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Optimisation of demand response in electric power systems, a review

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A R T I C L E I N F O

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A B S T R A C T

Demand response programs offer efficient solutions for many power system problems, such as high generation cost, high demand's peak to average ratio, high emissions, reliability issues and congestion in generation, transmission and distribution systems. Their main function is to assist power systems during peak demand hours and also during contingencies. They are a subcategory of the family of demand side management (DSM) strategies. DR programs are classified into two broad categories; price-based DR programs and incentive-based DR programs. In order to exploit their full potential, DR programs must be implemented optimally. Such a problem, which here is referred to as "DR optimisation problem", is a hot research topic and has been frequently researched in the literature. This paper aims to review different research works on DR optimisation problems. Based on the conducted review, some directions for future research are proposed.

1. Introduction

Electric power systems face different challenges such as reliability issues, low efficiency, high energy losses, high emissions and high possibility of market power exercise. In the traditional flat electricity tariffs, the disconnect between wholesale electricity market price and retail tariffs leads to inefficient usage of resources, because the consumers have no motivation to adjust their usage according to supply costs [1–7]. Moreover, the peak to average ratio (PAR) of demand in electric power systems is high [8–10]. Although, peak hours spans only a couple of hours per day, in order to supply peak demand, a high investment should be made on generation, transmission and distribution systems. This results in an increase in the cost of electricity supply. On the other hand, during contingencies, for instance during the outage of generating units or transmission lines, power systems have many problems in supplying the demand via the remaining generating units and transmission lines and incur high amount of costs. Therefore, during contingencies, power system reliability is jeopardized. A very efficient strategy for dealing with all the above-mentioned challenges in power systems, is to use demand side management (DSM) programs [11–14]. DSM includes everything that can be done on the demand side of a power system in order to improve its characteristics. As Fig. 1 illustrates, two broad sub-categories of DSM are energy efficiency programs and demand response programs. Demand response (DR) is defined as "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*" [1,15]. This definition indicates that DR programs mainly aim to help power systems during peak demand hours or contingencies. By DR programs, the utility incentivises consumers to reschedule their consumption patterns [2]. They are becoming very popular in today's modern electric power systems [16–19].

1.1. Classification of demand response programs

DR programs can be classified into two broad categories. In the first category of DR programs, referred to as "incentive-based DR programs", the consumers are awarded incentives for changing their consumption patterns as per the desire of the supply-side. In the second category of DR programs, referred to as "price-based DR programs", the consumers are charged with different rates at different consumption times, therefore, retail electricity tariff is affected by the cost of electricity supply.

1.1.1. Incentive-based DR programs

As mentioned before, these programs pay participating consumers, who reduce their consumption at peak hours or during events. There are different types of incentive-based DR programs that are introduced and described below.

- Direct load control (DLC) programs
  In these programs, some consumers or appliances are registered in the program and allow the utility to shut down or cycle them, when needed (normally during peak demand or events) [20–22]. The participating consumers are paid incentives.
- Load curtailment programs
  In these programs, the registered consumers are paid incentives for curtailing their consumption as the wish of the utility. Typically, registered consumers, who fail to respond to incentives, are severely penalised [1].

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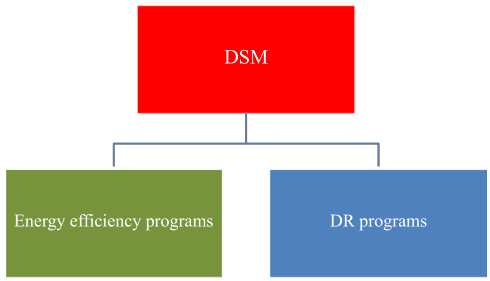

Fig. 1. Main sub-categories of DSM.

- Demand bidding programs
  These programs are typically offered to large-scale consumers (larger than 1 MW). During contingencies or peak demands, the consumers may bid to curtail part of their consumption at a certain bid price [1,23].
- Emergency demand reduction programs

As per this program, in severe contingencies, the consumers are paid a considerable incentive for reducing their usage. These programs may assist a power system to enhance its reliability.

1.1.2. Price-based DR programs

As mentioned before, in price-based DR programs, the consumers are charged with different prices at different times of consumption. In this way, the consumers are charged according to the supply cost of electricity. By increasing tariffs during peak demand hours and contingencies, utilities incentivise consumers to reduce their consumption. The main types of price-based DR programs are described below.

- Time of use (TOU) pricing
  In this DR program, the electricity price for consumers depends on the time interval that the electricity is used. Typically, a day is divided into three intervals, named as peak interval, mid-peak interval and off-peak interval. The consumers are severely charged for consuming electricity at peak interval. In this way, they are encouraged to reduce their consumption at peak hours and shift their shiftable loads to off-peak hours [24]. The economic implications of TOU pricing has been investigated in [25–29].
- Critical peak pricing (CPP)
  This program is akin to TOU, except for the time when the reliability of the power system is jeopardized and then the normal peak price is replaced by a very higher price [30,31]. This program is only employed for a couple of hours per year and improves power system reliability [2].
- Real-time pricing (RTP)
  In this type of pricing, the electricity tariffs typically change hourly, reflecting the fluctuations in the price of wholesale electricity market [32–37]. Typically, the consumers are notified on a day-ahead or hour-ahead basis [2]. RTP is becoming very popular in DR programs and smart homes. The economic advantages of RTP has been investigated in [38–42] and its environmental advantages have been investigated in [43]. In the cases that the prices are not published on day-ahead basis, a price prediction module is needed for energy management of consumers. Research works in real-time pricing may be classified into two categories; in the first category, the response of consumers to the known real-time prices are investigated [44], while in the second category, the real-time prices are set by the retailer or utility through an optimisation process and the response of the consumers to those prices are investigated [45].
- Inclining block rate (IBR)
  This program offers a two-level price, based on the total consumption of a consumer. The electricity price goes to a higher level, if the consumption reaches a threshold [2,46,47]. This program reduces the need for unnecessary investments in generation, transmission and distribution systems [48]. IBR program has been widely adopted by some utility companies since the 1980s. For instance the Southern California Edison, San Diego Gas & Electric, and Pacific Gas & Electric companies currently have two-level rate structures where the price in the second level is 80% or higher than the first level, depending upon the utility [49]. In Canada, the British Columbia Hydro Company adopts a two-level IBR with 40% higher prices at the second level [46].

The classification of DR programs can be seen as Fig. 2.

1.2. Implementation of demand response programs

DR programs may be implemented for residential, commercial or industrial consumers. For implementation of DR programs, advanced metering infrastructures (AMI) are installed in consumers' site. They have the potential to measure and memorize energy usage at different times and also have communication links that allow the utility to remotely retrieve current usage information [1]. Using innovative enabling technologies, including smart meters, communication devices and energy controllers is crucial for effective implementation of DR programs [50].

In order to make decision whether to enroll in DR programs or not, the consumers do a cost-benefit analysis, considering the inherent uncertainties and risks. Costs of DR for consumers are twofold; initial costs, including initial investment, enabling technology's cost and cost of preparation of a response plan. Event-specific costs of consumers includes discomfort costs, rescheduling costs and costs of on-site generation [1]. For utilities, the DR costs are also twofold; initial costs including costs of metering and communication devices, costs of upgrades of billing systems and consumers' education costs. The utilities' operating costs in DR include program administration costs and incentive payments to participating consumers [1]. Different types of DR costs for utilities and consumers can be seen as Fig. 3.

Among different types of consumers, residential consumers have proved to be more responsive in DR programs. This is due to the fact that residential appliances are more curtailable, shiftable, interruptible and elastic [2]. Typically, a two-way communication between utility

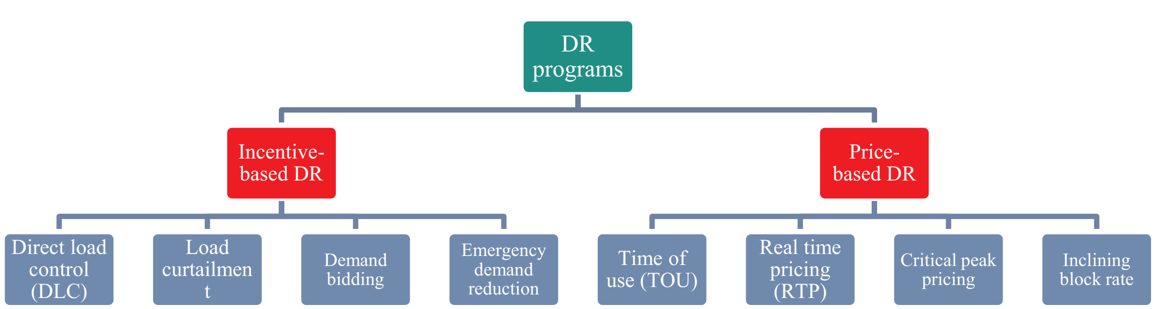

Fig. 2. Classification of DR programs.

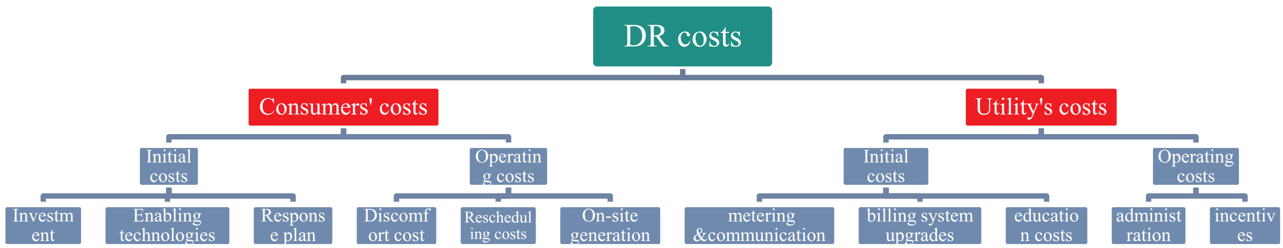

Fig. 3. Different types of DR costs for utilities and consumers [1].

and home is built up, using wide area networks (WAN's), neighborhood area networks (NAN's) and home area networks (HAN's). In a home, there exists a home energy management system (HEMS) that determines ON-OFF status of different appliances at different time slots, considering the information exchanged with the utility. Smart meters collect the detailed information of consumption patterns. In residential DR programs, home appliances are typically divided into three categories; must-run appliances such as lighting, shiftable and interruptible appliances such as PHEV's and shiftable but non-interruptible appliances such as washers or dryers.

In [51], the characteristics of response of industrial and commercial consumers to DR programs have been investigated. Although they are fewer in number than residential consumers, have a more load reduction potential. Two factors highly affect the desire of industrial and commercial consumers to respond to DR programs; the share of electricity bill in their total costs and the cost of participation in DR programs (production reduction,…). In [52], industrial sector has been divided into three groups, providing aggregate level estimates of price elasticities. The average elasticity of the most electricity-intensive group including petrochemical and metal industries is more than twice that of the least electricity-intensive group including textile printing industries. Another research by [53], showed that in industrial section, DR is mainly involved in manufacturing, transportation, agriculture, mining and construction segments. These segments form the 40% of the reference load but contribute more than 80% in DR programs.

Commercial businesses generally tend to show smaller response to electricity prices and incentives [53]. This is due to the fact that the majority of commercial businesses such as retail shops and office buildings operate within a fixed hours with low flexibility and incentive to shift their loads.

1.3. Advantages of demand response programs

DR programs offer many diverse advantages for electric power systems, utilities, retailers and consumers. Their main advantages are listed as below.

- DR programs lead to reduction in peak to average ratio (PAR) of demand [54]. This prevents unnecessary investments in generation, transmission and distribution systems and thereby supply cost of electricity is decreased. For instance, it is estimated that DR programs together with energy efficiency measures will reduce the needs for U.S new generation capacities from 214 GW in 2010 to 133 GW in 2030, by 38% [55].
- During peak-demand hours, the generating units with high amount of emissions are unavoidably commissioned, because the generating units with lower emissions have already been fully loaded. Therefore, DR programs, through reduction of peak-demand, decrease the amount of emissions.
- During power system contingencies, DR programs reduce the consumption level, especially through direct load control (DLC) programs and emergency load reduction programs. Therefore, the stress on power system is decreased, in a way that system operator is not obliged to shed some loads and conclusively, power system reliability is improved.
- Using DR programs that assist power systems during peak-demand hours or contingencies, the probability of occurrence of price spikes in wholesale electricity market is decreased and the need for market interventions by regulatory agencies is reduced.
- Using DR programs decreases the possibility of market power exercise by generation companies (GENCO's) in wholesale electricity markets, therefore, market efficiency is increased.
- In DR programs, the dependence of retail tariffs on the wholesale market price, leads to more efficient usage of resources in electric power systems.
- DR allows higher penetration of intermittent renewable energy resources in electric power systems. In balancing generation and demand, DR programs help power system to overcome difficulties arising from uncertain nature of intermittent renewable energy resources.
- Using DR programs, consumers enjoy bill savings by rescheduling their consumption patterns.

1.4. Objectives and organization of the paper

In order to exploit their full potential, DR programs must be implemented optimally. Such a problem, which here is referred to as DR optimisation problem, has been frequently researched in the literature [56]. This paper aims to review different research works on DR optimisation problems. The rest of the paper is organised as follows; in Section 2, the review of research works on DR optimisation is provided from different perspectives. Section 3 includes overall review and some directions for future research. The conclusions have been drawn in the Section 4.

2. Detailed review of research on demand response optimisation

In this section, the existing research works on DR optimisation are reviewed from the perspective of the used optimisation algorithm, the used DR program, the used objectives, constraints and decision variables. From the optimisation perspective, DR optimisation problem is typically formulated as a constrained optimisation problem, including binary decision variables. This review is mainly based on the used optimisation algorithm. The optimisation algorithms, used for solving DR optimisation problem, can be classified into two broad categories; classic optimisation algorithms and metaheuristic optimisation algorithms.

2.1. Classic optimisation algorithms for solving DR optimisation problems

DR optimisation problems may be formulated as linear or non-linear optimisation problems. Depending on the formulation of the problem, linear programming (LP) or nonlinear programming (NLP) may be used. In most cases, the ON-OFF status of various consumers or appliances at different time-slots must be determined, which represent binary decision variables. Therefore, typically mixed-integer linear programming (MILP) or mixed-integer nonlinear programming (MINLP) are used for solving DR optimisation problem.

2.1.1. Linear programming or mixed-integer linear programming for solving DR optimisation problems

In the literature, in a couple of research works, LP or MILP has been used for solving DR optimisation problem. In [46], DR optimisation problem has been formulated as a linear optimisation problem, whose objectives are minimisation of household's bill payment and appliances' waiting time. Linear programming has been used for optimising the objective function and finding optimal consumption of various appliances at different time-slots. A combination of RTP and IBR has been used as DR program. Assuming that prices are published only a couple of hours before scheduling, a price prediction module has been added. The results show 25% bill saving and 38% reduction in PAR, achieved by DR program. The simulation results also show that increasing the number of households of the utility facilitates load balancing and PAR reduction.

In [57], linear programming has been used for optimal scheduling of users in direct load control (DLC) program and also finding the optimal number of users participating in DLC program. The objective is to minimise peak demand of the utility. In [58], the consumptions of different appliances of a household at different time-slots have been determined in order to minimise the peak hourly load of the household. DR optimisation problem has been formulated as a linear optimisation problem, which is solved by MILP. The results show significant reduction in peak hourly load of the household. The results also imply that using multiple households in the DR program, a more balanced hourly load can be achieved.

In [59], optimal resource scheduling of a DR aggregator, which participates in day-ahead wholesale electricity market, has been done by mixed-integer linear programming (MILP). DR aggregation is acknowledged as an efficient way for increasing the exposure of large volumes of consumers to wholesale markets [59,60]. DR aggregator signs contracts with consumers to participate in DR program through load curtailment, load shifting, on-site generation and energy storage. DR aggregator aims to use shares of different DR resources in a way that its payoff, i.e., its revenue in wholesale electricity market minus its payments to consumers participating in DR program, is maximised. The results show the remarkable payoff, achieved for DR aggregator in Pennsylvania New Jersey Maryland (PJM) wholesale electricity market. The impact of market price and the impact of constraints of different DR resources on optimal scheduling of DR aggregator and optimal payoff of DR aggregator have been investigated.

In [61], MILP has been used for DR optimisation and OPF in CHP microgrids with energy storage systems. DR program in a bus has been considered as a virtual generator with a defined cost function. The problem has been formulated as a multi-objective optimisation problem, with both economic and environmental objectives. Fuzzy method has been used to find compromised solution in pareto-front. The results show the significant effect of DR on peak-load reduction, emission reduction and operational cost reduction. In [62], MILP has been used for unit commitment in microgrids with demand bidding DR program, while DR has been implemented for residential, commercial and industrial consumers. Industrial loads bid as multiple curtailment-price steps. Uncertainties of wind and PV generators have been considered and scenario-based analysis has been used for dealing with the uncertainties.

In [63], MILP has been used for DR optimisation and day-ahead operation cost minimisation in smart building microgrid. The smart building includes some smart homes and has its own microgrid with storage units. RTP has been used as DR program. Optimal schedule of home appliances is found in optimisation process. The results on two different smart buildings with 30 and 90 homes confirm the effect of DR program in reduction of MG's operational cost and peak demand.

In [64], MILP has been used for DR optimisation and generation scheduling in a residential community grid with renewable generation and ESS. The objective is to minimise the purchased energy cost of the residential community. TOU, RTP and CPP have been used as DR programs. A normal distribution function has been used to simulate the arrival time of EV's. An interesting result indicates that while prior to TOU program, most EV load is centralized in on-peak and mid-peak hours, the TOU program shifts around 96% of EV load to off-peak hours.

2.1.2. Non-linear programming or mixed-integer non-linear programming for solving DR optimisation problems

NLP or MINLP have been frequently used for solving DR optimisation problem, where the relationship between objective(s) and decision variables has been represented as a nonlinear function. In [65], NLP and MINLP has been used for solving DR optimisation problem. A nonlinear problem formulation has been provided, wherein, it is assumed that DNO has the authority to control demands in some nodes of the system and the effect of DR incorporation in a bus of the power system is modeled by the following equations.

$$P_{d,DR}(i,\, t) = P_d(i,\, t).\, \gamma(i,\, t) \tag{1}$$

$$Q_{d,DR}(i,\, t) = Q_d(i,\, t).\, \gamma(i,\, t) \tag{2}$$

where $P_{d,DR}(i, t)$ represents active power demand of ith bus at time t with demand response, $P_d(i, t)$ represents active power demand of ith bus at time t without demand response, $Q_{d,DR}(i, t)$ represents reactive power demand of ith bus at time t with demand response, $Q_d(i, t)$ represents reactive power demand of ith bus at time t without demand response and $\gamma(i, t)$ denotes DR coefficient of that bus at time t.

Optimal DR problem has been solved for two different scenarios, while distribution network operator functions as decision maker and does not consider the comfort of the consumers. In the first scenario, the buses with DR program are assumed known and the DR coefficients for buses with DR program at each time-slot are determined in a way that the daily loss payment is minimised. Due to the fact that energy loss is a nonlinear function of DR coefficients, this represents a nonlinear optimisation problem. In this scenario, the number of decision variables equals the number of buses with DR programs, times the number of time-slots. In the second scenario, the best buses for DR program are also found in the optimisation process, that is, the best buses for DR program and DR coefficients for those buses at each time slot are found in DR optimisation problem. This represents a nonlinear optimisation problem including both integer and non-integer decision variables and is solved by mixed- integer nonlinear programming (MINLP). The prices of day-ahead market are assumed unknown and are predicted by forecasting modules. In formulating the optimisation problem, the uncertainty of day-ahead prices are considered and robust optimisation has been used for dealing with uncertainties.

In [66], NLP with dual decomposition has been used for finding optimal consumption of different users at different time-slots in order to minimise generation cost of utility and maximise convenience of consumers. The preference of consumers and their consumption patterns have been modeled in the form of a convenience function. For each consumer, the convenience function has been formulated as a non-decreasing function of user's consumption as below.

$$U(x,\, \omega) = \begin{cases} \omega x - \frac{\alpha x^2}{2} & 0 \le x \le \frac{\omega}{\alpha} \\ \frac{\omega}{\alpha} & x > \frac{\omega}{\alpha} \end{cases} \tag{3}$$

where x represents the consumption level of the consumer, α is a predefined parameter and ω is a parameter that varies from consumer to consumer and from time to time.

The achieved results show significant reduction in generation cost for utility and a high convenience for consumers.

In [67], MINLP has been used for solving residential DR optimisation problem. Optimal ON-OFF status of 10 residential appliances in 10-min time-slots for a horizon of one day, has been found in DR program. Daily bill and consumer's inconvenience have been minimised for an optimisation problem with lots of binary decision variables. Eskom's tariff which is mainly based on TOU pricing and also incentivizes users during peak hours, has been used. The sum of disparities between baseline consumption of appliances and their scheduled consumption has been defined as the inconvenience metric. The results show that the described optimally-scheduled DR leads to more than 25% bill saving for the consumer.

In [68], mixed-integer nonlinear programming (MINLP) has been used for DR optimisation, wherein DR has been used in energy hubs and optimal day-ahead scheduling of resources in energy hubs is intended. Real-time pricing (RTP) program has been used. The consumption of different loads at different time-slots are determined in a way that total cost of energy hub, including the cost of purchased gas and the purchased electricity from grid, is minimised. The uncertainty of load and price has been modeled by normal probability density functions and has been handled by 2 m + 1 point estimate method (PEM). Heat demand has been considered both curtailable and shiftable, while electric demand has been considered shiftable, but not curtailable. The effect of DR on demand has been represented by (4).

$$P_{d,\ DR}(t) = (1-F(t))P_d(t) + sd(t) \tag{4}$$

where $P_{d,DR}(t)$ represents active power demand of a consumer at time t with demand response, $P_d(t)$ represents active power demand of that consumer at time t without demand response, $F(t)$ represents the fraction of the load, shifted to other time slots and $sd(t)$ denotes the load shifted from other time-slots to this time-slot.

DR has done both for thermal loads and electric loads, although only electricity price changes as RTP program and gas price has been considered constant. The simulations have been done for three different energy hubs as case studies and for three different scenarios for each energy hub. The first scenario conducts optimal scheduling of resources without demand response, the second scenario conducts optimal scheduling of resources with electric load demand response and the third scenario conducts optimal scheduling of resources both with electric and thermal loads demand response. The simulation results show that the implementation of electric load demand response decreases the total cost of energy hub with respect to optimal scheduling without DR and also show that the simultaneous implementation of electric and thermal loads demand response leads to the least cost in optimal scheduling. The results testify that the proposed 2 m + 1 point estimate method for dealing with uncertainties of loads and prices outperforms 2 m point estimate method.

In [69], NLP has been used for DR optimisation and unit commitment in microgrids, while the amount of load reduction and paid incentives for each time interval are found in DR optimisation. The benefit of the utility, in each time interval of DR program has been formulated as below.

$$B = \beta x - y \tag{5}$$

where β represents the cost of not supplying 1 kWh of consumption, x represents the reduced consumption in kWh and y represents the incentive paid to the consumer.

The total benefit of the utility in DR program is calculated by summation of B values for all consumers and time intervals. It is assumed that the parameters of customers' benefit function is known to the microgrid operator. A minimum benefit for consumers participating in DR program is guaranteed in the formulation of the problem and a maximum budget for incentives has been considered. The transferred power between microgrid and upstream grid, ON-OFF status and generated power of dispatchable generating units along with the incentive and load curtailment of different customers at different time intervals form the decision vector of the problem. The operation cost of microgrid and the total benefit of utility in DR program form the objective function. Linear weighted sum has been used for handling multiple objectives. The results have been found for a microgrid including PV, WT and diesel generators.

In [70], benders decomposition NLP has been used for unit commitment in microgrids with DR for residential, commercial and industrial consumers. Different DR programs including direct load control (DLC) and demand bidding programs have been used. The uncertainties of PV and wind generation have been modeled by their PDF's and are dealt with scenario-based analysis method. Indeed, microgrid uses the curtailment of different loads as a resource in energy and reserve management. The achieved results confirm that DR significantly reduces the operational cost of the microgrid.

In [71], NLP has been used to find the ON-OFF status of appliances of a smart home in different time-slots in different DR programs. The considered smart home is equipped with home energy management system (HEMS). It also includes renewable generation units, electric vehicles (EV's) and energy storage systems. The benefit of the home owner is the objective function, while a response fatigue index has been defined and it is assumed that the response fatigue in DR program should be less than a predefined threshold.

The uncertainties of renewable generation units, electric vehicles (EV's) and energy storage systems have been considered and are dealt with scenario-based analysis (SBA) method. Different price-based and incentive-based DR programs including CPP, RTP and TOU have been used. The degradation of batteries over time has been considered. The response fatigue index has been defined based on three factors; the frequency of DR signals/calls, duration of DR events and the importance of the appliances affected by DR program. By setting a maximum fatigue index, the DR provider ensures that the customer keeps participating in DR program. It is assumed that at the highest satisfaction level, the consumers charge their EV's at the arrival time and unplug them once their batteries are full. The results show that the proposed stochastic formulation leads to more profit for home owners than deterministic formulation. As expected, RTP leads to the highest response fatigue index, due to the high frequency of DR signals.

Other than the above-mentioned research works, in [72], NLP has been used for solving DR optimisation problem.

2.2. Metaheuristic optimisation algorithms for solving DR optimisation problems

Metaheuristics are very popular optimisation algorithms for solving formidable engineering optimisation problems. They are typically population-based, stochastic optimisation algorithms that try to find a near-optimal solution, with a limited computational burden. Metaheuristics are global optimisation algorithms that can easily handle constrained and discrete optimisation problems with large number of decision variables [73,74]. Therefore, despite their challenges, metaheuristics are considered as good choices for solving DR optimisation problem. Referring to the literature, it was found that four different metaheuristic optimisation algorithms have been applied to DR optimisation problem. They will be reviewed within this sub-section.

2.2.1. Particle swarm optimisation (PSO) for solving DR optimisation problems

Particle swarm optimisation (PSO) is the most commonly used optimisation algorithm, for solving DR optimisation problem [75–82]. In PSO, a swarm with N_P particles search for a near-global solution. The ith particle is represented as below.

$$X_i = [X_{i1},\quad X_{i2},\quad \dots,\quad X_{id}, \dots, X_{in}] \tag{6}$$

where n denotes the number of decision variables. The particles are randomly initialised and their initial position and objective value are set as their personal bests. The position with the best objective is set as the global best. At iteration t, velocities and positions of particles are updated by the following equations [83].

$$V_i(t+1) = \omega V_i(t) + C_1\ r_1(P_i - X_i) + C_2 r_2(P_g - X_i) \tag{7}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{8}$$

where V_i denotes velocity of ith particle, C_1 and C_2 are respectively cognitive and social acceleration coefficients, ω denotes inertia weight, r_1 and r_2 are two random numbers in [0,1] [84].

After updating particles' positions, their objectives are calculated and their personal bests and global best are updated, so, global best is improved iteration by iteration. The process of updating velocities, positions, personal bests and global best continues until stopping criterion is met [84,85].

In most of the cases, the ON-OFF status of appliances at different time-slots represent the decision vector of DR optimisation problem. Such a problem with binary decision variables, must be solved with binary version of PSO. In binary PSO, after updating velocities, sigmoid function is used to map V_{id} (dth dimension of ith particle's velocity) into interval [0,1] [86–89].

$$\mathrm{s}(\mathrm{V_{id}}) = \frac{1}{1+\exp(-\mathrm{V_{id}})} \tag{9}$$

Then a random number r in [0,1] is generated and then, the following equation is applied.

$$\mathrm{X_{id}}(\mathrm{t}+1) = \begin{cases} 1 & r < s(\mathrm{V_{id}}) \\ 0 & \text{Otherwise} \end{cases} \tag{10}$$

That is, $\mathrm{V_{id}}$ represents the probability that the variable $\mathrm{X_{id}}$ takes the 1 value.

In [75], binary PSO has been used for scheduling some interruptible loads for a 16-h time horizon in order to satisfy a schedule of required hourly requirements. A total of 19 interruptible loads have been used and the objective is to minimise the total payments (incentives) to the consumers. The hourly ON-OFF status of the interruptible loads are found in a way that the mentioned objective is minimised, therefore the number of binary decision variables is 304. The optimisation has been done from utility-side that aims to minimise the total incentive payments to consumers, but simultaneously aims to minimise the total number of interruptions to make DR socially acceptable. The constraints of the optimisation problem have been added to the objective function as a set of penalty functions. The results show the outperformance of the proposed binary PSO over fuzzy dynamic programming. Comparing the best scheduled curtailment, achieved by binary PSO, with the required curtailment, shows that it closely follows the required curtailment. Moreover, in [75], in order to improve the search behavior of PSO, the swarm is subdivided into a couple of subswarms, where the particles of each subswarm are attracted towards the leader of their own subswarm. The results show that multi-swarm PSO leads to better performance in DR optimisation problem than conventional single-swarm PSO. It was also found that the multi-swarm PSO performs better with independent sub-swarms than dependent subswarms.

In [77], binary PSO has been used for optimal scheduling of electric water heaters (EWH's) of 200 households in direct load control program (DLC). ON-OFF status of all electric water heaters in 15-min time-slots are found in a way that peak load demand of utility is minimised and the aggregate comfort of the consumers are maximised. Water temperature of EWH's as the criterion of consumers' convenience is maximised. EWH's represent a large portion of a household's load. In winter-dominated areas, they contribute to as much as 30% of household's load. Due to two reasons, EWH's are suitable candidates for DR programs and their control in DLC has attracted much attention [22,90–100]; The first reason is that the hot water in the their tank acts as an energy storage. The second reason is that their load profile closely mimics the aggregate load profile of the household, so using them in DLC programs, significantly reduces the peak demand of the utility. The thermal model of EWH has been described in [77] in order to find the water temperature, based on the data collected from smart meters. The results imply 500–700 W peak load reduction per household. Potential cost saving for utility for 200 households is as high as 1.260 $. The used objective function is as follows.

$$J = \sum_{i=1}^{N_{EWH}} W_1|T_{d,i} - T_{a,i}| + W_2|P_d - P_{a,i}| \tag{11}$$

where N_{EWH} denotes the total number of EWH's, $T_{a,i}$ denotes the estimated water temperature, $T_{d,i}$ represents the maximum water temperature, P_d is the desired load, $P_{a,i}$ denotes the load of ith EWH, W_1 and W_2 respectively represent the weight factors of peak demand minimisation and comfort maximisation.

In [81], binary PSO has been used for finding optimal ON-OFF status of manufacturing machines in different 15-min time-slots in TOU demand response program. The optimisation has been separately done for two different problem formulations. In the first formulation, which does not seem realistic, the total electricity consumption is minimised, while in the second formulation, the total cost of electricity consumption is minimised. In both formulations, the average cumulative production is bounded by a certain lower limit.

In [101], a mutation-incorporated PSO has been used for DR optimisation and finding optimal setting of on-load tap changers (OLTC's) in a low-voltage network. The setting of OLTC's and ON-OFF status of appliances are found in a way that the over-voltages and voltage unbalances are removed, DR costs and network losses are minimised, considering the comfort of the consumers. EV's. Washing machines, dishwashers, driers and pool-pumps have been included in the DR program. The utility collects each DR appliance's rated power, consumption preference and bid price for participation in DR program. DR and OLTC optimisation has been formulated as a mixed-integer nonlinear optimisation problem, while the constraints have been added as penalties to the objective function. In the proposed mutation-incorporated PSO, the mutation operator is applied if the global best is not improved after a certain number of iterations. A random particle is selected and a random perturbation is added to its velocity. In the proposed PSO, constriction factor is used instead of the common inertia weight. The results show that the simultaneous usage of DR and OLTC significantly reduces the overvoltages, voltage balances, network losses and network costs, while the consumers' comfort is respected. The results confirm the outperformance of the proposed mutation-incorporated PSO over conventional PSO, simulated annealing (SA) and GA. However, the uncertainties of PV generation and EV's have not been taken into account.

In [76], mutation operator is incorporated into PSO and is used for optimal scheduling of generating resources and DR resources. The results on a large-scale distribution network with 937 buses, 20,310 consumers and 548 DG's approve the efficacy of the proposed mutation-incorporated PSO. In [78], again PSO has been applied to DR optimisation problem. The problem has been formulated as a bi-level optimisation problem, wherein the objective of the upper level is the maximisation of retailer's payoff and the objective of the lower level is minimisation of the consumer's bill payment. The consumption of different appliances have been found for a time horizon of 24-h and with 15-min time resolution. The simulation results show that PSO performs better than GA. Moreover, in [82], fuzzy-based PSO has been used for solving DR optimisation problem in order to minimise power losses of the distribution network.

2.2.2. Genetic algorithm (GA) for solving DR optimisation problems

Genetic algorithm (GA) is a well-established evolutionary-based metaheuristic optimisation algorithm [102,103]. In few cases, it has been used for solving DR optimisation problem. It is inspired of the evolution of human beings from generation to generation and is mainly based on selection, crossover and mutation operators. At each iteration, crossover and mutation operators produce new individuals and a stochastic-based selection operator is used to select fitter individuals among the previous individuals and newly-generated ones.

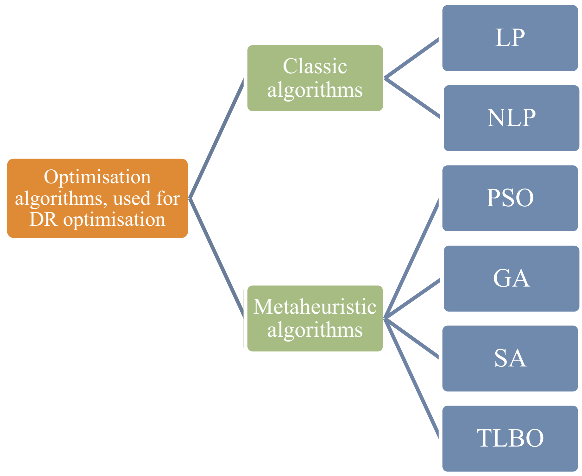

Fig. 4. Classification of optimisation algorithms, used for DR optimisation.

In [104], GA has been used for optimal scheduling of residential, commercial and industrial shiftable loads in RTP demand response program within a smart grid. The control system receives the desired load curve as an input and calculates the required load control actions to take the load curve as close as possible to the desired load curve. When a customer presses ON button of an appliance, the connection request is sent to the demand response controller. The DR controller either permits immediate connection of the appliance or permits it to connect at a later time-slot. The objective function of the optimisation process is as below.

$$J = \sum_{t=1}^{N} (P_{load}(t) - target(t))^2 \tag{12}$$

where $target(t)$ and $P_{load}(t)$ respectively represent the desired consumption and actual consumption at time t. It must be pointed out here that $target(t)$ is chosen in a way to be inversely proportional to electricity market prices.

The results of [104] approved that the proposed methodology manages to keep the consumptions close to the desired consumption levels. The savings in operating costs, achieved for residential, commercial and industrial loads were respectively 5%, 5.8% and 10%. The results also approved the benefits of the proposed DR to both consumers and the utility.

In [105], GA has been used for optimal scheduling of inverter air conditioners in RTP program, while the RTP prices are published as a day-ahead basis. DR optimisation has been done in a way that the maximum bill saving is achieved and peak demand is minimised, while thermal comfort of the residents has been included as the constraints of the problem.

In [106], GA has been used for DR optimisation of industrial consumers including EV and HVAC loads for minimisation of costs and maximising consumers' comfort. The results showed the significant effect of DR on cost reduction.

Moreover, in [107], GA has been used for DR optimisation in a smart home.

2.2.3. Simulated annealing algorithm (SA) for solving DR optimisation problems

Simulated annealing (SA) is another metaheuristic optimisation algorithm that in few cases has been used for solving DR optimisation problem. It takes inspiration from annealing process in metallurgy, wherein heating and then cooling of the material is done in a way to increase the size of its crystals and decrease its defects [108–110].

In [111], simulated annealing (SA) algorithm has been used for finding optimal set of the real-time prices in DR optimisation. The prices in RTP are set in a way that the aggregate surplus of consumers, retailer and utility is achieved, that is, demand's peak to average ratio (PAR) is minimised, the retailer's cost is minimised and consumers' payoff is maximised. The prices are determined at the beginning of each scheduling horizon. The consumers respond to the real-time prices in a way that their own payoff is maximised. This DR program has been applied to a smart grid with a retailer and 100 users which purchase their electricity from the retailer. The appliances have been classified into must-run appliances, shiftable appliances and interruptible appliances and have been scheduled for different time-slots through Lagrangian method. The achieved results show the benefit of the proposed methodology for the utility, the retailer and the consumers. In [112], SA has also been used for optimal scheduling of residential appliances in order to simultaneous minimisation of the household's bill payment and utility's generation cost.

2.2.4. Teaching learning-based optimisation (TLBO) for solving DR optimisation problems

Teaching learning-based optimisation (TLBO) algorithm is a metaheuristic optimisation algorithm, inspired from the interaction among students and teacher in a classroom [113]. In [114], TLBO has been used for optimal scheduling of residential consumers in a smart grid in order to minimise their bill payment. The consumers are under different DR programs, including TOU, RTP and CPP and some consumers are under flat tariff policy. The results show remarkable reduction in consumers' bill payments after applying optimal DR by TLBO. The results also indicate the outperformance of TLBO over shuffled frog leaping algorithm (SFLA).

The classification of optimisation algorithms, used for DR optimisation, can be seen as Fig. 4.

3. DR optimisation from other perspectives

From the perspective of the used objectives, five different objectives have been mostly used in the existing research works on DR optimisation. Bill saving maximisation [46,67,78,114], comfort maximisation [46,67,77], generation cost minimisation [66,68,115] and PAR minimisation [58,77] are the most commonly used objectives in DR optimisation problem. From the perspective of the used DR program, RTP [66,68,104,111,115] is the most commonly used DR program, although DLC in [65,77], and TOU in [81,115] has been used. Moreover, in [46], the combination of RTP and IBR and in [114], the combination of TOU, CPP and RTP has been used.

From the perspective of the type of users under DR program, in most of the cases, DR optimisation has been done for residential users [46,58,67,75,77,78,104,114]. Only in [46,104], commercial users and in [46,81,104], industrial users have been used. From the perspective of the consideration of the inherent uncertainties in the DR optimisation problem, only in [65,68], the uncertainties of some uncertain parameters have been considered. In [65], the uncertainty of the prices of day-ahead wholesale market has been considered and dealt with robust optimisation method, and in [68], the uncertainty of loads and price have been taken into account and have been handled by 2 m + 1 point estimate method. In other cases, the uncertainty of different parameters such as loads, generated powers and prices have not been taken into account. The main features of some selected research works on DR optimisation problem, can be seen as Table 1.

4. Overall review and some directions for future research

After reviewing the existing research works on demand response (DR) optimisation, the following points must be considered.

- A detailed comparison among different DR programs in the term of their effects on different objectives, such as PAR minimisation, reliability enhancement, etc. is missing in the literature and

Table 1
The main features of some research works on DR optimisation.

Ref	DR program	Optimisation algorithm	Objective function	Constraints	Decision variables	Consumer type	Case study	Remarks
[65]	Direct load control	NLP and MINLP (when DR buses are also found)	Daily payments for energy loss	Power flow equations, limits on voltages' buses, and currents of branches, minimum and maximum limits for DR coefficients, maximum curtailment rate for system	Load factors for different DR buses at different hours	General	IEEE 33 bus system	The uncertainty of prices of day-ahead wholesale market prices have been considered. DNO is the decision maker and does not consider the comfort of consumers. The results indicate higher benefits for consumers with respect to traditional loss minimisation.
[66]	RTP	NLP (dual decomposition)	Cost of generation for utility and the aggregate convenience of all users	There exist minimum and maximum consumption limit for each consumer. Total consumption of consumers must be below generation capacity.	Consumption of each consumer at different time-slots (in a day-horizon)	General	A system with 10 consumers	Consumers' preferences and their energy consumption patterns have been modeled in the form of convenience function.
[67]	A combination of TOU and incentives for load reduction at peaks (Eskom's tariff)	MINLP	Daily bill saving and consumers' inconvenience	Continuous operation of non-interruptible appliances, maximum limit for daily bill	ON-OFF status of each appliance at each time-slot	Residential (a home)	A residence with 10 appliances	Bill saving of more than 25% was achieved.
[68]	RTP	MINLP	Total cost of energy hub	Ramp up/down limits, Constraints of converters and storages	Consumption of loads at different time-slots	General	Three energy hubs. The first one has a CHP unit, a gas furnace, a transformer and the heat and power storage devices, with gas and electricity as inputs and electric and thermal energies as output.	Considering the uncertainties of loads and price and using RTP demand response program, optimal scheduling of resources in energy hubs has been done. It has led to low cost for energy hubs.
[46]	A combination of RTP and IBR	Mixed integer linear programming (MILP)	Bill saving and waiting time (convenience of consumers)	The constraints on the nature of different appliances, e.g. non-interruptible appliances	Consumption of different appliances at different time slots	Residential	A household with different appliances	A price prediction module has been used. The results show 25% bill saving and 38% PAR reduction. The simulations show that increasing the number of households of the utility facilitates load balancing and PAR reduction.
[59]	A DR aggregator using load curtailment, load shifting, onsite generation and energy storage.	MILP	Payoff of DR aggregator (its revenue in wholesale market minus its payments to consumers participating in DR)	For load curtailment, minimum and maximum duration for load reduction, maximum number of daily load curtailments, for on-site generation, ram up/down limits, availability of fuels, for energy storage, rate of charging and minimum number of daily charge/discharge cycles.	The share of different DR sources (load curtailment, load shifting, on-site generation and energy storage) at different time-slots	Residential, commercial and industrial	A DR aggregator in PJM wholesale market	The impact of market price and the impacts of constraints of different DR resources on optimal scheduling of DR aggregator and optimal payoff of DR aggregator have been investigated.
[58]	Not mentioned	MILP	Peak hourly load	The constraints on the nature of different appliances, e.g. non-interruptible appliances	Consumption of different appliances at different time slots	Residential	A household with different appliances	Significant reduction in peak hourly load of the household is achieved. The results also imply that using multiple households in the DR program leads a more balanced hourly load.
[75]	Load curtailment	Binary PSO	Minimisation of incentive payments to consumers	Minimum duration between curtailments, maximum curtailment for each time slot.	Hourly ON-OFF status of 19 users at a 16-h time horizon	Residential	A household with 19 appliances	The results shows that multi-swarm PSO leads to better performance in DR optimisation

(continued on next page)

Table 1 (*continued*)

Ref	DR program	Optimisation algorithm	Objective function	Constraints	Decision variables	Consumer type	Case study	Remarks
			and minimising the number of interruptions	The required hourly load curtailment schedule must be met.				problem. It was also found that the multi-swarm PSO performs better with independent sub-swarms than dependent sub-swarms.
[77]	Direct load control	Binary PSO	Minimisation of peak demand and maximisation of the comfort of consumers (maximising temperature of water)		ON-OFF status of different water heaters at different time slots (with 15 min time resolution and for 24 h time horizon)	Residential	Direct load control of electric water heaters, based on data gathered from 200 households.	The results show 500–700 W peak load reduction per household. Potential cost saving for utility for 200 households is 1.260 $.
[78]	Not specified	PSO	Maximisation of retailers' payoff and minimisation of household's bill	The constraints on shiftable and interruptible loads	Consumption of various appliances at different time slots	Residential	A household with different appliances	The results show the outperformance of PSO over GA.
[81]	TOU (three-segment)	Binary PSO	First formulation for minimisation of total consumption and second formulation for minimisation of total electricity cost	The average cumulative production must be lower than a limit.	ON-OFF status of different machines	Industrial (manufacturing)	A manufacturing system with three machines and two buffers	The proposed methodology has not been compared with other state of the art methodologies.
[104]	RTP	GA	The squared of differences between the load and the desired load	The number of devices shifted away from a time-slot cannot be more than the number of devices available for control at that time-slot	ON-OFF status of different shiftable loads at different time-slots	Residential, commercial and industrial loads	Residential load with over 2600 controllable appliances, commercial load with over 800 controllable devices and industrial load with over 100 controllable devices	The results approved that the proposed methodology manages to take the consumptions close to the desired consumption levels. The savings in operating costs, achieved for residential, commercial and industrial loads were respectively 5%, 5.8% and 10%. The results also approve the benefits of the proposed DR to both consumers and the utility.
[111]	RTP	Simulated annealing (SA)	Payoff of utility, retailer and consumers	The constraints on the nature of shiftable and interruptible appliances	ON-OFF status of different appliances at different time-slots and the set prices in RTP	Residential	A smart micro-grid with a retailer and 100 users which purchase their electricity from the retailer.	The results show the benefit of the proposed methodology for the utility, the retailer and the consumers.
[114]	A combination of TOU, RTP, CPP and flat tariff	TLBO	Bill payment of consumers	The constraints on the nature of shiftable and interruptible appliances	ON-OFF status of different loads at different time-slots	Residential	A smart grid with some residential households	The results show the outperformance of TLBO over SFLA.
[115]	TOU and RTP (Separately)	Projected gradient algorithm	Total cost of the energy hub	Balancing generation and demand, lower and upper bounds for hot water temperature, lower and upper bounds for building's temperature	ON-OFF status of different loads at different time slots	Residential	Ten residential energy hubs	The results show a remarkable reduction in energy hub's cost. The results, given by RTP are better than those given by TOU. The results show that RTP and TOU respectively lead to 30% and 20% reduction in demand's peak to average ratio.

recommended as a direction for future research.

- As per the conducted review, only in [65,68], the uncertainties have been considered in DR optimisation problems, while loads and generated powers are uncertain and metering and communication devices add to the uncertainties of the problem. Most importantly, the response of the consumers to DR program is very uncertain. Considering the uncertainties leads to a more realistic formulation and solutions for DR optimisation problem and is recommended as a thread for future research.
- Formulating DR optimisation problems in a more realistic way is recommended as a thread for future research.
- Despite the efforts made, due to the caused discomfort, most consumers are not attracted to register or respond to DR programs. Developing strategies to attract consumers, specially residential consumers to DR programs is recommended for future research.
- As per the conducted review, mostly DR optimisation have been done for residential consumers and in few cases, it has been done for industrial or commercial consumers. Putting more research effort on DR programs for commercial and industrial consumers is recommended.
- Only few research works have worked on the way that the real-time prices in RTP programs are set by retailer/utility. Putting more research effort on strategies for setting real-time prices is recommended.
- Detailed investigation of the effects of DR programs on electricity markets with imperfect competition is recommended as a thread for future research.
- Research efforts for mathematical modeling of DR programs is insufficient. Focusing on proper mathematical modeling of DR programs is recommended for future research.
- Few researches has been done on environmental effects of DR program and considering pollutions in objective function of DR optimisation problem. Investigating the environmental implications of DR programs and considering pollutions in the objectives of DR optimisation problem is recommended for future research.
- The comfort of the consumers is a paramount objective in DR optimisation problem. However, only in [66], a mathematical formulation for comfort has been provided. Putting more effort on mathematical formulation of the comfort is recommended.
- Considering PHEV's in optimisation of residential DR programs is recommended as a thread for future research.

6. Conclusions

Demand response programs have proved to be efficient in mitigation of many power system challenges, such as high generation cost during peak demand hours, reliability issues and congestion in generation, transmission and distribution systems. In order to achieve their full potential, DR programs must be implemented optimally. Such a problem, referred to as DR optimisation problem, has been frequently researched. This paper has classified and reviewed different research works on DR optimisation problems.

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