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Solar energy and wind power supply supported by battery storage and Vehicle to Grid operations

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ABSTRACT

Worldwide activity in renewable energy is a motive power to introduce technological innovations. Integrating intermittent energy sources such as solar energy and wind power with battery storage and Vehicle to Grid operations has several advantages for the power grid. The first advantage is that energy storage supports the power grid during the periods that the power grid is facing challenges from high peak demand. The second advantage is that using battery storage and Vehicle to Grid operations would shift the power grid load from the peak and busy time to less demand time. And the third advantage uses energy storage and Vehicle to Grid operations to smooth the fluctuating power supply fed into the power grid by intermittent renewable energy resources. This energy storage idea is of particular importance because, in the future, more renewable energy sources are integrated into the power grid worldwide. The research objective includes the results and examines the role and advantages of battery storage and Vehicle to Grid operations integrated into intermittent sources. The battery storage and Vehicle to Grid operations will create a renewable power supply and enhance the power grid reliability, including a large proportion of intermitted renewable energy sources.

1. Introduction

The future power grid integrates renewable energy sources such as solar energy, wind power, co-generation plants, and energy storage.

The nature of solar energy and wind power, and also of varying electrical generation by these intermittent sources, demands the use of energy storage devices. In this study, the integrated power system consists of Solar Photovoltaic (PV), wind power, battery storage, and Vehicle to Grid (V2G) operations to make a small-scale power grid. Such a system supplies sustainable power for loads connected to the large-scale and small-scale power grid.

Many research works are devoted to improving the models for wind characteristics [1]. One study [2] compared different methods to estimate Weibull distribution parameters for wind speed in the wind farm. Another study [3] presented a statistical analysis of the wind characteristics and wind energy potential at ordinary sites using the Weibull distribution model. The wind speed variations, as well as Weibull distribution parameters, were highlighted on alternative timescales. One study [4] utilized a Markov chain model to determine the stochastic behavior of wind direction and showed that it had a significant effect on the efficiency of wind farms. One study [5] investigated the sensitivity of wind speed distribution functions on wind data and identified more robust and accurate models. One study [6] investigated the application of extreme learning machines for the estimation of Weibull parameters more accurately.

V2G operations are a vital part of Electric Vehicle (EV) development. The increased number of EVs results in challenges to the power grid. Network support utilizes V2G operations and smart charging. Intermittent renewable energy requires energy storage and power regulation to keep demand and supply balanced. V2G operations along with battery storage increase the penetration of renewable sources. In V2G operations, batteries act as a frequency response reserve, spinning reserve, and non-spinning reserve. Batteries are appropriate for frequency regulation. The V2G operations may provide stable power frequency, power quality, and reliability of the power grid. Utilizing the V2G operations as a power regulation, EVs can be a crucial part of the power utility.

The V2G operations can supply ancillary services to stabilize the power grid. Such ancillary services are crucial for national security. Controlling generation and electrical load will stabilize fluctuating frequency. Electricity is transferred through the network and substations to customers. In an electricity network failure situation, customers can form islanded microgrids. General-purpose vehicles provide ancillary services to the islanded microgrid. Because electricity prices vary over time, V2G operations provide profit by charging batteries at lower prices and discharging them at higher prices. One study revealed decreased lifetime reduction in V2G operations and extended lifetime. V2G operations work with the most optimal state of charge

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level, and the driving situation operates with selected state of charge windows. The study is significant to the EV industry and is worthy of observation because it demonstrates an extended life with an EV battery management system instead of the development of battery chemistry. Research implications are the importance of EV battery management in V2G operations, and V2G operations demonstrate the more compelling technology. The research has addressed the defined research objective by decreasing lifetime reduction from V2G operations [7].

Energy storage technologies that are engaged in power systems [8] include the technology, performance, and capital costs of energy storage and emphasized directions for further research. As energy storage, V2G operations can provide ancillary services and enable higher utilization of renewable energy sources [8]. The availability of future electrical energy storage technologies is presented in [9].

One proposal investigated cycle life measurements and the cycle life model. The model included driving patterns, V2G operations, and EV battery lifetime. The study obtained how much V2G operations reduced battery cycle lifetime and operational cost. Driving distance, number of battery charging cycles, and battery operational cost increased the cost of V2G operations. The study covered measurements, cycle life models, driving patterns, battery lifetime, driving range, and grid-connected V2G. This research connects all these considered methods for the cycle life model. The study optimized battery charging and estimated the battery's life cycle. The novelty of this research was the use of charge limits according to driving distance [10].

Several studies investigated the importance of rated wind speeds on the energy production of wind turbines. One study [11] evaluated wind potentials along the coastal area and suggested small wind turbines ranging from 50 kW to 250 kW with moderate rated wind speeds of 9–11 m/s could be more suitable for the region. One study [12] defined a capacity factor based on wind speed and wind direction. They investigated the importance of both terms in the better estimation of wind energy potential. Another work applied a wind resource map to integrate both wind speed and wind direction for cost optimization of a wind farm [13]. One study [14] emphasized the effects of wind directions on maximizing the efficiency of wind farms. Temporal and spatial variability of wind speeds investigation revealed the effects of turbulence on the assessment of wind resources [15]. The wind energy potential in the southern Caspian Sea is studied [16]. They applied uncertainty analysis in their work.

One study presented automatic battery charging and discharging without EV drivers' control. Battery power provided frequency regulation, peak demand management, and a reserve power capacity. The battery charge was near the optimum point, and the battery charge was enough for the estimated next trip. The charging patterns aimed to provide a prolonged lifetime. Every time an EV was parked, the automatic charging provided battery charging. The driver did not need to participate in the charging process. The driver needed to park and plug into the power grid. Unnecessary communication is reduced between driver and battery communication systems. The automatic charging checks location, charging level, time, and availability to the V2G operations before the charge required battery capacity [17]. One study introduced the new equation for the capacity value and employed the two-variable model. The model specified the suitable rated wind speed for a variable speed wind turbine [18]. One review demonstrated technical challenges in renewable energy. This review integrated V2G operations into renewable energy systems, particularly in distributed generation systems [19]. The solar PV system has an empirical model, and the wind power operating curve utilizes the Weibull distribution and Monte Carlo methods. Solar energy and wind power are intermittent supplies, thus battery storage and V2G operations are supporting the power smoothing process of the power grid.

2. Modeling approach for integrating renewable energy sources

This research investigates a power supply system based on a baseload generator, a solar PV, a wind turbine, battery storage, and V2G operations. The solar PV curve uses an empirical polynomial function. The wind power curve employs the Weibull distribution. The wind is unsteady and random because of turbulent fluctuations. It is essential to use the probability density function to calculate the power output solution from the wind turbine power curve [20]. Solar energy and wind power supply a typical power grid electrical load, including a peak period. As solar energy and wind power are intermittent, this study examines the battery storage and V2G operations to support the power grid. The electric power relies on the batteries, the battery charge, and the battery capacity. Intermittent solar energy, wind power, and energy storage system include a combination of battery storage and V2G operations. These energy storages function simultaneously, supporting each other. The study investigated the simultaneous usage of battery storage and V2G operations. This study is significant and worthy of investigating the implications of V2G operations that contribute greatly to the convenience of electric vehicles in sustaining the power grid because of this kind of ancillary service. The study divided renewable energy supply systems into small-scale and large-scale supplies. The study presented energy generation, battery storage, and V2G operations. They compared V2G operations with battery storage. The study used battery storage and V2G operations to support the power grid. They adopted renewable source supply simulations from the power grid. The study used different power sizes, demonstrating the required renewable energy system for the power grid [21].

The challenges in EV charging, renewable energy, and demand response are investigated [22]. The uncertainty modeling methods have strengths and weaknesses for power systems [23]. The control strategy may reduce fluctuations and reduce electricity costs [24].

One study investigated battery wearing costs for EV battery packages. The study revealed the annual cost, the energy used for frequency regulation, and the energy price for V2G. Results indicated that V2G operations will supply inexpensive frequency regulation for the power grid and will return a profit for utilities and EV users [25].

Solar energy and wind power should smooth the high peak demand. Therefore, demand and supply estimation require an operational model of electrical load, solar energy, wind power, and energy storage as well as V2G operations. The advantages and disadvantages of wind farm optimization techniques are described [26]. This study describes the fundamental concept of integrated energy production.

One study presented the battery cycle aging model, which connects battery experiments, cycle life models, driving patterns, battery lifetime and driving distance, and V2G operations. The battery management used a battery model to enhance battery life. The novelty of the battery cycle aging model is utilizing charge limits to enhance driving distance. The model recognizes the battery charger and approximate battery life [27].

3. The operational baseload supply

The baseload power supply includes coal power stations, thermal power plants, and gas turbines. In this study, the baseload is constant. The capacity factor is the fraction of electric power generated by a particular facility relative to its nameplate potential. Capacity factors for renewable energy sources are typically much lower than those for coal, gas, and nuclear plants as the intermittent nature of the energy sources for the former [28].

Baseload power generation is considered the backbone of the power grid by some researchers [29]. In this view, the uninterrupted capacity of baseload electricity provides grid stability and reliability in an electricity system with a high share of variable renewable energy [30] as strengthening the reliability and security of the grid by electricity storage is considered an expensive option [31]. On the other hand,

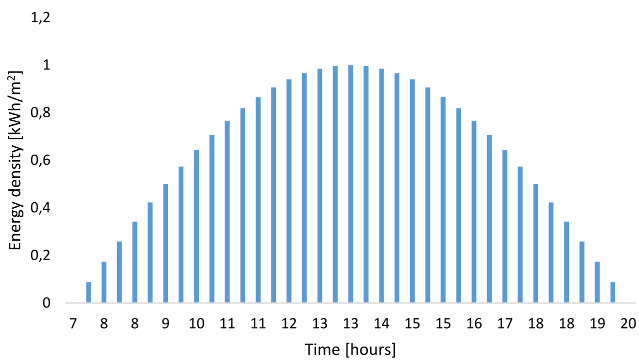

Fig. 1. Solar photovoltaic operational curve considering weather conditions.

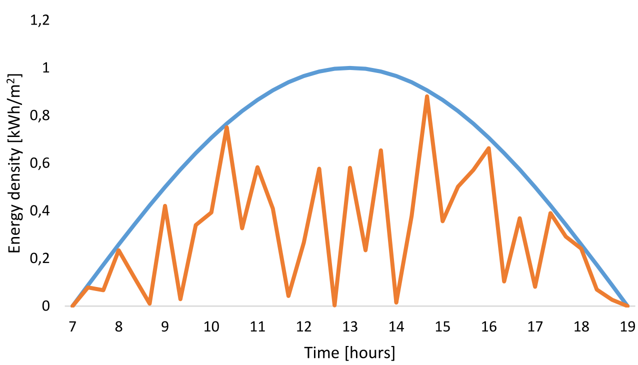

Fig. 2. Solar photovoltaic operational curves for fast-moving cloud conditions.

coupling the system with conventional dispatchable resources would limit possible emission cuts [32]. In recent years, however, the drop in the cost of variable renewable energy and storage options, as well as resource integration, are calling into question the need for significant volumes of baseload generation. Studies show that grid demand could be supplied by a mix of different renewable resources and storage options [33,34], even if bioenergy is avoided [35], making a 100% renewable power sector technically feasible and economically viable globally [21,36]. The electrical load for the system controller can be predicted using the forecasting method [37]. The system controller mitigates fluctuations and costs [24].

4. Solar photovoltaic supply and operational curve

Solar energy has time-based dependence, on solar radiation, and the weather. An empirical model and operational curve were constructed for solar PV operation to describe the solar PV power.

$$P_{PV} = aR_5 + bR_4 + cR_3 + dR_2 + eR_1 + f\,, \tag{1}$$

where R represents the solar radiation. The solar PV operational curve shows solar radiation from a clear sky in Fig. 1. The solar PV operational curve shows solar radiation with clouds in the sky in Fig. 2. Research and development of PV cells have led to higher efficiencies, significant cost reductions [38], and long operating lifetimes with minimal degradation [39]. Solar radiation data used in most simulation models, for example [40,41], are based on average values, such as ground measured or satellite-derived hourly values.

Increasing interest in renewable energy employs new technology solutions. Distributed power production is replacing centralized electricity generation. Intermitted energy such as solar energy and wind power create unfavorable effects on power attributes such as quality, voltage, frequency, and reliability. The intermittent nature of renewable production increases technical challenges for the power grid operation. Solar energy, wind power, battery storage, and V2G operations offer a promising alternative to the power grid. Conventional power production can supply backup generation to magnify reliability. The centralized and decentralized power systems can consume renewable energy sources. The study presented cost minimized large-scale renewable energy systems [42].

A distribution network, that has EVs and solar panels has power quality challenges [43].

Installation costs for solar energy are decreasing, ensuring solar energy is a more compelling technology [44].

5. Wind speed model

Employing new technology, the combination of solar energy, wind power, and energy storage solutions is under development [45].

The wind speed variation challenges can be avoided if accurate information is available and forecast service predicts weather changes. In general, meteorological methods as physical strategies are technologies that rely on real-time numerical weather prediction [46] and atmospheric data to forecast wind speed [47]. Power supply from a wind farm can be predicted to control power management to the power grid. Forecast service is an important factor in integrating renewable energy into the power grid.

These forecasts lead to operational modeling and estimation before a wind farm installation. The differential error between forecasts and measurements is updated to online systems. Numerical weather prediction strategies play an essential part in meteorological forecasting, and could also be reliable for certain wind resource assessments [48]. The nature of the power supply includes planned and unplanned factors. However, power stations meet industry requirements for planned and unplanned variations. The other significant factor is siting, showing available wind resources for a wind farm. Hydropower stations and geothermal energy sources are not flexible in siting because of their energy resource. Wind power development includes possibilities for various siting and scaling options. Careful siting research before construction has value for power output and magnifying power output difference over a turbine's operating lifetime.

The V2G operations can supply ancillary services to stabilize the power grid. Such ancillary services are crucial for national security. Controlling generation and electrical load will stabilize fluctuating frequency. Electricity is transferred through the network and substations to customers. In an electricity network failure situation, customers can form islanded microgrids. General-purpose vehicles provide ancillary services to the islanded microgrid. Because electricity prices vary over time, V2G operations provide profit by charging batteries at lower prices and discharging them at higher prices [49].

The wind power production capability is described. There are perspective challenges to improving the power frequency regulation [50]. Modeling wind power provides forecasting methods over a very short period. This is a challenge for research. Implementing forecasting methods for the wind power industry highlights their contribution to the electricity network and frequency regulation. The energy market legislation supports wind power supply. Still, the economic models for the power system stabilizing are not well recognized [50].

From site information, we can use wind speed hourly data, and we can estimate wind power and the power delivered by using Eq. (2).

$$P_{Wind} = \frac{1}{2}\rho A V^3 C_{p1} C_{p2}\,, \tag{2}$$

where ρ is the air density, A is the wind turbine cross-sectional area, V is the wind velocity, C_{p1} is the wind energy conversion coefficient (maximum 59%), and C_{p2} is the device power coefficient. Wind speed data is collected to calculate wind power.

We use Eq. (3) to calculate wind power from average wind speed.

$$P_{Wind} = \frac{1}{2}\frac{6}{\pi}\rho A V_{Ave}^3 C_{p1} C_{p2}\,, \tag{3}$$

Table 1
A wind turbine power output and wind speed.

Wind turbine power output	Wind speed
$P_{Wind} = 0$	$0 < V < V_{CI}$
$P_{Wind} = P_R \frac{V^3 - V_{CI}^3}{V_R^3 - V_{CO}^3}$	$V_{CI} < V < V_R$
$P_{Wind} = P_R$	$V_R < V < V_{CO}$
$P_{Wind} = 0$	$V_{CO} < V$

Performance evaluation uses the wind turbine power curve provided by the turbine manufacturer in the presence of wind speed information. Eq. (4) determines wind turbine power output using cut-in and cut-out wind speed.

$$P_{Wind} = P_R \frac{V^3 - V_{CI}^3}{V_R^3 - V_{CO}^3}, \tag{4}$$

where P_R is rated turbine power, V_{CI} is cut-in wind speed, V_R is rated wind speed, and V_{CO} is cut-out wind speed, which is the maximum wind speed to use power generation.

Table 1 defines wind power in different wind speed categories.

6. Performance evaluation with Weibull probability density functions

Probability density functions describe the wind speed frequency distribution. Wind speed distribution over wind speed determines operating conditions for a wind turbine. Two probability density functions, Weibull, and the Rayleigh probability density functions are most common in the wind power industry [51].

We can estimate delivered energy from Weibull statistics using average wind speed and available parameters shape parameter α and the scale parameter β.

A Weibull probability density function is formulated as shown in Eq. (5) [20].

$$f(v) = \frac{\alpha}{\beta}\left(\frac{v}{\beta}\right)^{\alpha-1} e^{-\left(\frac{v}{\beta}\right)^{\alpha}}, \tag{5}$$

where Weibull probability density parameters are the shape parameter α and the scale parameter β. Weibull probability density functions are used to estimate the wind turbine power output in Fig. 3. The mean annual wind speed and the measured Weibull parameters (α and β) at hub heights of 10 and 30 m are reported [52].

An empirical battery cycle aging model for V2G operation, including driving patterns, and estimated annual battery wearing cost [25]. A comparison of the research regarding cycle life models and V2G operations reveals that the majority of the literature typically covers measurements and models. Typically, driving patterns, battery lifetime, annual range, and gridconnected operations are not considered. The study integrated battery aging, driving pattern, and V2G operations into the cycle aging model. This model is previously developed empirical battery cell cycle aging model [25].

Only a few studies [25,53,54] discussed battery lifetime in years, calculated lifetime driving distance, and provided V2G operations. Therefore, future development could perform V2G operations through aggregation schemes, involving an agent and multi-agent logic, and grid operators will probably avoid using a direct real-time control scheme. The Rayleigh probability distribution function can be used to estimate wind turbine power output. The target axial induction factor is determined by the blade element momentum theory applied to determine the blade shape. The chord distribution, twist angle, and cross-sectional airfoil shape increase lift and decrease drag for the maximum lift to drag ratio [55] and also some improved stall or post-stall characteristics [56]. The performance of variable speed wind turbines was investigated [57] for horizontal axis rotor systems. One study [58] applied the blade element momentum theory to analyze the variable speed wind turbines, which operate continuously at maximum power coefficient.

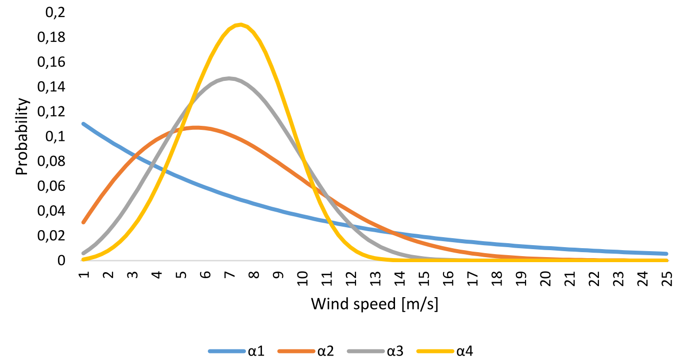

Fig. 3. Weibull Probability Density Functions for $\alpha = 1, 2, 3, 4$ and $\beta = 8$.

The Weibull probability density function for shape parameter $\alpha = 2$ Weibull probability density function is known as the Rayleigh probability density function shown in Eq. (6) [20]. With average wind speed, we can use Rayleigh statistics to estimate a wind turbine power output.

$$f(v) = \frac{2}{\beta}\left(\frac{v}{\beta}\right)^{2-1} e^{-\left(\frac{v}{\beta}\right)^{2}} = \frac{2v}{\beta^2} e^{-\left(\frac{v}{\beta}\right)^{2}}. \tag{6}$$

Average wind speed

$$V_{Ave} = \int 0 v f(v) dv = \frac{\sqrt{\pi}}{2}\beta, \tag{7}$$

thus

$$\beta = 2\frac{V_{Ave}}{\sqrt{\pi}}, \tag{8}$$

Wind speed can be derived from scale factor β providing estimation for a wind turbine power output.

The design tip speed ratio is one of the initial design parameters which depend on the blade numbers and it is generally taken as 6–8 in modern wind turbines [59].

For wind turbine blade designers, as can be found in Eq. (4), the rated wind speed and the rotor swept area are inversely related, which means a larger rated wind speed selection in the design process will result in smaller rotor diameter and vice versa. Smaller rotor size and larger rated wind speed also mean higher rotational speed of the electrical generator. Therefore, some compromise should be made between the selection of rotational speed of an electrical generator and the suitable rated wind speed to guarantee the maximum annual energy output of the wind turbine for a specific site [60].

The lifetime of battery cells can be calculated. The annual V2G compensation for battery cells with V2G cycles and the energy for battery cells can be calculated. The electricity between the power grid and EV batteries is transferred using V2G operations. The energy price for V2G operations can be calculated [25].

It is worth noting that the optimization of a wind farm can increase the annual energy production from 737.78 MWh to 756.16 MWh, an increase of 2.5% annual energy production [61]. Therefore, the present study shows great potential for improving wind farms' efficiency based on considering both the selected wind turbine power curves from real infield technical data and wind speed distribution using a Weibull distribution to find an optimum rated wind speed. However, the real-time wind hours will affect the overall performance of annual energy production [62], such economical analyses for 20–30 years can be integrated with the present study to discover the long term merits of reliable long term wind speed forecasting techniques such as [63–65] are employed.

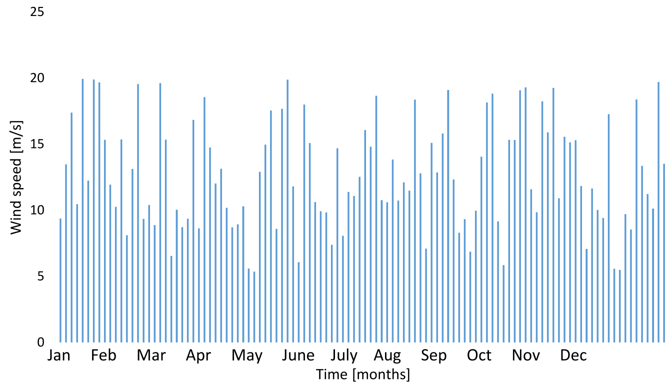

Fig. 4. Monte Carlo experiments for wind speed. Calculations used Weibull probability density functions.

In Eq. (6) we can replace scale factor β with an average wind speed. Rayleigh's probability density function determines the link between wind speed V and average wind speed. Eq. (9) calculates Rayleigh's probability density functions.

$$f(v) = \pi \frac{v}{2} V_{Ave}^{2} e^{-\frac{\pi}{4}(\frac{v}{V_{Ave}})^{\alpha}}, \tag{9}$$

Eq. (10) has another form of Rayleigh's probability density functions.

$$V = \frac{V_{Ave}}{\pi} \sqrt{-ln(1 - f(v))}. \tag{10}$$

7. The Monte Carlo experiments define available wind speed

Wind speed variation from Monte Carlo experiments is shown in Fig. 4. Eq. (11) determines wind speed using Weibull probability density functions. Random number N gets values from 0 to 1.

$$V = \frac{V_{Ave}}{\pi} \sqrt{-ln(1 - N)}. \tag{11}$$

Battery lifetime equations [25] for renewable energy solutions are implemented for solar energy and wind power battery storage. The probability function is shown in Fig. 5.

8. Results

The electrical load varies between days and between seasons. This study supplies power from conventional baseload and renewable energy sources. Baseload is considered constant whereas renewable energy sources vary over time. Battery storage and V2G operations are used to puffer energy flow to the power grid. Fig. 6 illustrates the combination of electrical load and generation. Results are shown in Fig. 6. At the bottom, the blue colors represent baseload and solar energy. In the middle, the yellow area represents the electric load. On the top locates a red color area, variable wind power. Batteries in battery storage and V2G operations absorb the power during low demand periods and release the power in high peak demand times. The balance between supply and demand without energy storage is shown in Fig. 7.

9. Interpretation and discussion

With a help of Rayleigh's probability density function and Monte Carlo experiments, we can build a modeling approach for integrating renewable energy sources. V2G operations are a vital part of EV development. The increased number of EVs results in challenges to the power grid. Network support utilizes V2G operations and smart charging. Intermittent renewable energy requires energy storage and

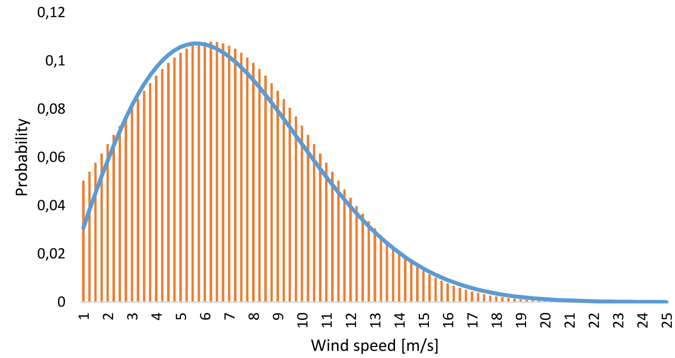

Fig. 5. Weibull probability density function curve with Monte Carlo experiment bars.

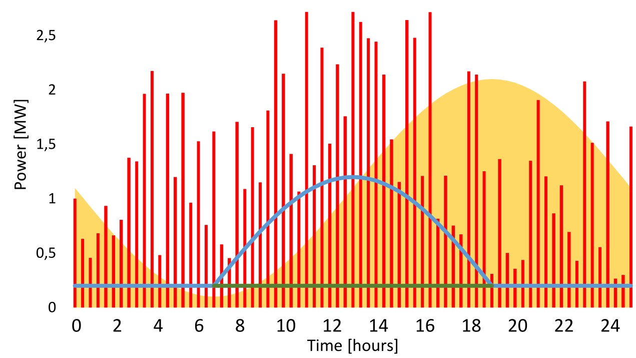

Fig. 6. The electrical load (yellow), the constant electrical baseload generator including the solar photovoltaic generator (blue), and the wind generator (red).

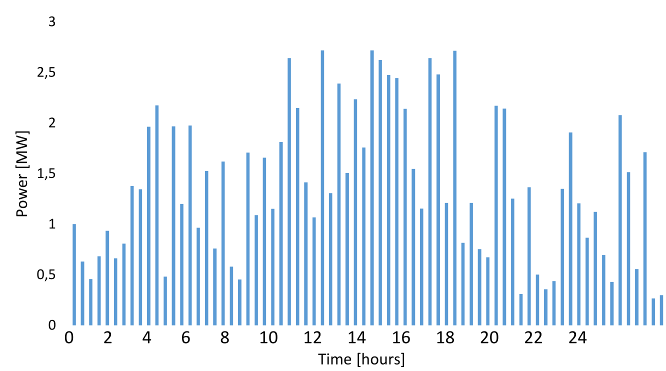

Fig. 7. Supply and demand balance without storage.

power regulation to keep demand and supply balanced. V2G operations along with battery storage increase the penetration of renewable sources. EV batteries are appropriate for power regulation. The V2G operations support the power grid to maintain a stable power frequency, power quality, and reliability. Utilizing the V2G operations as a power regulation, EVs can be a crucial part of the power utility [66].

Solar energy and wind power are intermitted power supplies and require energy storage. V2G operations and battery storage are combinations of energy storage. Battery storage provides ancillary services to the power grid. These two battery systems are working simultaneously as energy storage for renewable energy supply. Solar energy, wind power, battery storage, and Vehicle to Grid operations provide a promising option for energy production.

10. Conclusions

The probability density function is used to build a model for renewable energy systems and power regulation may balance power supply and consumption. Battery storage and Vehicle to Grid operations are integrated into intermittent sources. The Solar photovoltaic operation curve model and wind speed model were used to demonstrate intermittent renewable energy sources. Weibull distribution equations are utilized as an integral function of the rated wind speed through the modeling of wind and power performance of variable speed wind turbines. Battery storage and Vehicle to Grid operations increase the balance and reliability of the renewable energy power supply. Intermittent solar energy and wind power are increased power sources with a demand for energy storage. The results of such studies are useful for both wind turbine manufacturers and also wind farm developers to choose the most economical wind turbines with maximal annual wind energy production.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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