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Review

Smart Grid, Demand Response and Optimization: A Critical Review of Computational Methods

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Abstract: In view of scarcity of traditional energy resources and environmental issues, renewable energy resources (RERs) are introduced to fulfill the electricity requirement of growing world. Moreover, the effective utilization of RERs to fulfill the varying electricity demands of customers can be achieved via demand response (DR). Furthermore, control techniques, decision variables and offered motivations are the ways to introduce DR into distribution network (DN). This categorization needs to be optimized to balance the supply and demand in DN. Therefore, intelligent algorithms are employed to achieve optimized DR. However, these algorithms are computationally restrained to handle the parametric load of uncertainty involved with RERs and power system. Henceforth, this paper focuses on the limitations of intelligent algorithms for DR. Furthermore, a comparative study of different intelligent algorithms for DR is discussed. Based on conclusions, quantum algorithms are recommended to optimize the computational burden for DR in future smart grid.

Keywords: renewable energy resources; demand response; intelligent algorithms; machine learning; quantum computing; smart grid

1. Introduction

The advancement in technology desires for an exponential increase in electricity generation. In bridging this gap, fossil fuel resources are now facing a shortage. Henceforward, dependence on fossil fuels needs to be shifted towards renewable energy resources (RERs) to overcome the energy requirements, clean energy production, and a decrease in greenhouse effects [1]. The usage of RERs is an established trend. However, only 10% of the primary energy consumption is fulfilled through RERs. Carbon pricing is used as a market mechanism to arouse the need for RERs in today's world. Due to a major focus on non-renewable resources, economic aspects of utilization, the oil crisis, and environmental concerns have gained the attention of researchers [2]. The only viable solution to meet this problem is to switch from non-renewable to renewable resources [3,4]. In 2018's renewable energy report, the total generation from RERs excluding hydro had reached 1246 GW [5]. However, in 2020, the increase was only 7% [6].

Various techniques are available to integrate RERs with conventional grids. However, one major problem in the integration of RERs is to control the inherent characteristics of power system. Among inherent characteristics, frequency balance, power storage, consumer usage pattern, and electricity unit cost are needed to be analyzed. Firstly, the frequency balance constraint can only be met if the electricity supply and demand are equal. Secondly, economic constraint heads up when power is to be stored at a larger level. Thirdly, power consumption by the consumer varies with the customer. Finally, electricity unit generation cost is dependent on the sources involved [7]. Moreover, in a classical power system, consumers face annual rates in a fixed form instead of market-based dynamic unit rate. However, an independent system operator (ISO) can meet the above-mentioned constraints and operate it securely and safely in a deregulated power system [8].

Through the deregulated power system, the need for power plants for high-scale power generation can be overcome. Moreover, the generation from the main grid can be decentralized into local units of generation. These local units are called distributed energy resources (DERs) [9]. Furthermore, the issues faced in the conventional power system, discussed above, are already counteracted through DERs. Microgrid (MG) is one step further towards the efficient implementation of DERs. Practically in an MG, DERs are regulated with advanced communication protocols and controllers to enhance the operating efficiency of conventional power system. Generally, MG is a prototype of the system-of-systems (SOS). The key component of an MG is its converse cooperation of local generation units in a network [10]. Figure 1 shows the conceptual approach of smart grid (SG).

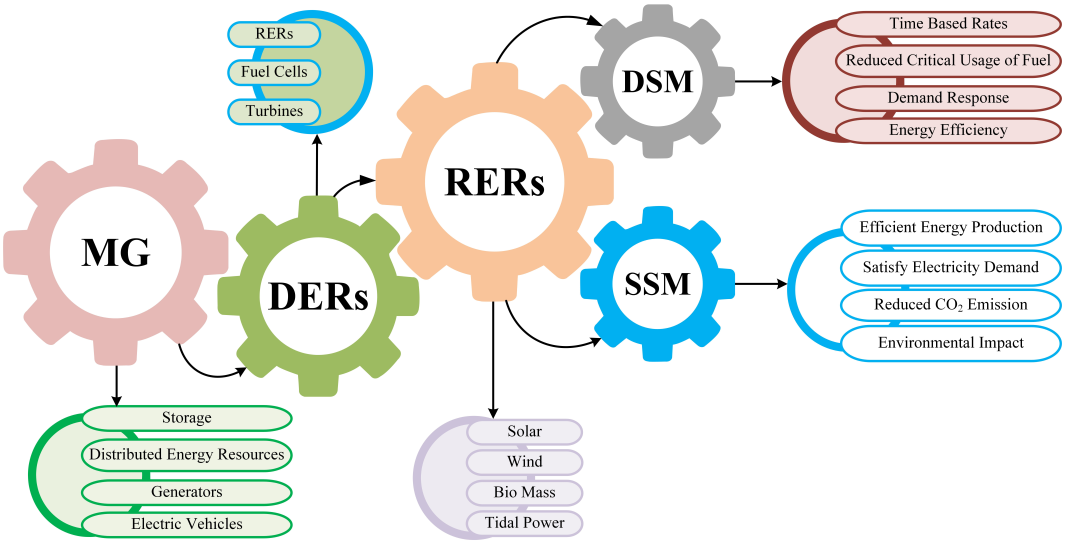

Figure 1. Conceptual approach of SG.

One important aspect of today's deregulated power system is electricity price. The companies involved in distribution, bid electricity price to maximize their profit. Moreover, electricity price varies with real-time demand. Demand and price are directly proportional to each other. In order to meet this proportionality, the grid management is divided into two main streams. First is supply-side management (SSM) and the second is demand-side management (DSM). Both management approaches allow to compensate the contingencies in the power system, enhance the load capacity of the network, and minimize the peak loads. The SSM can enhance the overall efficiency of the grid [11]. In contrast to SSM, DSM depends on electricity usage pattern and real-time load wattage instead of other external factors. Therefore, DSM proves itself to be more efficient than SSM. Furthermore, DSM can also meet the continuously increasing demand for electricity concerning the limited expansion rate of power system. Table 1 gives a detailed insight into the objective, benefits, and limitations of DSM.

Table 1. DSM insight.

Benefits	Limitations
Blackouts elimination	Awareness about efficient energy use
Blackouts elimination	Monopoly power market structure
Reduced CO_2 emissions	Absence of appropriate incentive schemes
Improved operating efficiency	Operational instability of power systems

The concept of MG emphasizes an energy-efficient power grid [12]. To obtain efficiency, real-time demand must balance out through renewable energy with the proper use of information available in the network. DSM manages the MG with the same idea. It targets all the parameters of MG in an attempt to restrict any change in the user's electricity pattern to balance the supply and demand. Moreover, supply is coped through efficient networking among RERs [13]. Furthermore, DSM offers a cost-effective solution for generation and transmission through the integration of DERs in MG [5]. Today, one of the main parameters of DSM is demand response (DR). DR makes use of RERs such as solar and wind energy to overcome environmental effects caused by conventional energy resources, and informs the utility and system operator to reduce their overall cost by updating electrical infrastructure. Figure 2 shows the detailed architecture of MG in distribution networks (DN). DR extends equally with energy efficiency activities and energy conservation techniques to complete the concept of DSM [14–16]. Table 2 shows the various areas where DSM has proved itself to be of benefit.

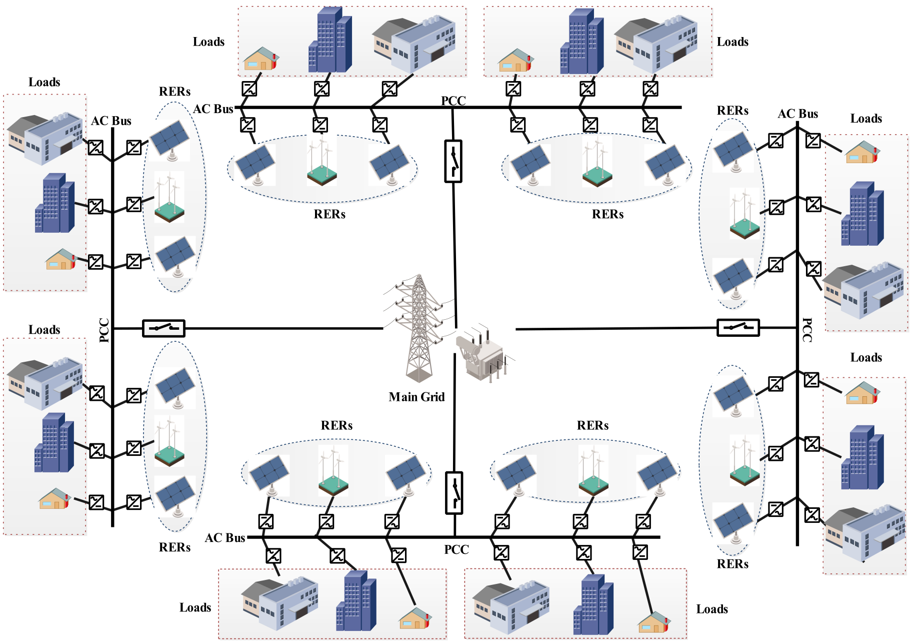

Figure 2. Architecture of MG.

Table 2. DSM and its applications.

Technique Focused	Reference
Techniques related to load control	[17]
DSM for electricity market	[18]
Remunerative effects of DSM	[19]
Commercial & non-commercial DSM effects	[20,21]
Integrating DSM with smart technologies	[22]
DSM as an enterprise	[23]
Benefits of DSM for power system operation	[24]
DSM optimization for SG	[25,26]
Price & load prediction using DSM	[27]

Recently, direct current (DC) microgrids (MGs) have gained progressive attention from researchers and industry. Many projects based on MGs can be seen in different applications (renewable energy source (RES) parks [28], DC homes [29,30], energy storage systems (ESSs) [31,32], electrical vehicles (EVs), and charging stations [33,34]). In the United Kingdom (UK) [35], China [36], North America [37], Kuwait [38], and Turkey [39], DSM has already been engaged for covering up the losses within SG. Based on these works, the futuristic strength of DC MGs in the market can be seen clearly [40,41].

To the best of authors' knowledge, an overview of existing literature on the impacts of DR in the DN is presented. DR can be characterized by control techniques (centralized and decentralized control), decision variables (energy management and task scheduling), and offered motivations (incentive and price based). However, these existing schemes indicate a need for optimization with the passage of time. Therefore, intelligent algorithms are used to optimize these DR techniques. The DN uses RERs to balance supply and demand through optimized DR techniques. However, state-of-art intelligent algorithms face parametric imbalance as a result of increased computational burden. Within this scope, machine learning comes up as a default approach. However, these approaches are unable to provide a complete probabilistic spectrum of predictions. This problem can be overcome using quantum computing based algorithms. Hence, quantum algorithms are recommended to quantify the uncertain nature of RERs in future DN to achieve the optimized DR. The The summary of the paper is described in Figure 3.

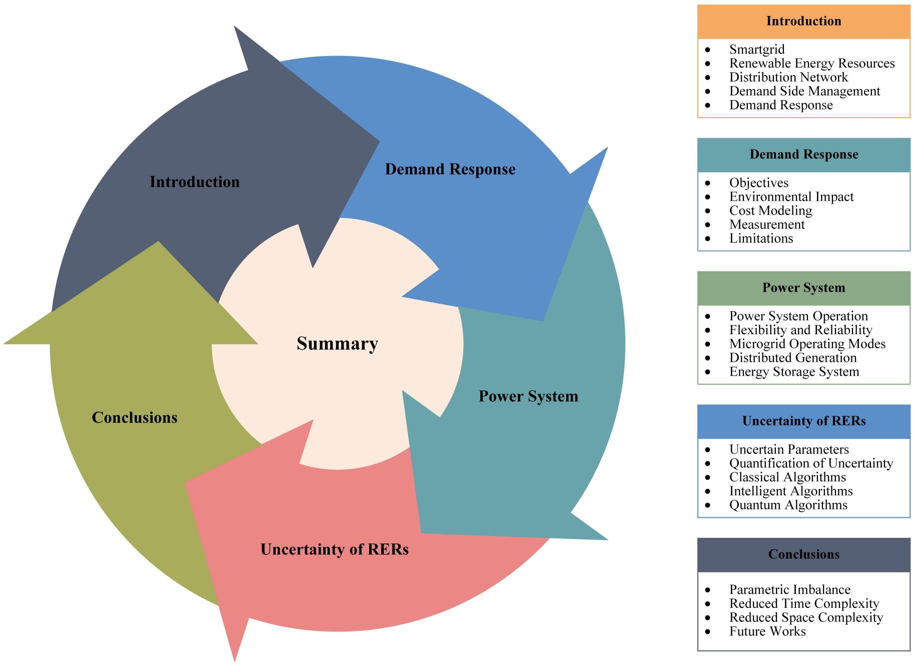

Figure 3. Summary of the paper.

The current paper is organized in the following manner: Section 2 gives a detailed insight of DR including objectives, societal impacts, cost modeling, measurement, and limitations. Section 3 explores the ways to integrate DR into power system with respect to MGs operating scenarios. Section 4 compares the computational models (classical, intelligent and quantum algorithms) to quantify the uncertainties of RERs through DR. Section 5 concludes the discussion.

2. Demand Response (DR)

Various descriptions for DR are available in the literature. However, one common stream among all is that DR covers the electricity demand which is flexible with respect to real market rates [42–45]. To distinguish DR from DSM, DSM through market policies drive DR to model the demand numerically. Moreover, to fulfill demand, RERs backup resources are incorporated into MG (energy conservation and energy efficiency) [35]. Figure 4 shows a detailed DR infrastructure.

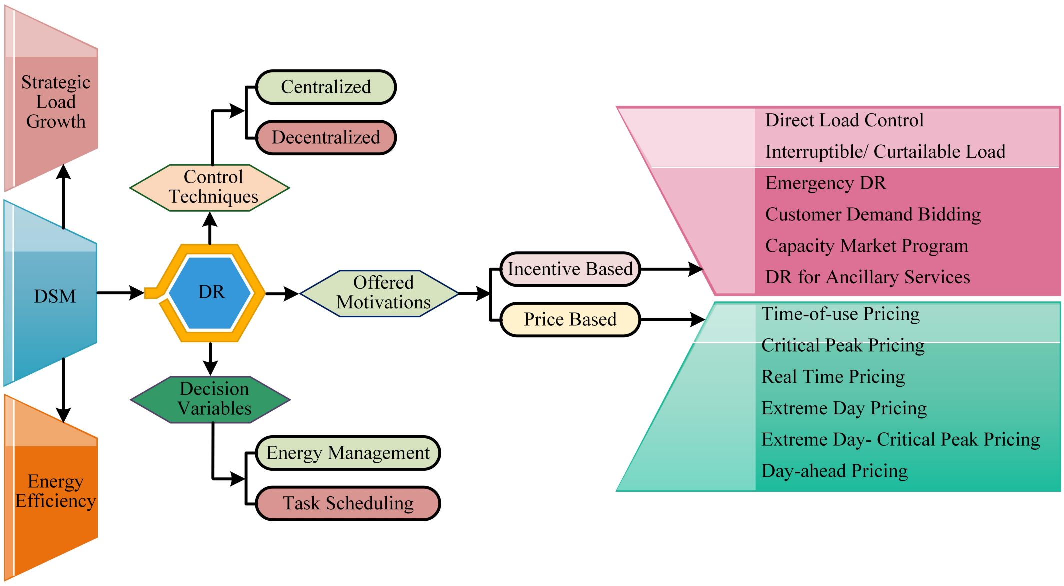

Figure 4. DR infrastructure.

Within the United States (US), 6.2% peak electricity demand is covered through DR. This has been implemented in 2014 accounting for 28,934 MW [46]. In Europe, large industrial customers are attracted to DR programs by introducing time-of-use pricing and interruptible tariffs. Furthermore, some industries also use large load avoidance criteria to obtain the intensives through DR [47]. In countries with the major focus of generation towards RERs, reliability of RERs has become a major issue. For example, in Germany, system reliability is sustained through flexible DR [48]. Ref. [49] defines DR as a flexible service, and specifies it through direction (up and down), time, location (zone and mode), and size (kW and KWh). These factors become important in regions with a high and large number of loads. Such networks require location-specific DR. However, in pursuit of system balance through demand responsiveness in comparison to market policies, time, direction and size become more important than location-specification.

2.1. DR Objectives

DR comprises short-term load management in such a manner that the energy usage pattern can be guided as per market policies. Hereafter, DR can be defined in particular to be the change in the user's energy portfolio aside from their routine consumption. This change is dependent on the following:

- Dynamic price rate with respect to real time.
- Incentives decided in accordance to cut down the electricity usage during peak hours.
- Whenever system reliability is of question [50].

Ref. [51] outlines that DR has a direct impact on load. This is one important advantage of DR due to which other DSM techniques are fading and recent market policies are defined through DR programs.

Figure 5 depicts the fact that DR can be used in various versions to modify conventional electricity demand. Peak clipping DR aims at diminishing peak time electricity consumption. If the aim is to reduce the peak hour electricity usage and shift to off-peak hours, then load shifting DR is focused. Valley filling DR is one that forwards high consumption low price tariffs and takes place when the generation through RERs is in excess. Strategic load growth and dynamic flexible load DR are also used to provide comfort to flexible load customers [52].

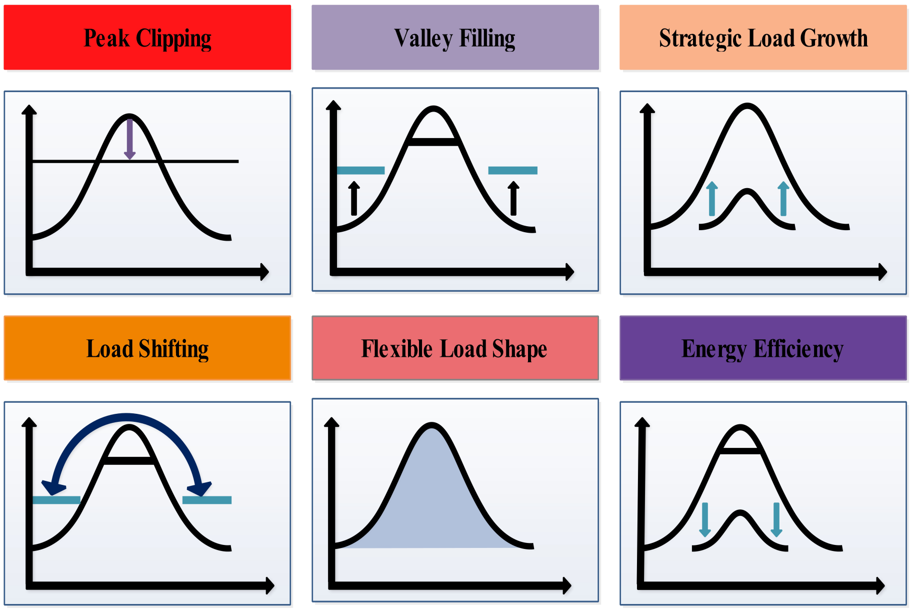

Figure 5. Various DSM load share techniques.

DR programs apply the valley filling technique to build load which can be operated during off-peak hours [53]. Peak clipping is used during peak hours to shred excessive load [36]. Load shifting provides the combined effect of peak clipping and valley filling activities [39].

DR programs further interconnect MG and the market through two main streams. One is a system reliability-oriented program and the second is market-oriented programs. Figure 4 shows detailed segregation of DR programs [54]. Through reliability-oriented DR programs, consumers receive economic incentives after defining a controlled use of appliances. The participation in this program is volunteered or maybe in-volunteered depending on the user [55]. Moreover, through market-oriented DR programs, consumers can receive flexible dynamic electricity prices in real-time and may define their load consumption depending on the current electricity rate.

Reliability oriented DR programs focus towards the nature of operation of energy consumption. Huge industries and commercial projects are covered through interruptible load DR program. The program requires the load to be cut off for short duration. In return, users will get a discounted electricity price rate because of tolerating service disruptions. Moreover, in case of not obliging with the program, users are penalized. Furthermore, toward the goal to reduce the peak hour consumption, direct load control programs are introduced [56]. These programs empower utility to interrupt directly into the load profile of user. However, users are notified prior to the change. As being part of this program, users will receive compensation [50,57]. In addition to this, emergency program is defined to deal with the system during any unforeseen event. However, this program does not apply any penalty to the users who cannot participate in it [58]. Emergency DR is another form of DR. This DR is activated to mitigate demand rebound. Demand rebound is an index for indicating the necessary reduction in load to avoid network congestion, transformer overloading, and customer inconvenience. Emergency DR is used to reduce the DN losses due to enhanced load requirements by the customers in the form of smart loads (EVs, dryers and heaters) [59]. To avoid this, a multi-objective agent-based approach is used focusing on the customer convenience and demand rebound. Moreover, transformer overloading is also calculated and optimized.

Market-oriented DR programs are subdivided into two main streams depending upon the user. One is the demand bidding program and the other is the real-time pricing program. The demand bidding program favors the huge energy consumers: users who can reduce their specific load with the need of time. These users face fixed electricity price rate under normal conditions. However, as the market price goes up, these users receive good incentives [50]. To avoid the fixed electricity price, real-time electricity pricing program is also an option for the consumers related to industry and commercial projects. In this program, electricity generation price faced by the consumers varies with time. However, the cost related to the hardware involved in transmission and distribution remains fixed [54]. Time-of-use pricing program comprises of the basic production costs and is voluntary. This rate inspires decreased consumption during peak hours [50]. To provide dynamic pricing to users, the critical peak pricing program is introduced. This scheme also focuses on the reliability of the system [54]. Real-time rate is defined to meet the supply contingencies. Users pay according to the rates that are a function of the real market. However, the pricing schedule is supplied day-ahead or on hourly basis to avoid any misunderstanding [58].

2.2. Societal Impacts of DR

The literature has addressed the impact of DR on environmental issues raised through energy generation. For example, in [60] Swedish electrical utilities have determined the possible benefits of load management. The objectives related to decarbonization with respect to available hardware is studied in [61] to plan an expansion in power generation capacity. Refs. [62,63] represents a structure based on mixed-integer programming for scheduling the maintenance associated with DR programs. The possible environmental trade-offs between system cost and emission reduction are suggested by [64]. Carbon-pricing policy and DR programs impacts on long-term integrated resource planning have been studied in the Indonesian power sector by [65]. The strength of energy policy association with economic, environmental, and reliability objectives unfolds the prospective benefits of DR to electrical power system [3].

The advantage of market-driven DR programs to the power system is the reduced price of electricity supply. Moreover, through short-term responses to market conditions sufficient reserve margins and stability of price can be maintained [66]. Finally, to maintain system reliability, a network-driven DR program is outrageous. This program maintains the supply and generation ratio in balance by dividing the demand into short time intervals.

1. Environmental Impact: Environmental damage can be avoided through reduced energy generation [61–65]. Through proper scheduling, excess fuel burning as in generator startup and ramping can be avoided, which results in no electricity generation. This scheduling is achievable through DR. Hence, DR results in visibly reduced emissions [60,67]. To overlook environmental issues such as reduced greenhouse gas effect, increased energy efficiency and decreased energy portfolio, an environment-driven DR program is used. Furthermore, it provides the social benefit of evaluating defined commitment to environmentally friendly generation.
2. Enhanced Efficiency in Real-Time: The compatibility of DR with real time results in enhanced efficiency of power system. To achieve this compatibility, time is divided into short, medium, and long terms. Moreover, for the short and medium terms, DR keeps the electricity flow within the technical bounds of systems. The peak of the network is decreased and hence system collapse can be avoided. During the long term, DR decreases the generation. The network maintenance cost decreases and the system efficiency are incremented [68].
3. Alignment of Technical System and Pricing: DR offers the physical alliance of a technical system and dynamic market pricing. In time-based pricing, DR focuses on optimization (day-ahead, hour-head, DG and RERs), peak load reduction, demand–supply balance, and real-time control. Furthermore, carbon dioxide (CO_2) emission and network costs get reduced [48].

2.3. DR in Power Systems

DR can be activated in the electric power system in various ways. Refs. [69,70] describes this through interruptible and price-based DR programs.

1. Interruptible DR Program: To maintain the supply reliability, these programs are made contract-based. They can be subdivided into direct load control (DLC), load shedding, and brownouts. The DLC works through the concept of a central factor-like

an aggregator or system operator. This factor has direct control overload and is also authorized to make a change in system parameters as per requirement. The idea of load shedding is to reduce electricity consumption in selected network sectors to meet the system supply constraint [70]. To reduce the load on the distribution and transmission of electricity on the system, the system operator decreases the value of voltage and frequency. Through these brownouts, the supply quality is still sustained within limits [71].

2. Price-Based DR Program: Ref. [72] describes this method as a change in electricity usage pattern by the customer from routine as a result of electricity price variation concerning time. Ref. [73] debated over the effects of price-based DR for large scale industries in theory. Ref. [70] shows the different types of available pricing methods. Real-time pricing (RTP), critical peak pricing (CPP), time-of-use (TOU) pricing, and peak time rebates (PTR) are drawn as a plan to various pricing schemes. The driving elements of these schemes are wholesale market prices or other technical constraints related to system reliability [52]. The RTP is more dynamic as compared to TOU. This is because real-time prices can be set according to hourly use. However, TOU prices are needed to be adjusted by blocks of time like four hours. Moreover, in CPP during a critical condition load reduction can be achieved with short notice to set the price at a higher rate. Incentives are offered to encourage load reduction. Furthermore, special incentives are given for standardizing consumption.
3. Hybrid DR Methods: Interruptible capacity (ICAP) DR and emergency DR can provoke extremely low consumption with a quick short notice to consumers. This is achieved through the system operator. Besides, TOU combined with demand change results in balancing of peak consumption or PTR [74].

The pricing rate offered to end-users depends on market design. A distribution system operator (DSO), aggregator, retailer, and/or a third party can propose different rates. In smart grids (SGs), the existing energy policy can be amended by incorporating price based on real-time supply and network technical state. For optimized results small users must be grouped. This will provide more flexible options and trading balance can be accomplished. To pursue grouping or aggregation, load can be divided as per need of consumer. For example, EVs can be considered as a separate entity and so is the home battery system.

2.4. Cost Modeling in DR

Keeping in view the voluntary choice of the end-user to take part in DR depending on the incentives offered, electricity pricing becomes an important issue. Tariff comprises of involved hardware cost and intents related to policy. Henceforth, this section discusses in detail the factors included in the modeling of the cost.

2.4.1. Cost Provision

Essentially, electricity billing is performed to offset the expense of the electricity service rendered. The cost can be seen as necessary expenses needed to be carried out by the provider to supply electricity. However, fees are the costs incurred for use of electricity by the individual customers. Cost provision determines the methods from which consumers receive electricity supply. To give a generalized notion, cost of system operation is the cause and electricity pricing is the effect [75,76].

Conventionally, electricity systems are operated through huge vertically integrated electricity retailers. The electricity billing and tariff structures are defined in consideration of the combined effect of generation and transmission. In many countries, this system is still used. The billing is done by the central operator governed by the government, whose tariff imitates the combined effect of supply and network costs deployed on end customer. However, when major electricity market is considered, transmission and distribution are separated from generation and retailing.

2.4.2. Electricity Generation

Usually, electricity is supplied progressively to high voltage grids from the conventional resources. The key aspect to be taken care of is supply–demand balance. Hence, a reliable electricity supply can be maintained by keeping a check on supply at each node in the network and at every moment in time. This is done by synchronously operating the generating units to supply the actual demand for electricity only. The perspective followed here is the supply-follows-demand perspective.

Nevertheless, SG enabled DR is now making use of the stochastic approach to meet the demand through energy supplied from RERs and distributed generators (DGs). The stochastic approach has opened a new doorway to supply low voltage rating grids via "presumption". Alongside, electricity is also supplied to high voltage rating grids. Furthermore, a futuristic practical approach is to focus on the demand-follows generation perspective rather than the generation-follows-demand perspective. This perspective shift entails dynamic pricing. The end-user should be able to receive real-time price change information [77]. Considering the economic perspective, electricity market is classified as follows:

1. Wholesale electricity market;
2. Substantial electricity market.

Wholesale market nowadays considers the short-term marginal costs.These marginal costs may be divided into time bundles ranging from 1 h to even 15 min. Based on the marginal cost the optimal economic signal of energy trading is derived [78]. However, to select the optimal economic energy signal, the maximum priced marginal generating unit in real-time is selected among the number of generating units available on the market. Therefore, real-time electricity rates for DR purposes are available in the wholesale market. Another way of trading electricity is substantial electricity markets. In these markets, producers and retailers can start mutual contracts for electricity supply. Moreover, minimal energy demand is leveraged in real-time. In cases where a substantial market is not available, the system operates all the generating units centrally. The demand is met through assigning the supply job at right time to the right unit.

2.4.3. Cost of Electricity Transmission and Distribution

To supply the electricity from the generating unit to the demand location requires electricity networks. High voltage networks responsible for transferring power from the production plant to the substation near the demand makes up the transmission network. To distribute the consumers with low voltage power, DNs are defined. The overall cost involved in these networks comprises of capital and operation and maintenance expenditures. These costs are more concerned with the network operators. Moreover, in price-based tariffs, this cost loses its importance. To overcome this issue, the total cost is used as the only input. This cost is then subdivided among different users in the network. Like customers, retailers, and prosumers. As far as distribution cost is concerned, in conventional electricity systems, distribution is the final step to carry the electricity from a transmission network to the individual user. In SG, enabled with emerging price allocation methods DR, distributed generator (DG) and presumption also play a role in anticipating the cost. Moreover, electricity flow within a DN is two ways in SG. Hence, it is suggested here that location-based pricing may become an important aspect in regulation policy [78]. In a system, running through an aggregator to trigger demand-side load management, location-based pricing plays its role by keeping the price low and convincing more customers into the program.

2.5. Charging the Customer

All the cost scenarios discussed above are included in the customer charges through regulated tariffs. However, political influence has its part in price designing. Some consumer gets rid of certain charges due to policy reasons.

While designing the pricing policy for regulated electric activities considering the cost, capital expenditure and operational costs are meant to be kept different. As there is no direct relation between both of them. As an example, to reduce the energy losses DSO invests in the fixed assets, which is capital expenditure for DSO. Moreover, this investment in essence is related to energy consumption, which becomes part of tariff design. Hence, it belongs to operational cost. Therefore, enumerating fixed and variable parts of retailing to achieve a clear distinction between capital expenditure and operational cost becomes difficult [49]. Moreover, long-term revenue collection is put to risk [78].

There is no categorization between consumers and prosumers with a standardized pricing structure. Furthermore, in SG where demand participation is adopted, consumer categorization can be considered. Customers and their tariffs are personalized by time and location [79].

In vertically integrated utilities, the application of the dynamic pricing concept is different as compared to substantial markets. In the case of integrated utilities, the tariff is singular (integral) in nature. However, the tariffs provided in a substantial market can come from regulated and private service providers. Hence, the electricity tariff is divided according to the nature of the cost. This may include distribution cost or price retailing, which can be flat or time-dependent. An independent aggregator is another way to set up the tariff.

In the case of an integral tariff, the full dynamic price involving retailing and distribution are representable as a combined price. However, these prices can also be dealt in singular manner using full dynamic pricing. Furthermore, in the case of semi-dynamic prices, price is broken down into parts. One part can be fixed price like the customers in the US. The other way around is that the aggregator comes up with a personalized tariff for DR.

2.6. Attracting the Customer into DR

During peak time rebates, it is important to know exactly the standard consumption of customers. Hence, installation of technical devices becomes necessary. It is required by the aggregator to communicate properly for contracting the flexibility of the end-user.

Demand flexibility is required throughout the year. However, the nature of the demand can vary within a year. For example, during the case of congestion in transmission lines frequent flexibility in demand is required, while during some uncertain conditions like weather conditions, infrequent demand flexibility is required. From a tariff viewpoint, such demand flexibilities need to differentiate between permanent and transient price signals. Permanent price include constraints related to transmission and distribution. Annually set TOU rates can be the best fit here to meet the frequent congestion in a zone or varying generation rates throughout the day. Transient price signals reflect variation in distribution costs. These signals can cover zones where congestion occurs for a few hours throughout the year. The CPP is referred to be best DR program in that case. Furthermore, dynamic and time-based pricing can be mandatory or voluntary with a relaxation of participation role [80].

In the US, with no retail competition, the regulator sets the rates for both small commercial utilities and households. However, the regulator holds the option of approving the dynamic price as default. While in the European Union (EU), dynamic price tariff is not optional. To lower the bill, customers have to adopt time-based pricing rates. Hence, the adoption rate is a critical point. The rate would fall too low if the customers have an option to switch between time-based pricing instead of making it a default choice

2.7. DR Measurement

Objectively observing, the DR program is introduced to minimize the peak demand. The most effective indexes to measure DR are:

1. Peak-demand reduction.
2. Demand price elasticity.
3. Demand rebound.
4. Costumer convenience.

Literature studies the price demand elasticity in following aspects. Substitute elasticity is useful for TOU and CPP DR programs. Mathematically, it is the ratio between peak to off-peak prices [81–83]. Furthermore, Ref. [84] studies the time based peak demand reduction as self-elasticity and interval based energy consumption as cross-elasticity. However, Ref. [85] describes a consumer as a long-range consumer looking for long-term benefits by keeping there energy consumption spread over range of pricing. In addition to this, short-range consumers are defined as one who are only considering current price at a given time. Another real-world energy consumers are those who are focusing on current pricing interval and also the forecasted price [84]. Henceforth, elasticity is basically used for leveraging peak demand reduction in combination with optimized price for consumers. For underdeveloped power DNs, sudden blackouts and overloading is a common problem. This problem had been addressed and modeled using DR activation function controlling the air conditioners and battery power from uninterruptible power supply (UPS) for peak and off peak hours. The DR activation function is based on stochastic model predictive control strategy [86]. However, this model only focused on the flexible customers. Furthermore, both flexible and inflexible customers are considered in [87]. The customers are encouraged to join the DR program giving them flexible profits as an incentive for following the DR. Dynamic price for customers is extracted using particle swarm optimization (PSO) [88]. The results indicated high profits for flexible customers. Moreover, an extension to the previous work included dynamic price based on linear regression and then solving the profit maximization problem using PSO, resulting in huge profits both type of consumers. Dynamic pricing is used to reduce the electricity bill for load customers through day-ahead decentralized coordination method to achieve the power balance. The multi-objective optimization problem is solved via genetic algorithm [89,90]. Furthermore, the optimization of DR achieved using the Wasserstein distance (DROW) concept is used in transactive energy framework. This framework is able to connect among individual nodes within a multi microgrid network. Due to interoperability, energy flow can be monitored and controlled resulting in optimized DR for consumers [91].

2.8. DR Practical Scenarios

DR is applied through various strategies in industrial and residential sectors. Some practical scenarios are shown to perceive the implementation extent of DR in industrial and residential electricity zones.

Precisely, industrial electricity load makes one-third of the total electricity consumption in the EU. Hence, it is of benefit to provide the large industrial loads with DR. The included benefit is that chances of better demand predictability arise with large loads as they affect the electricity system significantly [92]. The cost-effectiveness of DR comes from the concept of aggregation. Moreover, aggregation is a reliable technique for demand–price flexibility considering large volumes balancing and reserve market. Furthermore, dynamic pricing or time-based pricing can also be employed to encourage DR in large industrial users.

Below, various cases are discussed to show the significance of industrial/residential DR based on aggregator and dynamic pricing.

2.8.1. Industrial DR

In 2008, an aggregator, energy pool in France started its working by focusing on large industries. These industries were spread across the country and included hospitals, electric vehicles, data centers, warehouses, and water treatment plants. This aggregator made available 10,000 MW of energy with flexible capacity to reduce the peak load. Currently, the energy pool is also operating through contractors in Belgium and UK [93]. Flextricity, a UK-based aggregator, started operating in 2004 for providing industrial DR. Since 2004, this aggregator has been providing both production and demand aggregation. Flextricity can define a market policy for trading. This policy is based on increasing and decreasing demand management. The customer criteria of Flextricity are a commercial consumer (minimum 500 kW), large industries, low power hydro plants, and back-up generators. Moreover, the Flextricity aggregation program is customer convincing. It is because there are no charges to participate in this DR. The company makes the necessary installation (metering, control equipment, and communication) by itself. In addition to this, to meet unexpected demand and power failures, flexibility is designed for short-term operating reserve (STOR) that is generators. This leads to the supplying of active power gathered through peak reduction or from generation. Furthermore, this DR offers the benefit of triad management. Triad management is comparable to a critical peak. In this, revenues of involved traders are considered objectively. Through this, objective demand reduction and generation are carefully controlled. Hence, triad management is favorable for contingency circumstances. To sum up, Flextricity DR policy enables short notice management related to generation and demand fixation.

Likewise, dynamic pricing is also available to large industries and commercial users. Clients with intensive energy usage profile can enter into TOU or interruptible agreements with different retailers. In the same way, the transmission operator can also work up a deal with a large customers as a network activities balancer [47].

2.8.2. Residential DR

The DLC is a rough approach of DR to control the consumer load by a central operator. Its significance arises whenever there is a contingency situation. However, it takes away the freedom of the consumer. Voltalis is a residential based DR aggregator. It operates in Brittany, France, as a default DR. After signing a deal with Voltalis, a customer gets a free device installation at home. The device is named Bluepod; it controls the heating process in the home by dividing it into short-term intervals. It does so whenever the devices pick an alarming situations in the abundance of electricity supply. This device has a push-button for opting-in or opting-out of this DR. However, customers do not get the added financial benefit. Although, they are incentivized in their electricity bill by trading their current demand. Furthermore, this DR does not require any extra tariff adjustments, and hence is more applicable in real-world markets.

Electricit_e de France (EDF) introduced a dynamic DR for small traders who have already indulged in this combination of CPP and TOU. A color system is implemented in this EDF tariff to differentiate between the pricing rates on individual days of a week. Moreover, consumers have the flexiblility to choose between automatic or manual selection for participation into DR program. The program has resulted in visible reduction of load, 15% on "white" day and 45% on "red" day [85].

Within the EU, Sweden successfully implemented 100% smart metereing to overcome the halting issues for engaging DR at local level [94]. During the operation of this DR, a peak reduction of 7.5% and 9.3% was recorded among average individual residential consumers. Moreover, on the distribution side, an average peak reduction of 15.6% and 8.3% was experienced [95]. Moreover, customers faced a cost reduction in electricity ranging from 14% to 41%. Ref. [96] analyzed different project features comprising of TOU pricing were set at a low profit. Within the Netherlands, Enexis started a pilot project using transport tariff. On load consumption of above 80% in daily routine, the transport peak pricing is applied. During the peak morning hours, like weekends, the same pricing is applied [97]. In the pilot project, smart appliances also known as wet appliances are used to connect to the grid through necessary information and communication technologies (ICT) [98] components to respond automatically to the day-ahead prices. These wet appliances include appliances like washing machines, dishwashers, and tumble dryers. Time-varying tariffs dependent on both time and location may profile customers through different prices concerning a geographic area. Like zones with capacity issues may get higher prices and others might get low prices [99].

2.9. Barriers in DR Implementation

When it comes to the full-fledged implementation of DR, barriers in the form of power system characteristics and energy sector liberalization hinder the DR activation. The demanding concerns in this perspective are addressed in the following sections.

2.9.1. Hardware Setup

The primary constraint in engagement of DR is the necessary hardware required for monitoring and metering of the energy consumption. For example, within the EU, a smart meter cost ranges from EUR 200 to EUR 250. So, the question arises: Who will bear the initialization cost of DR among the consumer, the aggregator, the retailer, and the DSO? Hence, it becomes a common split incentive problem. Ref. [48] describes a resolution for this problem through splitting the demand between both aggregator and consumer. Further rectifying the problem, if the smart meter investment is made by the retailer and the customer at some point wants to change the retailer then the investment made by the retailer goes in vain. If the DSO invests in a smart meter then concerning retailer DSO can be one step ahead through price alteration capability for balancing the network. Hence, a crystal-clear trading model is required for investment so that no actor will be able to make a free move. However, it is mandatory for all involved in the DR, whether they are getting a benefit or not, to be required to pay for the cost [100]. Therefore, while making an energy policy, the overall expenses and profit should be distributed thoroughly across the electricity chain [101]. As indicated that through a clear business model DR benefits can be socialized, so the cost may also be handled socially. This will eventually lead to support of DR development in the market [48].

Another major hindrance in the deployment of DR is coordination problem [48]. To elaborate, in real-time some users may require the demand to be adjusted in a downward manner while at the same time some may require demand to be adjusted upward in the network. Hence, proper coordination of all the involved actors is a key element in DR. Moreover, this key element becomes important when generation and transmission is treated individually. For example, in Germany, over-supply from wind generation may lower the supply cost but the network capacity may apply high transmission cost. This leads to uncleared economic incentives considering overlooking within time frames. Customers behave in DR according to their price elasticity and not in response to load modification. Hence, while defining the incentive policy, load modification, price elasticity, and time horizon must be kept in view. The coordination problem necessitates forecasted tariff accomplishment and reassessment of regulation policy to define new rights for DSO.

Taxes in a liberalized electricity sector aside from retail and network charges becomes another supportive point in the deployment of DR. The clearer the final price rules are to customers, the lesser will be the coordination problem. Hence, it is recommended that the policy makers should work towards a prioritized set of objectives discussed above to secure the goal of DR deployment at a local level.

2.9.2. Bonding Local Market with Flexibility

The set of rules in policy governing balancing, supplementary, and real-time trading should match with the aggregated load flexibility. If the providers are loaded with complex constraints under the policy, the road towards the transformation of RERs based electricity system will become an enormous challenge. This indicated issue can be seen among traditional peaking units involved in MG. These units are continuously engaged in recovering stranded costs. Aggregator attracted income policy introduced through DR would harm the DR deployment scale.

Compensation mechanism is another issue highlighted by Eurelectric. The producers/suppliers require to be assured of a compensation mechanism in case of an activity done by an independent aggregator [102]. The aggregator has control over increasing and decreasing electricity consumption. Generally, any deviation in electricity consumption is reported to the transmission system operator (TSO). It is then up to the TSO to sustain the balance. In this case, charges must be paid to the balancing group and not to the aggregator. As aggregator was in control of deviation. However, if the aggregator is also a retailer, this compensation issue becomes less problematic. An efficient way to deal with this is that DSO can take control of DR aggregation. Nevertheless, DSO cannot deal with it on a global level as in liberalized electricity sector where DSO scope is reduced. The reduction is because DSO requires to be dealt with entirely independent of market functionalities. Conversely, the implementation of location-based pricing with extended boundaries can provide better resource efficiency.

2.9.3. Coping with DR Limitations

Shifting peak instead of peak reduction is another issue related to DR tariff schemes. It is mainly observed whenever the peak reduction and valley filling is bypassed. The reaction of this bypassing leads to recreation of the peak by valley filling technique during another time frame. This issue is overlooked in France by setting the prices according to location. This results in the smooth running of DR with anticipated loads. When a peak is shifted to off-peak hours, this load shifting results in energy-mixed peaks in another time frame. Moreover, to fulfill the peak energy requirement at that time may lead to the operation of a coal-fired plant (depending on the preference). Though the generated energy will be less expensive, the CO_2 emission would be increased. However, this energy need can also be met by more expensive but cleaner generation (gas-fired plant) [67,103]. Hence, a high-cost value of CO_2 emission can be used in the DR market policy to mitigate the effects of carbon emissions.

3. DR Integration with Power System

Figure 6 describes the intergration of DR with power system.

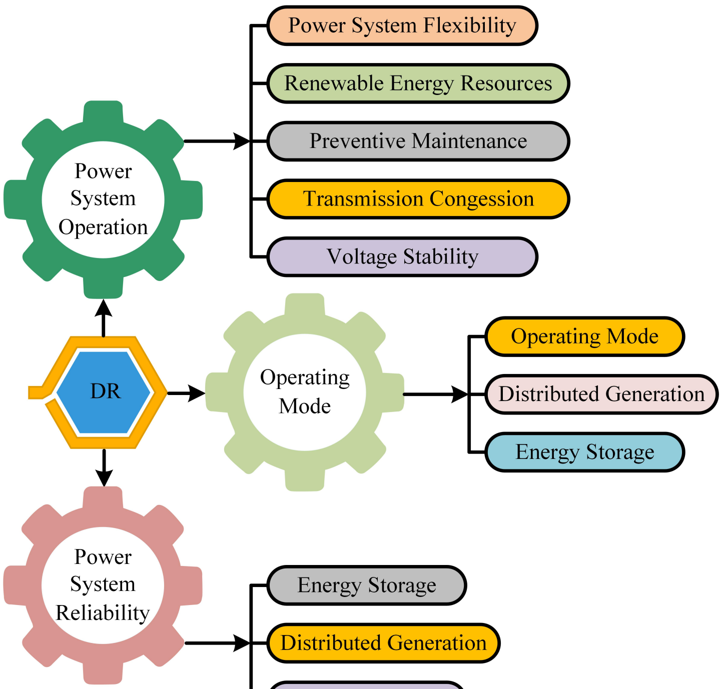

Figure 6. DR integration with power system.

3.1. Power System Operation

3.1.1. Voltage Stability

Voltage stability is termed as the ability of a power system to sustain the voltage across all buses within the prescribed scale during normal operation and after disturbances [104]. This voltage stability can be easily achieved through the proven capabilities of DR, which can avoid voltage violations by improving transmission congestions [105]. Moreover, DR can also maintain frequency stability issues [106].

3.1.2. Transmission Congestion

DR operates by flattening the demand profile and objectively reduces the peak demand time bundles. This way the DR decreases the required transmission capacity which results in reducing the transmission congestion [107,108]. Moreover, for better management of demand-side resources, power flow analysis is required to establish the numerical values for evaluating the benefits which power system can offer [109]. In addition to this, power flow and transfer capacity of DC system are combined to sort out the optimal buses for DR [108].

3.1.3. Preventive Maintenance

The DR also offers its services in MG through scheduled maintenance. This scheduled maintenance is also termed preventive maintenance. This maintenance is scheduled for the power outage. It is necessary but can also be deferred in case of emergency [110]. Preventive maintenance includes replacement or maintenance of components, once they approach their normal operation period or whenever some failure is foreseen [111]. DR, through its security-constrained preventive maintenance, is used to determine the optimal power outage schedule, which results in fewer emissions, reduced fuel cost, and lower reserve costs [62,63].

3.1.4. Renewable Energy Resources (RERs)

Literature studies stress the point that RERs are stochastic. RERs are unpredictable, intermittent, and uncontrollable. This chaotic behavior of RERs has been gauged by many researchers in both SSM and DSM at majority and medium level inclusion. However, to overcome these intermittency effects of only a solar photovoltaics-based energy storage system, a priority-based DR can be employed [112]. Furthermore, Portugal is using DR for the integration of the increasing number of RERs [113]. Ref. [114] implements a probabilistic approach in MGs to counter the uncertainty of RERs (wind and solar) power generation capability.

3.1.5. Power System Flexibility

The DSM is considered as an upcoming technique for energy management due to its capability of maintaining flexibility across resources. Moreover, it reduces the electricity demand by giving freedom to manage the system with flexibility [114]. As compared to a traditional power system running on fossil-fuel generators, an SG with a high mix of RERs is unable to fulfill the peak power requirement, which leads to high impact power outage in the form of finance and massive blackouts, while secondary services like battery storage systems (BSSs) play their role in overcoming these issues. However, through DR, peak energy consumption time can be reduced in case of low output across RERs. Moreover, it can be a very useful technique in sustaining the flexibility of the latest nuclear power plants [115]. Ref. [116] investigates the role of optimization technique to accommodate generation through fast ramping generators in SG through DR.

3.1.6. Power System Reliability

The attributes of power system reliability rely upon design, planning, and operating stages. Power system capability and security makes up the power system reliability.The first focuses on the customer demand by allocating required hardware. However, the latter responds to the sudden disturbance within the power system categorizing its behavior [110]. Furthermore, power system reliability analyses require the system to be categorized with respect to generation, transmission, and distribution. Hence, analyses are done in three hierarchical levels (HLs) [110]. The HL1 generation facility is analyzed at first level. The HL2 analyzes both generation and transmission facilities. The distribution facility is analyzed at HL3. Generally, HL1 and HL2 studies are conducted. However, HL3 comprises of complex evaluation given the nature of large-scale issues related to distribution. The HL1 and HL2 through DR aim to increase load point reliability. Moreover, HL3 through DR narrows down the disruptions on the customer side. Hence, HL3 is only analyzed individually and in distinction to HL2 and HL1 [117]. The literature cited in the Table 3 below shows the impact of DR techniques to improve the power system reliability.

Table 3. HLs of power system.

Power System Reliability	System Security	System Adequacy
Generation	[118–129]	[130–132]
Transmission	[133–135,135–143]	–
Distribution	[144–147]	[148]

3.2. MG Operating Modes

3.2.1. Operating Modes

The literature considers interconnected MGs while describing different modes of MG operation. However, the stand-alone operating mode is given preference by many researchers to provide a substitute for supplying rural areas or areas with no traditional grids [149]. Hence, both on- and off-grid operating modes are viable alternatives. Table 4 shows a detailed comparison of the literature.

Table 4. Modes of MG operation.

Micro-Grid Operating Mode	References
Grid-connected	[150–182]
Islanded MG	[155,183–206]
Grid-connected/Islanded	[149,156,207–216]

3.2.2. Distributed Generation (DG)

The DG allows decentralization of energy generation. This becomes possible due to the participation of RERs. Now users can take part in the electric energy at both individual and community level. Through DR it is now possible to grasp and increase the electricity production from RERs which will result in lower electricity costs guided through policies. DR is a promising scheme to overcome the stochastic nature of RERs [217]. However, the increasing penetration of DGs based on RERs as well as new loads in the form of EVs has created an imbalance problem at different nodes in a network [218]. This imbalance can be balanced by controlling the flow of current in a neutral line. For a balanced DN, this neutral line flow should remain zero. Ref. [219] proposes that neutral line current flow must be used as a warning signal. Through this warning signal, energy storage system (ESS) operation can be altered to sustain the required balance in voltage. Furthermore, to handle the voltage unbalancing issues due to RERs, uncertainty DR is combined with on-load tap changers (OLTCs) transformers with dynamic load controllers. DR plays its role in selecting optimal users with the objective of minimum disturbance of such users comfort [220].

Variation in demand at certain times leads to voltage unbalancing problems which finally surfaces as an imbalance in power which overall of the commutation processes of inductive loads resulting in the inclusion of capacitor banks [221]. Ref. [222] suggests that DG elements are capable of moderating unbalancing glitches in the power system. Therefore, in modern MGs, PVs and WTs are employed through maximum power point tracker (MPPT) controllers to meet the dynamic demand [223]. Moreover, the response time to voltage or power unbalancing has reduced to 0.1 s through MG.

3.2.3. Energy Storage

Energy storage techniques through electric batteries or electric accumulators have gained fame which can be seen from the literature [223–225]. Moreover, thermal storage is also discussed in [226,227]. In [228,229] water storage is focused on reserve energy generation. The main purpose of the storage system is linked to flattening of the demand curve during hours of peak consumption.

4. Uncertainty of RERs through DR

4.1. Prediction of Uncertain Parameters

Uncertainty is defined as the probability of the difference between real values and forecasted values due to the lack of information [230]. Ref. [231] further distinguishes between two types of parameters of uncertainty in MGs. Operational parameters represent the quantitative measure of generation and load in the power system. However, the economic perspective of the power system is evaluated through economical parameters. They comprise uncertainty in fuel supply, production cost, economic growth, and interest rates. Ref. [232] describes the prediction of uncertain parameters in connection to time frame.

In short-range prediction time frame varies from minutes to a few days. In mid-range prediction, variation ranges from weeks to months. In long-range prediction times, the horizon varies from various months to several years. However, considering the case of MGs, this prediction can be accomplished in hourly based time horizons. Hence short-range prediction is a viable way to predict uncertainty parameters in MG. Moreover, these short-range predictions are further sub-classified into classical and intelligent prediction methods [233]. The classical approaches for predicting the uncertainty are discussed in [234–236]. Furthermore, intelligent approaches are focused in [233,237–239]. The detailed discussion regarding classical and intelligent algorithms on the basis of DR is considered in Section 4.2.

4.2. Computational Models for Quantifying Uncertainty in DR

4.2.1. Classical Algorithms

Various mathematical solvers are also available to enhance the management capabilities of an MG. Ref. [240] used general algebraic modeling system (GAMS) package for evaluating linear equations within MG. It is used to solve for uncertainties related to the generation process [200]. Ref. [241] implemented a multi-scenario mixed-integer linear programming (MILP) model for the management of energy [242]. The complex solver is used to solving the mixed-integer programming (MIP) scheduling problem of MG [243]. Ref. [244] showed the capability of the complex solver to deal with large scale MILP problems. Sparse nonlinear optimizer (SNOPT) is another technique based on GAMS. Through this software, nonlinear optimization problems can be solved [245]. The energy management system modeled into the mathematical formula is a non-linear programming problem, which is solved through SNOPT solve [246]. Gurobi optimizer is used to optimize MILP problems [246,247]. Ref. [248] also used this optimizer for computational purposes.

4.2.2. Intelligent Algorithms

Using the stochastic methods, the probability distribution function (PDF) of the random variables can be approximated [249]. Dantzig was the first person to use a stochastic approach to model uncertainty [250]. However, to make use of the stochastic approach, the input factors must be known [251]. Models including uncertainty used for scenario-based generation requires to know the PDF. The process includes breaking PDF into multiple parts. By doing so, each part is divided into scenario-based outcome. The probability distribution of individual parts is focused on the preferred probability area [252]. Ref. [253] implemented scenario-based generation to cope with uncertainties involved in photo voltaic (PV) and wind turbines (WT) [254]. Ref. [241] used discrete distribution sets to represent scenarios for covering the uncertainties of solar and wind generation systems along with loads. Monte Carlo Simulation (MCS) and a roulette-wheel mechanism are also used to generate random scenarios for solar, wind, and loads. Moreover, the scenario reduction algorithm is structured to reduce computational complexity [200]. Ref. [243] used MCS for modelling PV and WT. In this method, to supervise input parameters, the PDF is used [255]. However, MCS is a procedure that requires repetition to generate samples. Hence, iterations are included in this method. For analysis of results achieved histograms and other stochastic criteria indicators are used in [256]. Ref. [257] approaches the analysis of wind energy generation investments through the Monte Carlo simulation (MCS) method for achieving the management of uncertainties. Ref. [256] uses optimization algorithm for analysis of uncertainties in solar power hybrid systems. Point estimation method (PEM) is also used by [230] to model the uncertainty of solar and wind power systems. Probalistic price based unit commitment is represented in [258] to model the uncertainty between market price and generation resources. Ref. [259] reviewed the applications of fuzzy theory to RERs. Ref. [260] conducted a study related to the effects of uncertain power output across the DNs in DG using the fuzzy method. Ref. [261] deals with parametric issues of uncertainty through robust optimization method using uncertain boundaries. In the absence of PDF parameters, robust optimization proves to be of interest. This method is used by [230] to overcome load uncertainties. Furthermore, Ref. [262] optimized solar and wind power systems using robust optimization. Refs. [263–265] made use of information gap theory (IGDT) for structuring the uncertainty. The IGDT is a decision-making technique that stands on certain assumptions. Furthermore, it is used by [264] to calculate optimized bidding for day-ahead market pricing. Ref. [265] implemented the IGDT based approach for equating procurement schemes of large customers.

With the availability of better coordination between demand and supply due to the DR feature of MG, great control can be achieved in the scenario of increased energy demand. However, the achievement of an optimal DR strategy is a multi-target optimization problem. In opting for solutions for these problems, different optimization strategies are available in the literature. They include swarm-based algorithms, quasi-static techniques, and mixed-integer approaches. These methods focus on energy balance in systems, improvement of technical parameters, operational restrictions, and minimization of total energy consumption [266,267]. In MGs, load control is optimized by achieving the concept of mutual operation of available DGs [268,269]. The integration of optimization techniques with DR can result in system stability and maximizing economic benefits with the help of mathematical mechanisms [270,271].

The provision of automation further empowers the capability of DR to control frequent disconnections. To overcome voltage fluctuation in electric charging stations for use of EVs, Ref. [272] automated the real-time pricing schemes. Refs. [273,274] proposed network optimization protocols to balance the demand and better communication among DR actors. To further enhance the control ability of DR, Ref. [275] proposed hierarchy-based power network structures in combination with DR. These structures skipped the need for redundant circuits, offered better dealing with flexible loads, fulfilled the comfort needs of users through dynamic operation within the whole network. This led to improved distribution and sustained minimum system voltage. Ref. [276] showed light on the fact that generally automated load management programs require users to keep the pact of lowered bills by allowing only allocated consumption sanctioned through DR. However, in the retail market, users often have to face unfavorable alterations in price and demand when they participate in DR programs. Hence, dynamic demand management algorithms provided the best by overcoming this additive perturbation. The primary objective of these algorithms is to optimize energy consumption and real-time price. Furthermore, these algorithms also integrate with automated control systems to make the consumer in-charge of their energy consumption [277]. The virtual power plant (VPP) is a special control structure. This structure is supported by network communication to manage conventional and DERs [2,270,278]. Ref. [279] indicates the availability of a bidirectional relationship between users and the network. This bi-directional linkage is a key element in the evaluation of DR applied at a large scale. System sustainability can also be improved through smart networks. This can be achieved by dynamic profiling of user load consumption [280]. Within DNs, communication between the nodes becomes an important issue when DR is focusing on reducing the power losses [281]. Under these circumstances, an optimized reconfiguration network framework to find the right network configuration can be of much greater use for DR [281,282].

The SG is a concept that incorporates the renovation of transmission and DNs [283–286]. Besides providing benefits like reduced losses and optimized grid operations, it also favors the market for DGs. This is achieved by utilizing ESSs [287,288]. Moreover, with the integration of DR in SGs energy reduction during peak hours can be achieved by keeping the comforts of consumers [289]. With the development in electrical networks, MGs play an important role in the management of DR, through acting as an in-charge. MG can organize all the users in the network. Moreover, current MGs are based on ESSs, RERs, and non-RERs through DG. This helps in better management of demand through DR. Now, MGs structure enables them for bi-directional transactions. Through this, during insufficient energy production from resources involved in MG, it can buy it from the distribution company. Furthermore, it can also sell energy to the distribution companies in case of excess generation from distributed resources [290].

With recent developments, MGs are now able to operate in isolated mode. This is achievable through topology adjustment of MGs, considering the peak demand adjustment or in case of any grounding failure faced across ESSs and DG elements [291]. The addition of interconnecting devices in MG like ESSs, DG elements, and interruption controllers equips the MG with dynamic configuration. However, this is only possible in presence of a multi-agent management system. This management system acts as an in-charge of sale and purchase of energy inside an MG [292]. Furthermore, MG faces defaults that are asymmetric like asymmetric short-circuits, grounding failures, and double failures including both grounding failure and open conductor failure [293]. To overcome these issues, ref. [294] stated asymmetric failure analysis techniques and established two matrices. One matrix describes the injected currents into the buses, and the second matrix encompasses voltage unbalance and bifurcated currents. Hence, MG will be able to give a technically efficient output. However, it is important to mention here that incentive-based DR programs can help in MG management by reducing the peak hour consumption. Thus, resulting in optimized DR related to the offered energy cost [295,296]. The application of classical computing algorithms in DNs can be seen in Figure 7.

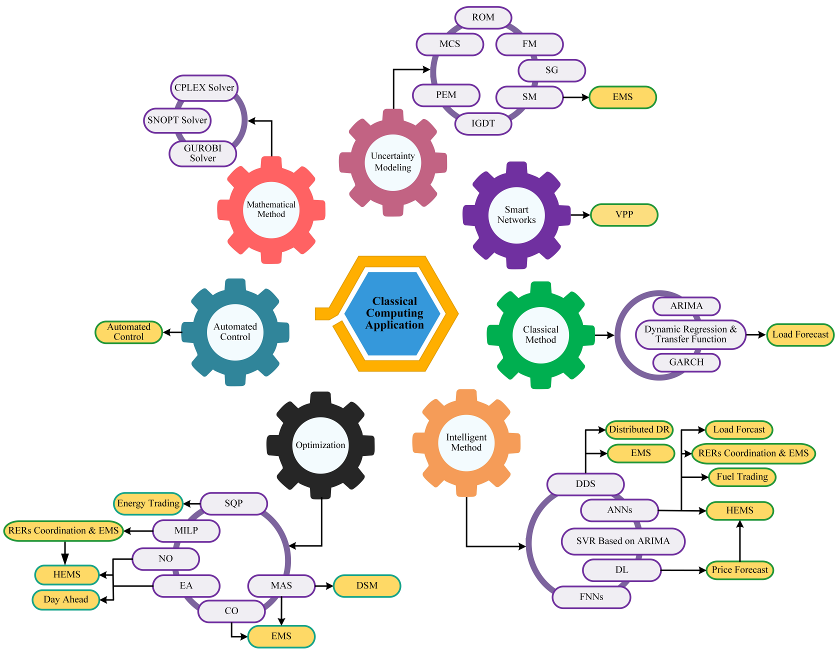

Figure 7. Application of classical computing algorithms.

4.3. Quantum Algorithms

Quantum mechanics, the study of energy and matter at the subatomic level, is the basis for the development of quantum computers. A quantum computer manipulates the activity of these particles to get the desired results. In terms of computational power, quantum computers represent a significant leap forward, perhaps outperforming even the most powerful supercomputers on the market today. The laws of quantum physics allow a quantum computer to acquire massive processing power over multi-state capacity and simultaneously execute numerous operations [297]. In recent years, quantum information processing has grown into a substantial interdisciplinary field at the junction of quantum physics and engineering. Many people worldwide are developing a quantum computer that can tackle issues that traditional computers cannot [298].

In the last two decades, significant progress has been made in creating a workable quantum machine, reviving interest in the subject. Proof-of-concept devices for analog and digital quantum computers are among the first steps in constructing quantum computers. A modest quantum computer was built in 1997, but the technology did not take off until D-Wave debuted its 28-qubit quantum computer in 2007 [299]. Google, IBM, and Honeywell are presently in a fierce rivalry to develop quantum computers that are both powerful and quiet [300–302]. It is still challenging to compute some applications despite the enormous capability of classical computers, and it appears that quantum mechanics is doing it instead; these involve mostly estimating quantum system attributes and behavior.

If you are looking for an approximate solution to a simple quantum system, you can use classical computers. However, as the simulated system grows in complexity, so does the amount of memory and processing power needed to run the simulation.

Problems that have yet to be solved or challenges yet to arise are necessary for constructing the future grid. Building a more resilient, reliable, safe, and secure grid of the future will benefit from quantum computing. During the preceding decades, numerous well-known strategies have been developed to deal with a wide range of computational challenges in power systems. Various numerical optimization approaches and stochastic search methods [303–309] can be used as examples as accurate enumeration methods (which are impracticable for realistic power systems). In addition, quantum-inspired evolutionary algorithms have recently been used to solve several power system challenges [310–312].

When it comes to grid transformation, present computing technologies may not meet the needs of a modernized grid. Customers and distribution networks (DNs) play a more prominent role in system design and management which is significant development. Since their separation, transmission and distribution have become increasingly interwoven. With this theory, transmission lines would deliver a specific voltage to the substation, and then distribution lines would provide the energy to individual clients. The transmission and DNs may interact differently if more DERs, such as solar and wind generation, batteries for EVs [313], and DR are integrated into the grid. Transient and tiny signal stability issues are one example of how DG impacts the energy system's dynamics. Consequently, it will be critical to build more comprehensive models that incorporate the dynamic interactions between transmission and DNs and suitable computational tools that can solve such models. Better scheduling models are also needed to deploy and utilize DERs.

It is important to note that the new grid topologies use several scales, introducing new mathematics and processing challenges for today's tools. Nonlinear dynamic systems are also included. For example, linear approximations and large-scale complexity make it difficult to completely predict or understand all the intricacies that might occur during off-normal system conditions. Sensing, processing, and control must increasingly be embedded at the component level. Systems that can communicate and share data at different system levels require linked and system models. The invention of computational tools to aid decision making on various time scales, whether fast, automated controls or design planning instruments, will necessitate sophisticated mathematics. The application of quantum computing-based algorithms in the DN can be seen in Figure 8.

Table 5 summarizes the use of intelligent algorithms to achieve goal-oriented DR. However, the intelligent models are unable to fully achieve the desired goal. In essence, it is not the algorithm that restrained the achievement of the goal; rather, it is the computational method itself. As can be seen in the table, artificial neural network (ANN) and deep learning (DL) algorithms have a time complexity of $O(n)$, which increases as the number of variables increase. Moreover, DL time complexity also comprises of SoftMax layer. The scenario gets worst when back propagation is also involved. Furthermore, optimization algorithms have a time complexity of $O(\sqrt{n}L)$, where L hides the details related to iterations. In addition to this, MILP and sequential quadratic programming (SQP) are used to solve NP-hard problems. These problems require exponential time to solve the problem by branch and bound. Henceforth, quantum computing based algorithms are recommended for modeling the uncertainty of RERs and overcome the problems mentioned above. The reason for this recommendation is the better time–space complexity properties inherited from quantum mechanics.

Table 5. Goal-oriented DR based on intelligent algorithms.

Algorithms	DR Goal	Objective Limitations	Algorithm Limitations
ANN	Load forecast	Model becomes in-efficient due to lack of computational power [314]	O(n)
	HEMS	The model does not integrate DR applications [315–320]	
		The algorithm lacks the accommodation of non-technical losses from user [321]	
		End-user comfort is not focused [322]	
		DR lacks the RERs integration [323]	
	Fuel trading	The pricing scheme does not involve the impact of RER [324]	
	RERs coordination	Operational parameters related to hardware are omitted [325]	
	EMS	Energy storage system is not considered [326]	
DDS	EMS	System security is not considered [327]	c*n
	Distributed DR	Home-based customers are not considered [328]	
DL	HEMS	Customers comfort is overlooked [329]	O(n)
	Price forecast	The pricing scheme lacks the users profile [330]	
MAS	EMS	Optimization technique is not present [331]	PSPACE-hard
	DSM	Domestic appliances are overlooked [332]	
NO	HEMS	Market price is not considered [333]	O($\sqrt{n}$L)
CO	EMS	Power balance equation is not shown [334]	O($\sqrt{n}$L)
		Dynamic load profile is missing [335]	
SQP	Energy trading	RERs integration into model is omitted [336]	NP-hard
MILP	HEMS	Generation perspective is overlooked [337]	NP-hard
		Home-based users are not considered [338]	
	RERs coordination	Cost function does not considers peak power consumption [339]	
	EMS	Battery storage system is omitted [340]	
EA	Day-ahead	RERs integration and user comfort are not considered [341]	$\Theta(n^n)$
	HEMS	DERs are not considered [342]	
		Users with limited appliances are focused [203]	
		Large load customers are not considered [343]	

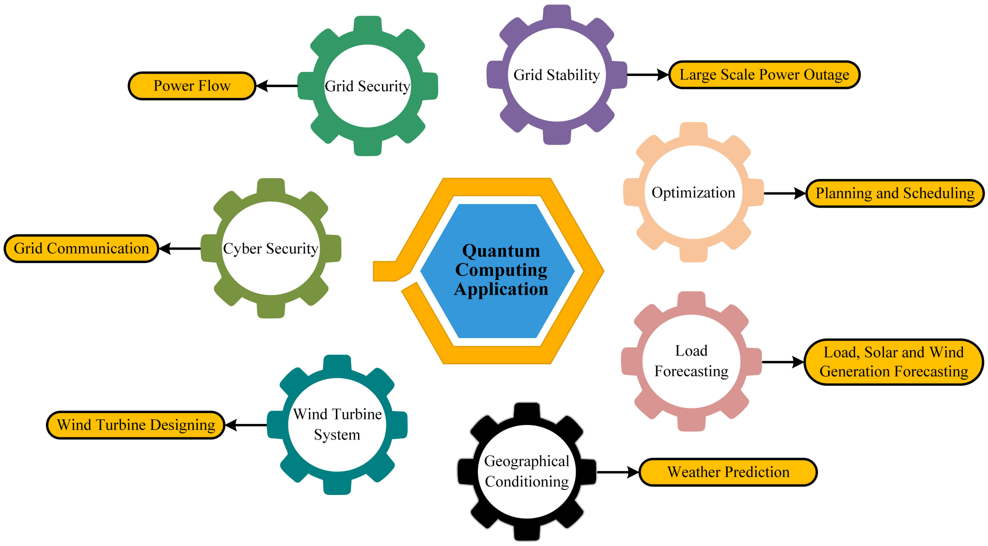

Figure 8. Application of quantum computing algorithms.

5. Conclusions

The use of DR to optimize the effectiveness of RERs based SG resulted in parametric imbalance of intelligent algorithms. This parametric modeling requires more pro-efficient algorithms to equate nonlinear nature of RERs. Moreover, the present intelligent algorithms still lack the computational logic to deal with the integration of RERs. In addition, quantum algorithms have the ability to deal with parametrically loaded systems. Therefore, the use of quantum algorithms for DR have been considered as an effective approach for future SGs. The reason for suggesting quantum algorithms is to reduce the time complexity as compared to classical intelligent algorithms. Moreover, the reduced space complexity equips the quantum algorithms to be able to accommodate more variables, henceforth, resulting in an optimized DR (maximized and minimized the profit and cost) in DN to maintain the supply (utility) and demand (customer).

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Abbreviations

The following abbreviations are used in this manuscript:

RERs	Renewable Energy Resources
ISO	Independent System Operator
DERs	Distributed Energy Resources
MG	Microgrid
SOS	System of Systems
SG	Smart grid

SSM	Supply Side Management
DSM	Demand Side Management
DR	Demand Response
DN	Distribution Network
DC	Direct Current
MGs	Microgrids
RES	Renewable Energy Source
ESSs	Energy Storage Systems
EVs	Electrical Vehicles
CO_2	Carbon Dioxide
DLC	Direct Load Control
RTP	Real Time Pricing
CPP	Critical Peak Pricing
TOU	Time-of-use
PTR	Peak Time Rebates
ICAP	Interruptible Capacity
DSO	Distribution System Operator
SGs	Smart grids
DGs	Distributed Generators
DG	Distributed Generator
US	United States
EU	European Union
UPS	Uninterruptible Power Supply
PSO	Particle Swarm Optimization
UK	United Kingdom
STOR	Short Term Operating Reserve
EDF	Electricit_e de France
ICT	Information and Communication Technologies
TSO	Transmission System Operator
BSSs	Battery Storage Systems
HLs	Hierarchical Levels
ESS	Energy Storage System
OLTCs	On-load Tap Changers
MMPT	Maximum Power Point Tracker
DNs	Distribution Networks
PDF	Probability Distribution Function
PV	Photo Voltaic
WT	Wind Turbine
MCS	Monte Carlo Simulation
PEM	Point Estimation Method
IGDT	Information Gap Decision Theory
VPP	Virtual Power Plant
GAMS	General Algebraic Modeling System
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
SNOPT	Sparse Non-linear Optimizer
HEMS	Home Energy Management System
EMS	Energy Management System
ANN	Artificial Neural Network
ANNs	Artificial Neural Networks
DDS	Data Driven Structure
DL	Deep Learning
MAS	Multi Agent System
NO	Numerical Optimization
CO	Complex Optimization
SQP	Sequential Quadratic Programming
EA	Evolutionary Algorithms

SVR	Support Vector Regression
FNNs	Fuzzy Neural Networks
ROM	Robust Optimization Method
FM	Fuzzy Method
SG	Scenario Generation
SM	Stochastic Method

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