Adaptive time resolution rolling dispatch with high renewable penetration

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Abstract. To cope with the energy crisis and the environment issues caused by the fossil fuels, the renewable energy generation developed rapidly. However, the inherent characteristics of uncertainty bring about difficulty to the operation of power system. Rolling dispatch can use the updated forecast data to adjust unit planning and it is a good method to cope with the volatility of renewable energy. But with the dispatch time resolution be finer, the computation burden of dispatch agent increases significantly and the allowable time limit of each round rolling dispatch shrank. This paper proposed a time sections clustering method, which could adaptively reduce the number of time sections that should be considered in the optimization model. In order to avoiding the interval of two successive dispatch horizon, this paper use an extended horizon to cover a first few hours of next day. To adopt the variable time resolution, a unified unit commitment model is proposed. The numerical experiment on a real provincial system in northwest China shows the effectiveness of the proposed model.

1. Introduction

To cope with the energy crisis and the environment issues caused by the fossil fuels, the renewable energy (RE) generation developed rapidly in recent years. In China, the installed capacity of RE units makes up a relatively significant share (38.3%) of the total installed capacity by the end of 2018, released by the Ministry of Ecology and Environment of PRC. However, the integration of large-scale volatile and uncertain RE generation into power system bring about challenges to the operation and control of power system. The traditional power system dispatch method decides the unit commitment (UC), which is a non-convex and time-consuming problem. The optimization time used by UC will be increased with the model scale grows. In traditional dispatch of power system with small-scale RE, the time resolution is coarse, for example, 1 hour, so that there are 24 time sections in one day. In response to the challenges brought by the uncertainty of RE, the dispatch agent prefers a finer time resolution, for example, 15
minutes or 5 minutes, there will be 96 or 288 sections in one day, which will increase the difficulty and decrease the maximum allowable time for optimization significantly [4]. While, not all the time sections’ information hold important value to the dispatch decision making, the dispatch agent cares the time sections with the net load ramping up/down more [5]. In [6] rolling dispatch uses the variable time resolution, the model uses 15-min time step for the first hour, 30-min for the second hour and 60-min for the remaining scheduling horizon, but this time resolution selection method is subjective. And the traditional dispatch method usually takes the whole day as the dispatch horizon, when the generation schedules of all time sections have been implemented, the dispatch agent will focus on the next day and do the work again. This dispatch method ignores the relation of the consecutive day, and the dispatch results of the last time section in Day 1 may be bad boundary conditions for Day 2, which will cause the uneconomical operation of power system, even the contingency, for example, load shedding.

To tackle with those issues mentioned above, this paper presents a novel unified adaptive time resolution rolling dispatch model. We use the time clustering method, which can figure out the similarity index of two consecutive time sections and merge two sections based on the index, to reduce the number of time sections, unlike the method proposed in [7], our method can adaptively decide the final number of time sections. Also we not only consider one day as the whole dispatch horizon, we define the dispatch window (DW) to cover the Day 1 that we need to decide the generation schedules, and forward-looking window (FLW) to cover the first few hours in Day 2, so that we can dispatch the power system based on the economy of Day 1 while take the feasibility of the operation in Day 2. Therefore, our contributions are a rolling dispatch method with adaptive time resolution.

2. Adaptive time resolution dispatch framework

Instead of using the whole day as the dispatch horizon as the traditional dispatch method, we define the DW to cover the day that need generation schedules, and the FLW to cover the first few hours of the next day. In general speaking, the longer time horizon, the better whole revenue. While considering the probability distribution of forecast error is time-varying [8], the forecast data at the end of the time horizon is likely to deviate from the real output. So that the time horizon of the FLW should not be too long. In this paper, we set the duration of FLW to 12 hours.

The procedure to reduce the scale of time sections is based on hierarchical clustering techniques, and the procedure can be described as follows:

1. Obtain the net load curve, and set every data point as a cluster.
2. Obtain the mean value of the cluster as the center of each cluster.
3. Compute the dissimilarity between the adjacent cluster using the Ward’s method [9].

\[
D(I,J) = 2N_iN_j (N_i + N_j)^{-1} \|c_i - c_j\|^2
\]

Where: \(N_i\) and \(N_j\) are the number of data point in cluster \(I\) and \(J\); \(c_i\) and \(c_j\) are the center of cluster \(I\) and \(J\).
4. Find the most similar adjacent cluster based on the dissimilarity matrix, which means the clusters pair with the smallest dissimilarity index may be merged.
5. Compute the mean value of the merged cluster, and compute the relative deviation of every data point in the merged cluster between the mean value. If the any relative deviation is bigger than the threshold given in advance, reject this mergence and stop the procedure. Otherwise, go to step (2).

Note that, the rolling dispatch need to take not only the global optimum of the operation, but also the feasibility of next time interval into consideration. So that we need use a finer time resolution, we take the next time interval as a special time section, which will not be merged with any time sections. Additionally, some generation station has the special operation objective, for example, the hydro generation station with reservoir has a duty to ensure water consumption, so that they need to consume a certain amount of water, which is decided day ahead by power and hydro dispatch agent collectively, in one day. So that the boundary time interval between the dispatch window and forward-looking window must be considered separately. The other special time interval can be handled in same way.

Therefore, the rolling dispatch framework and the update strategy of the dispatch horizon is shown in Figure 1.
3. Unified unit commitment formulation

This section presents the unified unit commitment formulation.

3.1. Objective function

\[
\min \sum_{g \in \Omega_g} C_g^S \left( S_{g,t}^S + S_{g,t}^E \right) + \sum_{t \in \Omega_t} \Delta t \left( \sum_{g \in \Omega_g} C_g^R P_{g,t} + \sum_{i \in \Omega_i} C_i^C P_{i,t} + \sum_{d \in \Omega_d} C_d^S P_{d,t} \right)
\]  

(2)

Where: \( C_g^S \) is the start-up and shutdown cost; \( S_{g,t}^S \) and \( S_{g,t}^E \) are binary variables for start-up and shutdown states; \( \Delta t \) is the duration for a certain time interval; \( C_g^R \), \( C_i^C \) and \( C_d^S \) are the cost of unit operation, RE curtailment and load shedding; \( P_{g,t} \), \( P_{i,t} \) and \( P_{d,t} \) is the power of unit output, RE curtailment and load shedding.

3.2. Constraints

3.2.1. Thermal unit

\[
S_{g,t} \cdot P_{g,t} \leq P_{g,t} \leq S_{g,t} \cdot \bar{P}_g
\]  

(3)

\[
S_{g,t} - S_{g,t-1} = S_{g,t}^S - S_{g,t}^E
\]

(4)

\[
S_{g,t}^S + S_{g,t}^E \leq 1
\]

(5)

\[
\sum_{t=1}^{r} S_{g,t}^S \leq S_{g,t}
\]

(6)

\[
\sum_{t=1}^{r} S_{g,t}^E \leq (1 - S_{g,t})
\]

(7)

\[
P_{g,t+1} - P_{g,t} \leq \bar{P}_g^{rampup} \cdot S_{g,t} \cdot \Delta t + \bar{P}_g^S \cdot S_{g,t+1}^S
\]

(8)

\[
P_{g,t} - P_{g,t+1} \leq \bar{P}_g^{rampdn} \cdot S_{g,t} \cdot \Delta t + \bar{P}_g^E \cdot S_{g,t+1}^E
\]

(9)

Where: \( S_{g,t} \) is binary variable for unit state; \( \bar{P}_g \) and \( \bar{P}_g \) are the maximum and minimum production of unit; \( T_{on} \) and \( T_{off} \) are the minimum start up and shutdown duration; \( \bar{P}_g^{rampup} \) and \( \bar{P}_g^{rampdn} \) are ramp-up and ramp-down limit; \( \bar{P}_g^S \) and \( \bar{P}_g^E \) are the start-up and shutdown ramp limit.

3.2.2. RE unit

\[
0 \leq P_{r,t} \leq \bar{P}_{r,t}
\]

(10)
\[ 0 \leq P_{e,j}^C \leq \overline{P}_{e,j} \] \quad (11)
\[ P_{e,j} + P_{e,j}^C = \overline{P}_{e,j} \] \quad (12)

Where: \( P_{e,j} \) and \( \overline{P}_{e,j} \) are the planning output and forecast output of RE unit.

### 3.2.3. Energy storage station (ESS)

\[ S_{e,j}^D \cdot P_{e,j}^D \leq P_{e,j}^D \leq S_{e,j}^D \cdot \overline{P}_{e,j}^D \] \quad (13)
\[ S_{e,j}^C \cdot P_{e,j}^C \leq P_{e,j}^C \leq S_{e,j}^C \cdot \overline{P}_{e,j}^C \] \quad (14)
\[ S_{e,j}^C + S_{e,j}^D \leq 1 \] \quad (15)
\[ E_{e,j} \leq E_{e,j} \leq \overline{E}_{e,j} \] \quad (16)
\[ E_{e,j} = E_{e,j-1} + (P_{e,j}^C \cdot \eta_{e,j}^C - P_{e,j}^D \cdot \eta_{e,j}^D) \cdot \Delta t \] \quad (17)

Where: \( P_{e,j}^D \) and \( P_{e,j}^C \) are the discharge and charge amount; \( S_{e,j}^D \) and \( S_{e,j}^C \) are the discharge and charge state; \( \overline{P}_{e,j}^D \) and \( \overline{P}_{e,j}^C \) (\( P_{e,j}^C \) and \( P_{e,j}^C \)) are the maximum and minimum limit of discharge (charge) power; \( E_{e,j} \) and \( \overline{E}_{e,j} \) are the energy level and the storage energy limit; \( \eta_{e,j}^D \) and \( \eta_{e,j}^C \) are the discharge and charge efficiency.

### 3.2.4. Power system

\[ 0 \leq P_{d,j} \leq P_{d,j}^A \] \quad (18)
\[ 0 \leq P_{s,j} \leq P_{s,j}^A \] \quad (19)
\[ P_{d,j} + P_{s,j} = P_{d,j}^A \] \quad (20)
\[ \sum_{g \in \Omega_g} P_{g,j} + \sum_{r \in \Omega_r} P_{r,j} + \sum_{c \in \Omega_c} P_{c,j}^D = \sum_{d \in \Omega_d} P_{d,j} + \sum_{c \in \Omega_c} P_{c,j}^C \] \quad (21)

Where: \( P_{d,j}, P_{s,j}^A \) and \( P_{d,j}^A \) are the served load demand, load shedding and the maximum load.

### 4. Numerical results

In this section, the proposed unified rolling dispatch model was compared with the traditional dispatch method. The test system used in our case is a real provincial system in northwest China, some data is gained base on the forecast for the 2025. The installed capacity proportion of different types of unit is shown in Table 1.

| Proportion/% | Thermal Unit | Hydro Unit | Wind Unit | PV Unit | ESS |
|--------------|--------------|------------|-----------|--------|-----|
| 65           | 2            | 14         | 15        | 4      |

We can see in the Table 1, the capacity of RE units makes up 31\% of the total capacity. We select one day in the history data as the typical scenario, which is shown in Figure 2.

**Figure 2.** Power variation in typical scenario.
The comparable experiments will be implementer, which will compare the performance of three different dispatch mode in the typical scenario. All experiments are implemented on a PC with i7-6700 3.4GHz CPU and 16 GB RAM. The Solver is Gurobi 8.1.1, we set dual gap to 0.002 to save the computing time.

Three cases were implemented. Case A uses the traditional mode, which decides the commitment day ahead and the base generation of the slow unit, and the real time generation of all unit base on principles of steady. Case B uses the rolling dispatch mode without time sections clustering method. Case C uses the rolling dispatch mode proposed in this paper. All cases use the same boundary condition. The forecast error can be generated using the sample method shown in [10], which is derived by Gaussian distribution, the mean value is zeros and the mean square error is:

$$\sigma_i = \sigma \cdot \bar{P}_{r,i} \cdot \left(1 + e^{(T-t)} \right)$$

(22)

Where: $\sigma$ is a constant parameter. The experiments’ result is shown in Table 2.

| Table 2. Proportion of different types unit |
|-------------------------------------------|
| Total cost/Y | Case A | Case B | Case C |
| Wind curtailment rate/% | 2.217 | 0.015 | 0.219 |
| Solar curtailment rate/% | 0.41 | 0 | 0 |
| Computing time/S | 224 | 26144 | 1396 |

We can see in Table 2, compared with the Case using the rolling dispatch method, Case A suffers higher operation costs because the day-ahead dispatch schedules are misguided by forecast error. The intraday dispatch based on day-ahead schedules can adjust to real time RE variations, but deviate from the global optimum. Which can be reflected by the RE curtailment rate, Case A performed bad compared with other two cases. However, Case A only build a long-term model in day-ahead step while a myopic model within a day, the total computing time is shorter than other cases. Benefited from the time sections clustering method, Case C reduces the scale of optimization model significantly, which causes the shorter computing time. While the adaptive method reserves the original characters of power data, so the dispatch results are similar to Case B, which is the best operation result.

5. Conclusion

In this paper, we propose a rolling dispatch method with adaptive time resolution clustering method and an extended time horizon, which can avoid the disadvantages in traditional dispatch model. The numerical experiments show that the proposed method could reduce the computing time while maintaining accuracy. Note that, the rolling dispatch framework proposed by this paper can be adopted to other optimization method, for example, robust optimization or stochastic optimization. In future research, we will study the time sections clustering method considering uncertainty.

6. References

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