

# Two-Stage Stochastic Optimization Model for Multi-Microgrid Planning

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**Abstract**—This paper presents a Two Stage stochastic Programming (TSSP) model for the planning of Multi-Microgrids (MMGs) in Active Distribution Networks (ADNs). The model aims to minimize the total costs while benefiting from interconnections of Microgrids (MGs), considering uncertainties associated with electricity demand and Renewable Energy Sources (RESs). The associated uncertainties are analyzed using Geometric Brownian Motion (GBM) and probability distribution functions (pdfs). The model includes long-term purchase decisions and short-term operational constraints, using Geographical information Systems (GIS) to realistically estimate rooftop solar limits. The planning model is used to study the feasibility of implementing an MMG system consisting of 4 individual Microgrids (MGs) at an ADN in a municipality in the state of São Paulo, Brazil. The results show that the TSSP model tends to be less conservative than the deterministic planning model, which is based on simple and pessimistic reserve constraints, while performing faster than a simple Stochastic Linear Programming (SLP) algorithm, with higher accuracy.

**Index Terms**—Multi-Microgrids, Planning, Renewable Energy Sources, Stochastic Optimization, Uncertainties.

## NOMENCLATURE

### Subscripts and Sets

|          |                                           |
|----------|-------------------------------------------|
| $I$      | Set of RES and ESS capacities $I = \{i\}$ |
| $S$      | Subset of RES $S = \{s\} \in I$           |
| $B$      | Subset of Batteries $B = \{b\} \in I$     |
| $b$      | Battery Type                              |
| $s$      | RES type                                  |
| $h$      | hours                                     |
| $y$      | years                                     |
| $\omega$ | scenarios                                 |

### Parameters

|                     |                                                           |
|---------------------|-----------------------------------------------------------|
| $\bar{\mathcal{I}}$ | Upper limit for solar capacity [kW]                       |
| $\alpha$            | Temperature coefficient of power for solar panels [pu/°C] |
| $\beta$             | Demand reserves coefficient [pu]                          |
| $\delta$            | Depth-Of-Discharge (DOD) of a battery [pu]                |
| $\eta^{Ch}$         | Efficiency of battery charging [pu]                       |
| $\eta^{Dch}$        | Efficiency of battery discharging [pu]                    |
| $\gamma$            | RESs generation reserves coefficient [pu]                 |

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|                       |                                                                                       |
|-----------------------|---------------------------------------------------------------------------------------|
| $C$                   | Total number of cycles of charge and discharge of a battery                           |
| $\mathcal{H}$         | Hours in a year [h]                                                                   |
| $\mathcal{R}$         | Capacity of RES [kW] or battery [kWh]                                                 |
| $\bar{\mathcal{I}}_m$ | Upper limit for installed capacity of RESs [kW]                                       |
| $\bar{P}_{PCC}$       | Upper limit for the power flow at the PCC [kW]                                        |
| $\tau$                | Solar cell temperature [°C]                                                           |
| $\tau_{stc}$          | Solar cell temperature at standard test conditions [°C]                               |
| $\theta_j$            | Weight of the $j$ th statistical property of interest for Moment Matching approach    |
| $\varphi$             | Derating factor of solar panels [pu]                                                  |
| $c$                   | O&M costs for RESs or batteries [\$/kWh]                                              |
| $d$                   | Discount rate [pu]                                                                    |
| $e_m$                 | Cost of energy sold by MG “ $m$ ” [\$/kWh]                                            |
| $e_n$                 | Cost of energy purchased from MG “ $n$ ” [\$/kWh]                                     |
| $e_q$                 | Cost of energy purchased from the ADN [\$/kWh]                                        |
| $G$                   | Incident solar irradiance on solar panels [kW/m <sup>2</sup> ]                        |
| $G_{stc}$             | Incident solar irradiance on solar panels at standard conditions [kW/m <sup>2</sup> ] |
| $K$                   | Unit cost of RES [\$/kW] or battery [\$/kWh]                                          |
| $P^d$                 | Power demand [kW]                                                                     |
| $t^{ch}$              | Time duration a battery can charge continuously at a fixed power [h]                  |
| $t^{dch}$             | Time duration a battery can discharge continuously at a fixed power [h]               |

### Variables

|               |                                                              |
|---------------|--------------------------------------------------------------|
| $\mathcal{A}$ | Capacity addition of RESs [kW] or batteries [kWh]            |
| $\mathcal{I}$ | Total installed capacity of RESs [kW] or batteries [kWh]     |
| $\mathcal{N}$ | Number of types of RESs or batteries considered              |
| $C$           | NPV of capital costs for the MMG system [\$/kWh]             |
| $E^{buy}$     | Total power purchased by the MMG system [kW]                 |
| $E^{sell}$    | Total power sold by the MMG system [kW]                      |
| $O^B$         | NPV of O&M costs of batteries for the MMG system [\$/kWh]    |
| $O^S$         | NPV of O&M costs of solar panels for the MMG system [\$/kWh] |
| $P'^r$        | Power received by a MG from the ADN [kW]                     |
| $P'^s$        | Power sent by a MG to the ADN [kW]                           |
| $P^{ch}$      | Battery charging power [kW]                                  |
| $P^{dch}$     | Battery discharging power [kW]                               |
| $P^r$         | Power received by a MG from other MGs [kW]                   |
| $P^s$         | Power sent by a MG to other MGs [kW]                         |
| $P_s$         | Power generated by solar panels [kW]                         |
| $SOC$         | Battery state-of-charge [kWh]                                |
| $u'^s, u'^r$  | ON/OFF state for sending/receiving power to/from the ADN     |

$u^{ch}, u^{dch}$  ON/OFF state of battery charging or discharging  
 $u^s, u^r$  ON/OFF state for sending/receiving power to/from a MG

## I. INTRODUCTION

**C**URRENT power systems encounter new challenges in supplying electricity demand, as global warming worsens and thus the use of Renewable Energy Sources (RESs) and Energy Storage Systems (ESSs) increases to help address climate change. These later technologies have remarkably matured in the last decade, which has facilitated their incorporation through different mechanisms, among which the implementation of Microgrids (MGs) stands out [1]. MGs have proven to be technically and financially feasible solutions to supply electricity demand while reducing operational costs and emissions. MGs use a wide range of Distributed Energy Resources (DERs), including RESs and ESSs, and can operate in both grid-connected and isolated forms. This allows MGs to interact with the existing electricity grid to enhance its capabilities, functionalities, and capacities, while optimizing energy use, improving power quality, reducing network congestion, increasing energy efficiency, reliability, and flexibility, and delaying investments in transmission and distribution systems [2]–[7]. In addition, coordinated and connected MGs, known as Multi-Microgrids (MMGs), can provide valuable benefits for both costumers and utilities, as these systems can share resources and thus enhance reliability and reduce costs [8]. Moreover, the coupling of one or more neighboring MGs can be used to overcome individual MGs voltage/frequency deviations and can also be a resource to overcome sudden loss of generation, since independent MGs can be disconnected and clustered to better withstand disturbances [7], [9]. Therefore, as individual MGs are known to be valuable to their stakeholders, it is also essential to consider the operation, management, and planning of MMGs in the short, medium, and long terms.

There are different topics of interest related to MMG systems. For instance, references [10]–[17] explore different strategies for the control and interconnection of multiple ac and dc MGs for reliability enhancement, considering existing and new DERs. Similarly, [17]–[20] discuss possible architectures for MMG systems connected to the grid, whereas reference [21] offers a concise guide for the design, operation, and integration of islanded MMG systems. The problems of day-ahead scheduling and energy management are examined by reference [22] and [23], and stability problems in MMG systems are studied in references [24]–[29]. Finally, the need for MMG long-term planning studies that consider the interactions among MGs and Active Distribution Networks (ADNs) is identified in [5], [18], [30], [31]. Thus, this paper focuses on the long-term planning of interconnected MGs to develop relevant decision-making tools that properly consider the integration of MGs with RESs and ESSs in the context of ADNs.

The planning of MMGs includes the optimal sizing and sitting of DERs, which can significantly improve the resilience of the systems. This important aspect of the operation of MGs has been analyzed through different planning-based resilience

enhancement methods [32]. For example in [33], a three-level Mixed-integer Linear Programming (MILP) problem to allocate DERs in MMGs is studied to reduce load shedding and increase resilience during extreme events. Similarly, [34] proposes an approach for the optimal reconfiguration of ADNs into MMGs, using stochastic models for representing uncertainties related to wind speed and solar irradiance, aiming at minimizing electricity costs and improve reliability and voltage profiles. In [35], the authors focus on the optimal interconnection of MMGs by using a probabilistic Minimal Cut-Set approach and a reliability cost/worth analysis to plan the optimal interconnection of MGs with RESs. Likewise, [36] proposes the inclusion of MMGs in ADNs within the context of generation and transmission expansion planning, considering load forecasting and Monte Carlo Simulations (MCS) for generation and transmission outages. Similarly, [37] and [38] propose the planning of MMGs within ADNs for resilience, while improving the use of existing local DERs. The authors in [39] propose an optimal partitioning of ADNs into interconnected MGs, considering grid-connected and islanded modes of operation. Even though these approaches focus on some essential aspects of power system operation such as resilience, the majority consider that DERs already exist in the ADN, and their goal is the planning of the optimal connection structure of MGs that would make the aggregated system more robust.

Uncertainties in RESs generation and electricity demand should be considered within the planning of MGs and MMGs [40], [41]. Thus, in reference [34], probability distribution functions (pdfs) are used to address uncertainties related to solar and wind generation, and growth factors based on historic data are used for demand. In [42], a two-stage chance-constrained stochastic model with enhanced bilinear Benders decomposition and stochastic scenarios for the sitting of networked MGs is presented. Reference [43] formulates a model for the operation and expansion planning of ADNs with MMGs, using robust optimization and a contingency-constrained approach. In [44]–[46], the authors use game theory and Nash equilibrium principles to address the transactions among all the participants; perfect forecast assumptions for electricity price and demand are used in [44], statistically-generated scenarios for RES generation are used in [45], and weather and demand forecast are used in [46]. The main focus of these references is the location/sitting of the MGs in ADNs, and there is no insight on the required investments along the planning horizon.

Based on the aforementioned discussion, the primary contributions and objectives of the present paper are as follow:

- Propose a novel long-term multi-year planning model for creating MMGs considering an ADN with no initial DERs. The model includes long-term purchase decisions and short-term operational constraints, and the formulation of the energy transactions among all participants, i.e., between the independent MGs and between each MG and the ADN.
- Apply Two-Stage Stochastic Programming (TSSP) to develop a new cost minimization model to consider uncertainties related to RESs and demand, based on

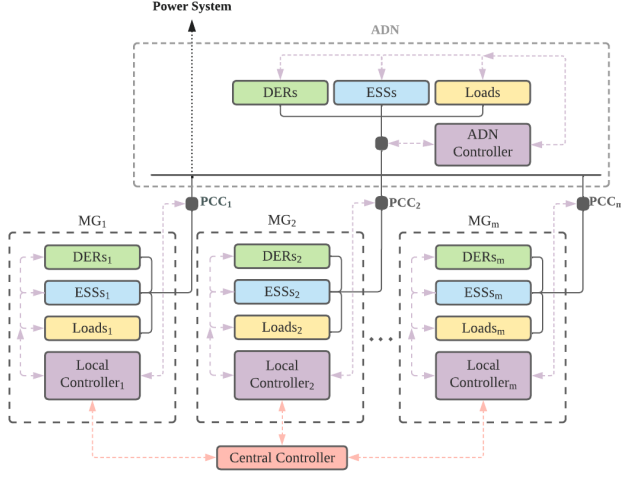


Fig. 1. General overview of an MMG system architecture [8].

an optimization-based scenario tree generation approach that includes Geometric Brownian Motion (GBM) and statistical measures to represent scenarios.

- Test and validate the planning model in a real system, with four MGs within the ADN of a municipality in the state of São Paulo Brazil, and compare the performance of the proposed TSSP planning model against deterministic, simple Stochastic Linear Programming (SLP) and MCS techniques.

The rest of the paper is organized as follow: In Section II, the background and theoretical framework that supports the presented work is reviewed. In Section III, the optimization model proposed for the long-term planning of MMGs is explained. In Section IV, the case study and all required data to apply the model to an ADN in a municipality in the state of São Paulo, Brazil, is introduced, and numerical results are presented and discussed. Finally, the main contributions and conclusions of the presented work, and possible future research directions are highlighted in Section V.

## II. BACKGROUND

In this section, an overview of MMGs and their planning, and a brief review of the stochastic theoretical framework applied for the solution of such problems are provided.

### A. Multi-Microgrid Systems

The concept of MMGs refers to a group of MGs that are networked with an ADN through their Point of Common Coupling (PCC), as depicted in Fig. 1, where each independent MG is managed by its own local controller, while the central controller coordinates the connection among MGs and the ADN. Thus, in the operation of MMGs, each self-governed MG can interact and exchange energy with any neighbouring MG and the ADN exclusively through its PCC, as depicted in Fig. 1 [3], [8], [21], [30]. MMG systems can operate in grid-connected and isolated mode, and the transition between both modes, which may occur as a result of a fault or a

scheduled event, needs to ensure minimum impact on users. The planning of an MMG system includes consideration of interactions among MGs and the ADN, in addition to the limitations of all participants, as described next.

### B. Multi-Microgrid Planning

The planning of MGs is the strategic process to decide and justify the installation/upgrades of new/existing equipment (generators, transformers, lines, compensation) to fully serve the interests of the electricity consumers [47]. The main tasks of the planning in a MMG system include the definition of the DERs configuration, electrical network structure, and the control system configuration, and the selection of the optimal location, size, and type of DERs that guarantees the demand supply and enable a continuous and secure interaction with the ADN and other MGs. In addition, depending on the interests of the stakeholders, legal, political, financial, social, geographical, and environmental restrictions can be considered to enable a more flexible and economic operation of the MGs [47], [48]. Thus, the planning of MMGs systems can be formulated through an optimization problem in which the size, type, and location of DERs are determined, while considering the demand requirements and operational constraints of the ADN and MGs.

### C. Stochastic Linear Programming

One of the common issues that long-term planning models face is the consideration of uncertainties such as RESs availability, fuel costs, electricity demand, and electricity prices, requiring their representation throughout the model and in the output [49]. A suitable linear stochastic approach for the solution of long-term planning problems is TSSP, which handles optimization problems in two stages to consider operational uncertainties into investment decisions.

1) *Two-Stage Stochastic Optimization Programming* [50]: TSSP considers stochastic problems where decisions are made in two stages, and the observation of the uncertainties take place in relation to the stages of the problem. Therefore, two optimization problems need to be solved. For clarity, the second stage problem is introduced first as follows:

$$\begin{aligned} \min_y \quad & q^T y \\ \text{s.t.} \quad & Tx + Wy = \Omega \\ & y \geq 0 \end{aligned} \quad (1)$$

where  $y$  is the second stage decision vector,  $\Omega$  is the uncertainties vector,  $x$  is the first stage decision vector, and  $q$ ,  $T$ , and  $W$  are constants. The optimal value of this stage of the problem is designated as  $q(x, \Omega)$ , where  $Q(x) = \mathbb{E}[q(x, \Omega)]$ . On the other hand, the first stage problem can be formulated as follows:

$$\begin{aligned} \min_x \quad & c^T x + Q(x) \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned} \quad (2)$$

where the equality constraint is deterministic, and  $c$ ,  $A$ , and  $b$  are constants. One of the most common ways to solve

this problem is by building a deterministic equivalent model, assuming the vector  $\Omega$  has a finite number of possible values or realizations, i.e.,  $\Omega = \{\omega_1, \omega_2, \omega_3, \dots, \omega_N\}$  with corresponding probabilities  $p_1, p_2, p_3, \dots, p_N$ . Then, the problem can be written as follows:

$$\begin{aligned} \min_{x,y} \quad & c^T x + (p_1 q^T y_1 + p_2 q^T y_2 + \dots + p_N q^T y_N) \\ \text{s.t.} \quad & Ax = b \\ & Tx + Wy_k = \omega_k; \quad \forall k = 1, \dots, N \end{aligned} \quad (3)$$

In this case, there is no need to deal separately with the second stage problem as the solution of (3) produces the solution of both first and second stage problems. Also, as an important feature, this model can be solved using any suitable linear solver. This requires a scenario generation mechanism as explained next.

#### D. Scenario Tree Generation

The uncertainties considered in the proposed planning model are associated with electricity demand and RESs availability. These uncertainties can be treated as continuous time random variables, and can be approximated by discrete pdfs using scenario trees [51], [52]. Thus, in this paper, the scenario tree is generated using a Moment Matching (MM) approach, where the uncertainties associated with RESs are handled using their inherent statistical properties. The uncertainties related to electricity demand are handled using GBM, since demand evolves with time and there is an underlying annual growth rate relative to previous years [52], [53]. This approach assumes a normal and log-normal fit of the data; however, other scenario generation and reduction techniques based on other pdfs could be used to build the scenario tree to fit the statistical properties of the data [54].

1) *Geometric Brownian Motion*: Any continuous stochastic process  $X(t)$  is a Brownian Motion (BM) with drift coefficient  $\mu$  and variance  $\sigma^2$  if  $X(0) = 0$ ,  $X(t)$  has stationary and independent increments, and  $X(t)$  is normally distributed with mean  $\mu t$  and variance  $\sigma^2 t$ . The stochastic process  $S(t) = e^{X(t)}$  is called GBM, where the measure  $w_t = \log\left(\frac{S(t+1)}{S(t)}\right)$  is normally distributed with mean  $u_S$  and standard deviation  $\sigma_S$ , and therefore has the following associated expected value  $\mathbb{E}$ , variance  $\text{Var}$ , and skewness  $sk$  of a Log-normal pdf [53]:

$$\mathbb{E}(S(t+1)) = S(t)e^{\mu_S + \frac{\sigma_S^2}{2}} \quad (4)$$

$$\text{Var}(S(t+1)) = S(t)^2(e^{\sigma_S^2} - 1)e^{2\mu_S + \sigma^2} \quad (5)$$

$$sk(S(t+1)) = (e^{\sigma_S^2} + 2)\sqrt{e^{\sigma_S^2} - 1} \quad (6)$$

2) *Moment Matching Approach* [52]: In order to generate scenarios with relevant states for RESs and electricity demand, MM technique is used. In this approach, some measure of distance between the statistical properties of the generated outcomes and the specified properties is minimized, as follows:

$$\begin{aligned} \min_{x,p} \quad & \sum_j \theta_j \left( f_j(X, P) - S_{VAL_j} \right)^2 \\ \text{s.t.} \quad & \sum_{j \in S} p_j = 1, \\ & p_j \geq 0 \end{aligned} \quad (7)$$

where  $S$  is the set of all specified statistical properties  $j$ , and  $S_{VAL_j}$  is the specified value for the  $j$ th statistical property in terms of the original random variables.  $X$  represents a single pair of representative values of the uncertainties, i.e., demand and RESs, and  $P$  represents the associated probabilities;  $f_j(X, P)$  is the mathematical discrete expression of the  $j$ th statistical property of interest, computed for  $X$  and  $P$ ; and  $\theta_j$  denotes the weight for the  $j$ th statistical property [52], [53].

### III. MULTI-MICROGRID PLANNING MODEL

The proposed planning model is formulated using the TSSP optimization framework introduced in Section II to plan the energy resources in an MMG system, using RESs and batteries. In addition to planning constraints defining the type and amount of RESs and ESSs in different years, the model contains operational constraints with binary variables associated with the hourly charging and discharging status of batteries, and the power transactions between the participant MGs and the ADN. Integer variables are used to specify the size of RESs and ESSs resources for planning decision, while the variables representing the power generation, batteries charge, discharge and hourly State of Charge (SOC), and the power transactions are continuous. The model can thus be characterized as an MILP problem, as described in detail next.

#### A. Objective Function

The objective function is formulated as the summation of the discounted, i.e., Net Present Value (NPV), of the capital costs (first stage objective function) and the expected discounted Operation and Maintenance (O&M) and energy transaction costs (second stage objective function) of different stochastic scenarios ( $\omega$ ), as follows:

$$Z = C + \sum_{\omega} (O_{\omega}^B + O_{\omega}^S + E_{\omega}^{buy} - E_{\omega}^{sell}) p_{\omega} \quad (8)$$

where the discounted capital cost, discounted O&M cost for RESs and batteries, and the discounted cost of the energy purchased and sold are given, respectively, by:

$$C = \sum_{i,y,m} (K_{i,y,m} A_{i,y,m}) \kappa \quad (9)$$

$$O_{\omega}^S = \mathcal{H} \sum_{s,y,h,m} (c_{s,y,m} P_{s,y,h,m,\omega}) \kappa \quad \forall \omega \quad (10)$$

$$O_{\omega}^B = \mathcal{H} \sum_{b,y,h,m} c_{b,y,m} (P_{b,y,h,m,\omega}^{ch} + P_{b,y,h,m,\omega}^{dch}) \kappa \quad \forall \omega \quad (11)$$

$$E_{\omega}^{buy} = \mathcal{H} \sum_{y,h,m} \left( \sum_n P_{y,h,m,n}^r e_n + P_{y,h,m,\omega}^{r'} e_q \right) \kappa \quad \forall \omega \quad (12)$$

$$E_{\omega}^{sell} = \mathcal{H} \sum_{y,h,m} e_m \left( \sum_n P_{y,h,m,n}^s + P_{y,h,m,\omega}^{s'} + P_{y,h,m,\omega}^d \right) \kappa \quad \forall \omega \quad (13)$$

where  $\kappa = 1/(1+d)$ . Factors  $\lambda = 30$  and  $\mathcal{H} = 288$  are used to carry out the calculations over the whole year, where  $\mathcal{H}$  is total number of representative hours in a year, i.e.,  $24 \times$

12 = 288 hours, based on a 24-hours average day for each of the 12 months, and  $\lambda$  indicates the representative number of days in a month. This approach is used to reduce the problem size in view of the long-term time horizon typical of planning models. The units of each parameter and variable, for this and the following definitions and equations, are presented in the Nomenclature section.

### B. Constraints

1) *Installed Capacity*: For each MG, the total installed capacity for each year is calculated by updating the total installed capacity of the previous year, as follows:

$$\mathcal{I}_{i,y,m} = \mathcal{A}_{i,y,m} + \mathcal{I}_{i,y-1,m} \quad \forall i, y, m \quad (14)$$

where the capacity additions are defined by the product of the number of generators added each year and their respective individual rated capacity, as follows:

$$\mathcal{A}_{i,y,m} = \mathcal{N}_{i,y,m} \mathcal{R}_i \quad \forall i, y, m \quad (15)$$

where  $\mathcal{N}_{b,y,m}$  is an integer variable and  $\mathcal{N}_{s,y,m}$  is a continuous variable, which is an assumption relevant to the installation of solar panels, which can accommodate power fractions in practice. Note that for wind generation this is a coarse assumption; however, in practice, the RESs of urban MGs, which is where MMG systems would likely develop, are mainly solar generators. In addition, RES generation is limited by the renewable resources; for example, the capacity of solar panels are limited by the real area roof of the houses inside each MG (e.g., see Fig. 2). Thus:

$$\sum_y \mathcal{A}_{s,y,m} \leq \overline{\mathcal{I}_m} \quad \forall s, m \quad (16)$$

Constraints (14)-(16) belong to the first stage optimization problem, where the decision on the capacities of DERs needed for each MG are made without any realization of the uncertainties. The following constraints belong to the second stage optimization problem, where the realization of the uncertainties influence the operation of the MMG system.

2) *Supply-Demand Balance*: The summation of the power generated by RESs, batteries storage discharge, the power received from other MGs, and the power received from the ADN should satisfy the MG consumer's demand plus the batteries storage charge, the power sold to other MGs, and the power sold to the ADN, as follows:

$$\begin{aligned} \sum_S P_{s,y,h,m,\omega} + \sum_B P_{b,y,h,m,\omega}^{dch} + P_{y,h,m,\omega}^r + P_{y,h,m,\omega}^{r'} = \\ P_{y,h,m,\omega}^d + \sum_B P_{b,y,h,m,\omega}^{ch} + P_{y,h,m,\omega}^s + P_{y,h,m,\omega}^{s'} \end{aligned} \quad \forall y, h, m, \omega \quad (17)$$

where the power received/sold from/to other MGs are defined as follows:

$$P_{y,h,m,\omega}^r = \sum_n P_{y,h,m,n,\omega}^r \quad \forall y, h, m, \omega \quad (18)$$

$$P_{y,h,m,\omega}^s = \sum_n P_{y,h,m,n,\omega}^s \quad \forall y, h, m, \omega \quad (19)$$

with  $P_{y,h,m,n}^r = P_{y,h,n,m}^s$  for any specific hour of the planning horizon. In addition, in order to prevent two MGs selling and receiving power at the same time, the following constraint is used:

$$P_{y,h,m,\omega}^r P_{y,h,m,\omega}^s = 0 \quad \forall y, h, m, \omega \quad (20)$$

Similarly, any independent MG is not allowed to sell/receive power to/from the ADN at the same time; thus the following constraint is imposed:

$$P_{y,h,m,\omega}^{r'} P_{y,h,m,\omega}^{s'} = 0 \quad \forall y, h, m, \omega \quad (21)$$

3) *Operating Reserves*: To accommodate uncertainties related to the disconnection of the individual MGs from the ADN, the batteries storage power capacity per hour  $SOC_{b,y,h}$  has to be greater than the hourly demand and RES generation as follows:

$$\sum_B SOC_{b,y,h,m,\omega} \geq P_{y,h,m,\omega}^d - \sum_S P_{s,y,h,m,\omega} \quad \forall h, y, m, \omega \quad (22)$$

This guarantees that each MG can withstand a failure that may disconnect it from the ADN at the PCC.

4) *Operating Limits*: The maximum power that any individual MG can sell to other MGs and the ADN at any hour and year, during the planning horizon, is given by the available RES power and battery storage discharge, as follows:

$$P_{y,h,m,\omega}^s + P_{y,h,m,\omega}^{s'} \leq P_{s,y,h,m,\omega} + P_{b,y,h,m,\omega}^{dch} \quad \forall y, h, m, \omega \quad (23)$$

In addition, the power flow at the PCC is limited by the upper limit of the link, as follows:

$$|(P_{y,h,m,\omega}^s + P_{y,h,m,\omega}^{s'}) - (P_{y,h,m,\omega}^r + P_{y,h,m,\omega}^{r'})| \leq \overline{P_{PCC}} \quad \forall y, h, m, \omega \quad (24)$$

5) *RESs Generation*: The solar power generation output is computed as a direct function of the hourly incident irradiance, hourly cell temperature, and derating factor, which is a scaling factor to account for effects of dust, wire losses, and other deviations of the solar output from its ideal value, as follows:

$$P_{s,y,h,m,\omega} = \varphi \mathcal{I}_{s,y} \left( \frac{G_{y,h,\omega}}{G_{stc}} \right) [1 + \alpha(\tau_h - \tau_{stc})] \quad \forall s, y, h, m, \omega \quad (25)$$

where *stc* stands for standard test conditions.

For wind power generation, similar equation considering wind speed and the turbine characteristics can be defined. However, as previously discussed, this type of generation is not expected in general in urban MGs, which are at the core of MMGs systems. Therefore, the models, simulations, and results presented in this paper focus on solar generation.

6) *Battery SOC and Limits*: The following constraints compute the SOC of the batteries as a function of the batteries' charge and discharge for every hour of operation, considering the charging and discharging efficiency rates:

$$\begin{aligned} SOC_{b,y,h+1,m,\omega} - SOC_{b,y,h,m,\omega} = \eta^{ch} P_{b,y,h,m,\omega}^{ch} \\ - \frac{P_{b,y,h,m,\omega}^{dch}}{\eta^{dch}} \end{aligned} \quad \forall b, y, h, m, \omega \quad (26)$$



Fig. 2. Sample of the roof areas considered in the case study, determined using GIS tools.

$$SOC_{b,y+1,1,m,\omega} - SOC_{b,y,H,m,\omega} = \eta^{ch} P_{b,y,H,m,\omega}^{ch} - \frac{P_{b,y,H,m,\omega}^{dch}}{\eta^{dch}} \quad \forall b, y, h, m, \omega \quad (27)$$

This SOC is subject to the following constraints reflecting the minimum and maximum capacity of the batteries:

$$SOC_{b,y,h,m,\omega} \leq \mathcal{I}_{b,y,m,\omega} \quad \forall b, y, h, m, \omega \quad (28)$$

$$SOC_{b,y,h,m,\omega} \geq \delta \mathcal{I}_{b,y,m,\omega} \quad \forall b, y, h, m, \omega \quad (29)$$

The following constraints reflect the maximum charging and discharging limits, respectively, and are functions of the Depth-of-Discharge (DOD), the total installed battery capacity, and the continuous time duration of charging and discharging, which are parameters chosen to keep reasonable equipment costs, while having adequate energy resources in a day:

$$P_{b,y,h,m,\omega}^{dch} \leq \left( \frac{1 - \delta}{t^{dch}} \right) \mathcal{I}_{b,y,m,\omega} \quad \forall b, y, h, m, \omega \quad (30)$$

$$P_{b,y,h,m,\omega}^{ch} \leq \left( \frac{1 - \delta}{t^{ch}} \right) \mathcal{I}_{b,y,m,\omega} \quad \forall b, y, h, m, \omega \quad (31)$$

Furthermore, the following constraints guarantee minimum charging/discharging power at a given hour:

$$P_{b,y,h,m,\omega}^{dch} \geq u_{b,y,h,m,\omega}^{dch} \quad \forall b, y, h, m, \omega \quad (32)$$

$$P_{b,y,h,m,\omega}^{ch} \geq u_{b,y,h,m,\omega}^{ch} \quad \forall b, y, h, m, \omega \quad (33)$$

In order to prevent charging and discharging occurring at the same time, the following equation is used:

$$P_{b,y,h,m,\omega}^{dch} P_{b,y,h,m,\omega}^{ch} = 0 \quad \forall b, y, h, m, \omega \quad (34)$$

Finally, the following constraint defines the life span of each battery for  $\mathcal{C}$  cycles of charge and discharge:

$$\sum_{h,y} (P_{b,y,h,m,\omega}^{ch} + P_{b,y,h,m,\omega}^{dch}) \leq \mathcal{C} \sum_y \mathcal{A}_{b,y,m} \quad \forall b, y, h, m, \omega \quad (35)$$

Equations (20), (21), (24), and (34) are nonlinear, and thus a common linearization technique such as big M and absolute value properties are applied [55]. Hence, using equations (8)-(35) the TSSP problem can be formulated as an MILP problem as follows:

$$\begin{aligned} \min \quad & \text{Eq. (8)} \\ \text{s.t.} \quad & \text{Eqs. (9) to (35)} \end{aligned} \quad (36)$$

### C. Simple Stochastic and Deterministic Models.

The planning model presented in Sections III-A and III-B can also be formulated as a simple SLP problem, where the first stage objective function and constraints are modified, as follows:

$$Z = \sum_{\omega} (C_{\omega} + O_{\omega}^B + O_{\omega}^S + E_{\omega}^{buy} - E_{\omega}^{sell}) p_{\omega} \quad (37)$$

$$C_{\omega} = \sum_{i,y,m} (K_{i,y,m} \mathcal{A}_{i,y,m,\omega}) \kappa \quad \forall \omega \quad (38)$$

$$\mathcal{I}_{i,y,m,\omega} = \mathcal{A}_{i,y,m,\omega} + \mathcal{I}_{i,y-1,m,\omega} \quad \forall i, y, m, \omega \quad (39)$$

$$\mathcal{A}_{i,y,m,\omega} = \mathcal{N}_{i,y,m,\omega} \mathcal{R}_i \quad \forall i, y, m, \omega \quad (40)$$

$$\sum_y \mathcal{A}_{s,y,m,\omega} \leq \overline{\mathcal{I}_m} \quad \forall m, \omega \quad (41)$$

Likewise, the equation defining the life span of the batteries needs to be adjusted, as follows:

$$\sum_{h,y} (P_{b,y,h,m,\omega}^{ch} + P_{b,y,h,m,\omega}^{dch}) \leq \mathcal{C} \sum_y \mathcal{A}_{b,y,m,\omega} \quad \forall b, y, h, m, \omega \quad (42)$$

Therefore, the planning model, represented as a simple SLP model is as follows:

$$\begin{aligned} \min \quad & \text{Eq. (37)} \\ \text{s.t.} \quad & \text{Eq. (38)} \\ & \text{Eqs. (10) to (13)} \\ & \text{Eqs. (39) to (41)} \\ & \text{Eqs. (17) to (34)} \\ & \text{Eq. (42)} \end{aligned} \quad (43)$$

The deterministic model can be obtained from the aforementioned stochastic model (43) with only one scenario with probability one, where the uncertainties are approximated by their average values. In addition, (22) needs to be modified as follows:

$$\sum_B SOC_{b,y,h,m,\omega} \geq (1 + \beta) P_{y,h,m,\omega}^d + \gamma \sum_S P_{s,y,h,m,\omega} \quad \forall h, y, m, \omega \quad (44)$$

where  $\beta$  and  $\gamma$  represent arbitrary reserve values for demand and solar power. This conservative adequacy constraint is typically used to guarantee enough reserves to manage demand and RES uncertainties, as for example in [56].

## IV. SIMULATIONS AND RESULTS

### A. Case Study

The planning model presented in Section III is used to study the feasibility of implementing an MMG system consisting of 4 individual MGs, as illustrated in Fig. 1 with  $m = 4$ , embedded in an ADN at a municipality in the state of São Paulo, Brazil. All the input data, including technical, economical, and environmental parameters used for this case study are introduced next.

TABLE I  
SOLAR PANELS PARAMETERS [59], [60]

| $K_{s,1,m}$<br>[\$/kW] | $c_{s,1,m}$<br>[\$/kWh] | $\alpha$<br>[pu/°C] | $df$<br>[%] | $\tau_{stc}$<br>[°C] | $G_{stc}$<br>[kW/m <sup>2</sup> ] | Lifetime<br>[years] |
|------------------------|-------------------------|---------------------|-------------|----------------------|-----------------------------------|---------------------|
| 871                    | 0.002487                | -0.041              | 98          | 25                   | 1                                 | 20                  |

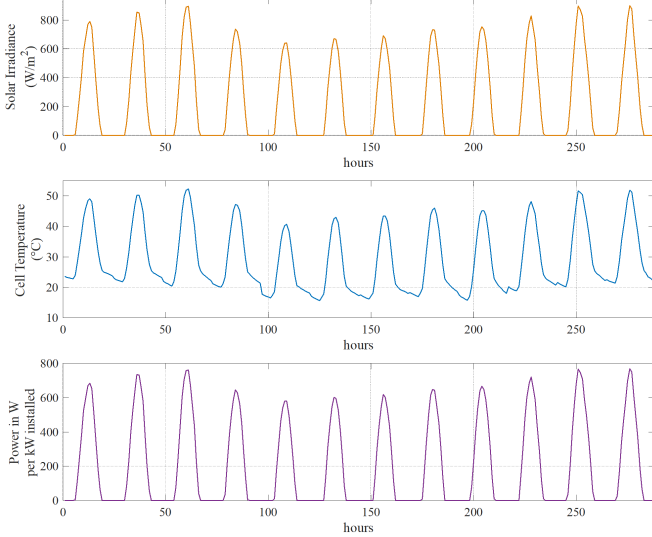


Fig. 3. Average solar irradiance, cell temperature, and resulting power availability in W per kW installed for a municipality in the state of São Paulo, Brazil [57], [58].

1) *Solar Panels*: Sets of 9.6 kW solar panels are assumed to be connected through an inverter to the MGs. The average solar irradiance, cell temperature, and resulting power obtained using (25) are presented in Fig. 3, which are computed using the monthly hourly average for cell temperature and solar irradiance as per [57], [58]. The operational parameters and costs associated with the panels are shown in Table I. In addition, the limits for solar capacity for all MGs, obtained using geoprocessing, are 3271 kW for MG<sub>1</sub>, 2665 kW for MG<sub>2</sub>, 3834 kW for MG<sub>3</sub>, and 1562 kW for MG<sub>4</sub>.

2) *Batteries*: The battery packs in the MMG planning model are lithium iron phosphate batteries with 20 kWh and 8 kW peak power of charge/discharge, i.e.,  $t^{ch} = t^{dch} = 2h$  with  $\delta = 0.2$ . The economic and technical parameters for the implemented battery model are presented in Table II, which yields a battery capital costs of 1,380 \$/kW.

3) *Electricity Demand*: The hourly load for the 4 MGs is used to calculate the hourly averages for a year with 288 representative hours, as explained in Section III-A. The load has been divided into two parts: variable and fixed, in which the fixed demand represents Electric Vehicle (EV) demand not changing thorough the planning horizon, as depicted in Fig. 4. The variable demand has been modeled using electricity demand and growth rates as per [62], while the fixed demand has been modeled considering users routine and traffic patterns in the state of São Paulo, Brazil, without considering smart chargers, as per [63] and [64].

TABLE II  
BATTERY PARAMETERS [60], [61]

| $K_{b,1,m}$<br>[\$/kWh] | $c_{b,1,m}$<br>[\$/kWh] | $\eta_{Ch}$<br>[%] | $\eta_{DCh}$<br>[%] | Lifetime<br>[Cycles] |
|-------------------------|-------------------------|--------------------|---------------------|----------------------|
| 654                     | 0.00187                 | 81.6 %             | 81.6%               | 10,000               |

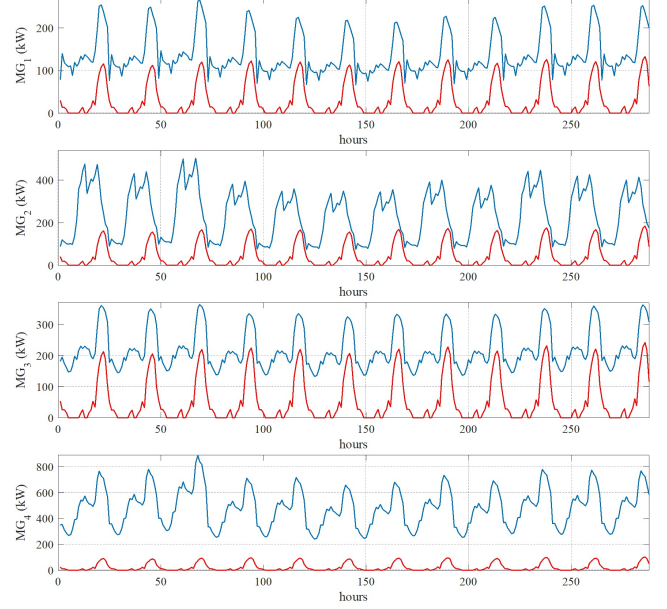


Fig. 4. MG demand: variable in blue, and fixed (EVs) in red [65].

4) *Scenario Tree*: The first step in building the scenario tree is the definition of the statistical properties of the uncertain parameters. Here, daily average solar irradiance between 1983 and 2007 and total electricity consumption for Brazil between 1985 and 2020 are used to estimate the load and irradiance pdfs from the given data. For the demand, a goodness-of-fit test indicates that the parameter  $w$  and the increments in demand can be approximated by a Normal distribution (Fig. 5a and Fig. 5b), and its statistical properties are presented in Table IV. A goodness-of-fit test is used for solar irradiance, as depicted in Fig. 5c, showing that this parameter can also be approximated with a Normal distribution, and its statistical properties are presented in Table III. This information is used to build the GBM statistical properties according to Section II-D1, which are presented in Table V.

The scenario tree presented in Fig. 6 has been created considering the expected value, the variance, and the skewness. In addition, the scenario tree has been built so that the probability of each scenario is greater than 2% or confidence levels greater than 98%; this assures that scenarios with extremely low probabilities of occurrence are not included in the planning process. The model follows the approach presented in Section II-D2, and aims to minimize the square distance between the specified discrete statistical measures and the observed statistical measures presented in Tables III and V, respectively. The total number of scenarios should at least be equal to the total number of statistical measures plus one degree of freedom. Therefore, for the present case study, there should at

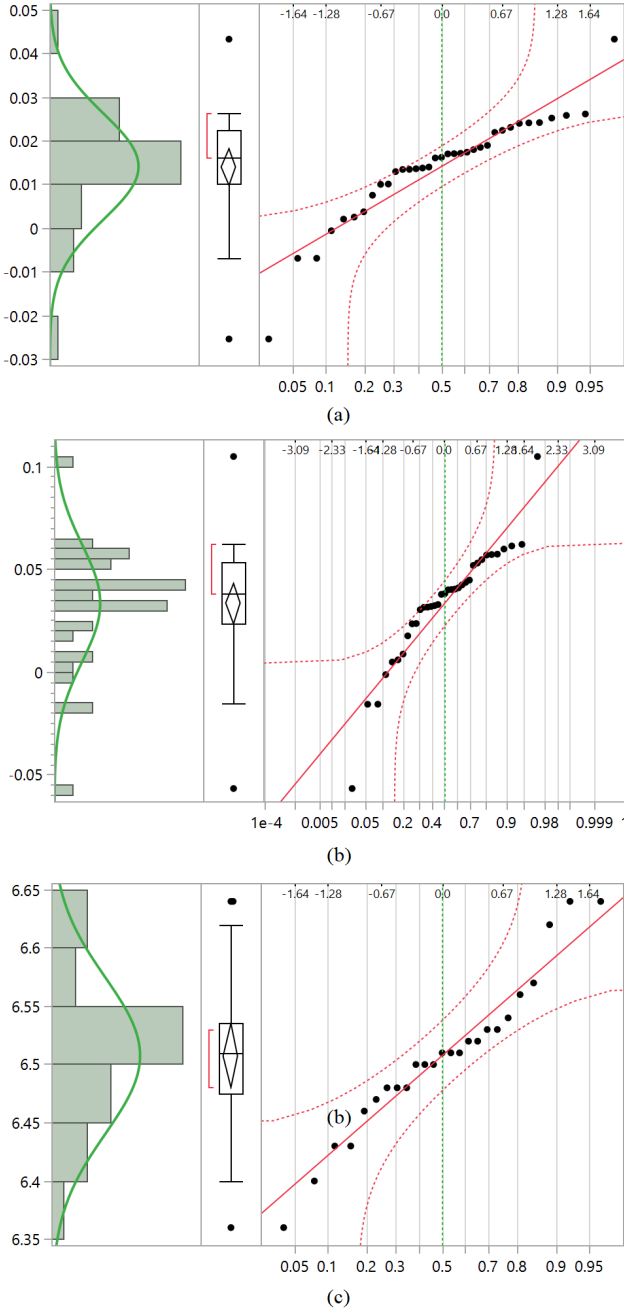


Fig. 5. Normal Quantile plots for (a)  $w$  factor, (b) demand growth, and (c) solar irradiance using JMP software.

least be 7 scenarios ( $2\mathbb{E}$ ,  $2\mathbb{V}ar$ ,  $2sk + 1$ ); thus, 9 scenarios are chosen to reduce computational burden [52], [53]. The nodes in the tree represent the states in the planning horizon for the demand growth rate with respect to year 0 and solar irradiance annual average with their respective probabilities. These scenarios are used for both the TSSP and simple SLP problems.

### B. Assumptions and Simulation Criteria

The Nonlinear Programming (NLP) problem needed for the generation of the scenario tree and introduced in Section II-D

TABLE III  
OBSERVED DAILY SOLAR IRRADIANCE PER YEAR [57]

| Expected Value | Variance  | Skewness |
|----------------|-----------|----------|
| 6.5076         | 0.0045107 | 0.132724 |

TABLE IV  
DEMAND STATISTICAL PROPERTIES [66]

| $w = \log(P_{y+1}^d / P_y^d)$ |          |        | $\Delta P_y^d = P_{y+1}^d - P_y^d$ |           |        |
|-------------------------------|----------|--------|------------------------------------|-----------|--------|
| Mean                          | Variance | Skw.   | Mean                               | Variance  | Skw.   |
| 0.014148                      | 0.00015  | 0.0036 | 0.0335                             | 0.0008112 | 0.1327 |

was solved in GAMS [67], using the SNOPT solver. The MILP models, described in Section III were solved using GAMS, with the CPLEX solver. All the models were solved in a computer with Intel Xeon CPU at 1.87 GHz. The following are the assumed values for the remaining model parameters [37], [38], [68]:

- The discount rate is  $d = 0.08$  u (8%), which is a typical private investment rate.
- The planning horizon chosen for this study is 5 years, as per [69]–[71], which is a typical horizon used in distribution system planning studies in Brazil.
- $\theta_1 = 2$  for the expected value  $\mathbb{E}$ ,  $\theta_2 = 2$  for the variance  $\mathbb{V}ar$ , to prioritize these measures over the skewness  $sk$  with  $\theta_3 = 1$ , as per [53], [72].
- Conservative operation reserves for system adequacy in the deterministic model: 25% for solar ( $\gamma = 0.25$ ), and 10% for load ( $\beta = 0.1$ ), as per [56].
- The base daily prices for a 24-hour operation are, as per [66]: 0.11 \$/kWh for  $h = 17$  (intermediate), 0.17 \$/kWh for  $18 < h \leq 20$  (peak), and 0.08 \$/kWh otherwise (off peak). These prices are the same for all participants, and therefore  $e_q = e_s = e_m$ .
- Electricity price growth 4.81%/year, as per [66].
- The cost of solar panels and batteries decrease every year, by 9% for solar panels and 21.1% for batteries, respectively, as per [73].
- The O&M costs increase by 3% every year, as per the current average inflation in Brazil [74].
- 800 iterations are needed for MCS since the moving average of the objective function converges at around this value.
- The limit for the power transfer at the MG PCCs are 1200 kW, as per the capacity of the existent distribution feeders.
- At least 10% of the maximum available capacity of solar generation should be included for each MG, otherwise the model does not include them due to the cost minimization approach and low grid electricity costs.

### C. Numerical Results

The results of the simulations are presented and discussed in this section. In Table VI, the capacities of solar panels and batteries needed for the MMG system and the total cost associated with each planning model are presented. The following observations can be made from the obtained results:

TABLE V  
GBM STATISTICAL PROPERTIES

| Expected Value                          | Variance                                | Skewness   |
|-----------------------------------------|-----------------------------------------|------------|
| $\mathbb{E}(P_{y+1}^d) = 1.014324P_y^d$ | $\text{Var}(P_{y+1}^d) = 0.000151P_y^d$ | $sk=0.036$ |

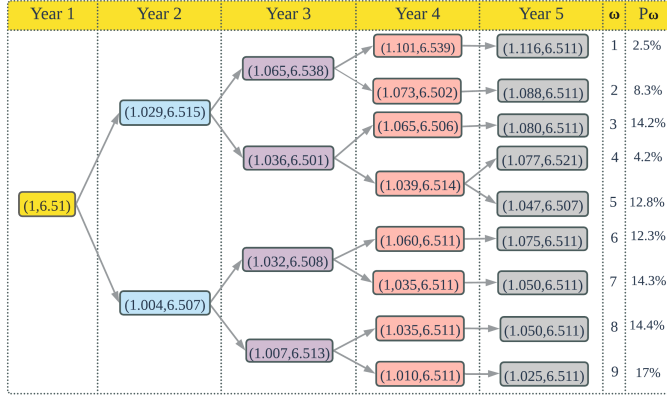


Fig. 6. Scenario tree for the planning of MMG in a municipality in the state of São Paulo, Brazil, with a grow factor for variable demand with respect to year 1 and average solar irradiance.

- The deterministic model is the most expensive and most conservative model, due to the arbitrary and conservative reserve requirements. Thus, the total cost is 15.6% higher than the simple SLP model, 14.1% higher than the TSSP model, and 12.7% higher than the MCS model, which is considered the benchmark for the planning results.
- The total cost of TSSP is 16.4% lower than the deterministic model, 1.6% lower than the MCS model, and 1.8% higher than the simple SLP model. This seems acceptable, since in this problem, the decisions on the amount of new equipment are made in the first stage, without any realization of the uncertainties. Thus, the mathematical model would attempt to satisfy all the operative conditions associated with the operative scenarios in the second stage. Moreover, the closeness of this model's performance to the MCS model's performance suggests that the number and statistical properties of the scenarios are neither under nor over specified.
- The simple SLP model is the cheapest, where the total cost is 18.5% lower than the deterministic model, 1.8% lower than the TSSP model, and 3.4 % lower than MCS. This model offers the least conservative results as the decision on the amount of batteries and solar panels that should be installed inside each MG is made considering the realization of the uncertainties happen beforehand.

In Fig. 7, the capacity additions for the MMG system are shown, and Fig. 8 presents the operation of the MMG system for one a in year 5. As observed in Fig. 7, the majority of the capacity is installed at the beginning of the planning horizon and smaller quantities are added later. This is of special interest for Brazilian distribution companies, as they seek to invest during the first years of the project, when government incentives for sustainable technologies are available. Moreover, as observed in Fig. 8, for each MG the model decides on the energy that needs to be purchased, the energy that can

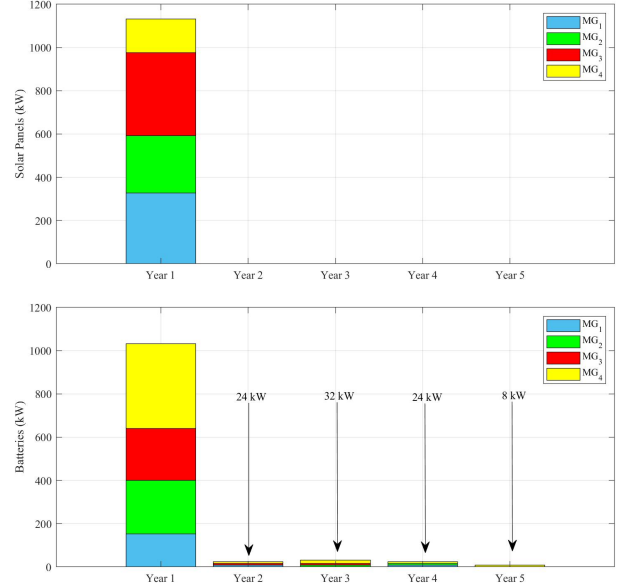


Fig. 7. Yearly capacity additions for TSSP model.

be sold, and guarantees the demand supply considering the internal generation and storage resources for every hour during the planning horizon. In addition, it can be observed how the internal generation is used to trade energy with other MGs, as expected, given the collaboration among the participants. For example, at 10 am, when there is high solar power generation, MG<sub>2</sub> is buying 200 kW from MG<sub>3</sub> and 70 kW from MG<sub>4</sub>; similarly, MG<sub>4</sub> is buying 171 kW from MG<sub>1</sub>. This decreases the amount of power that needs to be imported from the ADN, which reduces congestion and increases reliability.

As observed in Table VI, the total solar capacities for the MMG system are very similar among the planning models, since this RES has to be forced, as previously explained. Nevertheless, there is a difference in the capacities of batteries planned for each independent MG. As explained in Section II, TSSP models make an important differentiation of the variables according to whether they are enforced before or after the realization of the uncertain values, which is closer to an actual planning process. As depicted in Table VI, the total cost of the TSSP model is closer to the MCS benchmark value than the simple SLP model. In addition, the standard deviation of the difference in the battery capacity additions for each independent MG with respect to MCS benchmark is 11.6 kWh for the TSSP model and 19.6 kWh for the simple SLP model, which indicates that there is less variability or spread in the TSSP results. Thus, the TSSP model guarantees the optimal distribution of the required RESs and ESSs resources among the participant MGs, making it superior to the simple SLP model, at reasonable computational costs. Thus, the solution of the TSSP model is 81.03% faster than the MCS benchmark, and at least 2.43% faster than the simple SLP model, which is important considering that the larger the problem the more relevant the computational costs become.

TABLE VI  
PROPOSED MODEL COSTS AND CAPACITIES AT THE END OF YEAR 5

| Deterministic model   |           |      |       |            |            |
|-----------------------|-----------|------|-------|------------|------------|
| MG                    | Batteries |      | Solar | Total Cost | Comp. Cost |
|                       | [kWh]     | [kW] | [kW]  | [M\$]      | [hh:mm:ss] |
| 1                     | 460       | 184  | 327   | 2.18       | 00:02:13   |
| 2                     | 740       | 296  | 266   |            |            |
| 3                     | 720       | 288  | 383   |            |            |
| 4                     | 1200      | 480  | 156   |            |            |
| Total                 | 3120      | 1248 | 1132  |            |            |
| MCS model - Benchmark |           |      |       |            |            |
| MG                    | Batteries |      | Solar | Total Cost | Comp. Cost |
|                       | [kWh]     | [kW] | [kW]  | [M\$]      | [hh:mm:ss] |
| 1                     | 429       | 172  | 327   | 1.90       | 22:07:23   |
| 2                     | 689       | 275  | 267   |            |            |
| 3                     | 661       | 265  | 384   |            |            |
| 4                     | 1121      | 449  | 164   |            |            |
| Total                 | 2901      | 1160 | 1142  |            |            |
| TSSP model            |           |      |       |            |            |
| MG                    | Batteries |      | Solar | Total Cost | Comp. Cost |
|                       | [kWh]     | [kW] | [kW]  | [M\$]      | [hh:mm:ss] |
| 1                     | 420       | 168  | 327   | 1.87       | 04:11:51   |
| 2                     | 660       | 264  | 266   |            |            |
| 3                     | 640       | 256  | 383   |            |            |
| 4                     | 1080      | 432  | 156   |            |            |
| Total                 | 2800      | 1120 | 1132  |            |            |
| Simple SLP model      |           |      |       |            |            |
| MG                    | Batteries |      | Solar | Total Cost | Comp. Cost |
|                       | [kWh]     | [kW] | [kW]  | [M\$]      | [hh:mm:ss] |
| 1                     | 405       | 162  | 327   | 1.84       | 04:17:58   |
| 2                     | 642       | 257  | 266   |            |            |
| 3                     | 628       | 251  | 383   |            |            |
| 4                     | 1128      | 451  | 156   |            |            |
| Total                 | 2802      | 1121 | 1132  |            |            |

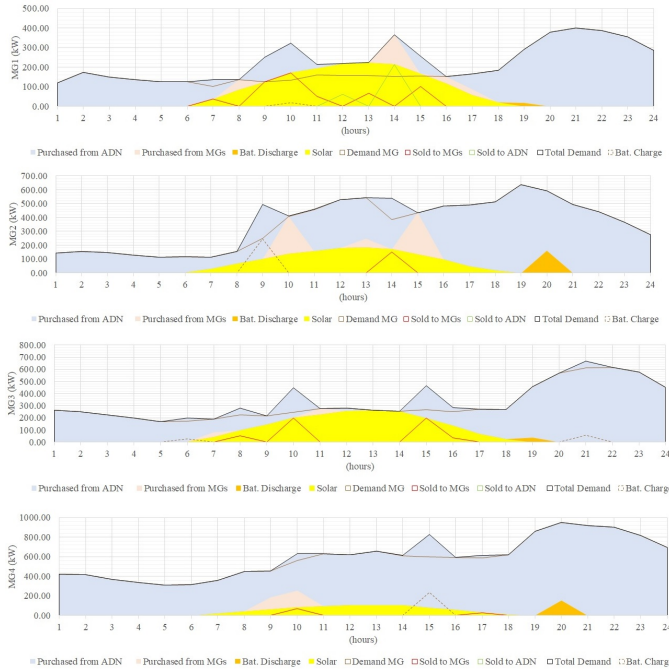


Fig. 8. Dispatch for each MG for the representative day of January at year 5.

#### D. Sensitivity Analysis

The impact of RES and EV penetration levels in the planning problem is examined here by considering different RES targets and EV demand levels. Thus, the RES requirements are

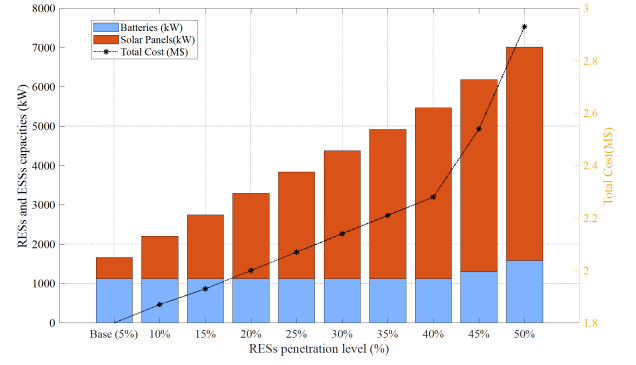


Fig. 9. Sensitivity analysis with respect to varying levels of RES penetration for the Base case EV demand.

varied from 5% to 50%, which is the maximum RES penetration for which a solution can be obtained, in 5% increments of the maximum available capacity of solar generation. On the other hand, given the low adoption rate of EVs in the region being studied, their demand is assumed to double in increments of 10%, corresponding to 10 to 50% of the MGs peak loads, which is not very likely in practice; nevertheless, to analyze a more significant EV penetration, an additional increase of 100% in EV demand is also simulated. For these studies, RES minimum penetration requirements are kept at 5% of the maximum available capacity of solar generation, so that proper comparisons with respect to the base values can be made.

The results of increasing the RES penetration requirements are presented in Fig. 9, where, for example, it can be observed that the total cost of planning is increased by 3.85% with respect to the costs with 5% penetration, if RES are 10% of the maximum available capacity of solar generation by the end of the planning horizon. Note that there is a sudden cost increase at 45% RES penetration, where the total cost increases by 11.5% and after 50% RES penetration, the problem becomes infeasible.

Fig. 9 illustrates the impact of EV penetration increases. Observe that a 10% increment in the EV demand results in a total cost increase of 1.79% on average, which is directly associated with an average 1.78% increase in ESS capacity. Also, observe that there is a slight increase in RES penetration for all MGs, which is also observed when the EV demand is increased to 200%, resulting in a 40.77% increment in total costs due mainly to a 40.71% increase in ESS capacity with respect to the Base case. From all these results, it can be concluded that the increase in RES penetration has a significant impact on the total costs and solution feasibility, while the increase in EV demand affects the total cost in proportion to the additional ESS capacity required to supply the EVs charging in the MMG system.

#### V. CONCLUSION

This paper presented a TSSP approach for the planning of MMG considering uncertainties associated with electricity demand and RES supply. It has been demonstrated that a TSSP

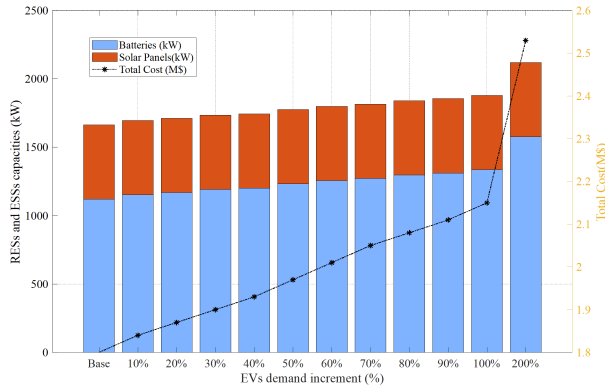


Fig. 10. Sensitivity analysis with respect to varying levels of EV demand for the Base case minimum required RES penetration.

approach provides a solution that is more accurate than the simple SLP problem, but not overly conservative as the case of the deterministic model. The proposed stochastic models are less conservative than the deterministic model, while the TSSP model is more precise than the simple SLP model, because of the hierarchical design of the decision-making process in the TSSP model. It is interesting to note that the use of GIS tools allowed having a more accurate estimate of the RES power availability for planning purposes. Therefore, this relevant application of GIS could be explored further in future MMG planning research work.

The proposed model could assist electricity system planners in planning and validating the formation of an MMG system inside an ADN while considering transactions among all participants, i.e., all the MGs and the ADN, the inclusion of long-term purchase decisions and short-term operational constraints, while using GIS to estimate rooftop solar limits. In addition, the optimal capacities of RES and ESS required to satisfy the demand of each MG can also be obtained, while offering insight into the operation of the MMG system and its flexibility during the planning horizon.

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