Energy Engineering

Tech Science Press

DOI: 10.32604/ee.2022.022217

EDITORIAL

Key Optimization Issues for Renewable Energy Systems under Carbon-Peaking and Carbon Neutrality Targets: Current States and Perspectives

Bo Yang[1], Zhengxun Guo[1], Jingbo Wang[1,*], Chao Duan[2], Yaxing Ren[3] and Yixuan Chen[4]

[1]Faculty of Electric Power Engineering, Kunming University of Science and Technology, Kunming, China

[2]Department of Physics and Astronomy, Northwestern University, Illinois, USA

[3]Warwick Manufacturing Group, The University of Warwick, Coventry, UK

[4]The University of Hong Kong, Hong Kong, China

[*]Corresponding Author: Jingbo Wang. Email: JingboWang96@outlook.com

Received: 28 February 2022 Accepted: 14 April 2022

KEYWORDS

Carbon-peaking and carbon neutrality targets; renewable energy; optimization modeling; power forecast; planning and dispatching; reliability and security analysis

1 Introduction

The United States, Japan, Canada, the European Union, and other developed countries and regions have all formulated climate strategies and pledged to achieve net-zero CO_2 emissions by 2050. China, meanwhile, has announced through the "carbon-peaking and carbon neutrality targets" in September 2020 that it aims to achieve "peak carbon use" by 2030 and "carbon neutrality" by 2060 [1]. According to statistical data from the International Energy Agency (IEA), Fig. 1 illustrates the carbon intensity of electricity generation in various regions in the Announced Pledge Scenario (APS) from 2010 to 2040 [2]. One can easily observe that each region aims to accomplish a sharp decrease in the carbon intensity of electricity generation after 2020.

Thus far, traditional fossil fuels, e.g., coal, oil, and natural gases, are still the main resources of power generation, which have witnessed a dramatic depletion. Besides depletion, greenhouse gases that cause many environmental problems are produced as well [3]. Therefore, various renewable energies (wind, photovoltaic, hydropower, biomass, geothermal, wave energy, etc.) have become the most promising candidates for energy conservation and emission reduction [4], upon which Table 1 shows the installed renewable capacity of representative regions in 2020 [5]. In general, the current energy structure and power generation models have achieved a rather dramatic transformation.

Due to the inherently strong intermittent and volatile characteristics of renewable energy, the integration of large-scale renewable energy leads to a series of tricky issues for current power systems, i.e., (a): Accurate modeling of large-scale integrated systems; (b): Precise power forecast of renewable energy; (c): Optimal planning and dispatching of distributed generation; (d): Reliability and security analysis of renewable energy systems and grid and so on [5–7]. It is difficult yet crucial to undertake some advanced techniques in the modern power system to ensure the power generation output can be well optimized and completely sufficient. Hence, the exploitation and implementation of various advanced techniques to deal with the consumption and optimization of renewable energy systems are imperative. This paper provides a comprehensive and systematic statement regarding the above problems, and proposes several promising perspectives for further study.

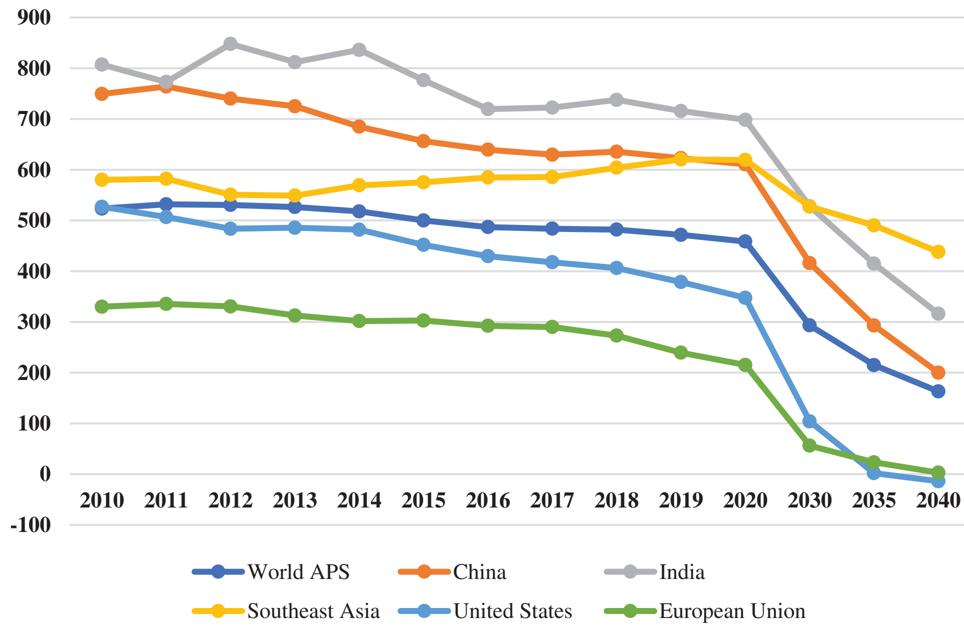

Figure 1: Carbon intensity of electricity generation in various regions in APS from 2010 to 2040

Table 1: Installed renewable capacity of representative regions in 2020 (GW)

Items	Hydropower	Ocean energy	Wind energy	Photovoltaic	Biomass	Geothermal
China	370.2	0.005	282.0	258.3	18.7	0.02
EU	156.4	0.243	201.3	150.5	41.8	1.65
USA	310.6	0.020	117.7	73.8	12.0	2.58
World	1332.9	0.527	732.4	709.7	127.2	14.01

2 The Current States of Key Issues

The integration of large-scale renewable energy into the power grid is a necessary, effective, and prospective solution for achieving both carbon-peaking and carbon neutrality targets. Nevertheless, on account of requirements of security and stability, the feasibility of renewable energy access to the power grid is usually evaluated by various simulation tests based on system models rather than actual experiments. Thus, accurate modeling is regarded as the primary challenge, which provides the model foundation for the real-time and reliable power forecasting of renewable energy. Furthermore, real-time and reliable power forecasting gives data foundation for optimal planning and dispatching. In addition, an optimal planning and dispatching scheme offers a data foundation for reliability and security analysis of renewable energy systems and grids while it requires a comprehensive evaluation by reliability and security analysis before execution. Lastly, Fig. 2 explicitly demonstrates major challenges and their inner relationships for renewable energy under carbon-peaking and carbon neutrality targets.

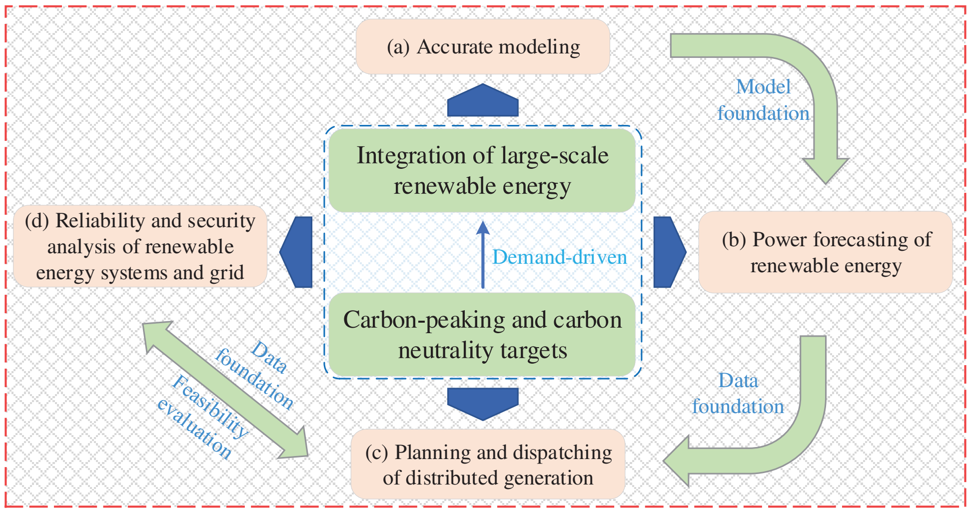

Figure 2: Major challenges and their inner relationships for renewable energy under carbon-peaking and carbon neutrality targets

2.1 Accurate Modeling

Accurate modeling is critical for simulation analysis, optimal control, fault diagnosis, and life prediction. For the sake of simplicity, it is generally transferred to the precise extraction problem of several crucial model parameters [8]. So far, various modeling methods for different renewable energies have been developed, which can be classified into the numerical method and artificial intelligence method (including meta-heuristic algorithm, machine learning, deep learning, etc.). The former mainly depends on mathematical equations and complex theory rather than numerous data, which is more intuitive but difficult to solve. On the contrary, the latter significantly depends on huge amounts of experimental data, which generally performs more accurately, with faster speeds, and powerful robustness. Thus, the artificial intelligence method has aroused wide attention around the world. In particular, references [9,10] thoroughly summarized and analyzed meta-heuristic algorithms-based modeling techniques for different photovoltaic (PV) modules. An extreme learning machine was used to implement rapid and precise modeling of PV modules [11] and solid oxide fuel cells [12] based on measurement data under various operation conditions. Kahraman et al. [13] developed a novel power density model of wind power plants by meta-heuristic prediction algorithm, which acquired higher accuracy and stability.

2.2 Power Forecasting of Renewable Energy

Power forecasting is one of the key measures to overcome a series of issues (e.g., power fluctuation, grid impact, system stability, etc.) caused by the large-scale renewable energy grid connection to construct a power prediction system with high prediction accuracy and relatively complete functions. In the past few decades, various prediction methods have been proposed based on different prediction models including physical, statistical, probabilistic as well as intelligent models [14]. The physical model-based method significantly relies on numerical weather predictions and usually requires complex computation procedures, which can obtain satisfactory performance in short-term predictions [15,16]. Meanwhile, other methods are uniformly determined as data-driven techniques, which require a large amount of historical data. Their validity and practicality have been excellently verified on different time scales in wind farms and PV stations [17–19]. However, the current power forecasting approaches of renewable energy are only validated and applied in some special operation conditions, which should be further tested in various complex and changeable scenarios. Thus, it is necessary to further improve the flexibility and adaptability of renewable energy power prediction modeling and the accuracy of prediction results. The power prediction technology will be developed to power prediction, probability prediction, and event prediction at multiple temporal and spatial scales.

2.3 Planning and Dispatching of Distributed Generation

The load demands and distributed generation are inversely distributed in many countries and regions, such as China. Hence, the planning and dispatching of distributed generation are considered common and complex problems [20]. Inspiringly, various planning and dispatching methods were presented in recent years, which are classified into deterministic methods (e.g., dynamic programming method [21], Lagrangian re-laxation method [22], etc.) and intelligence methods [23]. The objective function of the deterministic method is generally designed as a quadratic cost function, which is not suitable for its non-smooth and discontinuous search space caused by the inclusion of practical constraints. Therefore, their application is seriously limited. In addition, intelligence methods, especially those based upon meta-heuristic algorithms, are wildly applied due to their high efficiency and prominent optimization performance, such as simulated annealing (SA) algorithm [24], genetic algorithm (GA) [25], particle swarm optimization (PSO) algorithm [26], differential evolution (DE) algorithm [27], and the ant colony optimization (ACO) algorithm [23].

2.4 Reliability and Security Analysis of Renewable Energy Systems and Grid

The continued increase in the proportion of renewables improves the capacity and flexibility of the grid. Nevertheless, their intermittency and volatility potentially threatens the reliability and security of the grid or grids themselves [28,29]. Thus, it is crucial and significant to promote the implementation of low-carbon development by way of accurately analyzing and properly addressing the impact of renewable energy growth on reliability and security. Specifically, many researchers undertook quantitative analysis by calculating the capacity credit of renewable energies [30–32]. Besides, Flynn et al. [33] comprehensively analyzed the effects on voltage, frequency, small signal as well as transient stability when large-scale wind generations were connected to the grid.

3 Perspectives

Driven by the above key issues, three instructive perspectives are summarized as follows:

- The current modeling techniques mainly focus on the static modeling of a single object, such as PV, hydropower, biomass, geothermal, fuel cell, wind turbine generator, etc. The dynamic modeling of the integrated system needs to be further developed to comply with the development trend and requirements of the new and clean grid.
- A reasonable and effective planning and dispatching schedule must ensure the safe, stable, and clean operation of the grid, save the cost to the maximum extent and obtain the maximum economic benefits at the same time. Hence, it can be transferred to a multi-objective problem, which may be properly solved via multi-objective heuristic algorithms.

- With the rapid growth of big data statistics, data-driven-based techniques (e.g., neural network, machine learning, deep learning, digital twin, etc.) are regarded as efficient and promising solutions for the above issues.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present article.

References

1. Li, S. T., Li, Q., Shi, Z. P., Liu, H. Q., Tian, L. et al. (2021). Joint optimal operation of cascade hydropower stations in yandu river basin in dry season under the background of dual carbon target. *2021 IEEE 5th Conf. on Energy Internet and Energy System Integration (EI2)*, pp. 4352–4356. Taiyuan, China. DOI 10.1109/EI252483.2021.9713365.
2. IEA (2021). Carbon intensity of electricity generation in selected regions in the Announced Pledges and Net Zero scenarios, 2000–2040. https://www.iea.org/data-and-statistics/charts/carbon-intensity-of-electricity-in-selected-regions-in-the-announced-pledges-and-net-zero-scenarios-2000-2040.
3. Bogdanov, D., Ram, M., Aghahosseini, A., Gulagi, A., Oyewo, A. S. et al. (2021). Low-cost renewable electricity as the key driver of the global energy transition towards sustainability. *Energy, 227,* 120467. DOI 10.1016/j.energy.2021.120467.
4. Yang, B., Wang, J. B., Zhang, M. T., Shu, H. C., Yu, T. et al. (2020). A state-of-the-art survey of solid oxide fuel cell parameter identification: Modelling, methodology, and perspectives. *Energy Conversion and Management, 213,* 112856. DOI 10.1016/j.enconman.2020.112856.
5. IRENA (2021). Renewable energy statistics 2021. https://www.irena.org/publications/2021/Aug/Renewable-energy-statistics-2021.
6. Suman, A. (2021). Role of renewable energy technologies in climate change adaptation and mitigation: A brief review from Nepal. *Renewable and Sustainable Energy Reviews, 151,* 111524. DOI 10.1016/j.rser.2021.111524.
7. Yoro, K. O., Daramola, M. O., Sekoai, P. T., Wilson, U. N., Eterigho-Ikelegbe, O. (2021). Update on current approaches, challenges, and prospects of modeling and simulation in renewable and sustainable energy systems. *Renewable and Sustainable Energy Reviews, 150,* 111506. DOI 10.1016/j.rser.2021.111506.
8. Kim, D. E., El-Sharkawi Mohamed, A. (2015). Dynamic equivalent model of wind power plant using parameter identification. *IEEE Transactions on Energy Conversion, 31(1),* 37–45. DOI 10.1109/tec.2015.2470562.
9. Yang, B., Wang, J. B., Zhang, X. S., Yu, T., Yao, W. et al. (2020). Comprehensive overview of meta-heuristic algorithm applications on PV cell parameter identification. *Energy Conversion and Management, 208,* 112595. DOI 10.1016/j.enconman.2020.112595.
10. Lu, P., Ye, L., Zhao, Y., Dai, B., Pei, M. et al. (2021). Review of meta-heuristic algorithms for wind power prediction: Methodologies, applications and challenges. *Applied Energy, 301,* 117446. DOI 10.1016/j.apenergy.2021.117446.
11. Chen, Z., Yu, H., Luo, L., Wu, L., Zheng, Q. et al. (2021). Rapid and accurate modeling of PV modules based on extreme learning machine and large datasets of *I–V* curves. *Applied Energy, 292,* 116929. DOI 10.1016/j.apenergy.2021.116929.
12. Yang, B., Guo, Z., Yang, Y., Chen, Y., Zhang, R. et al. (2021). Extreme learning machine based meta-heuristic algorithms for parameter extraction of solid oxide fuel cells. *Applied Energy, 303,* 117630. DOI 10.1016/j.apenergy.2021.117630.

13. Kahraman, H. T., Ayaz, M., Colak, I., Bayindir, R. (2016). Applying the meta-heuristic prediction algorithm for modeling power density in wind power plant. *15th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pp. 447–451. Anaheim, USA. DOI 10.1109/ICMLA.2016.0079.
14. Ahmed, A., Khalid, M. (2019). A review on the selected applications of forecasting models in renewable power systems. *Renewable and Sustainable Energy Reviews, 100,* 9–21. DOI 10.1016/j.rser.2018.09.046.
15. Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N. et al. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. *Renewable and Sustainable Energy Reviews, 144,* 110992. DOI 10.1016/j.rser.2021.110992.
16. Richard, P., Sergey, K., James, S., Karl, H. J., David, R. et al. (2010). Validation of short and medium term operational solar radiation forecasts in the US. *Solar Energy, 84(12),* 2161–2172. DOI 10.1016/j.solener.2010.08.014.
17. Azad, H. B., Mekhilef, S., Ganapathy, V. G. (2014). Long-term wind speed forecasting and general pattern recognition using neural networks. *IEEE Transactions on Sustainable Energy, 5(2),* 546–553. DOI 10.1109/tste.2014.2300150.
18. Prema, V., Bhaskar, M. S., Almakhles, D., Gowtham, N., Rao, K. U. (2022). Critical review of data, models and performance metrics for wind and solar power forecast. *IEEE Access, 10,* 667–688. DOI 10.1109/ACCESS.2021.3137419.
19. Netsanet, S., Zheng, D. H., Zhang, W., Teshager, G. (2022). Short-term PV power forecasting using variational mode decomposition integrated with ant colony optimization and neural network. *Energy Reports, 8,* 2022–2035. DOI 10.1016/j.egyr.2022.01.120.
20. Yang, H. M., Chen, B. W., Xiang, S., Liu, J. P., Ackom, E. (2022). Distributionally robust optimal dispatch modelling of renewable-dominated power system and implementation path for carbon peak. *Computers & Industrial Engineering, 163,* 107797. DOI 10.1016/j.cie.2021.107797.
21. Sioshansi, R., Madaeni, S. H., Denholm, P. (2014). A dynamic programming approach to estimate the capacity value of energy storage. *IEEE Transactions on Power Systems, 29(1),* 395–403. DOI 10.1109/TPWRS.2013.2279839.
22. Jonathan, F. B. (1988). Short-term scheduling of thermal-electric generators using lagrangian relaxation. *Operations Research, 36(5),* 756–766. DOI 10.2307/171321.
23. Anand, K., Manoj, T., Garima, M. (2022). Planning optimal power dispatch schedule using constrained ant colony optimization. *Applied Soft Computing, 15,* 108132. DOI 10.1016/j.asoc.2021.108132.
24. Kit Po, W. (1995). Solving power system optimization problems using simulated annealing. *Engineering Applications of Artificial Intelligence, 8(6),* 665–670. DOI 10.1016/0952-1976(95)00042-9.
25. Swarup, K. S., Yamashiro, S. (2002). Unit commitment solution methodology using genetic algorithm. *IEEE Transactions on Power Systems, 17(1),* 87–91. DOI 10.1109/59.982197.
26. Gaing, Z. L. (2003). Particle swarm optimization to solving the economic dispatch considering the generator constraints. *IEEE Transactions on Power Systems, 18(3),* 1187–1195. DOI 10.1109/TPWRS.2003.814889.
27. Nasimul, N., Hitoshi, I. (2008). Differential evolution for economic load dispatch problems. *Electric Power Systems Research, 78(8),* 1322–1331. DOI 10.1016/j.epsr.2007.11.007.
28. Beyza, J., Yusta, J. M. (2021). The effects of the high penetration of renewable energies on the reliability and vulnerability of interconnected electric power systems. *Reliability Engineering & System Safety, 215,* 107881. DOI 10.1016/j.ress.2021.107881.
29. Al kez, D., Foley, A., McIlwaine, N., Morrow, D. J., Hayes, B. et al. (2020). A critical evaluation of grid stability and codes, energy storage and smart loads in power systems with wind generation. *Energy, 205,* 117671. DOI 10.1016/j.energy.2020.117671.
30. Michael, M., Kevin, P. (2006). The capacity value of wind in the United States: Methods and implementation. *The Electricity Journal, 19(2),* 91–99. DOI 10.1016/j.tej.2005.12.010.

31. Tapetado, P., Usaola, J. (2019). Capacity credits of wind and solar generation: The spanish case. *Renewable Energy, 143,* 164–175. DOI 10.1016/j.renene.2019.04.139.
32. Li, Y. X., Zhang, X. Y., Gao, W. J., Ruan, Y. J. (2020). Capacity credit and market value analysis of photovoltaic integration considering grid flexibility requirements. *Renewable Energy, 159,* 908–919. DOI 10.1016/j.renene.2020.06.054.
33. Flynn, D., Rather, Z., Ardal, A., D'Arco, S., Hansen, A. D. et al. (2016). Technical impacts of high penetration levels of wind power on power system stability. *Wiley Interdisciplinary Reviews: Energy and Environment, 6,* 1–19. DOI 10.1002/wene.216.