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Optimal Sizing Assessment of an Islanded Microgrid Based on Different EMS Strategies

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Abstract—Microgrids (MG) optimal sizing considering the minimization of life cycle emissions (LCE) of all MG components as well as their investment and operation costs was a main contribution of our recent studies [1], [2]. However, the design of the energy management system (EMS) in the MG is not the same in these studies. The MILP algorithm defining an EMS with minimal LCE generates power flow distribution on real-time basis in [1] while in [2] the energy management depends on future load power profile and available solar power in order to make the decision. A Genetic Algorithm (GA) is used to minimize in parallel two objectives: LCE and MG costs. The battery usage cost is considered just in the study with non real-time EMS to make sizing more accurate while compromising computation time. The goal of this paper is to compare the optimal sizing of the MG components obtained for a real-time EMS and non real-time EMS in order to evaluate the sizing robustness and accuracy. A new modelling approach was used to allocate LCE and costs on an hourly basis, which allows to avoid specifying when MG elements replacement occurs.

Index Terms—Microgrid optimal sizing, life cycle emissions, MILP, Genetic algorithm, real-time EMS, non real-time EMS, multiobjective optimisation, hourly modelling approach

I. INTRODUCTION

Islanded microgrids (IMG) gained a lot of interest by the end of the 20th century [3] since they have multiple advantages. In fact, when compared to centralized grids, IMG increase energy security to face natural catastrophes and cyberattacks. They also present economic strength and allow easy penetration of renewable sources by installing storage devices [3]. Many previous articles studied the optimal sizing of islanded microgrids taking into consideration only the minimization of Diesel combustion emissions and MG investment and operation costs [4] [5] [6] [7] [8]. The main contribution of [1] and [2] is that they take into consideration the life cycle emissions of all microgrid elements (including PV and batteries) and their related Capital Expenditure (CAPEX) and Operational Expenditure (OPEX) in the optimization of MG sizing and EMS. In [1], a real-time EMS is done using a MILP algorithm that minimizes LCE at each step time without considering future load power values. In [2], the EMS is generated also by a MILP. However it is not real-time since the power flow depends on future load power values and the MILP algorithm also minimizes future battery usage costs. Both [1] and [2] use a Genetic Algorithm to find the minimal MG life

cycle emission for a specified CAPEX and OPEX budget by generating a Pareto Front that shows a set of optimal MG elements sizing. A new modelling approach was used in [1] and [2] where LCE and costs were allocated on hourly basis. This model is most suitable for MG with very high lifetime so that there is no need to specify when replacements are occurring in the future.

In this paper, we are going to compare the set of optimal sizing obtained in [1] and [2] in order to study the impact of implementing whether a real-time or non real-time EMS on the optimal sizing solutions. This comparison allows us to validate the accuracy and the robustness of the MG sizing obtained in both studies. In case the optimal sizing found while using both EMS strategies does not differ very much, then we can use the real-time EMS which generates power flow faster than non-real time EMS.

This paper is organized as follows: the microgrid structure and an overview on the new modelling approach of LCE and costs are presented in section II. The optimization model used in both studies are shown in section III. A comparison of the optimal sizing solutions is simulated and analysed in section IV. The section V concludes this paper.

II. MICROGRID MODELLING

A. The microgrid structure

The microgrid studied is composed of 114 residential units (P_{dem}), PV pannels (P_{RE}), battery packs (charging power P_{bat-c} and discharging power P_{bat-d}) and a Diesel Generator (P_{DE}). Figure 1 presents an overview of the power flow of the microgrid. The load power profile is taken from [9]. The available solar irradiation in Victoria State Australia is gathered from [10]. Representative days of the four seasons of a year are chosen in order to generate the MG optimal sizing.

In both studies, service reliability is not an objective function. The load should be always met without any interruption so that Loss of Power Supply Probability (LPSP) is equal to 0.

In the following paragraphs of this section, we will present the new modelling approach that was used in [1] and [2] in order to model life cycle emissions and costs of the different microgrid components. This study explains more explicitly the aim of this new modelling approach.

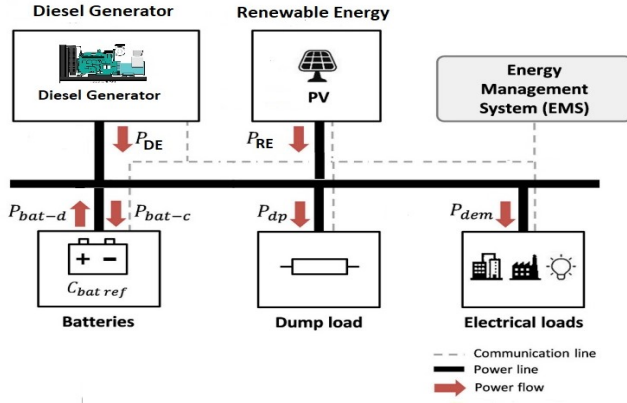


Fig. 1. Microgrid overview

B. Batteries Modelling

The model of batteries defines their state of charge SoC, hourly allocated life cycle emissions as well as hourly investment and operation costs.

1) *Batteries state of charge SoC*: The batteries SoC is given by Equations (1) and (2) detailed in [1] and [2].

$$SoC(t_k) = SoC(t_{k-1}) + \frac{\Delta t}{C_{batref}} \left(\eta_{bat-c} \cdot P_{bat-c}(t_{k-1}) - \frac{P_{bat-d}(t_{k-1})}{\eta_{bat-d}} \right) \quad (1)$$

$$SoC_{min} \leq SoC(t_k) \leq SoC_{max} \quad (2)$$

Where C_{batref} is the batteries capacity [Wh], P_{bat-c} the power of batteries during their charge [W], P_{bat-d} the batteries power during discharge in [W], Δt the time step [h], η_{bat-c} the batteries efficiency in charging mode and η_{bat-d} the batteries efficiency in discharging mode.

2) *Batteries emissions*: [1] and [2] proposed a new modelling approach for batteries emissions. The aim of this new model is to allocate the batteries LCE to an hour of operation. To better understand this model, if we take for example that the LCE of a battery is 3000 kg of CO₂ and it could perform 3000 cycles, this means that the battery LCE is 1 kg of CO₂ per cycle. Therefore, we should know the number of battery cycles done in a step time to allocate accordingly the LCE. Equation (3) shows batteries emissions computed through multiplying the number of cycles done in a step time by the emission allocated for one cycle.

$$Bat\ emissions = \frac{1}{2} \Delta t \sum_{k=1}^K \left(\frac{\eta_{bat-c} \cdot P_{bat-c}(t_k)}{C_{batref}} + \frac{P_{bat-d}(t_k)}{\eta_{bat-d} \cdot C_{batref}} \right) \cdot \frac{Bat_{f_p}}{N_{cycles}} \quad (3)$$

where N_{cycles} is the life time of the batteries [Cycles], Bat_{f_p} is the total LCE of the batteries [kg of CO₂].

In order to avoid charging and discharging batteries in the same time, a linear constraint is added in [1] and [2] by using a binary variable $b(t_k)$ that equals 0 during batteries discharging mode and 1 in charging mode. The linear constraints of the batteries are represented in the following equations.

$$0 \leq P_{bat-c}(t_k) \leq b(t_k) P_{bat-c\ max} \quad (4)$$

$$0 \leq P_{bat-d}(t_k) \leq (1 - b(t_k)) P_{bat-d\ max} \quad (5)$$

$$0 \leq b(t_k) \leq 1 \in N \quad (6)$$

3) *Batteries CAPEX*: Batteries CAPEX allocated to a step time is obtained through multiplying the number of cycles done in a step time by the price of a cycle. Equation (7) shows the CAPEX of batteries where $C_{inv,bat}$ is the batteries cost (with inverters cost) in USD per Wh of battery capacity.

$$CAPEX_{bat} = \Delta t \cdot \frac{1}{2} \left(\frac{\eta_{bat-c} \cdot P_{bat-c}(t_k)}{C_{batref}} + \frac{P_{bat-d}(t_k)}{\eta_{bat-d} \cdot C_{batref}} \right) \frac{C_{inv,bat}(USD/Wh) \cdot C_{batref}(Wh)}{N_{cycles}} \quad (7)$$

4) *Batteries OPEX*: Batteries OPEX is allocated per hour through dividing the total operation and maintenance costs in a year by the number of hours in one year as detailed in Equation (8).

$$OPEX_{Bat} = \Delta t \cdot \frac{C_{O\&M,bat}(USD/kWh/year) \cdot C_{batref}(kWh)}{365 \times 24} \quad (8)$$

where $C_{O\&M,bat}$ is the operational cost of batteries in USD per year per kWh of battery capacity.

C. Diesel generator Modelling

The new modelling approach presented in [1] and [2] allocates DG emissions and costs to one hour. To better understand this model, if for example the price of the DG is 50,000 USD and its lifetime is 50,000 hours, an investment cost (CAPEX) of 1 USD is allocated to one operational hour. A binary variable $d(t_k)$ is used to determine when the DG is ON or OFF. The same method is used to allocate DG emissions per hour. [1] and [2] elaborate equations that model DG emissions and costs in details as well as constraints related to DG operation. In this study, we will just pick some of these equations.

Equation (9) shows DG life cycle emissions (in kg of CO₂) where DE_{em} is the emission of CO₂ in kg per kWh of DG energy consumption.

$$DG\ Emissions = \Delta t \sum_{k=1}^K (P_{DE}(t_k) \cdot DE_{em}) \quad (9)$$

Equation (10) defines power constraints of DG.

$$\begin{aligned} 0.3 d(t_k) P_{n,DE} &\leq P_{DE}(t_k) \leq d(t_k) P_{n,DE} \\ 0 &\leq d(t_k) \leq 1 \in N \end{aligned} \quad (10)$$

Equation (11) models DG CAPEX allocated for a step time where T_{DE} is DG lifetime in hours.

$$CAPEX_{DG} = \Delta t \cdot d(t_k) \cdot \frac{C_{inv,DE}(USD/kW) \cdot P_{n,DE}(kW)}{T_{DE}(hr)} \quad (11)$$

D. PV Modelling

PV panels do not emit CO₂ during operation. However, extracting their raw materials, production, transport and installation do have emissions. The equivalent of these indirect emissions PV_{em} is attributed to the amount of electrical energy produced by these PV panels and presented in Equation (12).

$$PV\ Emissions(t_k) \quad (kg\ of\ CO_2) = \Delta t \cdot PV_{em}(kg\ CO_2/kWh\ produced) \cdot P_{RE}(t_k) \quad (12)$$

[1] and [2] also model PV CAPEX and OPEX allocated hourly as we can see in Equations (13) and (14).

$$CAPEX_{PV}(USD) = \Delta t \cdot \frac{C_{inv,PV}(USD/kWp) \cdot P_{n,PV}(kWp)}{N_{PV} \times 365 \times 24 (hr)} \quad (13)$$

$$OPEX_{PV} = \Delta t \cdot \frac{C_{O\&M,PV}(USD/kWp/year) \times P_{n,PV}(kWp)}{365 \times 24} \quad (14)$$

Where $C_{inv,PV}$ is the investment price of a PV panel expressed in USD per kWp of PV capacity, N_{PV} is the PV lifetime in Years and $C_{O\&M,PV}$ is the operation and maintenance cost of PV.

In section III, a comparison of the multiobjective optimization model used in [1] and [2] is studied in order to better understand the impact of each model on the sizing solutions.

GA Algorithm for multi objective optimisation : CO2 emissions/ CAPEX+ OPEX

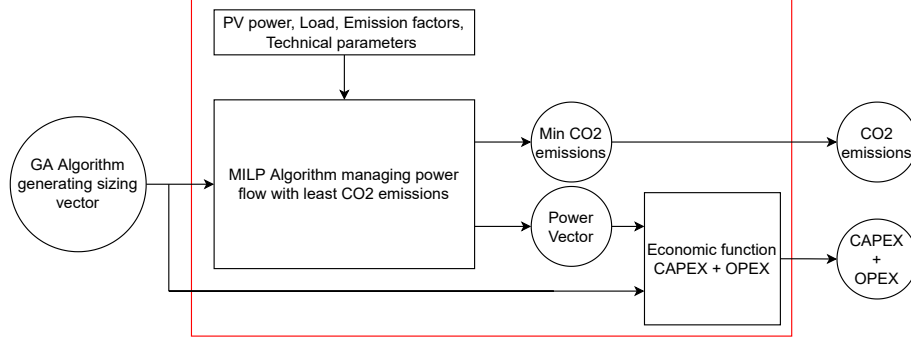


Fig. 2. Double loop multi-objective optimization

III. MODEL COMPARISON OF THE MULTI-OBJECTIVE OPTIMISATION

A. Overview of the Double loop multi-objective optimization

Both studies [1] and [2] use a double loop multi-objective function to optimize the microgrid sizing as shown in Figure 2. A Genetic Algorithm (outer loop) generates a sizing vector of PV pannels, battery packs and the Diesel Generator. The sizing vector then is used in the inner loop composed of two functions:

- A MILP function that minimizes life cycle emissions of the microgrid components
- An economic function that computes the MG CAPEX and OPEX costs

The GA used in the outerloop finds a set of sizing solutions through a Pareto Front that gives the minimal possible LCE for a defined budget.

B. Comparison of the MILP functions

Although the double loop optimization structure is the same in both studies, there are some differences in the model of the functions. The main differences of the MILP function are the following:

- In [1], the MILP function provides a real-time Energy Management System for the microgrid while the EMS in [2] depends from future MG power values, load demand and battery usage cost. This makes the EMS in [2] not real-time.
- In [2], the MILP is designed to return back to initial conditions at the beginning of each representative day, mainly for batteries SoC. While in [1], representative days are considered as if they were consecutive days without considering returning back to initial conditions.
- Sizing in [2] is more accurate than [1], but EMS calculation time of [1] is faster.

1) *Comparison of MILP decision variables:* In [1], at each point of time t_k there are 6 decision variables for a total of: $K = 24(hours) \times NRD(days)$ sample times, where NRD is the number of representative days. The decision variable vector X_k is:

$X_k = (P_{DE}(t_k), P_{bat-c}(t_k), P_{bat-d}(t_k), P_{dp}(t_k), b(t_k), d(t_k))$ knowing that $P_{DE}(t_k), P_{bat-c}(t_k), P_{bat-d}(t_k), P_{dp}(t_k)$ are Real and $b(t_k), d(t_k)$ are binary variables. The size of the decision variables vector is 6.

In [2], there are 7 MILP decision variables at each sample time. $SoC(t_k)$ is added to the sizing vector in order to make possible for the MILP to return back to initial conditions. The size of the decision variables vector in [2] is:

$$K = 24(hours) \times NRD(days) \times 7(Variables)$$

2) *Comparison of MILP objective function:* In [1], the variables decision vector is computed in order to minimize microgrid LCE at each sample time t_k . LCE of Diesel Generator and Batteries are minimized on real-time basis. The minimization strategy used is represented in Equation (15).

$$\min \sum_{k=1}^K emissions\ of\ (Diesel + Battery)(t_k) = \sum_{k=1}^K \min emissions\ of\ (Diesel + Battery)(t_k) \quad (15)$$

In [2], emission factors at a sample time t_k are not considered as constant because returning back to system initial conditions and battery future usage costs are considered. The MILP optimization strategy used in [2] is represented in Equation (16).

$$f = \min \sum_{k=1}^K emissions(t_k)\ of\ (Diesel + Batteries) \quad (16)$$

The power equilibrium should be met at each sample time t_k so that available source equals load demand. This balance is represented in Equation (17).

$$P_{RE}(t_k) + P_{DE}(t_k) + P_{bat-d}(t_k) = P_{bat-c}(t_k) + P_{dp}(t_k) + P_{dem}(t_k) \quad (17)$$

C. MILP function Solver

Both studies use *intlinprog* function in Matlab to compute decision variables knowing that the system model is linear. In [1], *intlinprog* computes 6 variables at each step time while in [2] all present and future variables are calculated in one step (a total of $K = 24(hours) \times NRD(days) \times 7(Variables)$ values).

The new modelling approach is used to allocate emissions and costs on hourly basis, making the algorithm computation time faster.

D. Comparison of the Economic function

[1] and [2] use the same economic function to compute microgrid hourly CAPEX and OPEX represented in Equation (18).

$$Total\ hourly\ cost = CAPEX(Batteries + DG + PV) + OPEX(Batteries + DG\ Variable + DG\ fix + PV) \quad (18)$$

However, even though the same formula is used in both studies, the power vector generated by the MILP function is different as seen in the previous comparison, which impacts the overall microgrid costs.

E. Comparison of the sizing optimization

A Genetic Algorithm is used to generate the microgrid sizing vector which defines PV nominal peak power P_{nPV} , the batteries capacity C_{batref} and the Diesel generator nominal power P_{nDE} . The GA minimizes 2 objectives:

- The LCE of all microgrid components computed using the new hourly modelling approach.
- The total microgrid costs.

The fact that MILP could generate or not a real-time EMS and that future batteries usage cost could be taken or not into consideration impact directly the set of sizing vectors solutions generated by the GA.

In the following section, we will compare the power profile generated for one day in the two studies. We will also check to which extent the sizing vectors solutions proposed by the GA differ in order to validate the robustness of optimal solutions found in both studies.

IV. COMPARISON OF SIMULATION RESULTS

Technical, cost and emission parameters used in both studies are represented in Table 1. The Genetic Algorithm is implemented on Matlab through *gamultiobj* function. A Pareto Front shows the minimal LCE of the microgrid components that could be obtained for a defined budget. The simulation results will be compared in this section in order to validate the accuracy of the set of sizing solutions.

A. Comparison of cumulative cost and emission results

Figure 3 shows the set of optimal sizing solutions represented in a Pareto Front for both real-time and non-real time EMS. As seen in Figure 3, Table 2 and 3, the cumulative MG costs using non-real time EMS is slightly higher than costs for a real-time EMS (a difference of 4.7 percent in cumulative minimum costs and 1.5 percent for the maximum costs). In order to better understand the increase of cost, we will analyze the MILP and the Genetic Algorithm. As seen before, when using the non-real time EMS, the MILP should ensure returning back to initial conditions (mainly batteries SOC) at the beginning of each representative day. We can see in Figure 6 that in order to meet this condition, batteries are even charged by the Diesel generator and by excess of PV power at the end of each day or discharge is stopped while DG supplies the load. When using real time EMS, Figure 6 shows that batteries SOC does not come back to initial value at the end of the day, which implies that batteries are charged by excess of PV power or when DG is supplying a load lower than 30 percent of its nominal capacity. Moreover, the Genetic Algorithm takes into account reducing battery usage cost on the long term in non-real time (NRT) EMS. This implies additional Diesel usage cost to satisfy the load and to compensate the decrease in battery usage. This is the reason behind the increase of MG cumulative costs. We can see clearly the consequence of this fact on the EMS shown in Figure 6 where the power flow distribution of the MG is very similar for both EMS strategies until the 16 th hour of the day. After this instant, the NRT EMS starts to take into consideration returning back to initial conditions.

The increase in Diesel Generator usage impacts directly the

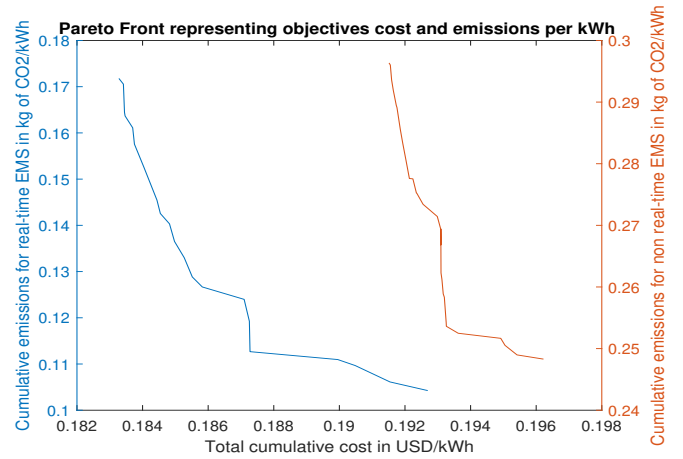


Fig. 3. Pareto Front Comparison

LCE of the microgrid. We can see in Table 3 that minimum emissions obtained in the Pareto Front are 52 Percent higher when using NRT EMS while maximum emissions are 41 percent higher in a NRT EMS. This is a direct consequence of relying more on the Diesel Generator to feed the load. Table 2 shows that for a specified sizing vector, cumulative cost (in USD per kWh) slightly varies when using different EMS strategies (2.6 and 3.1 percent) while emissions (in kg of CO2 per kWh) are significantly different (55 percent increase for NRT EMS).

B. Validation of sizing robustness

In order to validate the robustness of the sizing solution sets obtained in the Pareto Front, we will compare batteries sizing capacity and PV nominal sizing power that were computed using real-time and non-real time EMS.

The first insight is that sizing is not much impacted by how EMS is done. This means that the optimal sizing solutions are reliable and are in the same range regardless of the method used to determine the EMS, which is a good indicator for the sizing robustness.

If we consider battery sizing, the lowest optimal value of battery capacity with NRT EMS is 27 percent lower than minimal battery capacity with real-time EMS (Table 3). This could be explained by the fact that NRT EMS relies less on batteries since Diesel Generators take over the role of meeting the load demand to decrease battery usage cost and return back to initial batteries SOC. The maximum value of batteries capacity with NRT EMS is just 0.6 percent lower than maximum capacity with RT EMS. The overall look on batteries sizing confirms the robustness of the sizing decision. Concerning PV sizing, it is expected that PV nominal power with a NRT EMS should be a little bit lower than nominal power with RT EMS. In fact, DG is supposed to charge the batteries, so less PV capacity is needed. However, this decrease in sizing capacity is very minimal (7.8 percent as per Table 3), which means that sizing decision in both EMS methods is accurate and robust.

V. CONCLUSION

This article validates the microgrid sizing robustness conducted in our two previous studies. Their main contributions were to find optimal MG sizing while considering life cycle emissions of all MG components and their costs. The Energy

TABLE I
TECHNICAL, COST AND EMISSION PARAMETERS

Microgrid component	Parameters	Values	Units
Batteries	η_{bat-c}	0.96	pu
	η_{bat-d}	0.96	pu
	Bat_{fp}	80	kg of CO2 per kWh
	N_{cycles}	3000	Cycle
	$c_{inv,bat}$	667	USD per kWh
	$C_{O\&M,bat}$	0.0005	USD per kWh per hour
PV	PV_{em}	0.044	kg of CO2 per kWh
	$C_{inv,PV}$	1000	USD per kWp
	$C_{O\&M,PV}$	0.0007	USD per kWp per hour
	DE_{em}	0.8	kg of CO2 per kWh
Diesel Generator	$c_{inv,DE}$	100	USD per kW
	$c_{Operation,DE}$	0.3	USD per kWh
	T_{DE}	50000	Hour

TABLE II
COST AND EMISSIONS COMPARISON FOR A DEFINED PV AN BATTERIES SIZING

	PV nominal power (kWp)	Batteries capacity (kWh)	Cost RT (USD/kWh)	Cost NRT (USD per kWh)	Emissions RT (kg of CO2 per kWh)	Emissions NRT (kg of CO2 per kWh)	Cost variation percentage NRT vs RT EMS	Emissions variation percentage NRT vs RT EMS
Sizing 1	1600	1700	0.188	0.193	0.113	0.254	2.6 Percent	55 Percent
Sizing 2	1500	4150	0.186	0.192	0.120	0.271	3.1 Percent	55 Percent

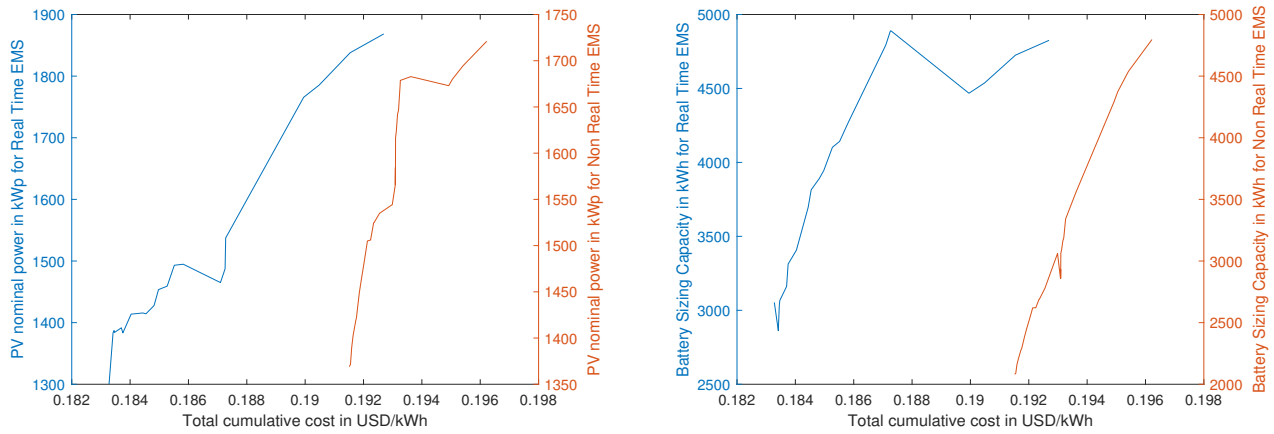


Fig. 4. PV and Batteries Sizing Comparison Considering Cost

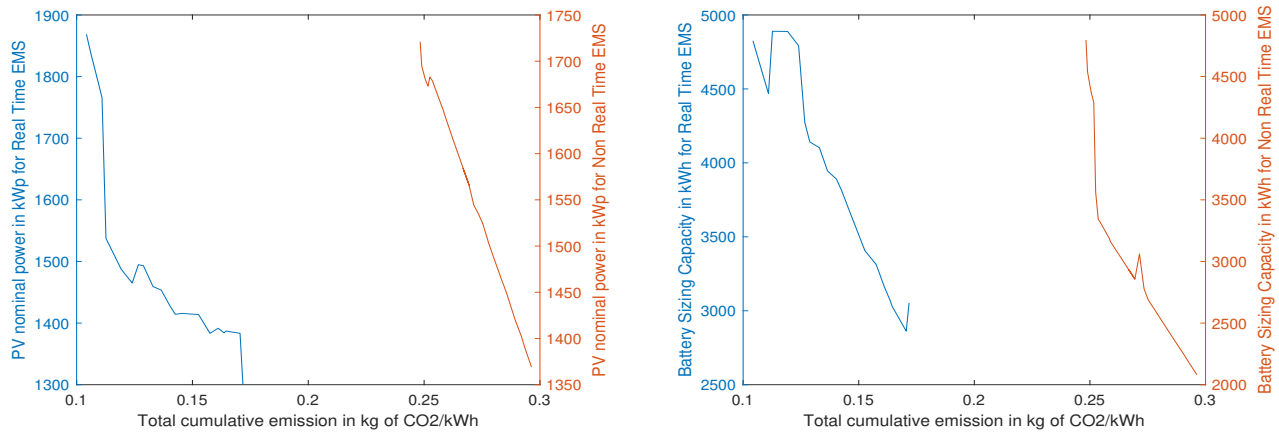


Fig. 5. PV and Batteries Sizing Comparison Considering Emissions

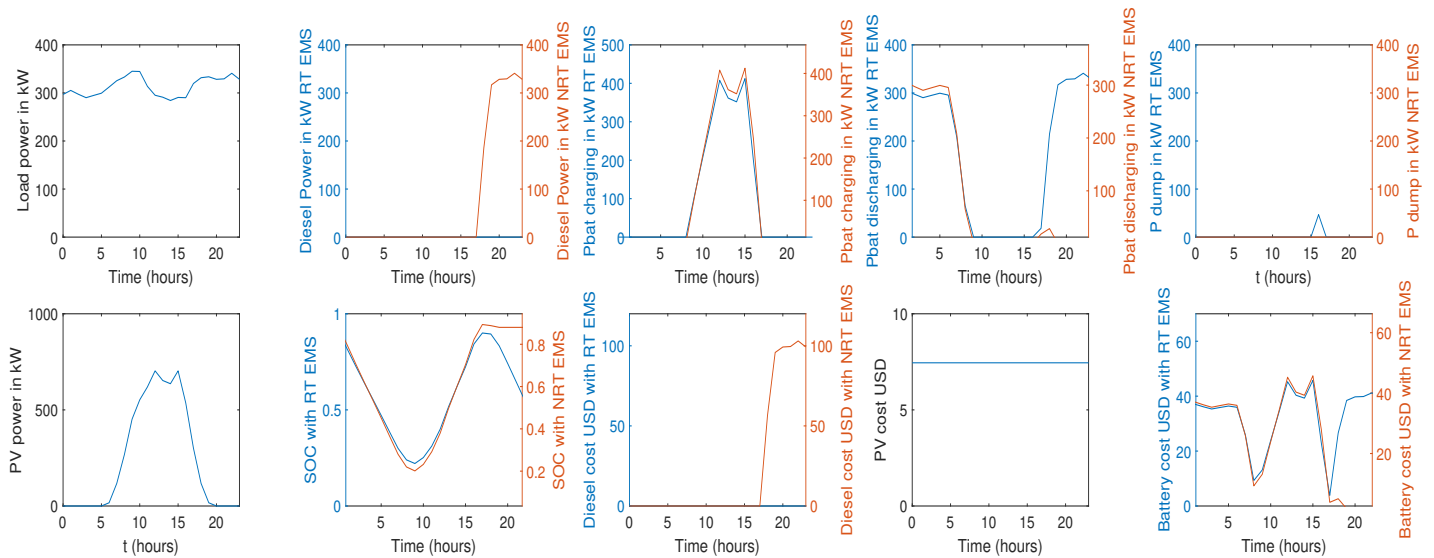


Fig. 6. EMS comparison considering RT and NRT strategies

TABLE III
COST, EMISSIONS AND SIZING PERCENTAGE VARIATION

	Percentage of Variation
Cumulative cost Minimums	4.7 Percent
Cumulative cost Maximums	1.5 Percent
Cumulative emissions minimum	52 Percent
Cumulative emissions maximum	41 Percent
Battery Size Minimum	27 Percent
Battery Size Maximum	0.6 Percent
PV Size Minimum	5 Percent
PV Size Maximum	7.8 Percent

Management System is real-time in a study and non-real time in the other. This article shows that the impact of the EMS method is very minimal on the microgrid sizing. The advantage of this result is to be able to generate a real-time EMS without having to sacrifice the accuracy of the sizing decision. This implies that no need to compromise between the precision of EMS and the computation time of the power flow management.

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REFERENCES

- [1] F. Boutros, M. Doumiati, J.-C. Olivier, I. Mougharbel, and H. Y. Kanaan, "Optimal sizing and real-time ems for low carbon emissions of a hybrid islanded microgrid," in *IECON 2022-48th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2022, pp. 1–6.
- [2] F. Boutros, M. Doumiati, J.-C. Olivier, I. Mougharbel, and H. Kanaan, "New modelling approach for the optimal sizing of an islanded microgrid considering economic and environmental challenges," *Energy Conversion and Management*, vol. 277, p. 116636, 2023.
- [3] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, 2018.
- [4] H. Akter, H. O. R. Howlader, A. Y. Saber, P. Mandal, H. Takahashi, and T. Senjyu, "Optimal sizing of hybrid microgrid in a remote island considering advanced direct load control for demand response and low carbon emission," *Energies*, vol. 14, no. 22, p. 7599, 2021.

- [5] M. A. Ashraf, Z. Liu, A. Alizadeh, S. Nojavan, K. Jermisittiparsert, and D. Zhang, "Designing an optimized configuration for a hybrid pv/diesel/battery energy system based on metaheuristics: A case study on gobi desert," *Journal of Cleaner Production*, vol. 270, p. 122467, 2020.
- [6] F. Fodhil, A. Hamidat, and O. Nadjemi, "Potential, optimization and sensitivity analysis of photovoltaic-diesel-battery hybrid energy system for rural electrification in algeria," *Energy*, vol. 169, pp. 613–624, 2019.
- [7] A. Roy, F. Auger, J.-C. Olivier, B. Auvity, E. Schaeffer, and S. Bourguet, "Energy management of microgrids: from a mixed-integer linear programming problem to a rule-based real-time algorithm," in *IECON 2021-47th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2021, pp. 1–6.
- [8] A. Roy, J.-C. Olivier, F. Auger, B. Auvity, E. Schaeffer, S. Bourguet, J. Schiebel, and J. Perret, "A combined optimization of the sizing and the energy management of an industrial multi-energy microgrid: Application to a harbour area," *Energy Conversion and Management: X*, vol. 12, p. 100107, 2021.
- [9] [Online]. Available: <https://traces.cs.umass.edu/index.php/Smart/Smart>
- [10] [Online]. Available: <https://pv-map.apvi.org.au/live#2022-01-01>