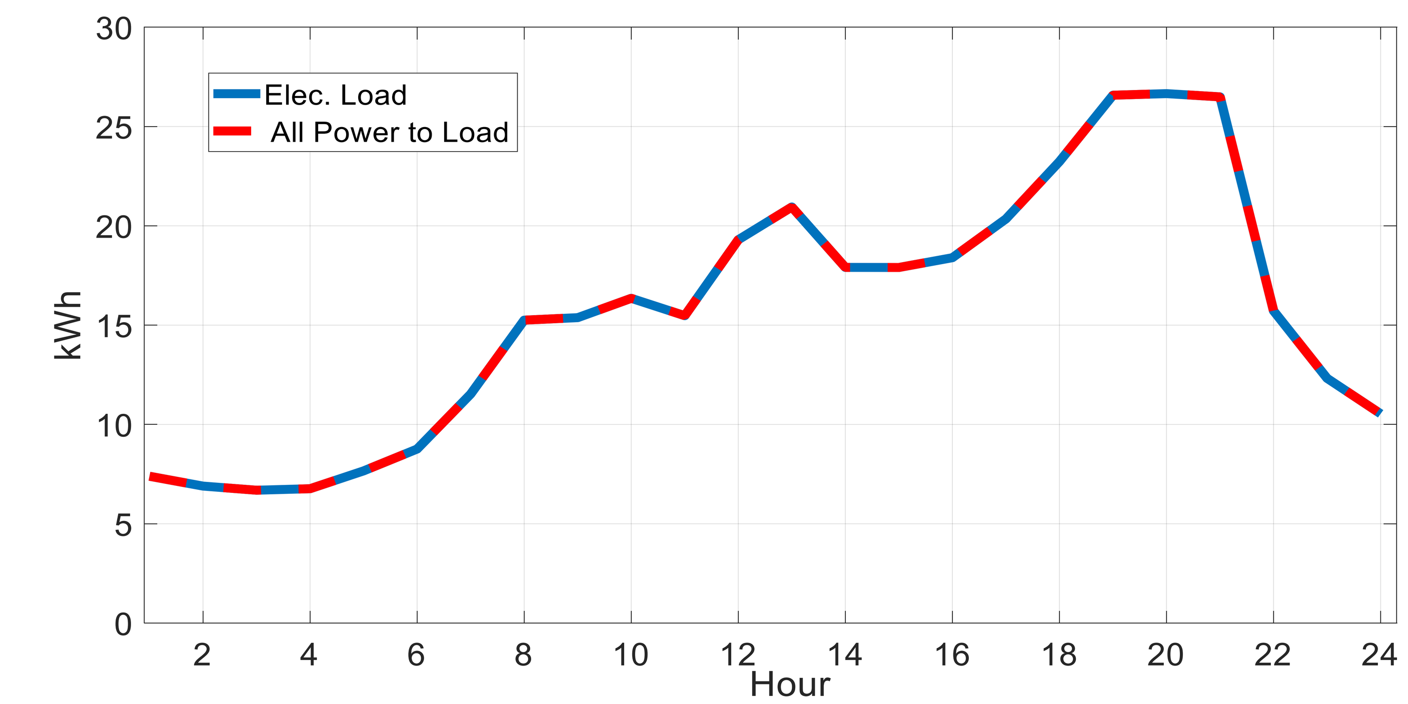

Fig. 6: The average daily of electrical load and energy dispatching (MPC). .

Conclusions

This work examines a renewable energy microgrid that provides power for a single mixed-use building, consisting of residential apartments and a single restaurant. The renewable energy supply is distributed to separate electrical and demand hot-water loads. Battery storage and a hot-water tank are used to collect excess renewable energy for later use, typically storing afternoon solar energy for use in the evenings. Previous work with this system determined optimum sizes for components (PV area, number of wind turbines, battery and tank capacities) to minimize annual economic cost. This was done while using non-predictive dispatching. In this work, the MPC algorithm is used with the same system size to optimize an objective function that includes both renewable penetration and curtailment. At each time step, MPC optimizes an objective function that primarily penalizes diesel generator usage, but also penalizes energy storage usage to force the system to directly use as much RER energy as possible. The optimization occurs over a window into the future, using forecasts to simulate future behavior. The optimized result is used to determine the dispatching for the current time, and the process then repeats for the next time step.

Both dispatching algorithms are applied for a simulated year. RER penetration for the non-predictive control system is 88.6%, and for the MPC algorithm it is 92.6%. Curtailed power for the non-predictive control system is 38.4%, which drops to 34.6% for the MPC algorithm.

ACKNOWLEDGMENT

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Selected References

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