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Review

Modelling Smart Grid Technologies in Optimisation Problems for Electricity Grids

Spyros Giannelos *, Stefan Borozan, Marko Aunedi, Xi Zhang, Hossein Ameli, Danny Pudjianto, Ioannis Konstantelos and Goran Strbac

Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, UK; s.borozan@imperial.ac.uk (S.B.); m.aunedi@imperial.ac.uk (M.A.); x.zhang14@imperial.ac.uk (X.Z.); h.ameli14@imperial.ac.uk (H.A.); d.pudjianto@imperial.ac.uk (D.P.); i.konstantelos@imperial.ac.uk (I.K.); g.strbac@imperial.ac.uk (G.S.)
* Correspondence: s.giannelos@imperial.ac.uk

Abstract: The decarbonisation of the electricity grid is expected to create new electricity flows. As a result, it may require that network planners make a significant amount of investments in the electricity grids over the coming decades so as to allow the accommodation of these new flows in a way that both the thermal and voltage network constraints are respected. These investments may include a portfolio of infrastructure assets consisting of traditional technologies and smart grid technologies. One associated key challenge is the presence of uncertainty around the location, the timing, and the amount of new demand or generation connections. This uncertainty unavoidably introduces risk into the investment decision-making process as it may lead to inefficient investments and inevitably give rise to excessive investment costs. Smart grid technologies have properties that enable them to be regarded as investment options, which can allow network planners to hedge against the aforementioned uncertainty. This paper focuses on key smart technologies by providing a critical literature review and presenting the latest mathematical modelling that describes their operation.

Keywords: coordinated voltage control; demand side response; dynamic line rating; electric vehicles; energy storage; grid to vehicle; vehicle to grid; vehicle to building; soft open point

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1. Introduction

The electricity system is undergoing significant changes as part of the global effort to tackle climate change. Examples of such changes include the electrification of the transport sector as well as the penetration of renewables in the generation mix, which are set to increase over the coming decades, on a global scale [1–5]. However, some of these changes are expected to increase the stress on the system. For instance, the electrification of transport is expected to give rise to higher electricity demand peaks [6]. As a result, these changes may trigger the need for investments in order to reinforce the electricity grids.

These investments may involve the deployment either of smart grid technologies or traditional/conventional technologies. Examples of the former include the Dynamic Line Rating system, Energy Storage [7], Vehicle-to-Building (V2B), Vehicle-to-Grid (V2G), Grid-to-Vehicle (G2V) [8,9], Demand-Side Response (DSR) [10], Coordinated Voltage Control (CV) and Soft Open Points (SOP) [11]. Such technologies have already been deployed in various regions such as in India [12], China, Brazil, the U.K. and countries of the European Union [13].

Conventional technologies include the construction of new lines, the upgrade of the capacity of existing lines and the upgrade/construction of new substations. Such traditional investments have been standard practice in electricity distribution grids over the past decades and are characterised by relatively larger investment costs and irreversibility [11]. The latter characteristic means that once distribution lines are constructed, they cannot be redeployed at another location of the grid if in the future it turns out that the current location is not optimal. This is because such investments are designed according to the specific geography and characteristics of the grid [14–17].

The irreversibility of conventional investments is reflected in the concept of stranding risk. This means that after these technologies have been deployed in the system they run the risk of turning out stranded assets. These are assets that are characterised by lower utilisation rates than initially expected. On the other hand, smart grid investments may be reversible as long as they can be reconfigured to adjust to another grid location. One example constitutes the Dynamic Line Rating system [18,19].

An important consideration related to investment decision-making is the "build time" or "investment delay". This is equal to the time difference, in years, between when the investment decision is made and when the technology becomes operational. In this context, smart technologies are typically characterised by relatively shorter build times than conventional technologies. Examples in the literature mention build times for conventional investments in distribution grids of around 2–3 years, longer than those of smart grid investments. This happens because conventional technologies typically involve lengthy licensing processes, and extensive public works while they may also encounter public opposition [11,20,21].

The remainder of the paper is structured as follows: Section 2 focuses on smart technologies related to the electrification of the transport sector. Section 3 is about novel technologies that enable the control of power flows and voltage. Section 4 focuses on technologies that enable the storage or the delay of the consumption of electricity such as Energy Storage and Demand Side Response. Section 5 focuses on decomposition methodologies that can enable the inclusion of the formulation of smart technologies within larger optimisation problems. Finally, Section 6 concludes by presenting key challenges associated with smart technologies and identifies possible pathways for future work.

The key contribution of this review paper is to include the latest literature review while presenting the most-recently-used mathematical formulation for a set of Smart Technologies that are geared to play an important role in the future smart electricity distribution grid. To the best of our knowledge, such a review paper has not been recently published. Recent review papers in the area of smart grids have focused on other topics such as the standards of communication and networking in smart grids [22], the Internet of Things in smart grids [23], issues related to the cybersecurity of smart grids [24], multi-agent systems for smart grids [25], on Big Data [26], and on the application of Deep Learning [27]. In this context, the current paper can be an interesting addition to the current literature.

2. Smart Grid Technologies for the Electrification of the Transport Sector

In the next few decades, the adoption of electric vehicles (EVs) can have a fundamental effect on the increase of electricity demand [19,28]. As a result, substantial infrastructure investments may be necessary to support the charging of EVs [29–32].

One important challenge that can affect the associated investment decision-making is the uncertainty surrounding the long-term development of power systems. This uncertainty involves the risk of these investments ending up stranded assets in the event that the uncertainty resolves unfavourably.

In this context, technologies such as Grid-to-Vehicle (G2V) (also known as Building-to-Vehicle), Vehicle-to-Grid (V2G), and Vehicle-to-Building (V2B), have the ability to defer or displace network reinforcements, until the uncertainty resolves. As a consequence, these technologies can constitute useful tools for managing uncertainty as has been shown in many examples [8,28,33–35].

In addition, the deployment of such technologies can help network planners accommodate higher levels of renewable generation [21,36–38], which is a fundamental objective of the effort to tackle climate change. Another associated benefit arising from their deployment includes the increase in the utilisation of existing network capacity as shown in [28,29,32,39].

It is important to mention that these technologies involve EV charging that can be conducted in a smart or non-smart (uncoordinated) manner. The former enables the control of the charging of an EV in an optimal way according to the real-time needs of the grid. As such, it has been shown to contribute to the reduction of the high demand peaks as well as of the wind curtailment as per [40]. This is also indicated in references [8,9] that demonstrate the substantial economic benefit resulting from smart EV charging. In addition, smart EV charging has been shown to play a pivotal role in efficiently managing network congestion. This is accomplished by preventing power lines from overloading at times when too many EVs are charging simultaneously. Effective congestion management is shown to enhance the ability of the system to integrate renewable generation, thereby leading to lower system operation costs and greater environmental benefits. These benefits when compared to uncoordinated (dumb) charging technologies are far superior in economic value [41–44].

Overall, these technologies have significant benefits as outlined in [45]. The main characteristics of these technologies are summarised in Table 1 below.

Table 1. Summary of Smart EV Charging Technologies, $P_c^{(r)}$ denotes a charger's rated power, and $P_b^{(t)}$ denotes the building's demand at time period t.

Charging Concept	Characteristics	Load Range Capability
G2V	• Unidirectional power flow (only charging) • Smart load control in response to signals from the grid	Between 0 and $P_c^{(r)}$
V2G	• Bidirectional power flow (charging and discharging) • Smart load control in response to signals from the grid • Can discharge to inject energy directly into the grid	Between $-P_c^{(r)}$ and $P_c^{(r)}$
V2B	• Bidirectional power flow (charging and discharging) • Smart load control in response to signals from the grid • Can discharge to inject energy into the building to which it is connected	Between $-P_c^{(r)}$ and $P_c^{(r)}$ or Between $-P_b^{(t)}$ and $P_c^{(r)}$

The next subsections include the mathematical formulation of these technologies used to describe their operation. These formulations can be included in the form of constraints inside mathematical optimisation problems.

2.1. Grid-to-Vehicle

G2V is a technology that involves the unidirectional flow from the grid to the battery of the vehicle. The modelling of a G2V-enabled EV fleet can be described by Equations (1) and (2) below, where the index n denotes a system busbar, t a single time period, and c denotes individual chargers.

$$\left|v_{n,t}^{G2V}\right| \leq \sum_{c\in\Omega_C} \Phi_c^{G2V} N_{n,c}^{G2V} \lambda_{n,c,t} P_c^{(r)} \tag{1}$$

$$\sum_{t=1+(k-1)T}^{\mathrm{k}T} v_{t,n}^{G2V} = 0 \tag{2}$$

In the above equations, $v_{n,t}^{G2V}$ is the decision variable for the aggregated power of the EV fleet, $N_{n,c}^{G2V}$ is the number of aggregated EVs, $\lambda_{n,c,t}$ is the uncoordinated EV load factor (i.e., the load factor for the regular/dumb EV charging that does not involve optimisation), and $P_c^{(r)}$ is the rated power of smart chargers. The participation factor Φ_c^{G2V} is a correction representing the ratio of EV owners willing and able to participate in load reduction at period t, accounting for any discrepancies from the characteristic behaviour of drivers and responsiveness to control signals. In the event of load reduction, constraint (1) limits $v_{n,t}^{G2V}$ according to the load reduction capability, while (2) forces all disconnected loads to be recovered within T periods (typically 12 or 24 h), where k is a positive integer.

2.2. Vehicle-to-X

Vehicle-to-X is a concept that includes the V2G and V2B use cases. These technologies involve the bidirectional flow of energy, from the grid to the battery and vice versa. Specifically, V2G enables energy from the EV's battery to be returned back to the grid directly, while V2B enables energy to be supplied locally in the connected building. The V2G operation is modelled by (3)–(6), where the indices have the same meaning as in the case of G2V in the previous subsection. Note that $\alpha_{n,c,t}$ is similar to $\lambda_{n,c,t}$ in that it is a factor between 0 and 1, but it is related to the percentage of EVs that are plugged in and hence available for smart charging. In this context, $\alpha^{+}_{n,c,t}$ and $\alpha^{-}_{n,c,t}$ denote the percentage of EVs that connect/disconnect in period t respectively.

$$\left|v^{V2G}_{t,n}\right| \leq \sum\nolimits_{c\in\Omega_C} \Phi^{V2G}_{c} N^{V2G}_{n,c} \alpha_{n,c,t} P^{(r)}_{c} \tag{3}$$

$$\sum\nolimits_{t=1+(k-1)T}^{\mathrm{k}T} \left(v^{V2G}_{t,n} - \Phi^{V2G}_{c} N^{V2G}_{n,c} \lambda_{n,c,t} P^{(r)}_{c}\right) \geq 0 \tag{4}$$

$$\begin{gathered}\sigma_{t,n} = \sigma_{t-1,n} + \tau\left(\eta^{+} v^{V2G,+}_{t,n} - \frac{v^{V2G,-}_{t,n}}{\eta^{-}}\right) \\ +\sum\nolimits_{c\in\Omega_C}\left(\Phi^{V2G}_{c} N^{V2G}_{n,c} \alpha^{+}_{n,c,t} \sigma^{(d)}_{c} - \Phi^{V2G}_{c} N^{V2G}_{n,c} \alpha^{-}_{n,c,t} \sigma^{(r)}_{c}\right)\end{gathered} \tag{5}$$

$$\begin{gathered}\sum\nolimits_{c\in\Omega_C}\left[\Phi^{V2G}_{c} N^{V2G}_{n,c} \alpha_{n,c,t} \sigma^{(d)}_{c} + \Phi^{V2G}_{c} N^{V2G}_{n,c} \alpha^{-}_{n,c,t+1}\left(\sigma^{(r)}_{c} - \sigma^{(d)}_{c}\right)\right] \\ \leq \sigma_{t,n} \leq \sum\nolimits_{c\in\Omega_C} \Phi^{V2G}_{c} N^{V2G}_{n,c} \alpha_{n,c,t} \sigma^{(r)}_{c}\end{gathered} \tag{6}$$

The V2G load is fully characterised by $v^{V2G}_{t,n}$, which takes both positive values for charging ($v^{V2G,+}_{t,n}$) and negative values for discharging ($v^{V2G,-}_{t,n}$). Constraint (3) restricts the V2G charge and discharge to the load range capability of participating and available EVs. Constraint (4) ensures that the deviations from the uncoordinated charging profile, which occur due to the V2G operation, are balanced over T periods, where k is a positive integer. Also, $\Phi^{V2G}_{c} N^{V2G}_{n,c} \lambda_{n,c,t} P^{(r)}_{c}$ characterises the uncoordinated charging demand. In other words, this constraint ensures that over T periods (e.g., 24 h) all EVs receive enough energy with V2G as they would with uncoordinated charging.

The V2G fleet's state of charge (SoC), represented by $\sigma_{t,n}$, is modelled explicitly with the help of Equations (5) and (6). The former updates the SoC with the required charge or discharge of EVs and with a step-change arising from the arrival or departure of EVs. The latter places limitations on the SoC, where the maximum is the aggregated energy capacity of available EVs (informed by $\alpha_{n,c,t}$ which is the percentage of plugged-in EVs in the grid), and the minimum is the allowed Depth of Discharge of connected EVs ($\sigma^{(d)}_{c}$) along with the energy difference to the full capacity of any departing vehicles in the next period $t+1$ (i.e., $\sigma^{(r)}_{c} - \sigma^{(d)}_{c}$). This ensures that all vehicles are fully charged before unplugging. Note that an auxiliary variable $\sigma_{0,n}$ for a single period directly preceding $t = 1$ must be defined and initialised, which acts as the reference SoC in (5) and final SoC in (6). Note also that τ is the time step, which depending on the modelling granularity can be 30 min, 1 h, etc. Additionally, η^{+} and η^{-} are the charging and discharging efficiencies respectively, while $\alpha^{+}_{n,c,t}$ and $\alpha^{-}_{n,c,t}$ are the ratios of arriving and departing EVs at time period t.

V2B supports bidirectional power flows as well and, from the grid's perspective, it follows a similar modelling approach to V2G, described in (7)–(10). However, as opposed to V2G which discharges directly into the grid, V2B can only supply the building to which EVs are connected. This is reflected in Equation (7), which marks the main difference to

V2G modelling. The second difference is that index c is excluded because all chargers and EVs belonging to the same building can justifiably be assumed to be of the same type.

$$-\inf\left(\Phi^{V2B}N_n^{V2B}\alpha_{n,t}P^{(r)}, \frac{\Phi^{V2B}N_n^{V2B}}{N_n^{(b)}}\mu_{n,t}P_n^{(b)}\right) \le v_{t,n}^{V2B} \le \Phi^{V2B}N_n^{V2B}\alpha_{n,t}P^{(r)} \quad (7)$$

$$\sum\nolimits_{t=1+(k-1)T}^{kT}\left(v_{t,n}^{V2B} - \Phi^{V2B}N_n^{V2B}\lambda_{n,t}P^{(r)}\right) \ge 0 \quad (8)$$

$$\sigma_{t,n} = \sigma_{t-1,n} + \tau\left(\eta^+ v_{t,n}^{V2B,+} - \frac{v_{t,n}^{V2B,-}}{\eta^-}\right) + \Phi^{V2B}N_n^{V2B}\alpha_{n,t}^+\sigma_n^{(d)} - \Phi^{V2B}N_n^{V2B}\alpha_{n,t}^-\sigma_n^{(r)} \quad (9)$$

$$\Phi^{V2B}N_n^{V2B}\alpha_{n,t}\sigma_n^{(d)} + \Phi^{V2B}N_n^{V2B}\alpha_{n,t+1}^-\left(\sigma_n^{(r)} - \sigma_n^{(d)}\right) \le \sigma_{t,n} \le \Phi^{V2B}N_n^{V2B}\alpha_{n,t}\sigma_n^{(r)} \quad (10)$$

According to the above, the lower limit for the maximum discharging power ($v_{t,n}^{V2B}$) is constrained by the lower between the sum of EV charger ratings and the sum of conventional demand of connected buildings. Due to this, the V2B model requires two additional assumptions to be made on the peak conventional demand ($P_n^{(b)}$) and the mean number of EVs per building ($N_n^{(b)}$), which can vary for each bus depending on the fleet and building types. Regarding constraints (8)–(10) they are equivalent to constraints (4)–(6) under V2G.

3. Smart Grid Technologies Related to Power Flow and Voltage Control

This section discusses smart technologies used for the control of power flows and voltages in electricity distribution networks, namely Soft Open Points, Dynamic Line Rating, and Coordinated Voltage Control.

3.1. Soft Open Point

Soft Open Point (SOP) is a technology that involves the installation of equipment at locations of normally open points in electricity distribution grids and enables control over the active power flows from one bus to another; this flow must respect the active power limit of SOP, which is represented by the input parameter P_c^{max} in the formulation below [45,46]. Note that SOP can also perform reactive compensation at any of its two terminals (i.e., buses), which involves either the absorption or generation of reactive power, with the objective of performing local voltage control [47,48].

The SOP technology has been shown to offer significant economic savings in electricity distribution grids [49]. This has been demonstrated in cases where SOP constitutes the single Smart Technology deployed in the system or one of the many Smart Technologies alongside others such as Energy Storage as shown in [50,51]. Benefits to system operation include real-time network reconfiguration [52,53], voltage control through reactive power compensation, and active power control [54–57]. Recently, this technology has also been shown to enhance distribution grids even against cyber attacks [58,59].

The operation of SOP can be modelled using constraints (11)–(13) below. Particularly, the installation of a SOP equipment at a normally open point c of the grid is represented by the state binary decision variable $\widetilde{S}_c$. The SOP will enable the control of power flows, represented by decision variables $H_{t,c}$ and $R_{t,c}$ for the real power drawn by the SOP at buses $n = n_c^a$ and $n = n_c^b$ respectively, at some time period t, and sent to the bus $n = n_c^b$ and $n = n_c^a$ respectively, at efficiency η_f. If the SOP has not been deployed at c then $\widetilde{S}_c = 0$ and then the corresponding controlled power flow must be zero i.e., $R_{t,c} = 0$ and $H_{t,c} = 0$ as in (1) and (2). As mentioned, an SOP that is installed at c (i.e., $\widetilde{S}_c = 1$) can perform reactive compensation at any of its two buses n so that the reactive power that it can absorb or generate, symbolised by $H_{t,c,n}^Q$, positive or negative, must not exceed its reactive power limit Q_c^{max}, which is an input parameter, as in (2). Note that the corresponding decision variables must also appear in the power balance equations, which state that at every time period and at every bus the total incoming power flows must be equal to the total outgoing power flows.

$$R_{t,c} \leq P_c^{max} \cdot \widetilde{S}_c \qquad \forall t, \tag{11}$$

$$H_{t,c} \leq P_c^{max} \cdot \widetilde{S}_c \qquad \forall t, c \tag{12}$$

$$\left| H_{t,c,n}^{Q} \right| \leq Q_c^{max} \cdot \widetilde{S}_c \qquad \forall t, c, n \tag{13}$$

3.2. Dynamic Line Rating

Dynamic Line Rating (DLR) constitutes a Smart Grid Technology that is deployed at a critical point along an overhead line [60]. Its purpose is to provide up-to-date information about the actual thermal line rating on a continuous basis [61]. As a result, the network operator can have a better insight into the actual line rating using various methodologies [62–65]. This rating depending on weather conditions can be higher or lower than the static line rating [66]. As a result, at certain times it may be possible to allow power flows that exceed the static line rating, which the planner would otherwise not have the ability to do. This can have significant economic benefits in terms of optimal network planning in the presence of renewables [67] as well as benefits related to grid reliability [68,69].

One significant aspect in terms of DLR operation is the uncertainty of wind power that can introduce forecasting errors and which might bring in some severe consequences to the power system, such as line overloads. The most recent approach to deal with this issue is a tri-level preventive dispatch model based on decomposition approaches [70].

The following formulation describes the operation of DLR and can be included in optimisation problems in the form of constraints.

Constraints (14)–(15) describe the operation of this smart grid technology. Specifically, constraint (14) models the power flows across line l and at time period t, denoted by the continuous decision variable $F_{t,l}$ according to the DCOPF model. According to constraint (15), these power flows must, in absolute value, not exceed the line rating at any time period t. When a DLR system is deployed on the line ($\Delta_l = 1$), the right-hand side includes the terms $F_l R_t \Delta_l$ where the input parameter F_l is the initial/static thermal rating of line l, and R_t is the DLR capacity factor (%) in time period t; this factor is a dimensionless number by which the static line thermal rating is multiplied so as to yield the value for the dynamic/actual line rating, which is changing on a continuous basis based on weather conditions such as the wind speed and temperature. Authors in [71,72] mention locations of high wind potential that are characterised by actual line ratings with an average of 29% increase over their static rating over a year.

$$F_{t,l} \leq \frac{\theta_{t,u_l} - \theta_{v_l}}{x_l} \qquad \forall t, l \tag{14}$$

$$\left| F_{t,l} \right| \leq F_l R_t \Delta_l + (1 - \Delta_l) F_l \qquad \forall t, l \tag{15}$$

3.3. Coordinated Voltage Control

Coordinated Voltage Control (CVC) is a Smart Grid Technology that can be installed at the substation and allows for optimal voltage control across an area of the grid [73,74]. This technology has been shown to offer significant economic benefits in grids with distributed generation [75–77]. In [78], the authors present a novel CVC scheme based on solar PV inverters with significant benefits to voltage stability. In [79] the authors demonstrate the coordinated operation of a CVC scheme alongside a soft open point, showcasing significant economic benefits to system operation. Novel methodologies based on reinforcement learning and model predictive control [80,81] have also been shown to contribute to optimal CVC operation in [82]. This technology can be explained by the following constraints.

Specifically, constraint (16) imposes the statutory limits, denoted by the input parameters V_{min} and V_{max}, on voltage magnitudes, denoted by the decision variable $V_{t,n}$, at time period t and across all buses n in the grid, except the substation (denoted by $n - \{1\}$). Specifically, the voltage magnitude at the substation is defined in (17) to be equal to the voltage target value V_t^{noc} (a decision variable) of the automatic voltage control (AVC) relay of the On Load Tap Changer (OLTC) transformer, or the voltage V_t^{cvc} (a decision variable) which is determined by the CVC operation.

Particularly, when the CVC technology has not been deployed (denoted by the decision variable $\widetilde{C}_m = 0$) then $V_t^{cvc} = 0$, as per (18), and $V_t^{noc} = V_{set}$, where V_{set} is an input parameter denoting the fixed voltage-target policy for the OLTC at the substation. For instance, in [11], it is assumed that in the absence of CVC a fixed voltage target policy is applied to the AVC relay scheme, with the voltage target kept fixed at a value selected traditionally above 1 pu, to prevent voltage drops at remote buses.

On the other hand, if a CVC scheme has been deployed (denoted by $\widetilde{C}_m = 1$) then $V_t^{noc} = 0$ i.e., the substation voltage magnitude no longer follows a fixed voltage target policy. Rather, it can be controlled optimally based on real-time information about the system state; in this case, it is $V_{t,1} = V_t^{cvc}$, where $V_{min}^{cvc} \leq V_t^{cvc} \leq V_{max}^{cvc}$.

$$V_{min} \leq V_{t,n} \leq V_{max} \qquad \forall\, t, n - \{1\} \tag{16}$$

$$V_{t,1} = V_t^{cvc} + V_t^{noc} \qquad \forall\, t \tag{17}$$

$$V_{min}^{cvc} \cdot \widetilde{C} \leq V_t^{cvc} \leq V_{max}^{cvc} \cdot \widetilde{C} \qquad \forall\, t \tag{18}$$

$$V_t^{noc} = V_{set} \cdot \left(1 - \widetilde{C}\right) \qquad \forall\, t \tag{19}$$

The Table below (Table 2) presents a summary of the presented technologies in this section.

Table 2. Summary of presented technologies.

Technology	Characteristics
Soft Open Point	• Can be installed at locations of Normally Open Points. • Enables control of the active power flow between its two terminals. • Can perform reactive compensation at its two terminals (absorb or generate reactive power).
Dynamic Line Rating	• It is installed at critical points of overhead power lines • Informs about the actual thermal rating of the line, which may or may not be greater than the static rating
Coordinated Voltage Control	• Can be installed at the substation level. • Coordinates the voltage level across the downstream grid.

4. Smart Grid Technologies Related to the Storage and Delay of Consumption of Electricity

The deployment of Energy Storage and Demand Side Response (DSR) can provide flexibility in the context of grid balancing and security of supply [83–85]. This operational flexibility has been shown to help deliver decarbonisation targets at a lower cost and support the integration of variable renewable sources [86–88].

4.1. Energy Storage

Energy Storage is a technology that can charge and discharge energy at different time periods, thereby contributing to the economical grid operation [89]. The benefits of energy storage result from its ability to participate in energy arbitrage while at the same time providing reserve and frequency regulation services, as well as other balancing and network services [90]. Previous whole-system assessments have identified a significant potential role for a range of energy storage technologies, including battery storage [90], pumped-hydro storage [91] liquid-air and pumped-heat energy storage [92], and thermal storage deployed in nuclear power plants [93].

The following constraints describe the operation of energy storage. Constraint (20) determines the energy capacity of a storage unit at time period t, denoted by the decision variable $E_{t,n}$. This is equal to its capacity at the previous time period $t-1$, denoted by $E_{t-1,n}$, taking into account the storage efficiency, denoted by the input parameter η, plus/minus the energy charged/discharged, denoted by the decision variable $J_{t,n}$. The latter represents power and can take both positive values (i.e., storage is charging) and negative values (i.e., storage is discharging). This power is multiplied by δ, which is the time duration such as 1 h.

Constraint (21) defines the bounds on energy capacity where the input parameter Ψ refers to the maximum capacity that an energy storage unit can have, where Π_n is the decision variable denoting investment in the storage unit at bus n. Constraint (22) sets the bounds on power $J_{t,n}$ for the storage unit located at bus n for time period t, where Ξ is the maximum power that a storage unit can have. Finally, constraint (23) defines the system energy balance per bus n, according to which the total generation (where $P_{t,g}$ is the output of a generation unit g at period t) plus the algebraic sum of power flows (where $F_{t,l}$ denotes the power flows at period t across line l) and $d_{t,n}$ is the demand at period t and at bus n.

$$E_{t,n} = \eta E_{t-1,n} + \delta \cdot J_{t,n} \qquad \forall\, t, n \tag{20}$$

$$E_{t,n} \leq \Psi \cdot \Pi_n \qquad \forall\, t, n \tag{21}$$

$$|J_{t,n}| \leq \Xi \cdot \Pi_n \qquad \forall\, t, n \tag{22}$$

$$\sum\nolimits_g P_{t,g} + \sum_l F_{t,l} = J_{t,n} + d_{t,n} \qquad \forall\, t, n \tag{23}$$

4.2. Demand Side Response

Demand Side Response (DSR) is a common term for technologies that enable the temporal shifting of various types of electricity demand in response to system conditions. It is demonstrated in [94] that DSR can reduce the operational cost of gas and electricity networks by up to 11%. Recent research has shown that DSR can support a more cost-effective transition of energy systems toward the zero-carbon objective [88]. This is particularly relevant for future electrified heat and transport sectors, where smart operating paradigms can significantly reduce system peak demand and enhance the operational efficiency of the system [36]. DSR in the form of smart EV charging [95] or Vehicle-to-Grid [96] have the potential to mitigate the cost of integration of variable renewables while avoiding a disproportionately high increase in network peak demand. Deployment of residential electric heat pumps with thermal storage [97] or hybrid heat pump concepts [98] has been shown to significantly decrease the cost of integrating low-carbon heating demand by reducing the associated network infrastructure cost. References [99,100] have also demonstrated how demand-side technologies can be effective providers of fast-responding frequency regulation services. Reference [101] demonstrated that DSR could decrease the investment in thermal power plants and improve the system integration of renewables.

The following constraints describe the operation of DSR. In particular, constraint (24) imposes energy equality ensuring that a flexible load is eventually served within a specified period Ω (e.g., a day). Note that decision variables $\xi^d_{t,n}$ and $\xi^c_{t,n}$ represent the disconnected and connected load, respectively. Disconnected load is the load shifted away from period t, while connected load is the load shifted to period t. Note also that each of these decision variables is bounded above as per constraints (25) and (26), where $\widetilde{D}_n$ is the state decision variable representing an investment in DSR at bus n. Additionally, the input parameter $f_{t,n}$ is the percentage of the load that is available at bus n and at period t to be controlled by DSR (i.e., the flexible load), while $d_{t,n}$ is the real power demand at bus n and in period t.

$$\sum\nolimits_{t\in\Omega}\left(\xi^{d}_{t,n}-\xi^{c}_{t,n}\right)=0 \qquad \forall\, n \tag{24}$$

$$\xi^{d}_{m,t,n}\leq \widetilde{D}_n\cdot f_{t,n}\cdot d_{t,n} \qquad \forall\, t,n \tag{25}$$

$$\xi^{c}_{m,t,n}\leq \widetilde{D}_n\overline{D}_{t,n} \qquad \forall\, t,n \tag{26}$$

The Table below (Table 3) presents a summary of the presented technologies in this section.

Table 3. Summary of presented Technologies.

Technology	Characteristics
Demand Side Response	• Can be installed at any busbar in the grid. • Enables control of the load by deferring consumption to later hours.
Energy Storage	• Can be installed at any busbar in the grid • Charges with energy and discharges it depending on the system state.

5. Including Smart Grid Technologies in Large Optimisation Problems

Optimisation problems can become very large, which may lead to relatively long solution times. As a result, large optimisation problems often lend themselves to decomposition approaches, such as Benders decomposition and outer approximation.

Benders Decomposition constitutes an iterative decomposition algorithm that can be applied to Mixed Integer Linear Programming (MILP) problems characterised by a number of variables and constraints that negatively affect the solution time as well as the memory required for the implementation of the problem. According to this decomposition methodology, the original problem is broken down into a master MILP subproblem and a continuous operational subproblem [102].

The master problem solves the investment part of the original problem while approximating the operational subproblem and the optimal solution that is yielded is passed as an input to the operational subproblem, which is then optimally solved. Part of its solution involves the dual variables corresponding to the "coupling constraints" (i.e., those that couple the investment variables in the operational subproblem with the inputs from the master subproblem). These are passed as inputs to the master subproblem of the next Benders iteration so that they can be used to construct linear constraints ("Benders cuts") that are appended to the master problem.

This is illustrated in Figure 1 below. At every iteration of the algorithm, the master problem is first solved and the 'trial' investment decisions it yields are passed as inputs onto the operational subproblems that are solved in parallel after the master problem has been solved. In turn, these generate Lagrangian multipliers that are used by the master problem of the subsequent iteration to construct one extra constraint known as the Benders cut; this cut approximates the optimal value of the operation subproblem. As the Benders iteration index increases, more Benders cuts are gradually appended to the master problem. Ultimately, the algorithm converges when the difference between the lower and the upper bounds, of the original problem's objective function, is sufficiently close to zero. The lower bound is essentially the objective function of the master problem, while the upper bound is equal to the objective function of the original problem.

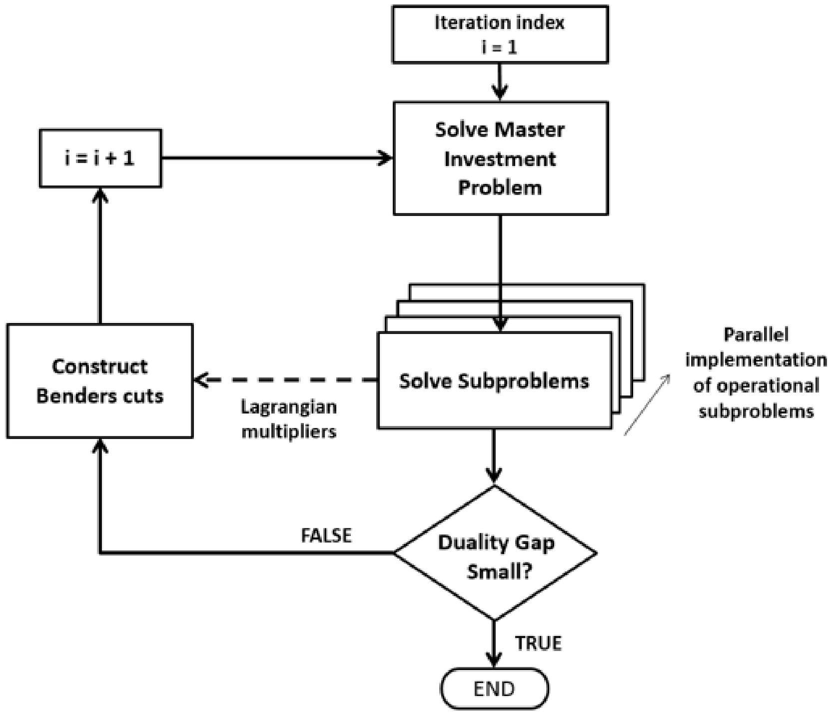

Figure 1. Principle of operation of the Benders Decomposition Algorithm (parallel implementation of operational subproblems).

In this context, the formulation for Smart Grid Technologies can be accommodated within a Benders decomposed problem. In such a formulation, the investment-related constraints are placed within the master subproblem, while the operation-related constraints are placed within the operational subproblem.

For Mixed-Integer Non-Linear Programming (MINLP) problems, the outer approximation decomposition method could be applied. In this method, the upper bound and the lower bound of the objective value are generated for each iteration to solve the MINLP problem. Figure 2 shows the structure of the outer approximation decomposition method. The upper bound is derived from the primal problem, while the lower bound is derived from the master problem. Binary variables are fixed in the primal problem. To solve the master problem, the Lagrangian multipliers associated with the non-linear equality constraints and the upper bound are obtained from the primal problem. In the master problem, using the Lagrangian multipliers, the non-linear inequalities are relaxed into linear inequalities, which are obtained from the primal problem. Solving the master problem provides information about the lower bound and the fixed binary variables used in the next iteration of the primal problem. Finally, the upper and lower bounds converge in a finite number of iterations as the iteration proceeds [103].

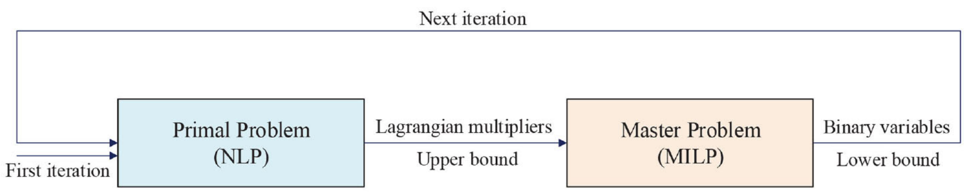

Figure 2. Principle of outer approximation decomposition algorithm [104].

6. Conclusions and Future Work

The current review paper focuses on key Smart Grid Technologies that are geared to be deployed in smart electricity distribution grids. The presented Smart Grid Technologies include Grid to Vehicle, Vehicle to Grid, Vehicle to Building, the Soft Open Point, Dynamic

Line Rating, Coordinated Voltage Control, Energy Storage, and Demand Side Response. Key literature reviews and mathematical formulation are provided for each of the technologies. An important conclusion is that investing in Smart Grid Technologies may constitute a viable alternative to investing in conventional solutions.

It has been shown that Smart grid technologies can bring numerous benefits to the electricity system. However, they can also present many challenges. A key challenge is related to interoperability, which involves the synchronised optimal operation of many different smart technologies in the same system. To overcome this challenge network planners would need to develop an appropriate regulatory framework that would establish proper standardisation principles to be followed by all vendors and manufacturers. This is the most important challenge as it has the potential to hinder seamless data exchange across the grid.

Another challenge involves data privacy. Given that smart grid technologies will be able to gather vast amounts of data, it would be necessary to define protocols that will guarantee that data sensitivity will be respected and protected against all possible threats, including from within cyberspace.

Finally, it all comes down to forming the appropriate regulatory and policy frameworks to enable the seamless integration of smart grid technologies. Such frameworks need to also take into account recent technological advances such as Artificial Intelligence. Overcoming the difficulties in developing such frameworks requires collaboration among all possible stakeholders, including utilities, policymakers, and consumers. However, overcoming such hurdles can be crucial for achieving an optimised operation of the Smart Grid.

Regarding future work, an interesting application area for future work is to study the operation of Smart Grid Technologies under Decision-Dependent or Endogenous Uncertainty [104]. This is a type of uncertainty that can be resolved only after an investment decision has been made. Another topic for future work is the comparison of the solutions obtained from different network planning frameworks, such as Stochastic Optimisation, Least-Worst Regret, Backwards Induction Method [105], and the F-Factor methodology [106] when one or more of the presented Smart Technologies are available for investment.

Stochastic optimisation problems can become computationally expensive and cumbersome, especially when applied to large power systems consisting of hundreds of buses and lines. In such settings, the modelling can result in unrealistically long solution times, making it very challenging to conduct in-depth sensitivity analysis. This has led to the development of decomposition methodologies, which allow for better performance and lower solution times [107]. Future work in this area may focus on developing decomposed mathematical formulations to enable the inclusion of Smart Technologies in larger power systems.

Application of Machine Learning techniques [13], such as reinforcement learning [108], may also be considered possible future work pathways [109] with a special focus on peer-to-peer trading and multi-agent microgrids [110].

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