Optimization of Integrated Design and Operation of Microgrids Under Uncertainty

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***Abstract*—We present two Mixed-Integer Linear Programming (MILP) models for a microgrid planning problem which considers uncertainties in the main input data (hourly solar irradiance, wind speed and electric demand). The first model adopts a Two-Stage Stochastic Integer Programming (2SSIP) formulation with discrete scenarios of input data, whereas the second model adopts a Robust Optimization (RO) formulation with polyhedral uncertainty sets for the input data. The aim is to determine an optimal microgrid installment plan considering hourly combined operation of all the components, and uncertainties in the main input data. The 2SSIP model offers the possibility to obtain a planning solution considering a subset of discrete scenarios sample from an appropriate probability distribution. The RO model aims at determining a planning solution which is guaranteed to be feasible for any realization of input data within certain deviation specified in a so-called uncertainty set. To demonstrate the effectiveness and applicability of these models, we present a case study where we apply the two approaches to plan a standalone microgrid using real data from the Singida region in Tanzania. We show and compare results..**

***Index Terms*—microgrid planning, optimization, robust optimization, stochastic integer programming, uncertainties**

NOMENCLATURE

Indices

b	Index of types of storage battery (SB).
c	Index of types of bidirectional converters (BC).
d	Index of number of typical days.
g	Index of types of diesel generators (DG).
h	Index of number of hours.
p	Index of types of photovoltaic (PV) arrays.
q	Index of the segment in PWLA functions.
s	Index of scenarios.
w	Index of types of wind turbines (WT).

Sets

ℓ	Set of index of components to be considered $\ell \in \{g, p, w, b, c\}$.

Variables

$\overline{C_b}$	Maximum capacity of SBB of type b.
$\overline{E_b}$	Maximum energy of SBB of type b.
$E_{d,h,b}$	Total energy of SBB of type b in hour h of day d.
$P^{ch}_{d,h,b}$	Power to SBB of type b in hour h of day d.
$P^{dch}_{d,h,b}$	Power from SBB of type b in hour h of day d.
$P_{d,h,g}$	Output from DGs of type g in hour h of day d.
$P^{ch}_{d,h}$	Total charging to the SBBs in hour h of day d.
$P^{dch}_{d,h}$	Total discharging from the SBBs in hour h of day d.
$P^{dg,ch}_{d,h}$	Total charging power from DGs.
$P^{dg,exc}_{d,h}$	Total excess power from DGs.
$P^{dg}_{d,h}$	Total power from online DGs.
$P^{pv}_{d,h}$	Total generation from PV arrays.
$P^{ren,ch}_{d,h}$	Total charging power from RESs.
$P^{ren,L}_{d,h}$	Total power from RES supplied directly to the load.
$P^{ren,spl}_{d,h}$	Total RESs power which is spilled.
$P^{ren,tot}_{d,h}$	Total generation from RESs.
$P^{wt}_{d,h}$	Total generation from WTs.
$U_{d,h,g}$	Number of online DGs of type g in hour h of day d.
$V_{d,h,g}$	Number of started DGs of type g in hour h of day d.
$w^{inv}_{d,h}$	Binary variable to indicate BC inversion mode.
$w^{rec}_{d,h}$	Binary variable to indicate BC rectification mode.
$x^{ch}_{d,h}$	Binary variable to indicate charging of SBB.
$x^{dch}_{d,h}$	Binary variable to indicate discharging of SBB.
$Z_{d,h,g}$	Number of shut down DGs of type g in hour h of day d.

Parameters

$\hat{D}_{d,h}$	Electric demand in hour h of day d.
$\hat{G}_{d,h}$	Incident irradiance in hour h of day d.
$\hat{V}_{hwd,h}$	Turbine hub wind speed in hour h of day d.
$\pi_{d,s}$	Probability of discrete scenario of typical day d.
$\underline{SOC_b}$	Minimum relative SOC of SBB of type b.
$\overline{AC_\ell}$	Annualized capital cost for component of type ℓ.
C_{fuel}	Fuel cost.
Cbw_b	Battery wear cost.
DOD	Depth of discharge of SBB of type b.
f_d	Weighting factor of typical representative day d.
N_{ℓ,n_ℓ}	Number of component of type ℓ.
SDC	DGs shut down cost.
SUC	DGs start-up cost.
Y_ℓ	Lifetime of component of type ℓ.

I. INTRODUCTION

Microgrid planning is performed to determine optimal combination of types and sizes of Distributed Energy Resources (DER) of different technologies in order to provide reliable and continuous supply of electric power at minimum cost. In microgrids, a significant part of the total Life Cycle Costs (LCCs) is made up by its operational costs. This reveals a strong interdependence between microgrid operational and planning problem and thus make it necessary to integrate the operation problem when dealing with microgrid design.

However, the presence of discrete design and operational decisions, the nonlinear characteristics of Diesel Generators (DGs), and the dynamics of Storage Battery Bank (SBB) make the resulting model a Mixed-Integer Nonlinear Programming (MINLP) problem, which is difficult to solve (see, e.g., [1] for an experience on a similar problem). Furthermore, the generation from renewable based technologies such as Photovoltaic (PV) arrays and Wind Turbines (WTs) are characterised by uncertainties and variations which must be considered in microgrid planning stage. Therefore, a challenging planning aspect which must be addressed is how to determine the optimal mix of microgrid power generation components and the size of SBB in order to achieve continuous and reliable supply of power at minimum cost. The optimal plan must take into account operational flexibility requirements resulting form uncertainties and variations in renewable resources and electric demand.

Microgrid planning has received considerable critical attention in recent years, as it is fundamental to achieving technical, economic, and environmental benefits expected from microgrids deployment. Most of the existing work in the literature focus on the deterministic sizing and operational problems [2]–[4]. These works apply different techniques, such as heuristic algorithms [], mathematical optimization [] or commercial planning softwares such as HOMER and DER-CAM [2]. However, these approaches fail to address the instrinsic uncertainty of renewable resources and electric demand.

The two main frameworks for modelling uncertainties in microgrid planning are Stochastic Optimization (SO) and Robust Optimization (RO) [5], [6]. Within the SO framework, microgrid planning model falls naturally under the Two-Stage Stochastic Integer Programming (2SSIP) framework. In 2SSIP, planning variables are considered as the first stage "here-and-now" variables that are decided prior to the realization of uncertain parameters, whereas operational variables are considered as the second stage "wait-and-see" variables, which are decided when the uncertain parameters have been observed. SO approaches require rather detailed information on probability distributions for all the uncertain parameters. Furthermore, SO problems are computationally expensive due to large number of scenarios used to quantify uncertainties. The recent work in [7] applies SO-based Monte Carlo approach to model uncertainties in capacity expansion planning of an isolated grid with WTs, DGs, and SBBs. Another approach to solve 2SSIP is to adopt a hybrid decomposition algorithm, in which evolutionary algorithms (EA) decide the first-stage investment decisions and mathematical programming solve the second stage operational decisions is presented in [8], [9]. This approach gives sufficiently good solution, but EA does not guarantee global optimality. The authors in [10] present a Bender Decomposition (BD) algorithm to solve a SO model which optimizes the configuration of hybrid power system with DERs and storage system. In that paper all integer operational variables are lifted to the first stage decision level to allow for the use of the cutting plane method.

In contrast to SO, RO models parameter uncertainties by using uncertainty sets. This approach is suitable for microgrid planning problems particulary when planning a new microgrid in which information on probability distributions for renewable energy resources and electric demands are not readily available [11]. Indeed, with RO, only information on the support interval of the parameters is necessary. In [12], RO is applied to determine the optimal mix of power generation and storage components in an autonomous system for supplying power to a remote telecommunication station. In a recent paper by Khodaei et al., RO is applied to model uncertainties in electric demand, renewable resources, and market prices in microgrid planning [13]. The authors apply a BD algorithm, which consists of an investment master problem, solved annually, and operational subproblems, which are solved hourly, that are used to generate optimality cuts. It is worth pointing out that the work in [12] does not consider DGs and assumes the component capacities to be continuous variables, also neglecting all combinatorial aspects of the operational problem, whereas [13] consider a simplified operational model, with only maximum and minimum generation limits for DGs.

In this article, we present 2SSIP and RO formulations for the microgrid planning problem under uncertainty taking into account the discrete aspect of the operations. The proposed formulations consider integer commitment variables in the second-stage, in order to achieve more realistic and accurate approximation of operation costs. For the 2SSIP model, uncertainties are modeled by hourly probability distributions of electric demand, solar irradiance and wind speed. Discrete scenarios are generated by Latin Hypercube Sampling (LHS) and reduced to a finite and manageable number of input data scenarios by the fast forward algorithm in GAMS/Scenred2. This allows solving the 2SSIP model in its equivalent deterministic form, as a large Mixed-Integer Linear Programming (MILP) problem, by using a state-of-the-art mathematical programming solver such as Gurobi [14]. In addition to the SO with discrete scenarios, we also consider polyhedral uncertainty sets, allowing us to write a RO formulation of the problem. With the robust approach, we determine a solution which is guaranteed to be feasible for any realization of the input parameters in the uncertainty sets. The resulting semi-infinite program can be reformulated as a mixed-integer program with the addition of a polynomial number of auxiliary variables and constraints.

The main contributions of this paper are twofold: first, we integrate the detailed operational problem in a microgrid planning model, and, second, we consider the uncertainties in demand and renewable resources combining features of stochastic and robust optimization. These improvements clearly introduce modelling and computational challenges which are not encountered in deterministic planning problems.

Section II presents the topology of the modeled microgrid followed by Section III which presents the 2SSIP microgrid planning model. The RO formulation is described in Section IV. A case study to demonstrate applicability of the proposed models is presented in Section V. Computational results are presented and discussed in Section VI Finally, in Section VII we give some conluding remarks and future plan.

II. Microgrid Architecture

This work considers a parallel hybrid microgrid topology with AC and DC bus bars, as shown in Fig.1. It is assumed that WTs, PVs, and SBB are connected to the DC bus bar, whereas DGs and electric loads are connected to the common AC bus bar. The DC bus bar is connected to the AC bus bar via a Bidirectional Converters (BCs) capable of operating in inversion and rectification mode. Charger controller represents a bidirectional DC/DC converters which control charging and discharging of the SBB based on State of Charge (SOC) history. This topology offers superior performance over other topologies, such as single bus DC or AC topologies, because it enables all or part of electric demand to be supplied directly by any combination of PV arrays, WTs, SBBs and DGs [15].

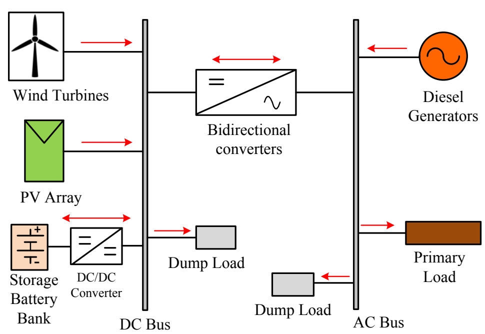

Figure 1. Topology of a parallel AC-and-DC bus microgrid (*arrows represent power flow*).

III. SIP Model for Microgrid Planning

A. Objective function

The objective function minimizes total annualized life cycle investment and operation cost computed over typical representative day for each season, with scenarios for renewable resources and electric demand hourly data.

$$
\begin{aligned}
\min \Bigg[& \sum_{p}\sum_{n_p} x_{p,n_p} N^{par}_{p,n_p} N^{ser}_{p} AC_p + \sum_{w}\sum_{n_w} x_{w,n_w} N_{w,n_w} AC_w + \\
& \sum_{b}\sum_{n_b} x_{b,n_b} N^{par}_{b,n_b} N^{ser}_{b} AC_b + \sum_{c}\sum_{n_c} x_{c,n_c} N_{c,n_c} AC_c + \\
& \sum_{g}\sum_{n_g} x_{g,n_g} N_{g,n_g} AC_g + \sum_{d}\sum_{h}\sum_{g}\sum_{s} \pi_{d,s} f_d U_{d,h,g,s} RC_g / Y_g + \\
& \sum_{d}\sum_{h}\sum_{b}\sum_{s} \pi_{d,s} f_d C_{bw,b} P^{dch}_{d,h,b,s} + \sum_{d}\sum_{h}\sum_{g}\sum_{s} \pi_{d,s} f_d U_{d,h,g,s} OMC_g + \\
& \sum_{d}\sum_{h}\sum_{g}\sum_{s} \pi_{d,s} f_d C_{fuel} \left(B_{q,g,c_g} P_{g,c_g,s} + U_{d,h,g,s} A_{q,g,c_g}\right) + \\
& \sum_{d}\sum_{h}\sum_{g}\sum_{s} \pi_{d,s} f_d \left(V_{d,h,g,s} SUC_g + Z_{d,h,g,s} SDC_g\right) \Bigg]
\end{aligned} \tag{1}
$$

Where the first five terms represent annualized investment costs for PV arrays, WTs, SBBs, BCs, and DGs; the sixth and seventh terms express replacement costs for DGs and SBB respectively; the eighth term represents O&M costs for DGs; the ninth term represents fuel cost for DGs; and the tenth term expresses start-up and shut down costs for DGs.

B. Constraints

The objective function (1) is minimized subject to the following constraints:

- For each type of components, only one binary variable which selects the number of component to install is allowed in the plan.

$$\sum_{n_\ell} x_{\ell,n_\ell} \le 1 \qquad \forall \ell \in \{g,p,w,b,c\} \tag{2}$$

- For each scenario, power balance constraints are expressed by:

$$P^{dg}_{d,h,s} + \left(P^{dch}_{d,h,s} + P^{ren,L}_{d,h,s}\right)\eta_{inv} - P^{dg,ch}_{d,h,s}$$
$$-P^{dg,exc}_{d,h,s} = \hat{D}_{d,h,s} \qquad \forall d,h,s \tag{3a}$$
$$P^{ren,L}_{d,h,s} = P^{ren,tot}_{d,h,s} - P^{ren,ch}_{d,h,s} - P^{ren,spl}_{d,h,s} \qquad \forall d,h,s \tag{3b}$$
$$P^{ren,tot}_{d,h,s} = P^{pv}_{d,h,s} + P^{wt}_{d,h,s} \qquad \forall d,h,s \tag{3c}$$
$$P^{dg}_{d,h,s} = \sum_{g} P_{d,h,g,s} \qquad \forall d,h,s \tag{3d}$$
$$\left(P^{dch}_{d,h,s} + P^{ren,L}_{d,h,s}\right) \le w^{inv}_{d,h,s}\overline{P^{inv}} \qquad \forall d,h,s \tag{3e}$$
$$P^{dg,ch}_{d,h,s} \le w^{rec}_{d,h,s}\overline{P^{rec}} \qquad \forall d,h,s \tag{3f}$$
$$w^{inv}_{d,h,s} + w^{rec}_{d,h,s} \le 1 \qquad \forall d,h,s \tag{3g}$$
$$P^{dg,ch}_{d,h,s} \le \underline{P^{dg}_{d,h,s}} - P^{dg,exc}_{d,h,s} - w^{rec}_{d,h,s}\hat{D}_{d,h,s} \quad \forall d,h,s \tag{3h}$$
$$w^{rec}_{d,h,s} \le \sum_{g} U_{d,h,g,s} \qquad \forall d,h,s \tag{3i}$$

Constraint (3a) defines the power balance at the AC bus bar of Fig.1, implying that the demand can be supplied by any combination of DGs, SBB, PV array, and WTs. Part of total generation from Renewable resources (RES) which is supplied directly to the load is equal to the difference between total RES's generation and the sum of charging and spilled power from RESs (3b). Total RESs generation is given by sum of generation from PV array and WTs (3c). Total power from DGs is the sum of generation from all types of DGs which are online at a particular period (3d). Exchange of power between the two buses is limited by inversion and rectification capacity of installed BC as described by (3e) and (3f). The binary variables ensure that power flow from the DC to AC bus or from AC to DC bus happens only when the BC is in the inversion or rectification mode, respectively. The BC cannot operate in inversion and rectification mode at the same time (3g). Any online DGs may charge the SBB when it operates at its minimum limit and the demand is less than this DG minimum limit (3h). The rectification mode can happen only when there are DGs online (3i).

- DGs operation constraints are formulated based on the Clustered Unit Commitment (CUC) method which models DGs commitment by integer variables. This allows modelling hourly discrete operation decisions for one or group of generators of the same type [16].

$$U_{d,h,g,s}\underline{P_g} \le P_{d,h,g,s} \le U_{d,h,g,s}\overline{P_g} \qquad \forall d,h,g,s \tag{4a}$$

$$V_{d,h,g,s} - Z_{d,h,g,s} \leq U_{d,h,g,s} - U_{d,h-1,g,s} \qquad \forall d,h,g,s \quad (4b)$$

$$U_{d,h,g,s} \leq \sum_{n_g} x_{g,n_g} N_{g,n_g} \qquad \forall d,h,g,s \quad (4c)$$

$$V_{d,h,g,s} \leq \sum_{n_g} x_{g,n_g} N_{g,n_g} - U_{d,h,g,s} \qquad \forall d,h,g,s \quad (4d)$$

$$Z_{d,h,g,s} \leq U_{d,h,g,s} \qquad \forall d,h,g,s \quad (4e)$$

DGs power generation limits are specified in (4a). Relationship between number of start-up, shut-down and online DGs is expressed by (4b). Number of online DGs must be less than or equal to the number of installed DGs (4c). The number of DGs that can be started-up or shut-down is restricted to the number of remaining offline and online DGs respectively, (4d) - (4e).

- Constraints for SBB operation

$$E_{d,h,b,s} = E_{d,h-1,b,s} + \Delta h(\eta_b^{ch} P_{d,h,b,s}^{ch} - P_{d,h,b,s}^{dch}/\eta_b^{dch}) \qquad \forall d,h,b,s \quad (5a)$$

$$\underline{E_b} \leq E_{d,h,b,s} \leq \overline{E_b} \qquad \forall d,h,b,s \quad (5b)$$

$$0 \leq P_{d,h,b,s}^{ch} \leq x_{d,h,s}^{ch} \overline{P_{d,h,b,s}^{ch}} \qquad \forall d,h,b,s \quad (5c)$$

$$0 \leq P_{d,h,b,s}^{dch} \leq x_{d,h,s}^{ch} \overline{P_{d,h,b,s}^{dch}} \qquad \forall d,h,b,s \quad (5d)$$

$$x_{d,h,s}^{ch} + x_{d,h,s}^{dch} \leq 1 \qquad \forall d,h,b,s \quad (5e)$$

$$C_b^{bb} = \sum_b \sum_{n_b} x_{b,n_b} N_{b,n_b}^{par} N_b^{ser} C_b V_b \qquad \forall b \quad (5f)$$

$$\overline{E_b} = C_b^{bb} \qquad \forall b \quad (5g)$$

$$\underline{E_b} = (1 - DOD_b) C_b^{bb} \qquad \forall b \quad (5h)$$

$$E_{0,b} = SOC_{0,b} C_b^{bb} \qquad \forall b \quad (5i)$$

Constraint (5a) relates the current energy in SBB to the previous energy and the current charging and discharging power. Energy in the SBB must be greater than or equal to its minimum energy limit and less than or equal to its maximum energy limit (5b). The maximum charging and discharging limit for the SBB are expressed by (5c) and (5d), that also enforce the complementarity condition between charging and discharging power in combination with (5e). Capacity of installed SBBof type b is defined by (5f). Maximum, minimum and initial energy in the SBB are defined by (5g), (5h), and (5i) respectively.

IV. RO Model for Microgrid Planning

In our robust model, we are going to consider a typical days for each season. However, as opposed to the SIP model, we will not consider a discrete number of scenarios, but an uncertainty set for each season. The RO model allows us to determine a solution that is robust against the uncertainties for each season (typical day).

A. Objective function

The objective function for RO model is similar to that of 2SSIP model presented in section III, except that the subscripts for scenarios is dropped. We are still minimizing the fixed annualized installment cost, while also taking into account the operational costs. However, instead of a different operational schedule for each scenario, in this case we only have one robust operational schedule per season, whose cost has to be accordingly weighted in the objective function.

B. Constraints

In the RO model, account for uncertainties in PV and WT generation and electric demand. In particular, for each season we consider all possible realizations of the uncertain parameters that belong to an uncertainty set. The uncertainty sets are defined according to the budget of uncertainty framework introduced in [17], as follows:

The parameter Γ controls the conservatism of the approach, as it is an upper bound on the number of deviations that can occur in the time horizon. From a theoretical standpoint, the parameter Γ also gives probabilistic guarantees, thanks to the bound described in [17]. The RO model is a semi-infinite programming problem, since the robust constraints must be satisfied for all the (infinitely many) parameters in the uncertainty sets. However, for polyhedral uncertainty sets, the problem can be easily reformulated exploiting duality in linear programming, obtaining a robust formulation that is of the same class as the deterministic problem (in this case, MILP), except for a (manageable) number of additional continous variables and constraints. We do not dwell in further details about the reformulation, as it is rather standard practice (see reference [17], and examples of usage in similar contexts in [18], [19]). However, before applying the robust reformulation, it is worth noting that we have to modify a part of the constraints to render the model suitable for the robust reformulation.

- As a first step, Constraints for SBB operation, which replace (5a) and (5b), are written in an aggregated form as follows:

$$\underline{E_b} \leq E_{0,b} + \Delta h \sum_{\tau=1}^{h} (\eta_b^{ch} P_{d,\tau,b}^{ch} - P_{d,\tau,b}^{dch}/\eta_b^{dch}) \leq \overline{E_b} \quad \forall d,h,b. \quad (6a)$$

  This is close in spirit to the approach suggested in [18], where the storage variables is replaced by its aggregated form.
- Similarly, we get rid of all the equality constraints where the uncertain parameters PV, WT, D appear, projecting out the redundant variables (whose value is completely determined by the remaining ones) by substition, namely .... We do not write the complete model here for sake of readability.
  These substitutions allow us to have a model where the uncertain parameters only appear in inequalities, thus we can easily apply the RO framework.
- Note that DGs operation constraints (4a) - (4e) remain the same, without the subscript for scenarios, as well as all the remaining inequality constraints.

V. Microgrid Planning Case Study

The proposed 2SSIP and RO models are applied to optimize the plan of a community microgrid considering PVs, WTs, SBBs, and DGs. For the 2SSIP model, uncertainties in solar irradiance, wind speed, and electric demand are modeled by Beta, Rayleigh, and Normal probability density functions (PDFs), respectively. Since the site is located in a tropical region (...), annual hourly input data are divided into dry and rainy seasons in order to generate scenarios which retain seasonal variations. Then, probability distributions for irradiance, wind speed, and electric demand for each hour of the days falling in the dry and rainy seasons are estimated. Using these distributions, LHS is applied to generate 4000 discrete scenarios for irradiance, wind speed, and electric demand. Each season is represented by one typical day containing 20 reduced scenarios obtained by applying the fast forward algorithm in GAMS/Scenred2 to reduce the 4000 scenarios generated above. Reduced scenarios for irradiance and wind speed are used in calculation of per unit generation of each type of PV panel and WT considered in this study. ??? Figure 2 shows the 20 reduced scenarios for electric demand, power from PV of type PV1, and power from WT of type WT1, for each typical day representing the dry and rainy season.

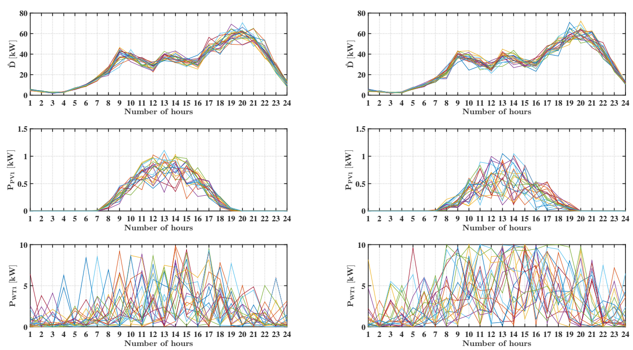

Figure 2. Scenarios for electric demand ($\bar{\boldsymbol{D}}$), power from PV1($\bar{\boldsymbol{P}}_{\mathbf{PV1}}$) and WT1($\bar{\boldsymbol{P}}_{\mathbf{WT1}}$) for the typical day of dry season (left) and rainy season (right)

For the RO model, input data simply consists of average and standard deviations of electric demand, per unit generation from each PV and WT model. Figure 3 shows the input data for the RO model. We make the assumptions that each uncertain parameter will belong to the support interval $\mu \pm \sigma$.

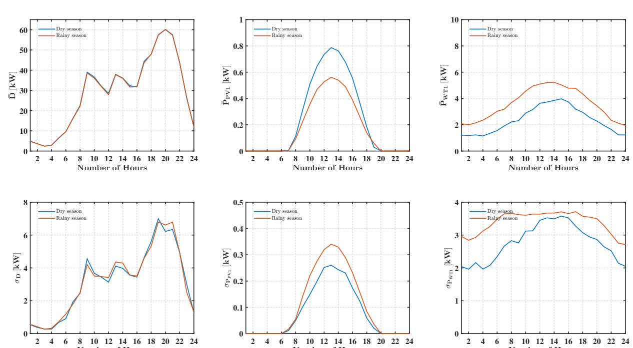

Figure 3. Sample input data for RO model, average electric demand ($\hat{\boldsymbol{D}}$), power from PV1($\bar{\boldsymbol{P}}_{\mathbf{PV1}}$) and WT1($\bar{\boldsymbol{P}}_{\mathbf{WT1}}$), and their corresponding standard deviations

A. Components input data

Table I summarises technical and economic input data for DGs.

TABLE I. SPECIFICATIONS OF DIESEL GENERATORS

Type	$\overline{P_g}$	$\underline{P_g}$	B_1	A_1	AC_g	RC_g	OMC_g	Y_{dg}^g	SUC	SDC
	$[kW]$	$[kW]$	$[L/h/kW]$	$[L/h]$	[€]	[€]	[€/h]	[h]	[€]	[€]
DG1	16.0	4.80	0.3000	0.4336	949.89	11000	0.2080	15000	0.4	0.20
DG2	7.2	2.16	0.3611	0.3830	335.99	3890.88	0.1008	8200	0.2	0.10

One type of PV array with specifications given in Table II was considered.

TABLE II. SPECIFICATIONS OF PV PANELS

Type	$\overline{P_p^{STC}}$	T^{STC}	G^{STC}	f_{der}	$V_p^{pv,n}$	$NOCT$	γ	AC_p	Y_{pv}^p
	[kW]	$[^oC]$	$[kW/m^2]$	$[^oC]$	[V]	$[^oC]$	$[\%/^oC]$	[€]	[yr]
PV1	1	25	1	1	6	47	-0.5	355.73	25

Table III summarises specifications two types of WTs with costs which include the economy of scale. Table IV presents

TABLE III. SPECIFICATIONS OF WIND TURBINE MODELS

Type	$P_w^{wt,n}$	$V_w^{wt,n}$	V_w^{ci}	V_w^{co}	AC_g	Y_w^{wt}
	$[kW]$	$[m/s]$	$[m/s]$	$[m/s]$	[€]	[yr]
WT1	10	12.5	3.0	25.0	3052.09	15
WT2	3	12.0	3.0	20.0	1277.88	15

specifications for the SBB. A bidirectional converter of 10 kW

TABLE IV. SPECIFICATIONS OF STORAGE BATTERY MODELS

Type	C_n	$\overline{C_b^{sb}}$	V_{bn}	DOD	η_{ch}	η_{dch}	$\overline{I_{ch}}$	$\overline{I_{dch}}$	$\overline{Ch_{rb}}$	AC_b	$C_{bw,b}$	Y_b^{sb}
	$[Ah]$	$[Ah]$	$[V]$	$[\%]$	$[\%]$	$[\%]$	$[A]$	$[A]$	$[A/Ah]$	[€]	[€/kW]	[yr]
SB1	820	1151.56	6	60	90.0	90.0	82	500	1	153.62	0.1275	12

with annualized costs of € 1179.4 and lifetime is set to 20 years is considered. The converter rectification and inversion efficiencies are both assumed to be 90%. Maximum allowable number of converters to be installed is set to 10.

VI. RESULTS AND DISCUSSIONS

Table V shows the optimal number of each type of component and the total annualized cost of microgrid obtained by 2SSIP model and RO model.

TABLE V. OPTIMAL COMPONENTS MIX FROM 2SSIP AND RO MODELS

Descriptions			**Number of Installed Components**	
Components/Costs	**Symbol**	**Unit Capacity**	**2SSIP Model**	**RO model**
Diesel generators	$DG1$	16.0 kW	3	?
	$DG2$	7.2 kW	3	?
Photovoltaic panels	$PV1$	1.0 kW	30	?
Wind Turbines	$WT1$	10.0 kW	3	?
	$WT2$	3.0 kW	0	?
Storage Battery	$SB1$	4.92 kWh	12	?
Bidirectional converter	$BC1$	10.0 kW	4	?
Total annualized cost of system	$TACS$	–	€ 86812.43	€ ??

Breakdown of the total annualized cost of microgrid obtained by the proposed 2SSIP and RO models are summarized in Fig.4.

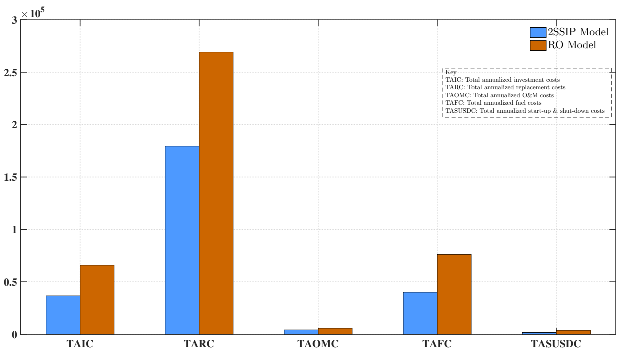

Figure 4. Decomposition of planning costs obtained by 2SSIP and RO models

VII. Conclusions

This study considers integer planning decision variables which reflect the real-world application in which component capacities are not continuous. One of the limitation of this study is the long computation time. However, such long computational for planning problems can be accepted since the problem is solved off-line and only once during the planning stage.

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