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Review

A Review of Improvements in Power System Flexibility: Implementation, Operation and Economics

Umar Taiwo Salman [1,*], Saifullah Shafiq [2], Fahad S. Al-Ismail [1,3,4] and Muhammad Khalid [1,3,4,*]

1 Electrical Engineering Department, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; fsalismail@kfupm.edu.sa
2 Electrical Engineering Department, Prince Mohammad Bin Fahd University (PMU), Khobar 31952, Saudi Arabia; sshafiq@pmu.edu.sa
3 Center for Renewable Energy and Power Systems, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
4 K.A. CARE Energy Research & Innovation Center, Dhahran 31261, Saudi Arabia
* Correspondence: g201706090@kfupm.edu.sa (U.T.S.); mkhalid@kfupm.edu.sa (M.K.)

Abstract: This study presents a literature review on the concept of power system flexibility in terms of its definition, indices, algorithms, implementation, economic impacts, operational impacts, and security. Although there are tremendous reviews on this subject in the literature, each paper discusses specific aspects of flexibility. Moreover, the literature is devoid of a comprehensive review of the latest improvements in terms of implementation, operation, and economics, which are addressed by the collections presented in this study. This paper, therefore, surveys some improvements that have been made in recent decades. Furthermore, we highlight the impact of the high penetration of renewable energy and energy storage systems towards enhancing the improvement of power system flexibility.

Keywords: flexibility; flexibility improvement; power system; energy storage; renewable energy

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Citation: Salman, U.T.; Shafiq, S.; Al-Ismail, F.S.; Khalid, M. A Review of Improvements in Power System Flexibility: Implementation, Operation and Economics. *Electronics* **2022**, *11*, 581. https://doi.org/10.3390/electronics11040581

Academic Editors: J. C. Hernandez and Oscar Danilo Montoya

Received: 18 November 2021
Accepted: 5 January 2022
Published: 15 February 2022

1. Introduction

There is no denying the fact that electricity is crucial for the world economy to thrive in this and the coming centuries. The demand for electricity increases not only because the human population increases, but also because the social-economic activities of humans are rapidly shifting from manual processes to automated processes, which are essentially driven by electricity. Therefore, electricity becomes inevitable for the sustainability of modern civilization because it has found its way to the root of many human establishments [1,2]. Electricity can be generated from various sources and its generation from many sources is desired to boost the total generation capacity to meet the ever-growing demand. As electrical power cannot be stored, instantaneous balancing becomes a necessity and it is considered a key design parameter in power systems [3].

The increased demand, generation, multiple sources of generation and absolute dependence on electricity call for a high reliability and security and consequently high flexibility of the power system. Power system flexibility requires a control structure that ensures a spatial and temporal balancing of the electricity generation and consumption at all times; therefore, flexibility should be an integral part of the planning and operation of power systems [4].

1.1. Definition of Power System Flexibility

Power system flexibility has been defined in the literature and the definition encompasses the usefulness and purpose of flexibility in various applications of the power system. It was mentioned in [5] that these definitions have been provided by various organizations such as North American Electric Reliability Corporation (NERC) and International Energy Agency (IEA). Reference [5] further mentioned that different research groups defined it based on the major field of study. The flexibility studies have been classified into two:

short-term operational flexibility and long-term planning flexibility. In [6,7], power system flexibility is defined as the ability of the power system to model the feed-in and feed-out power across the grid over time so that variations in net load can be accommodated. In [6], flexibility is defined as the ability of a system to exploit all resources to respond to the net changes in demand. Babatunde et al. [2] mentioned that the concept of flexibility should include flexible demand-side management and demand response, the reinforcement of distribution and transmission facilities, ESS, electric vehicles, generator output curtailment, and unit commitment. Hence, power system flexibility is described in [8] as the power and ramp capability required to adjust generation in response to demand within a specific time interval. It enables the system to adjust the demand and generation in response to deliberate or accidental aberrations that occur within power systems [9]. A flexible power system is described in [10] as a system that is able to competently respond to some form of diversion in the operation of a power system determined by risk-management criteria.

1.2. Component of Power System Flexibility

A flexible power system should possess certain facilities that enable it to overcome uncertainties in addition to being able to compensate for deviations in generations and demands whilst maintaining the system's reliability [11,12]. The key components of flexibility (Figure 1) are (i) supply, (ii) demand, (iii) network and (iv) system. These components interact together to form a power system. Electricity is supplied through the use of various generation sources, with VRE becoming more popular in these systems. The generation system also includes energy storage systems.

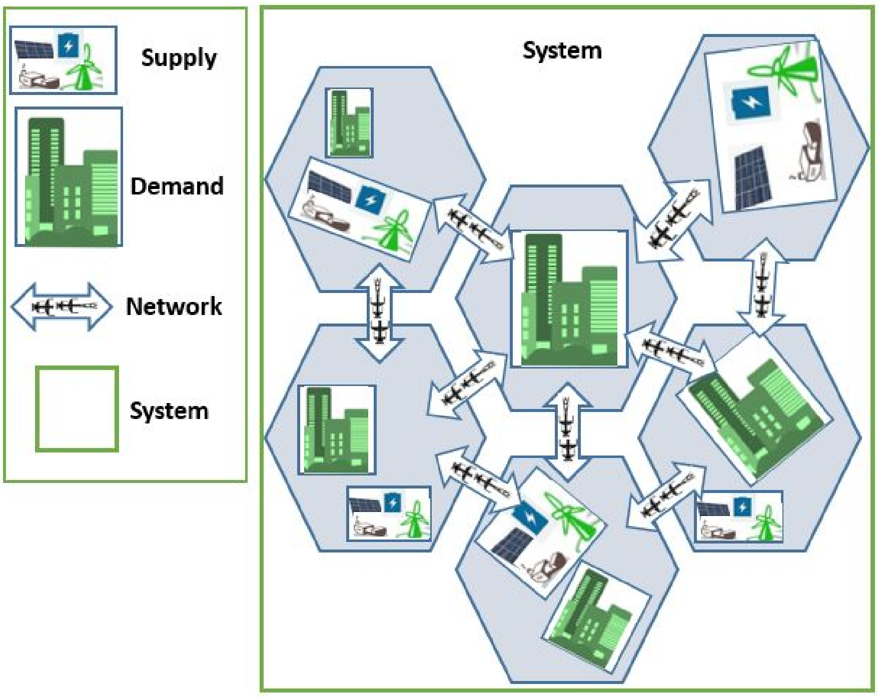

Figure 1. Interaction between the key components of flexibility.

A power system is governed by some operational rules; these rules may be difficult to implement for the power system, but they are imperative to ensure the system's security, reliability, and economic operation [13]. The power system operations should be flexible to absorb disruptions [14]. The demand is partly controllable and is usually controlled by the consumers in response to signals from the system operators. This provides some flexibility to compensate for the uncertainty in generation from the VRE sources [15,16].

1.3. Effects of and Need for Increased Penetration of VRE in Power Systems

The electricity sector is the biggest contributor of carbon (IV) oxide [17], accounting for almost 43% of the world carbon (IV)oxide emissions [2]. This amount is expected to decrease drastically to achieve the Paris agreement, which aims to lower the global temperature rise to below 2 °C [18]. Diversifying electricity generation from fossil fuels based on other sources that are harmless or produce no emissions is already identified as a potential solution and variable renewable energy sources (VRES) are at the forefront of this move [19,20]. Additionally, other possible measures that could be taken are to improve the efficiency of existing power plants, the adoption of demand-side management, the use of energy storage systems, and the formulation of special policies or techniques that can minimize the consumption of power. For example, the authors in [21] proposed a technique for the flexible operation of microgrid using the battery energy storage system. The strategy allows a reliable power balance between the demand and supply while ensuring that the BESS is safely operated within its operating time horizon.

One of the critical challenges of the electricity industry is achieving a balance between the power demand and power supply [20,22,23]. Technically, the power systems with more distributed methods of generation experience more fluctuations [24–26], and the growth in the penetration of RES further compounds this problem. Meanwhile, it is reported in [27] that wind power penetration causes critical instabilities in power systems, different to the corresponding solar PV penetration. Recent studies that discuss the impact of high wind penetration in power systems can be found in [28–32] and that of solar PV in [33–36]. The RES possesses some characteristics which differ from conventional generation systems. These features are the reasons why they pose serious change to power systems [37]. These include:

1. RES generation is stochastic and is largely dependent on weather conditions [37,38]. Consequently, a high degree of varying penetration results in a drastic disturbance in the power system [39–41]. Some of this may be due to system clouding [37] and a variation of system inertia, leading to frequency variation [42], and reference [43] explained that a high penetration can cause under-reach and over-reach problems in over-current protection since the fault current changes dynamically with the fluctuation of RES.
2. Another argument is that government policies across the world serve as strategies favoring the production of RES. Comprehensive policies and strategies including long-term and short-term strategies are reported in [44,45].

In a bid to solve this problem [46], many other issues ranging from technical and economic problems arise. In this study, we present the classification of flexibility impacts in power systems. We identified and presented some of the studies on flexibility based on five major aspects that affect power system flexibility, as described in Figure 2. Furthermore, we report many studies that have good insights into the various aspects discussed, and then provide a conclusion and recommendations.

The remainder of this study is organized as follows: Section 2 presents the need for and consequences of power system flexibility. Section 3 presents the power system flexibility indices. Section 4 presents a flexibility requirement assessment. Section 5 discusses the classification flexibility impact in power systems. The flexibility improvement based on RES is given in Section 6, the flexibility improvement based on DSM is given in Section 7, the flexibility improvement based on ESS is given in Section 8, the flexibility improvement based on energy forecasting is given in Section 9, the flexibility improvement based on economic impact is given in Sections 10 and 11 concludes the study.

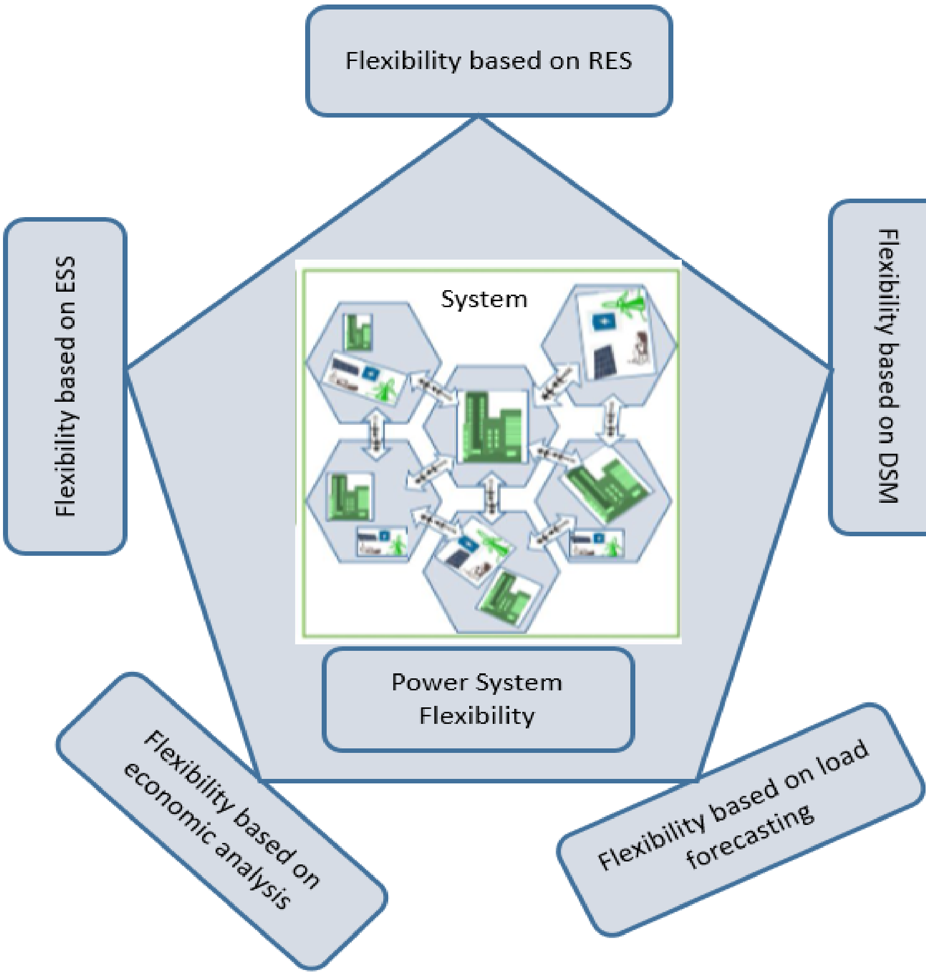

Figure 2. Approach to power system flexibility in this study.

2. Need for Flexibility Study in Power System

The need for PFS increases as power demand increases, which necessitates the need for more generation systems. However, the need for clean sources of energy necessitates VRG [47–49]. Consequently, the power systems become more complex, making the systems more susceptible to fluctuations and variations and leading to poor power quality [50,51].

2.1. Consequence of Nonflexible Systems

If the power system is unable to maintain stability or ensure a continuous supply of electrical power to the end-users due to some form of disturbance, such a power system becomes inflexible [39,51–53]. Additionally, there is an increase in faults and failures when a power system is spread over a large region due to power transmissions leading to instability and uncertainty in the power system [53,54]. One of the most critical consequences of the inflexibility of power systems is blackouts [6,55–57]. The authors of [51] have highlighted the consequences of power system failure due to a lack of flexibility. These consequences have social, political, and economic impacts on the daily activities of humans. This makes the concept of PSF very crucial in modern power systems.

2.2. Drivers of Power System Flexibility

As power systems shift from conventional systems to VRG-based systems, the need for PSF increases and the methods of achieving PSF change gradually [2]. Various techniques that are adopted for realizing PSF are listed in [2,58] mentioned the various PFS options. Some of the sources of flexibility include: distributed generation, demand response, grid interconnection, multi-mode operation of combined cycle units and ESS.

2.2.1. Distributed Generation

A distributed generation offers flexibility to power systems in local networks when responding to system uncertainty [59]. The distributed generators connected to the local power networks are able to respond to a system's dynamic imbalance and varying conditions [60]. Furthermore, it helps to improve the self-healing capability of the power system, allowing the system to respond faster than the usual operations [61].

2.2.2. Demand Response

There are several techniques of demand response that have been used in the literature. Consumers are tactically encouraged to change their power consumption patterns to enable flexibility in the overall demand of the power network [62,63]. This helps consumers to reduce their energy usage [64].

3. Parameters for Measuring Flexibility (Flexibility Indices)

It will be interesting to review the terms used to measure flexibility along with the equations that have been used to model flexibility in power systems. The indices of flexibility in power systems have been categorised as energy capacity (C_e), power capacity (C_p) and ramping limit (δ) [37].

3.1. Energy Capacity

This refers to the energy of a power source, and it may also refer to the fuel supply to a power source. The (C_e) is categorised as finite and infinite [65]. Dispatchable distributed generation, ESS and fuel supply in the case of central generating unit have a significant effect on the energy capacity. It is demonstrated in [66] that the available generating capacity of a system essentially represents the mechanical reliability of the equipment, which makes it statistically interdependent not only the generation sources alone but also on the loads. Additionally, instead of C_e, the authors of [8] identified ramp duration as an index of flexibility. The time duration is the time period during which a unit has its output continually changing.

3.2. Power Capacity

The power capacity, C_p, is the limits of (minimum or maximum) power outputs of a generation source and is usually bounded by inequality constraints. The C_p is an essential parameter in evaluating the adequacy of a generating system [67].

3.3. Ramping Limit

This refers to the maximum allowable change of a unit on its operation point at a specific time. The term ramping limits refer not only to the generation sources but also to some industrial loads whose operation have significant effects on the demand response.

The relationship between C_e, C_p and δ is represented in (1). It should be noted that each index is a successive integral of the previous one. Additionally, the rate duration $(\triangle R)$, as defined in [8], is described by (2).

$$C_p = \int C_e = \int \int \delta \tag{1}$$

$$\triangle R = \frac{\triangle P}{\triangle T} \tag{2}$$

3.4. Determination of Flexibility Requirements

As noted in the literature, the triads (magnitude, ramp rate and ramp duration) are jointly interrelated and are useful in the modeling of deviation in the net load [8,68–70]. For example, if the ramping is not enough, it may cause further capacity requirements. According to the study of [8], the optimization of flexibility requirements of a set of net load deviations, classified into (i) primary, (ii) secondary, and (iii) tertiary intervals, can be represented by a three dimensional (3-D) space to show the three categorizations of deviations. The coordinate of each of the 3-D models on rectangular parallel pipes are the $\triangle P$, $\triangle R$, and $\triangle T$, as shown in Figure 3. Each rectangle is sized and positioned according to the possible deviation, d_i, and also the flexibility requirements. Furthermore, the boxes covered the regulation intervals for positive, negative, ramp rate duration, ramp rate, magnitude up, and magnitude down. Depending on the values of each of these triads at any position in the box, the volume data inside the box V_{in} and the data outside V_{out} can be measured and be used to determine the probability of being outside or inside. In this approach, if a point lies outside the box, it means that the requirements are not satisfied at that point.

$$P_{out} = \frac{V_{out}}{V_{in} + V_{out}} \tag{3}$$

Equation (3) computes the probability of a point being outside the box. It, therefore, means that to reduce the number points where the requirements are not satisfied, then P_{out} should be made to be at its minimum value.

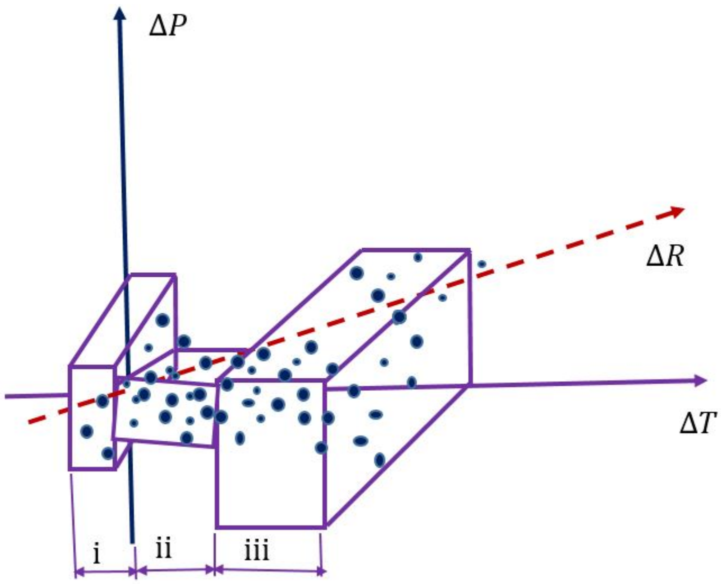

Figure 3. Flexibility requirement by a set of net load deviations over three regulation intervals: (**i**) primary, (**ii**) secondary, and (**iii**) tertiary.

4. Assessment of Flexibility Requirement

While serious efforts have been made to keep the power output from different generation sources modest enough to reduce the errors resulting from a mismatch between sources and demand, the controllable loads offer even more flexible means to compensate for these errors [8], the uncertainty in loads can be minimized by using rolling scheduling [71,72] good forecasting techniques [73]. The authors of [74] modeled a 24 h unit commitment to computing the absolute value of real-time power imbalance for a day within some regulation intervals. This study obtained, over multiple time scales, the variability in stochastic generation. The turning point of load variability was found in [68] using the swinging window method. The hourly requirements for capacity, ramping duration, and ramping capability were obtained.

Dvorkin et al., in [8], showed that any deviation, d_k, of index k existing between the actual and forecasted net loads is a function of $\triangle P_k$, $\triangle R_k$ and $\triangle T_k$, expressed in (4). The parameters responsible for said deviation were obtained from the analysis of the historical data of the system within a specific operating interval.

$$d_k = f\{\triangle P_k, \triangle R_k, \triangle T_k\} \tag{4}$$

Furthermore, the study of [8] proposed Equation (5) to measure the deviation between the metered net load (P^{met}) and the forecasted size (P^f) at every minute m.

$$P^d(m) = P^{met}(m) - P^f(m) \quad (5)$$

where $P^{met}(m)$ is the net load characteristics obtained after accounting for flexibility due to RE curtailment and controllable loads. The P^d is then analyzed at different time scales $\triangle T$ to ensure that all the characteristics of the deviation are captured. Additionally, the difference between deviation—$\triangle P$ at the beginning and $\triangle T$ at the end of the time—is measured as in (6).

$$\triangle P = P^d(m + \triangle T) - P^d(m) \quad (6)$$

The interesting thing about the outcome of $\triangle P$ is its sign, which tells us whether the system requires up flexibility ($\triangle P$ is positive) or down flexibility ($\triangle P$ is negative). The up flexibility can be achieved by adjusting the loads to ensure a reduced consumption or by subjecting the generators to more loads. The reverse of this process is carried out when down flexibility occurs.

Many studies have made attempts to investigate the consequence of a high renewable penetration on the power system ramping characteristics [11,69,75,76]. However, a better understanding of ramp characteristics in power systems could be achieved by studying both load and net load [69]. Additionally, different renewable sources present different characteristics of ramping in net loads [77] and a large amount of flexibility is required by the power system to reduce the balance or mismatch in the power system [32].

Characteristics of Ramping Events by Wind and Solar Sources

In the literature, renewable power ramp events (RPRE) for wind and solar have been grouped into three and two groups, respectively [69,78,79]. Wind power renewable events (WPRE) have been grouped into wind power ramp forecasting (WPRF), wind power ramp detection (WPRD), and wind power ramp application (WPRA) [80]. Tinghui et al. [81] predicted wind power ramp events based on residual correction with an improved swinging door algorithm to improve both the wind power prediction and ramp prediction [69]. Zhang et al., in [82,83], extracted ramp events from wind power time series using the swing door algorithm to improve the performance ramp detection. The authors of [83] extend this topic to a forecasted wind power series in addition to the actual wind power time series. Ramping in wind generation has been determined using the method of feature selections in [84–86]. In recent studies, wind power ramping forecasting problems being modeled as stochastic processes are solved using neural networks [87]. The probability distribution of three properties of wind power ramping events was investigated in [88] using the neural network and scenario generation method to realize the stochastic process in wind power generation. Additionally, in [89], a wind power ramp event was considered while studying coordinated dispatch processes for energy storage systems; the process was used to achieve an improved economic dispatch of units of ESS. A method for the optimal control of ramp events characteristics using the ESS is presented in [90]. This study proposed a strategy to determine an appropriate ESS size that can be reserved for anticipated WPRE. The study of [91] presented a strategy to exit the operation of an offshore wind turbine but under extreme weather such as the occurrence of a typhoon in an offshore wind power system.

Solar ramp events have been categorized into solar power ramp events (SPRE) and solar irradiance ramp events (SIRE). While SPRE helps in the management of balanced ramp events, SIRE is critical for the dispatch and operation of solar power plants [92]. Ramp decreases or increases in the rate of output to follow net load as its capability [93] and can respond to needed variations in expected or unexpected demand [94]. It is reported in [69] that SPRE usually occurs during midday when the solar generation output is peak, and this coincides with hours of high demand in most cases. The study of [95] used the BESS to reduce the rate of SPRE and also addressed frequency fluctuations. Recent studies that discussed the role of ESS in analyzing the SPRE can be found in [96–98]. Table 1 highlights some articles that discussed the characteristics of ramping events from wind, solar and ESS sources.

Table 1. Highlights of articles that discussed the characteristics of ramping events from wind and solar sources.

References	Model Applied/Method	Highlights/Strategy
[69,78–80]	ANN	Studied WPREs and classifications
[81–83]	improved swinging door algorithm	Prediction of WPREs
[84–86]	Feature selections	Ramping in wind power generation
[87,88]	ANN, stochastic process	WPRE forecast
[89–91]		WPRE with ESS
[96–98]		SPRE , SIRE with ESS
[69,92,93]		Definition and characteristics of SIRE
[95,98]		SIRE with ESS

5. Classification of Flexibility Impacts on Power Systems

Many studies have attempted to classify the impact of flexibility on power systems. The most general classification found in [11,37] is based on the duration impacts. These include long-term, mid-term, short-term, and super-short-term impacts.

5.1. Super-Short-Term Impacts

These are millisecond control systems, such as reactive power control, low-voltage ride-through [99,100], voltage control, ramp rate control, supervisory control and data acquisition, power electronic control [101,102], and dynamic modeling of prime movers of turbines in large wind plants.

5.2. Short-Term Impacts

For utility and plant operators to ensure an adequate quality of balanced supply and demand, they must understand, in depth, the level and kind of uncertainties that are introduced by the latest innovations in the short-term operation of the power systems [103]. Additionally, an important system metric is the system's ability to respond to short-term changes in system load, net load changes, and variable generation units' outage in long-term planning context [6]. There are three short-term flexibility impacts, as identified in [88,104]. These three are minimum output limits, increasing needs for reserves, and increasing requirements for ramping. The reserves are the extra capacity on stand-by to account for the future possibility of an insufficient generating capability, which may occur when demand is higher than expected or if some generation is unexpectedly unavailable. In a thermal plant, the increase in net load changes forces the plant against its ramp rate limits. An adequate reserve allocation must be in place to mitigate the uncertainty in demand and supply arising from the imperfect forecasting of either of each or both. Regulation service and load following are used to maintain flexibility in the short term (seconds or minutes).

5.3. Mid-Term Impacts

In large power systems, there is a high penetration of VRES, such as wind powers. There are increased needs for the system to undergo frequent starts-up or ramping. This is called cycling [11]. An empirical approach to study the impact of VRE penetration on cycling is presented in [105]. It is reported that cycling can cause serious damages within the power plant components, which necessitates an increase in maintains and outages within the power system [106]. It may even resort to corrosion, erosion, or thermal shock, which in turn increases the cost of the maintenance of the generators. Additionally, frequent cycling essentially leads to a loss of revenue due to a persistent shut down of plant units and the reduced efficiency of the systems [107]. Hence, the use of ESS to mitigate these effects should be explored.

5.4. Long-Term Impacts

Some technologies, such as nuclear and geothermal technologies, have little flexibility in operation because they have limited output levels and ramping rates. The low flexible characteristics of these technologies mean that they remain shut down for a long time, leading to a low return on any investment that is dependent on such facilities. Moreover, it is noted that some nuclear plants can ramp around their power output. However, this capability is limited due to reasons such as the economy or security in terms of contingencies. Alternative means such as ESS or demand-side management should be explored.

6. Flexibility Improvement with Renewable Energy Sources

Technically, flexibility improvement concerns both the supply and the demand sides of the power system since it is largely related to the maintenance of the balance of the share of variable RE generations within the RE-penetrated power system while ensuring the continuous production of stable and high-quality electricity [108]. However, flexibility improvements based on the renewable energy system have a significant impact on both sides because the RE powers are usually integrated at both the supply end and the demand end of the power system.

As the campaign for green energy grows, there is a rapid increasing penetration of RES, such as wind power, solar power and hydrogen power, in the form of fuel cells in the electricity grid. Moreover, there has been a steady usage of individual residential microgrids in the form of rooftop solar PV, wind turbines and hybrid systems, whose capacities range from tens of kW to 1000 kW [109]. In essence, the new system of the energy market is placing more responsibility in the hands of private investors, such as renewable energy planners, generation companies and individual residential microgrid owners, not just to meet the future electricity demand but to also guarantee system security [110].

Salman et al. present strategies to conduct a techno-economic analysis and assessment of wind power generation in the microgrid. In [111], the authors investigated the impact of RE integration based on long-term load expansion and, in [112], the authors sized an ESS for its optimization and placement in solar PV-integrated network. In [113], the authors investigated the future adoption of RE in balancing power mismatch while maintaining deep decarbonization in a city-level energy system. This study further investigated the possibility of producing zero emissions for the city of Helsinki by the year 2050. Das et al. [114] presented the flexibility requirement for the integration of a large-scale RE in the Indian power system. This study identified technological policies and modeling options feasible for the power system in India. In addition, they also included the market design regulatory mechanism and some policy structures that would support flexible sources that would enhance the country's national development goal. The flexible pathways for the integration of RE in the power system of China, which is heavily coal based, has been suggested in reference [115]. The authors presented a balanced RE-integration analytical framework and technical economic performance of the major flexible sources. This study provided recommendations for the adoption of the framework and how it would enhance the flexibility of their power system. The authors of [116] presented a quantitative evaluation of a power system's flexibility based on an improved universal generating function using Zhangjiakou as a case study. The authors built a multi-state probabilistic model of main components in the power system and proposed flexibility metrics for the analysis of the measures proposed. More studies on RE-based flexibility strategies and challenges for power systems are reported in [117–120].

Furthermore, the authors incorporated demand-side management (DSM) in the model using electric vehicles (EV) and flexible load in the form of a chilled water thermal storage air-conditioning system (CSACS). The problem was formulated based on total profit maximization and the MILP was used to solve the optimization problem, with the result proving satisfactory. Diag Wang et al. [121] presented a study investigating the role of hydrogen in the improvement of flexibility in the energy sector. In particular, this study quantified the interaction between fuel-cell electric vehicles, hydrogen production for fuel cells and the electric power grid.

7. Use of Demand-Side Management for Improving Flexibility

The DSM has been classified as one of the low-cost methods of improving the flexibility of PSF [122]. Although Qin Wang et al. opined that implementing demand response (DR) resources in an energy market can substantially improve the grid flexibility, such techniques have been implemented in building automation, plug-in electric vehicles (PEV), thermostats, etc. [123]. However, there is a clear difference between DMS and DR. While DMS seeks to maintain balance between the demand and supplied energy from the sides of system operators, utilities and consumers, the DR does the same only from the consumer's end. It is therefore sufficient to view the impact of DSM on PFS without a special reference to the to DR. In DSM, some high-demand customers (heavy manufacturing industries) are offered special contracts where a part of their loads are required to be disconnected within a specific time-frame and occasionally to help the utility minimize costs or certain network constraints [124]. The typical DSM explained here is uncommon because the it usually requires a high load; however, its impact on flexibility improvement is felt in the network since it requires a large amount of power. A special type of DSM is needed for lower-demand customers, such as the residential consumers, which is proposed in [125–127]. However, a large amount of residential loads are needed to make aggregated loads which have a potential tremendous effect in improving the flexibility of the power system [128]. The study of [129] introduced a probabilistic method of generating load profiles for residential and non-residential buildings. Said study performed a quantitative evaluation of the benefits of demand optimization.

The authors of [122] present a comprehensive review of market-based flexibility ramping products and how they are implemented in optimization frameworks involving energy and ancillary services. They further identified different industrial strategies in the implementation of market-based flexibility ramping products in different market structures. Pierluigi et al. [123] present a survey of the benefits of demand response (DR) in smart grids, with a focused analysis on industrial research and installed projects. The survey identified some key elements of a smart grid that can potentially enhance the efficiency of a smart grid, which would consequently improve system flexibility. Some of the components of the smart grid identified include: communication systems, energy controllers, smart meters, and well designed programs that would facilitate the implementation of DR. Examples of such programs include direct load control programs, critical-peak pricing, real-time pricing and time-of-use pricing. The other strategies identified are spinning reserve and day-ahead prediction. Moreover, there is also a need to understand and factor in the consumption styles of the consumers. Customers have been categorized into residential, large commercial and industrial, small commercial and industrial, individual PEV and fleet PEV customers. By understanding the behaviors of these customers, it would be easy to identify the appropriate strategy for each customer.

Daniel, in [124], explores the use of demand-side resources to achieve a fast flexibility in PSF. The approach presented in this study is based on an extended unit commitment optimization strategy, formulated as mixed-integer linear programming considering short-term and long-term investments and operation costs. The unit commitment is used to minimize the cost of scheduling the cost of designated generators within a given time horizon. A year horizon is split into component weeks of four seasons with an additional special case of an extreme winter season, tagged the worst-case scenario. The other seasons are encoded with the number of weeks; these include autumn (13 weeks), spring (9 weeks), summer (13 weeks), winter (16.75 weeks) and extreme winter (0.25 weeks). Out of a number of units considered, the model optimization ascertains the type and optimum number of units, for which the minimum sum of investment and annual operating cost is obtained. Furthermore, a part of the loads are allowed to be curtailed for some hours but are recovered later in the same day by this technique, and the DSM (which is a fraction of the demand at some hours shifted to be supplied at other hours) is implemented in the model. Equation (7) was used to maintain power balance (between $P_D(t)$, $P_G(t)$ and $DSM(t)$) and it is one of the key constraints to the proposed objective function.

$$P_D(t) - DSM(t) - \sum_{i=1}^{I} P_G(t) \quad \forall t \in 1, T \tag{7}$$

where $P_D(t)$ is the power demand, $P_G(t)$ is the generated power and $DSM(t)$ is the aggregated capacity of the DSM scheme. Additionally, the reserve constraint is presented in (8):

$$\sum_{i=1}^{I} u_{i,t} \times (\omega DSM(t) + \omega P_G(t)) \geq SR(t) \tag{8}$$

where $\omega DSM(t)$ and $\omega P_G(t)$ are the capacity still available for DSM and P_G, respectively, and are both defined as in (9) and (10). DSM^{max} and P_G^{max} maximum DSM and maximum P_G, respectively.

$$\omega DSM(t) = DSM^{max} - DSM(t) \tag{9}$$

$$\omega P_G(t) = P_G^{max} - P_G(t) \tag{10}$$

A scheduling strategy was proposed by Illia et al. [130] to unpin the flexibility power system in Europe. The strategy adopts a day-ahead multi-timing strategy to procure ramp products in real time with a simultaneous utilization or optimization of energy and reserves over hour intervals. This study further presents a probabilistic approach for quantifying the flexibility requirements. Table 2 summarises the ideas and references of articles that discussed the use of DSM for flexibility enhancement.

Table 2. Highlights of flexibility approach based on DSM.

References	Model Applied/Method	Highlights/Strategy
[122,125–127]	Review	DSM classification, market flexibility
[123]	Review	DR applied in grid flexibility, automation, PEV
[128–130]	Probabilistic approach	Flexibility in residential and non-residential sector
[124]	MILP	Flexibility with DSM, model optimization for short-term and long-term

8. Use of Energy Storage System for Improving Flexibility

The ESS has been used to improve the flexibility of a high-VRE-power systems [131–133]. It can be used to mitigate imbalances in power and voltage deviations to improve the power indices [134,135]. Reference [136] has classified the flexibility capabilities of ESS based on individual responsiveness. The classification includes: a fast response, mid-response and electric vehicle, as described in Figure 4. The study of [133] improved the flexibility of coal-fired power plants using the integration of thermal energy storage (TES). This study developed a dynamic power plant model in the Dynamola simulation environment to decouple the firing rate and net rate, and the TES enables an easy initiation of the start-up process and control of power. Niu et al. [132] studied the dispatch of a building energy system using the TES and BESS. They proposed a linear model to predict dynamic cooling load while developing complexity-evaluation and accuracy-evaluation indices as criteria for selecting a building thermal model. Furthermore, this study uses MILP to develop and test the flexibility capacity of both battery and building thermal storage. The problem is formulated as an optimization problem, with the objective to minimize electricity and maintenance costs. This accounts for all supplies and loads in the building. The maintenance costs are made up of the expenses of the power subsystem and cooling subsystem, which are key components of the model because the effectiveness of the thermal storage is stochastically model around several parameters, including the behavior of the building occupants, weather parameters and other controllable parameters. Some of the parameters were constrained for the objective function together with power systems, photovoltaic and battery energy constraints. This study found that a compromise exists between flexibility enhancement and increasing investment on infrastructure. Additionally, an accurate forecast of the dynamic cooling load in buildings could potential enhance the flexibility dispatch of power using the building thermal storage.

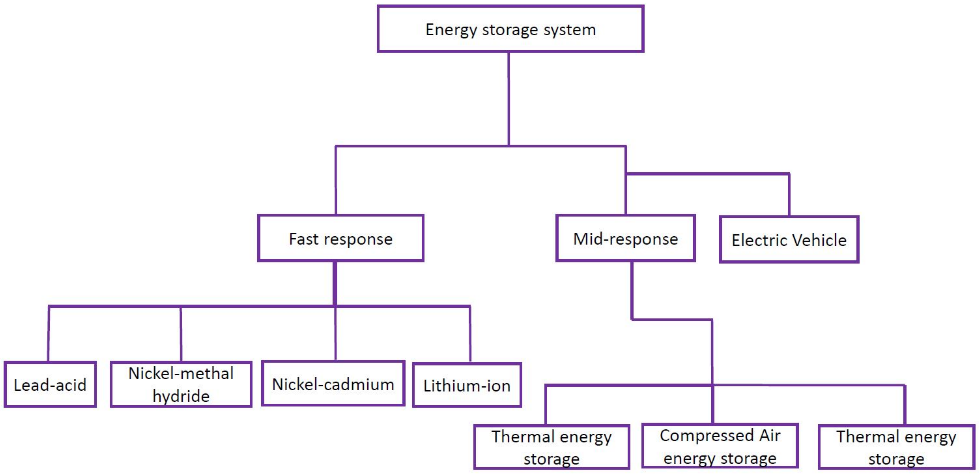

Figure 4. Flexibility response of energy storage system.

As part of the network component to enhance the flexibility of active distribution networks, ESS was explored in [134] in a quantification of node analysis. ESS showed a potential strength in improving the power imbalance and voltage deviation of the distribution system. In [135], the authors demonstrate the role of ESS in the interaction between conventional generation and renewables in a market environment. A variety of structures for the participation of ESS in such a market were investigated. This study proposed a multi-period market equilibrium model, capturing generator ramping constraints, which indicate generator flexibility and inter-temporal storage. This model is made up of a bi-level, multi-period spot-market equilibrium and is divided into upper level problems and lower level problems. While an upper level problem depicts a profit-maximizing generator and energy storage operators in offering capacity to the market, the lower level is the spot market that is cleared by the market operator. While solving the bi-level problem, the lower level is addressed first, and the lower level problem is replaced by necessary and sufficient optimal conditions, resulting in a mathematical problem of equilibrium constraints (MPEC). Then, all MPECs of the firms are combined to obtain an equilibrium program with equilibrium constraints (EPEC) for the profits. This formulation forms a series linearized problem and it is solved using a mixed-integer linear program (MLIP). The process involved in the formulation of the problem includes many equations and is reported in the appendix of the article.

Gang-Gai and Mun-Kyeom [131], demonstrated the use of pump hydroelectric storage (PHES) for flexibility improvement in power systems. A flexible-based reserve scheduling method was proposed for PHES to improve flexibility. While implementing the strategy, this study considers ramping capabilities and related risks involved in the modeling of the proposed system. It evaluates flexibility using a risk index identified as ramping capability shortage expectation (RSE). The RSE, which is defined in [137], is described in terms of ramping capability. The ramping capability is the ability of a generator to change its power output within a targeted period. The $SRC(t)$ defined in [131] is given by (11), while the ramping capability requirement RCR is modeled in (12).

$$SRC_t = \sum_{i=1} A_{i,t-\triangle t} O_{i,t-\triangle t} min(P_{max,i} - P_{i,t-\triangle t}, rr_i \triangle t) \tag{11}$$

where $P_{i,max}$ is the maximum output of the generator, $P_{i,t-\triangle t}$ is output of the generator at hour t and target period, $A_{i,t-\triangle t}$ measures the generator uncertainty calculate from the Markov chain generator model, and $rr_i \triangle t$ is a characteristic unique for each generating unit. One interesting thing about Equation (11) is that it models the unavailability generation schedule of each unit based on the transition rate between each individual generator's state.

$$RCR_t = P_t^{NFE} + P^F \sum_{i=1} A_{i,t-\triangle t} O_{i,t-\triangle t} P_{i,t-\triangle t} \tag{12}$$

where P^{NFE} is the net load forecast error defined by (13).

$$P_t^{NFE} = P_t^F - P_t^{VGFE} \tag{13}$$

P^F, $VGFE$ represent the load forecasted and variable generation forecast error, respectively, and both follow a stochastic Gaussian distribution.

It can be inferred from Equation (12) that increases in failures or unexpected failures of the generators lead to the need for more ramping capabilities. Consequently, a power imbalance can occur if the satisfaction of RCR_t is not met by SRC_t, as noted in [131,137].

Joseph et al. [110] presented a methodology for applying ROA to a BESS project for private investors in order to determine the optimal energy capacity and investment time of the BESS; it was found that the BESS capital expenditure has a significant effect on energy sizes but a smaller effect on investment timing. The influence of the time horizon was studied in [138] by comparing a 48 h time horizon with a 24 h horizon; an energy arbitrage performance of a residential MG was evaluated. This study revealed that a 48 h time horizon generates more profit for a residential MG operator than the 24 h based horizon. Furthermore, the 48 h horizon strategy leads to an overall reduction in the operation of such an MG.

The authors of [139] proposed a stochastic control energy management strategy for smart homes using solar panels and plug-in hybrid vehicles (PEV) with the aim to minimize energy bills and meet the power requirement of the demand and PEV charging. In [140], the authors present a battery-based multi-objective home energy management system (EMS). Batteries are used to decrease home energy consumption bills during the peak hours of consumption of the home. The performances of different ESS technologies were evaluated in [141] in an electricity market, while also measuring the economic effect of a PV-based MG both in the grid-connected mode and stand-alone mode. A strategy for evaluating the ESS depreciation cost was studied in [142]. The authors of [143] present a similar study but use the depth of discharge (DoD) as a function battery depreciation cost function while [142] uses the C-rate evaluation for energy arbitrage to model ESS depreciation costs. Table 3 captions a number of articles where the application of ESS in a power system flexibility have been studied.

Issues of power system flexibility are linked to power dispatchability, economics, reliability and stability are also serious concerns to system planners, operators, and researchers. In a hybrid system, with wind and solar renewable energy sources (RES), for example, there is the advantage that the maximum supply can be tracked at all times, which would enhance flexibility in the network. For example, solar power is available and picked during the day, while wind power may be available through the day and night. The peak periods could be targeted for maximum power dispatch and profitability. Furthermore, in order to reduce the charging/discharging operation of the BESS, the hybrid system could be allowed to operate in different penetration modes, which can further help to enhance the flexibility of the microgrid.

Table 3. Highlights of the flexibility approach based on ESS.

References	Model Applied/Method	Highlights/Strategy
[136]	Simulation	Classification of ESS flexibility capabilities
[133]	Dynamola	Used integrated thermal energy storage to improve flexibility
[132]	linear model, MILP	Dispatch of building energy using TES and ESS
[134]	Simulation	ESS in distribution network based on quantification analysis
[135]	MILP	Role of ESS in between RE and conventional generation in a market environment
[131]	RSE	PHES for improving power system flexibility
[131,137]	RSE	Ramping capabilities in power system

9. Flexibility Based on Energy Forecasting

Demand prediction is an attempt to estimate the future level of demand based on historical and present knowledge and experience, to avoid both the overproduction and underproduction of power. The argument here is that the ability to predict demand correctly in advance will enable system planners and generation companies to prepare adequately for the amount of power to meet the demand. By implication, it will help to meet the planning of both utility and generation planners, thereby improving the flexibility of the power system. Moreover, the accurate prediction of energy demand can potentially reduce the amount of energy consumption, leading to the availability of more power reserves and reduced contingencies [144].

There are several methods and techniques that have been adopted for the prediction of demand. They are categorized into survey methods and statistical methods. Figure 1 shows some of the methods and techniques that have been used to forecast demand in the literature. We will further discuss the statistical techniques and highlight various machine learning algorithms that have been used for energy demand prediction. Moreover, Figure 5 highlights some of the parameters associated with energy demand predictions. These parameters serve as inputs and outputs to the different machine learning techniques developed for future prediction.

Salman et al. [145], proposed the artificial neural network (ANN) for the restoration of different load categories after a fault is cleared. This study adopts a smart and dynamic prioritization of different load categories, such as commercial, residential, hospital and industrial, based on the load importance, available power and reliability at a particular time. These parameters are used to trained the ANN to develop a model for the future restoration of loads after fault occurs. The model makes intelligent decisions when tested under different conditions, it is able to make good judgements so as to decide which load should be isolated or which should never be interrupted. This study proposed a strong idea based on NN forecasting that could improve the flexibility of power systems.

Yabin et al. [146] presented a comprehensive study for the prediction of energy demand using seven different meteorological features along with other parameters such as indoor temperature, time and, operating parameters. The forecasting models were developed using an ML algorithm, such as a back-propagation neural network, extreme ML, support vector regression (SVR) and multiple linear regression (MLR). This study further evaluates the performance of the four models by using the real data of a heating building sourced from heat pump system. It was found that the extreme ML model performed better than the other three. Additionally, this study revealed that the thermal response of the building where this study was conducted took forty minutes. Nikolaos et al., in [147], demonstrated the capabilities of deep learning in the forecast of aggregated load prediction and compared it with nine ML techniques. The training parameters include energy, feed price, temperature, irradiation, wind capacity and wind velocity. This study showed that multilayer perceptron

(MLP) could perform better than most of the common forecasting techniques if enhanced with deep learning and appropriate tuning of the algorithm settings.

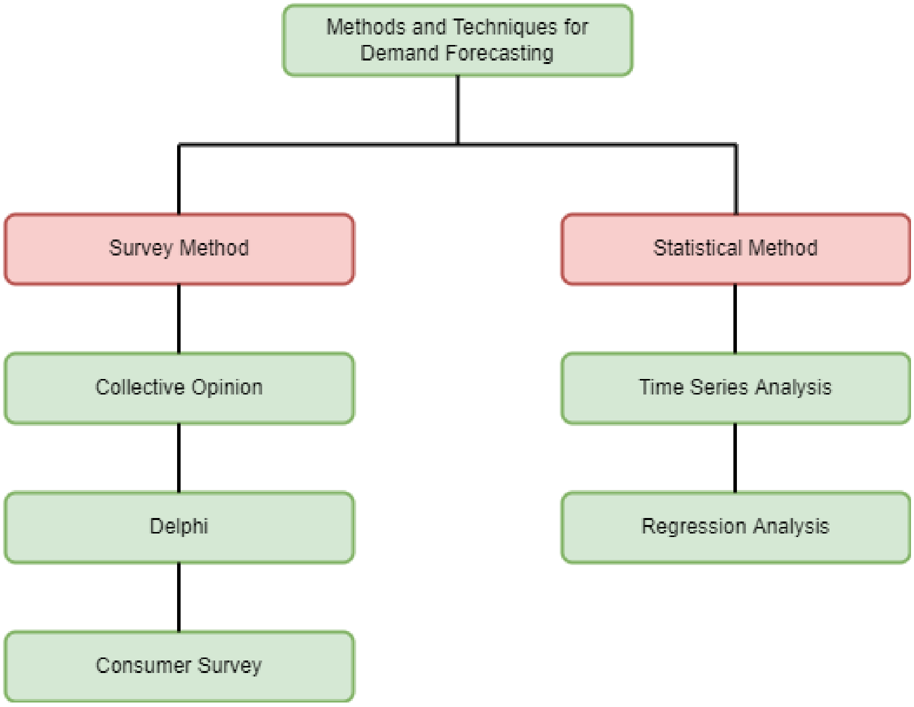

Figure 5. Methods and techniques for energy demand forecasting.

The study of [144] proposed three ML algorithms for the prediction of charging demand of plug-in electric vehicles (PEV) in a charging session based on the available information at the beginning of the charging operation. The three algorithms are SVM, random forest (RF) and extreme gradient boosting (XGB). This study expressed the predicted charging demand as a function of twelve different parameters associated with the charging system and extracted the dataset collected from a public charging station in Nebraska. This study found that the XGB algorithm performed better than the other two and 50 percent of the variance in charging demand at any point is accounted for in the behavior of the users. A similar study is proposed in [148], by a method called federated energy demand learning (FEDL) for the prediction of energy demand of EV and charging stations (CS). The learning data in this study include CS identity, transaction identity, EV charging date, consumed energy, transaction identity of CS, and EV charging time, where the consumed energy is the learning target of the model. The FEDL was compared with two other techniques of federated energy demand (EDL), which are centralized EDL and clustering-based EDL. It is interesting to learn that each of the EDL algorithms proposed in [144] has a unique application for a particular scenario as defined in this study. The FEDL, however, provides the most accurate prediction and, in addition, enhances the communication between charging stations and charging station providers. The techniques adopted in [144,149] can be extended to the application of PEV in vehicle-to-grid (V2G) and grid-to-vehicle (G2V) power systems and would enhance the flexibility of such systems.

In [150], the authors proposed an ensemble learning technique to predict the energy demand for a residential building. The model combined four ML algorithms, including extreme learning machine (ELM), multiple linear regression (MLR), XGB and, SVM. Additionally, the training features include weather data, energy consumption data, time and unit operation data. The model metrics showed that the ELM is most accurate amongst the four methods and the ensemble network led to a greater improvement in the prediction accuracy than any of the four networks. However, this study further showed that the predictive accuracy of a model can also be influenced by the feature selection of the training data. Yekuan et al. [151] developed ML models for the prediction of building demand and a hybrid advanced controller aimed at enhancing the short forecasting prediction of energy management in the building. This study employed four ML algorithms, including SVM, MLR and back propagation neural network (BPN). This study showed that the model with the cross-entropy function learned with more accuracy and faster than other algorithms; this study further showed that selecting more training factors and training for a longer time increased the accuracy of the forecast of energy demand. All of the mentioned strategies could be used to enhance the flexibility of power systems if appropriately implemented. Table 4 presents some studies where the application of energy forecast have been employed to improve power system flexibility.

Table 4. Highlights of flexibility approach based on energy forecast.

References	Model Applied/Method	Highlights/Strategy
[145]	ANN	Load prioritization during power system restoration after fault.
[146]	SVM, MLR, MLP	Prediction of demand based meteorological parameters
[144,148]	SVM, RF, XGB,	Charging demand in PEV in V2G and G2V applications
[150,151]	SVM, BPN, MLR, MLP	Prediction of residential demand based on energy parameters and weather factors.

10. Economic Impact on Flexibility Improvement

The electricity market and its economics have a great economic impact on power system flexibility and hence on the security enhancement of the system. Reference [2] emphasized the importance of the cost of power plants in maintaining the power system flexibility. It was opined that the plants should have minimum marginal costs in order for them to successfully compete as ways to increase flexibility. Additionally, references [5,152,153] have discussed the interaction between the energy markets and power system flexibility with an in-depth report of some studies that had conducted investigations on related topics.

There are some concepts and terms in electricity trading that form the basic operation of the market. The concepts are important in making certain decisions that directly or indirectly affect the RE power generation, RE power consumption and economic trading between generation and distribution sectors. Such concepts include renewable electricity, market models, power purchase agreement, energy balancing, green certificate trading, and carbon trading or carbon emission rights. The literature is rich with discussions of many of these terms. The studies of [154–157] have investigated the future development trends of the electric selling firms and the possible behavior of the participants of the green certificate trading market. In particular, they examined the effects of green certificate storage, prices and behavior of market participants in the green certificate trading market.

Additionally, in another concept, RES together with other power sources and loads are teamed up and aggregated in the form of a virtual power plant (VPP). A VPP is a cloud-based data control center that uses the aggregated production data from various DERs. Such data are useful for power plant operators to monitor and control the output production from the RE generation plants. On the other hand, this enables the utilities to meet the load requirements of their customers with more production from the RES, thereby leading to a cheaper, more reliable and a more flexible power supply. The role of VPP in the improvement of power system flexibility is reported in [110,158–162]. Reference [158] provides a definition and the types and concepts of VPP in power systems and the flexibility benefits of VPP and their impact on power systems are discussed in [159,160]. However, studies have discussed the importance of VPP and the transformation of the microgrid to VPP [161] and the ESS have been considered as important components of both systems, even after the transformation.

A unifying central control of the distributed energy resources (DER) or distributed power plant (DPP) is the virtual power plant (VPP), which essentially participates in the electricity market transaction by aggregating distributed wind power generation and energy storage to promote the consumption of new energy. The VPP is a cloud-based DPP that aggregates the capacities of heterogeneous DER in order to boost power generation and the trading power in the electricity market [162]. The VPP also facilitates the trading of carbon in the carbon-trading market, thereby benefiting the environment [163].

In VPP, issues of dispatchability, economics, reliability and stability are also a serious concern to system planners, operators, and researchers [164]. In a hybrid VPP system using wind and solar renewable energy sources (RES), for example, the maximum supply may be tracked at all times. For example, solar power is available and is picked during the day, while wind power may be available through the day and night. The peak periods could be targeted for maximum power dispatch and profitability [165]. Furthermore, in order to reduce the charging/discharging operation of the BESS, the hybrid system could be allowed to operate in different penetration modes.

The authors of [166] examined an optimal dispatch model for VPP made up of gas turbines, PV, wind power and demand response (DR) to include the participation of trading in carbon emissions. This study uses the probabilistic model to solve the problem of uncertainties in the output of the RE generation.

In [167], a feasibility study of a green certificate circulation mechanism based on a quota system is presented. Furthermore, this study discussed the possibility of having a green certificate transaction deployed on the block-chain and transaction processes in different chain platforms. The authors of [168] revealed the capability of green certificate transactions in the promotion of RE generation in market competition. This was achieved by the implementation of a complementary and a multi-regional green certificate and power market models.

The authors of [169] proposed a two-level decision-making optimization technique for internal purchases and electric sales, as well as for the external multi-market. The technique allows the VPP to participate in the electricity market, green certificate trading market and carbon-trading market so as to optimize the total income. This study first presents model for the operation of the VPP by analyzing the various roles of all the distributed energy resources (DER) and participants in the carbon-trading market and the green certificate market. Then, this study constructed a two-level optimization model of the VPP which established the participation of the VPP in the green certificate transaction and power purchase and sales transactions. This study found that the VPP is capable of increasing the output of DER and recommends that a coordinated optimization of carbon-trading market and green certificate market when a VPP is to take part in the market decision making. In [170], the authors discussed carbon emission rights trading with a special focus on emission rights and the electricity market trading based on market allocation strategies and election mechanisms. The authors of [169,171] investigated the relationship between the stock price of the new and old energy firms and carbon emission rights. It was discovered that both the new and the old companies were seriously affected by carbon emission rights. Many of these models and strategies, if properly implemented, would help make some important decisions regarding generation, transmission and utility, and consequently help to improve the flexibility of power systems.

11. Conclusions

Power system flexibility is an important concept that has received a large amount of attention in the literature. This topic becomes more significant as power systems experience a high penetration of renewable powers. In this study, we have discussed the various definitions of power system flexibility, its impacts, and methods of enhancing it. Additionally, we discussed the classification of flexibility impacts on power systems. We identified and presented some of the research on flexibility based on five major aspects that affect power system flexibility, including flexibility improvements based on RE, DMS, ESS, energy forecasting, and an economic analysis of the electricity market operations. This study reports many studies that provide good insights into the highlighted areas. We note that flexibility studies require continuity as the power system architecture and operation change with advancements in these areas. Moreover, more strategies based on technical, economic and operational flexibility are required in future research, not just in the conventional power sources but also in other flexibility sources that have great potential to improve the flexibility of the power system.

Author Contributions: Conceptualization, U.T.S. and F.S.A.-I.; formal analysis, U.T.S. and M.K.; funding acquisition, S.S.; investigation, U.T.S.; methodology, U.T.S.; project administration, F.S.A.-I. and M.K.; resources, U.T.S.; supervision, S.S. and M.K.; validation, S.S.; writing—original draft, U.T.S.; writing—review & editing, S.S., F.S.A.-I. and M.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Center of Renewable Energy and Power Systems at King Fahd University of Petroleum & Minerals under Project No. INRE2106.

Acknowledgments: The authors would like to acknowledge the support provided by the Center of Renewable Energy and Power Systems at King Fahd University of Petroleum & Minerals under Project No. INRE2106 and King Abdullah City for Atomic and Renewable Energy (K.A.CARE).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BESS	Battery energy storage system
BO	Butterfly optimization
BOA	Butterfly optimization algorithm
ESS	Energy storage system
CS	Charging station
EPEC	equilibrium program with equilibrium constraints
FDEL	Federated energy demand learning
DOD	Depth of Discharge
DPP	Distributed power plant
DR	Demand response
EMS	Energy Management Strategy
IEA	Intentional Energy Agency
LP	Linear Programming
MG	Microgrid
MPEC	mathematical problem of equilibrium constraints
MILP	Mixed-Integer Linear Programming
NLP	Non-Linear Programming
NERC	North American Electric Reliability Corporation
GWO	Grey Wolf Optimization
PSO	Particle Swarm Optimization
PHES	pump hydroelectric storage
PV	Plug-in electric vehicle
RES	Renewable energy system
RF	Random forest
SOC	State of Charge
SVM	Random forest
XGM	extreme gradient boosting
VPP	Virtual power plant
VRG	Variable renewable generation

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