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Research papers

Energy management supported on genetic algorithms for the equalization of battery energy storage systems in microgrid systems

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ABSTRACT

Energy management plays a fundamental role in ensuring the optimal operation of a microgrid (MG). Since MGs rely heavily on renewable energy sources, having batteries provides a reliable backup. Equalization is important when using batteries in an MG, ensuring their health and prolonging their lifetime. Due to the use of batteries in electric vehicles, they can be considered mobile sources that support energy management in an MG. Two methodologies are presented in this paper for the process of equalization and energy management that seeks to minimize grid usage. The first one prioritizes equalization, performing it quickly but slightly sacrificing grid usage. The second methodology focuses on slow equalization while prioritizing energy management, thereby reducing overall costs. The optimization was performed using a genetic algorithm that evaluates the MG parameters and as a result, provides the optimal current that each battery in the MG must deliver. Two case studies in MATLAB and Simulink are presented to demonstrate the effectiveness of the proposed optimizations. The results showed that both methods allow for achieving energy management and equalization in an MG without compromising its optimal operation. With the first method, equalization was achieved in 29 s with a consumption of 47 kW*s from the grid, while with the second method, equalization was obtained in 110 s with no energy consumption from the grid.

1. Introduction

The increase in electricity demand and the issues associated with conventional generation have driven the search for generation alternatives. Among these alternatives are distributed energy resources (DERs), which are micro-generators generally located near the users. DERs include wind turbines, photovoltaic panels (PVs), fuel cells, small diesel generators, as well as energy storage devices, such as flywheels, batteries, and supercapacitors [1].

As the use of DERs increases, the deployment of microgrids (MGs) becomes more widespread. As defined by the Microgrid Exchange Group, "A microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid" [2]. An MG can operate connected or disconnected from the main grid and still guarantee the reliability of the local power system [3].

Given the popularity and easy access to renewable energies, such as PV and wind, these DERs have become increasingly common in MGs. However, the problem with these is generation uncertainty since they are affected by weather variability. This affects the operation of traditional energy management systems, requiring the design of systems specifically focused on MGs [4]. To reduce uncertainty in renewable energy generation, energy storage systems (ESS) based on battery technologies such as lead–acid and lithium-ion batteries have been widely used. These systems provide an additional level of flexibility and energy backup in MGs [5,6].

On the other hand, electric vehicles (EVs) currently represent a modest yet swiftly growing segment of the transportation industry. EVs play a crucial role in supporting low-carbon initiatives and offer the potential for multiple batteries that can serve as mobile ESS. These batteries enable the implementation of vehicle-to-grid operations, allowing EVs to actively contribute to the development of environmentally sustainable, reliable, and adaptable energy systems [7,8]. EVs offer a variety of services that can be leveraged.

For example, they can participate in the energy market and help reduce peak demand through effective scheduling. In addition, EVs can contribute significantly to voltage and frequency regulation by operating charging stations in standby mode. In addition, they can serve as spinning reserves and uninterruptible power supply systems during power outages, supplying electricity when it is most needed [9].

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Therefore, EVs present a favorable choice for bolstering the energy management of an MG. This is especially notable considering that EVs are typically utilized for commuting between work or home, and subsequently, they tend to remain connected to charging stations until their next usage. The inherent characteristics of EVs make them well-suited for contributing to efficient energy utilization within an MG context. It is crucial to note that lithium-ion batteries have experienced significant growth in their use in different fields, including EVs, due to their high energy density, low self-discharge rate, absence of memory effect, and cost-effectiveness. Therefore, EVs can be modeled as lithium-ion batteries from an electrical perspective [10,11].

On the other hand, when working with several batteries in an MG environment, one of the main concerns is their performance. Battery over-discharge and over-charge caused by a state of charge (SoC) unbalance can affect the lifespan of the batteries. There are many reasons for SoC unbalance, such as voltage variability at the battery terminals due to power line reactance, variability of power electronic converters, or initial SoC unbalance that occur when EVs are used for energy management in an MG. Balancing the SoC of batteries through a control strategy is vital to enhance battery lifespan [12].

The SoC equalization problem has been broadly explored recently in the literature by proposing solutions that consider SoC equalization as an independent problem without considering its effect on electrical system operation [13]. Other approaches address equalization within system operation but not from an optimal approach [14].

Hence, this paper presents an energy management system supported by genetic algorithms (GA) to equalize an MG with PV systems, EVs operating as ESS, and loads. The EVs will operate in support mode for the MG. When EVs connect to the grid, they have a specific SoC that may be different than distributed units. An initial optimization is conducted to minimize the difference of SoCs in all batteries in the shortest time. In addition to this, two additional optimizations minimize the energy supplied by the grid, while at the same time perform battery equalization.

1.1. Literature review

According to the literature, one of the most common methods of battery equalization in MGs is the use of droop control. This approach consists of adjusting the droop coefficients of the batteries as a function of their SoC [15].

An illustrative example of the application of droop control for equalization can be found in the work conducted in [16], where battery equalization in an AC MG was achieved by employing the Pf-droop function. Although battery equalization was achieved, there were variations in the frequency caused by the droop control. Likewise, energy management in the MG was not considered. In contrast to the previous study, [17] focused on energy management and battery equalization in a DC MG using droop control, aiming to coordinate the operation of a fuel cell and batteries.

Similarly, in [15], energy management and battery equalization were performed in a DC MG but, unlike the previous one, they replaced the classical droop control with a fuzzy controller. Hence, an evident research gap includes the lack of optimizing the time required for battery equalization, and the limits imposed by the batteries, such as charge and discharge currents, as well as SoC limits.

Evidently, although droop control is an effective strategy for power distribution between the batteries, it has the major disadvantage of causing voltage and frequency variations. This implies the need to use an additional secondary controller, which further complicates the overall system [18,19]. In [20], the authors addressed the problem of variations caused by droop control in a DC MG by implementing a secondary controller. This approach allowed them to mitigate such variations and thus achieve battery equalization and voltage control. However, the work did not address energy management in the MG.

In [21], new alternatives were explored by moving away from the use of droop control for battery equalization and focusing on directly controlling the power supplied by the batteries. Here, the authors focused on battery equalization and energy management in a system that included PV systems. Using optimization techniques, their objective was to minimize the power consumed by the grid and reduce the SoC variation of the batteries. However, this approach did not consider minimizing the time required to perform battery equalization.

1.2. Research contributions

This paper presents an energy management strategy that aims to integrate the equalization process of distributed ESSs in an MG with PV systems. EVs have been considered as mobile ESSs in this study, which emphasizes the importance of equalization due to the initial SoC of each EV.

An alternative technique to droop control is proposed in this paper to carry out the equalization process. In this technique, an optimizer directly provides reference current and power to the power electronic converters used in ESS and PV systems. This technique can be used to mitigate the voltage and frequency variations that usually occur when using droop control. In addition, models of a two-stage converter and an inverter are presented, along with their respective current and power controllers used in ESS and PV systems.

On the other hand, three optimizations for equalization are presented that consider battery and MG constraints. The first optimization focuses on efficiently equalizing the batteries to minimize the required time for the equalization process. The second optimization not only addresses battery equalization but also incorporates energy management within the MG. Lastly, the third optimization combines the advantageous features of the first two optimizers to provide a comprehensive approach to equalization and energy management within the MG. This optimization process utilizes GA, where the algorithm takes the parameters of the MG as input and provides reference currents and powers for the power electronic controllers as output. To summarize, the main contributions of this research are as follows:

- An alternative technique to the traditional droop control is defined for distributed ESS equalization in a grid-connected MG. This technique may help to mitigate voltage and frequency variations commonly caused by conventional droop control techniques.
- The proposed ESS equalization technique is suitably integrated into an optimal GA-based energy management system for an MG. This integration enables the simultaneous execution of battery equalization and energy management tasks within the MG.
- The optimization process considers the minimization of the time required to perform the ESS equalization, carefully considering the constraints imposed by the MG energy management system.
- To test the performance of the proposed technique, models of the inverters and their respective controllers have been developed. In this way, the hierarchical control approach for MGs is considered in the validation.

In summary, this research provides an innovative technique for ESS equalization and energy management that optimizes the time required to achieve equalization, considering MG and ESS constraints. In addition, models and controllers are provided for the practical implementation of the proposed strategy.

This paper is organized as follows: Section 2 presents the networked MG model, while Sections 3 and 4 address energy management and equalization, and the case study results, respectively. Finally, Section 5 discusses the conclusions.

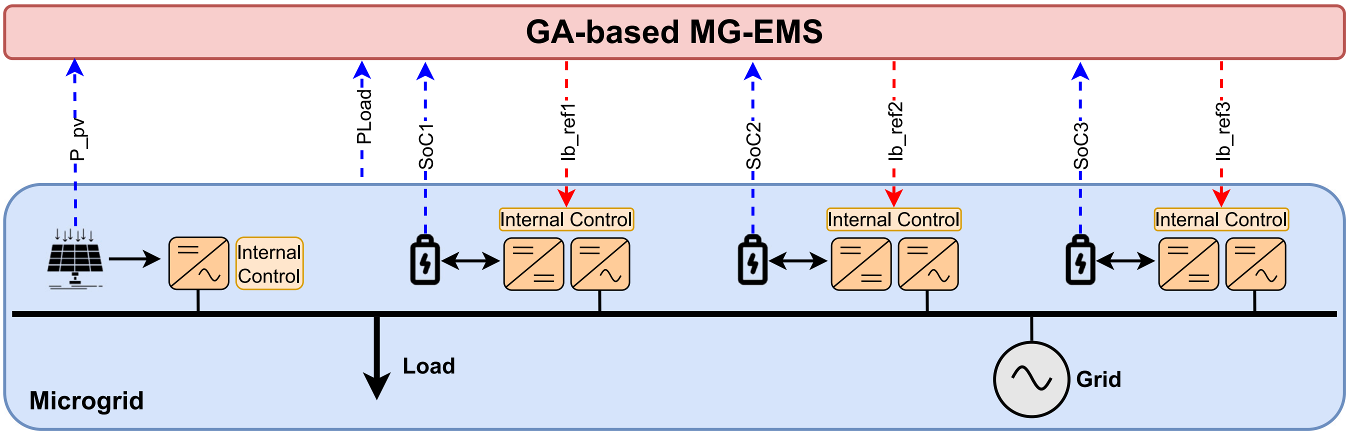

Fig. 1. MG topology studied, which includes PV systems, batteries, loads, and the grid.

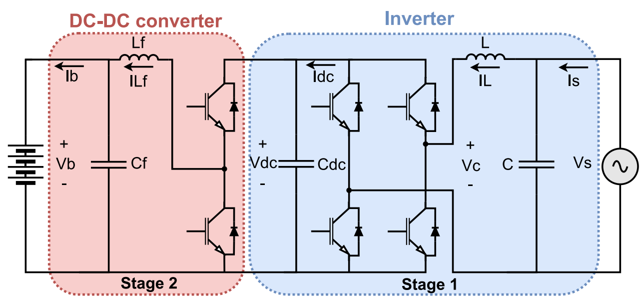

Fig. 2. Single-phase bidirectional battery charger topology.

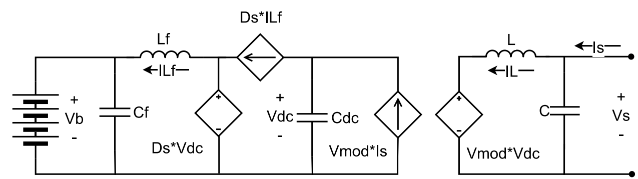

Fig. 3. Average bidirectional charger model used for batteries.

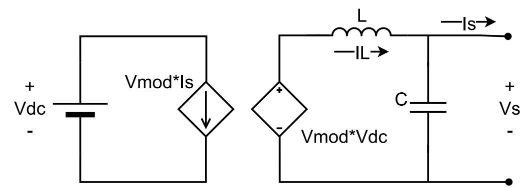

Fig. 4. Averaged inverter model used for PV systems.

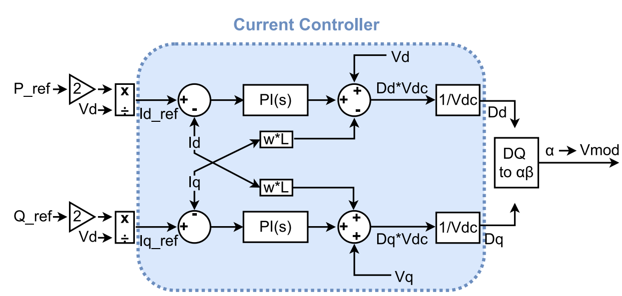

Fig. 5. Inverter P-Q controller in the DQ frame used to control the power injected by a PV system.

2. Networked microgrid model

The model of an interconnected MG with PV systems, batteries, and loads, was developed in MATLAB and Simulink. A scheme of the modeled interconnected MG is shown in Fig. 1. In the diagram, there is a busbar to which the grid, a PV system, three-battery systems, representing EVs, and a load are interconnected. Batteries make use of a two-stage converter which consists of an inverter, and a DC-DC converter with current control to control the charge and discharge current of the batteries [22,23]. The PV system makes use of an inverter with active and reactive power control that sets its delivered power in each period throughout the day [24]. In this way, energy management can be conducted after an optimization process to deliver the charge and discharge current references for the batteries.

The model of the two-stage converter used for batteries is shown in Fig. 2. The first stage consists of a buck-boost converter, while the second stage consists of a full-bridge inverter. The inverter model used by the PV system is identical to the second stage of the two-stage converter. In the case of batteries, the control is based on two transistors in the buck-boost converter, and in the case of the PV system, it is based on four inverter transistors.

In order to reduce the computational cost in the simulation, the averaged models of the converters, shown in Figs. 3 and 4, were used. The advantage of using averaged models is that it neglects the high-frequency components, focusing only on the frequency components that are essential for the power flow [25].

The design of control loops used on buck-boost and inverters is out of the scope of this work. However, detailed literature has been reviewed for this purpose. Over the years, the implementation of inverter controllers uses the direct quadrature (DQ) frame of reference. Since a steady-state error of 0 is achieved, the linear control theory for time-invariant systems can be applied in a straightforward manner [26,27]. Some of the works that focus on the design of current and power controllers are [28,29], and [30]. On the other hand, among the works that consider the design of voltage controllers include [25,31], and [32]. Similarly, among the works related to current control in a buck-boost converter are the studies conducted in [23], and [22].

The active power (P) - reactive power(Q) controller used for the inverter is shown in Fig. 5. This controller consists of an internal current controller and a previous stage to obtain the current references. The controller receives, as input, the P and Q references, and as output, it delivers the modulating signal for the inverter.

On the other hand, Fig. 6 shows the bidirectional current controller of the buck-boost converter used. The controller receives, as input, the

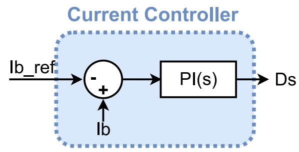

Fig. 6. Buck-boost current controller used to control the current that delivers/absorbs a battery.

battery current error, and as output, it delivers the duty cycle for the buck-boost converter.

3. Energy management and equalization methodology

For this research, the EV batteries are being used to provide support for the MG while they are equalized, therefore the priorities are to equalize the batteries and to perform energy management in the MG.

Since batteries are one of the most expensive parts of an EV and renewable energy-based systems, considering battery life is an important factor when using them to support MGs. When batteries are used to compensate the deficiencies caused by the variability of renewable sources, all batteries should deliver or consume energy proportional to their capacity, maintaining their discharge and charge current limits. The phenomenon of over-discharge and over-charge caused by imbalances in the SoC of the batteries is one of the main causes that affect the battery life. When a battery is connected to an MG, it has a specific SoC. So, it is important to perform a quick and continuous equalization considering energy management in the MG. This fact becomes even more crucial when the batteries coupled to the MG are part of an EV connected to their charging stations since differences in use and trajectories will result in uneven SoCs.

The final SoC (SoC_f) for a given period dt can be calculated with Eq. (1) [33].

$$SoC_f = SoC_i - \frac{\int_0^t i_b\, dt}{Cap} \tag{1}$$

where SoC_i refers to the initial SoC, Cap to the battery capacity and i_b to the battery current.

Assuming that the current is constant for short periods Δt,

$$SoC_f = SoC_i - \frac{Ib\Delta t}{Cap} \tag{2}$$

therefore,

$$Ib = \frac{Cap(SoC_i - SoC_f)}{\Delta t} \tag{3}$$

Eq. (3) is used to calculate the current required for a battery to reach a certain SoC_f after a period Δt, knowing the Cap and the SoC_i. In this equation, a positive current Ib means that the battery is delivering energy and a negative current Ib means that the battery is consuming energy from the MG.

In order to improve the accuracy of equalization and energy management, a three-optimization process is performed, which considers the maximum battery currents Ib_{max} (charging current was considered to be equal to discharging current), the capacity of each battery, and the SoC limits.

Optimization 1 (Opt 1): A first optimization is conducted to equalize all the batteries in the shortest possible time, as shown in Eq. (4). In this case, the time required to for batteries to reach the same SoC_f is minimized, since the time required depends on the capacity, SoC variation, and the current flowing through each battery. The optimizer chooses the values of SoC_f and Ib that minimize this cost function. The results obtained include the SoC_f, Ib, and minimum time required to achieve the equalization Δt. SoC_f and Ib have maximum and minimum limits. For this case, the SoCs were limited to 20% and 90%, and the battery current was limited by the maximum charge and discharge current which were considered the same for this work.

This first optimization was performed because of the variability between batteries and their SoC_i when interconnected to the MG (especially when they are part of EVs). Thus, in the first optimization, priority is given to equalization without considering energy management.

$$\min_{Ib_i, SoC_f} \quad \Delta t \tag{4}$$

$$st: \quad |Ib| \le Ib_{max} \tag{5}$$

$$0.2 \le SoC_f \le 0.9 \tag{6}$$

where

$$\Delta t = \frac{Cap_i(SoCi_i - SoC_f)}{Ib_i} \tag{7}$$

$Ib, Ib_{max}, Cap, SoC_i \in \mathbb{R}^n$

with

$$\Delta t = \Delta t_1 = \Delta t_2 = \cdots = \Delta t_n$$

$$SoC_f = SoC_{f1} = SoC_{f2} = \cdots = SoC_{fn}$$

where i represents the ith battery and n represents the total number of batteries. The SoC_f and Δt are the same for all batteries. This ensures that SoC_f is the same for all batteries after a period Δt.

Optimization 2 (Opt 2): The second optimization performs energy management in the MG while simultaneously equalizing the batteries. The objective function is presented in Eq. (8). As can be seen, the power delivered/absorbed by the grid is minimized. Since the grid power depends on the battery power, the algorithm delivers the battery currents that minimize the use of the grid. With this optimization, it is intended that the MG only depends on the PV system and the battery for as long as possible. Like the previous optimization, this one is subject to the current and SoC constraints.

$$\min_{Ib_i} \quad \left(\frac{Pg}{Pg_{max}}\right)^2 \tag{8}$$

$$st: \quad |Ib| \le Ib_{max} \tag{9}$$

$$0.2 \le SoC_f \le 0.9 \tag{10}$$

where

$$Pg = \sum_{i=1}^{m} Pl_i - \sum_{i=1}^{n} Pb_i - \sum_{i=1}^{p} Ppv_i \tag{11}$$

$$Pg_{max} = \sum_{i=1}^{m} Pl_i - \sum_{i=1}^{n} (Ib_{max} * Vb) - \sum_{i=1}^{p} Ppv_i \tag{12}$$

where m, n, and p are the number of loads, batteries, and PV systems respectively. with

$$Pb_i = Ib_i * Vb_i \tag{13}$$

$$Ib_i = \frac{Cap_i(SoCi_i - SoC_f)}{\Delta t} \tag{14}$$

$$\Delta t = \Delta t_1 = \Delta t_2 = \cdots = \Delta t_n$$

$$SoC_f = SoC_{f1} = SoC_{f2} = \cdots = SoC_{fn}$$

where the SoC_f are equal for all batteries, to ensure equalization after a period Δt.

For this optimization, an initial Δt was assigned. If the variation of the SoCs is very large and the Δt is very small, it is likely that the algorithm will not converge due to the current limits of each battery. Therefore, this optimization can be applied when the variation of the SoCs is minimal. The allowable SoC variation of each battery to apply

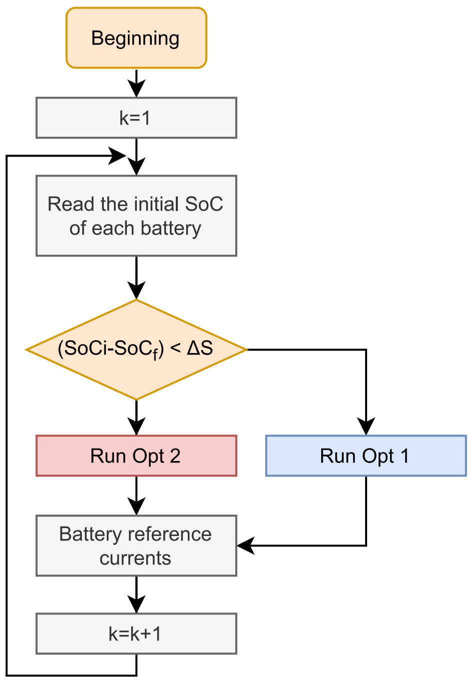

Fig. 7. Optimizer selection flowchart for the equalization and energy management process.

this optimization is shown in Eq. (15), which is obtained by substituting Eq. (2) into Eq. (9).

$$(SoCi - SoC_f) \leq \frac{Ib_{max} * \Delta t}{Cap} \tag{15}$$

To take advantage of the benefits of Opt 1 and Opt 2, a combination of the two algorithms was done based on the SoC variation. A threshold labeled ΔS is defined in Eq. (16) based on the limit of SoC variation.

$$\Delta S = \frac{Ib_{max} * \Delta t}{Cap} \tag{16}$$

Thus, if the variation of all the SoC_i is less than ΔS, the optimization to be performed is the second one, in which energy management of the MG is considered. Otherwise, the chosen optimization is the first one that prioritizes equalization in the shortest time without energy management.

Since Opt 2 starts when all the SoCs are almost equal, the period allocated to reach the equalization can be small. This ensures that all batteries are equalized in the shortest time and then energy management is performed while equalizing the batteries. The flowchart in Fig. 7 shows the optimization to be used according to the SoC_i of each battery.

Optimization 3 (Opt 3): A third optimization is proposed to overcome the limitations of Opt 2. This strategy seeks to perform energy management and battery equalization without requiring a minimum SoC variation. In other words, it aims to achieve these objectives without the need to set a minimum limit for SoC variation.

Eq. (17) represents the cost function to be optimized. This cost function has two parameters to be minimized: the power delivered/absorbed by the batteries and the power delivered/absorbed by the grid. Two weight constants, Ks and Kg, were assigned to prioritize either the minimization of battery power or grid power. The higher the value of the constant, the higher the priority in optimizing the term to which it is multiplied.

In addition, a third term, K_{SoC}, is added, which is multiplied by the battery power. This term is variable and depends on the SoC of each of the batteries, as shown in Eq. (18). Thus, when there is a deficit in PV generation, the battery with a higher SoC delivers more power, while the battery with a lower SoC delivers less power. In the case of excess PV generation, the roles are swapped and the battery with a lower SoC consumes more power, while the battery with a higher SoC has a lower consumption. Once the SoCs of all batteries are equal, each battery has the same weight and the power they deliver or consume is proportional to its capacity. In this way, battery equalization is ensured while performing energy management.

Table 1
Battery parameters used in energy management and equalization process.

Battery	Cap (Ah)	Ib_{max} (A)	SoC_i
1	1	7	0.7
2	2	10	0.65
3	3	12	0.61

Also, unlike the second, this optimization can work with small time periods since the SoC_f are not necessarily the same for all batteries. This allows the algorithm to converge without the need for all SoC_f to be the same. Like the previous optimizations, this one is subject to the current and SoC constraints.

$$\min_{Ib_i} \quad \left[Ks * K_{SoC} * abs(Pb) + Kg * abs(Pg)\right] \tag{17}$$

with

$$K_{SoC} = \begin{cases} (max(SoC_f) - SoC_f), & Pl \geq Ppv \\ (SoC_f - min(SoC_f)), & Pl < Ppv \end{cases} \tag{18}$$

$$st: \quad |Ib| \leq Ib_{max} \tag{19}$$

$$0.9 \geq SoC_f \geq 0.2 \tag{20}$$

where the SoC_f after a period Δt are not necessarily the same for all batteries.

Given the discontinuities inherent in the cost function of Opt 3, the utilization of derivative-based optimizers is unfeasible as they exhibit subpar performance when dealing with discontinuous functions. Instead, a viable solution lies in employing artificial intelligence algorithms, specifically metaheuristic algorithms. Among these algorithms, the GA stands out as a compelling choice, leveraging a probabilistic search mechanism inspired by natural and genetic selection.

Similar to particle swarm optimization, and ant colony optimization, GA is a global randomized search optimizer that belongs to the metaheuristic methods available in artificial intelligence [34]. These algorithms were developed inspired by biological evolution. GA is based on Darwin's theory of evolution, which includes stages of selection, crossover, and mutation [33]. In this research, GA is used to carry out the three optimizations proposed. Fig. 1 shows the data that GA receives from the MG and the data that it returns as a result of the optimization.

4. Case study results

To evaluate equalization and energy management, the MG shown in Fig. 1 was modeled in Simulink. This MG consists of three batteries, a PV system, and a load. For the modeling of batteries, the Simulink generic model of a lithium battery was used, which allows to adjust different parameters such as nominal voltage, capacity, initial SoC, and maximum charge and discharge current. The parameters of the batteries used are shown in Table 1. Small battery capacities were considered so changes in the SoCs could be observed earlier in the simulation.

On the other hand, the PV system considered is one with a maximum power of 2 kW, which delivers a variable power mimicking the power delivered by a conventional PV system throughout the day. Also, a constant load of 1 kW was considered to better visualize the behavior of the power delivered by the batteries during the simulation.

Table 2
Battery buck-boost converter parameters.

Description	Parameter	Value	Unit
DC/DC Filter inductor	L_f	1.5	mH
DC/DC Filter capacitor	C_f	1	mf
DC link capacitor	C	100	mf
AC Filter inductor	L	1.65	mH
Proportional gain	Kp	0.001	
Integral gain	Ki	1	

Table 3
PV inverter parameters.

Description	Parameter	Value	Unit
Filter inductor	L	30	mH
Filter capacitor	C	2.34	uf
Inverter source	Vpv	500	V
Proportional gain D axis	Kpd	15	
Integral gain D axis	Kid	160	
Proportional gain Q axis	Kpq	10	
Integral gain Q axis	Kiq	80	

Table 4
Parameters used in GA to perform the three optimizations.

Parameter	Opt 1	Opt 2	Opt 3
Max. number of iterations	500	500	1000
Population size	100	100	100
Probability of crossover	1	1	1
Probability of mutation	0.02	0.02	0.02
Bits	20	16	16

Table 2 presents the values of the elements used in the two-stage buck-boost converter which served to control the current supplied by the batteries. Similarly, Table 3 shows the values of the elements used in the inverter which was used to control the power supplied by the PV system.

To examine the performance of the proposed equalization and energy management methods, two cases were conducted, each case with a simulation of 240 s. In the first case, a combination of optimization 1 and 2, as illustrated in Fig. 7, was utilized. Meanwhile, the second case solely employed optimization 3. Table 4 displays the GA parameters employed for each optimizer. These parameters were selected based on various simulations, prioritizing those that exhibited superior speed and accuracy in achieving the desired outcomes. Since the PV system generation is continuous, the optimization algorithm was programmed to read the MG parameters every second, so every second, it optimizes and delivers new current references to the batteries.

4.1. Case 1

In this case, energy management and battery equalization were performed using the combination of optimization 1 and 2. The SoC threshold ΔS considered for the change of optimization was 0.005. Thus, when the standard deviation of the SoC_i is less than the ΔS, the second optimization is performed, which considers energy management.

Fig. 8 shows the SoCs of the three batteries during energy management and equalization process. In the beginning, because the value of ΔS is not met, optimization 1 focuses on achieving fast equalization of the SoCs of the three batteries. As a result, batteries 1 and 3, which present a SoC further away from the target, are discharged and charged using their maximum discharge and charge current, respectively. As a result of this process, the three batteries achieve equalization around second 29, at which time the threshold ΔS is met and the second optimization starts. With the second optimization, the SoCs of the three batteries are kept equal while simultaneously performing energy management in the MG.

On the other hand, Fig. 9 shows the power of the load, the grid, the PV system, as well as the sum of the power in the batteries. It is evident

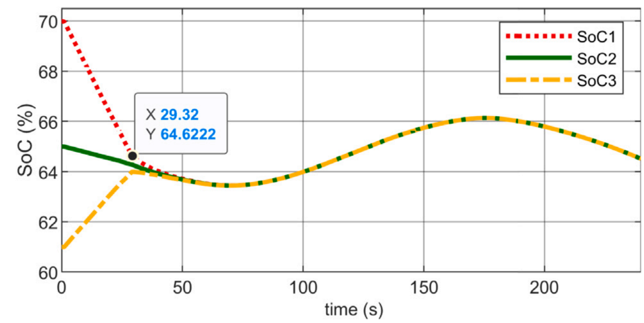

Fig. 8. SoCs — Energy management and equalization process using Opt 1 and Opt 2.

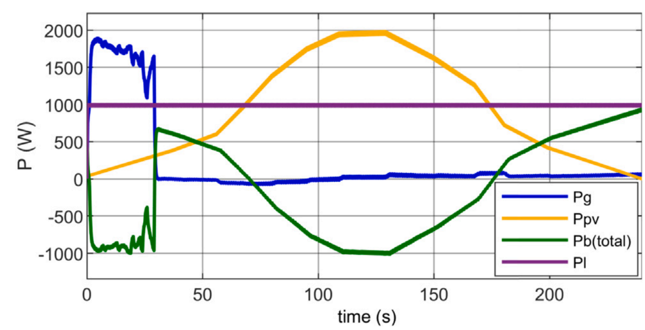

Fig. 9. Grid, PV, battery, and load power — Energy management and equalization process using Opt 1 and Opt 2.

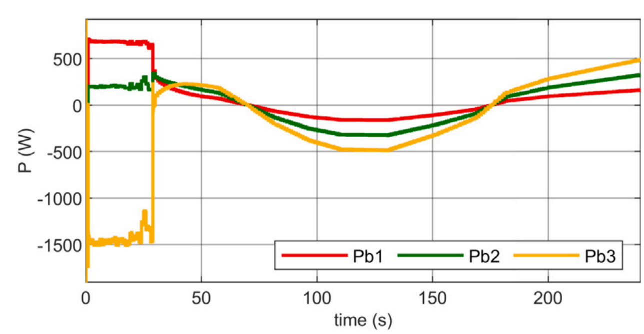

Fig. 10. Power delivered by each battery — Energy management and equalization process using Opt 1 and Opt 2.

that at the beginning, the grid supplies enough power to supply both the load and the batteries during the equalization process. This initial power peaks near 2 kW and gradually decreases as the PV begins to generate, having a consumption of about 47 kW*s. Once the second optimization starts, the power coming from the grid decreases to zero and remains at that value throughout the simulation.

Fig. 10 depicts the power delivered by each battery. It is evident that higher battery capacities result in greater power delivery, ensuring SoCs equalization. In Fig. 11, the reference currents from GA and the corresponding currents at the battery outputs are illustrated. It is observed that the currents of the batteries closely match the reference values. It can also be seen that when the first optimization is active, the currents of batteries 1 and 3 are at their maximum. The voltage variation for each battery is also shown in Fig. 12. It is observed that once the batteries are equalized, the voltage of each one of them is identical because the same type was chosen for the three batteries.

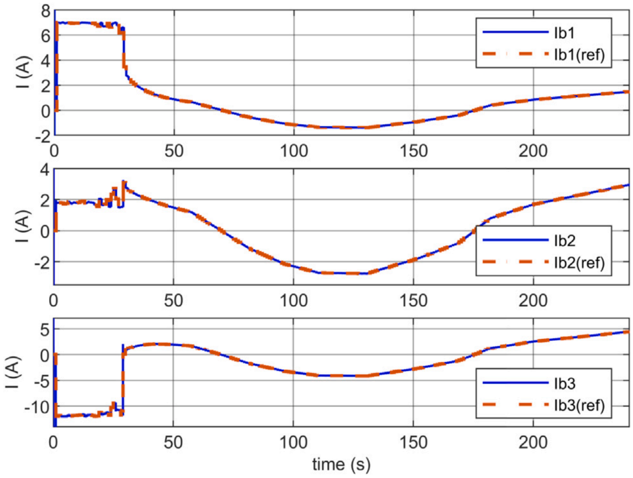

Fig. 11. Battery currents and references provided by GA — Energy management and equalization process using Opt 1 and Opt 2.

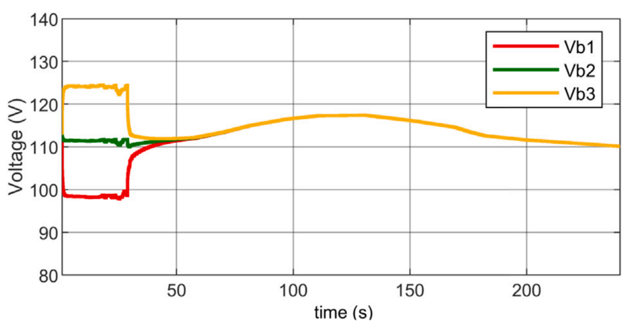

Fig. 12. Battery voltage variation during equalization process — Energy management and equalization process using Opt 1 and Opt 2.

4.2. Case 2

In this case, energy management and battery equalization were performed using the third optimization. A constant Ks equal to 100 and a constant Kg equal to 5 were used. The battery characteristics and SoC_i used for this case are the same as those used for Case 1.

Fig. 13 shows the SoC of the three batteries after performing energy management and equalization. It can be observed that, at the beginning, when there is a shortage in PV generation, battery 1 experiences the most significant discharge, followed by battery 2 with a lower discharge, and battery 3 with zero discharge. This variation is due to the presence of the variable K_{SoC} in the cost function, which depends on the SoCs of each battery. In addition, during the discharge process of batteries 1 and 2, there is no constant discharge of these batteries. This is because their SoC varies every second, which in turn affects the value of K_{SoC}.

At second 50, the SoCs of batteries 1 and 2 are equalized, which means that their K_{SoC} values are also identical. As a result, from that point on, both batteries supply equal power. At second 70, the PV system starts to generate more power than demanded, creating excess PV generation. In this situation, the variables K_{SoC} undergo abrupt changes according to Eq. (18), causing abrupt changes in the charging and discharging of the batteries. At that time, battery 1 has a lower SoC, which gives it priority in charging. This process continues until about second 110 when the SoCs of the three batteries equalize. At this point, all three batteries have an identical K_{SoC} value, which implies they will charge and discharge proportionally, maintaining a uniform SoC.

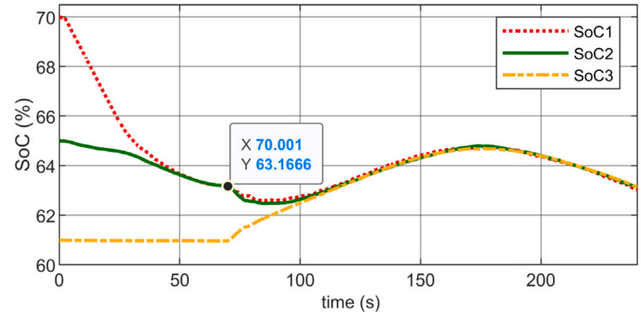

Fig. 13. SoCs — Energy management and equalization process using Opt 3.

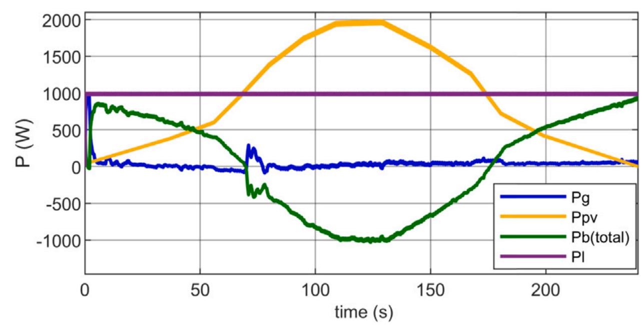

Fig. 14. Grid, PV, battery, and load power — Energy management and equalization process using Opt 3.

Fig. 14 shows the power of the different elements of the MG. Initially, the energy supply comes mainly from the grid, since the optimizer starts working from second 1. However, as the simulation progresses, the optimization achieves its objective of minimizing the power delivered/absorbed by the grid. This power is maintained at levels close to zero throughout the simulation, which shows that all the energy demands of the load are supplied by the PV system and the batteries.

Furthermore, it is observed that, unlike the previous case, in this simulation, energy management and equalization are carried out from the beginning, which allows to reduce costs caused by grid generation. On the other hand, the abrupt change in the K_{SoC} parameters at second 70 is also reflected in the grid and battery power, which generates a small distortion that is quickly restored.

4.3. Discussion of results

After analyzing both cases, it can be stated that the two proposed methods meet the objective of energy management and battery equalization in an MG. The first method has the advantage of prioritizing fast battery equalization before performing energy management. So, equalization is performed in only 29 s. This is beneficial since it was considered that the MG batteries correspond to EVs and these usually present different SoCs when arriving at the charging station. However, the main disadvantage of this method is that grid intervention is required to achieve fast battery equalization, obtaining a consumption close to 47kW*s, which increases overall costs.

In contrast to the first method, the second method prioritizes energy management over fast equalization. As a result of this approach, the three batteries are equalized in a longer period than the first method, being 110 s. However, energy management is implemented from the beginning, making the grid deliver close to zero power during the entire simulation. This considerably reduces the dependence on the grid and thus minimizes the associated overhead costs.

The choice between one method or the other will depend on whether priority is given to fast equalization despite incurring additional costs during energy management, or to both energy management and equalization that minimizes costs as much as possible.

On the other hand, it was also observed that the reference currents for the batteries provided by GA are fed to the buck-boost controllers used in the batteries. As a result, the buck-boost converters provide currents identical to that of the references, thus demonstrating that the proposed type of control meets its objective.

Since current commercial inverters have several functions, including bidirectional current controllers, it would simply be necessary for the proposed optimizers to send the current references. In this way, optimizers designed for energy management and battery equalization could be implemented in any real system. It would only be necessary to adjust the quantity and characteristics of the batteries to be equalized to suit the specific system. This flexibility allows an easy integration of the proposed methods in different commercial inverter configurations, which is highly favorable in terms of applicability.

Finally, this work was carried out considering a typical situation in which a large number of EVs remain parked for extended periods at a charging station. This feature offers the opportunity to take advantage of the integration of EVs into MGs and to involve them in energy management, thus reducing the use of the grid.

5. Conclusion

This paper proposes an approach for energy management and battery equalization in an MG. All the batteries involved have been considered to be EVs, which implies that the EVs themselves provide support to the MG in terms of energy storage and supply. To achieve this goal, GA was used as the optimization manager. GA is in charge of collecting data from the MG and, as a result, provides the reference currents to be used in the battery converters. This methodology of operation makes it possible to dispense with the traditional droop control commonly used for this type of task. Hence, it is possible to eliminate the voltage and frequency variations that are usually caused by droop control.

Three optimizations were proposed for the energy management and equalization process in the MG: Opt 1 had the sole objective of minimizing the time in battery equalization. Opt 2 was able to perform energy management and equalization simultaneously as long as the variation of the initial SoCs was not too large. Opt 3 was able to perform energy management and equalization without the limitations presented by the second optimization.

In this way, equalization and energy management in an MG was achieved in two ways: first by combining Opt 1 and Opt 2, and second, by making use of Opt 3. To test the performance of the optimizations, an MG with 3 batteries, a PV system, and a load was used. The main results obtained from the simulation are shown below:

- The combination of Opt 1 and Opt 2 resulted in battery equalization in as little as 29 s. However, the only drawback of this combination is the need for interaction with the grid, which resulted in a consumption of 47 kW*s. This implies an additional cost due to using the grid to speed up the equalization process.
- Optimization 3 achieved full battery equalization in 110 s. Although this approach has a slower equalization speed, it has the advantage of performing energy management from the beginning, which significantly reduces grid dependence and thus associated costs.

From the results obtained, it can be concluded that energy management and battery equalization can be performed with either of the two methods proposed. The choice between one method or the other will depend on whether priority is given to fast equalization despite incurring additional costs during energy management, or whether both energy management and equalization minimize costs as much as possible.

In future work, several improvements and extensions to the study can be considered. Some suggestions include considering EV exit and entry times, EV charging levels desired by users, initial EV charging levels, and the use of EVs to improve power quality in an MG while performing equalization. These suggestions provide opportunities to expand and improve research in terms of optimization, and leveraging EVs in energy management and equalization in the MG.

CRediT authorship contribution statement

Calloquispe Huallpa Ricardo: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing. **Luna Hernandez Adriana:** Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – review & editing. **Diaz Aldana Nelson:** Conception and design of study, Analysis and/or interpretation of data, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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All authors approved version of the manuscript to be published.

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