A multi-agent system approach for optimal microgrid expansion planning under uncertainty

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Abstract

Power system planning for modern distribution networks is undergoing a change because of distributed power generation and grid ancillary services. The vast electricity retail utility industry with many distribution network operators plans generation and transmission expansion planning for determining optimal investment decisions. This paper addresses this planning problem in a decentralized and distributed context.

This paper introduces a coordinated decision making approach for optimal investments in generation and transmission expansion planning problems for distribution networks. The distribution networks are further classified into microgrids. Considering an agent as the functional information exchanging entity just like an energy meter with the objective to coordinate the expansion decisions of participants; a novel math-heuristic optimization model Coordinated Microgrid is presented. To simulate the coordination of information a multi-agent-system based coordinated decision making method is adopted and the value of coordination is investigated. The evolutionary vertical sequencing protocol, a heuristic method, is developed and implemented to simulate the coordination process among agents on the top level. The proposed protocol produces smart permutations of microgrids for coordination. On the bottom level, a two-stage chance-constrained stochastic MILP formulation for investment decisions with operational uncertainties is modelled. For market clearing a nodal-pricing scheme is adopted that maintains the Nash equilibrium among and across the microgrids for energy transactions. The proposed model is tested with consumption, network configuration data from three islands in west-coast of Norway. The models are solved to optimality and results lead to the observations that the value of coordination lies in profit increment of individual microgrid. The novel protocol proposed demonstrates an advantage of retrieving smart permutations from combinations of microgrids. In summary, CoMG is a novel expansion planning model for optimal investments in modern power distribution networks.

Keywords: microgrid; generation and transmission expansion planning; multi agent systems; coordinated decision making; math-heuristic technique; integrated uncertainty, mathematical optimization

1. Introduction

This paper introduces a novel approach for coordinated and strategic expansion planning under uncertainty with a multi-agent system. Microgrids (MGs) are small geographical areas with self-sufficient local production to mitigate the consumption of energy. MGs are becoming smart due to the integration of emerging smart information and communications technologies such as smart metering, lighting and thermostats. Meanwhile, one of the biggest retail utility infrastructures, the energy utility, is undergoing a reformation process to accommodate higher share of carbon-neutral alternative energy sources. Integrated Generation and transmission expansion planning(GTEP) problems for electrical power network expansion are standard power system problems. There are many variants of these problems considering the long term or short-term uncertainty levels and generation technologies [1]. Typically a GTEP is a mixed integer linear programming(MILP) formulation with the objective of minimizing the total investment cost

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that is comprised of cost of investment and operations. MILP approaches are widely used to evaluate the cost of capacity expansion through installation of new generation units and new transmission lines in a power network [2]. Fig. 1 shows the evolution of grid structures from the dispatchable type conventional resources based "top-down"

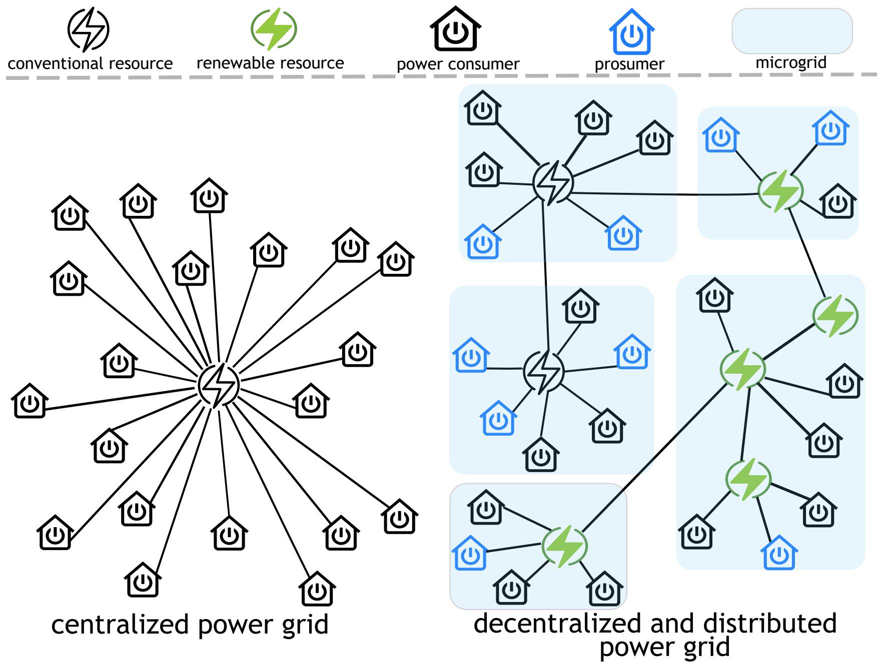

Figure 1: Grid structures: centralized, decentralized and distributed

power flow to contemporary high share of renewable resources (non-dispatchable) based distributed flow of power. The centralized power flow has a single conventional resource while in the other case there are multiple actors such as renewable energy resources, prosumers. Furthermore, the power flow in case of decentralized power flow is bi-directional. The transition from conventional to high renewable share based power system brings challenges in optimal power system planning such as balancing the demand-supply, prolific utilization of resources and optimal reserve capacity allocation to name a few. The traditional capacity expansion planning is not applicable to such a problem. Therefore, there is a need for strategic coordination for planning. For such a coordination, the information of power shortage and power surplus is the key. Grouping one or more non-dispatchable generation unit, prosumers and demand formulates a local microgrid. The demand and supply are local and therefore there is improvement in energy security.

1.1. Literature Overview

Energy Informatics is a relatively new field of research that combines the energy system and informatics into one[3, 4]. Microgrids can be termed as a power system network which spans over a geographically small region. Utilization of internet of things and smart appliances e.g, smart energy meters [5, 6] makes the MG a Smart-MG. An SMG essentially consists of modular energy production, dynamic load demand and smart control mechanisms formulating a local distribution system [7, 8, 9, 10]. Moreover an SMG can be decentralized i.e, autonomous power system of an island. Alternatively an SMG can be grid integrated meaning one or a group of SMGs tied together through many connections with the main power grid [11, 12]. An SMG permits the expansion of load demand without overloading the existing energy infrastructure or capacity expansion [13]. It facilitates grid security, stability and resiliency. It has geographical flexibility in deployment and therefore increases energy accessibility. An SMG has the advantage of easier reconfiguration and restructuring of the grid for new technology adaptation (i.e, information and communication technology), intelligent electronic devices (such as the Internet of Things) and smart control of responsive loads. Therefore an SMG has the advantages of proficient energy management and flexibility. Many studies have been conducted on multi-period GTEP considering uncertainty. Centralized control for the grid connected hybrid renewable energy system is proposed in [14]. However energy spillage and energy not served are the key challenges in optimal MG management. To overcome this, unit commitment and economic dispatch models are studied in [15, 16]. A dynamic reserve allocation method for dynamic day ahead unit commitment is proposed in [17]. Stochastic optimization models for MG expansion through investment decisions appear in literature as in [1, 18, 19, 20]. In [21, 22, 23, 24] hierarchical GTEP models are presented from central planner's perspective. However in modern power distribution network, there are many distribution network planners involved. In this context, coordination among the planners is essential for optimal and feasible investments. Note that, the power system reliability is a separate problem in this case where the central system planner's perspective is both optimal and feasible. A comprehensive analysis of multi-MG system is carried out and the permeability of the individual MG found to be improved in [25, 26]. However, the efficient and reliable co-ordination of the multi-MG is expressed as being something of a concern. In [27], a mesh of networked smart grids is presented to be the future power system. Multi-Agent-System (MAS) is extensively studied as the solution to automatize the grid operation [28, 29]. Furthermore MAS based control schemes for MG are found to be effective [30, 31]. A real time framework for SMG control using MAS is presented in [32]. These studies clearly outline that the synchronization and coordination among agents are important issues in the shared and connected information power infrastructure. The energy market is dynamically evolving with peer to peer energy transactions. In this new setup the role of system operators and prosumers is changing: specifically the role of SO is shifting from being an aggregator to provide energy security through network maintenance [33, 34]. To identify this transition the power industry uses the term "transactive energy". Transactive energy refers to the value added energy transaction within and across power system utilizing the economic and control techniques [35, 36, 37, 38]. Beyond theoretical studies, practical applications of transactive energy begins with LO3 energy [39].

A leader-follwer based model for generation and transmission expansion planning is presented in [40]. The proposed model has two layers, in first layer is dedicated for planning and second level for operations. In [41] a stochastic investment planning model to determine new microgrid installation is presented. However, the proposed model takes a decentralized approach to the planning problem from the distribution system operators perspective. Where each distribution operator determines optimal and practical investment strategies for generation and transmission capacity expansion through coordination with other distribution operators in the region. In [42] the authors reviewed various optimization models developed and applied to power distribution expansion planning problem in the last decade. The research outlines a shift from traditional static to integrated and multi-objective planning techniques. The proposed CoMG model based on math-heuristic technique is a step towards integrated and coordinated decision making for optimal and practical expansion. The following section will explain the key contributions of the proposed paper compared to the available scientific literature that have been discussed above.

1.2. Key Contributions

In the previous section some of the existing GTEP formulations were discussed. Nevertheless, distribution systems are different from transmission systems. For example in one country there maybe a single transmission network operator while there are several distribution system operators. While existing GTEP formulations can be applied to the transmission sector, they do not fit the contemporary distribution sector. The investment planning for a distribution system operator very much depends on the surrounding environment and thus MG coordination. Besides that, there is a growing interest in demand side participation (DSM) that increases the number of stakeholders. In contrast, a traditional centralized decision making no longer serves such a problem with conflicting interests exist. For the first time, this paper introduces the CDM (Coordinated Decision Making) approach in a GTEP context for distribution systems with operational uncertainties. The proposed CDM is a methodology which allows an optimal decision to be taken when considering the surrounding environment. The key contributions of this paper is the inclusion of a two-stage stochastic math-heuristic model within a CDM methodology. This results in a coordinated microgrid (CoMG) expansion planning formulation. Furthermore, the value of coordination and interactive decision making is reported. CoMG has been tested with real-world data from islands near Trondheim (Norway) and has turned out to be a tractable and scalable model for optimal grid expansion planning. To the best of the knowledge of authors, this is the first time that the MG GTEP problem has been addressed by integrating a two-stage stochastic MILP model with an heuristic CDM methodology. The inter-operation of heuristic algorithms with mathematical programming can be defined as a math-heuristic technique [43, 44]. The use of heuristics offers an advantage in terms of computational time by means of compromising the exact solution. Contrary to this, the mathematical model guarantees an exact solution. Combining them results in a "best of both worlds" solution. CoMG is a collaborative strategy based math-heuristic model: in a collaborative strategy, protocols exchange information but are not part of each other (in other words they they can be executed independently of one other). The advantage is that both models can be executed sequentially or in parallel. This paper focuses on the sequential approach. At the top layer of CoMG, a novel evolutionary heuristic protocol is implemented, known as an evolutionary vertical sequencing protocol.

In mathematical optimization models the problems are simplified with assumptions and adjusted as per context [45, 46, 47, 1, 48]. This work presents an investment model with operational insights. The objective of the optimization model is to determine total investments in installing new generation units and new power transmission lines. This is the initial power system investment planning phase and consideration of optimal power flow is not in the scope. The optimal power flow is considered in the successive paper. The model presented in the paper is developed in the context of decentralized power distribution system. A decentralized network refers to a network wherein multiple producers, consumers and prosumers are present. The motivations behind this model are:

- In a power infrastructure, there are usually one or two transmission system operators but many distribution system operators.
- The traditional generation and transmission expansion planning approach is inapplicable in this case because each DSO acts with the objective of profit maximization.
- Since it is a bottom-up model, the granularity of the problem is high when considering the scheduling of dispatchable generators, hourly time resolution and a complex distribution network structure.
- Dismantling such a big problem into smaller microgrids presents the advantages of tractability of an investment and realization.

The authors present a coordinated decision-making approach that coordinates the quantity and price information among newly formed microgrids. The newly formed microgrids are considered as being agents and therefore, the system becomes a multi-agent-system (MAS). For the purpose of information sharing, an evolutionary vertical sequencing (EVS) protocol is presented. The paper explains in detail the proposed EVS and the associated mathematical model. Its application in regard to a distribution network data-set is presented as a result to validate the model and technique. In a conventional combinatorial approach, the model explodes with combinations. To overcome this issue EVS is developed with the objective of minimizing the number of combinations. The results are presented side by side in the paper through the result table.

The rest of the paper is organized as follows: in section 2, the multi-agent-system is presented with its functions and coordination protocol; section 3 elaborates upon the mathematical model; in section 4, the information structure is depicted; thereafter section 5 describes computational experiments and discusses the results. Finally, in section 6, the paper is concluded with possible future directions for further research.

2. Coordinated Decision Making

This section describes the coordinated decision making process. It has two subsections: multi-agent systems (MAS) and the strategy to be used in terms of coordination. The coordination in this context refers to coordination in investment decision making plus the online coordination of transactions. While the information about investments and operations is coordinated between agents, the market is the platform for transactions. Notice that the only decisions that are made are about investments with stochastic operational insights.

The proposed mathematical optimization model is based on math-heuristic technique. A math-heuristic formulation is not globally optimal due to intrinsic heuristic properties. However, the math-heuristic formulation has two levels. On the top there is the heuristic technique for coordination, while on the bottom is an exact optimization model: individual problems for investment in each microgrid are in-fact solved to optimality. The results are then used within the math-heuristic approach for the communication and coordination framework. This is clarified in the section 2.2 coordination strategy. An optimal decision that is acted upon without taking into consideration information regarding decisions that have been taken by one's peers within the environment can be termed self-contained decision making. Contrary to this, an environmentally aware or informed decision-making process is termed coordinated decision making. The latter refers to the problem addressed in this paper that can be encapsulated as follows: given an existing SMG, there is a possibility of expansion taking place owing to foreseen increments in load demands, along with uncertain production from renewable resources, but the process of facilitating optimal expansion requires an optimal strategy both for the operations and investments. Note that optimal operation refers to optimal utilization of existing resources and optimal investment refers to installation of new resources. The main purpose of this paper is to provide a framework for investment planning under the conditions of carrying out peer-to-peer coordination between agents.

2.1. Multi Agent Systems

An agent is a computer system that is situated in a specific environment and is capable of autonomous action within this environment, in order to meet its design objectives. Communication between agents takes place through signals [49] . The multi-agent-system is an emerging trend in the decentralization of complex electrical networks and system operations. Elucidating upon this, each SMG consists of an agent and therefore the system is a multi agent system in which all agents are interconnected in a decentralized and distributed manner. This structure presents the advantage of a fault tolerant mechanism: in fact distributed power generation reduces the risk of total system blackouts and facilitates less reserve allocation. Furthermore the effect of the individual agent behavior in the MAS can be tracked throughout the system. The three layers of the agent with its strategies and functions is presented in fig. 2. The primary layer is reserved for internal operations that include scheduling of dispatchable generation, controlling the state of charge for the storage units that leads to optimal utilization of renewable resources. The secondary layer performs exact optimization in terms of optimal investments for generation and transmission expansion (GTEP). The tertiary layer is responsible for the coordination of information: the marginal cost of generation, energy available from dispatchable generation (the difference between nominal capacity and what is produced) and energy from renewable resources. The tertiary layer broadcasts the grid status and receives status update from other agents. Note that the marginal cost of generation becomes the price signal for other agents for the market clearances with the Nash equilibrium. For instance if new investments in energy resources are planned in an SMG, a neighborhood SMG may decide to participate in such activities instead of proceeding with investments of its own. The transactive energy (surplus or lack) information of every SMG are revealed to the peers through the tertiary layer of agents. The sharing of transactive energy information is the core of the CDM approach in contrast to the traditional decision making approaches, where every SMG is independent and therefore unaware of peers decisions. The CoMG, a two-stage stochastic optimization model, functions as the first and second layer of the agent. The proposed EVS protocol simulates the third layer of the agent.The information coordinated also includes the decisions taken in each stochastic scenario. Specifically, in this context case refers to scenarios (with probabilities of occurrences) of wind, demand and prices. Based on the stochastic information, energy volume (requirement and availability) with associated price signals, an SMG is presented an opportunity to perform a transaction with the peers: for instance an SMG can either buy or sell energy according to its individual profit. Such a decision may require additional investments in terms of establishing additional links between the grids.

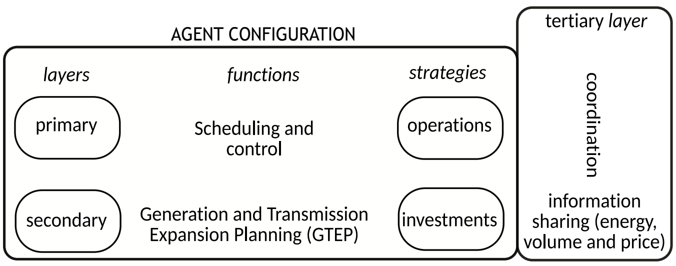

Figure 2: Agent configuration

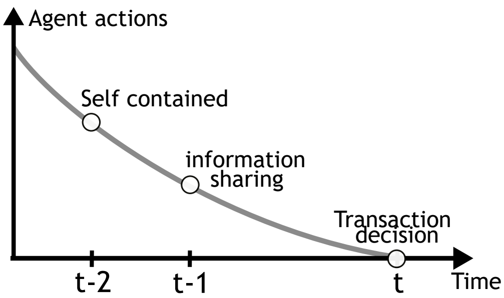

Figure 3: Coordination activities of an agent

The energy transaction prices are determined through the market clearing principle: energy flows from a lower price to a higher price. In CoMG, the market operates on the basis of the marginal cost of production i.e, perfect information of the cost for serving demand (risk neutral perfect information based Nash equilibrium pricing). Assuming that there is sufficient capacity for energy flow within the SMG, a zonal pricing scheme can be adopted. The zonal price is typically the average of the marginal nodal price in all nodes. Each zone refers to a single SMG with demand and production units [50, 51, 52, 53]. An SMG with central market connection or connected to transmission line follows the market pricing as an exogenous input for energy exchange price. An exchange price is set only among the SMG taking part in an energy transaction. The peer-peer interactive transactions are handled and settled on the market. The levels of CDM for an agent is presented in fig. 3. At level $t-2$ the self contained model is solved. This level determines the need for energy transactions. At level $t-1$ information sharing stage the information is broadcast and received. Finally in level t the transactions takes place. The planning time-horizon for CoMG is one year for investment decisions with hourly operational decisions. Therefore it can be seen that this approach takes short term uncertainty into consideration.

2.2. *Coordination Strategy*

The investment decisions can be individual or joint because cooperation between different participants is optional. This is because different actors in the optimization process have different objectives. The value of coordination lies in minimizing the gap between individual and joint decision making. It is an extremely complex and computationally expensive task to solve such a problem using traditional node-flow architecture [23, 54, 55]. In addition to that, the formulation of the problem when considering a group of SMGs which all may have different perspectives may make the problem intractable when it comes to solving it. Therefore to be able to overcome this problem, the CDM splits the total system into groups of multiple SMG with common properties. In other words actors with similar properties are grouped together.

Algorithm 1 Evolutionary Vertical Sequencing Protocol

```
P: a set of permutations
SP: a reduced set of permutations
G: a set of Microgrids
size: (large, medium, small)
capacity: (high, medium, low)
procedure EVS
    SP: get-smart-combinations (size, capacity, P)
    win-combination = null
    win-profit = 0
    for each permutation p in SP do
        lg = get-last-grid(p)
        for each grid g in p − 1 do
            solution[g]=solve-grid(g)
        end for
        update-grid(lg, solution)
        cur-profit=solve-grid(lg)
        if cur-profit ≥ win-profit then
            win-profit = cur-profit
            win-combination = c
        end if
    end for
    Return win-profit, win-combination
end procedure
```

Algorithm 1 depicts the pseudo code for the evolutionary vertical sequencing protocol. The *get-smart-combinations* function considers the size, capacity and permutations involved when it comes to grouping the grids. The *win-combination* is a variable that stores the best combinations. These combinations are then passed on to the CoMG to solve. The *win-profit* stores the data of profit that is retrieved from the result of the solving an instance of the model. The *cur-profit* refers to the current profit that is earned by solving the current combination. The *update-grid* function places the particular grid that is in need of power at the end of the combination. The *Solve grid function* solves the stochastic MILP for operations and investment with energy volume and price signals from other agents. The grids evolve with more information being added in each sequence, thereby demonstrating that they are evolutionary. Consequently, the grid at the end of each permutation makes the final decision in terms of stochastic energy price and volume signals from neighboring smart microgrids. The grids are organized in an descending or ascending order based on their size and capacity, thus vertical. In a complete enumeration all the permutations are evaluated, in a brute-force manner, to find out the winner. In EVS protocol the grids are smartly organized to reduce the permutations. In EVS the decision of an individual agent is fixed and not changed throughout the process. The strategy of an agent is presented as evolutionary vertical sequencing protocol. The protocol enforces the coordination scheme with an objective of faster convergence compared to complete enumeration strategy through permutations. To achieve this, EVS collects the power system information and then classifies the network into microgrids based on size and capacity. Another aspect of the strategy is to protect the internal information (covering power flows, apparatus and exact location) and also its control. Optimal power flow studies are not within the scope of this paper and are instead addressed in a subsequent paper.

3. Mathematical Model Description

3.1. Self-containted Microgrid

The mathematical model based on the parameters listed in nomenclature is presented in this section considering design and operation of the MG. A self-contained optimization model refers to a model that is only concerned to find the optimal solution without considering decisions of neighborhood micro-grids m that could offer better alternatives. For instance a MG is considering an investment for an additional non-dispatchable generation unit such as wind power while another neighboring MG has additional generation; in certain cases investing on the expansion to exploit the available energy from a neighbor might be more profitable than investing in capacity expansion. But it can only happen if the MG is aware and can coordinate with surrounding MG. A self contained optimization model is blind to surrounding information. A top-down model is an example of such model.

3.1.1. Objective function

The objective function 1(a) minimizes the total costs (tc) which consists of investment cost (ic) and operational cost (oc). The ic in 1(b) refers to the investment costs of the wind plants $\mathring{R}_i$, batteries $\mathring{B}_b$, cables $\mathring{A}_{ij}$ taking into account the respective capital recovery factors (CRF). The capital recovery factor for the wind plant w, battery unit b and cable type a are represented by $R_w^{CRF}, B_b^{CRF}, A_a^{CRF}$ respectively. The oc in 1(c) summaries the operational costs that occur in energy procurement from dispatchable generator and power market. The first three terms refer to the operational cost $\mathring{G}_g^{op}$, turning on cost $\mathring{G}_g^{on}$ and start-up costs $\mathring{G}_g^{start}$ associated to dispatchable generators. Producing, working and on status of generator are represented through the indicator variables g^+_{gits}, $\widehat{g}^{op}_{gits}$, $\widehat{g}^{on}_{gits}$ respectively. The indicator variables are used to capture the scenarios when the generator g is working but not producing to avoid a high start-up cost. The fourth term represents the energy bought from market $\widetilde{h}^{buy}_{its}$ at the buying price $\mathring{H}^{buy}_{ts}$. The operational costs are summed over the stochastic scenarios s multiplied by their probabilities Ω_s. Chance constraint in 1(d) ensures that the confidence level of the solution by restricting the feasible region of the solution [56]. In 1(d) the decision to meet demand $\widehat{d_s}$ is restricted to be higher or equal to the the probability of meeting demand Ω^{dem} in all the scenarios S. In other words, demand is met in most of the scenarios.

$$minimize \quad (tc) = ic + oc \tag{1a}$$

$$ic = \sum_i R_w^{CRF} \cdot \widetilde{r}_i \cdot \mathring{R}_i + \sum_{b,i} B_b^{CRF} \cdot \widetilde{b}_{bi} \cdot \mathring{B}_b + \sum_{i,j} A_a^{CRF} \cdot \widehat{a}_{ij} \cdot \mathring{A}_{ij} \tag{1b}$$

$$oc = \sum_s \Omega_s \Big(\sum_{t,i,g} g^+_{gits} \cdot \mathring{G}_g^{op} + \sum_{t,i,g} \widehat{g}^{op}_{gits} \cdot \mathring{G}_g^{on} + \sum_{t,i,g} \widehat{g}^{on}_{gits} \cdot \mathring{G}_g^{start} + \sum_{i,t} \widetilde{h}^{buy}_{its} \cdot \mathring{H}^{buy}_{ts} \Big) \tag{1c}$$

$$1 - \left(\frac{\sum_s \widehat{d_s}}{|\mathsf{S}|} \right) \geq \Omega_t^{dem} \qquad \forall\, t \tag{1d}$$

3.1.2. Electrical network

The power network or electric grid is modeled as a node-arc formulation wherein the sum of flow in and out of a node is zero. Each node presents an electrical substation and an arc as a cable connecting them. Collectively they formulate an SMG or one energy community. Equation 2(a) imposes that the energy flow in and out of a node should be equal to the demand at all nodes i in every time step t and for all scenarios s. Demand D_{its} is multiplied with the percentage of demand $\widetilde{D}$ that the MG is supposed to fulfill. Such demand is imposed to be equal to the production from dispatchable power plant g^{+}_{gits} plus production from existing and newly installed wind power plant r^{+}_{wits}, r^{+new}_{wits} respectively, plus the energy discharged and charged from the battery b^{-}_{bits}, b^{+}_{bits}. Energy sold $\widetilde{h}^{sell}_{its}$ is subtracted and energy bought $\widetilde{h}^{buy}_{its}$ is added. The dual or shadow price of this constraint is presented as λ_{mits}. 2(b,c) explains the flow must be within the range of $\underline{F}_{ij}$ and $\overline{F}_{ij}$. The directed network can be mapped through the flow direction $\widehat{f}_{ijts}$. The flows are mutually exclusive as imposed through a big M disjunctive formulation in 2(d,e). Note that in 2(d) f_{ijts} refers to energy flow from node i to node j as opposed to 2(e) where f_{jits} refers to the flow from j to i.

A linearised power flow is selected for the distribution network active power power flow. A more accurate AC-OPF model is presented in a successive paper. The linearised optimal power flow is formulated as in (2)(f-i) [1]. In (2)(f,g) the total power flow is restricted within the interconnection capacity. In (2)(h) the voltage angle between start and end node is set to zero. In (2) the total flow in and out of node, voltage angle in that node is equated, such that power flow to and from node is accounted in the power flow.

$$\sum_g g^{+}_{gits} + \sum_w r^{+}_{wits} + r^{+new}_{wits} - \sum_j f_{ijts} \cdot \widehat{L}_{ij} + \sum_j f_{jits} \cdot \widehat{L}_{ij}$$

$$+ \sum_b b^{-}_{bits} - \sum_b b^{+}_{bits} - \widetilde{h}^{sell}_{its} + \widetilde{h}^{buy}_{its} = D_{its} \cdot \widetilde{D} \quad (\lambda_{mits}) \qquad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S}, b \in \mathsf{B}, g \in \mathsf{G}, w \in \mathsf{W} \tag{2a}$$

$$f_{ijts} \leq \overline{F}_{ij} \quad | \quad \widehat{L}_{ij} = 1 \ \vee \ \widehat{a}_{ij} = 1 \qquad \forall\, i, j \in \mathsf{N}, t \in \mathsf{T}\ s \in \mathsf{S} \tag{2b}$$

$$f_{ijts} \geq \underline{F}_{ij} \quad | \quad \widehat{L}_{ij} = 1 \ \vee \ \widehat{a}_{ij} = 1 \qquad \forall\, i, j \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{2c}$$

$$f_{ijts} \leq \widehat{M} \cdot \widehat{f}_{ijts} \qquad \forall\, i, j \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{2d}$$

$$f_{jits} \leq \widehat{M} \cdot (1 - \widehat{f}_{ijts}) \qquad \forall\, i, j \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{2e}$$

$$V_{ij}\ (\delta_i - \delta_j) \leq \overline{F}_{ij} \qquad \forall i, j \in N \tag{2f}$$

$$- V_{ij}\ (\delta_i - \delta_j) \leq \overline{F}_{ij} \qquad \forall i, j \in N \tag{2g}$$

$$\delta_{ij} = 0 \qquad \forall i, j \in N \tag{2h}$$

$$f_{i,j} = \sum_{i \in N} \sum_{j \in N} V_{ij}\ (\delta_i - \delta_j) \tag{2i}$$

3.1.3. Dispatchable generation

Sources of electricity with controllable production functionality can be termed as dispatchable generator. It is modeled as power injection and situated in a node. Constraint 3(a,b) bounds the power generation from generator g with upper ($\overline{G}_{gt}$) and lower ($\underline{G}_{g}$) limits at nodes i at time t. Constraint 3(c,d) imposes the mutual exclusivity of the status of the generator g. That means it can only retain on or off status at a time and not both. Constraint 3 (e,f) implies the minimum on and off time for each generator to perform maintenance [57]. It is important to note that the generator can retain the status on while not producing anything to avoid the start-up cost. This is specially useful if there is a long start-up time or cost for turning a unit on.

$$g^{+}_{gits} \leq \overline{G}_{gt} \cdot \widehat{g}^{op}_{gits} \qquad \forall\, g \in \mathsf{G}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{3a}$$

$$g^{+}_{gits} \geq \underline{G}_{gt} \cdot \widehat{g}^{op}_{gits} \qquad \forall\, g \in \mathsf{G}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{3b}$$

$$\widehat{g}^{op}_{gits} - \widehat{g}^{op}_{gi(t-1)s} = \widehat{g}^{on}_{gits} - \widehat{g}^{off}_{gits} \qquad \forall\, g \in \mathsf{G}, i \in \mathsf{N}, t \in |\mathsf{T}| > 1, s \in \mathsf{S} \tag{3c}$$

$$\widehat{g}^{on}_{gits} \leq (1 - \widehat{g}^{off}_{gits}) \cdot \widehat{M} \qquad \forall\, g \in \mathsf{G}, i \in \mathsf{N}, t \in |\mathsf{T}| > 1, s \in \mathsf{S} \tag{3d}$$

$$\sum_{t+1}^{min\left(|\mathsf{T}| \,\vee\, (t + \widetilde{G}^{on}_{g} - 1)\right)} \widehat{g}^{op}_{gits} \geq \quad min\left((\widetilde{G}^{on}_{g} - 1) \vee\ (\mathsf{T} - t)\right) \cdot \widehat{g}^{on}_{gits} \qquad \forall g \in \mathsf{G}, \forall i \in \mathsf{N}, \forall t \in \mathsf{T}, \forall s \in \mathsf{S} \tag{3e}$$

$$\sum_{t+1}^{min\left(|\mathsf{T}| \vee (t+\widetilde{G}_g^{on}-1)\right)} \widetilde{g}_{gits}^{op} \leq min\left((\widetilde{G}_g^{off}-1) \vee \ (\mathsf{T}-t)\right) \cdot (1-\widetilde{g}_{gits}^{off}) \qquad \forall g \in \mathsf{G}, \forall i \in \mathsf{N}, \forall t \in \mathsf{T}, \forall s \in \mathsf{S} \tag{3f}$$

3.1.4. Non-dispatchable resource: Wind Power Production

Constraint 4(a) restricts the new installation capacity $\widetilde{r}_i$ of wind plants within the maximum limit capacity $\widetilde{R}_{wits}^{max}$. Similarly the production from newly installed wind power plant r_{wits}^{+new} must be under the available capacity $\widetilde{R}_{its}$ multiplied with the extractable percentage of power $\widetilde{R}_{its}$ as in 4(b). Similarly in 4(c) production from existing wind plant r_{wits}^{+} is restricted within the upper limit of power production $\widetilde{R}_{wits}^{max}$. In 4(d) the $\widetilde{R}_{wits}^{max}$ is calculated as a forecast wind power production obtained by multiplying the capacity of existing plant $\overline{R}_{wi}$ by the percentage of the nominal capacity that can be produced $\widetilde{R}_{its}$.

$$\widetilde{r}_i \leq \overline{R}_i^{new} \qquad \forall i \in \mathsf{N} \tag{4a}$$
$$r_{wits}^{+new} \leq \widetilde{r}_i \cdot \widetilde{R}_{its} \qquad \forall i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{4b}$$
$$r_{wits}^{+} \leq \widetilde{R}_{wits}^{max} \qquad \forall w \in \mathsf{W}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{4c}$$
$$\widetilde{R}_{wits}^{max} = \overline{R}_{wi} \cdot \widetilde{R}_{its} \qquad \forall w \in \mathsf{W}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{4d}$$

3.1.5. Battery

Constraint 5(a) states that the state of charge (SOC) of the battery b_{bits}^{soc} has to be less than or equal to the newly installed quantity of battery unit $\widetilde{b}_{bi}$ multiplied by the nominal capacity $\overline{B}_b$ plus the existing battery unit multiplied by the existing quantity installed$\widetilde{B}_{bi}$. Constraint 5(b) imposes that the SOC of the battery in every time step t is given by the SOC in the previous time steps $t-1$ minus the charge b_{bits}^{+} and discharge b_{bits}^{-} from the battery. Battery discharge b_{bits}^{-} is also multiplied with the efficiency of the battery B_b^{eff}. Lower bound of SOC, minimum SOC of the battery, is restricted in constraint 5(c). In particular, the SOC b_{bits}^{soc} has to be greater than or equal to the minimum battery capacity $\underline{B}_b$ multiplied by the existing and new quantity of batteries. Constraint 5(d) states that the battery discharge multiplied by the efficiency of battery unit must be less than or equal to the rating of the battery bank multiplied by the installed quantities of battery units. Similarly constraint 5(e) imposes that the battery charging must be less than or equal to the rating of the battery bank multiplied by the quantity installed.

$$b_{bits}^{soc} \leq \widetilde{b}_{bi} \cdot \overline{B}_b + \overline{B}_b \cdot \widetilde{B}_{bi} \qquad \forall\ b \in \mathsf{B}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{5a}$$
$$b_{bits}^{soc} = b_{bi(t-1)s}^{soc} - b_{bits}^{-} \cdot \left(\frac{1}{B_b^{eff}}\right) + b_{bits}^{+} \qquad \forall\ b \in \mathsf{B}, i \in \mathsf{N}, t \in |\mathsf{T}| > 1 \tag{5b}$$
$$b_{bits}^{soc} \geq \underline{B}_b \cdot \left(\widetilde{b}_{bi} \cdot \overline{B}_b + \overline{B}_b \cdot \widetilde{B}_{bi}\right) \qquad \forall\ b \in \mathsf{B}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{5c}$$
$$b_{bits}^{-} \cdot \left(\frac{1}{B_b^{eff}}\right) \leq B_b^{rate} \cdot \left(\widetilde{b}_{bi} \cdot \overline{B}_b + \overline{B}_b \cdot \widetilde{B}_{bi}\right) \qquad \forall\ b \in \mathsf{B}, i \in \mathsf{N}, t \in \mathsf{T} \tag{5d}$$
$$b_{bits}^{+} \leq B_b^{rate} \cdot \left(\widetilde{b}_{bi} \cdot \overline{B}_b + \overline{B}_b \cdot \widetilde{B}_{bi}\right) \qquad \forall\ b \in \mathsf{B}, i \in \mathsf{N}, t \in \mathsf{T} \tag{5e}$$

Capital recovery factor (CRF) stands for the annualized unitary investment costs taking into account the interest rate I, predicted lifetime for battery B_s^L, wind R^L and cables A^L as in 6.

$$B_b^{CRF} = \frac{I(1+I)^{B_s^L}}{(1+I)^{B_s^L-1}} \quad R_w^{CRF} = \frac{I(1+I)^{R^L}}{(1+I)^{R^L-1}} \quad A_a^{CRF} = \frac{I(1+I)^{A^L}}{(1+I)^{A^L-1}} \tag{6}$$

There is a physical connection to the energy market meaning energy can be imported or exported based for the market price where the connection exists. Just as a node, there is a bi-directional flow along with the restriction of mass balance and capacity. In this market formulation there are two types of markets: local market among the microgrids and central energy market. If a microgrid is isolated then there is no direct access to the central power central market. Note that there is a local market for all microgrids with the nodal pricing scheme derived from the shadow price of mass balance. The constraints 7(a,b) defines the market upper bound $\bar{H}_{ts}$ for the quantum of energy bought $\widetilde{h}^{buy}_{its}$ and sold $\widetilde{h}^{sell}_{its}$ respectively. Following that the mutual exclusive buying and selling energy to market are presented in 7(c,d) in a disjunctive big M formulation.

$$\sum_i \widetilde{h}^{buy}_{its} \leq \bar{H}_{ts} \qquad \forall\, t \in \mathsf{T}, s \in \mathsf{S} \tag{7a}$$

$$\sum_i \widetilde{h}^{sell}_{its} \leq \bar{H}_{ts} \qquad \forall\, t \in \mathsf{T}, s \in \mathsf{S} \tag{7b}$$

$$(1 - \widehat{h}^{sell}_{its}) \cdot M \geq \widetilde{h}^{buy}_{its} \qquad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{7c}$$

$$\widehat{h}^{sell}_{its} \cdot M \geq \widetilde{h}^{sell}_{its} \qquad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{7d}$$

3.2. Tertiary layer: Coordination

This section refers to the model for the MG expansion problem. This is an extension of the self-contained optimization problem. This means that the MG has access to the neighborhood information and can take coordinated decisions. MG expansion is a typical Distribution expansion problem with high co-relation to that of the generation and transmission expansion problems. Technical aspects of the electrical network are not in the scope of this paper and will be considered for subsequent extensions.

3.2.1. Potential arcs

Considering the nodes from the surrounding SMG which have either surplus capacity or load demand, the current SMG takes an investment decision in-terms of investing in a connection with another MG. Therefore potential nodes belonging to a neighbourhood MG are introduced. In addition potential arcs for MG expansions are introduced as well. The maximum flow along potential arcs corresponds to the size of the cable that is available. Further we allow potential arcs only among certain nodes, because in a realistic world there might be environmental constraints for example the grid structure, limited connection points, closer to the node of interest. Therefore cables installations are evaluated in only certain circumstances. Constraint 8 imposes that the possible power flow f_{ijts} in a potential arc must be less or equal to the maximum permissible flow $\overline{F}_{ij}$.

$$f_{ijts} \cdot \widehat{A}_{ij} \leq \widehat{a}_{ij} \cdot \widehat{A}_{ij} \cdot \overline{F}_{ij} \qquad \forall\, i, j \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{8}$$

f^{C}_{mits} and f^{R}_{mits} represent the energy that comes from the surplus power flow from the renewable and dispatchable sources from a neighborhood MG m. $\mathring{G}^{exc}_{tm}$ and $\mathring{R}^{exc}_{tm}$ are the corresponding prices for energy purchasing. Thus the changes the oc and the objective function become as in 9. In the coordination framework the surplus energy from the current MG $m = 1$ becomes input to another $m\{\neq 1\}$.

$$oc + \left(\sum_{i,t} f^{C}_{mits} \cdot \mathring{G}^{exc}_{tm} + \sum_{i,t} f^{R}_{mits} \cdot \mathring{R}^{exc}_{tm} \right) \tag{9}$$

Two parameters $\widetilde{D}$ and $\widehat{N}_i$ were introduced in this section. The former takes in to account the minimum percentage of the actual demand that can be mitigated by the MG and the later takes a binary range in accordance to the presence of a potential node. A potential node comes to be in the presence of increased demand or surplus energy that provides an opportunity for potential linking or arc formulation. A potential node belongs to a self-contained MG where there is either surplus capacity that can be used by another MG or surplus demand that can be mitigated by another MG. In presence of a power market the energy is sold to the market unless there is a congestion in the cable link. Constraint 10(a) is a modified version of 2(a) where two additional terms related to potential arcs are added: $\sum_j f_{jits}\widehat{A}_{ij} - \sum_j f_{ijts} \cdot \widehat{A}_{ij}$. In presence of a potential node, the flow is relaxed to cover a certain potion $\widetilde{D}$ of the demand in place of the full demand. This gives the flexibility and incentive to a MG to decide how to participate in the coordination. Constraint

10(b) ensures that the demand can be met up to the upper limit that is the actual demand at the potential node and not more. Coupled together they ensure that at least a certain portion of the actual demand is met.

$$\sum_g g^+_{gits} + \sum_w r^+_{wits} + r^{+new}_{wits} - \sum_j f_{ijts} \cdot \widehat{L}_{ij} + \sum_j f_{jits} \cdot \widehat{L}_{ij} - \sum_j f_{ijts} \cdot \widehat{A}_{ij} + \sum_j f_{jits}\widehat{A}_{ij} + \sum_b b^-_{bits} \tag{10a}$$
$$- \sum_b b^+_{bits} - \widetilde{h}^{sell}_{its} + \widetilde{h}^{buy}_{its} \quad \geq D_{its} \cdot \widetilde{D} \quad (\lambda^1_{mits}) \quad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S}, \widehat{N}_i = 1$$
$$\sum_g g^+_{gits} + \sum_w r^+_{wits} + r^{+new}_{wits} - \sum_j f_{ijts} \cdot \widehat{L}_{ij} + \sum_j f_{jits} \cdot \widehat{L}_{ij} - \sum_j f_{ijts} \cdot \widehat{A}_{ij} + \sum_j f_{jits}\widehat{A}_{ij} + \sum_b b^-_{bits} \tag{10b}$$
$$- \sum_b b^+_{bits} - \widetilde{h}^{sell}_{its} + \widetilde{h}^{buy}_{its} \leq D_{its} \quad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S}, \widehat{N}_i = 1$$

3.2.2. Energy transaction

The energy transaction between grids is captured in the variables $\widetilde{r}^{exc}_{its}$ and $\widetilde{g}^{exc}_{its}$ considering the installed and newly installed units. Energy flow takes place from lower price region to higher one. In addition, the decision to invest in a power line between an isolated SMG and the market is also accounted. Equation 11(a,b) represents the mode of calculation of the surplus energy. In 11(a) the surplus energy from renewable installations is defined and in 11(b) surplus energy from dispatchable plants is calculated.

$$\widetilde{r}^{exc}_{its} = \sum_w \left(\widetilde{R}^{max}_{wits} - r^+_{wits}\right) + \left(\widetilde{r}_i \cdot \widetilde{R}_{ist} - r^{+new}_{wits}\right) \qquad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{11a}$$
$$\widetilde{g}^{exc}_{its} = \sum_g \left(\overline{G}_{gt} \cdot \widetilde{g}^{op}_{gits} - g^+_{gits}\right) \qquad \forall\, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{11b}$$

The information regarding portion of surplus energy from renewable $\widetilde{R}^{exc}_{itsm}$ and dispatchable plants $\widetilde{G}^{exc}_{itsm}$ that is not completely utilized by current SMG is made available for other agents. The stochastic information of surplus energy that comes as output of the optimization from a neighborhood grid ($\widetilde{r}^{exc}_{its}$ and $\widetilde{g}^{exc}_{its}$) are considered by the decision making grid in terms of input parameters: ($\widetilde{G}^{exc}_{itsm}$ and $\widetilde{R}^{exc}_{itsm}$). The surplus capacity is restricted by the equation 12 stating that the flow from the potential node must be less than the surplus capacity available in that node.

$$f^C_{mits} \leq \widetilde{G}^{exc}_{mits} \qquad \forall\, m \in \mathsf{M}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{12a}$$
$$f^R_{mits} \leq \widetilde{R}^{exc}_{mits} \qquad \forall\, m \in \mathsf{M}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{12b}$$
$$\widetilde{g}^{pot}_{its} = \widetilde{G}^{exc}_{mits} - f^C_{mits} \qquad \forall\, m \in \mathsf{M}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{12c}$$
$$\widetilde{r}^{pot}_{its} = \widetilde{R}^{exc}_{mits} - f^R_{mits} \qquad \forall\, m \in \mathsf{M}, i \in \mathsf{N}, t \in \mathsf{T}, s \in \mathsf{S} \tag{12d}$$

4. Information Structure and Description of Uncertainty

In this section the structure of the stochastic tree is presented, followed by that of the scenario generation technique. Wind, demand and energy prices are chosen as the stochastic variables in order to capture their inherent uncertainty. A two-stage tree is chosen, where investment decisions are taken in the first stage and operational decisions in the second. The investment decisions are here-and-now decisions. The operational decisions in the second stage affect the investment decisions in the first stage (anticipatory constraint). Fig. 4 depicts the main structure of the two-stage stochastic tree and functions at each stage with four ramifications being included. The time horizon for planning is one year with an hourly time resolution.

For computational tractability a typical week representation being adopted for the demand and wind data. This means four typical weeks are repeated for each of the four seasons of winter, spring, summer and autumn. This is inline with best practice adopted in the available literature when developing a data-set for model validation and

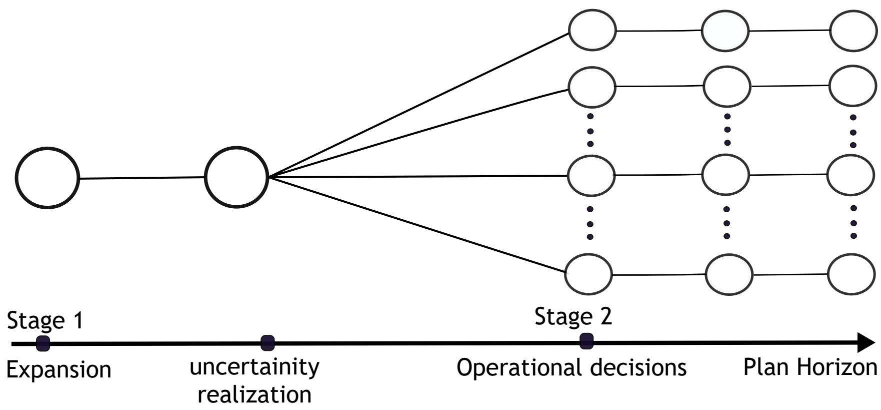

Figure 4: Stochastic scenario tree structure with planning stages

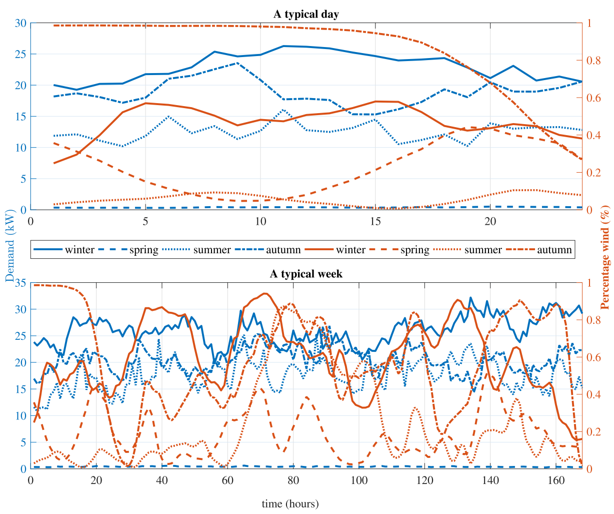

Figure 5: Seasonal representation of the demand and wind power

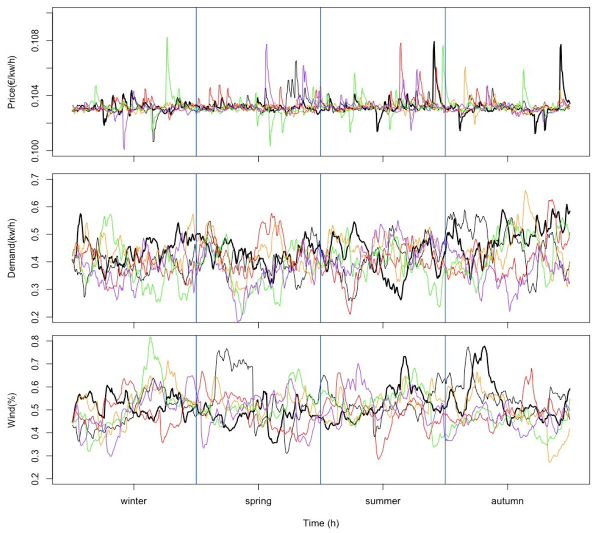

Figure 6: Generated scenarios for stochastic variables demand, wind and electricity price

testing. An example of this can be found in [58]. Fig. 5 presents the pattern of demand (with the primary y-axis being shown in blue) and wind power production as a percentage of the installed capacity (the secondary y-axis is shown in orange). In fig. 5 the typical day power consumption and production from wind turbine is presented. The bottom section of 5 a typical trend over the course of a week, while the top section shows the magnification of a twenty-four hour period. These data comes from four Norweigian islands (Gjessingen, Nordøya, Sauøya and Sørbuøya), being procured from TrønderEnergi Nett AS, an energy company in Trondheim, Norway. The data is normalized using a time-series moving average filter with weighted averaging method being applied. The wind power production potential is assumed to be the same across the region. The energy prices are retrieved from the Nordpool website [59].

4.1. Scenario generation

ARIMA models are a popular and widely-used statistical method for time series forecasting [60, 61, 62, 63]. Combined scenario generation and forecasting using auto-regressive process and principal component is studied and presented in [64]. The proposed data driven scenario generation method is based on ARIMA and Cholesky decomposition [65].

$$y^a_{s,t} = \sum_{j=1}^{\eta^a} \phi^a_j \cdot y^a_{t-j,s} + \varepsilon^a_{s,t} - \sum_{j=1}^{\tau^a} \varphi^a_j \cdot \varepsilon^a_{t-j,s} \tag{13a}$$

$$y^b_{s,t} = \sum_{j=1}^{\eta^b} \phi^b_j \cdot y^b_{t-j,s} + \varepsilon^b_{s,t} - \sum_{j=1}^{\tau^b} \varphi^b_j \cdot \varepsilon^b_{t-j,s} \tag{13b}$$

$$y^c_{s,t} = \sum_{j=1}^{\eta^c} \phi^c_j \cdot y^c_{t-j,s} + \varepsilon^c_{s,t} - \sum_{j=1}^{\tau^c} \varphi^c_j \cdot \varepsilon^c_{t-j,s} \tag{13c}$$

$$\varepsilon^1_{s,t} = \begin{pmatrix} \varepsilon^a_{s,t} \\ \varepsilon^b_{s,t} \end{pmatrix} \quad \varepsilon^2_{s,t} = \begin{pmatrix} \varepsilon^a_{s,t} \\ \varepsilon^c_{s,t} \end{pmatrix} \implies \varepsilon = \begin{pmatrix} \varepsilon^1_{s,t} \\ \varepsilon^2_{s,t} \end{pmatrix} \tag{13d}$$

Considering the correlation between the price-demand and wind-demand a multi-dimensional and quasi-contemporaneous ARIMA(ϕ, φ) processes are modeled for stochastic variable price ($y^a_{s,t}$), demand ($y^b_{s,t}$) and wind ($y^c_{s,t}$) as in 13(a-c). In this process the residuals are the starting point to generate the scenarios. The residuals $\varepsilon^a_{t,s}, \varepsilon^b_{t,s}, \varepsilon^c_{t,s}$ are statistically dependent. Thus the dependency structure of the stochastic processes can be stated as $\varepsilon\{\varepsilon^a_{t,s} \cdot \varepsilon^b_{t-j,s} \cdot \varepsilon^c_{t-j,s}\} \neq 0$. $\varepsilon^a_s, \varepsilon^b_s, \varepsilon^c_s$ are the series of errors simulated to produce residual cross-correlogram of stochastic process. In 13(d) the error correlation between stochastic process a & b, a & c are presented and finally reduced to a product of an orthogonal matrix B and identity matrix $\psi(E[\psi \cdot \psi^T] = I)$. The cross correlation between $\varepsilon^a_{t,s}$ and $\varepsilon^b_{t,s}$ can be represented through variance-covariance matrix G. G is essentially a positive semi-definite and symmetric matrix as in $G = cov(\varepsilon, \varepsilon^T) = BB^T$. This matrix is further decomposed using Cholesky decomposition ($G = LL^T = BB^T \cdot \psi$) [47, 66, 67, 68]. Moreover, this whole exercises is to capture the correlation between stochastic processes where the scenarios are discrete and correlated. It is the Cholesky decomposition that ensures that the scenarios are co-related.

Table 1: Quality-test based on RMSE

Variable	RMSE	ARIMA	Distribution
Demand	0.094	(2,0,2)	normal
Wind	0.024	(4,0,0)	$log(x + 1)$
Price	0.0029	(2,0,2)	normal

Different ARIMA models and distributions were used to sample the 3 variables. Wind is sampled using the logarithmic transformation and an ARIMA (4,0,0) while price and demand are sampled by the normal and an ARIMA (2,0,2). Therefore, the scenarios proposed are the combination of 3 different sampling. Fig. 6 depicts the sampling of the 5 scenarios for demand, price and wind as an example. To verify the quality of the sampling is measured and presented in terms of root mean square error (RMSE). The RMSE is the square root of the variance of the residuals. Lower values of RMSE indicates a better fit. Table 1 shows the RMSE values obtained.

5. Computational Experiments

This section summarizes the computational experiments and the outcome of the experiments are presented in table 2. To better explain the results and its implications, one instance from the results is depicted in fig. 8. There are two subsections that present the outcome from two protocols: complete serial enumeration and evolutionary vertical sequencing protocol. The former computes all the combinations and the later computes permutations.

The models are developed in AIMMS and Python using the pyomo algebraic language [69, 70, 71] and the GUROBI solver [72] under academic license. The computations are carried out at the HPC lab: *Solstorm.iot.ntnu.no* (HPC standing for High Performance Computing at the NTNU lab for Computational Economics and Optimization). Moreover the Message Passing Interface (MPI) is used to execute the EVS. Fig. 7 (shows the grid classifications which are based upon production capacity and the geographical size. Specifically, the grid capacity can either be high (H), medium (M) and low (L) based upon the total installed generation capacity while the grid size can be big (B), medium (M) or small (S) based on the number of nodes (each node being a point of demand or production). A grid is classified by basing it on comparison with those of its peers within a geographical region(this being classed as a group of SMGs). The value of high, medium and low are not absolute, but they depend on how the grid is ranked in comparison within their particular region. In fact, this extends the scope of the application of this methodology. Fig. 7(a) illustrates the combinations that are being studied in this paper. For instance HB refers to an SMG which has high capacity and is of a big size (B). Of course, more combinations could be possible if a different number of participating grids were to be included according to a specific case study. The proposed coordination protocol enforces the solution sequence based on the geographical distance, size and capacity of the microgrids. Algorithm 1, Evolutionary Vertical Sequencing protocol, presents in detail the process of grouping.

Fig. 7(b) presents a comparison between two methods of communication between grids that belong to a group: the complete enumeration is shown on the left in contrast to the vertical hierarchical protocol on the right. According to the pseudo-code that is presented in Section 2.2, when using a complete enumeration technique, the SMGs, a, b and c will first solve their self-contained optimization (refer to Section 3.1 for details covering self-contained optimization). Afterwards, an SMG of type a will lock down its self-contained decision and will send information about its energy transaction requirements and availability to an SMG of type b. At this point an SMG of type b will optimize its own requirements according the new information that it has received, locking in its new optimal decisions and sending the updated energy transaction requirements and availability to an SMG of type c. Finally an SMG of type c will optimizes its own processes according to a full set of information that has been received from the previous grids and will take its final decision based upon this infomation. The stochastic information about energy volume can be denoted by surplus from renewable $\widetilde{R}^e xc_{itsm}$ and conventional $\widetilde{G}^e xc_{itsm}$ resources. This provides a hint about the energy mix of the SMG and the factor of energy produced from each type of resources. Notice that with each sequence the information shared is stochastic and it energy surplus or lack with a price signal. This information is an outcome of model decision of investment and operation.

An EVS protocol will work in a different way: all the SMGs, whether types a, b and c will first solve their self-contained stochastic optimization problem. Afterwards, both SMGs of type a and b will lock down their decisions and will send stochastic information about the energy price and volume (whether that is a surplus or shortage) to an SMG of type c. Finally the type c SMG will optimize its own requirements according to the stochastic information that it has received and will take the final decision. The information that is transferred is stochastic in nature i.e, the uncertainty is captured and propagated during the the process of coordination through stochastic energy volume and price signals.

Moreover, when compared to the enumeration technique, the EVS protocol can reach a final decision with a fewer number of permutations by reducing the combinations by as much as half. In an EVS, since the decision-maker is the one who receives the stochastic information from the other participants, the order of initialization is not relevant. However the sequence is key to reducing the available combinations. However, all of the participants get the opportunity to be the decision-maker thereby covering all possible combinations. The most profitable permutation of the three is the best coordination possible. It is also possible to have one stage coordination, meaning that the grid that foresees any possible expansion will be the decision-maker.

5.1. *Complete serial enumeration*

Complete enumeration takes in to account all possible combinations. In this scenario all of the participants get multiple opportunities to initialize the coordination. The demand is the same with all three SMGs and is equally distributed with respect to the number of nodes. Fig. 8 presents one sequence for Group-1 from fig. 7(b). In fig. 8(a) the structure of three SMG considered for the test case are provided. The nodes are colour coded according to the existing energy units as follows: silver for dispatchable generators, violet for batteries, green for renewable and white where there is no installation. The LS (low capacity and small size) has access to the power market through a cable capacity of 50kW. In fig. 8(b) self-contained optimization results of the SMG are presented. It is clear that the MM type SMG is required to install additional five units of batteries plus six wind turbines to support its demand fully. LS and HB were self sufficient to mitigate their demand therefore no new installation is required. LS extensively used the availability of power market while HB has excess existing production capacity at its disposal. Fig. 8(c,d) presents the enumeration wherein LS is at the decision maker position. In Fig. 8(c) the coordination began with HB and in Fig. 8(d) with MM. It is possible to note that in 8(c) there was a connection built among HB and MM and therefore less new installation for MM compared to the basic self contained optimisation presented in fig. 8(b).

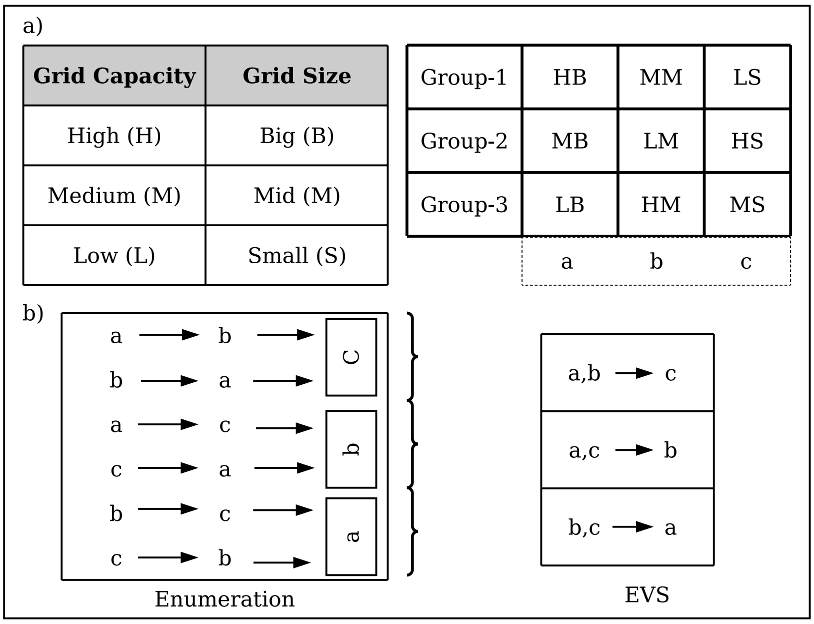

Figure 7: Classification and permutations of microgrids a) grid states based on size, capacity of generation units and transmission line capacities b) reduction of permutations from left to right using evolutionary vertical sequencing protocol

In fact, MM is now getting energy from the HB through the newly built connection. In this case, building a new connection with a peer is cheaper than the investment in new installations. Then LS also builds a new connection to procure energy from the dispatchable resource available in MM. Capacity constraint between the LS and the market and competitive pricing was the motivation. Thus the excess installation from HB was fully utilized while avoiding the energy spillage. Further, this increases the social welfare for all the participants. The table 2 summarizes the results of the analysis for the selected test cases as shown in fig. 7 (b). Each stochastic optimization model was solved to an optimality with a gap of 0.0% in the Gurobi solver. A comparison is demonstrated between self-contained and coordinated decision-making processes. The value of coordination lies in the extra profit earned through coordination or synchronization with peers by a single SMG. In table 2, group-wise results from serial enumeration in comparison with coordinated decision making using EVS protocol is presented. The comparison is made on the basis of profit realization by an individual microgrid in terms of M € between self-contained method and coordinated decision making for capacity expansion. Maximum total system profit was 13% better than the one of the total profit made by solving the three self contained grids in scale of M €. The LS-HB-MM combination in group-1 has the same exact profit as that of the coordination. In group-2 where MB is decision maker, the maximum and minimum total profit are 18% and 0% respectively. It is clear that the placement of the grids in serial coordination plays a vital role. In group-3 9% better profit was realized. Initialization of the coordination process increases or decreases the potential profit and the effectiveness of coordination.

5.2. Evolutionary vertical sequencing protocol

As in fig. 7(e) HB and MM are solved in a self contained manner. The solutions are then passed to the LS who is the decision maker. Evidently LS chooses to build connection with HB and not with MM. LS meets its energy demand with cheap renewable power from HB while also benefiting by selling it to the connected market. This solution is the same as the MM-HB-LS of the enumeration procedure shown in Figure 7(d). It is important to underline that from the prospective of LS, the decision maker, it is more profitable to retrieve the energy from HB.

In table 2 on the right side, the results from the application of the proposed coordination protocol are presented. The horizontal dashed line highlights the combinations that are replaced and thus steps reduced. For instance, the vertical protocol HB,MM to LS replaces the two serial enumeration HB-MM-LS and MM-HB-LS. The rest of the table can be interpreted in a similar way. In group-1 the result achieved is the same as the serial enumeration case MM-HB-LS.

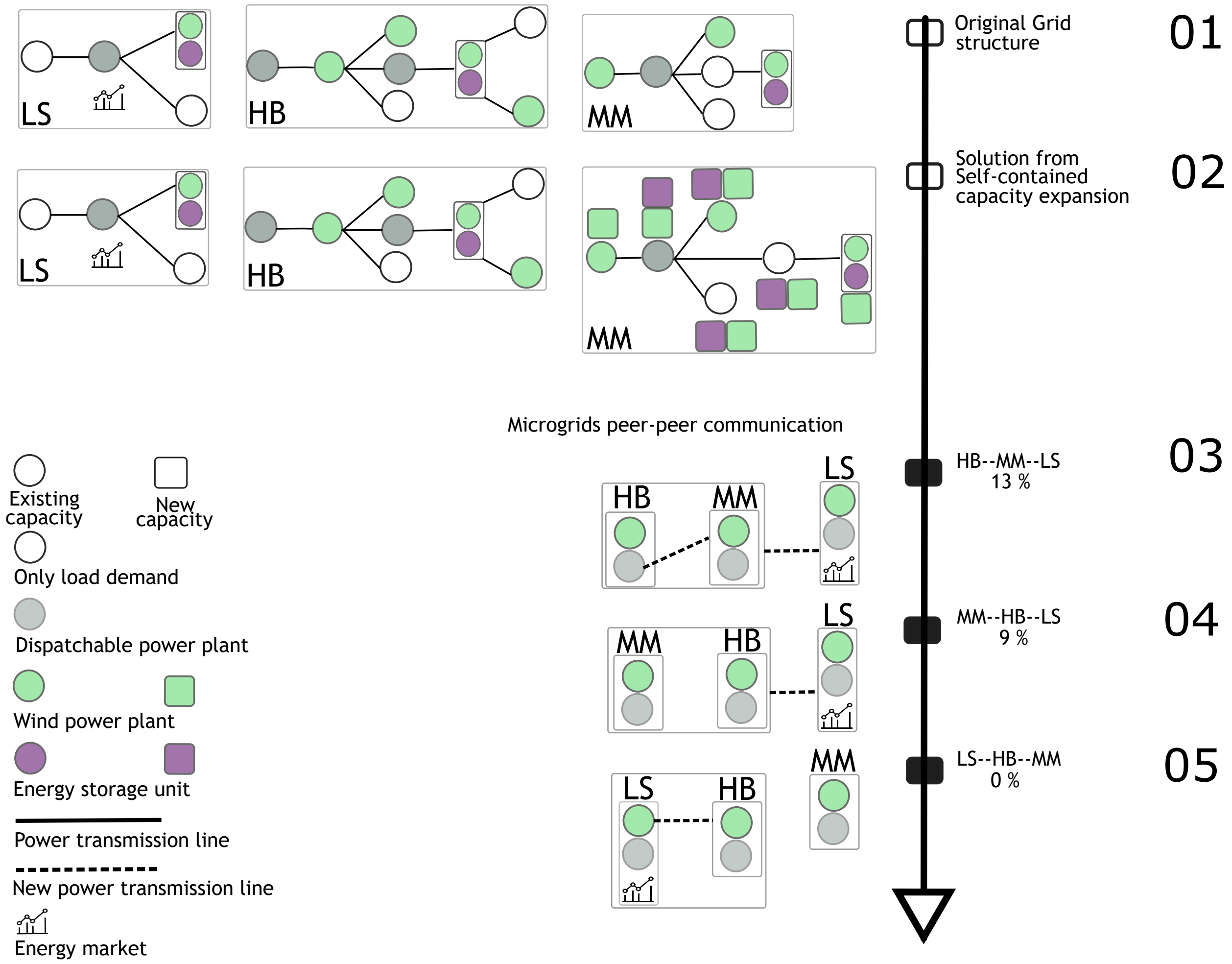

Figure 8: Optimal solutions for capacity expansion of group-1 microgrids presented in fig. 7. Begins with original grid, followed by solution from self-contained capacity expansion and subsequently sequences for coordination.

However the result is lower than the HB-MM-LS. The reason is that LS is the decision maker in this scenario and thus the best profit achievable is 9%. Similarly in group-2 the best potential profit for the MB is 7%. Finally in group-3 the maximum profit is 9%.

The CDM is a bottom-up approach that allows the SMG to make the most profitable decision. The total foreseeable profit from a coordination in the proposed vertical sequencing protocol is the same as that of the best possible individually in serial combinations. This outlines that the EVS conserves the cohesiveness from individual prospective and ensures the optimal result in 50% less step-sizes than that of the enumeration. Further, in group-1, HB and MM as the decision makers have less coordination potential since HB as the decision maker has no motivation to receive energy. But HB is a potential energy producer for other SMG in the region. MM has potential to utilize energy only from HB and thus perfectly obvious coordination.

The effect of high volume and low-cost renewable production from HB makes LS interested in investing in the line while considering the general uncertainty levels. The nested generators of HB and LS reduces the reserve requirement for LS and HB. Furthermore, any energy spillage due to high renewable production levels is reduced by means of coordination with MM and LS. Any up-front investment in LS, for instance, is avoided through energy that can be procured from HB. The synchronicity between stake holders is improved in terms of information sharing and flexibility in decision making is therefore improved.

Table 2: Results and comparison between solutions from conventional and proposed method

Serial enumeration					EVS protocol			
Sequence	Grids			% better from self contained in scale of M €	Sequence	Grids		% better from self contained in scale of M €
Group-1					Group-1			
a→ b→c	HB	MM	LS	–				
Profit increment in %	–	6	7	13				
b→a→c	MM	HB	LS	–	a,b →c	HB MM	LS	**9**
Profit increment in %	–	0	**9**	**9**				
c→a→b	LS	HB	MM	–				
Profit increment in %	–	–	–	0				
Group-2					Group-2			
b→c→a	LM	HS	MB	–	b,c→a	LM HS	MB	**7**
Profit increment in %	–	11	**7**	18				
c→b→a	HS	LM	MB	–				
Profit increment in %	–	0	0	0				
a→ b→c	MB	LM	HS	–				
Profit increment in %	–	4	7.9~8	13				
Group-3					Group-3			
a→c→b	LB	MS	HM	–				
Profit increment in %	–	0	0	0				
c→a→b	MS	LB	HM	–	c,a →b	LB MS	HM	**9**
Profit increment in %	–	0	**9**	**9**				
b→c→a	HM	MS	LB	–				
Profit increment in %	–	8.9~9	0	9				

6. Conclusions and Future Investigations

This paper presents the value of coordinated decision-making in terms of making investments in generation and transmission capacity expansion planning for microgrids from a "bottom-up" perspective. A math-heuristic model with a two-stage stochastic MILP at the bottom and an heuristic coordination protocol on top, coordinated microgrid (CoMG), is formulated. An evolutionary vertical sequencing protocol is developed and implemented simulating the coordinated decision making framework. Given that the smart microgrid acts as the network operator, each network operator consist of an agent that facilitates the coordinated decision-making. The model was tested by using consumption and simplified network data from islands along the west coast of Norway. The results verified the value of coordination by increments in the profit share for an SMG while providing cost-savings across all of the smart-microgrids. The tests lead to the observation that the coordinated decision making strategy out-performs the self-contained hierarchical decision-making strategy in 6 out of 9 cases. In some instances the difference is as high as 13% better in terms of profit than that of the self-contained ones. In addition to that, the proposed evolutionary vertical sequencing protocol ensures the same results while having to consider half the combinations to solve. The sequence in which the microgrids are organized impacts the potential profit. The coordinated decision making framework is developed by using evolutionary vertical sequencing protocol. It has a two-fold advantage (having the required time to reach a decision) in computational solution time while ensuring the optimal results in comparison to the use of the complete serial enumeration. Thereby the CoMG can be seen as being tractable: being computationally viable whilst also being practically feasible. In particular, the investigation facilitates a contemporary distributed energy resources based energy architecture. What is more, it considers the future transition to smart grids with local energy markets. The coordinated decision making process that has been proposed in this paper supplies multiple advantages over conventional modeling techniques as it enhances power security and grid resiliency through:

- coordinated planning: in the context of a modern power distribution network with many planner's having their own perspective
- planning efficiency: in terms of reduced power generator and reserve requirements through the provision of nested generators
- information synchronizing: which provides for reduced power threats due to system status synchronization between system planners
- optimal utilization: in terms of optimal utilization of non-dispatchable production from renewable energy resources (such as avoiding energy spillages)

A further investigation about the value of coordination would follow this work based on the cooperative game theory approach. A direction to explore for future investigation could be to record the energy transactions and facilitate smart contracts amongst agents in a block-chain mechanism. A possible improvement to CoMG could be seen in the utilization of the be synchronization of responsive loads and power apparatus within a microgrid. Specifically, the information that is shared across also covers the responsive load signals. The proposed smart coordination protocol can be improved in a future work by incorporating weather and geographical and network topology factors so that it is even more accurate in terms of selection of permutations. Further investigation could also lead to parallelize the CDM to investigate the tractability.

G	Set of conventional generators g
W	Set of wind plants w
B	Set of batteries b
T	Set of time t
M	Set of Micro-grids m
S	Set of Scenarios s
Parameters	
D_{its}	Demand at node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\mathring{E}_{ts}$	Electricity price at time t for scenario s (€/kWh) [$\mathbb{R}^+$]
$\mathring{H}_{ts}^{sell}$	Market selling price at time t for scenario s (€/kWh) [$\mathbb{R}^+$]
$\mathring{H}_{ts}^{buy}$	Market buying price at time t for scenario s (€/kWh) [$\mathbb{R}^+$]
I	Rate of interest [0,1]
B_b^{CRF}	Capital recovery factor for battery b [0,1]
R_w^{CRF}	Capital recovery factor for wind plant w [0,1]
A_a^{CRF}	Capital recovery factor for new cables a [0,1]
$\overline{F}_{ij}, \underline{F}_{ij}$	Maximum and minimum power flow limit between nodes i, j (kWh) [$\mathbb{R}^+$]
$\widehat{M}$	Big M
$\widehat{L}_{ij}$	Binary parameter is 1 if a line existing among nodes i, j, 0 otherwise
$\widehat{N}_i$	Binary parameter is 1 if there are potential nodes i, 0 otherwise
$\widehat{G}_{gi}$	Binary parameter is 1 if a conventional generator g exists at node i, 0 otherwise
$\mathring{G}_g^{op}$	Cost for operating generator g (€/kWh) [$\mathbb{R}^+$]
$\mathring{G}_g^{on}$	Cost of keeping on generator g (€/kWh) [$\mathbb{R}^+$]
$\mathring{G}_g^{start}$	Cost of starting up generator g (€/kWh) [$\mathbb{R}^+$]
$\underline{G}_g, \overline{G}_{gt}$	Minimum and maximum capacity of conventional power plant g [$\mathbb{R}^+$]
$\widetilde{G}_g^{on}, \widetilde{G}_g^{off}$	Minimum on and off time for conventional plant [$\mathbb{Z}^+$]
$\overline{R}_{wi}$	Capacity of the existing wind plant w at node i [$\mathbb{R}^+$]
$\mathring{R}_i$	Investment cost for wind plant at node i (€) [$\mathbb{R}^+$]
$\overline{R}_i^{new}$	Maximum new wind plant capacity allowed at node i (kWh) [$\mathbb{R}^+$]
$\widetilde{R}_{its}$	Percentage of wind power that can be produced at node i at t for scenario s [0,1]
$\widetilde{R}_{wits}^{max}$	Maximum power production from wind plant w at time t for scenario s (kWh) [$\mathbb{R}^+$]
R^L	Nominal life span of wind plant (years) [$\mathbb{Z}^+$]
B^L	Nominal life span of battery unit (years) [$\mathbb{Z}^+$]
$\mathring{B}_b$	Investment cost for battery unit b (€/kWh) [$\mathbb{R}^+$]
$\overline{B}_b, \underline{B}_b$	Maximum and minimum capacity of individual battery unit b [$\mathbb{R}^+$]
B_b^{eff}	Efficiency of battery unit b of battery b (%) [0,1]
B_b^{rate}	Battery rating b [0,1]
$\widehat{B}_{bi}$	Binary parameter is 1 if battery b exists at node i
$\widetilde{B}_{bi}$	Existing quantity of battery b at node i (kWh) [$\mathbb{Z}^+$]
$\widetilde{B}^{perc}$	Battery discharge rate from the nominal capacity [0,1]
$\overline{H}_{ts}$	Capacity of market at time t for scenario s (kW)[$\mathbb{R}^+$]
$\mathring{H}_{ts}^{buy}$	Buying price from market at time t for scenario s (€/kWh) [$\mathbb{R}^+$]
$\widehat{A}_{ij}$	Binary parameter that is equal to 1 if a potential arc can be placed between nodes i and j
$\mathring{A}_{ij}$	Cost of potential arcs among nodes i, j (€) [$\mathbb{R}^+$]
A^L	Life of new cables (years) [$\mathbb{R}^+$]
$\widetilde{G}_{itsm}^{exc}$	Exceeding generation from conventional from micro-grid m at node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\widetilde{R}_{itsm}^{exc}$	Exceeding generation from renewable from micro-grid m at node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\mathring{G}_{tm}^{exc}$	Price of exceeding conventional at time t from micro-grid m (€/kWh) [$\mathbb{R}^+$]

$\mathring{R}^{exc}_{tsm}$	Price of exceeding renewable at time t from micro-grid m for scenario s (€/kWh) [$\mathbb{R}^+$]
Ω_s	Probability of scenario s [0,1]
Ω^{dem}	Probability of meeting demand [0,1]
$\widetilde{D}$	Fraction of demand [0,1]
V_{ij}	Absolute value of suseptance (physical constant) of the interconnection between nodes i and j
Variables	
tc, ic, oc	Total, investment and operational Cost (€) [$\mathbb{R}$]
$\widetilde{h}^{sell}_{its}$	Energy sold to the market (energy not used to satisfy the demand at the node) (kWh) [$\mathbb{R}^+$]
$\widetilde{r}^{exc}_{its}$	Exceeding renewable energy at node i at time t for scenario s
$\widetilde{r}^{pot}_{mits}$	Potential exceeding energy from renewable resources from current micro-grid m at node i at time t for scenario s
$\widetilde{g}^{pot}_{mits}$	Potential exceeding energy from conventional resources from current micro-grid m at node i at time t for scenario s at the end of the optimization (kWh) [$\mathbb{R}^+$]
$\widetilde{g}^{exc}_{its}$	Exceeding conventional energy at node i at time t for scenario s at at the end of the optimization (kWh) [$\mathbb{R}^+$]
f_{ijts}	Power flow as a semi-continuous variable that has to take a value between $\overline{F}_{ij}$ and $\underline{F}_{ij}$ from node i to j at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\widehat{f}_{ijts}$	Binary variable equals to 1 where there is a flow and 0 otherwise from node i to node j at time t for scenario s
$\widehat{g}^{on}_{gits}$	Binary variable equal to 1 if the generator is turned on at time t
$\widehat{g}^{off}_{gits}$	Binary variable equal to 1 if the generator is turned off at time t
$\widehat{g}^{op}_{gits}$	Binary variable equal to 1 if the generator is working at time t
g^{+}_{gits}	Production of generator g in time step t (kWh) [$\mathbb{Z}^+$]
r^{+}_{wits}	Production of existing wind plant w in node i at time t (kWh) [$\mathbb{Z}^+$]
$\widetilde{r}_i$	New wind capacity installed in node i (kW) [$\mathbb{Z}^+$]
r^{+new}_{wits}	Production of new wind plant of type w in node i at time t (kWh) [$\mathbb{R}^+$]
$\widehat{b}_{bi}$	Binary variable that decides if a battery of type b is installed in node i
$\widetilde{b}_{bi}$	Quantity of battery b to be installed at node i (kWh) [$\mathbb{R}^+$]
b^{-}_{bits}	Energy out of the battery b in node i at time t (kWh) [$\mathbb{R}^+$]
b^{+}_{bits}	Energy flow into the battery b in node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
b^{soc}_{bits}	State of charge of the battery of type b in node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\widetilde{h}^{buy}_{its}$	Energy bought from the market in node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\widehat{h}^{sell}_{its}$	Binary variable equal to 1 if energy is sold and 0 otherwise
$\widehat{a}_{ij}$	Binary variable that decided if a potential arc is created between nodes i and j
f^{C}_{mits}	Flow from conventional plants from neighbor microgrid m with which a connection happens in node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
f^{R}_{mits}	Flow from renewable plants from microgrid m with which a connection happens in node i at time t for scenario s (kWh) [$\mathbb{R}^+$]
$\widehat{d}_s$	Binary variable is 1 if the demand is met and 0 otherwise for scenario s
$\lambda_{mits}, \lambda^{1}_{mits}$	dual variables or shadow prices of the demand meeting constraint of the micro-grid m at node t at time t for scenario s
δ_i, δ_j	Voltage angles (state variable) at node i, j

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