A Planning Model for a Hybrid AC/DC Microgrid using a Novel GA/AC OPF Algorithm

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Abstract—This paper focuses on developing an appropriate combinatorial optimization technique for solving the optimal sizing problem of hybrid AC/DC microgrids. A novel two-stage iterative approach is proposed. In the first stage, a meta-heuristic technique based on a tailor-made genetic algorithm is used to tackle the optimal sizing problem, while, in the second, a nonlinear solver is deployed to solve the operational problem subject to the obtained design/investment decisions. The proposed approach, being able to capture technical characteristics such as voltage and frequency through a detailed power flow algorithm, provides accurate solutions and therefore can address operational challenges of microgrids. Its capability to additionally capture contingencies ensures that the proposed sizing solutions are suitable both during normal operation and transient states. Finally, the genetic algorithm provides convergence of the model with relative computational simplicity. The proposed model is applied to a generalizable microgrid comprising of AC and DC generators and loads, as well as various types of storage technologies in order to demonstrate the benefits. The load and natural resources data correspond to real data.

Index Terms—AC/DC microgrid, Microgrid planning, Genetic algorithm, AC optimal power flow, Hybrid storage

NOMENCLATURE

Parameters

- $\Delta t$: Time interval
- $\delta_{\text{lim}}$: Maximum permissible voltage angle variation between two buses
- $\eta_c$: Efficiency of storage device(s) in bus $b$ during charging
- $\eta_d$: Efficiency of storage device(s) in bus $b$ during discharging
- $\gamma_p$: Interlinking converter active power droop gain
- $\gamma_q$: Interlinking converter reactive power droop gain
- $\omega_{\text{max}}$: Maximum permissible value of frequency $\omega$
- $\omega_{\text{min}}$: Minimum permissible value of frequency $\omega$
- $B_{bp}$: Susceptance of branch connecting AC buses $b, p$
- $c_{ls}$: Cost associated with load shedding

Sets

- $G_{\text{bus AC}}$, $G_{\text{bus DC}}$, $G_{\text{bus}}$: Total number of AC-side generator buses, total number of DC-side generator buses, total number of generator buses, $G_{\text{bus}} \subset N_{\text{bus}}$
- $L_{\text{bus AC}}$, $L_{\text{bus DC}}$, $L_{\text{bus}}$: Total number of AC-side load buses, total number of DC-side load buses, total number of load buses, $L_{\text{bus}} \subset N_{\text{bus}}$
- $N_{\text{br}}$, $N_{\text{bus AC}}$, $N_{\text{bus DC}}$, $N_{\text{bus}}$: Total number of branches, total number of AC-side buses, total number of DC-side buses, total number of buses
- $N_g$: Total number of AC-side generators, total number of DC-side generators, total number of generators
- $S_{\text{bus}}$, $S_{\text{bus}}(c)$: Total number of buses with storage device(s), total number of buses with storage device(s) for contingency $c$, $S_{\text{bus}} \subset N_{\text{bus}}$

Variables

- $\delta_e$: Error between the normalized frequency, $\hat{\omega}$, and the normalized DC voltage, $V_{dc}$
- $\delta(b, t, c)$: Voltage angle of AC bus $b$ at time $t$ for contingency $c$
- $\delta(p, t, c)$: Voltage angle of AC bus $p$ at time $t$ for contingency $c$
- $\delta_{bp}(t, c)$: Voltage angle difference between buses $b, p$ at time $t$ for contingency $c$
- $\hat{\omega}$: Normalized value of frequency $\omega$

Cost associated with overslack (i.e. an artificial generator)
- $c_{os}$
- $E_{S_{\text{max}}}$: Maximum state of charge
- $E_{S_{\text{min}}}$: Minimum state of charge
- $G_{bp}$: Conductance of branch connecting AC buses $b, p$
- $P_{g_{\text{max}}}$: Maximum power of a generator $g$ (active)
- $P_{g_{\text{min}}}$: Minimum power of a generator $g$ (active)
- $Q_{g_{\text{max}}}$: Minimum stable generation of a generator $g$ (reactive)
- $Q_{g_{\text{min}}}$: Maximum stable generation of a generator $g$ (reactive)
- $S^{\text{lim}}(i)$: Capacity limit of branch $i$
- $S_{\text{max}}$, $S_{\text{min}}$: Maximum and minimum storage power
- $V_{dc_{\text{max}}}$, $V_{dc_{\text{min}}}$: Maximum and minimum permissible DC voltage
- $V_{\text{max}}$, $V_{\text{min}}$: Maximum and minimum permissible AC voltage

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As far as the operational challenges are concerned, the mathematical formulation of such problems is considered of utmost importance, since it can determine whether critical measures are captured or not. For example, capturing voltage and frequency characteristics of the networks can facilitate enhanced monitoring of their stability indexes and eventually lead to increased resilience and security of supply, even under contingencies. However, relevant literature survey ([9], [10], [11]) indicates that detailed formulations are not often met; typically, energy management systems (i.e. only power balance equations to control the power flows) are employed for the analysis of MGs without detailing the classical power flow equations, which capture voltage, frequency and angle variation and can therefore lead to more accurate solutions. Reference [9] presents an algorithm for optimal scheduling of an AC MG considering islanding constraints. The power flow algorithm considered is a linear algorithm, as the power flow equations capturing voltage are not included and a simplified, linear model is adopted for the storage devices. In a similar context, the work presented in [10] proposes a multi-objective optimal scheduling of a DC microgrid consisting of a PV system and an electric vehicle charging station. In this paper, the cost of electricity and energy circulation of storage systems in an integrated manner [6]. Energy management across various timescales is achieved via the coordinated use of heterogeneous ES technologies (i.e. hybrid storage) effectively combining high power and high energy properties [7], [8]. This paper focuses on developing appropriate optimization formulations and techniques for further studying the benefits of such hybrid MGs both in terms of operational and design challenges.

I. INTRODUCTION

MICROGRIDS (MGs) will play a crucial role in the development of future energy systems worldwide due to the essential benefits they provide over the traditional top-down radial network philosophy [1]. Although great uncertainty surrounds the prevailing MG architectures that will emerge, it is apparent that building-scale and local-aggregator MGs will become common in the coming decades [2]. In both cases, the MG operator can have access to a plethora of different resources; AC and DC generators, such as wind turbines (WTs) and PV plants respectively, AC and DC loads (e.g. electric vehicles), and various types of energy storage (ES) technologies (e.g. fuel cells and supercapacitors) [3], [4]. Substantial savings can be achieved by optimizing the MG connectivity architecture and AC/DC interface due to increased efficiency and reduced capital expenditure on unnecessary conversion stages [5]. This is especially topical given recent advances in power electronics; multiport converters, which offer the capability of multiple voltage level outputs, can provide controllability across several AC and DC subsystems in an integrated manner [6]. Energy management across various timescales is achieved via the coordinated use of heterogeneous ES technologies (i.e. hybrid storage) effectively combining high power and high energy properties [7], [8]. This paper focuses on developing appropriate optimization formulations and techniques for further studying the benefits of such hybrid MGs both in terms of operational and design challenges.
the optimal operation of the MG. It reports how the total operational cost of a MG can be reduced by utilizing storage and flexible demand. For this reason, in the mathematical formulation proposed in this paper the full equations pertaining both AC and DC grid operation are included as well as relevant constraints for a DC voltage-AC frequency coupling aiming to demonstrate through appropriate case studies how the onerous constraints imposed by a complete AC OPF may affect the optimal operation strategy of hybrid MG.

Regarding optimal sizing of hybrid AC/DC MGs, there is no significant amount of research focused on this area. Therefore, this paper proposes a method that can bridge a gap in this respective area. Having said that, however, various techniques have been proposed over the years for optimal sizing of AC MGs, since research in this area is a lot more mature. Specifically, mathematical programming methodologies (linear, non-linear, mixed-integer, etc.) and evolutionary techniques have been utilized amongst others for solving this issue. In [13], a dynamic programming (DP) method has been employed to optimally size an ES system for a MG. The method can successfully point out the optimal capacity of the ES system taking into account different modes of operation (i.e. grid-connected and islanded), particularly due to the way the search space is broken down (i.e. sequence of steps considering at each step the subsequences of the previous step). However, the authors point out that this method can prove to be a barrier for large-scale systems, as it would required high computational power to parse the search space. In [14], a mixed-integer programming formulation has been used to size an ES system by additionally incorporating a reliability criterion (i.e. loss of load expectation) into the model and investigating various power system operation scenarios through Monte Carlo simulations. Binary and continuous variables introduced by the reliability consideration would lead to unreasonable computational time if a highly accurate solution was sought, hence suitable scenario reduction was proposed. In [15], a MG, comprising of photovoltaic (PV) arrays, a diesel generator and ES systems is designed utilizing heuristics, directly exploiting the capabilities of a commercially available software, HOMER Pro. However, heuristics have proven to be ineffective for such types of studies, as their inherent trade-off between computational simplicity and solution accuracy is an unresolved challenge [16]. In response to this, so-called metaheuristic approaches or evolutionary techniques have been developed trying to overcome the issue of providing non-optimal solutions with relatively more efficient computational time; genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization, etc. belong in this category [17]. Each evolutionary strategy exhibits different advantages in comparison to others. For example, PSO is possibly one of the simplest strategies being able to explore the search space in lower computational time, which is an important factor in large and/or non-linear systems [18]. However, PSO is characterized by the drawback that a maximum of three parameters can be evaluated (i.e. based on defining the coordinates of particles on a (x,y,z) plane); this leads to limitations when it comes to sizing large systems, which may include more than three parameters for optimal sizing.

In this paper, a GA is employed since it does not suffer from the limitation explained right above and is additionally very efficient in terms of computational time and programming simplicity. Especially, given that the formulation proposed is highly non-linear and the integers introduced by the sizing problem further increase the complexity, the utilized algorithm is shown to have critically improved the performance, ensuring convergence of the algorithm at all times. The contributions of this paper are summarized hereafter:

- A detailed AC optimal power flow (OPF) algorithm is developed, which provides the added benefit of being able to capture operational characteristics of the network under consideration. This ensures that the optimal design satisfies all operational constraints of the network.
- The formulated OPF is time-coupled, hence ES devices are included. The benefit of utilizing different storage types (rather than simply lead-acid or other traditional types of batteries), when evaluating the optimal design candidates, is demonstrated through appropriate case studies.
- The adopted formulation considers contingencies occurring at the network and discrimination of loads into critical and non-critical. In the specific case study shown in this paper, a contingency of the interlinking converter (IC) is assumed. Regarding the loads, 30% of the loads are considered to be critical to enable the simulation of a real-world scenario, where uninterruptible operation of essential equipment would be required. These modeling details indicate the effect contingencies and load discrimination have on the optimal design of a MG.

The paper is organized as follows: Section II discusses the challenges and considerations when optimally designing and operating hybrid MGs and responds to how these challenges are addressed in this work. It additionally presents the proposed GA and AC OPF algorithm for optimally designing and evaluating the operation of the system respectively. Section III introduces the MG under consideration, and subsection III-A demonstrates the simulation results. Finally, in Section V conclusions are drawn.

II. Design and Operation of Hybrid Microgrids

The optimal design and operation of a hybrid MG, as any other power system, is a notoriously hard problem due to the increased modeling complexity [19]. On the one hand, the planning aspect introduces numerous binary variables to determine asset sizing, voltage levels, etc. On the other hand, the operational modeling involves non-linear constraints pertaining to the AC power flow formulation. Additionally, in order to successfully model the energy exchange between the AC and DC subsystems a coupling strategy needs to be proposed. In this paper a unified approach is adopted that embeds the control scheme of the interlinking converter within the problem in the form of voltage-frequency coupling
constraints [20]; in this way, effective communication between the two grids is established not only via the power balance equation, but also through measures critical during transient states. More importantly, a credible set of contingencies shall be considered while determining the optimum solution. This will ensure that operation is feasible (e.g. no curtailed demand, no voltage violations, etc.) under all credible contingencies [21]. The objective function corresponds to the minimization of investment and operational cost, while respecting the operational constraints. Multiple operating points are considered through a 24-hour operating horizon to capture demand and renewables variability. Note that this study deals with static planning; i.e. the assets are to be sized once and the possibility for future additions/upgrades is not considered. Hence, and even though it is good practice to consider a large number of operating points, it is important to note that planning decisions are, for the most part, driven by a small number of operating points, such as peak electrical demand, least amount of PV available, etc. The topic of optimally choosing which operating points to be included in a planning exercise is still an open research topic; e.g. see [22] for more details on the topic.

The above considerations result in a large Mixed Integer Non-Linear Program (MINLP). To address the computational complexity that arises, a novel two-stage iterative solution approach is developed. In the first stage, a meta-heuristic technique based on a tailor-made GA is used to tackle the optimal design problem. In the second stage, a non-linear solver is used to solve the operational problem subject to the previously- obtained design/investment decisions. A random selection of candidates (with pre-defined bounds) forms the initial population of candidate investments. Each individual of the population is evaluated according to the fitness function, which involves the total system cost. The results are fed back to the design stage in order to derive a new set of individuals; improvements are achieved via successive crossovers and mutations for a pre-defined number of generations. The sections below describe in detail the two stages.

A. Genetic Algorithm

As already explained, a custom GA is employed to solve the design problem aiming at a better computational performance in this MINLP problem. A GA, categorized as a global search metaheuristic, mimics natural biological procedures. According to [23], [24], the basic components of a GA are:

- A representation of potential solutions of the problem.
- A way to create an initial population of potential solutions (i.e. randomly selected values, user-defined, etc.)
- An evaluation function (i.e. fitness function) which is utilized for rating solutions in terms of their ‘fitness’. The evaluation function is usually cost minimization or equivalently fitness maximization.
- Genetic operators (i.e. crossover and mutation) that alter the composition of the children.
- Algorithmic parameters of the GA.

GAs exhibit certain advantages over other mathematical programming or evolutionary techniques reported in the literature for sizing components of MGs, and that is why a GA has been developed for this problem. For clarity, a few of their advantages are mentioned below [17], [25], [26], [27]:

- A GA can attain global optimum with relative computational simplicity; this attribute is especially related to the mutation procedure adopted by the GAs.
- It works with a pre-defined number of population generations. For a large system, other evolutionary algorithms may not be able to stop, as no such good solution exists. However, the way a GA works ensures that the iterative process will eventually stop.
- It has been proven to be highly applicable to cases of large non-linear systems, such as the case of a hybrid MG integrating renewable generation and storage.
- It is effective for sizing studies of such MGs (i.e. with large number of decision variables for sizing equipment).

A GA starts from an initial population of chromosomes or individuals (e.g. \( x_1 = [a_1, b_1, c_1] \), \( x_2 = [a_2, b_2, c_2] \), etc.), and looks for the optimal solution as it evolves. Evolution in this case translates into altering the genes that every chromosome is comprised of in some certain fashion (e.g. \( x_1 = [a_1 + 0.5a_2, b_1 + 0.5b_2, c_1 + 0.5c_2] \), etc.). This procedure is followed until a pre-specified number of iterations or generations has been performed. In every step, the optimizer calculates the objective function and searches for these combinations of equipment (i.e. chromosomes) that satisfy the fitness function. Only the ones that satisfy the fitness function are moved to the next generation, where a mutation happens and the next generation is evaluated; this procedure is continued until the pre-defined number of generations has been finished. Then the solution with the optimal value is selected.

In the system under investigation, a GA, with the structure illustrated in Fig. 1, is employed to size two parameters for minimizing the system cost: the capacity of the PV plant and the capacity of the WT (refer to Section III).

As indicated in Fig. 1, a main difference of the proposed GA comparing to traditional and widely used approaches relates to the way the fitness function is constructed. The main steps for constructing the fitness function are described below:

- The OPF determines the total system cost as per the objective function shown in equation 1 (refer to Subsection II-B for more details on the AC OPF). This includes the investment cost relating to the PV, wind turbine and storage capacities determined within the GA, as well as the operational cost determined by the OPF itself for a given set of capacities.
- The total system cost is fed back to the GA via an appropriate communication channel and constitutes the fitness function for evaluating the effectiveness of the selected individuals.
- The GA selects the best candidates (i.e. selection based on a tournament) and applies crossover and mutation to effectively continue with the next generations.
B. An AC OPF for a Hybrid AC/DC Microgrid with Voltage-Frequency Coupling Constraints

The AC OPF introduced in this section is utilized for assessing the operation of the problem at hand, specifically for minimizing the total system cost; i.e. the summation of any cost associated with investments required for ensuring that the imposed constraints are satisfied (e.g. covering the demand), and the total generation cost including the cost of any involuntary loadshedding of the MG. In mathematical terms, the objective function of the problem can be given by (1). The first term denotes the costs associated with investments; in the case study presented in this paper the cost will include expenditure on PV arrays and WTs. The second term involves the generation cost; i.e. the cost for operating the two conventional generators included in the MG. The third term is included to capture the cost of load shedding; it is a prerequisite of every power system that the demand is covered to the extent possible leading to high security of supply figures and as such the value of lost load is exceptionally high (i.e. in comparison with the most expensive generator). Finally, the fourth term is included to avoid infeasibilities, and in practice it is modeled as an artificial, very expensive generator.

\[
F = \sum_{c \in C} \sum_{t \in T} \sum_{g \in N_{AC}} c_g \cdot (P_{AC}(g, t, c) + Q_{AC}(g, t, c)) + \sum_{c \in C} \sum_{t \in T} \sum_{b \in L_{bus,AC}} c_{b} \cdot (P_{sAC}(b, t, c) + Q_{sAC}(b, t, c)) + \sum_{c \in C} \sum_{t \in T} \sum_{b \in G_{bus,AC}} c_{os} \cdot (P_{osAC}(b, t, c) + Q_{osAC}(b, t, c)) + \sum_{b \in N_{WT}} C_{WT} + \sum_{c \in C} \sum_{t \in T} \sum_{g \in N_{PV}} c_{g} \cdot P_{DC}(g, t, c) + \sum_{c \in C} \sum_{t \in T} \sum_{b \in L_{bus,DC}} c_{ls} \cdot P_{lsDC}(b, t, c)
\]

+ \sum_{c \in C} \sum_{t \in T} \sum_{b \in G_{bus,DC}} c_{os} \cdot P_{osDC}(b, t, c) + \sum_{b \in N_{PV}} C_{PV} \tag{1}

The optimization problem can be posed as a minimization problem, i.e. \( min(F) \), subject to the constraints represented by (2) - (11). Specifically, (2) - (4) introduce the operational constraints of the MG. Inequalities (5) and (6) represent the minimum and maximum active and reactive power limits of the generators. Inequalities (7) and (8) denote the limits for the charging and discharging power of the energy storage devices, while equation (9) is introduced to ensure that charging and discharging cannot occur simultaneously. Additionally, inequality (10) corresponds to the maximum depth of discharge and state of charge rating for an energy storage device, and equation (11) ensures that energy stored in a storage device shall be conserved from one time step to the next one. The equations shown below capture only the constraints relevant to the AC network operation, however this formulation has been developed to provide an OPF solution for both an AC and a DC grid. Therefore, equations (2), (3), (5), (7) - (11) have been duplicated in the developed model and accordingly modified to account for the DC grid as well (i.e. excluding the equations related to reactive power and voltage angle); more information can be found in [28], [29]. The equations are solved following a unified approach, according to which the AC and DC subproblems are solved simultaneously [20].

\[
V_{\min} \leq V_{AC}(b, t, c) \leq V_{\max} \quad \forall c \in C, \forall t \in T, \forall b \in N_{bus,AC}
\]

\[
\max(S_{AC}(i, t, c)) \leq S(i)_{\text{lim}} \quad \forall c \in C, \forall t \in T, \forall i \in N_{br,AC}
\]

\[
|\delta_{(b, t, c)} - \delta(p, t, c)| \leq \delta_{\text{lim}} \quad \forall c \in C, \forall t \in T, \forall b, p \in N_{bus,AC}
\]

\[
P_{g,\min} \leq P_{g}(g, t, c) \leq P_{g,\max} \quad \forall c \in C, \forall t \in T, \forall g \in N_{gAC}
\]

\[
Q_{g,\min} \leq Q_{AC}(g, t, c) \leq Q_{g,\max} \quad \forall c \in C, \forall t \in T, \forall g \in N_{gAC}
\]

\[
0 \leq S_{AC}^{e}(b, t, c) \leq S_{AC}^{a}\max, \quad \forall c \in C, \forall t \in T, \forall b \in S_{bus,AC}
\]

\[
0 \leq S_{AC}^{d}(b, t, c) \leq S_{AC}^{a}\max, \quad \forall c \in C, \forall t \in T, \forall b \in S_{bus,AC}
\]

\[
S_{AC}^{e}(b, t, c) \cdot S_{AC}^{d}(b, t, c) = 0, \quad \forall c \in C, \forall t \in T, \forall b \in S_{bus,AC}
\]

\[
E_{S_{AC}^{e}}^{\min} \leq ES_{AC}(b, t, c) \leq E_{S_{AC}^{e}}^{\max}, \quad \forall c \in C, \forall t \in T, \forall b \in S_{bus,AC}
\]

\[
ES_{AC}(b, t, c) = ES_{AC}(b, t - 1, c) + (\eta_{c} \cdot S_{AC}^{e}(b, t, c) - \eta_{d} \cdot S_{AC}^{d}(b, t, c)) \cdot \Delta t, \forall c \in C,
\]

\[
\forall t \in T - \{1\}, \forall b \in S_{bus,AC}
\]
Equations (12) and (13) represent the active and reactive power balance equations at each bus $b$, where $P_{ex}^{c}(t)$ and $Q_{ex}^{c}(t)$ are given by (14) and (15), which are the classical equations pertaining to power flow problems.

$$S_{AC}^{d}(b,t,c) - S_{AC}^{g}(b,t,c) + \sum_{g \in NG_b} P_{AC}(g,t,c) + P_{is,AC}(b,t,c) = P_{ex}^{c}(b,t,c) + P_{l,AC}(b,t,c) + P_{os,AC}(b,t,c) + P_{ic}(t,c)$$

(12)

$$Q_{ex}^{c}(b,t,c) = \sum_{P \in N_{bus,AC}} V_{AC}(b,t,c) \cdot V_{AC}(p,t,c) \cdot (G_{bp} \cdot cos\delta_{bp}(t,c) + B_{bp} \cdot sin\delta_{bp}(t,c))$$

(13)

$$\forall c \in C, \forall t \in T, \forall b \in N_{bus,AC}$$

$$Q_{ex}^{c}(b,t,c) = \sum_{P \in N_{bus,AC}} V_{AC}(b,t,c) \cdot V_{AC}(p,t,c) \cdot (G_{bp} \cdot sin\delta_{bp}(t,c) - B_{bp} \cdot cos\delta_{bp}(t,c))$$

(14)

Note that equations (12) and (13) include the terms $P_{ic}(t,c)$ and $Q_{ic}(t,c)$ respectively, which represent the power flow through the interlinking converter connecting the AC and DC grids. $P_{ic}(t,c)$ and $Q_{ic}(t,c)$ are accordingly determined by (16) and (17), which correspond to a droop control strategy implemented in the converter [20], [30], [31]. The implemented droop control strategy is intended to assist with power sharing across the interlinking converter.

$$P_{ic} = \frac{1}{\gamma_p} \cdot \Delta c$$

(16)

$$Q_{ic} = \frac{1}{\gamma_q} \cdot \Delta c$$

(17)

Local measurements of the frequency at the AC terminal and determination of the DC voltage at the DC terminal in the two ends of the interlinking converter are utilized to effectively calculate $\Delta c$, which represents the difference between the frequency and DC voltage. To allow comparison of the latter two measures, a normalization procedure is followed to bring the measurements in a per unit basis (what is called ‘feature scaling’ in statistics), as described by (19) and (20). These equations convert the given dataset in values within the range of $[-1, 1]$. The error, $\Delta c$, is continuously calculated over the time horizon to determine the power flow between the two grids in each time period. A positive value of $\Delta c$ corresponds to power transfer from the AC grid to the DC, and vice versa.

$$\Delta c = \hat{\omega} - \hat{V}_{dc}$$

(18)

III. DESCRIPTION OF CASE STUDY

The methodology described in the previous sections has been applied to the generalizable MG illustrated in Fig. 2; note that this work focuses on islanded MGs, hence a utility grid has not been included. The network includes an AC wind turbine and a DC photovoltaic array that need to be optimally sized. The wind and solar irradiation profiles utilized are illustrated in Fig. 3. It can be observed that the weather conditions selected correspond to a rare occasion (i.e. both resources are very high); this selection will force the optimizer to utilize both renewable generators.

On the demand side, both typical DC loads (e.g. electric vehicles) and AC loads (e.g. water pumps) are considered. AC and DC loads inputted into the OPF are shown in Fig. 4. It is highlighted that the load and natural resources
data correspond to real data of the Electrical & Electronic Engineering department of Imperial College London.

The MG includes also two conventional generators with a capacity of 150 kW each. As far as the storage devices are concerned, the base scenario includes one storage device in either subgrid, this being a typical low energy - low power battery. However, an alternative scenario has been investigated to find out the effect of other battery technologies (e.g. high energy, etc.) on the MG design (refer to Section III-A2 for additional information). Through the extensive analysis of this case study the paper addresses fundamental modeling and conceptual challenges pertaining to the design and operation of the emerging hybrid AC/DC MG paradigm.

A. Simulation Results

The GA described in Section II-A is utilized to solve the sizing problem. The individuals are evaluated through the OPF, which means to say that the fitness function is the total system cost provided iteratively for each chromosome (i.e. a pair \((PV_{\text{rating}}, WT_{\text{rating}})\) of individuals) through the AC OPF. In the case study shown below, a set of 100 generations has been pre-set, each generation comprising of 10 chromosomes, and the allowed range for the component sizing has been set to \([0 \text{ kW}, 500 \text{ kW}]\). The crossover and mutation probabilities are equal to 0.97.

1) Scenario I – Optimal design under normal operation: Fig. 5 illustrates the evolution of the total system cost across the GA’s evolution and the chromosomes corresponding to these values. The optimal design corresponds to capacities of 55 kW and 101 kW for the PV and WT respectively.

The most significant results of optimal power flow for the best candidate are depicted in Figs. 6 and 7. Fig. 6 indicates how the DC-side storage charges during the hours of high sunshine, while the AC-side battery charges in the morning and discharges at the afternoon hours when the loads are significantly increased (see Fig. 4). Fig. 7 illustrates power flowing from the AC side to the DC one, as expected given the increased renewable generation on the AC side.

2) Scenario II – Optimal design with the consideration of contingencies: To demonstrate the impact of contingencies in the optimal decision, this section presents the results when a contingency is assumed in the interlinking converter (i.e. being out of operation for a whole 24-hour period). Assuming exactly the same range of integers for the sizing

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1Renewable generation data have been extracted from the Renewables.ninja database (https://www.renewables.ninja/) [33], [34], while the load profiles have been constructed from data kindly provided by the estate management office of the Electrical & Electronic Engineering Department of Imperial College London.
and probabilities as previously (i.e. [0 kW, 500 kW] and 0.97), Fig. 8 illustrates the evolution of the GA fitness and the determined chromosomes. The optimal design is shown to be 463 kW for the PV array and 91 kW for the WT, however the total system cost is particularly high in comparison with the previous case study. This is expected, as with the IC out of service during hours of low or no sunshine, and the utilization of a low power - low energy battery, it is unavoidable that there will be loadshedding. This is observed in Fig. 9, which clearly shows significant DC-side loadshedding over a 24-hour period; note that the loadshedding becomes a lot smaller when the PV array produces power (i.e. between 9am to 5pm). For completeness, it is noted that the AC-side loadshedding is zero, as there is wind generation across the whole 24-hour period.

![Figure 8](attachment:figure8.png)

Fig. 8. (a) GA total system cost evolution and (b) selected individuals considering contingencies.

![Figure 9](attachment:figure9.png)

Fig. 9. DC-side loadshedding (as a percentage of the total DC load) during the contingency.

It is worth pointing out that the optimal size of the WT is in the same scale as in the previous scenario, which proves the robustness of the GA. Of course, it is smaller as in the current scenario no power transfer between the two subgrids is required (the results of the OPF in the previous section indicated that typically power flows from the AC to the DC subgrid, as expected due to the WT’s capability to generate power across the whole 24-hour period).

3) Scenario III – Optimal design with the consideration of contingencies - Discrimination of critical & non-critical loads: By observing the results of the previous subsection, it becomes apparent that for this onerous contingency the amount of load shed is the critical term of the objective function that leads the optimizer to determine significant oversizing of the PV generator. This raises an opportunity to assess the impact of the load discrimination into critical and non-critical on the optimal sizing. Besides, it is a more realistic scenario to assume that not all of the loads would be essential. For example, consider the case of a building-scale MG, where the critical loads could be lights, lift motors, etc. and the non-critical loads could be kitchen and toilet appliances. As such, it is assumed that 30% of the loads are critical and 70% non-critical; note that the difference lies in the value of lost load assumed for each load type. The results of the GA are illustrated in Fig. 10.

![Figure 10](attachment:figure10.png)

Fig. 10. (a) GA total system cost evolution and (b) selected individuals considering contingencies and discrimination of loads.

It can be observed that the optimal candidate is now [208 kW, 82 kW]. The optimal size of the PV generator as well as the total system cost are significantly reduced, as it now becomes inefficient to oversize the PV generator and instead curtailment of the non-critical loads is preferred (i.e. with a much lower value).

4) Scenario IV – Optimal design with the consideration of contingencies - Use of a medium power - high energy battery: Even though the sizing is significantly affected by the discrimination of loads, the shedding of the non-critical loads is so high that the resulting operational cost is excessive. This subsection focuses on the utilization of an alternative battery to investigate its impact on the optimal sizing and the total system cost. In fact, even though a very onerous contingency is considered, the issue could have been resolved if an appropriate battery has been installed in the DC side, so as to prevent loadshedding for the hours of no sunshine. The battery currently installed in the DC side is a typical low power - low energy battery (e.g. a lead-acid battery). For this reason and in order to demonstrate the effectiveness of
other battery types in the reduction of the total system cost, a new case study has been performed including a medium power - high energy battery (e.g. a vanadium redox battery or a modern lithium-ion battery [35]) on the DC side. The results are depicted in Fig. 11.

The optimal design corresponds to the set of ratings [189 kW, 74 kW] for the PV and WT respectively. It can be observed that the PV capacity is significantly higher than the optimal design without considering contingencies and that is due to the fact that there is a need for additional energy to charge the DC-battery during the day, which would in turn reduce the loadshedding during the night. For clarity, the charging and discharging patterns of the updated DC battery are illustrated in Fig. 12. An interesting observation relates to the charging of the DC battery which is basically capped at approximately 4 kW. This happens due to the DC voltage reaching its minimum limit (i.e. 0.90 p.u.). Additionally, it is highlighted that the loadshedding in the DC side is zero.

5) Scenario V – Optimal design of PV, WT and storage devices with the consideration of contingencies: The previous sections have clearly demonstrated the effectiveness of the proposed approach for optimal sizing of a hybrid AC/DC MG. As such, in this scenario, the framework is extended to additionally undertake optimal sizing of storage devices (i.e. one on the AC-side and one on the DC-side as illustrated in Fig. 2). Specifically, the storage capacity is turned into a decision variable, while it is considered that the energy content of each storage device can be as high as four times the selected capacity. Contingencies have also been considered in this scenario.

Assuming exactly the same range of integers for the sizing and probabilities as previously (i.e. [0 kW, 500 kW] and 0.97), the optimal sizing has been determined to be [250 kW, 81 kW, 52 kW, 24 kW] for PV, WT, AC-side and DC-side storage respectively. Fig. 13 and 14 illustrate the variables tested over 100 generations. It can be observed that the storage capacity included in the previous scenarios was unnecessarily large, hence the optimizer now determines a much smaller capacity in comparison with Scenarios I – IV (i.e. smaller values for the total system cost are associated with smaller capacities for the storage devices). This result basically suggests that storage devices shall be sized in parallel with the rest of the resources to avoid unnecessary investments.

IV. DISCUSSION

This section serves as a comparison between Scenarios I – IV. Table I reports the total system cost for each scenario, split into investment and operational cost as well as the loadshedding corresponding to each scenario. An interesting observation relates to the loadshedding for Scenario IV which is not zero, even though the optimizer has not utilized the full potential of the resources installed (i.e. either determining a
larger capacity of the PV or even better discharging more power from the DC-side storage (see Fig. 12). This relates to the fact that the voltage on the DC side reaches its limits in the relevant buses, so no further power can be transferred, and in turn demonstrates the need for accurate optimal power flow algorithms that capture the various operational characteristics apart from power flows across the lines. Additionally, the loads shed for Scenarios II & III are approximately the same, even though the cost is significantly different. This means that the optimizer has determined loadshedding of non-critical loads, which comes with a lower cost. In a more general context, it can be argued that this result indicates the potential of flexible demand for enhancing the system operation.

### Table I

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total system cost [£]</th>
<th>Investment [£]</th>
<th>Operation [£]</th>
<th>Loadshedding [kWh] (% of total load)</th>
<th>Optimal PV capacity [kW]</th>
<th>Optimal WT capacity [kW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>13,917</td>
<td>12,996</td>
<td>921</td>
<td>-</td>
<td>55</td>
<td>101</td>
</tr>
<tr>
<td>II</td>
<td>876,035</td>
<td>36,516</td>
<td>839,519</td>
<td>(6.2%)</td>
<td>463</td>
<td>91</td>
</tr>
<tr>
<td>III</td>
<td>89,561</td>
<td>20,352</td>
<td>69,209</td>
<td>(6%)</td>
<td>574</td>
<td>82</td>
</tr>
<tr>
<td>IV</td>
<td>19,285</td>
<td>18,444</td>
<td>841</td>
<td>(0.8%)</td>
<td>80</td>
<td>74</td>
</tr>
</tbody>
</table>

This paper has dealt with the optimal design of hybrid AC/DC MGs. A tailor-made GA has been proposed to solve the design problem with relative computational simplicity, while a detailed AC OPF with the ability to capture contingencies has been utilized to evaluate the design candidates determined by the GA. This approach provides a benefit over other design tools found in the literature, as it ensures that the optimal design candidate satisfies all operational constraints of the MG. A generalizable AC/DC MG has been utilized for demonstrating the benefits of the approach. Additionally, through appropriate simulations the paper indicates the benefit in cost savings of utilizing different types of storage devices (i.e. a mix of high/low power-energy) and appropriately discriminating loads into critical and non-critical. As future work, since the problem under investigation is that of optimal design, it is necessary to consider a much longer planning horizon (i.e. at least several representative days/weeks) to ensure that the system is not oversized due to using a peak day. It is also of paramount importance to capture within this planning horizon the effects of stochasticity both for loads and natural resources. To achieve this, it is anticipated that an appropriate decomposition method, splitting the problem into two subproblems (i.e. one per subgrid) would allow a much longer horizon to be simulated with considerably less computational expense.

### References


