

Improving wind power utilisation under stormy weather condition by risk-limiting unit commitment

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Published in *The Journal of Engineering*; Received on 11th October 2017; Accepted on 2nd November 2017

Abstract: Wind power generation has constituted a major body of generation portfolio in many countries. In stormy weather conditions, however, wind power generation would be curtailed due to the over-speed protection of wind turbines. In this study, the authors propose to apply the risk-limiting unit commitment (UC) in a rolling framework to improve the efficient utilisation of wind power. The proposed method includes three modules, namely, day-ahead UC, hourly-ahead UC, and real-time load shedding. The first module provides the baseline of hourly dispatch, whereas the latter two serve as recourse means applied during stormy event unfolding. Illustrative examples are provided, demonstrating that the proposed method will reduce the overall generation cost of the time horizon under consideration, as compared to conservative dispatch methods, by postponing the timing of proactive wind curtailment.

1 Introduction

Wind power generation has been playing an important role in the generation portfolio across the world. For example, in 2015, annual wind power installations had reached 63 GW globally, increased by 22% as compared to 2014. Meanwhile, 433 GW wind power generation had been installed globally by the end of last year, a cumulative 17% increase [1]. A total of 12.5 GW of new wind power capacity was installed and grid-connected in the EU during 2016. Wind power had accounted for about 51% of total power capacity in the EU [2]. Over 54 GW wind power was installed globally in 2016, a cumulative 12.8%, reaching a total of 486.8 GW [3].

The variability and uncertainty of wind power impose great challenges in operation of electric power grids. Particularly, in stormy weather conditions, the output of wind farms being hit by the storm will drop significantly due to the shutdown of wind turbines. For example, in the storm of January 2005, the output of wind farm in Denmark dropped by 80% in 6 h [4]. Under extreme weather conditions, the operational resilience of electric power grids with significant wind power generation has become a major concern.

This paper aims to improve wind power utilisation during stormy weather events by identifying optimal timing and amount for wind curtailment. Two extreme cases are given as follows to motivate our work. On the one hand, if the wind farm that will be hit by the storm is shut down in advance far from the advent of the storm, wind power will be curtailed in vain. On the other hand, if the wind farm is shut down reluctantly during the storm unfolds, the sharp decrease in a generation may lead to emergent load shedding (LS) for power balance. In this perspective, we propose a risk-limiting (RL) unit commitment (UC) method to achieve a trade-off between efficient utilisation of wind power and operational resilience of electric power grids under stormy weather conditions.

Our proposed RL method consists of three building blocks, namely, day-ahead UC, hourly-ahead UC for fast-start units, and wind curtailment/LS as emergency measures. By continuously updating the storm front prediction, these building blocks are applied

in a sequential manner yet collaboratively to achieve the optimality over the time horizon being considered, i.e. minimising the expectation of operational cost during stormy events. The operational cost includes the fuel cost, start-up/operation cost of quick-start units, and the loss due to wind curtailment or LS.

The remaining of this paper is structured as follows. The RL dispatch methodology is briefly reviewed in Section 2. The proposed RL UC method is elaborated in Section 3. Illustrative examples are provided in Section 4 to demonstrate the merits of our proposed methodology. We conclude our work with discussions in Section 5.

2 Methodology of RL dispatch

Several methodologies have been successfully applied to solve power dispatch problems with significant uncertainty, such as scenario-based stochastic programming, look-ahead dispatch, and RL dispatch [5].

2.1 Scenario-based stochastic programming

Scenario-based stochastic programming consists of three major steps. The first step is to sample continuous probability density function into discrete scenarios. An $s(t)$ continuous probability can be sampled into N points with different probabilities. Each point is described as $s_i(t) (i \in \{1, \dots, N\})$.

The second step is to build a scenario tree. We use t to denote a time interval within the entire time horizon, i.e. $t \in \{1, \dots, T\}$. The first step is repeated for each time interval t , the scenario tree is then formed for the entire time horizon. Each branch in this tree represents a scenario.

Finally, the stochastic optimisation model is constructed to minimise the operational cost under the scenario tree.

2.2 Look-ahead dispatch

Look-ahead dispatch uses model predictive control (MPC) to deal with the dynamic receding horizon optimisation control problem. The MPC uses stochastic model to deal with uncertainty problem.

This method is capable to reduce static error and compensate the random terms in the model.

At each stage, the system operators determine operations of current period by predicting n steps ahead and update prediction with coming information. A multi-stage optimisation model is solved and the action on the first stage is implemented. At the next period, the similar procedure is repeated. As time goes on, a number of optimisation models have been solved by rolling forward until the final period.

The advantage of look-ahead dispatch is rolling forward. The operator can use the updated information to decide the optimal operation. However, the strategy of look-ahead dispatch is not globally optimal as far as the entire time horizon is concerned.

2.3 RL dispatch

RL dispatch also uses dynamic strategies to the solved stochastic problem. RL dispatch reduces the uncertainty risk by adding a series of recourse decisions between the initial stage and the final stage. And the final stage can be a single time point or a time horizon. On condition that adequate prediction information is obtained, RL dispatch is able to find the global optimal scheduling strategy. At the recourse stages, the operation strategies are revised with updated prediction information. The prediction information is modelled using conditional probability. The recourse means are calculated to safeguard potential risks. The model of RL dispatch is shown as below:

$$\text{Min } E \left\{ s_1 c_1 + \sum_{i=2}^{n-1} s_i c_i + s_n c_n \right\} \quad (1a)$$

$$\text{s.t. } P \left\{ \left(s_1 + s_n + \sum_{i=2}^{n-1} s_i + s_w = d \right) | Y_n \right\} \geq \eta \quad (1b)$$

where s_1, c_1 are the power of unit and the operating cost of unit at the initial stage, respectively, s_i and c_i are the unit's power and the operating cost of unit at i recourse stage, respectively. s_n and c_n are the power of unit and the operating cost of unit at the final stage, respectively. s_w is the power of wind, d is the power demand and Y_n is the prediction information in stage n .

RL dispatch comprises three features. The first feature is that it can reduce the computation complexity. And risk index can change with the operation requirements; it brings more flexibility on solving operation problem. Second, this methodology uses dynamic strategies to solve stochastic problems. Third, the strategy of RL is the global optimal, if providing the conditional probability of renewable energy. The advantages of RL dispatch are very obvious, so it often is used to solve some actual problems.

Particularly, the RL dispatch methodology has gained much research attention in renewable energy integration to the electric power grids owing to its desirable features [6, 7]. In [8–10], RL dispatch is applied to determine the price of uncertainty and the price of renewable energy sources. In [11], RL dispatch is employed to integrate renewable energy sources with ramping products. In [12], multi-period RL dispatch is proposed for large-scale renewable integrations. RL methodology has also been applied to active distribution system [13], load scheduling [14], and energy storage dispatch [15]. Solution methods to solve RL dispatch are also developed to account for realistic operational constraints [16] and congested transmission networks [17, 18].

In this work, the RL dispatch methodology is applied to improve the wind power utilisation under stormy weather conditions due to the following considerations. First, RL methodology allows inserting recourse actions (i.e. starting up quick-start units and emergent LS) in between multi-stage dispatch. In other words, hourly-ahead and real-time dispatch can be applied during the stormy event unfolding. Second, the prediction accuracy for the storm front and its intensity can be improved gradually. As a result, recourse actions within the RL dispatch methodology can be established more accurately and

less conservative. Third, the amount of LS can be restricted by the RL constraints. That is, a trade-off between reliability and economy of generation dispatch can be achieved by the proposed method.

3 RL UC

Our proposed RL UC method consists of three building blocks, namely, day-ahead UC, hourly-ahead UC, and real-time LS program.

Day-ahead UC aims to compute the power and state of normal units and quick-start units during 24 h. And the state of normal unit and quick-start units are the precondition of units in hourly-ahead UC. Hourly-ahead UC acts for getting power and state of these units during six hours before the storm by update prediction information. Real-time LS will adopt an emergency dispatching strategy in case wind generation drop unexpectedly sharp.

We elaborate the aforementioned models as follows.

3.1 Day-ahead UC

Day-ahead UC model is composed of one units' cost objective function and some constraints. The objective includes quadratic cost, linear cost, fixed cost and startup/shutdown cost. The constraints include unit generation constraints, the system power balance constraints, unit ramping up/down constraints, units startup/shutdown cost constraints. Four samples are involved with this model. Each sample represents a situation of prediction information of units running in 24 h.

3.1.1 Mathematical model of day-ahead UC: The model for day-ahead UC is formulated as (2a)–(2k). The objective function (2a) is a quadratic formulation of the cost of day-ahead UC. Equations (2b) and (2c) are the formulas of the total startup/shutdown cost. The first inequality (2d) means that real power generation of the unit cannot be over the upper limit of unit power, and should not be lower than the lower limit of unit power. The second equality is the system power balance constraints (2e). We can know that the power generation of the unit between two adjacent moments should be considered only when the state of the unit is all start from (2f) to (2g). If one unit's state is start or stop, it must keep the same state at a period time, according to (2h) and (2i). The startup/shutdown cost must be positive (2j) and (2k).

(i) Objective function

$$\text{Min Objective}_{\text{day-ahead}} = as^2 + bs + c_s + c_{\text{up}} + c_{\text{down}} \quad (2a)$$

(ii) Unit startup/shutdown cost

$$c_{\text{up}} = \sum_{i=1}^{\text{NG}} \sum_{t=1}^{\text{DT}} [I_{i,t} - I_{i,t-1}] \times c_i^{\text{up}} \quad (2b)$$

$$c_{\text{down}} = \sum_{i=1}^{\text{NG}} \sum_{t=1}^{\text{DT}} [I_{i,t-1} - I_{i,t}] \times c_i^{\text{down}} \quad (2c)$$

(iii) Unit generation constraints

$$s_i^{\text{min}} \times I_{i,t} \leq s_{i,t} \leq s_i^{\text{max}} \times I_{i,t} \quad (2d)$$

$$(i = 1, \dots, \text{NG}; t = 1, \dots, \text{DT})$$

(iv) The system power balance constraints

$$\sum_{i=1}^{\text{NG}} (s_{i,t} \times I_{i,t}) + s_{w,t}^f = s_{d,t}^D + s_{l,t}^D \quad (i = 1, \dots, \text{NG}) \quad (2e)$$

(v) Unit ramping up/down constraints

$$s_{i,t} - s_{i,t-1} \leq [1 - I_{i,t}(1 - I_{i,t-1})]UR_i + I_{i,t}(1 - I_{i,t-1})s_i^{\min} \quad (2f)$$

$$s_{i,t-1} - s_{i,t} \leq [1 - I_{i,t-1}(1 - I_{i,t})]DR_i + I_{i,t-1}(1 - I_{i,t})s_i^{\min} \quad (i = 1, \dots, NG; t = 1, \dots, DT) \quad (2g)$$

(vi) Unit minimum on/off time constraints

$$[X_{i,t-1}^{\text{on}} - T_i^{\text{on}}] \times [I_{i,t-1} - I_{i,t}] \geq 0 \quad (2h)$$

$$[X_{i,t-1}^{\text{off}} - T_i^{\text{off}}] \times [I_{i,t} - I_{i,t-1}] \geq 0 \quad (i = 1, \dots, NG; t = 1, \dots, DT) \quad (2i)$$

(vii) Unit startup/shutdown cost constraints

$$[I_{i,t} - I_{i,t-1}] \times c_i^{\text{up}} \geq 0 \quad (2j)$$

$$[I_{i,t-1} - I_{i,t}] \times c_i^{\text{down}} \geq 0 \quad (i = 1, \dots, NG; t = 1, \dots, DT) \quad (2k)$$

In the above model, a is the coefficient of the quadratic item, b is the coefficient of the linear item. s is a generation of the generating unit. c_s is the fixed cost of the unit. c_{up} and c_{down} are the total startup and shutdown costs, respectively. s_i^{max} and s_i^{min} are the upper limit of real power generation of the unit i , respectively. $s_{i,t}$ is the generation of the unit i in time t . $I_{i,t}$ is commitment state of the unit i at time t . c_i^{up} and c_i^{down} are the cost of units starting and stopping of the unit i , respectively. $X_{i,t}^{\text{on}}$ and $X_{i,t}^{\text{off}}$ are ON time and OFF time of unit i at time t , respectively. T_i^{on} and T_i^{off} are minimum ON time and minimum OFF of unit i , respectively. $s_{w,t}^{f1}$ is the forecasted generation of wind power unit at the time t of day-ahead UC. $s_{d,t}^D$ is system demand at the time t of day-ahead UC. $s_{l,t}^D$ is system losses at the time t of day-ahead UC. DT is the number of periods under 24 h. NG is the number of units. UR_i is the ramp-up rate limit of the unit. DR_i is the ramp-down rate limit of the unit.

3.2 Hourly-ahead UC

Hourly-ahead UC model includes cost objective function and some constraints. The form and meaning of objective function and constraints are similar to them in day-ahead UC. However, the time horizon of hourly-ahead is six hours and the space of time between two adjacent sampling points is a half hour. Four samples are involved in this model. Each sample represents a situation of prediction information of units running in 6 h. Samples have different probabilities. The value of samples should be higher than them of day-ahead UC.

3.2.1 Mathematical model of hourly-ahead UC: The model of hourly-ahead UC is similar to day-ahead UC.

(i) Objective function

$$\text{Min Objective}_{\text{hourly-ahead}} = as^2 + bs + c_s + c_{\text{up}} + c_{\text{down}} \quad (3a)$$

(ii) Unit startup/shutdown cost

$$c_{\text{up}} = \sum_{i=1}^{\text{NG}} \sum_{t=1}^{\text{HT}} [I_{i,t} - I_{i,t-1}] \times c_i^{\text{up}} \quad (3b)$$

$$c_{\text{down}} = \sum_{i=1}^{\text{NG}} \sum_{t=1}^{\text{HT}} [I_{i,t-1} - I_{i,t}] \times c_i^{\text{down}} \quad (3c)$$

$$(i = n, \dots, NG; t = 1, \dots, HT)$$

(iii) Unit generation constraints

$$s_i^{\min} \times I_{i,t} \leq s_{i,t} \leq s_i^{\max} \times I_{i,t} \quad (i = 1, \dots, NG; t = 1, \dots, HT) \quad (3d)$$

(iv) The system power balance constraints

$$\sum_{i=1}^{\text{NG}} (s_{i,t} \times I_{i,t}) + s_{w,t}^{f2} = s_{d,t}^H + s_{l,t}^H \quad (i = 1, \dots, NG) \quad (3e)$$

(v) Unit ramping up/down constraints

$$s_{i,t} - s_{i,t-1} \leq [1 - I_{i,t}(1 - I_{i,t-1})]UR_i + I_{i,t}(1 - I_{i,t-1})s_i^{\min} \quad (3f)$$

$$s_{i,t-1} - s_{i,t} \leq [1 - I_{i,t-1}(1 - I_{i,t})]DR_i + I_{i,t-1}(1 - I_{i,t})s_i^{\min} \quad (i = n, \dots, NG; t = 1, \dots, HT) \quad (3g)$$

(vi) Unit minimum on/off time constraints

$$[X_{i,t-1}^{\text{on}} - T_i^{\text{on}}] \times [I_{i,t-1} - I_{i,t}] \geq 0 \quad (3h)$$

$$[X_{i,t-1}^{\text{off}} - T_i^{\text{off}}] \times [I_{i,t} - I_{i,t-1}] \geq 0 \quad (i = n, \dots, NG; t = 1, \dots, HT) \quad (3i)$$

(vii) Unit startup/shutdown cost constraints

$$[I_{i,t} - I_{i,t-1}] \times c_i^{\text{up}} \geq 0 \quad (3j)$$

$$[I_{i,t-1} - I_{i,t}] \times c_i^{\text{down}} \geq 0 \quad (i = n, \dots, NG; t = 1, \dots, HT) \quad (3k)$$

$s_{w,t}^{f2}$ is the forecasted generation of wind power unit at the time t of hourly-ahead UC. $s_{d,t}^H$ is system demand at the time t of hourly-ahead UC. $s_{l,t}^H$ is system losses at the time t of hourly-ahead UC. HT is the number of periods of this model. In this model, we suppose quick-start units are the unit n to unit NG. The meaning of other variables and parameters is similar to them of day-ahead UC.

It should be noted the state of units at this stage. Units' state should base on the state of units of the same moment in day-ahead UC. And the normal unit state cannot change. Six hours before the storm, the system uses hourly-ahead UC.

3.3 Real-time LS

Before one hour of the storm, the system uses real-time LS to carry out the storm. There is a drastic decline in wind power in this condition. So conventional units and quick-start units must generate more power for this condition. If conventional units and quick-start units cannot carry out lacked power by wind power reducing, the system has to remove a part of the load. And there is a virtual unit for representing LS. The time horizon of real-time LS is one hour and the space of time between two adjacent sampling points is a quarter of an hour.

3.3.1 Mathematical model of real-time LS: The constraints of real-time LS are similar to day-ahead UC, whereas the load is modelled as generators with the negative output.

(i) Objective function

$$\text{MinObjective}_{\text{real-time}} = as^2 + bs + c_s \quad (4a)$$

(ii) Unit generation constraints

$$s_i^{\min} \times I_{i,t} \leq s_{i,t} \leq s_i^{\max} \times I_{i,t} \quad (i = 1, \dots, \text{NG}_r; t = 1, \dots, \text{RT}) \quad (4b)$$

(iii) The system power balance constraints

$$\sum_{i=1}^{\text{NG}_r} (s_{i,t} \times I_{i,t}) + s_w^{f3} = s_{d,t}^R + s_{l,t}^R \quad (i = 1, \dots, \text{NG}_r) \quad (4c)$$

(iv) Unit ramping up/down constraints

$$s_{i,t} - s_{i,t-1} \leq [1 - I_{i,t}(1 - I_{i,t-1})]UR_i + I_{i,t}(1 - I_{i,t-1})s_i^{\min} \quad (4d)$$

$$s_{i,t-1} - s_{i,t} \leq [1 - I_{i,t-1}(1 - I_{i,t})]DR_i + I_{i,t-1}(1 - I_{i,t})s_i^{\min} \quad (i = n, \dots, \text{NG}_r; t = 1, \dots, \text{RT}) \quad (4e)$$

s_w^{f3} is the forecasted generation of wind power unit at the time t of real-time LS. $s_{d,t}^R$ is system demand at the time t of real-time LS. $s_{l,t}^H$ is system losses at the time t of real-time LS. RT is the number of periods. NG_r is the number of units including a virtual unit. The meaning of other variables and parameters is similar to them of day-ahead UC.

In conclusion, we can create a complete model of RL UC. The mathematical model is as follows:

$$\text{Min Objective}_{\text{day-ahead}} + \text{Objective}_{\text{hourly-ahead}} + \text{Objective}_{\text{real-time}} \quad (5a)$$

$$\text{s.t. (2d) - (2k), (3d) - (3k), (4b) - (4e)} \quad (5b)$$

$$P \left\{ \left(\sum_{i=1}^n s_i + s_w = s_d + s_l \right) | Y_n \right\} \geq \eta \quad (5c)$$

where s_i is the power of all units of the stage i . s_w is the power of wind. s_d is the power demand. s_l is system losses. Y_n is the prediction information in the stage n .

4 Illustrative examples

In this section, illustrative examples are used to demonstrate the merit of the proposed method. The RL dispatch and the conventional dispatch are implemented on MATLAB with YALMIP. The MILP solver is CPLEX V.12.5.

We compare conventional dispatch and the RL dispatch during stormy weather condition. We set four conventional units and four quick-start units. There is an additional unit for simulating LS. In the conventional dispatch, we build a model for power dispatch that includes storm in the next day.

The operation cost and capacity of the quick-start units were two factors which influenced the total cost. Then we would analyse the impact of these two factors. In order to simplify the calculation, we made the parameters' value of all quick-start units same and did not change the parameters' value of the conventional units. The analysis of these two factors is as follows.

4.1 Effect of the quick-start unit capacity

In order to study the impact of the capacity of the quick-start units on the total cost, we increased the capacity of each quick-start unit from 80 to 260 mW by an increase of 20 MW per unit every time. We define r is the ratio of the cost of conventional dispatch and the RL dispatch to represent the advantage of RL dispatch compared with conventional dispatch. The computational results are given below.

According to Figs. 1 and 2, the decrease of the cost in the two dispatch methods with the increase of the capacity of the quick-start units, there was an obvious advantage in the utilisation of wind power in the RL dispatch compared with the conventional dispatch. There was no change in the cost of the conventional dispatch when the capacity of each unit increased over 200 MW because the total

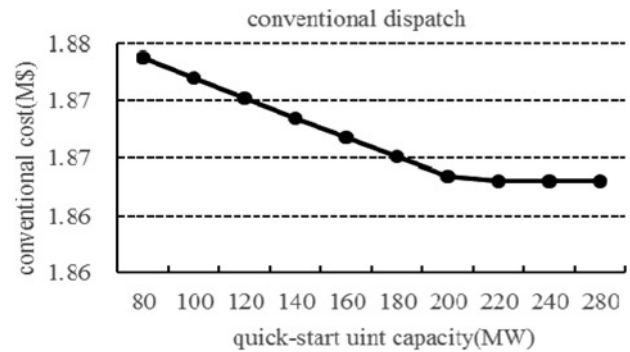


Fig. 1 Trend of cost of conventional dispatch in capacity effect

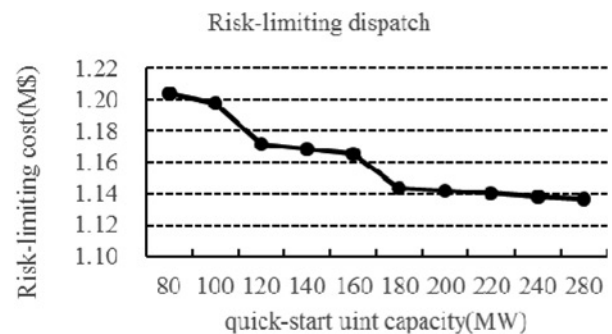


Fig. 2 Trend of cost of RL dispatch in capacity effect

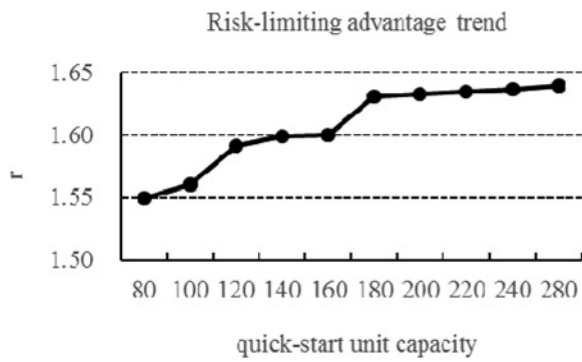


Fig. 3 Trend of advantage of RL dispatch in capacity effect

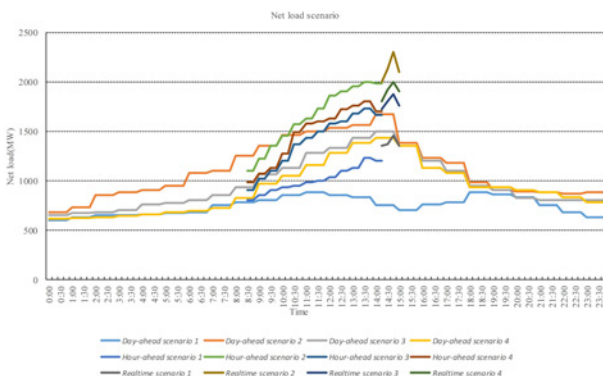


Fig. 4 Net load scenario

amount of power generated by all units was sufficient to deal with the storm, and there was no demand of the LS. According to Fig. 3, with the increase of the capacity of the quick-start units, there were more and more advantages in the RL dispatch compared with the conventional dispatch. Next, we would study the impact of the operation cost of the quick-start units on the total cost of scheduling. The net load scenario is shown in Fig. 4.

4.2 Effect of the operation cost of the quick-start unit

For ease of demonstration, we studied only the linear cost and the quadratic cost of the units on the total cost. Similarly, the conventional units' parameters were constant, and perturb the linear cost and the quadratic cost of the quick-start unit from 100 to 30% by a decrease of 10% simultaneously. We use the per-unit value to indicate the linear cost and quadratic cost. The cost in the initial stage is the baseline value. Similarly, we define r is the ratio of the cost of conventional dispatch and the RL dispatch to represent the

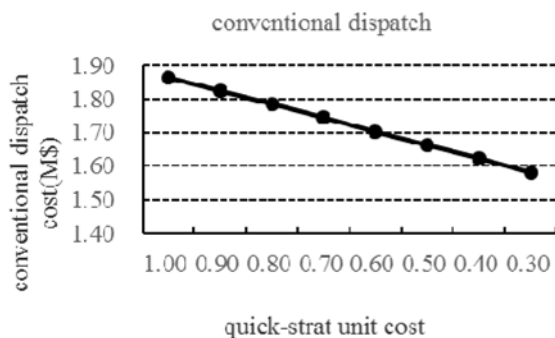


Fig. 5 Trend of cost of conventional dispatch in unit cost effect

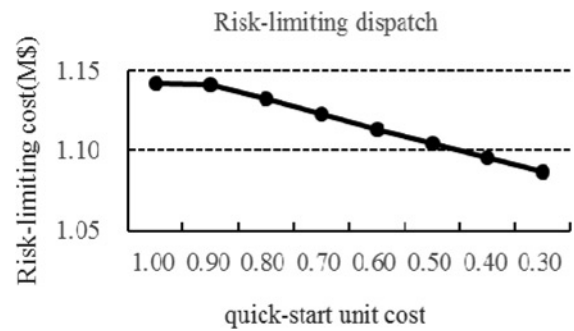


Fig. 6 Trend of cost of RL dispatch in unit cost effect

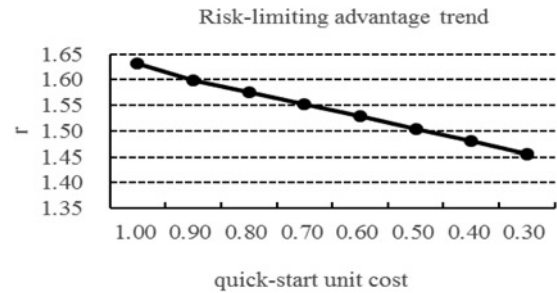


Fig. 7 Trend of advantage of RL dispatch in capacity effect

advantage of RL dispatch compared with conventional dispatch. The calculation result is as follows.

According to Figs. 5 and 6, with the reduction of the linear cost and the quadratic cost of the quick-start unit simultaneously, the total cost in the two kinds of scheduling methods is decreased. There were obvious advantages in the RL dispatch compared with the conventional dispatch. According to Fig. 7, these advantages would shrink as the cost of quick-start units decreased.

5 Conclusions

In this paper, we propose a RL UC model to improve the efficient utilisation of wind power generation in stormy weather conditions. Our proposed method constructs a sequential operational strategy with continuous update of storm front and intensity information. Therefore, the proactive wind curtailment is postponed and the risk of LS is restricted. Our major findings are twofold. On the one hand, the RL dispatch method is superior to conservative strategies (i.e. considering severe scenarios in advance) if quick-start units are available. On the other hand, such superiority will reduce if the linear cost and the quadratic cost of quick-start units decrease concurrent with the same range. Further work will study the composite effect of cost and capacity of quick-start units on the RL dispatch method.

6 Acknowledgements

This work was supported by the start-up funding from Guangxi University.

7 References

- [1] Global Wind Energy Council: 'Global wind report: annual market update 2015', 2016. Available at <http://www.gwec.net/publications/global-wind-report-2/global-wind-report-2015-annual-market-update/>
- [2] Wind Europe: 'Wind in power 2016 European statistics', 2017. Available at <https://windeurope.org/wp-content/uploads/files/about-wind/statistics/WindEurope-Annual-Statistics-2016.pdf>

- [3] Global Wind Energy Council: 'Global wind report 2016: annual market update', 2017. Available at <http://www.gwec.net/publications/global-wind-report-2/global-wind-report-2016/>
- [4] Wind Energy Association: 'Powering Europe: wind energy and the electricity grid', 2010. Available at http://www.ewea.org/fileadmin/ewea_documents/documents/publications/reports/Grids_Report_2010.pdf
- [5] Peng C., Lei S., Hou Y., *ET AL.*: 'Uncertainty management in power system operation', *CSEE J. Power Energy Syst.*, 2015, **1**, (1), pp. 28–35
- [6] Varaiya P.P., Wu F.F., Bialek J.W.: 'Smart operation of smart grid: risk-limiting dispatch', *Proc. IEEE*, 2011, **99**, (1), pp. 40–57
- [7] Qin J., Zhang B., Rajagopal R.: 'Risk limiting dispatch with ramping constraints'. 2013 IEEE Int. Conf. Smart Grid Communications (SmartGridComm), 2013, pp. 791–796
- [8] Zhang B., Rajagopal R., Tse D.: 'Network risk limiting dispatch: optimal control and price of uncertainty', *IEEE Trans. Autom. Control*, 2014, **59**, (9), pp. 2442–2456
- [9] Wu C., Hug G., Kar S.: 'Risk-limiting economic dispatch for electricity markets with flexible ramping products', *IEEE Trans. Power Syst.*, 2016, **31**, (3), pp. 1990–2003
- [10] Puggelli A., Sangiovanni-Vincentelli A.L., Seshia S.A.: 'Robust strategy synthesis for probabilistic systems applied to risk-limiting renewable-energy pricing'. 2014 Int. Conf. Embedded Software (EMSOFT), 2014, pp. 1–10
- [11] Yo M., Ono M., Williams B.C., *ET AL.*: 'Risk-limiting, market-based power dispatch and pricing'. 2013 European Control Conf. (ECC), 2013, pp. 3038–3045
- [12] Peng C., Hou Y., Yu N., *ET AL.*: 'Multiperiod risk-limiting dispatch in power systems with renewables integration,' *IEEE Trans. Ind. Inf.*, vol. **13**, no. 4, pp. 1843–1854, 2017
- [13] Georgiev D., Janeček E.: 'Risk limiting dispatch with optimal curtailing in active distribution networks'. 2013 European Control Conf. (ECC), 2013, pp. 3046–3052
- [14] Bahlke F., Liu Y., Pesavento M.: 'Stochastic load scheduling for risk-limiting economic dispatch in smart microgrids'. 2016 IEEE Int. Conf. Acoustics, Speech and Signal Processing (ICASSP), 2016, pp. 2479–2483
- [15] Qin J., Su H.I., Rajagopal R.: 'Storage in risk limiting dispatch: control and approximation'. 2013 American Control Conf., 2013, pp. 4202–4208
- [16] Gang H., Yunfeng W., Yingkai B., *ET AL.*: 'Comprehensive decoupled risk-limiting dispatch'. 2015 IEEE Power & Energy Society General Meeting, 2015, pp. 1–5
- [17] Rajagopal R., Tse D., Zhang B.: 'Risk limiting dispatch in congested networks'. 2012 50th Annual Allerton Conf. Communication, Control, and Computing (Allerton), 2012, pp. 1900–1907
- [18] Zhang B., Rajagopal R., Tse D.: 'Risk limiting dispatch in congested networks'. 52nd IEEE Conf. Decision and Control, 2013, pp. 7568–7575