DREAM-GO

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Components and Resource Models and Optimization Algorithms for Smart Grid Operation Considering Uncertainties and Short and Real-time DR

MARIE CURIE ACTIONS

Deliverable

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1. Introduction

Addressing short and real-time demand response (DR) in smart grid requires advanced energy resources models and optimization algorithms capable of achieving satisfactory solutions in reasonable execution time. The energy resource models handling short and real-time DR need to consider an accurate representation of the smart grid components, which include load models (e.g., electric water heater, heat pumps), distributed generation, and energy storage systems such as electric vehicles and energy storage systems. Some of the involved smart grid components are uncontrollable generation devices, e.g., small wind energy generation and solar photovoltaics facilities installed in homes, buildings and commercial or industrial compounds. Indeed, the output generation of wind generation and solar photovoltaics is not dependent on a human control action but instead on the weather conditions and nature events. These resources represent a source of uncertainty for the smart grid operation that must be considered. In addition, it is well understood that new loads such as electric vehicles (EVs) will add an additional source of uncertainty that cannot be deemed insignificant. DR can play a significant role to tackle and mitigate variable generation and uncertainty as it can be activated whenever it is not possible or too expensive to supply additional load demand or disconnect renewable generation. Being able to rapidly increase or decrease the demand and generation (i.e., flexibility) is a desired feature in the new paradigm of the smart grids.

This report presents an overview and context of DR in smart grid operation in section 2. In Section 3 the resources and components modelling of smart grid. This report discusses a summary of smart grid (SG) optimization models in short and real-time, including uncertainty modelling of smart grid components, namely DR, while highlighting the contributions of the DREAM-GO project in what concerns the development of new models. In section 4 optimization algorithms for SG optimization are discussed. Classification of the main works (developed by the DREAM-GO partners and other authors), e.g., stochastic programming and metaheuristics that can deliver solutions that address and enable short-term and real-time DR in SG operation. DREAM-GO team contributions to this field of optimization are also discussed in this section. Finally, section 5 drawn the main conclusions of this report.

2. Overview and context of demand response in smart grid operation

In the new paradigm of Smart Grid (SG) and electricity markets there are a diversity of players, such as Distribution System Operator (DSO), Transmission System Operator (TSO)[1], market operator, market regulator, aggregators and retailers [1], [2]. Figure 1 shows the smart grid operation players, namely interactions among the several players within the SG environment. In this context, traditional consumers can also act as prosumers, i.e., both consumers and producers. In this market arena, several aggregators and retailers can operate in the same or distinct areas or exclusive parts of the low voltage grid. It can also be possible that a larger part of the electricity network, like a medium voltage grid, could be independently operated by an aggregator in the future. Despite the worldwide blooming of efforts, the associated complexity of the SG operation problem at every scale along with the prosumers behavior raises the question of whether new methods will be able to address reliable and efficient response [3].

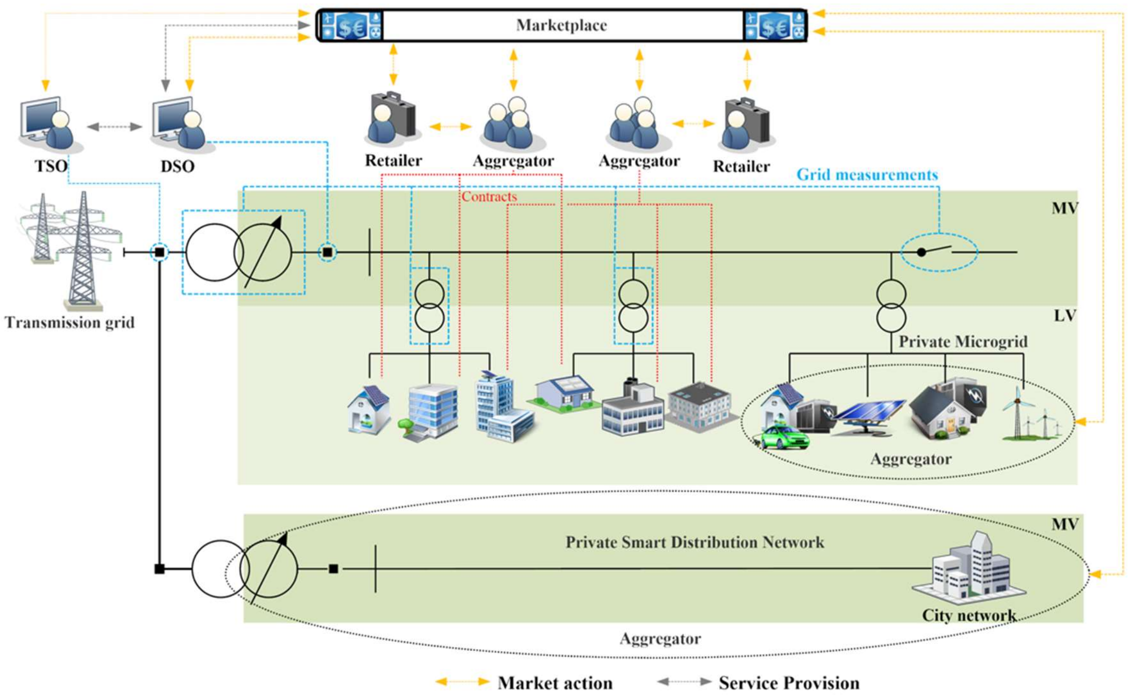

Figure 1. Smart grid operation players and interactions [4]

During the last decades, new visions and approaches have been proposed to deal with the increment of renewable energy sources [5]. In the scope of SG solutions, buildings and other end-users could purchase and sell the generated energy locally [6]. Consequently, energy management systems, smart metering and adequate demand response (DR) are necessary to deal with varying renewable generation and ultimately achieving an economic improvement through the automation technologies and network communications [7].

On the other hand, SG will allow optimizing the supply of energy to households. The development of the different technologies that make up the Internet of Things and the adoption of laws aimed at improving energy efficiency, have contributed to the development of smart energy distribution [8]. Although, at present only 30%-40% of the population lives in cities, population is growing rapidly in developing countries and as a result, urban areas will expand

[1] The TSO is also known as Independent System Operator (ISO) in United States.

and increase in population. The implementation of smart grids is part of the concept of smart cities; it will help solve many of the problems that cities face. In particular, key contributors to solve this problem are:

1) **automated fault detection**: Automated fault detection in power lines will make power supply more reliable and will reduce the duration of power outages. These intelligent networks locate and detect faults automatically and within seconds. In this way, the majority of consumers can continue being supplied with electricity, since supply to the faulty line is cut off automatically. Knowledge of the damaged area will enable technical crews to respond more quickly to major and minor faults. This will also save transformers from unnecessary damage.

2) **smart meters:** The introduction of smart metering will help solve many of the current problems, such as electricity theft, faulty transmission and distribution lines and errors in accounting. At present, in such circumstances, the supply of electricity to consumers is stopped automatically, in order to clarify the circumstances. According to statistics, once old meters are replaced with smart meters, the number of electrical overloads and crashes due to illegal connections to network substations will reduce significantly. At some local networks, the implementation of smart meters caused a fivefold decrease in the load on the grid and transformer substations.

3) **demand response:** Demand response prosumers' engagement into this dynamic scenario by means of their adapted DR would change the performance of the whole system. The use of Distributed Energy Renewable (DER) sources combined with IT are drivers of major changes happening today [9] [10].

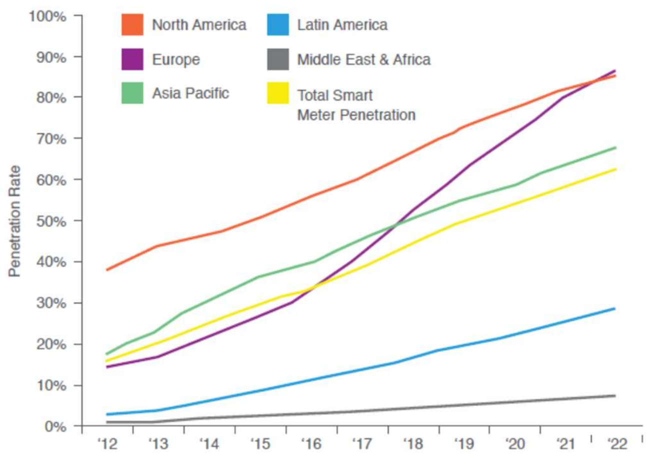

Figure 2. Predicted penetration of smart meters by region [11]

This is why many countries are beginning to invest in the development of alternative energy. Also, in the construction of new types of electricity networks; smart grids, and the installation of smart meters. Figure 2 compares the smart meters' penetration rate in the different regions of the world up to 2022. According to forecasts [12], sales on the smart meter market will reach 165.5 million units and revenues will be between \$5.3 billion to \$22.18 billion by 2020, with more than 80% of meters being installed in private households. Differences in the estimates are due to the variety of methods used for their calculation. However, they do give a general idea of the smart meter market being an area for future investment.

Smart metering implementation is seen as a very relevant step towards the massive layout of demand response programs [13]. Smart meters will allow the following according to [13]:

1) Bi-directional communication between the consumer and its supplier, which will provide a simple way of structuring programs and gain consumer's awareness;
2) Data storage that enables the analysis of consumption profiles of the consumers (using data mining), allowing a more comprehensive view about the consumer's needs;
3) Energy metering concerning different time periods which will enable the adoption of time-of-use programs;
4) Facilitate the consumer's interface with the energy activities, for example, by providing analysis between dynamic pricing programs and single tariff programs. In this way, smart metering will provide several advantages regarding the presentation of data, namely, in what concerns demand response events and dynamic pricing.

The following DR programs are briefly described according to OpenADR [14]–[16]:

1) **Critical Peak Pricing** – programs that use time distinct tariffs to influence the consumer to reduce its consumption during peak demand periods;
2) **Capacity Bidding Program** – programs that allow consumers to bid in energy markets, similar to how suppliers participate, specifying an amount of reduction, at a given time;
3) **Direct Load Control** – programs where the consumer's loads are controlled directly by the program organizer, without any influence from their owner;
4) **Ancillary Services Program** – these programs provide monetary incentives to consumers, in exchange for load reduction during moments where the network is at risk;
5) **Electric Vehicle DR Program** – has the same principle as CPP, however, applied to the charging of EVs, i.e., the price of charging EVs is time differentiated;
6) **Distributed Energy Resources DR Program** – related with the integration of distributed energy resources into a smart grid.

Figure 3 shows the temporary concepts involved with demand response application. The envisaged concepts are notification, deployment, which involves the ramp period and the sustained response after reduction deadline is fulfilled. Next, the release stage, after which there is a recovery period and resumes to normal status [13]. The deployment and the recovery period are known as the demand response event.

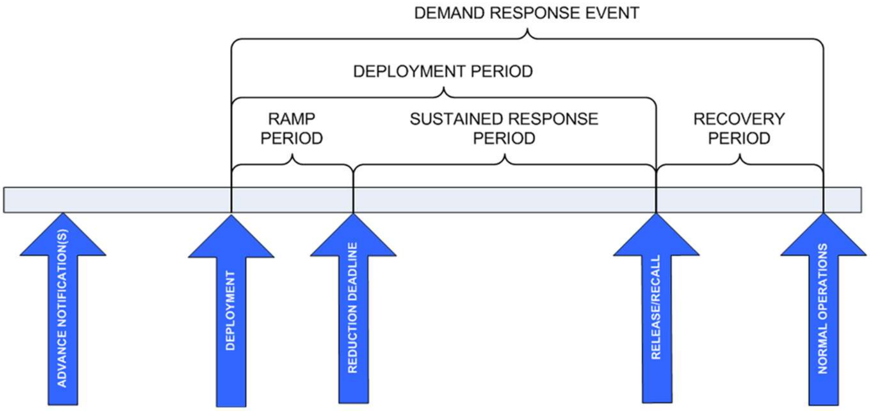

Figure 3. Periods involved in a demand response event [17].

2.1. DREAM-GO vision

The overall DREAM-GO vision to enable effective demand response is illustrated in Figure 4. The involved players in this vision are briefly described in this section. This vision relies on the backbone of the smart grid infrastructure, namely advanced smart metering, communications; as well as adequate optimization models and algorithms. The optimization related to this vision is discussed in subsequent sections of this report, namely 2.2 and 2.3. In DREAM-GO ontologies are envisaged to enabled system interoperability in communications between the involved players and energy resources. In fact some work has already been published by the team in [18].

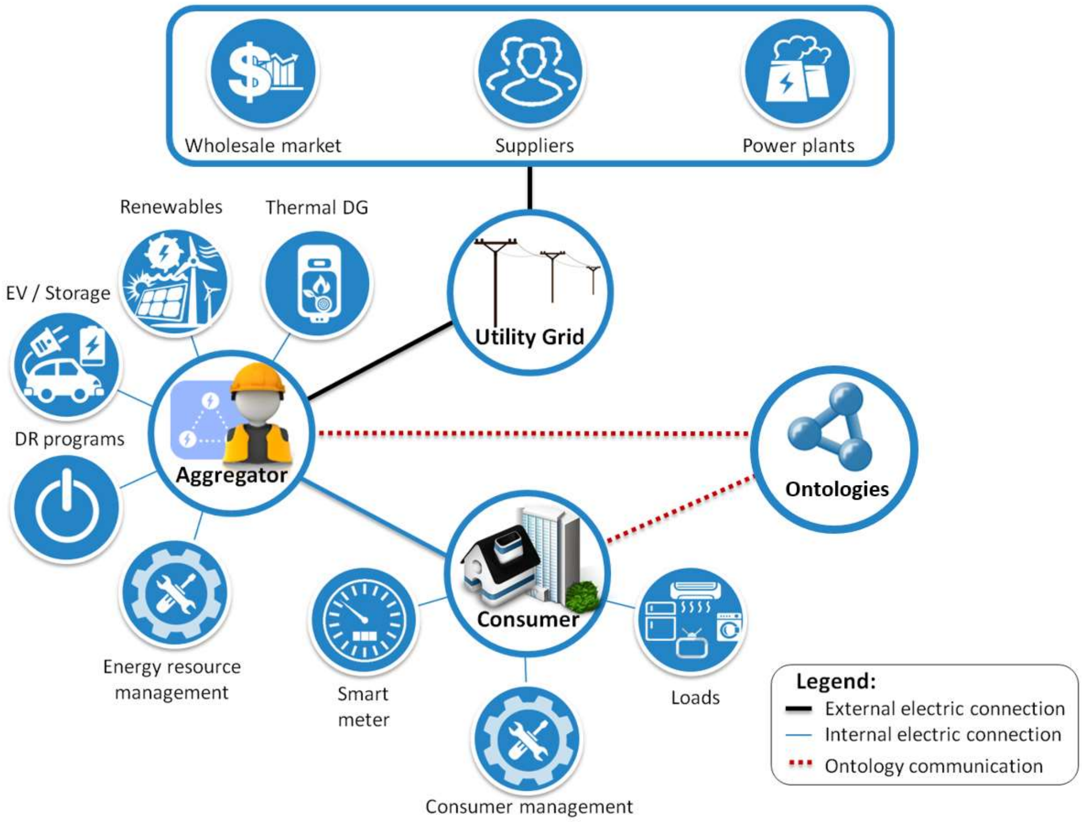

Figure 4. DREAM-GO vision: enabling effective demand response

The aggregator entity enables the intelligent management of the energy resources and consumers as a single entity. Aggregator interfaces with those energy resources throughout an electric connection (distribution grid) and with larger producers and the electricity market via a larger grid (known as the transmission grid). The involved energy resources are distributed generation (DG) such as renewables or thermal units, EVs, energy storage systems and DR programs. DR programs are considered an energy resource in this vision since they allow load reduction, load increase or load shifting, thus allowing dynamic changes of the energy load profile. DREAM-GO advocates that energy resource management is an essential tool to allow the energy aggregator to effectively deal with the involved energy resources, DR programs, market transactions, bilateral contracts with energy suppliers and larger producers. The energy resource management can have distinct phases from day-ahead to real-time [19][20]. The success of the DREAM-GO vision relies on adequate optimization models and algorithms to enable effective DR application, which is further discussed in subsequent sections. Another important and complementary player of the smart grid and this vision is the consumer (or prosumer). As stressed before, smarter metering is key to enable efficient control and monitoring on the consumer side. Consumer management allows to adequately control energy devices namely throughout efficient home energy management systems (HEMS) to enable effective consumption scheduling and adequate DR implementation.

2.2. Aggregator contribution for effective demand response

Several DR program schemes have been proposed in the literature, representing the DR scheduling from the viewpoint of the energy aggregators[2], e.g., [21]–[38]. Compared to the DR setups that can be implemented by the Transmission System Operators (TSO) and the distribution companies, this problem has been less explored from this perspective. References [21], [22] have developed a Direct Load Control (DLC) program to manage the residential loads. These plans are based on an agreement between the electricity aggregators and the customers to control the operation and the consumption of specific household appliances during peak demand periods and critical situations.

Alternatively, to the DLC programs, the Incentive-based and price-based DR programs are implemented, which are more acceptable to the customers and the aggregators in liberalized markets. These programs introduce flexibility for retail customers on a voluntary basis [38]. The customers adjust load profiles according to the varying price of electricity and the financial incentives [29]. In a price-based scheme, the aggregator offers time varying rates for the electricity to the end-users. Price-based DR programs are investigated in several models to show how the aggregators can benefit from them to manage the electricity consumption of the end-users [23]–[29], [36]. For example, [27]–[29] have introduced the real-time pricing (RTP) approach to model the price-based DR to maximize the profit of the aggregator and to reduce the peak-to-average load ratio in smart grids. Ref. [26] proposed a model for setting the price variations, which can encourage the customers to shift their loads considering time-of-use (TOU) tariffs. The hybrid market structure is considered for the aggregators' DR scheduling in references [24], [25]. A dual price scheme is used for the customers, where some customers see the real-time prices and the rest are offered with a flat regulated pricing scheme.

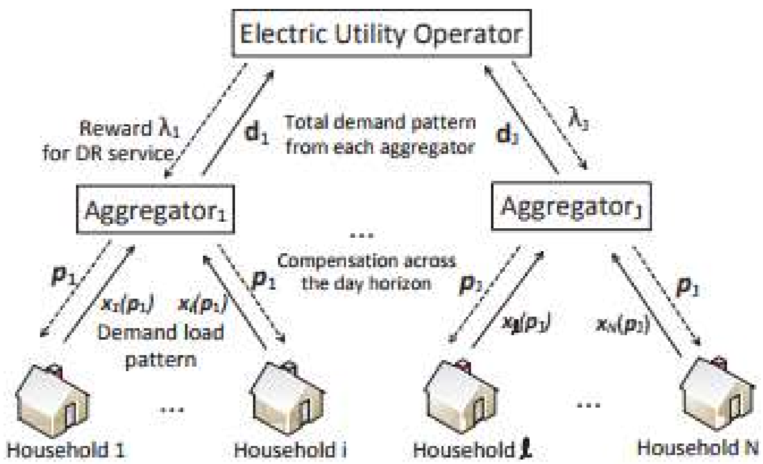

Figure 5. Hierarchical structure for incentive-based DR as proposed in [39]

The incentive-based DR programs that the aggregators could offer to their customers are formulated in references [31], [33]–[35], [37]–[39]. Figure 5 shows a hierarchical structure with aggregators as proposed in [39]. At the bottom level, the users modify their demand pattern according to the compensation broadcasted by their aggregators; at the intermediary level, the aggregators determine their compensation strategy in order to maximize their profit,

[2] Retailers are included in this concept, however only load is aggregated.

considering the incentives DSO can provide. Finally, in the upper level the operator computes the reward per unit of cost reduction for each aggregator so as to minimize its operational cost [39]. Employing incentive-based DR programs stimulates the consumption with the rewards offered to the customers for demand reduction [40]. References [31], [37] have considered the uncertain behavior of customers in designing the DR programs. The DR scheme is considered as an energy source of the aggregators. Ref. [31] develops a DR scheme, where the aggregator is not involved in the technical aspects of the DR program and procures various DR agreements from aggregators or large consumers. Ref. [38] proposes a coupon incentive-based DR program to induce flexibility in the retail customers on a voluntary basis. The program is designed for customers equipped with smart meters yet still paying a flat electricity rate. Ref. [36] introduces a particular business model for DR programs in electricity markets. A platform for DR exchange has been developed in the context of a pool-based market. In this model, the residential and industrial customers deal with multiple DR-involved players in the market. They submit the hourly DR capacity and price to the market to sell the DR as a public good. Electricity aggregators in liberalized retail markets, such as PJM and ERCOT, are widely employing diverse types of DR programs to increase their payoff in energy markets, capacity markets and ancillary service markets. Designing an appropriate DR scheme that guarantees their benefit in the market is an important issue for them.

The retailers are load aggregators or electricity suppliers that connect the end-users to the wholesale market. They are always at the risk of buying electricity at prices higher than their selling prices. Therefore, it is essential for them to manage contracts with the supply side in the pool market and with the demand side in the retail market to ensure expected returns [41]. They can implement a combination of approaches to manage the financial risks. Well-designed DR programs reduce the consumption during the periods with high electricity prices. It also makes the demand bids more price elastic during the periods with higher prices or the periods with a higher risk for the market power experience. Another possible solution is using the DG units and the ESSs owned by the aggregators during the price spikes. Instead of buying the whole electricity demand from the wholesale market, they can serve part of the loads with their light physical assets at the distribution network.

The aggregators determine the optimal bidding strategy for the day-ahead market in an uncertain environment. They make the optimal decisions based on uncertain and volatile locational marginal prices (LMP), uncertain supply offers and demand bids of other market agents and unpredictable energy consumption of their customers. In this situation, the stochastic programming is an appropriate tool for them to manage their financial risks.

The financial risk management strategies of aggregators for short-term markets, compared with the generation companies, have been less observed in recent research publications. In [42], the aggregators determine the optimal portfolio to balance between the benefit and risk in day-ahead and real-time market with or without the bilateral contracts with the supply side. The only way that the pure aggregators in this deterministic model employ the financial risks is by vertically integrating with the supply side. In [43] the aggregator respectively employs light physical assets and incentive-based DR programs to manage the financial risks and limit the potential for market power in day-ahead market. In [44], it has been demonstrated through numerical simulations that in the current market context, pure portfolios of contracts are incomplete risk management strategies compared to physical hedging.

In [45], the aggregators procure a portfolio of demand-side and supply-side resources to trade off the profit against risks in serving loads. Spot market purchases, forward contracts, and DR programs in the form of interruptible contracts are collected in the aggregator's portfolio. The demand-side management model introduced in [29] is designed to be employed by the aggregators. The proposed programs require continuous monitoring and control of electricity end-users over their consumption. These approaches theoretically promote the competition in the wholesale and the retail markets. However, in practice; the end-users do not show interest in plans that require their continuous awareness about the consumption.

Entities like system operators or market operators look to be the ideal candidates for implementing DR programs [46]. They run day-ahead markets, real-time markets and the electricity wholesale markets where the aggregators and generation companies participate to trade electricity. However, these entities are not usually well-equipped to deal with the individual end-users in most of the electricity markets. Therefore, the responsibility of implementing DR programs remains with the aggregator in the foreseeable future [46]. In [47], three schemes are proposed to foster economic DR in the Midwest ISO. In all these schemes, the aggregators in the form of load-serving entities (LSE) and curtailment service providers (CSP) play the main role. In [48], LSEs and CSPs submit DR bids to the market operator. The proposed model introduces an approach for the market/system operator to include the DR bids of electricity buyers in the wholesale market. It does not consider the relation between aggregators and the end-users. The distribution system and the end-users should develop further to enable the implementation of DR programs [49]. Advanced metering infrastructure networks that additionally provide the two-way communication between the distribution system operators, aggregators and the end-users via smart meters promote the implementation of DR programs by aggregators in order to guarantee their return in the volatile market [49].

2.3. Consumer contribution for effective demand response

Consumers are a crucial part involved in the demand response implementation. As stressed, a key component of SG optimization and DR application is HEMS. Over the last decade, domestic buildings by communications channels (that are commonly termed smart homes) are involved as active players [7] in electrical grids. These constitute the building blocks in smart grid, and have an important role in the optimization of electrical energy scheduling [50]. In this regard, HEM is necessary for achieving an economic improvement through automation technologies [51]. HEMS can be classified in centralized and decentralized models. The former involves an aggregator or retailer that is able to remotely control home energy devices (e.g., electric vehicle, storage system, heating devices, etc.) by establishing contractual conditions with the final user. In the decentralized models, the HEMS manages locally the energy devices of the home and may react to price signals or incentive schemes sent by the supplier. In what regards DR application, centralized models are believed to be more effective, because the decisions can take immediate action whereas in decentralized models rely on the expectation that the user may react the price signals or incentives [52]. However, decentralized models are less complex to implement than centralized ones.

Figure 6 represents a schematic of the smart household with decentralized HEMS [7]. The electricity retail company sends the price and incentive data to the HEMS on a daily basis and receives the consumption data in real-time from smart meters. The historical data and price data are also provided to the HEMS. The ON/OFF status, charging, cycling, or mode switching of the appliances are controlled and monitored wirelessly through the HEMS. Customers' preferences are a priority for HEMS, and the consumption scheduling should not deteriorate defined comfort levels. The built-in parameters of the appliances are stored in HEMS and the customer is allowed to update several settings of the HEMS before each scheduling.

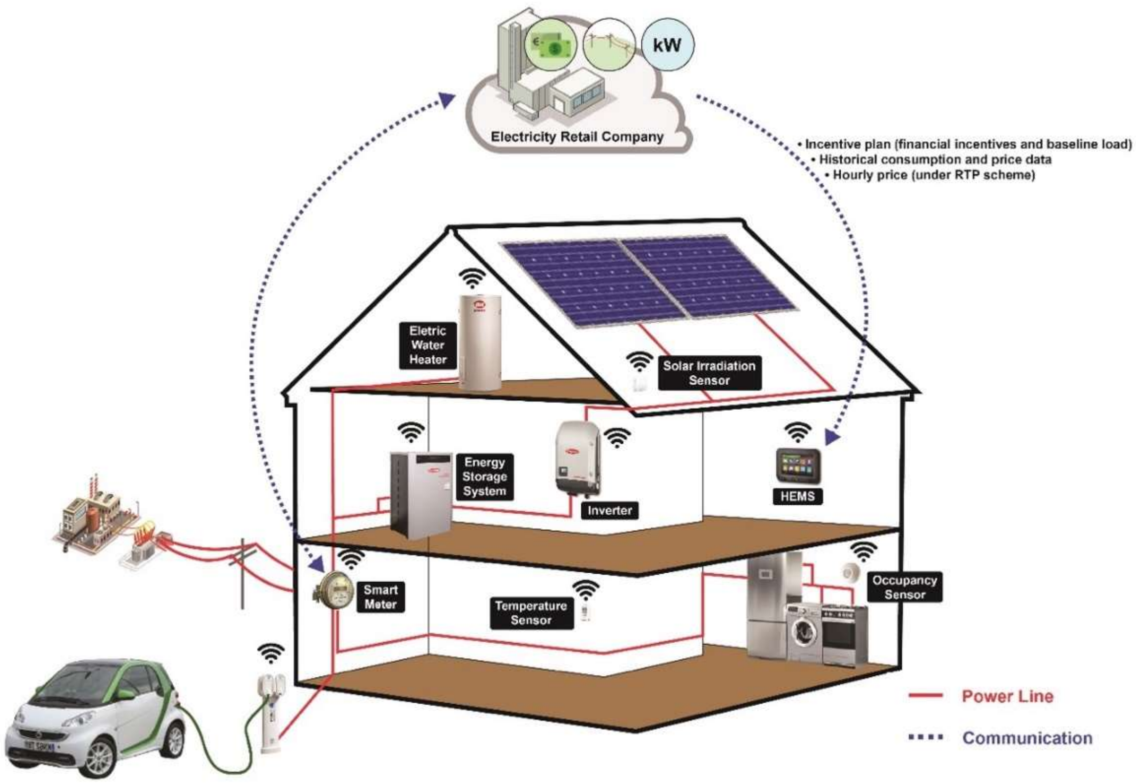

Figure 6. Decentralized representation of a smart household with HEMS [7].

There are different strategies to optimize the scheduling of home energy. Several approaches used different statistical models to improve HEM problems. In particular, [6] models the controllable loads and the loads that depend on weather conditions using a Markovian approach. In [53], demand response program following classical methods has been applied automatically to the controllers to use and control the appliances under uncertainty of outdoor temperature and electricity price. In [54], three HEM methods have been solved applying an observable Markovian decision process to reduce the domestic energy costs in the time-varying electricity price market. In [55], authors have discussed about the necessities of using computational intelligence in the HEMSs. In [56], each smart home has been considered as an autonomous agent that can buy, sell, and store electricity. Furthermore, uncertainty is modeled through generating the random data and functions in [56]. In [57], HEM has been defined as an intelligent Multi-Agent System (MAS). Also, JADE is used to implement the proposed model of [57]. In [58], a MAS has been demonstrated in the distribution network scale, while agents consist of home agents and retailer agents. In [58], the purpose of the authors was to minimize the payment cost of electricity. In [59], authors proposed a method to apply the local energy resources optimally through minimizing the loss of energy. The main purpose of [59] is to minimize the purchasing cost of electricity. In [60], HEM problem in connection with transactive energy nodes has been discussed. Moreover, co-simulation of smart homes and transactive energy market has been studied in [60].

HEMS optimization is not completed with the retailer and/or aggregators counterpart. Most of the models reported in the literature propose a single-objective problem to address the portfolio optimization problem of the profit-seeking retailers [38], [41], [61]–[63]. The retailers are usually defined as entities with no physical assets that sign the bilateral forward contracts with the generation companies to manage the financial risks in the market. Significant changes have been observed in the structure and the operation of the retailers that participate in the liberalized electricity markets. Some of them have vertically integrated with the generation companies or started to invest on generation and storage facilities. Furthermore, with the recent developments in the smart metering infrastructure and the home energy management systems, DR programs can be effectively implemented for the electricity end-users to manage the financial risks [64].

Electric vehicles are an important aspect of SG since they will constitute a significant portion the electric load demand. EVs contribution to DR can be valuable if adequate DR programs are in place. Currently, some aggregators are introducing a variety of schemes for the EVs based on special tariffs. However, it is fair to recognize that these schemes are based on discount rates and still very limited, not adequately adapted for the future smart grid. Specific DR programs have been developed in the literature, which include a few works executed by the DREAM-GO team. These programs include incentive-based programs – smart charging, V2G, trip shifting, trip reduced – and one optimal pricing DR model (price-based). Figure 7 represents a classification of the mentioned DR programs.

The smart charging and V2G approaches are effective types of DR resources use in the context of EV management [65]. The EV charging can be effectively controlled while reducing operation costs and network problems, while still maintaining the comfort of the users. The drawback of V2G and smart charging is the high complexity and high capital costs of the infrastructure. Nevertheless, aggregators may convince users to shift from uncontrolled charging to smart charging by financial incentives and convenience of charging, e.g., with smart charging, the user could benefit from discounted flat tariffs.

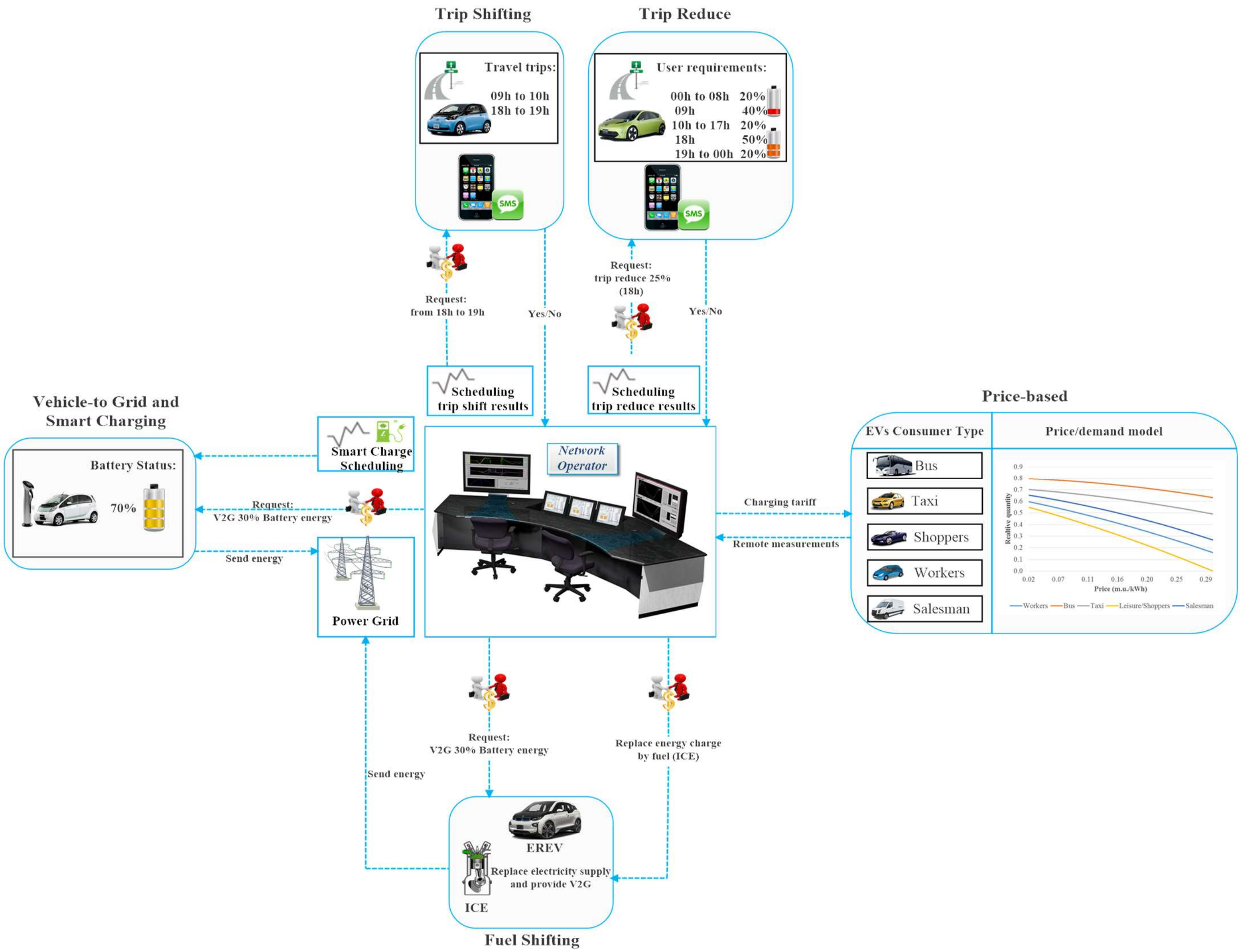

Figure 7. Representation of the specific DR programs for EVs.

3. Resources and components modelling

This section of the report presents smart grid resources and components used in optimization models developed by DREAM-GO team. Then, it leads to how uncertainty is modelled by the stochastic processes. Next, energy scheduling models are analyzed, namely those on the current literature and those developed by DREAM-GO, namely those that include modelling uncertainty of energy resources and components of the smart grid operation.

3.1. Resources and components

Several resources and components can be found in the smart grid operation context that are suitable for SG application models in the context of DR. Each of the resources has its intrinsic characteristics that need to be properly modelled. In fact, some parameters of these models are subject to random noise and uncertainty. For instance, the energy management problem involves several sources of uncertainty in the problem data, namely in the load demand, electric vehicles, wind and solar generation forecasts. Some inputs, outputs and parameters of the models are briefly described in this section, namely the DG (PV and wind), storage, electric water heater, electric vehicle and heat pump.

Figure 8 shows the typical input parameters that are used in PV models [66]. Such inputs are used directly in DREAM-GO PV models both in the optimization or simulation models. When performing studies on short-term horizon (like 24 hours), irradiance and temperature is difficult to know accurately in advance and therefore constitute sources of uncertainty. However, to simplify the optimization models, the AC power output of the PV panel can be modeled as an uncertainty variable with the associated forecast error if historical data is available, thus, skipping the need to firstly forecast irradiance, temperature and wind speed and to apply the estimated PV model.

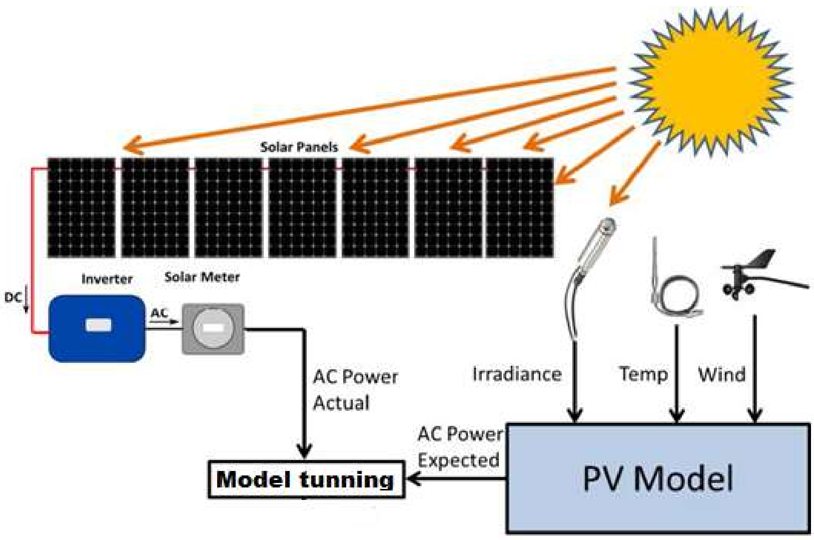

Figure 8. PV model parameters (adapted from [66]*)*

Different types of wind power generators have distinct power output curves and performance. Therefore, the models used to accurately describe the performance is also different. Figure 9 depicts an example of theoretical wind power output in function of steady wind speed [67]. This model can be described by a set of equations, namely 0 before the *Vc* or cut-in speed (where the wind turbine starts to generate some power), a linearized or nonlinear equation between *Vc* and *Vr*, where *U* is the wind speed, *A* is the frontal area, *C* is the coefficient of performance and *p* is the density of the air, and a constant value or decreasing linear equation between *Vr* and *Vco* (cut-out speed of the generator):

$$\begin{cases} 0, & 0 \le U \le Vc \\ P_{out} = \frac{1}{2} \cdot \rho \cdot U^3 \cdot A \cdot C, & Vc \le U \le Vr \\ Const, & Vr \le U \le Vco \\ 0, & U \ge Vco \end{cases} \tag{1}$$

DREAM-GO uses these models to approximate wind power wind generators in optimization models with DR and in static situations. Associated uncertainty lies in the wind speed parameter which is directly associated with forecast error. For dynamic models refer to section 3.4.

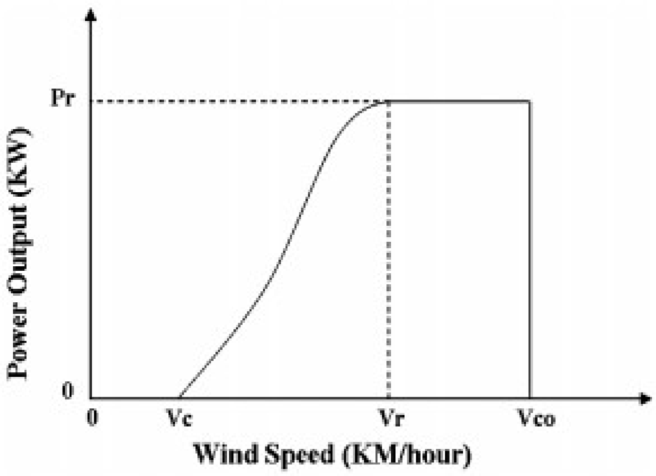

Figure 9. Wind power output in function of steady wind speed [67]

Figure 10 shows the block diagram of an Electric Water Heater (EWH) load [7]. The built-in parameters are shown in the gray box and the inputs are the parameters that require updates before each load scheduling. Hot water consumption profile and the desired temperature range of hot water are the most important inputs. An average hourly hot water consumption profile can be estimated for each household [68]. Hot water usage can be predicted by historical data that has been provided from the flow meter or the hourly electricity consumption of an EWH. Average hourly consumption refers to the mean volume of the hot water consumed during the specified time interval [69]. Several studies on hot water consumption have developed forecasting methods to forecast the individual hot water usage profile [70]. Forecasting hot water usage pattern is useful for demand-side management. The bounds on temperature reflect individual needs of the users. They are considered as operational constraints in the scheduling process [71]. Customers can provide more flexibility in scheduling by increasing the temperature range of the EWHs. This behavior can decrease their energy costs [71]. The set point temperature can be adjusted according to the hourly price changes [70]. Considering a wide range of the comfortable temperature provides more flexibility for the EWH for DR implementation [70].

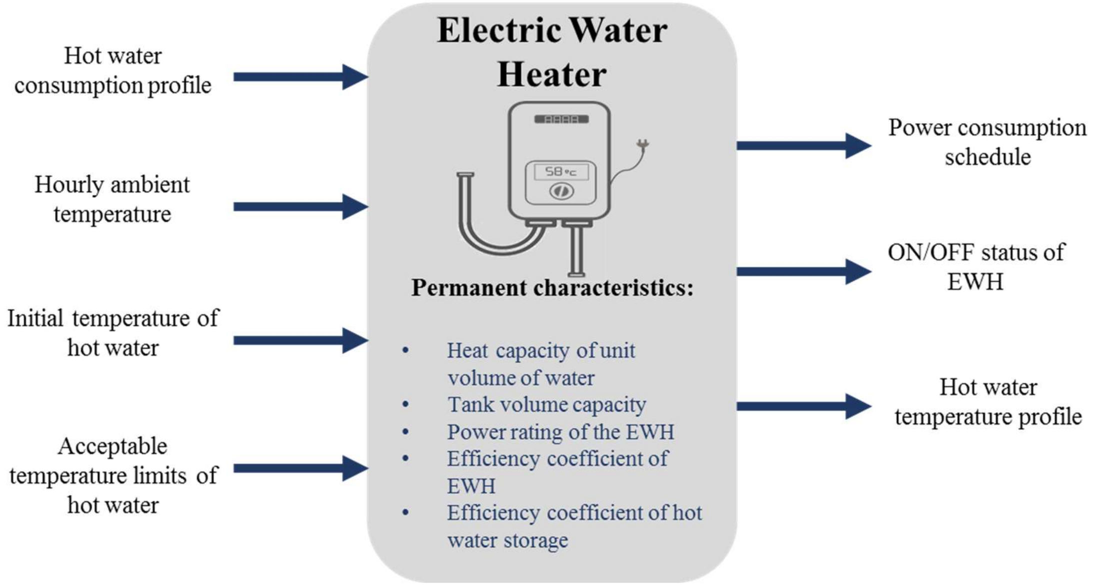

Figure 10. Electric water heater mode [7]

The presence of EVs poses an additional source of uncertainty in the smart grid operation because trips and energy demand of EVs depend on the users' behavior, which is not easy to predict. The aggregator requires knowing the timing of the trips and the associated expected energy consumption, as well other parameters, such as battery size. This means that the drivers would need to notify the aggregator of their planned trips in advance, or eventually, machine learning algorithms could be used to forecast driving needs [72]. Figure 11 shows an EV model that define the EV device as a component of the smart grid. There are some built-in parameters within these loads, which do not require updating before each consumption scheduling. They are permanent characteristics of the EVs. Other inputs should be updated before each scheduling. Some intelligent algorithms may be used to estimate these inputs, for instance, the initial level of battery stored energy can be estimated based on the historical data of the EV owner. The estimated inputs are sources of uncertainty that must be handled by the stochastic processes.

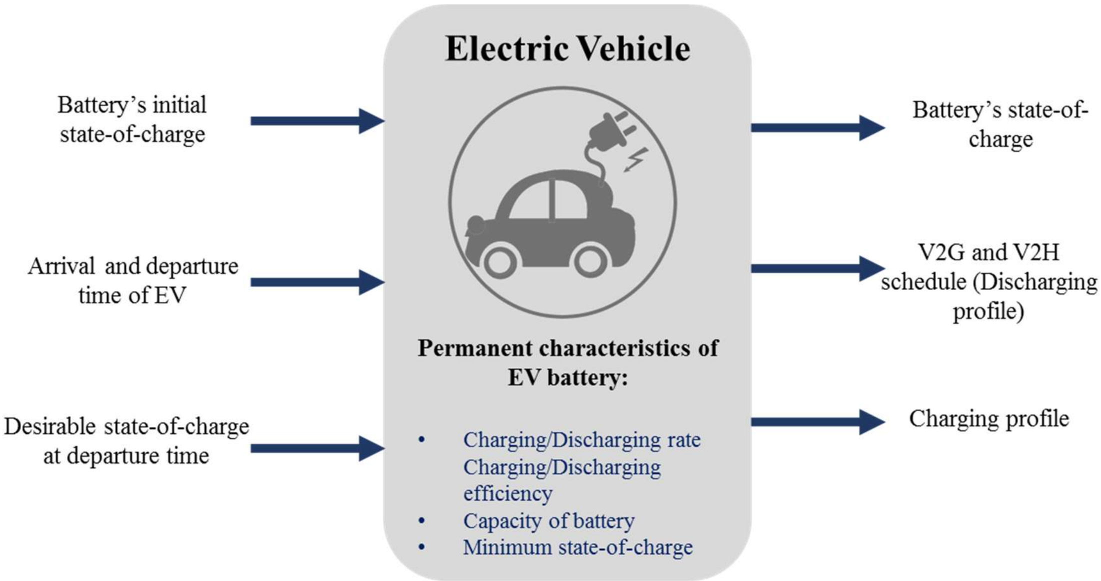

Figure 11. EV load model [7]

The flexibility of heating systems has been analyzed in several works [73]. It is observed that there is a large potential for the application of DR schemes on control of those devices. Figure

12 shows the inputs that require a daily update are shown on the left, the built-in or Heat Pump (HP) loads and the houses' characteristics are represented in the middle and the outputs are to the right. The permanent characteristics are input characteristics (which may be associated with uncertainty) are then used by models and algorithms to reach a decision (right part).

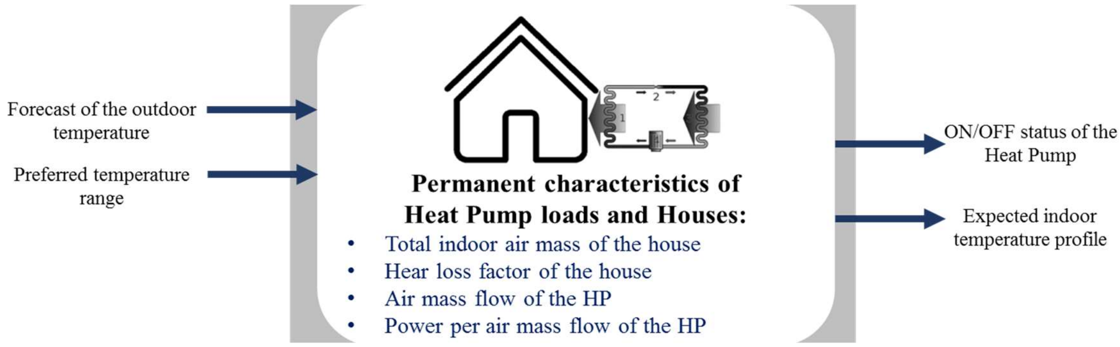

Figure 12. Heat pump load model

3.2. Uncertainty modelling

SG operation faces several sources of uncertainty during the operation of active distribution networks, namely the forecast errors of EV fleet characteristics, hourly load demands and the generation profile of the renewable sources. The uncertainties associated with the EV fleet characteristics is caused by the random driving pattern of the EV drivers and their uncertain behavior [74]. They are considered as potential uncertainties [74]. The uncertainties can be taken into account in scheduling problems and modeled as stochastic scenario-based optimization model.

In this form of problems, where a set of scenarios needs to be handled, the main issue is to generate a set of realizations for the random variable, i.e., uncertain variable. These scenarios should adequately represent the probabilistic characteristics of the data [43]. The initial set of scenarios is a large data set generated by the probabilistic sampling techniques. There are several techniques for sampling data based on known probabilistic distributions. The point estimate method, as a subcategory of probabilistic models, is a suitable tool for modeling of power system uncertainties [75]. Monte Carlo Simulation (MCS) technique can also be used for representing power system uncertainties. The MCS parameters are the probability distribution functions of the forecast errors [76].

In order to include the forecast error, an additional term which can be positive, or negative is added to the forecasted profile ($x^{forecasted}$):

$$x^{s}(t) = x^{forecasted}(t) + x^{error,s}(t), \qquad \forall t, \forall s. \tag{2}$$

The error term ($x^{error,s}$) is a zero-mean noise with standard deviation σ [43], [77]. Scenarios are represented with x^{s} The uncertainties of the forecast errors are modeled with the probability distribution functions, which are obtained from the historical data [43]. In this model, the forecast errors for the uncertain inputs are all represented by normal distribution functions.

The scenario tree concept can clearly illustrate how the discrete outcome for each stochastic input can be combined to construct the larger set of scenarios. A scenario tree consists nodes that represent the states of the random variable at particular time points, branches to show different realizations of the variable and the root which shows the beginning point where the first stage decisions are made [43]. Figure 13 shows the scenario tree model for the proposed scenario-based stochastic programming model [43]. X_n^S refers to the n^{th} random variable. Variables can have different natures. For instance, X_1^S may represent load demand and X_2^Scan denote market prices. The number of the nodes at the second stage is equal to the total number of scenarios. The occurrence probability of each scenario is equal to the product of the branches' probabilities [43].

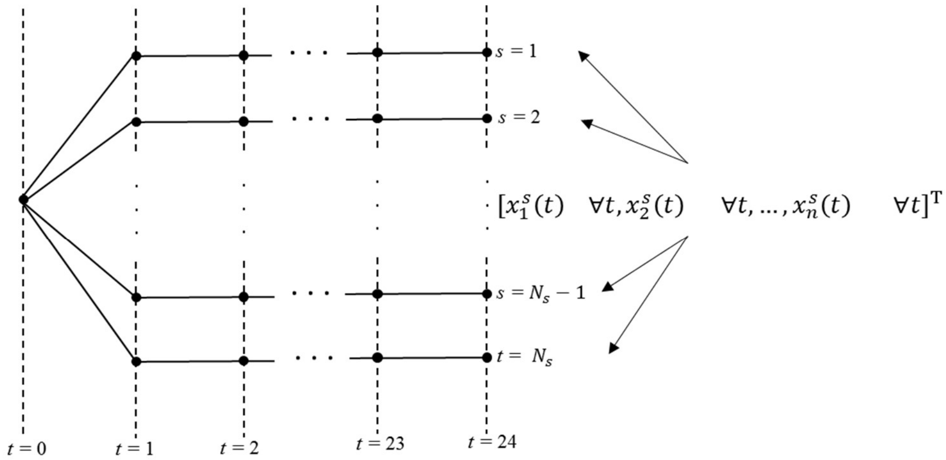

Figure 13. Scenario tree representation [78]

Including all the generated scenarios in the optimization problem results in a large-scale optimization problem [43]. Generally, there should be a tradeoff between model accuracy and computation speed [74], [79]. In order to handle the computational tractability of the problem, the standard scenario reduction techniques developed in [80] is used. These scenario reduction algorithms exclude the scenarios with low probabilities and combine those that are close to each other in terms of statistic metrics [80]. They determine a scenario subset of the prescribed cardinality and probability which is closest to the initial distribution in terms of a probability metric [76]. The main purpose of scenario reduction is to reduce the size of the problem. The number of variables and equations are reduced after applying these algorithms. Consequently, the solutions can be found more efficiently, without losing the main statistical characteristics of the initial dataset [81]. However, the potential cost of applying these approaches is introducing imprecision in the final solution [79]. The reduction algorithms proposed in [80] consists of algorithms with different computational performance and accuracy, namely fast backward method, fast backward/forward method and fast backward/backward method. The selection of the algorithms depends on the problem size and the expected solution accuracy [76], [80]. For instance, the best computational performance with the worst accuracy can be provided by the fast-backward method for large scenario trees. Furthermore, the forward method provides best accuracy and highest computational time. Thus, it is usually used where the size of the reduced subset is small [76].

3.3. Smart grid operation models considering uncertainty

Advanced simulation tools and energy scheduling models are a key part of the paradigm of smart grid operation. The literature has a vast collection of proposals. DREAM-GO team has selected a portion of the vast literature that is related to the project main goals (see Table 1). Some of the works consider DR for short and real-time. However, the majority of the proposals still lack the consideration of full component uncertainty and/or DR in the models. Table 1 summarizes the characteristics of the main works in terms of components/resources and in terms of uncertainty consideration, 13 not lead by DREAM-GO team and 8 including at least an author from the DREAM-GO partners. It is important to remark those recent works developed in the scope of DREAM-GO project have been published in major journals indexed in SCI. DREAM-GO' partners have made joint efforts to publish significant contributions to the literature in several fronts of SG operation research.

As seen by Table 1 very few works attempt to consider most source of uncertainties in a joint scheduling model, as e.g. the models developed by DREAM-GO team [78], [82]. Moreover, it is difficult to identify works that incorporate V2G, DG, DR and ESS simultaneously as in [78], [82], [83] [84] both led by the DREAM-GO team. From a total of the reported works in this table not lead by DREAM-GO only 3 works incorporated at least 3 components/resources, namely [85], [86] and [87]. In addition, only 4 works not lead by the DREAM-GO team incorporating DR and uncertainty at the same time are reported, namely [88], [85], [86] and [87]. The works reported by DREAM-GO team include DR, however not all the models consider uncertainty. In this case 5 works consider uncertainty. For example, the team proposes in [82] a two-stage stochastic model that addresses several sources of uncertainty, namely wind, photovoltaic (PV), EVs, demand and market price in a joint model (addressed as in 3.2). Jointly with Clemson University new model is proposed in [78], which adds network constraints, namely power lines capacity and voltage control to the original problem in [82]. The problem is solved using Benders decomposition scheme. The results of this work from DREAM-GO demonstrate that the very large-scale problem with uncertainty can be solved in its most complex form, dealing at the same time with the aggregator challenging number of resources and the DSO technical constraints as part of the equation. However, it is fair to recognize these models require large amounts of computational resources to be able to solve the stochastic model with an adequate number of scenarios (even if scenario reduction techniques are adopted). In fact, scenario reduction techniques decrease the accuracy of the uncertainty representation. Since smart grid operation is dealing with an increasing number of energy resources and consequently more components associated with uncertainty, it remains a major challenge to tackle these optimization models under uncertainty with adequate representation. A solution may lie in metaheuristics and decomposition techniques combined with uncertainty models and/or robust optimization models that deal with a range of uncertainty instead of probabilistic scenarios. A robust model proposed by DREAM-GO team is adopted in [89] which tackle market price and load demand uncertainty for aggregators that are new entrants to the market and have little knowledge have the behavior of the market and their customers. In [84], USAL proposes an energy resource management for domestic loads that considers uncertainty in the PV power for the day-ahead and real-time approach. The work considers EVs, DR as flexible loads and energy storage system units. Two different stochastic methods are compared and evaluated using a realistic case study.

Table 1 – Summary of energy scheduling models: resources and uncertainty sources

Ref.	Resources/components present in the work				Considered sources of uncertainty
	V2G	DG	DR	ESS	
[72]	No	Yes	No	No	Driving patterns and market bids
[90]	No	Yes	No	Yes	Only in wind and PV
[88]	No	Yes	Yes	No	Only in wind
[91]	No	Yes	No	No	Only in energy demand
[92]	No	Yes	No	Yes	Only in the fuel cell outages
[85]	No	Yes	Yes	Yes	Load, renewable generation and electricity price
[93]	Yes	Yes	No	Yes	Load, renewable generation, EV demand and price
[75]	No	Yes	No	No	Renewable generation, load and electricity price
[86]	No	Yes	Yes	Yes	Wind/PV, load demand and market price
[87]	No	Yes	Yes	Yes	Wind/PV only

Ref.	Resources/components present in the work				Considered sources of uncertainty
	V2G	DG	DR	ESS	
[94]	No	Yes	No	No	Wind, market bids and price rivals' offers
[95]	No	Yes	No	No	Wind and market price
[96]	No	Yes	No	Yes	Intermittent source and market price
[82]*	Yes	Yes	Yes	Yes	Wind. PV, EVs, load demand and market price
[7]*	No	No	Yes	Yes	-
[97]*	No	Yes	Yes	Yes	Wind, PV, EVs, load demand
[83]*	Yes	Yes	Yes	Yes	-
[2]*	No	Yes	Yes	No	-
[78]*	Yes	Yes	Yes	Yes	Wind/PV, EVs, load demand and market price
[89]*	No	Yes	Yes	No	Market price and load demand via robust model
[84]*	Yes	Yes	Yes	Yes	PV power

**Works developed in scope of DREAM-GO*

Table 2 classifies the works reported regarding its main purpose, namely technical, economic, and environmental aspects. It can be seen that most of the works related to uncertainty deal with economic aspects. Technical aspects are often common and related to power losses and voltage control (when network constraints are considered) such as in [72] and [93]. Some of the works consider environmental, reliability and building dynamics aspects such as in [92] and [85]. [78], [83] developed in DREAM-GO includes both technical and economic aspects. However, [83] does not incorporate the resources' uncertainty as formulated later by the DREAM-GO team in [78], despite not including environmental aspects as in [83].

Table 2 – Summary of energy scheduling models: technical and economic aspects

Ref.	Technical aspects			Economic aspects
	Power losses	Voltage control	Other[1]	
[90]	No	No	No	The goal of the aggregator is to minimize purchases in spot market.
[72]	Yes	Yes	No	Expected operational costs over the next 24 hours.
[88]	No	No	No	Minimum production costs with cost of DR reserves.
[91]	No	No	No	Maximize system utility.
[92]	No	No	Yes	Financial aspects (costs) but also environmental and reliability.
[85]	No	No	Yes	Maximize profits of microgrid considering building dynamics.
[93]	Yes	Yes	No	Expected operation costs over the next 24 hours.
[75]	No	No	No	Maximize expected profits over the next 24 hours.
[86]	No	No	No	Minimize expected costs.
[87]	No	No	No	Maximize operation revenue.

Ref.	Technical aspects			Economic aspects
	Power losses	Voltage control	Other[1]	
[94]	No	No	No	Maximize profit over the scheduling horizon.
[95]	No	No	No	Maximize utility function in day-ahead and real-time markets.
[96]	No	No	No	Maximize profit in the day-ahead and balancing market.
[82]*	No	No	No	Minimize expected operation costs.
[7]*	No	No	No	Minimize household energy costs under DR programs
[97]*	No	No	No	Maximize aggregator profit and EV user charging opportunity
[83]*	Yes	Yes	Yes	Maximize aggregator profit
[2]*	No	No	No	Minimize aggregator operation costs and suitable remuneration groups
[78]*	Yes	Yes	No	Minimize operation costs considering market transactions
[89]*	No	No	No	Maximize aggregator payoff considering price risk
[84]*	No	No	No	Maximize domestic energy profit

*[1] fault location, network restoration, island operation; *Works developed in scope of DREAM-GO*

Table 3 depicts a summary of SG optimization models concerning other important aspects related to the scope of DREAM-GO studies that the team finds important to analyze. Some important aspects not envisaged in previous tables but are briefly described. These models are used in SG context taking into account different purposes such as tackling environmental aspects, DG allocation, fault location, network restoration and island operation. [83] developed in DREAM-GO presents a multi-objective model that includes maximizing aggregator profits and minimizing CO_2 emissions.

Table 3 – Summary of other SG optimization models: identification of other aspects

Ref.	Other considered aspects						
	Environmental impact	DG allocation	DG capacity	Reliability	Fault location	Network restoration	Island operation
[92]	Yes	No	No	Yes	No	No	No
[85]	No	No	No	No	No	No	No
[97]*	Yes	No	No	No	No	No	No
[98]	No	Yes	Yes	Yes	No	No	No
[99]	Yes	Yes	Yes	No	No	No	No
[100]	No	Yes	Yes	No	No	No	No
[101]	No	No	No	Yes	No	No	No
[102]	No	Yes	Yes	No	No	No	No
[103]	Yes	Yes	Yes	No	No	No	No

Ref.	Other considered aspects						
	Environmental impact	DG allocation	DG capacity	Reliability	Fault location	Network restoration	Island operation
[104]	No	Yes	Yes	No	No	No	Yes
[105]	No	No	No	Yes	No	No	No
[106]	No	Yes	Yes	No	No	No	No
[107]	No	No	No	No	Yes	No	Yes
[108]	No	No	No	No	Yes	No	No
[109]	No	No	No	No	No	Yes	No
[110]	No	No	No	No	No	Yes	No

**Works developed in scope of DREAM-GO*

3.4. Advanced smart grid resources and component models

This part focuses on several real implemented models of consumption and generation resources in a SG. All represented models are emulated by several laboratorial and commercial components, which are controlled and managed by a real-time digital simulator machine called OP5600 (www.opal-rt.com). Therefore, in this section at first, the details on OPAL-RT simulator will be presented, then, the real hardware components used for consumption and generation resources modeling in a SG will be demonstrated, and finally, performance results of the system will be illustrated.

3.4.1. Real-Time simulator

The real-time simulator machine (OP5600) is referred to a real-time digital simulator that is a powerful tool for rapid control prototyping and Hardware-In-the-Loop (HIL) applications. In fact, OP5600 is based on MATLAB/Simulink, somehow it enables the users to execute Simulink models in real-time. Additionally, the OP5600 is equipped with several Digital and Analog Input Output boards that are designed for HIL methodologies. In other words, by using these boards of OP5600, real hardware equipment can be controlled and managed via Simulink models, and also real data outside of simulation environments can be monitored in Simulink models. Figure 14 illustrates that how a real hardware equipment can be controlled and monitored by the OP5600 and Simulink model.

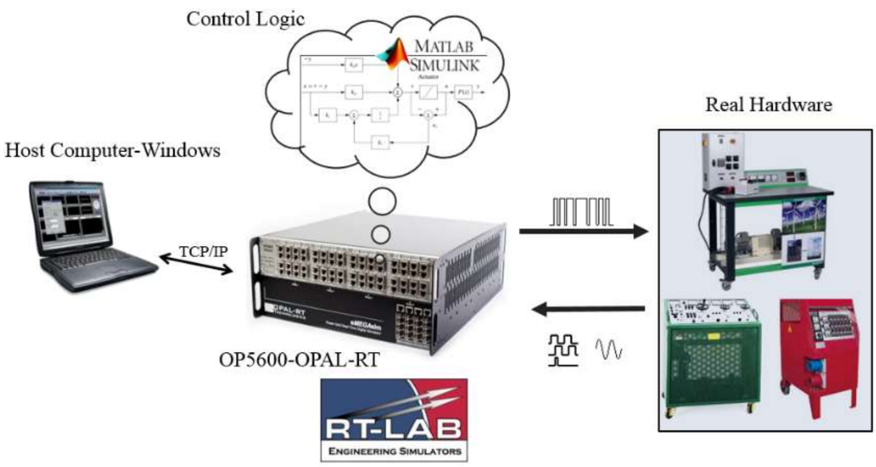

Figure 14. Real-Time simulator (OP5600) controlling process.

Generally, Simulink models embedded in OP5600 is developed in two subsections of computation and console subsections. The computation subsection contains of all computational elements and mathematical operations that will be executed in real-time on the OP5600. The console subsection includes all user interface blocks such as scopes, displays, constants, switches and other controller blocks used in a Simulink model. As Figure 14 shows, the console subsection is displayed on a host computer and allows interaction with the computation subsection executed on OP5600 via TCP/IP communication protocol. Therefore, by this way, the users would be able to remotely control and monitor real hardware equipment using a MATLAB/Simulink model. Figure 15 represents the implemented consumption and generation resources modeling for a SG by using OP5600 as a main controller unit. This resource modeling is an improved version of the work presented in [111] and only the related information and the updated parts have been mentioned here, and more details are available on those references.

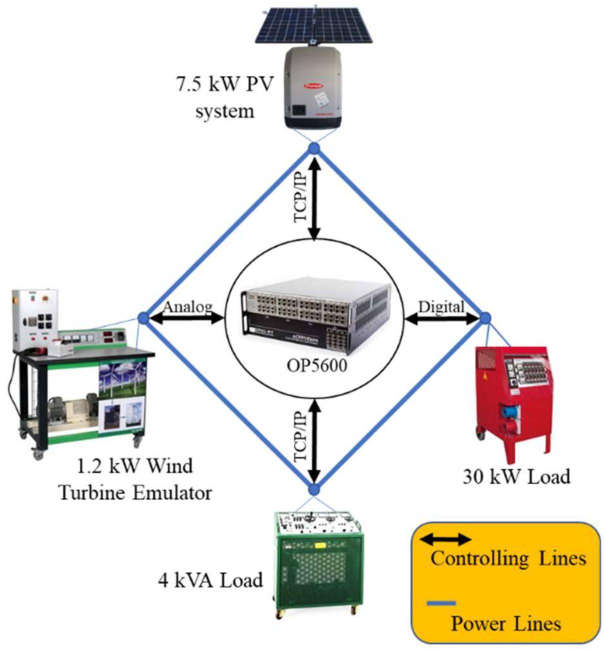

Figure 15. Resource modeling for a SG in OP5600.

In this model, 4 kVA and 30 kW loads are the two resources for modeling consumption profiles of small and medium consumer in a SG, and 7.5 kW PV array and 1.2 kW wind turbine emulator models the Distributed Renewable Energy Resources (DRERs) in a SG.

3.4.2. Consumption and Generation Resources Modeling

In this section the integration of implemented hardware resources in the OP5600 is presented. At first, we will focus on the consumption resource modeling, and then, DRERs resource modeling will be presented.

Small Consumer Resource

Small consumer is a three-phases 4 kVA variable load (shown on Figure 15), which enables the system to simulate the consumption profile of a small-scale consumer, such as a residential house, in a SG. This load, by default, was a manually controlled device somehow the operator should manually control a resistive gauge for increasing or decreasing the consumption. However, for integrating this load in the OP5600, an automatization idea has been implemented in order to be controlled and monitored by a Simulink model. Figure 16 demonstrates the implemented automation equipment on the 4 kVA load in order to be controlled and monitored by OP5600.

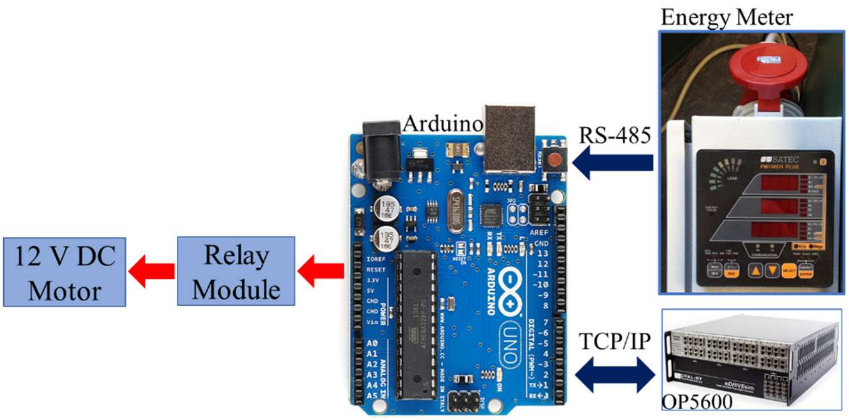

Figure 16. Implemented components on 4 kVA load for automatization.

As you can see in Figure 16, an Arduino (www.arduino.cc) equipped with an Ethernet shield enables is responsible to control the consumption of 4kVA load. In this way, Ethernet shield of Arduino enables the 4 kVA load to receive the desired power rate that sent from the OP5600 via TCP/IP protocol. Simultaneously, the real-time energy consumption of the load is measured by an energy meter installed on the load. Therefore, Arduino requests the measured data from the energy meter through Modbus RTU-RS485 protocol, and compare it with the desired power rate transmitted by OP5600. If the real-time consumption is smaller than the desired power rate, Arduino activate a 12V DC motor in clockwise direction, and therefore, it increases the consumption of 4 kVA load until the desired power rate. If the real-time consumption of 4 kVA load is greater than the desired power rate, Arduino activates the 12V DC motor in counterclockwise direction, therefore, the consumption will be decreased. By this way, OP5600 not only would be able to control the consumption of 4 kVA load, but also it will be informed from the real-time consumption data of this resource.

The developed MATLAB/Simulink model developed for the 4 kVA load and embedded on OP5600 is shown on Figure 17.

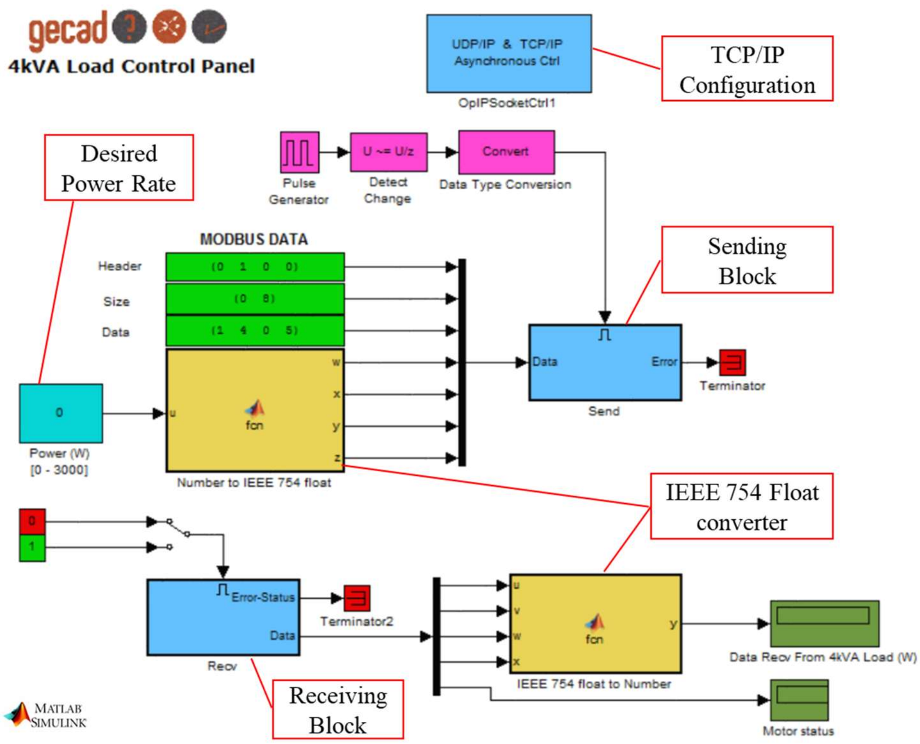

Figure 17. MATLAB/Simulink model for controlling and monitoring 4 kVA load.

As Figure 17 shows, the TCP/IP configuration of the model has been configured first. Then, the desired power rate is set via a Constant block and is given to a MATLAB Function Block, which convert it to IEEE 754 standard. In the same time, the received data from 4 kVA load (real-time consumption), will be considered as an input of another MATLAB Function block, which converts the data from IEEE 754 to a normal decimal number.

Medium Consumer Resource

The medium consumer unit is related to a 30 kW resistive load (shown on Figure 15), which enables the system to model medium consumers of a SG, such as commercial or office buildings. This load has several switches in front, which enables the user to control its consumption through these switches. However, for controlling this load by OP5600, four relays have been installed. In fact, the relays were substituted with the manual switch, and they were connected to the digital output board of OP5600. Figure 18 shows the installed equipment on the 30 kW load, and Figure 19 illustrates the MATLAB/Simulink model for controlling this resource by OP5600.

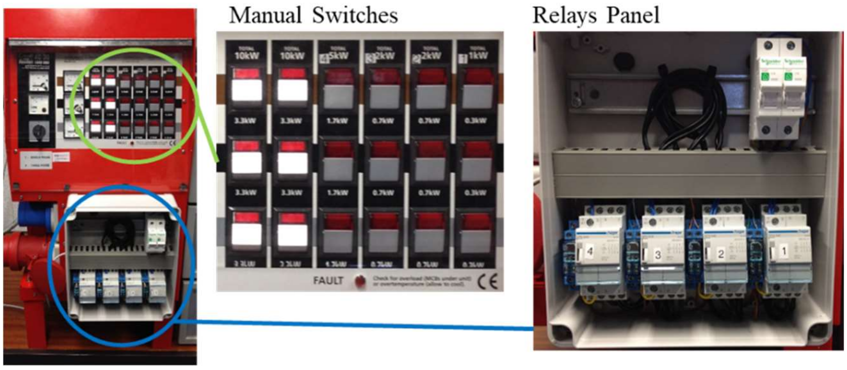

Figure 18. Implemented automation components for medium consumer resource modeling.

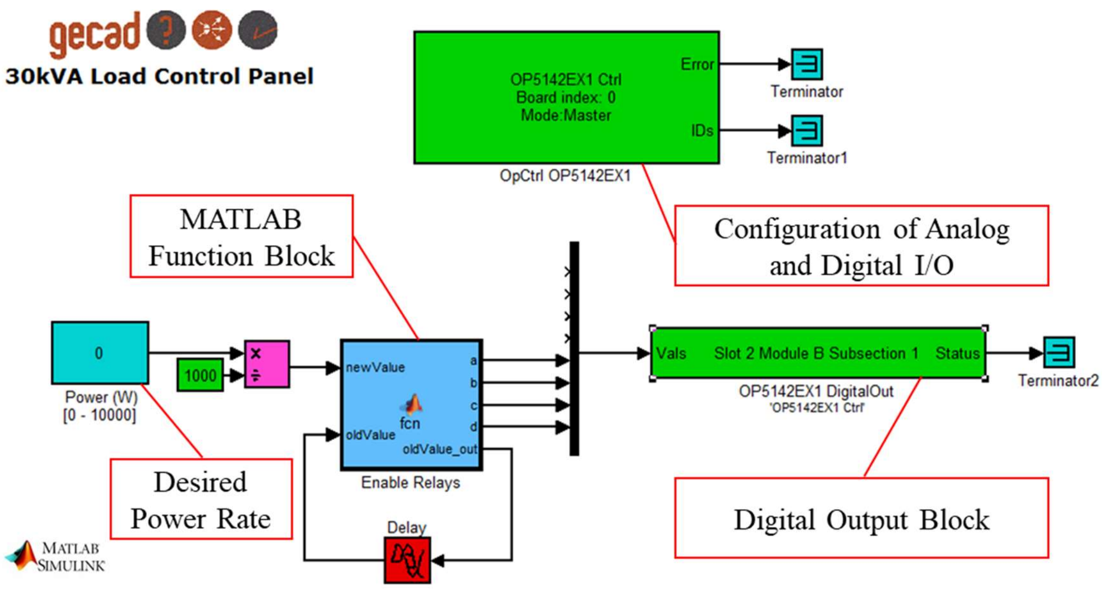

Figure 19. MATLAB/Simulink model for controlling 30 kW load by OP5600.

Based on Figure 19, at first, the desired power rate that OP600 tends to be consumed by 30 kW load is defined as a constant in the model. Secondly, this power rate converts from watt to kilowatt and enters as an input to a MATLAB function block. The outputs of this block are connected to the last four channels of the digital output board. The MATLAB function block activates the appropriate relay on the 30 kW load by regarding to the desired power rate that defined as a constant in the developed Simulink model.

Wind Turbine Modeling

In order to model a wind generator in a SG, a 1.2 kW wind turbine emulator (shown on Figure 15) is a facility that allows the user to have wind turbine modeling. In this emulator, an inductive three-phase generator has been coupled with a three-phase asynchronous motor with variable speed. This motor simulates the blades of the wind turbine. By this way, the operator can simulate the wind speed by controlling the speed of the motor.

For controlling this resource, one analog output channel of OP5600 was applied. This output channel has the output range of 0 to 10 V with the resolution of 0.01 V. Therefore, the wind speed variation should be converted to the voltage range of the analog output board in OP5600. The computations of this conversion have been done in Simulink environment. Figure 20 demonstrates the controlling process of this unit.

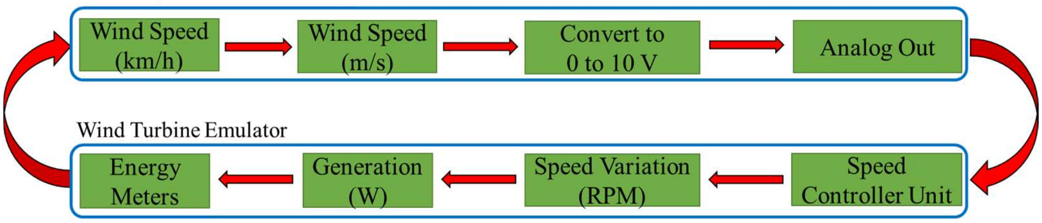

Figure 20. Controlling process of wind turbine emulator by OP5600.

In the first step of this controlling method, wind speed data should be converted from km/h to m/s. In the second step, the wind speed in m/s should be converted to a reasonable value for the analog output range, which is 0 to 10 V. By this method, the amount of the voltage that analog output should present to the speed controller unit were achieved. In this system, if the wind speed is less than 2.3 m/s and more than 20.3 m/s, the wind turbine will be stopped due to economic and safety reasons. In the next step, the generated power is measured by the energy meters mounted on this unit, and in the final step, the measured data are transmitted to OP5600. All of these computational steps have been implemented in MATLAB/Simulink environment as Figure 21 shows.

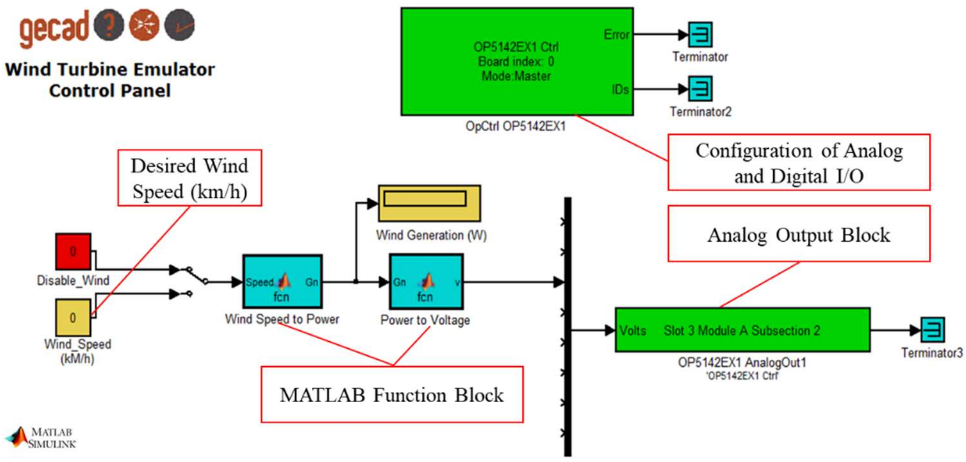

Figure 21. MATLAB/Simulink model for controlling and monitoring wind turbine emulator by OP5600.

Two MATLAB function blocks have been placed on this model for converting the wind speed data to a reasonable value for the analog output board of OP5600. These two blocks are “Wind Speed to Power” and “Power to Voltage” blocks. In the first block, the proportion between the generated energy and the wind speed data has been modeled. In "Power to Voltage" block, the results of an experimental test have been applied. In this test, the amount of the voltage that OP5600 should provide to the analog input terminal of the speed controller unit in order to increase the produced power for 50 W, was acquired. Therefore, by this controlling method, it would be possible to insert the wind speed values as an input and acquires the amounts of generated power of the wind turbine.

PV Modeling

In fact, the model presented for PV (shown on Figure 15) is real implemented PV system in GECAD Research center building, located in Porto, Portugal. The installed PV system is equipped with a grid-connected inverter, and has maximum generation capacity of 7.5 kW.

In order to have a complete generation modeling in OP5600, MATLAB/Simulink model shown on Figure 22 has been developed in order to request the real-time generation data from PV inverter.

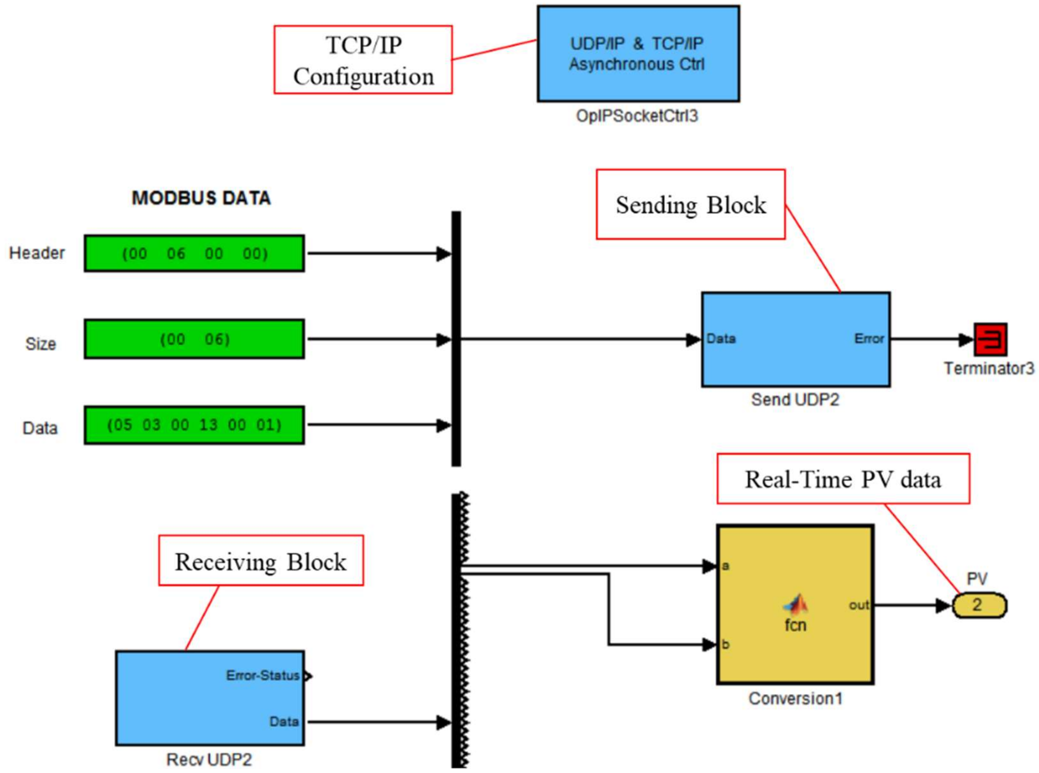

Figure 22. MATLAB/Simulink model for PV system.

As you can see in Figure 22, TCP/IP parameters have been configured first, and then MODBUS request data will be transmitted to the PV inverter by "Sending Block". After that, the responses of the PV inverter, which is real-time PV generation data, will be received by "Receiving Block" of the Simulink model.

3.4.3. Performance Results

In this section, the proposed resources modeling will be executed during a short period in order to validate and evaluate the system performance. The main focus of this section is given to the moments that OP5600 transmits a desired power rate to the consumer models or to the wind turbine model. The PV system is not in the scope of this section, since the OP5600 have no control on that.

Therefore, in order to evaluate the system performance for consumer models, we run the MATLAB/Simulink model of consumers by OP5600 for a period of 600 seconds. The results of this simulation period are shown on Figure 23. These results are real-time data acquired in MATLAB/Simulink environment.

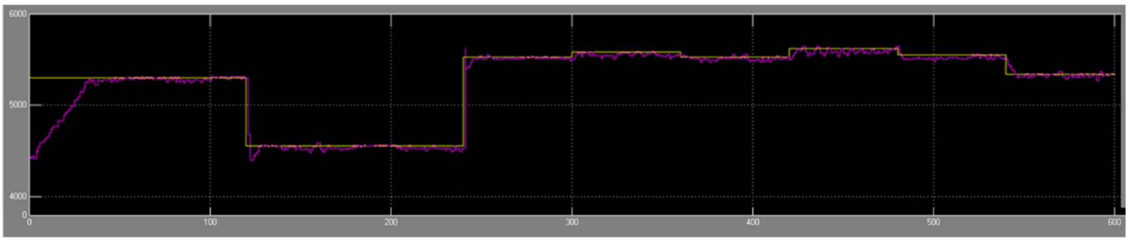

Figure 23. Simulation results of consumers modeling by OP5600.

In Figure 23, the desired power rate that OP5600 transmitted to the consumer resources (4kVA and 30 kW loads) are illustrated by yellow color, and the real-time consumption profile of 4 kVA and 30 kW loads are illustrated by purple color. In this simulation, 12 V DC motor of 4 kVA load attempts to reach to the desired power rates and according to voltage variations of the utility grid, it tries to be static and equal to the desired power rates, which leads to send back various values to the target. These variations are more sensible on high power rates. Also, it is visible on Figure 23 that when OP6500 transmits the desired power rates, the both loads need some times to reach the desired value.

Moreover, for testing the performance of the wind turbine emulator, we run the MATLAB/Simulink model of wind turbine by OP5600 for a period of 120 seconds. The results of this simulation period are shown on Figure 24 . These results are real generation data acquired in real-time by MATLAB/Simulink.

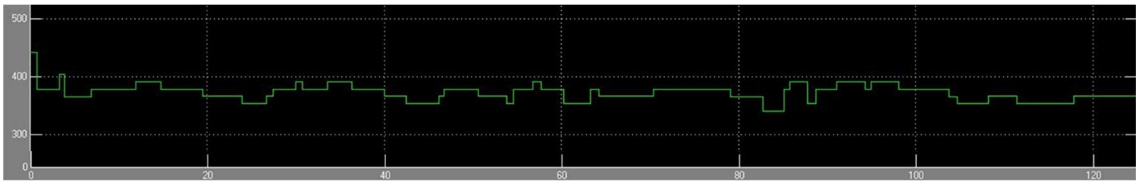

Figure 24. Simulation results of wind turbine modeling by OP5600.

In this model, we insert 25 km/h as wind speed and input for the Simulink model, and as you can see in Figure 24, the real-time generation data regarding the wind turbine emulator is between 350 to 450 W, which is based on voltage variations of the utility grid. This amount of generation is the power that the wind turbine emulator actually injected to the utility grid.

4. Optimization algorithms for smart grid operation

This section presents optimization algorithms that are being studied and adopted to solve the short-term and real-time DR problem in DREAM-GO project. The optimization algorithms include non-exact and exact methods, namely metaheuristics and mathematical optimization, respectively. Later, this section presents some works that have been classified according to the optimization algorithm used, objective function (e.g., if multi-objective or single-objective) and the DR program.

4.1. Meta-Heuristics approaches

The goal of combinatorial optimization is to find a finite mathematical object that maximizes or minimizes a specified objective function for the problem domain. The set of possible solutions for a single problem is called the search space. Development in the field of combinatorial optimization seeks the development of efficient techniques to find maximum and minimum values of a function with a high set of independent variables [112]. This function, usually called cost function or objective function, represents a quantitative measure of the "quality" of a certain complex system. The cost function depends on the exact detail level of the system.

All methods known to determine the optimum solution to a wide variety of problems require a computational effort that grows exponentially, so that in practice the exact solution can only be carried out with a reduced number of parameters.

Since this kind of NP-hard or NP-complete problems produce a variety of situations of practical interest, heuristic and metaheuristic methods have been developed to reduce the problem to N. Heuristics are, in many occasions, specific to the problem so there is no guarantee for the heuristic process to obtain a quasi-optimal solution for an NP-hard problem.

The main strategy of the heuristic method is based on the key concept of "divide and conquer" and an iterative improvement. First, it is important to divide the problem into smaller problems of manageable size and then solve each one of them. Solutions of the sub-problems must be re-pooled. For this method to produce acceptable results, the division into sub-problems must be disjoint and appropriate, so that the errors made in the fusion of the solutions do not question the benefits obtained in the application of methods more appropriate to the subproblems.

This set of techniques, despite not assuring the resolution of the problem in an optimal way, include a set of heuristics and metaheuristics that reduce the search space in favor of reducing the computing time necessary to solve the problem that is usually of NP-hard type.

The inherent prosumers' behavior uncertainty, combined with the dynamic conditions of a partially centralized system, has led to the conclusion that the most effective way of tackling some SG problem might be using meta-heuristics. Counter to exhaustive optimization methods, meta-heuristics allow finding reliable sub-optimal solutions in reasonable times. Figure 25 presents some popular heuristics and a wide classification of them. Then, Table 4 summarizes the advantage and disadvantages of some of the heuristics that have been used in SG related problems [114].

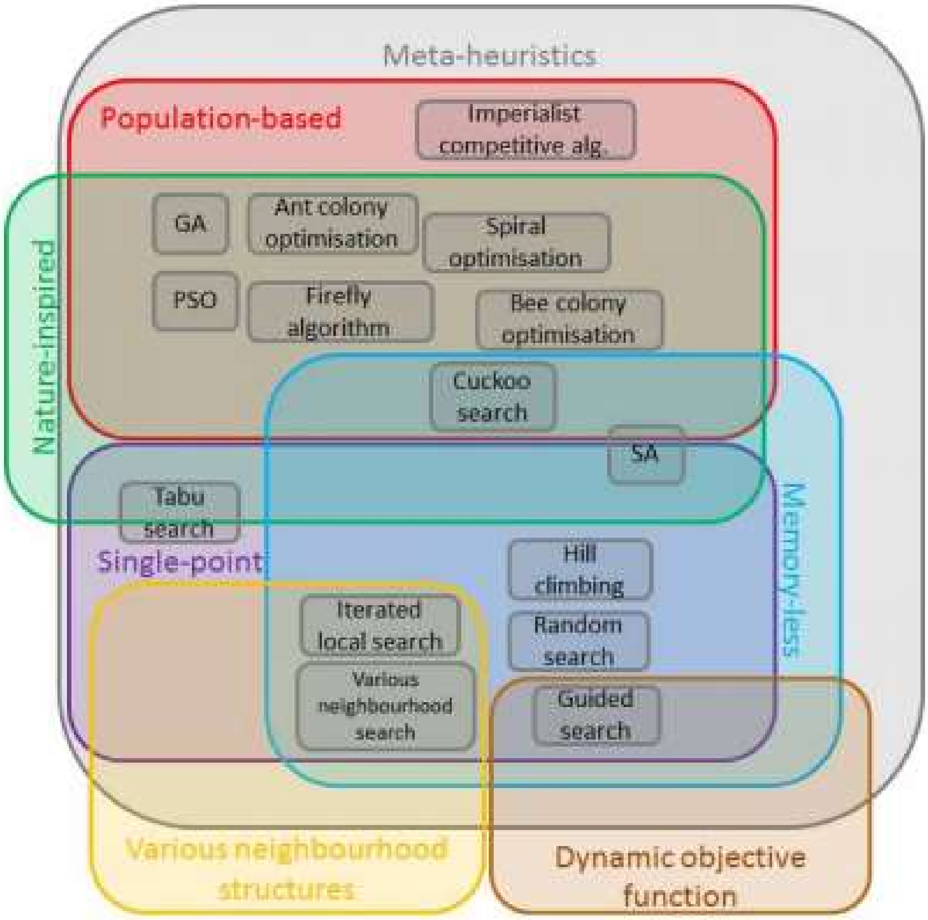

Figure 25. Most popular metaheuristics [113]

Table 4 – Used metaheuristics in SG operation: main characteristics

Method	Population	Advantages	Disadvantages
Genetic Algorithm	Yes	Capable of solving problems with multiple solutions, easily comprehended and assimilated into existing model frameworks, as well as readily implemented via MATLAB toolbox interface; Low development complexity, tolerant with objective functions with chaotic attributes, and suited for topological and categorical variable optimization.	Prone to prematurely convergence to local optimal and divergence, and inconsistent response time due to random implementation; More limited convergence speed than other stochastic methods, and complex approach of termination criterion determination.
Differential Evolution	Yes	Few control parameters; Easy implementation; Very robust for real-value problems; Flexible for hybridization.	Tend to converge to local optimality; the parameters have a huge impact in the quality of solutions.
Particle Swarm Optimization	Yes	Fast implementation, rapid completion, low cost, high adaptability, and flexible for hybridization with other algorithms due to computational simplicity.	Could not solve problems without coordinates system, and tend to converge to local optimality; Lack of solution diversification at convergent state.

Ant Colony	Yes	Compatible for concurrently solving multiple problems, simple in architecture, and superior in searching for local and global optimal solutions.	Probabilistic nature of search algorithm associated with density of deposited pheromone, which could be prone to certain solution.
Estimation of Distribution Algorithm	Yes	Provide an optimization practitioner with a series of probabilistic models that reveal a lot of information about the problem being solved; Almost no parameter tuning is required.	The estimation of the joint density function is a tedious task; There are different categories depending on the degree of dependency that they take into account.
Simulated annealing	Yes/No	Compatible with solving highly non-linear, complex, large-scale and highly constrained models, with highly fluctuating and stochastic data set.	Difficult balance between solution precision and response time, and over-precision in parameter fine-tuning with significant impact on solution precision and fitness.
Tabu Search	No	Enhances the performance of local search by relaxing its basic rule, namely by introducing *prohibitions* (henceforth the term *tabu*) to discourage the search from coming back to previously-visited solutions or solutions without no improvement.	It can get stuck in local optimally if the size of the memory is not properly chosen. The stochastic search does not guarantee optimal solutions.
GRASP	No	It is applicable to combinatorial optimization. Easy to implement.	The initialization and construction phase affect the convergence of the algorithm. The greedy function should be designed according the problem and sometimes is difficult to device.
Variable neighborhood search	No	Can solve discrete and continuous optimization problems. Avoid the stagnation of local search methods. VNS and its extensions are simple and require few, and sometimes no parameters.	Requires incorporating user knowledge to improve the resolution process.

4.1.1. Robust optimization in Particle Swarm Optimization

The particle swarm algorithm has attracted the interest of researchers around the globe and has undergone many changes since its introduction in 1995 [115]. The initial ideas on particle swarms of Kennedy (a social psychologist) and Eberhart (an electrical engineer) were essentially aimed at producing computational intelligence by exploiting simple analogs of social interaction, rather than purely individual cognitive abilities. The particle swarm is a population-based stochastic algorithm for optimization which is based on social-psychological principles like flocks of birds or schools of fish. In PSO a number of particles is placed in the search space and each particle evaluates the objective function at its current location. Each particle keeps track of the coordinates associated with the best solution found it so far. This value is named "personal best" (pbest). The particle also has access to information on the best solution found in their vicinity called "global best" (gbest). The basic idea of PSO is to accelerate every particle in the direction for the local of pbest and gbest. The value of acceleration varies randomly during the research. While searching each particle uses the information from her best position in the past and the current best position among its neighbors. The movement is determined from the combination linear vectors with different weights.

Figure 26 shows the flowchart of PSO for robust optimization proposed by DREAM-GO team to handle the uncertainty of energy resources in SG. It is important to note that the main factor of innovation presented in this model focuses on the consideration of the uncertainties regarding production from photovoltaic panels and wind turbines. This algorithm is based on robust optimization approach that focuses on finding robust solutions that represent the worst-case scenario. After being performed the typical steps of PSO, for each particle the variables with uncertainty are disturbed by a set of scenarios generated by Monte Carlo Simulation (MCS).

For each particle, the variables with uncertainty (wind and photovoltaic), which in this case could correspond to the production forecast values, are disturbed by a prediction error value, creating several different scenarios for the PV and wind production. These scenarios are generated by using the MCS method, following a normal distribution and assuming the underlying forecast error [90]. Each perturbated solution is evaluated in the objective function and the solution that represent the worst case is chosen. This process is made for each particle of the initial population and the cycle will be repeated until a set number of iterations.

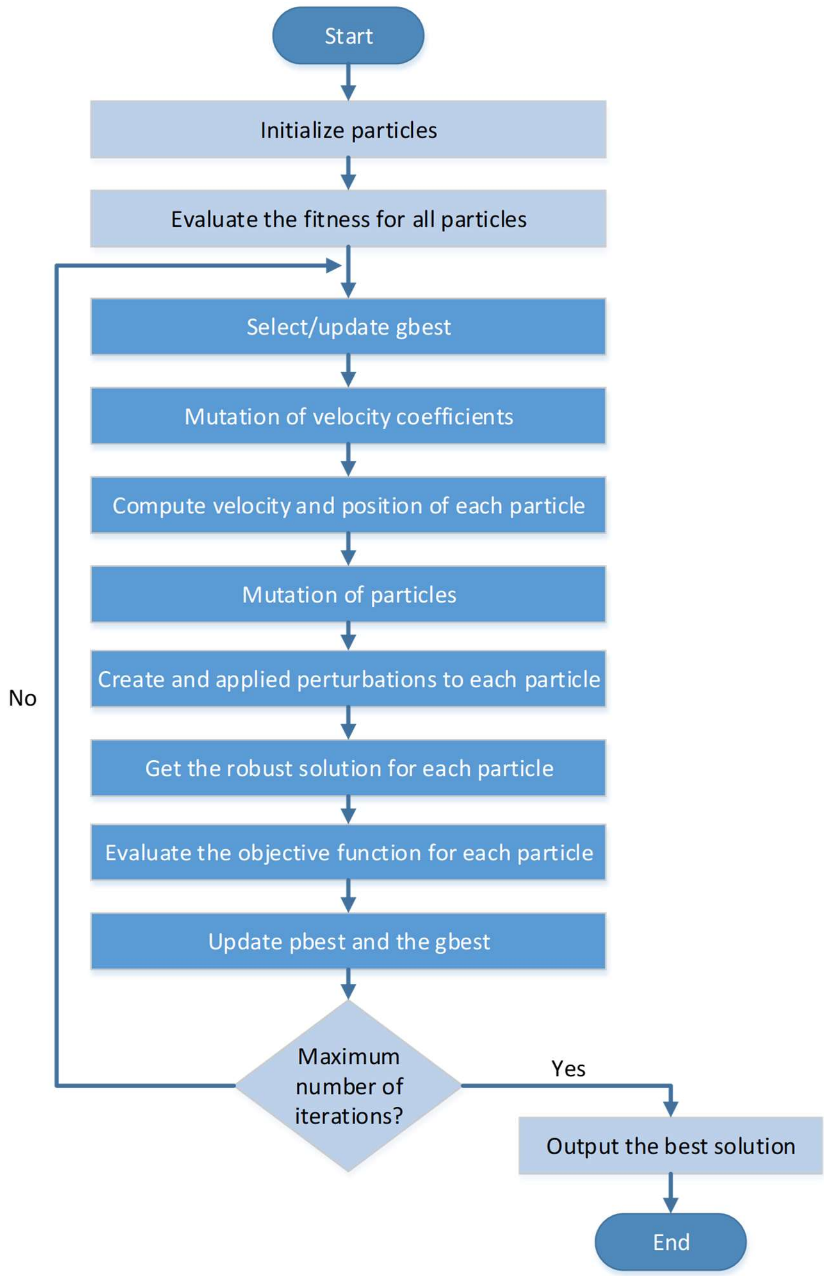

Figure 26. Flowchart of the PSO for robust optimization

4.2. Mathematical approaches

This section presents the main mathematical optimization models used to solve the short-term and real-time DR problem in DREAM-GO project. The stochastic programming approach used to tackle optimization problems with uncertainty (which is the case, for instance, of SG problems considering the uncertainty of renewables) and a specific decomposition method, namely Benders' decomposition, are presented respectively.

4.2.1. Stochastic programming

In mathematical optimization, stochastic programming is used to model optimization problems that involve uncertainty. Deterministic models are used when all the parameters of the problem are known in advance (minimize the material used in a package for a given object). Unfortunately, in many real-world problems, there are usually unknown parameters. If the parameters are known only within certain bounds and the probability distribution is not known, then robust optimization can be used. Stochastic programming takes advantage of the probability distribution, therefore, unknown data can be estimated. The aim is to maximize or minimize the decision-maker's goal and satisfy most of the problem instances (scenarios). The stochastic models usually can be converted to Mixed Integer Linear Programming (MILP) and solved analytically as linear problems. A two-stage stochastic model comprehends two stages, a first stage decision that is affected by random realizations and a second stage that mitigates the bad effects that may be experienced by the first-stage decision.

To measure the advantage of using stochastic programming, some metrics are implemented. The Expected value of Perfect Information (EVPI) represents the quantity that the decision maker would need to pay to obtain perfect information about the future. The Value of Stochastic Solution (VSS) represents the advantage of using stochastic programming over a deterministic one [116].

4.2.2. Benders' decomposition

Decomposition techniques are applied to problems in which it is possible to identify complicating binary variables. Nowadays, the decomposition techniques are frequently used in order to solve several problems with complex characteristics, namely in the fields of power systems, planning, network design, transportation, and military applications, to name a few [117]–[119]. An example of decomposition technique is Benders decomposition, proposed in 1962 [120]. This method is adequate to solve MINLP problems, as well as large-scale problems with binary variables. The problem is usually divided into a master problem and one or more slave problems. The master problem is generally an integer or mixed integer problem while the sub-problems are linear or nonlinear. The master problem includes fewer technical constraints while the slave problem checks if the solution of the master satisfies all the technical constraints of the original formulation. An infeasibility cut will be added to the master problem when the slave problem is infeasible by means of a new constraint and objective function in the master. This will generate a new solution to be analysed by the slave problem again. Several iterations of the mentioned process may be necessary between the master problem and slave problems to obtain the final solution. Eventually, the method converges when there are no infeasibilities in the slave, and the optimal solution of the original problem is obtained [117].

The multi-period energy resource scheduling considering full AC network constraints is a MINLP problem. MINLP optimization techniques require high execution time to deal with the ERM for real-size distribution networks with large number of EVs. Benders decomposition overcomes the difficulties to solve nonlinear optimization with discrete variables [117]. The hourly power flow approach proposed by [118] is not the most adequate when temporal dependencies arise with ESS and EVs, because the hourly optimization cannot see minimum energy requirements ahead, thus resulting in sub-optimal solutions. The multi-period approach procedure is presented in Figure 27.

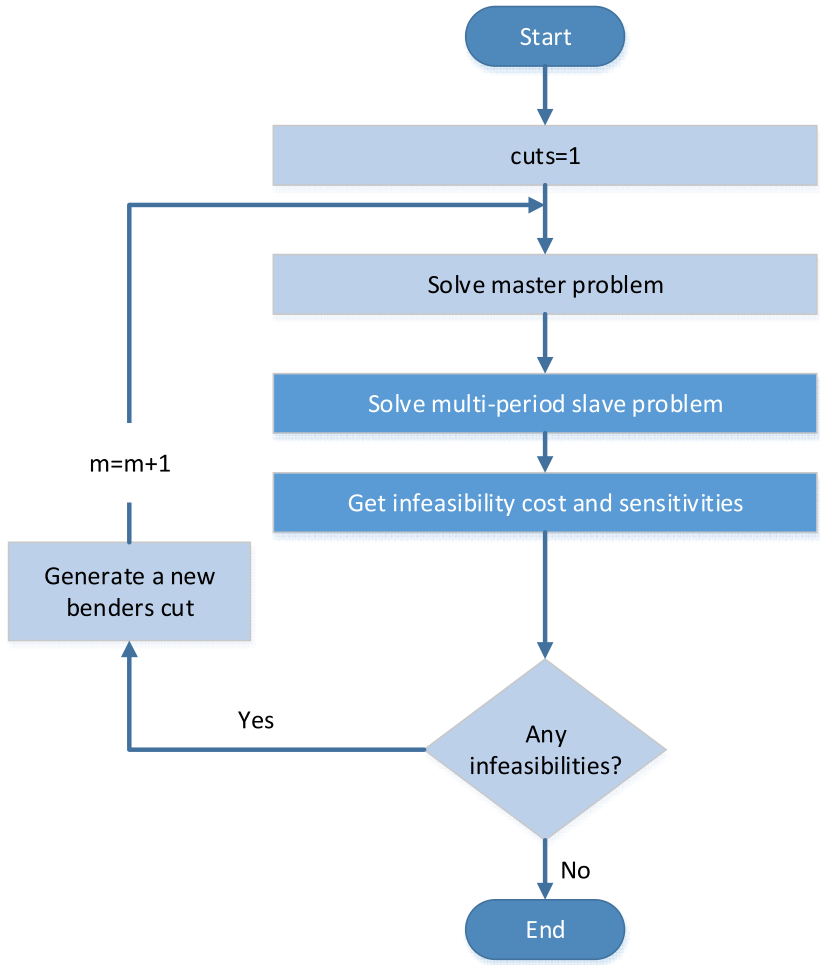

Figure 27. Benders decomposition flowchart for energy resource scheduling [121]

The difference of the hourly approach compared with the multi-period approach is that the slave problem is an hourly distribution optimal power flow whereas in the multi-period approach the optimization is larger and the 24-periods are simultaneously optimized. The master problem solves a relaxed formulation of the original ERM problem, namely a MILP without considering the network constraints. The second part, called slave problem, solves a NLP formulation with fixed variables (binaries of the master MILP) and with network constraints. The master and slave problem are solved iteratively until no more cuts can be generated [117]. The cuts are new constraints discovered by the slave problem concerning limits violations in the optimization process that are added to the master problem. The results found in the last master and slave problem is the solution to the original formulation [117]. This method allows to appropriately handle the non-convexity associated with binary variables and divide the original problem into two easier problems to solve.

4.3. Characteristics of smart grid optimization applications

The variety of models applied to solve SG operation problems can be classified in many ways. In this deliverable, we have identified two main groups for classification, namely approaches that use mathematical (or classical) models, and a second group based on computational intelligence and the use of heuristic and metaheuristic optimization. Mathematical models can be considered more reliable and accurate than CI approaches. However, mathematical models have some scalability issues typically requiring a large amount of memory and time to deal with large-scale problems. CI approaches, on the other hand, cannot guarantee an optimal solution but usually can find near-optimal solutions in acceptable times.

Table 5 summarizes the mathematical approaches adopted to solve SG problems. The table also identifies the type of function (i.e., single objective or multi-objective), the objective of the formulation (e.g., minimization of operational costs, maximization of profits, etc.), and if the approach considers DR programs and which type. It can be noticed that most of the mathematical methods formulate the problem as a two-stage stochastic model due to the presence of uncertainty. Two-stage stochastic models can be solved using MILP formulations, bi-level optimization, or in the case of large-scale problems, with the use of decomposition schemes. Highlighted in blue, we can find the contribution of Dream-go project in this regard. All Dream-go mathematical contributions consider DR programs and mainly focused on minimization of expected cost and maximization of profits.

Table 5 – Summary of mathematical optimization approaches applied in SG operation

Ref.	Approach	Multi-objective	Objective function	DR program
[87]	Bi-level robust stochastic-MILP scheduling model	yes	Maximum revenue of VPP and minimum net load and minimum operation cost.	Price-based demand response (PBDR) and incentive-based demand response (IBDR).
[88]	Two-stage stochastic programming with Benders decomposition	-	Minimum production cost considering system reliability.	Demand response reserve (DRR).
[72]	Bi-level problem and MILP	-	First level: minimum charging. Second level: Market clearing.	EVs coordination charging.
[93]	Two-stage stochastic centralized dispatch scheme	-	Minimize the expected total operating cost.	EVs coordination charging.
[75]	MILP Optimization	-	Maximize expected net profit of VPP.	Incentive-based three-level DR.
[122]	Two-stage stochastic programming.	-	Maximize expected day-ahead profit of VPP.	Incentive-based three-level DR.
[86]	Stochastic self-scheduling as MILP.	-	Minimize the operation costs.	The time-of use (TOU) rate.
[82]	Stochastic optimization	-	Minimize expected cost.	Direct load control (DLC).
[82]*	Two-stage stochastic programming	-	Minimize the expected operation costs.	DLC.

[78]*	Two-stage stochastic programming and Benders decomposition	-	Minimize operation costs considering market transactions.	DLC.
[84]*	Hybrid Interval-Stochastic method	-	Maximize domestic energy profit.	DLC.
[97]*	Two-stage stochastic programming	-	Maximize the expected profit.	Optimal pricing for EVs DLC.
[7]*	Intelligent HEMS algorithm and Rule-based HEMS	-	Minimize the daily energy cost of the household.	Price-based DR, incentive-based DR, TOU pricing.
[2]*	MILP and hierarchical and fuzzy c-means clustering	-	Minimize aggregator operation costs and suitable remuneration groups.	Real-time pricing (RTP) and incentive-based DR.
[89]*	Robust optimization	-	Maximize aggregator payoff considering price risk.	Price-based DR.
[92]	Stochastic linear programming	yes	Financial and environmental minimization.	-
[90]	Two-stage stochastic model with a decomposition scheme	-	Minimize the expected operational cost.	-
[91]	Stochastic optimization and distributed Newton's method	-	Maximize the expected system utility.	-
[85]	Two-stage stochastic program	-	Expected profit of the MG.	-

**Works developed in scope of DREAM-GO*

Regarding heuristics models, Table 6 summarizes some advanced metaheuristics are implemented (and in some cases, modified) to provide near-optimal solutions in acceptable times. The heuristics presented in this table include an original extension of a glowworm swarm particles optimization algorithm, Tabú search, greedy randomized adaptive search procedure, and a novel hybrid optimization algorithm, Particle Swarm Optimization (PSO), Teacher-Learning-Based Optimization (TLBO), and Biogeography Based Optimization (BBO) algorithm, among others. The reader can also be referred to [114], [123] for an extended analysis of different approaches in the area. Dream-go has also contributed on the application of computational intelligence in SG problems, namely by the use of multi-dimensional signaling which is a technique that enhances the capabilities of metaheuristics [83].

Table 6- Summary of computational intelligence approaches applied in SG operation

Ref.	Approach	Multi-objective	Objective function	DR program
[83]*	Multi-dimensional signaling with weighted PSO (W-PSO), multi-objective PSO and NSGA-II	Yes	maximize profits and minimize carbon dioxide (CO_2) emissions.	EVs scheduling and Direct Load Control (DLC).

[124]	Extension of a glowworm swarm particles optimization algorithm	Yes	Minimize yearly joule losses and yearly fuel consumptions cost.	Directly controlled shiftable loads.
[125]	Particle Swarm Optimization (PSO) with MILP	Yes	maximization of the minimum available reserve and the cost minimization, considering reliability of the system.	EV charging scheduling.
[126]	Tabu search, GRASP, and a hybrid optimization algorithm	-	Minimizing the total operational costs.	EVs charging coordination.
[127]	Teacher-Learning-Based Optimization (TLBO)	-	Minimizes the total operational cost.	-
[128]	Biogeography Based Optimization (BBO) algorithm	-	Minimizing the total operational cost guaranteeing the availability of energy.	-

**Work developed in scope of DREAM-GO*

5. Conclusions

This report presented an overview of the DR application in smart grid operation in short and real-time. Smart metering is key to the successful deployment of DR applications. It is remarked that DR can play a meaningful role when combined with SG optimization, e.g., home energy management systems, energy scheduling, etc. SG players such as aggregators can take advantage of sophisticated optimization algorithms to improve financial results and reduce risk while home energy management can benefit the end user. DR is key to manage financial risks and uncertainty related to new components and resources of the smart grid, e.g., electric vehicles, renewable generation. The deliverable then digs into specifics of smart grid components such as the electric water heater, electric vehicle and heat pumps, seen as potential controllable devices to foster demand response application. A summary of energy scheduling models dealing with uncertainty is discussed, regarding the type of resource considered, uncertainty, optimization algorithms used, etc. Due to the nature of the problem, sophisticated algorithms are required to handle short and real-time DR in SG optimization in adequate execution time as it is remarked in the last section of this deliverable.

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