Model Predictive Control based Energy Collaborative Optimization Management for Energy Storage System of Virtual Power Plant

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Abstract **—This paper presents an energy collaborative optimization management for an energy storage system (ESS) of virtual power plant (VPP) based on model predictive control (MPC). This method uses long-short term memory (LSTM) neural network to obtain the one hour-ahead forecasting information for the load, the generation of wind and photovoltaic within the jurisdiction of VPP. With the minimum economic cost of VPP as the optimization goal, the optimal scheduling is solved by an improved particle swarm optimization (PSO) algorithm in the concept of the MPC framework. Through the comparison with the conventional VPP optimization solution, the numerical results clearly demonstrated that the proposed method improves the utilization of distributed generators (DGs) and reduces the impact of prediction errors on the optimization results.**

Index Terms—Virtual power plant (VPP); Model predictive control (MPC); particle swarm optimization (PSO) algorithm.

I. INTRODUCTION

In recent years, the proportion of distributed generators (DGs) represented by renewable energy (e.g. photovoltaic, wind turbines) connected to the power grid has increased [1]. However, randomness and intermittency are their salient features. To reduce their impact on grid operation, the concept of virtual power plant (VPP) was proposed. VPP is a virtual system that effectively integrates DGs, energy storage system (ESS), and controllable load within its jurisdiction, connected to the power grid as a whole to improve economic benefits. It can coordinate the distributed units to both control the transmission power and achieve an appropriate allocation of resources [1].

The energy scheduling problem of VPP usually comes down to the offline optimization and open-loop control. The traditional scheduling method is based on the predictions of the load and DGs' outputs, and all the optimal scheduling of each unit at each time are delivered in the offline stochastic optimization process. Its premise is to assume that the predicted values are accurate. However, this is difficult to achieve in practice, because of the uncertainty of load, intermittency and fluctuation of DGs. When accurately predicted values can be obtained, optimal decisions can be better arranged to improve the overall economic benefits of VPP, so improving the accuracy of prediction is one of the directions to solve the problem. Another direction is to develop online algorithms to solve the energy scheduling problem in real-time. These methods do not have high requirements for prediction with some simplifications of the system model or optimization process, which both meet real-time requirements and obtain relatively satisfactory solutions.

Model predictive control (MPC) is a model-based algorithm for closed-loop optimal control in a finite time domain [2]. Its basic framework includes three parts: predictive model, rolling optimization, and feedback correction. The rolling optimization uses measured information for feedback, forming a closed-loop optimization and improving its performance. In this MPC-based solution for the energy scheduling of VPP, the optimization process is non-convex caused by the complexity and nonlinearity of the system model. The meta-heuristic algorithm [3-4] is regarded as an effective technique to solve complex optimization problems in a short time. So this paper will use an improved particle swarm optimization (PSO) [5] algorithm to solve the model.

In this paper, the long-short term memory (LSTM) neural network is used to predict the load demand, generation of wind turbine and photovoltaic generator of the next hour. Then the PSO algorithm is used to solve the MPC-based VPP energy scheduling problem. With simulation results compared to the traditional method, it is verified that the proposed method improves the utilization rate of DGs and reduces the impact on the public grid. Fig. 1 illustrates the structure of VPP studied in this paper. It includes load, small thermal unit (SMU), wind turbine, photovoltaic generator and VPP dispatch center.

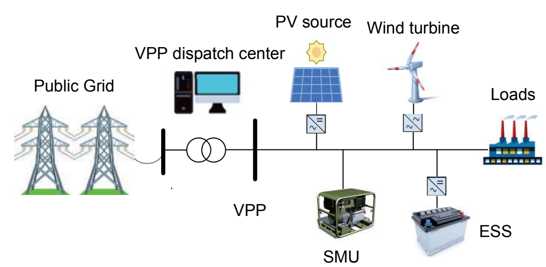


Fig. 1 Illustration of a typical VPP

II. SYSTEM MODELING

A. Using LSTM Neural Network for Prediction

To obtain high-precision predicted data, this paper uses the LSTM neural network, which is considered to be a variant of recurrent neural network (RNN). LSTM is composed of an input layer, hidden layer and output layer [6]. The network and unit structure are explained in [7]. One year of historical data, whose time interval is 5 minutes, is used to enable the network to learn dependencies between time series. The time scale of prediction is 1 hour with a resolution of 15 minutes. At every predicted time, the input to LSTM is the actual value within 2.5 hours before it and the output is the predicted value 1 hour after it.

B. Optimization Goals and Constraints

Once the forecast data for dispatch is obtained, the optimization model needs to be established to determine optimal scheduling values, that is, the output of STU and ESS, electricity purchased from the public grid.

a. Optimization Goal

The VPP operation scheduling cost minimization is considered as the optimization goal, described as follows:

$$\min\ Cost\left(P_d, P_{ess}, P_{grid}, M\right) = Cost_d + Cost_{ess} + Cost_{grid} \quad (1)$$

where M is the number of optimized periods, here taking 4; $Cost_d$ is the power generation cost of SMU; $Cost_{ess}$ is the dispatching cost of ESS; $Cost_{grid}$ is the cost of purchasing electricity from the public grid. The formulas are as follows：

$$\begin{cases} \mathrm{Cos\,t}(P_d, M) = \sum_{k=t}^{M}\left[c_{d,2}P_d^2(k) + c_{c,1}P_d(k)\right] \\ \mathrm{Cos\,t}(P_{ess}, M) = \sum_{k=t}^{M}\left[c_{ess,2}P_{ess}^2(k) + c_{ess,1}\left|P_{ess}(k)\right|\right] \\ \mathrm{Cos\,t}(P_{grid}, M) = \sum_{k=t}^{M}\left[EP(k)P_{grid}(k)\right] \end{cases} \quad (2)$$

where $c_{d,1}, c_{d,2}$ is the primary and secondary cost coefficient of power generation of SMU; $c_{ess,1}, c_{ess,2}$ is the primary and secondary cost coefficient of ESS; $EP(k)$ is the ToU (time of use) electricity price.

b. Constraints

Constraints include power balance, unit output limit, and ESS' state of charge (SoC, which is current storage capacity as a percentage of maximum capacity). The formula is as follows:

$$s.t.\begin{cases} P_{wind}(t) + P_{pv}(t) + P_d(t) + P_{ess}(t) + P_{grid}(t) = P_{load}(t) \\ P_{d,\min} \le P_d(t) \le P_{d,\max} \\ P_{ess,\min} \le P_{ess}(t) \le P_{ess,\max} \\ SoC_{\min} \le SoC(t) \le SoC_{\max} \\ t = 1, 2, ..., N \end{cases} \quad (3)$$

where $P_{wind}(t)$ and $P_{pv}(t)$ are the output power of wind turbine and photovoltaic generator at time t; similarly, $P_{load}(t)$ is the demand of load; $P_d(t)$ is the output power for SMU; $P_{ess}(t)$ is the output power of ESS, which is controlled by VPP's control center; it is positive for discharging and negative for charging; $P_{grid}(t)$ is the exchange power between VPP and the public grid, and the positive value represents the purchase of electricity from public grid while the negative value represents the sale of electricity to the public grid; $P_{d,\min}, P_{d,\max}$ are the lower and upper limit of the output power of SMU respectively; $P_{ess,\min}, P_{ess,\max}$ are the lower and upper limit of the output power of ESS respectively; $SoC_{\min}, SoC_{\max}$ are the lower and upper limit of SoC respectively.

C. Particle Swarm Optimization (PSO) Algorithm

Among meta-heuristic algorithms, particle swarm optimization (PSO) algorithm has attracted much attention because of simple and powerful performance. PSO is a group-based search algorithm. The overall size of the particles represents the solution space, and each solution is represented by a particle of the group, that is, each high-dimensional particle encodes a set of decision variables.

In PSO, the optimal solution path of each particle is called its local optimal solution (*pbest*). It is searched to obtain the globally optimal solution (*gbest*). Particles have two properties: position and velocity, whose definitions and update formulas are given in (4). By iterating and updating the position and velocity of particles, the optimal solution that meets the termination condition of iteration is obtained.

$$\begin{cases} v_{i+1} = \omega * v_i + c_1 * rand_1 * \left(pbest_i - x_i\right) + ... \\ c_2 * rand_2 * (gbest_i - x_i) \\ x_{i+1} = x_i + v_{i+1} \end{cases} \quad (4)$$

where x_i is the position of particles; v_i is the velocity of particles; $rand_1, rand_2$ are two random numbers between 0 and 1; c_1, c_2 are learning factors, which often take 2; ω is the inertia factor, which usually takes non-negative values. The larger ω helps global optimization while the smaller one helps local optimization. Instead of a fixed value, the dynamically changing ω can improve the optimization effect, so the linearly decreasing weight (LDW) strategy in (5) is used.

$$\omega^{(t)} = \frac{(\omega_{\mathrm{int}} - \omega_{end})(N_{iter} - \tau)}{N_{iter}} - \omega_{end} \quad (5)$$

where $\omega_{\mathrm{int}}, \omega_{end}$ are the inertia factors at the start and end; τ is the current iteration number; N_{iter} is the maximum iteration number.

D. Model Predictive Control (MPC)

MPC is a closed-loop optimal algorithm in the finite time domain. It can overcome the difficult problems such as time-varying and non-linearity of parameters that general methods cannot solve. The basic framework of MPC is as follows:

(1) *Prediction model*: it refers to the function of predicting the system's future state. MPC focuses on the function rather than the form.

(2) *Rolling optimization*: considering the prediction error, the optimization process of MPC is not done offline, but repeatedly online. Specifically, at each optimization moment, the optimal decision variable sequence in the future is solved. But only the first value in the optimal sequence is executed, and the above process is repeated at the next optimized moment.

(3) *Feedback correction*: as the actual values of the predicted object will not be completely updated according to predicted values, it is necessary to constantly revise some iteration variables according to measured values during the optimization process so that the rolling optimization process of MPC can effectively use the measured information, making the optimization process a closed loop.

E. Proposed algorithm

Fig. 2 shows the algorithm flow proposed in this work and the detailed steps are described as follows:

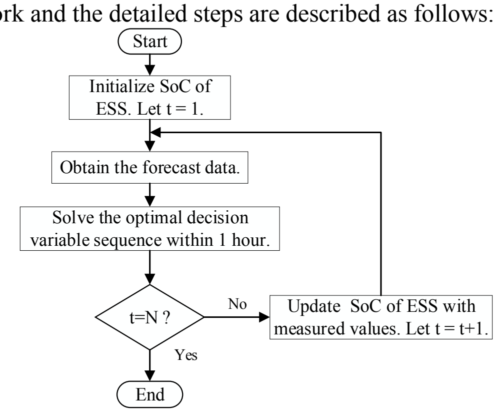


Fig. 2 Proposed algorithmic solution

Step 1: Let scheduling time t=1 and divide a day into N (N=96) scheduling times, that is, optimize every 15 minutes. SoC of ESS will be updated at every optimized scheduling moment and will affect the optimal scheduling decision. SoC is usually initialized to 0.5 before the start of the day's scheduling.

Step 2: Obtain the forecast data of load, wind power and photovoltaic output.

Step 3: Perform optimization. The goal is to minimize the overall scheduling cost at the subsequent 4 moments. The sequence of optimal decision variables is shown in Eq. (6), solved by PSO algorithm based on the predicted data :

$$\begin{cases} P_{d,best} = [P_d(t), P_d(t+1), ..., P_d(t+3)] \\ P_{ess,best} = [P_{ess}(t), P_{ess}(t+1), ..., P_{ess}(t+3)] \\ P_{grid,best} = [P_{grid}(t), P_{grid}(t+1), ..., P_{grid}(t+3)] \end{cases} \tag{6}$$

Step 4: Use the first value of the sequence in (6) as the dispatched value.

Step 5: Update the SoC of ESS. According to the power balance condition in (3), SoC can be calculated before the next optimization time, as shown in the following formula:

$$\begin{cases} ESS(t+1) = ESS(t) + P_{ess}(t) \\ P_{ess}(t) = P_{load}(t) - P_{wind}(t) - P_{pv}(t) - P_d(t) - P_{grid}(t) \end{cases} \tag{7}$$

where $ESS(t)$ is the storage capacity of ESS. Eq. (7) will be used in PSO iteration based on predicted values whose purpose is to determine whether SoC exceeds the limit. Here measured values are used to update SoC of ESS. This makes the rolling optimization of the next scheduling time using measured information, thus reaching a closed-loop optimization and improving performance of optimization.

Step 6: Let t=t+1, then repeat step 2-6 until t=N. The optimal dispatch value of $P_d(t)$, $P_{ess}(t)$, $P_{grid}(t)$ is gradually completed and the optimal energy dispatch for VPP is realized.

III. SIMULATION EXPERIMENTS AND RESULTS

This section adopted the one-year data measurements of a certain area to evaluate the performance of the proposed algorithmic solution mainly from two aspects, i.e. the DG utilization efficiency and the impact reduction on the public grid. Table I shows the values of the parameters used in this simulation. Fig. 3 and Fig. 4 show the ToU electricity price and the predicted and real data, respectively.

TABLE I VALUES of PARAMETERS

SoC_{min}	SoC_{max}	$P_{d,min}$	$P_{d,max}$	$P_{ess,min}$	$P_{ess,max}$
0.1	0.9	100kW	500kW	250kW	1000kW
$c_{d,1}$	$c_{d,2}$	$c_{ess,1}$	$c_{ess,2}$	ω_{int}	ω_{end}
0.00015	0.58	0.00015	0.57	0.9	0.4
N_{iter}	number of particles		dimension of particles		
500	100		8		

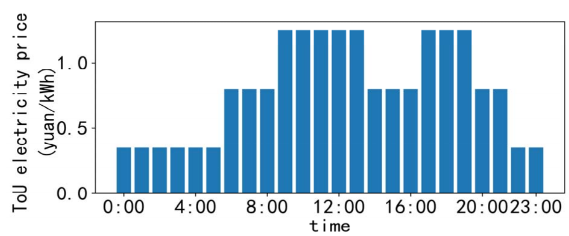
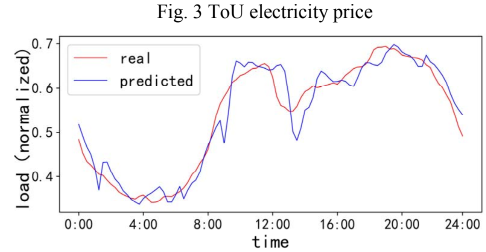
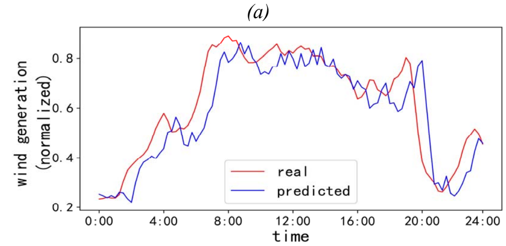


Fig. 3 ToU electricity price



(a)



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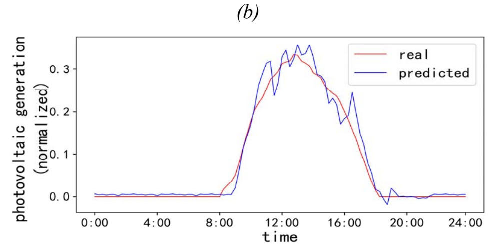


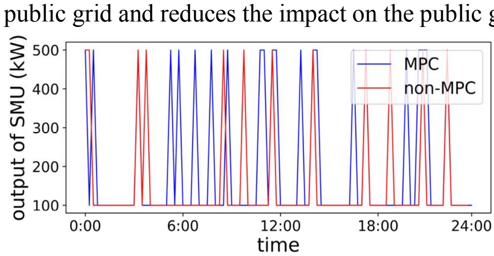
(c)

Fig. 4 Predicted data. (a) load demand; (b) output of wind turbine; (c) output of the photovoltaic generator

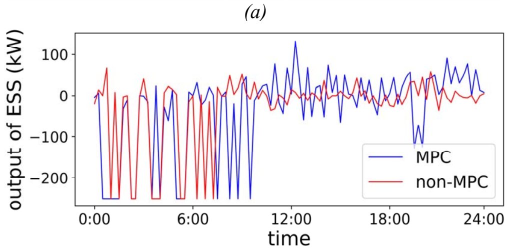
Fig. 5(a) gives a comparison of the output of SMU. With MPC, the power generation of SMU is increased, which increases its utilization rate. A comparison of the output of ESS is demonstrated in Fig. 5(b). ESS is charged when electricity demand is low or electricity prices are low and discharged when electricity demand is high or electricity prices are high. This helps to reduce the amount of electricity purchased from the public grid, thereby reducing the overall dispatch cost. At the same time, MPC will extend the charging time of ESS to be able to output more electricity during peak electricity demand in the afternoon.

Fig. 5(c) presents the changes in the energy storage capacity of ESS. MPC makes the usable interval of ESS larger, which improves economic benefits. The charging and discharging conditions are relatively gentle, which is more conducive to extending the life of ESS.

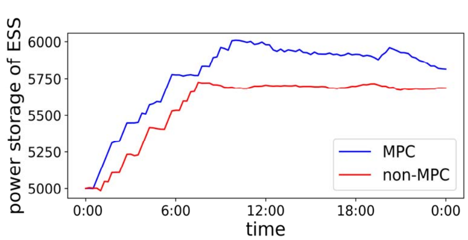
Fig. 5(d) shows the exchange power between VPP and the public grid. Both scheduling methods can play the role of "peak clipping and valley filling". During the two peak periods of electricity demand (noon and about 8 pm), MPC significantly reduces the electricity purchased from the public grid and increases the electricity purchased during the low period of electricity demand (late night) and staggers the peak period of the electricity demand of VPP and the public grid. Also, VPP can sell the surplus generation to the public grid during the low electricity demand period (early morning), which can also reduce dispatch costs. MPC increases the amount of electricity above. Overall, MPC can smooth the power exchange curve between VPP and the public grid and reduces the impact on the public grid.



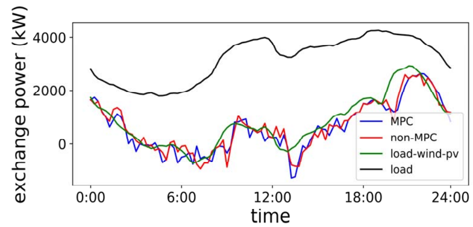
(a)



(b)



(c)



(d)

Fig. 5 Performance evaluation: (a) output of SMU; (b) output of ESS; (c) energy storage capacity of ESS; (d) exchange power curve

IV. CONCLUSION

This paper presents an energy collaborative optimization control method for VPP-ESS based on MPC. This method uses the prediction data from the LSTM neural network to establish the energy scheduling model of VPP based on MPC, which is solved by an improved PSO algorithm. In the case of errors in the prediction data, this method uses the measured information for feedback, which makes the optimization process a closed-loop and reduces the impact of prediction errors on optimization. The simulation results verify that this method improves the utilization rate of DGs, smooths the power exchange curve, and reduces the impact on the public grid.

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