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Network and Market-Aware Bidding to Maximize Local RES Usage and Minimize Cost in Energy Islands with Weak Grid Connections

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Received: 15 June 2020; Accepted: 27 July 2020; Published: 5 August 2020

Abstract: The increasing renewable energy sources RES penetration in today's energy islands and rural energy communities with weak grid connections is expected to incur severe distribution network stability problems (i.e., congestion, voltage issues). Tackling these problems is even more challenging since RES spillage minimization and energy cost minimization for the local energy community are set as major pre-requisites. In this paper, we consider a Microgrid Operator (MGO) that: (i) gradually decides the optimal mix of its RES and flexibility assets' (FlexAsset) sizing, siting and operation, (ii) respects the physical distribution network constraints in high RES penetration contexts, and (iii) is able to bid strategically in the existing day-ahead energy market. We model this problem as a Stackelberg game, expressed as a Mathematical Problem with Equilibrium Constraints (MPEC), which is finally transformed into a tractable Mixed Integer Linear Program (MILP). The performance evaluation results show that the MGO can lower its costs when bidding strategically, while the coordinated planning and scheduling of its FlexAssets result in higher RES utilization, as well as distribution network aware and cost-effective RES and FlexAsset operation.

Keywords: energy islands; local energy communities; flexibility; optimal bidding RES siting and sizing; price maker

1. Introduction

Energy islands and remote energy communities with weak grid connections can be the "front-runner" use case towards the energy transition [1], as they can benefit from: (i) low cost of renewable energy sources RES compared to the high energy production costs of conventional generators; (ii) local deployment of local RES and storage systems, which can both enhance cost effectiveness and decarbonize the local energy system in the long term; (iii) the exploitation of the close social bonds of the local community members that increase the end users' engagement [2,3].

Recent regulations that incentivize local investments in integrated energy systems, such as [4], highlight that the need for optimal RES investments triggers investments in flexibility assets, or FlexAssets (e.g., electric vehicles, battery storage systems, demand side management, etc.). Their efficient siting, sizing and scheduling become an apparent problem to solve towards the effective utilization of local RES usage.

Moreover, the underlying network of a typical energy island is vulnerable to severe instability issues, because: (i) its interconnection point with higher voltage networks (i.e., main grid at the transmission network level) is weak, and (ii) its existing lines at the distribution network level are usually inadequate to accommodate the continuously increasing RES, especially at the edges of the low-voltage distribution network [5]. Finally, when not operating in islanded mode, the Microgrid Operator (MGO) purchases/sells energy from/to the main grid to cover/sell its excessive demand/supply. Hence, network and market-aware bidding is required to minimize the energy cost and maximize the end users' welfare.

A more general term than MGOs is Energy Service Providers (ESPs). Without harm of generality, ESPs are smart grid stakeholders that dispose RES and/or flexibility assets and participate in the traditional energy markets and/or in local flexibility markets. In more detail, ESPs could be categorized in four major categories which are: (i) RES producers/traders and/or RES aggregation service providers, (ii) aggregators of loads from home electric appliances (e.g., HVAC, EVs, etc.) towards the provision of Demand Side Management (DSM) services, (iii) owners and operators of Battery Storage System (BSS) as well as providers of flexibility services through them, and (iv) retailers, who just purchase energy from wholesale markets in order to serve the loads of their customers and thus may not possess any RES, DSM and BSS assets. Recently, ESPs compose hybrid business models, which means that they may fall into more than one of the aforementioned categories as extensively described in the use case scenarios' analysis of the ongoing European Commision (EC)-funded H2020 FLEXGRID project [6].

The business model that ESPs may adopt highly depends on the architecture of the smart grid and the energy market. Our work in FLEXGRID [7] proposes innovative smart grid architectures, trying to identify efficient interactions between the grids' and energy markets' operations. In more detail, FLEXGRID proposes three major innovations. The first is the monitoring of the distribution network towards stable and distributed RES and flexibility asset installations in it by the ESPs. The second is that it follows an open data approach, which means that ESPs are able to exploit information that is relevant with the network topology and the market of the underlying grid towards efficient investment plans (i.e., sizing, siting) and optimal scheduling of their flexibility assets. The third is an innovative interaction between the distribution and transmission network towards the efficient and coordinated management of RES and flexibility assets.

In the context of this work, we focus on a specific business model through which an MGO entity efficiently represents the interests of local energy communities through the co-design and co-optimization of a set of services. In more detail, the services that MGO operates on behalf of the local energy community are: (1) optimal sizing, siting and operation for RES, Battery Storage System (BSS) and aggregated Demand Side Management (DSM) assets, (2) modeling and management of the distribution network through the use of optimal power flow algorithms in order to deal with local congestion and voltage control problems, and (3) advanced models for the optimal MGO's participation in the existing energy markets.

According to the aforementioned innovative business model, a major contribution of this paper is the development of the algorithms that this business model needs. In more detail, this work develops a holistic MGO operational framework, which can concurrently:

- Coordinate the short-term scheduling and long-term planning of various types of FlexAssets, thus providing an optimal integrated operation and an investment tool that facilitates decision makers by acting as an evaluator of possible investments.
- Exploit Optimal Power Flow (OPF) algorithms, which take into consideration local congestion and voltage-related constraints and allow a network-aware RES and FlexAssets' exploitation policy.
- Co-optimize the operation of RES and FlexAssets, as well as execute scenarios that facilitate the co-design of investments with their optimal mix.
- Model the competition in the day-ahead energy market and thus allow MGO to exploit the competition. In contrast to the related literature that mainly considers large price-maker entities at the transmission system level, we showcase that MGO's profits can also be significant,

despite the fact that its portfolio represents only a small portion of the market's total energy production/consumption. In this way, we assist energy islands and remote energy communities in order to mitigate their inherent RES-related and geographic-related negative externalities.

The rest of this paper is structured as follows. Section 2 analyzes the related work. Section 3 presents the proposed model. Section 4 formulates the problem, presents the mathematical models that we use and the solution that we propose. Section 5 evaluates the proposed solution, while Section 6 concludes and presents hints for future work.

2. Related Work

According to [8], there are real and practical examples, which exploit RES in order to develop energy autonomy in energy islands. Moreover, there are many recent studies (with real examples) on the optimization of RES and the flexibility assets' mix in energy islands and in local communities that operate RES [9]. In more detail, [10] exploits fuzzy logic in order to derive an efficient sizing of RES and BSS and analyzes the "robustness" level that it offers. In our previous work [11], we analyzed an approach that further increases this robustness through the development of a modern community aware and self-organized Demand Side Management architecture.

Although these works are promising studies towards sustainable energy islands, they do not adequately model the underlying network and they do not accurately model the interaction between energy islands and existing smart grid energy market architecture.

As far as it concerns the exploitation of flexibility assets (e.g., BSS) at the transmission network level, there are already many works that explored this case in the international scientific literature. In [12], a stochastic optimization problem is formulated that allows a price taker (i.e., non-strategic bidder) ESP to exploit its BSSs (that it installs in various network locations) in existing energy markets in order to maximize its profits. More progressively, [13] considers a price maker (i.e., strategic bidder according to a sensitivity analysis of market prices) ESP that owns and operates a number of geographically dispersed storage units at different network buses and participates in day-ahead energy market. A bi-level stochastic optimization model is used to optimize the ESP's offering/bidding strategy, which is transformed into a Mathematical Program with Equilibrium Constraints (MPEC). In the upper level, the ESP's profits are maximized, while in the lower level a DC-OPF optimization algorithm clears the market that manages the transmission network. Furthermore, [14] analyzes the case in which multiple ESPs provide flexibility services through the use of BSS (again in a day-ahead energy market regarding the transmission network level where the network data are available to all participants). The bidding strategy of the ESP is modeled as a bi-level optimization problem. In the upper-level the revenues of the ESP from the various energy markets are modeled and in the lower-level problem the clearing of the day-ahead energy markets are modeled. The aforementioned MPEC problem is extended to an Equilibrium Problem with Equilibrium Constraints (EPEC) in cases where there are more than one ESPs. The solution of this problem exploits a diagonalization method.

The proposed solution builds on the logic of these works, especially in the strategical bidding of ESPs towards their financial sustainability. It additionally extends them by: (i) modeling ESPs that operate and exploit an optimal mix of RES and flexibility assets instead of BSS, and (ii) models the topology of the underlying distribution network and its constraints. In this way, it facilitates and co-optimizes distributed investments at the distribution network level.

Beyond their interaction with existing energy markets, ESPs are able to offer services to end consumers such as energy arbitrage, minimization of dependence on the main grid and revenues from P2P markets. In more detail, a pioneering work is analyzed in [15], which presents an operation strategy of an ESP to facilitate DSM. In order to achieve this, it allows BSS to be operated from end consumers and network operators in a cooperative fashion. Furthermore, [16] proposes an algorithm towards the optimal interaction between: (i) energy consumers with DSM capabilities, and (ii) an ESP which operates its DSM. Finally, in [17], there is a trade among the end users and the BSS owners with the energy markets according to the prices of the latter. In this context, there is a harmonization

between production and demand, while at the same time, the end users trade energy with the BSS or the grid according to the announced prices. This process is modeled as a non-cooperative Stackelberg game among the aforementioned participants.

The proposed work advances these works by allowing an ESP to co-optimize the RES and flexibility assets with respect to the distribution network constraints and by modeling the existing energy markets. In this way, it achieves higher financial sustainability for the FlexAsset operator (i.e., MGO) and thus energy services with lower cost for the end users (i.e., members of the local energy community).

3. System Model

Without loss of generality, this work considers a transmission grid that is characterized by a set of buses and a set of transmission lines. We also assume a Distribution Network (DN), which could be seen as a tree whose root is located at a given bus of the transmission grid (cf. outlined area in Figure 1). The DN is operated by a local DN operator or else MGO. The business model of the MGO is analyzed earlier in the introductory section. According to it, MGO is responsible for controlling the BSSs and the flexible loads in order to strategically participate in the day-ahead energy market. In this way, it offers energy services with minimum cost to the local community and high financial sustainability for local RES operators. Ideally, the objective of the MGO is to use all its available local RES and thus avoid RES spillage. In addition, if the energy that the local RES produces is smaller than local demand, MGO buys energy from the main grid at the lowest possible cost. At the same time, the MGO has to ensure the reliable operation of its network, which is a quite difficult task especially in high RES penetration scenarios, where local RES curtailment should be kept at a minimum. Without loss of generality, in this paper, RES curtailment is not considered, and it is assumed that the MGO is obliged to take any necessary measures in order to avoid RES spillage. In this way, the occurring infeasibilities and the need for investments is emphasized. For example, as shown in Figure 1, a congestion problem may occur due to the weak connection linking the energy island/remote energy community with the main grid. Moreover, at the network edges, it is highly probable that various local voltage and congestion problems may occur frequently due to the expected high RES penetration and the rather weak connections within the local DN. The goal of this paper is to calculate the MGO's optimal bidding strategy in the day-ahead energy market and the optimal schedule of the FlexAssets, while simultaneously taking into account the distribution network constraints.

The proposed system model is applicable to energy communities, cooperatives (i.e., RESCoops [18]), islands and municipal/local electric utilities, which own/aggregate local RES, local FlexAssets and operate the local DN at the same time. In these cases, the facilitation of local and bottom-up RES and FlexAsset investments is essential, strengthening the energy autonomy and having lower costs in the long term. This is due to the fact that investments in stronger interconnection points with the main grid or local network reinforcements have higher financial cost and/or very high uncertainty due to bureaucratic procedures. In order to adequately present the advantages of the proposed business model of this work, we evaluate two main RES penetration scenarios. The first is the high RES penetration scenario. Its objective is to eliminate local RES curtailment and achieve network feasibility at the same time (i.e., satisfy the constraints of the distribution network). Thus, this case is dedicated to network-aware bidding. On the second scenario, where RES penetration is low, we assume that demand cannot be satisfied by local RES. Thus, this case is dedicated to market-aware bidding to minimize energy costs. Both network-aware and market-aware bidding aspects of the proposed framework are formulated below.

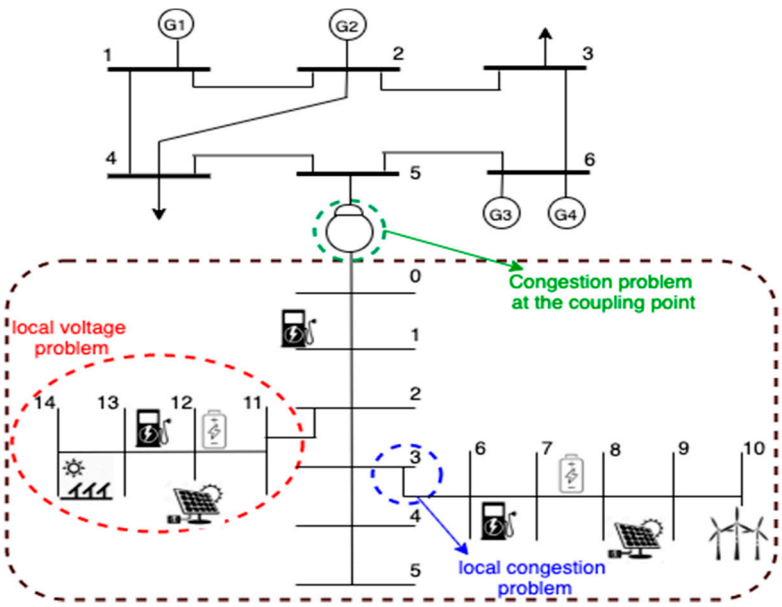

Figure 1. System model.

4. Problem Formulation

The MGO's decision process can be formulated as a bi-level problem [19], where the Upper-Level (UL) problem represents the minimization of MGO's energy costs and the Lower-Level (LL) represents the market clearing process that derives the Locational Marginal Prices (LMPs) at the transmission network level. The generated Mathematical Problem with Equilibrium Constraints (MPEC) constitute the MGO, a price maker entity that is able to anticipate the electricity market's reaction to its decisions (quantity/price bids) and affect the system's marginal price. In order to model this process, a Stackelberg Game is formulated in which the MGO is the "Leader" and the day-ahead energy market is the "Follower". The problem is solved from the MGO's point of view that acts strategically. Hence, an Optimization Problem constrained by an Optimization Problem (OPcOP) is formulated, in which the UL problem is constrained by the LL problem. The LL problem can be substituted by its KKT conditions, since it is a standard LP. This set of constraints corresponding to the KKT conditions of the LL problem, is equivalent to an equilibrium problem, since it contains the complementary slackness constraints. Complementary slackness constraints constitute the complementarity conditions which are the basic characteristics of an equilibrium problem. Thus, the final problem is formulated as an MPEC, namely an optimization problem constrained by an equilibrium problem.

4.1. Upper Level (UL) Problem—MGO Minimizes Its Costs

In order for the MGO to schedule its FlexAssets in a network- and market-aware manner, its cost function is defined as:

$$\min_{X_U} \sum_{t \in H} \sum_{i \in N^G} \lambda_{i,t} \cdot p^M_{i,t}, \tag{1}$$

This optimization problem is subject to various constraints related to the operation of the: (i) shiftable loads (i.e., DSM units), (ii) BSS units, (iii) DN, and (iv) quantity bids. When a DN located at bus $i \in N^G$ supplies power to the main grid at timeslot t, it sells this power in the pool market at price $\lambda_{i,t}$, which is the nodal price (LMP) at bus i. In contrast, when a DN i draws power from the grid, it buys that power from the pool market at price $\lambda_{i,t}$. The amount of power to be sold or purchased at a specific bus and timeslot denoted as $p^M_{i,t}$ is a decision variable of MGO's problem.

4.1.1. Modeling of Battery Storage System (BSS) Units

MGO manages the BSS' charging/discharging schedules. At each DN $i \in N^G$ and timeslot $t \in H$, a BSS $b \in B_i$ (physical or virtual through the aggregation of several distributed BSS) has to be charged or discharged. Charging (or discharging) power $r^{ch}_{i,b,t}$ ($r^{dis}_{i,b,t}$) is limited by the BSS' maximum charging (or discharging) rate $r^{ch,max}_{i,b}$ ($r^{dis,max}_{i,b}$), respectively. Thus:

$$0 \leq r^{ch}_{i,b,t} \leq \left(1 - x_{i,b,t}\right) r^{ch,max}_{i,b}, \forall i \in N^G, b \in S_i, t \in H \tag{2a}$$

$$0 \leq r^{dis}_{i,b,t} \leq x_{i,b,t} r^{dis,max}_{i,b}, \forall i \in N^G, b \in S_i, t \in H \tag{2b}$$

where $x_{i,b,t}$ is a binary variable indicating the operating status of each DN's BSS at t (i.e., $x_{i,b,t} = 1$ when BSS s located in DN i is discharged at t, and $x_{i,b,t} = 0$ when it is charged). We denote by $H = \{1, 2, \ldots, T\}$ the scheduling horizon considered. Moreover, the State of Charge $SOC_{i,t,b}$ of BSS b in DN i at any time interval t cannot exceed a lower bound $SOC^{min}_{i,b}$ and an upper bound $SOC^{max}_{i,b}$:

$$SOC_{i,b,t} = SOC_{i,b,0} - \sum_{\tau=1}^{t} \left(\eta^d_{i,b} \cdot r^{dis}_{i,b,\tau} - \eta^c_{i,b} \cdot r^{ch}_{i,b,\tau}\right), \forall i \in N^G, b \in S_i, t \in H \tag{2c}$$

$$SOC^{min}_{i,b} \leq SOC_{i,b,t} \leq SOC^{max}_{i,b}, \forall i \in N^G, b \in S_i, t \in H \tag{2d}$$

The constants $\eta^d_{i,b} > 1$ and $\eta^c_{i,b} < 1$ denote the discharge and charge efficiency factors, respectively.

4.1.2. Modeling of Shiftable Loads (DSM Units)

Shiftable loads form the second type of FlexAssets that are managed by the MGO. A shiftable load $l \in F_i$, $i \in N^G$, must fulfill a specific task within a desired time schedule $\left[\alpha_{i,l}, \beta_{i,l}\right] \subseteq H$, meaning that a certain amount of energy $E^{fl}_{i,l}$ must be consumed by load l within that interval. Outside its desired time interval, the power consumption of the shiftable loads is zero, while inside, it has an upper limit $p^{fl,max}_{i,l}$ on its consumption rate. Thus, the operating constraints of the shiftable load $l \in F_i$ are:

$$\begin{cases} 0 \leq p^{fl}_{i,l,t} \leq p^{fl,max}_{i,l}, \text{ if } t \in \left[\alpha_{i,l}, \beta_{i,l}\right] \\ p^{fl}_{i,l,t} = 0, \text{otherwise} \end{cases} \tag{3a}$$

$$\sum_{t=\alpha_{i,l}}^{\beta_{i,l}} p^{fl}_{i,l,t} = E^{fl}_{i,l}, \forall i \in N^G, l \in F_i \tag{3b}$$

4.1.3. Modeling of the Distribution Network (DN)

All MGO's scheduling decisions must satisfy the DN's power flow constraints. In order to model the DN, we use the linearized DistFlow equations introduced in [20] and widely used in the literature. The DistFlow model may be less accurate than various AC-OPF models, but it is far more scalable in terms of network size, while it maintains voltage-related constraints:

$$\sum_{k \in \Omega^d_i(n)} p_{i,nk,t} = \sum_{j \in \Omega^p_i(n)} p_{i,jn,t} - p^{fl}_{i,n,t} - p^{infl}_{i,n,t} + p^{rg}_{i,n,t} + r^{dis}_{i,n,t} - r^{ch}_{i,n,t}, \forall i \in N^G, n \in V_i, t \in H \tag{4a}$$

$$\sum_{k \in \Omega^d_i(n)} q_{i,nk,t} = \sum_{j \in \Omega^i_p(n)} q_{i,jn,t} - \delta^{fl}_{i,n} p^{fl}_{i,n,t} - \delta^{infl}_{i,n} p^{infl}_{i,n,t} + \delta^{rg}_{i,n} p^{rg}_{i,n,t}, \forall i \in N^G, n \in V_i, t \in H \tag{4b}$$

$$U_{i,n,t} = U_{i,j,t} - 2 \cdot \left(r_{i,jn} \cdot p_{i,jn,t} + x_{i,jn} \cdot q_{i,jn,t}\right), \forall i \in N^G, (n, j) \in B_i, t \in H \tag{4c}$$

$$U_{i,n}^{min} \leq U_{i,n,t} \leq U_{i,n}^{max}, \forall i \in N^G, n \in V_i, t \in H \tag{4d}$$

$$p_{i,nk}^{min} \leq p_{i,nk,t} \leq p_{i,nk}^{max}, \forall i \in N^G, (n,k) \in B_i, t \in H \tag{4e}$$

$$q_{i,nk}^{min} \leq q_{i,nk,t} \leq q_{i,nk}^{max}, \forall i \in N^G, (n,k) \in B_i, t \in H \tag{4f}$$

Equation (4a–c) are the branch flow equations. Variables $p_{i,nk,t}$ and $q_{i,nk,t}$ denote the active and reactive power, respectively, flowing on the branch nk connecting nodes $n \in V_i$ and $k \in V_i$, $i \in N^G$. Furthermore, $p_{i,n,t}^{fl}$, $p_{i,n,t}^{infl}$, and $p_{i,n,t}^{rg}$ are the active powers of flexible loads, inflexible loads and RES in node $n \in V_i$ at timeslot t, respectively. In addition, $\delta_{i,n}^{fl}$, $\delta_{i,n}^{infl}$ and $\delta_{i,n}^{rg}$ convert the active power of the shiftable loads, inflexible loads and RES units at node $n \in V_i$ into their reactive power $\left(\delta = \tan(cos^{-1}(powerfactor)\right)$. Furthermore, $U_{i,n,t}$ is the square of the voltage, while $r_{i,jn}$ and $x_{i,jn}$ are the resistance and the reactance, respectively, of branch jn in DN i. Equation (4d) imposes the lower ($U_{i,n}^{min}$) and the upper ($U_{i,n}^{max}$) limit on the voltage amplitude of node $n$in DN i. Finally, Equation (4e,f) constraint up ($p_{i,nk}^{max}$, $q_{i,nk}^{max}$) and down ($p_{i,nk}^{min}$, $q_{i,nk}^{min}$) the active and reactive power flows of branch nk in DN i, respectively. The sets $\Omega_i^d(n)$ and $\Omega_i^p(n)$ represent the decedent and precedent nodes, respectively, connected to node n in radial DN i. The root of each radial DN ($n = 0$), connected to the transmission grid, is the substation. In substations (where the power is sold/purchased to/from the market), the active and reactive power balance equations must hold:

$$\sum_{0k} p_{i,0k,t} = p_{i,t}^M, \forall i \in N^G, (0,k) \in B_i, t \in H \tag{4g}$$

$$\sum_{0k} q_{i,0k,t} = Q_{i,t}, \forall i \in N^G, (0,k) \in B_i, t \in H \tag{4h}$$

In Equation (4g), $p_{i,t}^M$ denotes the power that DN i draws from the grid at timeslot t. A negative value of $p_{i,t}^M$ indicates that DN i supplies power to the grid. In Equation (4h), $Q_{i,t}$denotes the reactive power that i exchanges with the grid at timeslot t.

4.1.4. Modeling of the Quantity Offers/Bids

We assume a nodal wholesale electricity market, in which MGO has to optimally choose for each DN i and timeslots $t \in H$ its energy offers/bids ($o_{i,t}$, $b_{i,t}$). The latter are limited by each DN's total power net capacity ($o_{i,t}^{max}$ and $b_{i,t}^{max}$):

$$0 \leq o_{i,t} \leq h_{i,t} \cdot o_{i,t}^{max}, \forall i \in N^G, t \in H \tag{5a}$$

$$0 \leq b_{i,t} \leq (1 - h_{i,t}) \cdot b_{i,t}^{max}, \forall i \in N^G, t \in H \tag{5b}$$

In Equation (5a,b), $h_{i,t} = 1$ if DN i sells power in wholesale market at timeslot t and $h_{i,t} = 0$, if it purchases power. We have:

$$o_{i,t}^{max} = \sum_{n \in R_i} p_{i,n,t}^{rg} + \sum_{n \in S_i} r_{i,n}^{dis,max} - \sum_{n \in L_i} p_{i,n,t}^{infl}, \forall i \in N^G, t \in H \tag{5c}$$

$$b_{i,t}^{max} = -\sum_{n \in R_i} p_{i,n,t}^{rg} + \sum_{n \in S_i} r_{i,n}^{ch,max} + \sum_{n \in F_i} p_{i,n}^{fl,max} + \sum_{n \in L_i} p_{i,n,t}^{infl}, \forall i \in N^G, t \in H \tag{5d}$$

Equation (5c,d) express the maximum quantity offer ($o_{i,t}^{max}$) and bid ($b_{i,t}^{max}$) that DN i can submit at time t, respectively. Recall that R_i, S_i, L_i and F_i denote the sets of nodes in which RES, BSS, inflexible load and flexible loads are located in DN i, respectively. Quantity offers/bids are also limited by the active power capacity of the coupling point between the DN i and the transmission grid, that is:

$$o_{i,t}, b_{i,t} \leq \sum_{0k} p_{i,0k}^{max}, \forall i \in N^G, (0,k) \in B_i, t \in H \tag{5e}$$

Finally, the MGO decides on the price bid that DN i submits to the day-ahead market in timeslot t, which is denoted by $c^M_{i,t}$.

Conclusively, the set of decision variables of MGO's problem (1) can be denoted as $X_U = \left\{r^{dis}_{i,b,t}, r^{ch}_{i,b,t}, x_{i,b,t}, SOC_{i,b,t}, p^{fl}_{i,l,t}, p_{i,nk,t}, q_{i,nk,t}, U_{i,n,t}, Q_{i,t}, o_{i,t}, b_{i,t}, h_{i,t}, c^M_{i,t}\right\}$.

4.2. Lower Level (LL) Problem—Market Operator (MO) Minimizes Social Cost

The energy market is cleared by solving problem (1), to calculate the dispatches and the LMPs. This minimizes the social cost, while accounting for: (i) the transmission grid constraints, (ii) the participants' quantity offers/bids and (iii) price bids. Thus, MO decides on the energy dispatch schedules of the market participants (generators, demand aggregators and MGO) by solving a DC-OPF problem:

$$\min_{X_L} \sum_{t\in H}\left(\sum_{i\in G}\left(c^g_{i,t}\cdot g_{i,t}\right) - \sum_{i\in D}\left(c^d_{i,t}\cdot d_{i,t}\right) + \sum_{i\in V^M}\left(c^M_{i,t}\cdot p^M_{i,t}\right)\right) \tag{6}$$

$$s.t. - g_{i,t} + d_{i,t} - p^M_{i,t} + \sum_{j\neq\iota} y_{ij}\cdot\left(\theta_{i,t} - \theta_{j,t}\right) = 0, \forall i \in N, (i,j) \in L, t \in H, (\lambda_{i,t}) \tag{6a}$$

$$g^{min}_i \leq g_{i,t} \leq g^{max}_i, \forall i \in G, t \in H, (\varphi^{gmin}_{i,t}, \varphi^{gmax}_{i,t}) \tag{6b}$$

$$-RD_i \leq g_{i,t} - g_{i,t-1} \leq RU_i, \forall i \in G, t > 1, (\varphi^{grd}_{i,t}, \varphi^{gru}_{i,t}) \tag{6c}$$

$$-RD_i \leq g_{i,1} - g_{i,0} \leq RU_i, \forall i \in G, (\varphi^{grd}_{i,1}, \varphi^{gru}_{i,1}), \tag{6d}$$

$$d^{min}_{i,t} \leq d_{i,t} \leq d^{max}_{i,t}, \forall i \in D, t \in H, (\varphi^{dmin}_{i,t}, \varphi^{dmax}_{i,t}) \tag{6e}$$

$$-b_{i,t} \leq p^M_{i,t} \leq o_{i,t}, \forall i \in N^G, t \in H, (\varphi^{mmin}_{i,t}, \varphi^{mmax}_{i,t}), \tag{6f}$$

$$-T^{max}_{ij} \leq y_{ij}\cdot\left(\theta_{i,t} - \theta_{j,t}\right) \leq T^{max}_{ij}, \forall (i,j) \in L, i < j, t \in H, (\varphi^{lmin}_{ij,t}, \varphi^{lmax}_{ij,t}) \tag{6g}$$

The decision variables of optimization problem (6) are: (i) the power supply $g_{i,t}$ of each generator $i \in G$, (ii) the power consumption $d_{i,t}$ of each demand aggregator $i \in D$, (iii) the power supply/consumption $p^M_{i,t}$ of each DN and (iv) the voltage phase angles $\theta_{i,t}$ at all buses $i \in N^G$ at timeslot t. The price bids of generators and demand aggregators at timeslot t are denoted by $c^g_{i,t}$ and $c^d_{i,t}$, respectively. Equation (6a) expresses the power balance at bus i of the grid. The dual variables of these constraints provide the LMPs. In Equation (6a), y_{ij} is the admittance of transmission line $ij \in L$. Equation (6b) refers to the generators' minimum and maximum capacity, while Equation (6c) and (6d) express the constraints on the ramp up and down limits, denoted by RU_i and RD_i respectively. Equation (6e) refers to demand loads' upper ($d^{max}_{i,t}$) and lower bounds ($d^{min}_{i,t}$), while Equation (6g) constraints the power flow to the transmission lines' ij capacity limits (T^{max}_{ij}). Furthermore, constraint Equation (6f) enforces MO's decision concerning the power that is traded with the DNs to not be higher than the submitted offers/bids. The dual variables pertaining to each constraint of DC-OPF are specified in the parentheses following each constraint (Equation (6a–g)).

4.3. Solution Method

The formulated problem has a bi-level structure and has to be converted into a single optimization problem in order to be solved using a commercial solver. Thus, we follow the same procedure as in [12–14]. In our bi-level optimization problem, the constraining LL problem (6) is a Linear Program and therefore, Slater's condition holds [21]. Thus, DC-OPF problem's Karush–Kuhn–Tucker conditions are necessary and sufficient optimality conditions (satisfy convexity and constraint qualification). Therefore, solving the DC-OPF is equivalent to solving its KKT conditions, which is a non-linear system of equations. As a result, the LL problem is converted into a set of non-linear constraints

of the UL problem, and our problem becomes a single Mixed Integer Nonlinear Problem (MINLP). The non-linearities coming from the complementarity conditions (subset of KKT conditions) are tackled using the Big-M linearization [22]. More specifically, the complementarity conditions are of the form:

$$x \cdot y = 0 x, y \geq 0$$

or using the perpendicular symbol:

$$0 \leq x \perp y \geq 0$$

First, we introduce a binary variable u which indicates whether x or y is non-zero. Then, we replace each complementarity condition with the following set of linear inequalities:

$$0 \leq x \leq M \cdot u$$

$$0 \leq y \leq M \cdot (1 - u)$$

where M is a large constant.

The non-linearities in the objective function are linearized using the Strong Duality Theorem applied to the LL problem as in [13,14,23]. Finally, the initial bi-level problem is transformed into an equivalent single Mixed Integer Linear Problem (MILP), which can be easily solved using a commercial MILP solver.

5. Performance Evaluation Results

5.1. Simulation Setup

In order to evaluate our proposed model and framework, we use a 6-bus test system with four conventional generators and two load buses. A 15-node radial DN is connected to bus 5 (Figure 1). The transmission grid lines, generators and load data can be found in [23]. Loads are located on nodes 1, 2, 3, 4, 6, 7, 10, 11 and 12 of the DN. Load and line data for the DN are based on data in [24] and can be found in our recent work in [25]. We discretize the time horizon into 24 hourly timeslots. The interested reader can find extensive details about all the input data and performance evaluation results of this paper in [26].

In the following, we consider two main scenarios. The first scenario called "high RES penetration" considers a long-term future context, in which the MGO will be required to make optimal RES and FlexAsset investments in order to maximize local RES usage (or else minimize local RES spillage) for the sake of its local energy community members. On the contrary, the second scenario called "low RES penetration" considers a shorter-term future context, in which the MGO is mostly interested in minimizing the energy cost of its local energy community by optimally scheduling its RES and FlexAssets through temporal arbitrage.

5.2. High RES Penetration Scenario

In this scenario, we evaluate the network-aware bidding property of our model to maximize local RES usage. We assume that the MGO acts as a price taker in the wholesale energy market. This means that MGO schedules its RES and FlexAssets in a market-price-sensitivity agnostic manner. We also assume that local RES curtailment is not allowed so that a feasibility of network flows is achieved in a zero local RES spillage context. It should be noted that the proposed model can support an acceptable level of RES spillage (e.g., a maximum of 10% or 20% of nominal RES capacity to be curtailable) in a straight-forward manner.

5.2.1. Impact of RES and FlexAssets' Siting (Location) in the DN

In this subsection, we study the impact of RES siting in the MGO's FlexAssets' investment decision. First, we consider two cases for the locations that the RES units will be installed within the distribution

network (cf. Table 1). In the first case, we consider nodes 2, 8, 11 and 13 for RES installation (i.e., non-critical location case), while in the second case (Case 2), we select nodes 2, 5, 10, 11 and 13 (i.e., critical location case). By the term "critical location", we mean that intermittent and variable RES assets are sited at the edge nodes of the network (i.e., nodes 5 and 10) incurring greater problems in terms of local congestion and voltage management. We consider both types of RES (i.e., PVs and wind turbines). In both cases mentioned above, we have selected nodes 5, 8, 10 and 13 to install identical BSSs and we assume that a part of the loads in nodes 2, 3, 4, 6 and 7 are flexible, resulting in a total capacity of 1MW flexible load. This load is assumed to operate during the peak hour (i.e., 18:00); however, it can be shifted from 16:00 to 20:00. In each one of the two aforementioned cases, we examine two subcases. In the first case (Cases 1a, 2a), the nominal RES capacity is 1.5 times higher than the nominal peak load, while in the latter case (Cases 1b, Case 2b), the nominal RES capacity is two times higher than the nominal peak load. The two subcases are noted in Figure 2 as 150% and 200% RES penetration, respectively.

Table 1. High RES penetration Scenario—Summary Table.

	RES Penetration (%)	RES Location (nodes)	BSS Location (nodes)	Flexible Loads Location (nodes)	Flexible Loads Size (MW)
Case 1a	150	2, 8, 11, 13	5, 8, 10, 13	2, 3, 4, 6, 7	1
Case 1b	200	2, 8, 11, 13	5, 8, 10, 13	2, 3, 4, 6, 7	1
Case 2a	150	2, 5, 10, 11, 13	5, 8, 10, 13	2, 3, 4, 6, 7	1
Case 2b	200	2, 5, 10, 11, 13	5, 8, 10, 13	2, 3, 4, 6, 7	1

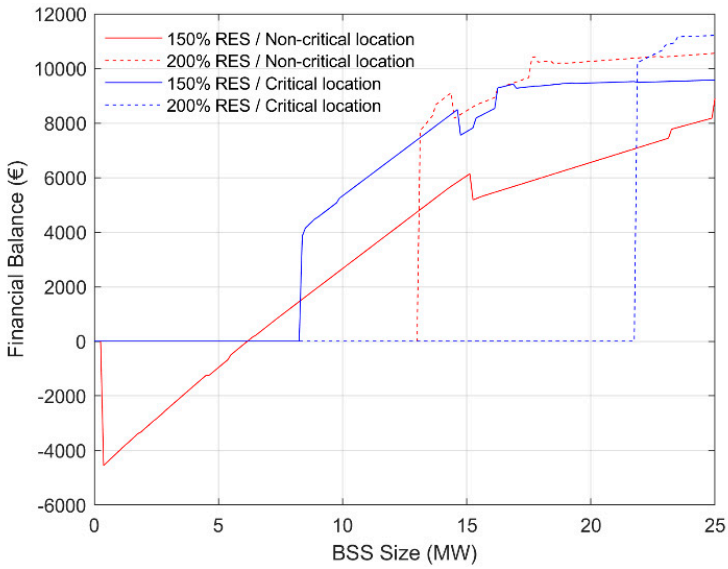

Figure 2. Microgrid Operator (MGO)'s financial balance as a function of Battery Storage System (BSS) size for critical and non-critical Distribution Network (DN) location cases under two RES penetration subcases.

Figure 2 depicts the financial balance (profit/deficit) that MGO has as a function of BSS size. BSS is needed in order to keep the distribution network within its operating limits and avoid, in this way, a RES spillage phenomenon. Note that the size of BSS highly depends on the siting and the sizing of the RES units (which is depicted and handled as an input parameter in the two subcases). In Figure 2, zero financial balance implies an infeasible distribution network operation. In other words, the MGO will have to pay the very high Value of Lost Load (VOLL) for all the time that the network is in an unstable condition. Positive and negative financial balance implies that MGO has profits and deficit, respectively. In the non-critical location case and for 150% RES penetration, MGO needs to install at least 375 kW of total BSS power capacity in order to safely operate its network, while for 200% RES

penetration, it needs to install at least 13,130 kW BSS. In the critical location case and in the subcases of 150% and 200% RES penetration, the MGO has to install at least 8375 and 21,880 KW of BSS power capacity, respectively. We see that, in these specific setups and under both the non-critical and critical location cases, 200% RES penetration requires the most BSS power capacity and leads to more market profit for the MGO, but this comes at the expense of higher BSS investments. Given the very high VOLL, the eligible distribution network nodes that are to put more RES units in in the future are the ones in the "non-critical" case. This is quite important for the MGO's business model in order to be able to prioritize the installation of its future RES and respective FlexAssets in the correct nodes of the distribution network.

5.2.2. Impact of RES and FlexAsset Sizing

As far as it concerns the impact of the RES sizing on the MGO's financial balance and based on siting results from Figure 2 above, we select the eligible RES sizes in order to have network feasibility outcomes. Thus, we continue only with the "non-critical location" network case presented above, as it would not be useful to consider infeasible network setups (which take place in critical location cases), where the MGO's investment costs on FlexAssets would be huge.

The next step is to examine the financial outcome for the MGO (either profit or deficit) under four high RES penetration scenarios. In more detail, Figure 3 depicts the financial balance of the MGO as a function of the installed BSS power capacity under 120%, 140%, 160% and 180% RES penetration scenarios (note that zero values of financial balance imply network infeasibility). As expected, based on the results of Figure 2, for RES penetration up to 140%, the distribution network can operate safely even without (i.e., zero) BSS installations, but with 1MW flexible load capacity (see non-zero financial balance values for all BSS size values). Of course, MGO's financial balance increases linearly as the BSS size increases, too. For 160% RES penetration, the minimum total BSS capacity that is needed to ensure zero RES spillage is 2400 kW, while for 180% RES, the minimum BSS power requirement is 6500 kW. An MGO can reduce its daily operating cost by installing centralized BSSs or aggregating distributed residential storage units. In order for a price taker MGO to make profits by selling energy to the grid, a significant amount of investment has to take place. For example, for 160% RES, a 5400 kW BSS power capacity is needed. This is very important for the MGO, who can easily measure the CAPEX (i.e., Capital Expenditures) versus OPEX (i.e., Operational Expenditures) trade-off in order to incorporate this type of calculations in its business model.

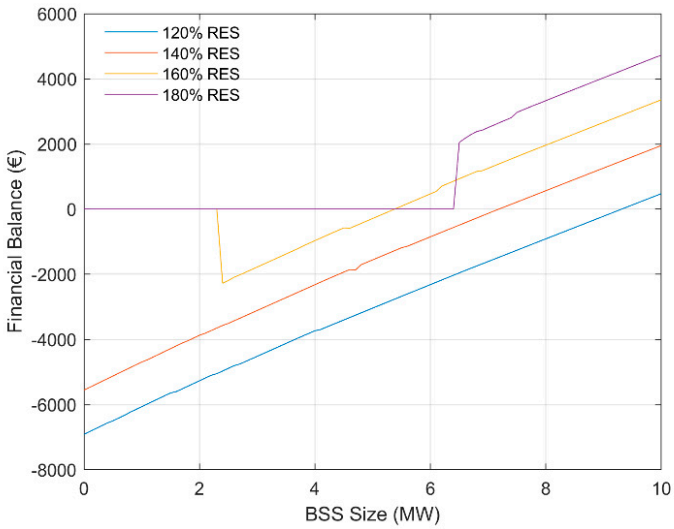

Figure 3. MGO's financial balance as a function of BSS size for different RES sizes under the non-critical locations case.

5.2.3. Optimal FlexAssets' Sizing and Scheduling

We now proceed to find the optimal FlexAsset size to maximize MGO's profits for a few RES penetration setups. As already seen, for the specific RES and FlexAsset siting, up to 140% RES penetration is safe for the network to operate within its limits. Thus, we now examine three more conservative subcases of RES production, namely 100%, 120% and 140% RES penetration.

Figure 4 depicts MGO's financial balance as a function of BSS under the three aforementioned subcases. From Figure 4, it is observed that, in all RES penetration cases, the MGO's financial benefit increases with the total power capacity of the BSS, up to a saturation point. This is the optimal BSS sizing. Beyond this BSS size, the MGO does not gain any more profit, corresponding to an over-investment context that should be avoided by the MGO. It is highlighted that in the higher RES penetration subcase, the MGO's profits stop increasing for less BSS capacity (29,000 kW) than in the other two subcases (33,500 and 38,000 kW for 120 and 100% RES penetration, respectively). This is because the less RES production capacity is installed in the distribution network, the more the FlexAssets are dispatched in order to maximize MGO's profits by employing temporal arbitrage.

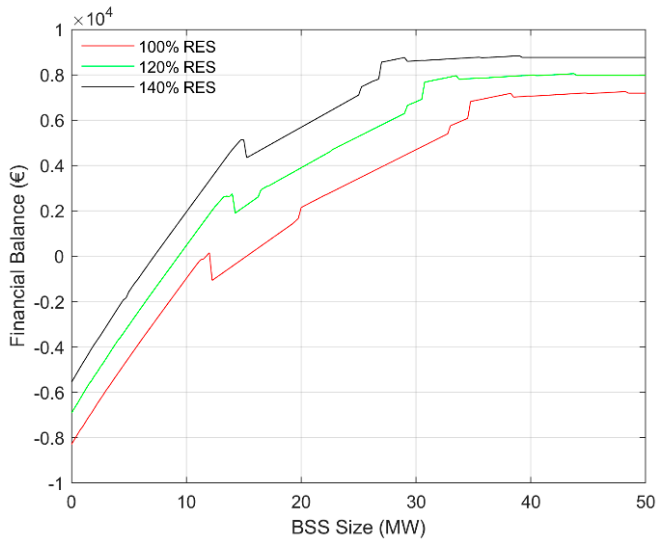

Figure 4. MGO's financial balance as a function of BSS size (optimal FlexAsset sizing to maximize MGO's profits).

5.3. Low RES Penetration Scenario

So far, we have only examined high RES penetration cases that will most probably appear in some years from now. However, we ask, how could an MGO lower its energy costs today where it possesses a relatively low amount of local RES and FlexAssets and it mostly draws power from the higher-level transmission grid? Therefore, we now evaluate the market-aware bidding property of our model to minimize the energy cost in a more realistic today's low RES penetration scenario. In this scenario, the MGO is a price-maker market entity (i.e., we model the affection in the prices of the wholesale energy market that MGO's bidding policy has). We compare the price-maker algorithm to the price taker solution. In more detail, Figure 5 depicts the MGO's cost under six network setups with low RES penetration (in this scenario the financial balance is always negative, and we note it as "MG cost"). In the first three network setups of Figure 5, we assume 80% RES penetration and in the last three, 60%. In setups 1 and 4, MGO decides to invest only in DSM (i.e., 35% of the nominal peak load can be shifted) and not at all in BSSs. In setups 2 and 5, the MGO has 500 kW of BSS power installed and 30% of the nominal peak load DSM capacity. Finally, in setups 3 and 6, the installed BSS power capacity increases to 2000 kW, while the DSM capacity remains at 30% of the nominal peak load. As can be seen in Figure 5, our algorithm outperforms the price taker solution in every setup by an average percentage of 8% in terms of the MGO's energy cost. This indicates that, even if its portfolio represents a small

portion of the wholesale market, the MGO can achieve a significantly smaller energy cost by acting strategically and implementing our proposed model, as opposed to adopting the price taker solution.

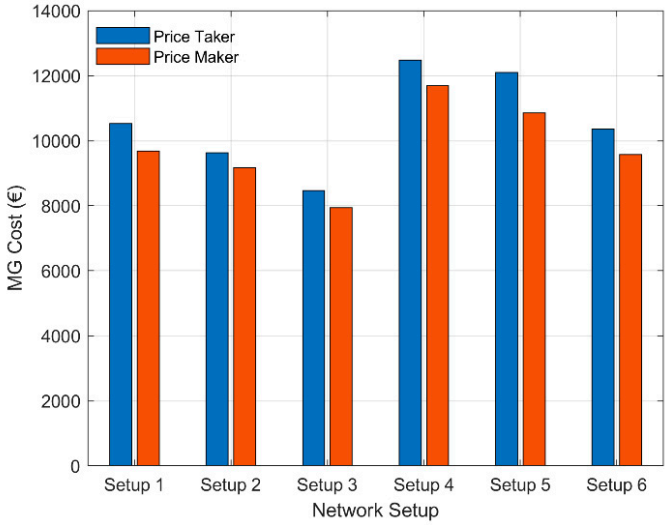

Figure 5. MGO's costs (price taker vs. price maker bidding).

6. Concluding Remarks and Future Work

We proposed a network- and market-aware bidding strategy to co-optimize RES and flexibility asset usage in energy islands (or else remoted local energy communities), which have a weak connection with the upper-level transmission network as well as have weak connections within the distribution network (and especially the network edges). In more detail, we proposed an MGO's operational framework, which can concurrently: (i) coordinate the scheduling and planning of various types of RES and FlexAssets, (ii) take into consideration local congestion and voltage-related constraints and allow a distribution network-aware RES and FlexAssets' exploitation policy, (iii) Co-optimize the operation of RES and FlexAssets and execute scenarios that facilitate the co-design of investments and (iv) model the competition in the day-ahead electricity market and thus allow MGO to exploit the competition and act as a price maker.

In this way, energy cost in an energy island setting is minimized, where weak grid connections and unstable network operation in a high RES penetration environment are considered. According to these, we assumed that the local energy communities may opt for RES and FlexAsset investments instead of traditional network upgrade and reinforcement investments. Simulation results show ways that optimal and coordinated planning and scheduling of RES and FlexAssets can boost green energy investments. As future work, we aim at looking more closely into optimal planning strategies using stochastic and robust optimization models. We also plan to elaborate on optimal FlexAsset scheduling policies in order to maximize profits through participation in several energy markets simultaneously, such as day-ahead, balancing, reserve and other emerging distribution network level flexibility markets. In addition, more accurate and detailed models regarding storage degradation cost, shiftable load cost and demand side management can be included in this framework. In that way, the formulation will become more practical and realistic.

Author Contributions: Conceptualization, N.E. and P.M.; Data curation, K.S. (Konstantinos Sterioti); Formal analysis, K.S. (Konstantinos Smpoukis) and G.T.; Funding acquisition, N.E., P.M. and E.V.; Investigation, N.E. and G.T.; Methodology, K.S. (Konstantinos Smpoukis); Project administration, P.M. and E.V.; Software, K.S. (Konstantinos Steriotis); Supervision, N.E., P.M. and E.V.; Visualization, K.S. (Konstantinos Steriotis); Writing—original draft, K.S.; Writing—review & editing, P.M. All authors have read and agreed to the published version of the manuscript.

Funding: The work presented in this paper received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No. 863876 in the context of the FLEXGRID project. Konstantinos Smpoukis is co-financed by Greece and the European Union (European Social Fund—ESF) through the Operational Program "Human Resources Development, Education and Lifelong Learning 2014–2020" in the context of the project "Strengthening Human Resources Research Potential via Doctorate Research—2nd Cycle" (MIS 5000432). Georgios Tsaousoglou received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 754462.

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

Nomenclature

Indices and Sets	
t	Timeslot index
i	Index of Distribution Networks (DNs)
b	Index of Battery Storage Systems (BSSs)
l	Index of shiftable loads
n, k, j	Indices of DNs' nodes
i, j	Indices of transmission grid buses
H	Scheduling horizon
N^G	Set of DNs
S_i	Set of BSSs in DN i
R_i	Set of renewable generators in DN i
F_i	Set of shiftable loads in DN i
L_i	Set of inflexible loads in DN i
V_i	Set of nodes in DN i
B_i	Set of branches in DN i
$\Omega_i^d(n)$	Set of decedent nodes of node n in DN i
$\Omega_i^p(n)$	Set of precedent nodes of node n in DN i
N	Set of buses of transmission grid
L	Set of transmission lines
G	Set of generators participating in energy market
D	Set of demand loads participating in energy market
X_U	Set of upper level optimization problem primal variables
X_L	Set of lower level optimization problem primal variables
Parameters	
$r_{m,b}^{ch,max}, r_{m,b}^{dis,max}$	Charging/Discharging power limits of BSS b located in DN i
$SOC_{i,b}^{max}, SOC_{i,b}^{min}$	Maximum/Minimum limits in SoC of BSS b located in DN i
$SOC_{i,b,0}, SOC_{i,b,T}$	Initial / Final SoC of BSS b located in DN i
$\eta_{i,b}^d, \eta_{i,b}^c$	Discharging/Charging efficiencies of BSS b located in DN i
$p_{i,l}^{fl,max}$	Maximum power that shiftable load l located in DN i can consume in a timeslot
$E_{i,l}^{fl}$	Total energy amount that shiftable load l located in DN i must consume in a time horizon
$a_{i,l}, b_{i,l}$	Plug in/Plug out times of shiftable load l located in DN i
$p_{i,n,t}^{infl}$	Power consumption of inflexible load located in node n of DN i in t
$p_{i,n,t}^{rg}$	Power production of renewable generator located in node n of DN i in t
$\delta_{i,n}^{\mathrm{fl}}, \delta_{i,n}^{\mathrm{infl}}, \delta_{i,n}^{\mathrm{rg}}$	Equals $\tan\left(cos^{-1}(Power\ Factor)\right)$ for shiftable loads, inflexible loads and renewable generators, respectively
$r_{i,jn}, x_{i,jn}$	Resistance/Reactance of line jn of DN i

$U_{i,n}^{min}, U_{i,n}^{max}$	Minimum/Maximum limits of nodal voltage magnitude of node n in DN i
$p_{i,nk}^{min}, p_{i,nk}^{max}$	Minimum/Maximum active power capacities of line nk in DN i
$q_{i,nk}^{min}, q_{i,nk}^{max}$	Minimum/Maximum reactive power capacities of line nk in DN i
$o_{i,t}^{max}, b_{i,t}^{max}$	Maximum quantity offer/bid that DN i can submit in t
$c_{i,t}^{g}, c_{i,t}^{d}$	Price bids of generators/demand loads located in bus i of transmission grid in t
B_{ij}	Element of Susceptance Matrix concerning line connecting buses i and j of transmission grid
g_i^{min}, g_i^{max}	Minimum/Maximum production limits of generator located in bus i of transmission grid
RD_i, RU_i	Ramp down/up capacities of generator located in bus i of transmission grid
$g_{i,0}$	Initial production state of generator located in bus i of transmission grid
$d_{i,t}^{min}, d_{i,t}^{max}$	Minimum/Maximum limits of demand load located in bus i of transmission grid at t
T_{ij}^{max}	Line capacity of line connecting buses i and j of transmission grid
Variables	
$r_{i,b,t}^{ch}, r_{i,b,t}^{dis}$	Charging/Discharging power of ESS b of DN i in t
$x_{i,b,t}$	Binary decision variable indicating the operating status (charging/discharging) of ESS b of DN i in t
$SOC_{i,b,t}$	Energy stored in t of ESS b of DN i
$p_{i,l,t}^{fl}$	Consumption of shiftable load d of DN i in t
$p_{i,nk,t}, q_{i,nk,t}$	Active/Reactive power that flows in line nk of DN i in t
$U_{i,n,t}$	Nodal voltage magnitude at node n of DN i in t
$p_{i,t}^{M}$	Active power that is traded between DN i and main grid in t
$Q_{i,t}$	Reactive power that flows from/to the substation of DN i in t
$o_{i,t}, b_{i,t}$	Quantity offer/bid of DN i in t
$h_{i,t}$	Binary decision variable indicating whether DN i sells or buys power in t
$c_{i,t}^{M}$	Price bid of DN i in t
$g_{i,t}$	Production level of generator located in bus of transmission grid in t
$d_{i,t}$	Consumption level of demand load located in bus i of transmission grid in t
$\theta_{i,t}$	Voltage phase angle at bus i of transmission grid in t
$\lambda_{i,t}$	Locational Marginal Price at bus i of transmission grid in t
φ	Lagrange multipliers of DC-OPF problem

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