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Introduction to Sustainable Energy Systems

The shift toward sustainable energy systems worldwide requires new ways of overcoming the barriers of renewable intermittency and electrical grid complications together with the optimization of the resources. The potential transformation that could be brought about by artificial intelligence (AI) is that predictive analytics, real-time optimization and decision-making can be applied in the entire generation, storage and distribution networks. This chapter gives an introductory description of AI applications in the field of sustainable energy where an individual can listen to machine learning, deep learning, reinforcement learning (RL) and graph-based methods. It sheds light on the way AI can be used to improve energy efficiency, promote the use of renewable energy and help maintain the process of equitable and resilient energy management with the help of case studies and concept models. The combination of smart technologies and sustainable approaches will turn AI into one of the main factors leading to the realization of the net-zero goals and the creation of a stable, low-carbon energy future.

1.1. Introduction

The global energy landscape is undergoing tremendous change due to the efforts of individual countries to realize sustainable development and fight climate change. The shift to sustainable energy systems has become an urgent goal, which was predetermined by the necessity to decrease the emission of greenhouse gas, eliminate climate change consequences and secure energy security in the long term. Traditional energy systems, which are mostly dependent on fossil fuels like coal, oil and natural gas, have been known to offer stable and consistent energy that could be scaled. Nevertheless, their effects on the environment – such as excessive carbon

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emissions, air pollution and interference with the ecosystem – have compelled the rest of the world to consider cleaner and more renewable alternatives. Sustainable energy systems are sought to promote the combination of various sources of renewable energy, including solar, wind, hydropower, geothermal and biomass, in order to develop a balanced, resilient, environmentally responsible energy infrastructure (Catalão et al. 2011; Colak et al. 2012; Foley et al. 2012; Tascikaraoglu and Uzunoglu 2014; Du et al. 2019).

The creation of a reliable sustainable energy system is complex because renewable energy sources are generally variable and intermittent. Unlike the production of fossil-fuel-based energy that can be brought online to meet demand, the production of solar and wind energy depends on the weather conditions and diurnal cycles. Such variations pose big challenges to energy management, in terms of the stability of the grids, achieving equilibrium between supply and demand, and anticipating consumption patterns. Distributed energy resources (DERs), including rooftop solar panels and microgrids, make the management of energy flows even more complex and require real-time monitoring, adaptive control and predictive planning. The conventional energy management practices that are typically rule based, and grounded on historical trends, cannot adequately deal with these dynamic complexities. AI is a promising technology with the power to revolutionize the problem of sustainable energy systems. AI is able to predict future analytics and real-time optimization, as well as adaptive decision-making, by using advanced computational models. Machine learning models have the potential to predict demand in energy, predict the variability of renewable generation and optimize storage and distribution resource scheduling. Deep learning models are capable of identifying intricate trends in massive power data, such as intake patterns, climatic effects and generation distortions. The RL methods will be able to create adaptive control methods that constantly learn and improve based on the feedback of the system, increasing the effectiveness and stability of smart grids (Wu et al. 2013; Ouyang et al. 2019; Jahangir and Babbar 2020; Sankar et al. 2021). Furthermore, AI enables the composite activation of diverse sources of data such as IoT sensor networks, satellite images and market signals to enable a complete management of the energy system.

Operational efficiency is not the only aspect that AI will apply to sustainable energy systems. It can also assist in strategic planning and policy development, as well as decision-making on many levels, between buildings and national energy systems. Tools based on AI can be used to maximize investment in renewable infrastructure, forecast the effects of regulatory modifications and model the energy situation in different environmental and economic factors. With the ability to make decisions based on the data, AI can help the stakeholders to cut out uncertainty, enhance the use of available resources and speed up the process of transition toward a low-carbon energy future. The advantages of implementing AI in the energy system of sustainability are further upscaled, in association with other complementary technologies like energy storage and smart grid networks. Surplus renewable energy can be captured and used when there is low generation by use of energy storage such as batteries, pumped hydro and thermal storage, which overcome the problem of intermittency. Smart grids have the ability to balance loads in real-time and achieve two-way energy flows. They also allow automatic fault detection and have digital monitoring and communication capabilities. These systems can be optimized with AI algorithms to increase resilience, energy loss and operational costs, which will eventually make energy delivery more reliable and sustainable. Table 1.1 demonstrates the fundamental elements of sustainable power systems and AI contribution to make the system more efficient (Landberg 1999; Lei et al. 2009; Azad et al. 2014; Colak et al. 2015; Feng et al. 2017; Borunda et al. 2020).

Component	Description	Role of AI in enhancement
Renewable energy sources	Solar, wind, hydropower, geothermal, biomass	Forecasting generation, predicting variability, resource planning
Energy storage	Batteries, pumped hydro, thermal storage	Optimal charge/discharge scheduling, loss minimization
Smart grids	Digitized networks enabling two-way energy flow	Real-time optimization, fault detection, load balancing
Energy efficiency	Reducing consumption in buildings, industry and transport	Predictive control, consumption pattern analysis, anomaly detection
IoT and sensors	Field sensors, smart meters, satellite monitoring	Data collection, real-time monitoring, predictive analytics
Predictive and prescriptive AI	Machine learning, deep learning, reinforcement learning	Forecasting demand/supply, adaptive decision-making, optimization

Table 1.1. *The core components of sustainable energy systems and the role AI plays in enhancing their performance*

The combination of AI with these parts converts the sustainable energy systems into intelligent and adaptable infrastructures that should react to the dynamic demands of the modern management of energy. With predictive services, optimization methods and autonomous decisions, AI allows systems to perform effectively in the case of uncertainty, increase the reliability of the grid and minimize the environmental footprint. Moreover, AI-based insights are helpful in policy-making, risk management and planning as they offer stakeholders practical knowledge to promote sustainable energy projects.

1.2. Components of sustainable energy systems

Sustainable energy systems are complicated infrastructures that are created to produce, store, deliver and use energy in a manner that will result in minimum environmental damage without compromising reliability and efficiency. They are based on a number of interdependent elements, each of which is significant to achieve sustainability and resilience. The main elements are renewable energy, energy storage, smart grids and energy conservation.

1.2.1. *Renewable energy sources*

Renewable energy sources form the backbone of sustainable energy systems. Figure 1.1 shows the different types of renewable energy systems. These include the following:

– Solar photovoltaics (PV): solar power transforms sunshine into electricity and is commonly implemented both at home, and at the commercial and utility level. Solar energy is free, clean and very affordable because of technological advancements.

– Wind turbines: these utilize wind as a source of kinetic energy to produce electricity. Wind farms may be onshore or offshore and offer scalable energy solutions in various geographical locations.

– Hydropower: this is a source of electricity that uses flowing or falling water. Hydropower has the potential for energy generation as well as storage using pumped storage plants.

– Geothermal: this uses the heat that is available at the center of the earth to generate electricity or give direct heating. Geothermal energy is very dependable and available 24 hours a day, thus it is good as a baseload power.

– Biomass: this includes organic substances such as crop residues, wood and waste, which may be converted into energy by burning, gasification or biochemical conversion. Biomass reduces waste and generates renewable energy.

– Intermittency and spatial variability are some of the challenges associated with renewable energy integration. High-level forecasting models, which can be based on AI, assist in predicting the patterns of generation, as well as the usage of these resources.

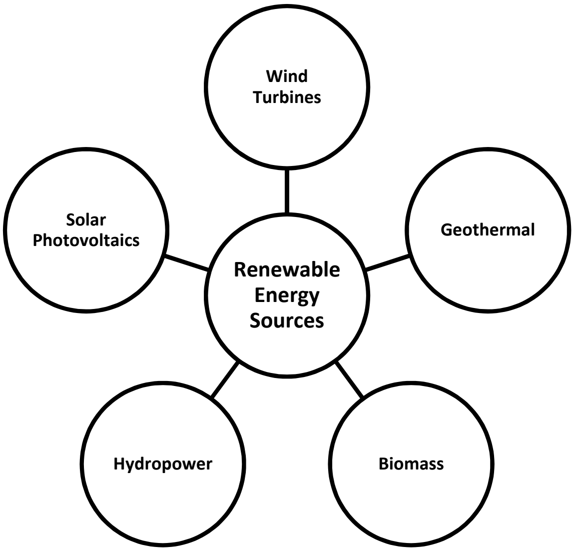

Figure 1.1. *Types of renewable energy sources*

1.2.2. *Energy storage*

Energy storage systems are essential for balancing the supply–demand fluctuations inherent in renewable energy generation. Storage technologies include the following:

– *Batteries*: lithium-ion and flow batteries are widely used for short-term storage, providing rapid response to demand peaks.

– *Pumped hydro storage*: excess electricity pumps water to elevated reservoirs, which is later released to generate power when needed.

– *Thermal storage*: it stores energy in the form of heat or cold for later use in heating, cooling or power generation applications.

– *Emerging technologies*: they include compressed air energy storage (CAES), supercapacitors and hydrogen-based storage.

Efficient storage systems ensure grid stability, allow better utilization of intermittent renewables and reduce dependency on fossil-fuel backup power.

1.2.3. *Smart grids*

Smart grids are digitally integrated electricity networks that monitor, control and optimize energy flow in real-time. They enable:

– *Two-way communication*: between utilities and consumers, facilitating demand response and dynamic pricing.

– *Grid reliability*: rapid fault detection, isolation and restoration during disturbances.

– *Integration of DERs*: seamlessly connects rooftop solar, microgrids and electric vehicles to the main grid.

– *Data analytics*: advanced AI algorithms analyze real-time sensor data for predictive maintenance, load balancing and efficient dispatch of energy resources.

Smart grids transform conventional grids into intelligent, adaptive networks capable of managing complex and decentralized energy systems.

1.2.4. *Energy efficiency*

Energy efficiency reduces energy waste and optimizes consumption across residential, industrial and transportation sectors. Key measures include the following:

– *Building energy management*: AI-based systems optimize heating, cooling, lighting and appliance usage.

– *Industrial process optimization*: it reduces energy use in manufacturing, mining and chemical processes through predictive analytics and automation.

– *Transportation efficiency*: electric vehicles, route optimization and smart charging reduce energy demand and emissions.

By lowering overall energy demand, efficiency measures complement renewable generation and storage solutions, enabling more sustainable and cost-effective energy systems.

1.3. Sustainability issues in energy

Despite impressive technological advancements, the systems of sustainable energy are being faced with diverse challenges that should be resolved to ensure that they offer reliable, efficient and low-carbon energy supply. This is all as a result of the nature renewable energy sources, infrastructures and difficulties in the areas of regulation and data management.

1.3.1. *Unpredictability of renewables*

Renewable energy sources, namely, solar and wind energy, are naturally variable as they are reliant on the weather and environmental conditions. The amount of solar energy that can be generated depends on the cloud cover and day-night cycles, while in comparison, the speed and direction of wind determines the amount of wind power generated. This intermittency poses a challenge of formation of the supply and demand real-time balance. The variability can lead to grid instability, energy shortage or overgeneration without the proper forecasting and adaptive management (Andrade and Bessa 2017). The solutions required to mitigate these fluctuations and ensure stable power supply are energy storage, demand response and predictive analytics powered by AI.

1.3.2. *Investment and infrastructure*

Transforming existing infrastructure into a sustainable energy system is a huge investment. This includes renewable generation facilities, energy storage facilities, smart grids and transmission systems that would support decentralized energy outflows. The high capital costs may be an obstacle to both developed and developing countries. Moreover, retrofitting the existing grids to enable two-way communication, automation and new monitoring should also be properly planned, approved by policy and financed in the long-run (Ramirez-Rosado et al. 2009).

1.3.3. *Policy and regulation*

The implementation of the technologies of sustainable energy is frequently hindered by disjointed policies and differentiated regulations. The differences in incentives, subsidies and technical standards in different regions may impede investment and the adoption of advanced technologies. There should be clear policy directives, supportive regulatory frameworks and international cooperation in order to hasten the integration of renewable energy and obtain the participation of the private sectors. Environmental, social and economic concerns should further be taken care of in policies to make the development of energy sustainable and fair.

1.3.4. *Data and forecasting*

The key to ensuring proper management of sustainable energy systems is the capacity to process and analyze bulk data of a heterogeneous nature from multiple sources, such as weather forecasts, energy consumption patterns and real-time grid monitoring. The proper time series prediction of renewable generation and demand is essential for operational planning, dispatching the energy and reducing the risks. Nonetheless, complex, multi-source data are difficult to manage during data collection, assurance, integration and computation. Predictive analytics, real-time monitoring and decision support can be done with the help of AI and machine learning, although their applications require specific skills and strong digital infrastructure (Hill et al. 2011).

1.4. AI in sustainable energy systems

AI technology has emerged as a disruptive technology in the field of sustainable energy, enabling the control of complex energy systems in an intelligent and data-driven manner. AI can help optimize the design, operation and control of renewable energy networks in the areas of production, storage and distribution, with the assistance of advanced algorithms. It is capable of predictive analytics, optimization, automation and integration with the Internet of Things (IoT) and edge computing, which comes in handy when it comes to dealing with the variability and complexity of sustainable energy systems.

Predictive analytics

The AI-driven predictive analytics can be utilized to predict the demand of energy, renewable generation and storage with specific accuracy. It is possible that the machine learning models can be used to predict short-term and long-term variations by using the past trends in energy consumption, weather and grid data. Such predictions help the utilities and operators to predict their energy dispatch early in advance to minimize shortages and waste.

Optimization

AI algorithms can be used to improve the performance of an energy system, making the system more stable, optimize its loads and coordinate the dispatch of distributed resources. RL and evolutionary algorithms are the search techniques with the potential of finding the most effective operational strategies for microgrids, energy storage and renewable generation plants, to make them as efficient and cost-effective as possible.

Automation

AI-driven automation facilitates the use of smart meters, demand-response and automated control of DERs. Automated systems are capable of dynamically regulating energy consumption based on the real-time conditions, lowering the peak demand and optimizing the use of energy in residential, commercial and industrial sectors.

IoT and edge computing

The synergies between AI, the IoT and edge computing enables collection, analysis and decision-making in real-time with the distributed sensors and smart devices. The edge-based AI systems handle data at the edges, eliminating latency and reliance on centralized servers, which is especially critical to remote or large-scale renewable systems. This integration will guarantee fast adaptive decisions, enhancing the reliability and resilience of the energy network. Table 1.2 demonstrates the main AI applications in sustainable energy systems.

AI capability	Description	Examples/applications
Predictive analytics	Forecast energy demand, renewable generation and storage requirements	Short-term load forecasting, solar/wind generation prediction
Optimization	Enhance grid performance, balance load and coordinate energy dispatch	Microgrid management, storage scheduling, cost optimization
Automation	Enable smart meters, demand response and autonomous control of distributed resources	Dynamic energy pricing, automated HVAC control, EV charging
Integration of IoT and edge computing	Collect and analyze real-time data from distributed sensors for rapid adaptive decision-making	

Table 1.2. *Key roles of AI in sustainable energy systems*

1.4.1. *AI techniques*

The field of AI deals with a wide range of approaches to enhance the operation, management and oversight of the sustainable energy system. Such approaches are applicable and can be used to make accurate predictions, optimize, offer adaptive control and make improved decisions in the renewable generation, energy storage and smart grid networks. Machine learning, deep learning, reinforced learning and graph neural networks (GNNs) are the key AI techniques that are applied in the domain of sustainable energy.

– Machine learning: machine learning is also common in predicting the needs of energy demand, generation and storage. ML models, including regression, classification and ensemble models, can be trained on historical data and make predictions about future trends. To give an example, electricity load and renewable energy output forecasts can be made with random forests and gradient boosting models, and anomalies in grid processes can be identified with classification models. Ensemble models can use several algorithms to enhance accuracy and strength.

– Deep learning: deep learning methods and especially neural networks are good at identifying intricate patterns in energy consumption and production data. CNNs can be used to handle the spatial data of a solar or wind farm, whereas RNNs and long short-term memory (LSTM) networks should be utilized to make time-based predictions of load and generation.

Deep learning models are able to process large amounts of heterogenous data, sensor readings, satellite images and weather predictions to make the predictions accurate and real-time.

– Reinforcement learning: maximization of dynamic energy management tasks involving energy storage dispatch, microgrid operation and balancing grid loads is optimized using RL. RL algorithms gain the best strategies by means of trial-and-error experiences within the environment and they continuously optimize their performance. As an illustration, RL can be used to select the optimal charge–discharge cycle of batteries or to organize energy transfer between distributed generation units to minimize expenses and achieve maximum efficiency.

– Graph neural networks: the model of GNNs has complex interactions in energy networks that capture the relationships between nodes, including the power plants, substations and consumption points. GNNs are specifically useful in predictive maintenance, fault detection and adaptive control of smart grids. By representing the energy system as a graph, GNNs can analyze the flow of electricity, predict potential bottlenecks and support decision-making for load distribution and renewable integration. Table 1.3 shows the applications and AI techniques used in energy systems.

AI technique	Description	Example applications
Machine learning	Regression, classification and ensemble models for prediction	Load forecasting, renewable generation prediction, anomaly detection
Deep learning	Neural networks for pattern recognition in complex data	Solar/wind output forecasting, energy consumption prediction, satellite image analysis
Reinforcement learning	Learning optimal strategies through trial-and-error interaction	Battery dispatch optimization, microgrid energy management, dynamic grid control
Graph neural networks	Modeling networked energy systems and their interactions	Smart grid monitoring, fault prediction, adaptive load balancing

Table 1.3. *AI techniques and applications in sustainable energy*

1.5. Case studies and applications

There are numerous ways in which AI can be applied to sustainable energy systems, for example, when making operational and strategic decisions. Using big, multi-source data, AI will improve energy production, delivery and use efficiency, reliability and sustainability. The subsequent paragraphs point out the most successful spheres of AI application.

1.5.1. *Smart grid optimization*

Smart grids are networks that are digitally incorporated with the monitoring and control of electricity flows in real-time. AI is of great importance in optimizing these grids since it allows us to predict loads, faults and dynamic control of energy. As an example, machine learning models can forecast peak energy demand so that grid operators can dispatch generation or storage upstream. Deep learning algorithms will be able to notice anomalies or possible failures in the distributed networks, reducing maintenance expenses and mini-outages. RL is becoming a popular means of optimizing the flow of energy in real-time in microgrids and DERs (Dowell and Pinson 2015).

1.5.2. *Renewable integration*

The unpredictability of renewable energy sources like solar and wind is problematic for predictable energy supply. The predictive models based on AI can accurately predict the renewable generation and help grid operators to balance the demand and supply. An example is LSTM networks, which are able to predict short-term solar power production when they receive weather data, whereas ensemble models can predict wind energy production over a number of hours or days. The combination of AI and storage and demand–response will guarantee that renewable energy is used effectively and avoid curtailment, as well as the necessity to rely on fossil-fuel backup power (Flores et al. 2012).

1.5.3. *Energy efficiency management*

AI helps in energy efficiency by optimizing energy consumption for the energy, which is used in homes, businesses and industries. The energy management systems that are constructed on the basis of AI are used to observe the heating, ventilation, air conditioning (HVAC), usage of lights and usage of appliances in order to reduce energy waste. In the industrial setting, AI can determine when equipment requires maintenance, run operations during off-peak periods and detect areas of inefficiency on production lines. This optimization helps to save energy money and contributes to sustainability, but does not decrease the performance.

1.5.4. *Decision support systems*

AI is also helping policymakers and energy planners make informed decisions in the transition to sustainable energy. Decision support systems use historical, environmental, economic and technological information to compare various energy scenarios. These systems assist in determining the best places of deployment of renewable, determining policy impacts, efficient allocation of resources and simulating long-term effects of strategic interventions. AI also improves the accuracy of planning by giving practical information, and speeds up the process of implementing strategies of sustainable energy (Yuan et al. 2016).

1.6. Future directions

The extent to which AI can be implemented into sustainable energies remains to be developed, and a lot of opportunities to increase efficiency, resilience and sustainability await exploration. The future is directed toward enhancing transparency, simulating, optimizing resources and providing equitable access to energy. Such innovations would solve the current constraints and introduce smarter and adaptive energy systems.

1.6.1. *Explainable AI (XAI)*

Transparency and interpretability are of great importance as AI-driven systems gain increasing power in energy operations and policy decisions. Explainable AI (XAI) offers information about how models make predictions and recommendations, and enables stakeholders to interpret, trust and justify AI decisions. XAI can be used to explain the basis behind load forecasts, renewable generation predictions or energy dispatch recommendations in energy systems, and hold people accountable and comply with regulations.

1.6.2. *Digital energy systems twins*

Digital twins refer to virtual models of real-life energy systems that replicate, analyze and optimize real-time operations. With the combination of AI and digital twins, operators are able to test the situation and predict failures, as well as assess operational strategies, without endangering real equipment or interrupting energy delivery. An example is a digital twin of a solar farm or smart grid that can simulate the effect of weather variations, demand variability or equipment failures on operation and then perform proactive maintenance and operational efficiency.

1.6.3. *Circular economy integration*

Circular economy principles can be applied to sustainable energy systems and include the efficiency of the resources, the recycling process and the reduction of waste. AI can be used to optimize the use of materials in energy production and storage technology, handle end-of-life technology and achieve energy-efficient production. As an example, AI will be able to predict battery degradation in storage systems; therefore, it is capable of timely recycling or reusing it to increase asset life and minimize environmental impact.

1.6.4. *AI for energy equity*

Equitable access to sustainable energy can also be encouraged by AI so that disadvantaged populations will be served by the deployment and efficiency of renewable energy. Algorithms have the ability to detect areas with limited access, distribute energy and reduce social and environmental risks. AI enables efficient, sustainable and equitable policies and strategies by relying on social, environmental and operational data.

1.7. Conclusion

The future of sustainable energy systems is AI, which allows smarter approaches to generation, distribution and consumption based on data. Thanks to predictive analytics, optimization and autonomous decision-making, AI enables the shift toward resilient, low-carbon and equitable energy systems. The coming together of AI and sustainable energy is one pathway of critical importance toward reaching net-zero goals and creating an energy ecosystem for the future, one that is environmentally friendly and sustainable.

1.8. References

Andrade, J.R. and Bessa, R.J. (2017). Improving renewable energy forecasting with a grid of numerical weather predictions. *IEEE Transactions on Sustainable Energy*, 8(4), 1571–1580.

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.

Borunda, M., Rodríguez-Vázquez, K., Garduno-Ramirez, R., de la Cruz-Soto, J., Antunez-Estrada, J., Jaramillo, O.A. (2020). Long-term estimation of wind power by probabilistic forecast using genetic programming. *Energies*, 13(8), 1885.

Catalão, J.P.S., Pousinho, H.M.I., Mendes, V.M.F. (2011). Short-term wind power forecasting in Portugal by neural networks and wavelet transform. *Renew Energy*, 36(4), 1245–1251.

Colak, I., Sagiroglu, S., Yesilbudak, M. (2012). Data mining and wind power prediction: A literature review. *Renewable Energy*, 46, 241–247.

Colak, I., Sagiroglu, S., Yesilbudak, M., Kabalci, E., Bulbul, H.I. (2015). Multi-time series and-time scale modeling for wind speed and wind power forecasting part II: Medium-term and long-term applications. In *2015 International Conference on Renewable Energy Research and Applications (ICRERA)*. IEEE.

Dowell, J. and Pinson, P. (2015). Very-short-term probabilistic wind power forecasts by sparse vector autoregression. *IEEE Trans Smart Grid*, 7(2), 763–770.

Du, P., Wang, J., Yang, W., Niu, T. (2019). A novel hybrid model for short-term wind power forecasting. *Appl Soft Comput.*, 80, 93–106.

Flores, J.J., Graff, M., Rodriguez, H. (2012). Evolutive design of ARMA and ANN models for time series forecasting. *Renew Energy,* 44, 225–230.

Foley, A.M., Leahy, P.G., Marvuglia, A., McKeogh, E.J. (2012). Current methods and advances in forecasting of wind power generation. *Renewable Energy*, 37(1), 1–8.

Hill, D.C., McMillan, D., Bell, K.R., Infield, D. (2011). Application of auto-regressive models to UK wind speed data for power system impact studies. *IEEE Trans Sustain Energy*, 3(1), 134–141.

Jahangir, L. and Babbar, S. (2020). Medium term wind speed using random forest algorithm. *Int Res J Comput Sci Technol*, 47–53.

Landberg, L. (1999). Short-term prediction of the power production from wind farms. *J Wind Eng Ind Aerodyn*, 80(1–2), 207–220.

Lei, M., Shiyan, L., Chuanwen, J., Hongling, L., Yan, Z. (2009). A review on the forecasting of wind speed and generated power. *Renew Sustain Energy Rev*, 13(4), 915–920.

Ouyang, T., Huang, H., He, Y. (2019). Ramp events forecasting based on long-term wind power prediction and correction. *IET Renew Power Gener*, 13(15), 2793–2801.

Ramirez-Rosado, I.J., Fernandez-Jimenez, L.A., Monteiro, C., Sousa, J., Bessa, R. (2009). Comparison of two new short-term wind power forecasting systems. *Renew Energy*, 34(7), 1848–1854.

Sankar, S., Amudha, S., Madhavan, P., Lamba, D.K. (2021). Energy efficient medium-term wind speed prediction system using machine learning models. *IOP Conference Series: Materials Science and Engineering*, 1130(1), 012085.

Tascikaraoglu, A. and Uzunoglu, M. (2014). A review of combined approaches for prediction of short-term wind speed and power. *Renew Sustain Energy Rev.*, 34, 243–254.

Wu, G.Z., Zhang, Y.B., Su, C., Liu, Y.J. (2013). Study on medium-term and short-term wind power forecasting methods. *Applied Mechanics and Materials*, 361, 318–322.

Yuan, C., Liu, S., Fang, Z. (2016). Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model. *Energy*, 100, 384–390.