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Electrical Engineering

Sodium sulfur batteries allocation in high renewable penetration microgrids using coronavirus herd immunity optimization

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1. Introduction

Energy crises and fossil fuel reliance are important technical, economical, social, and political issues affecting the future of the energy sector around the world [1]. As a result, renewable energy sources (RESs) need to be deployed on a large scale to fulfill power demand, promote transportation electrification, facilitate enhanced employment of green buildings/networks, and lessen the notable augmented environmental hazards [2]. Wind turbines (WTs) and solar photovoltaics (PVs) are the most promising RESs due to their mature potential and technology worldwide [3,4]. From an economic standpoint, the conventional sources of power generation, such as fossil fuel-based power stations, provide a cost competition for them [5]. Thus, to make RESs more cost-efficient, they should be used with increased self-consumption rates (ScR), i.e., the energy generated through RESs is not hosted in the transmission or distribution systems but is utilized by the investor (according to contracts agreed with the operator) [6], in which ScR refers to the proportion of renewable energies produced and used to meet demands for total renewable energies. In this way, RESs production prioritizes ScR before exporting to transmission/distribution systems or nano/micro-based networks when RESs output exceeds total demand requirement [7,8]. In this context, improving the ScR of RESs and reducing the power loss of energy grids is essential to facilitate energy alteration from fossil fuels bases to renewables-constructed systems [9,10].

It is possible to classify battery storage system (BSS) applications into four categories: bulk energy, auxiliary, end-use energy, and RESs integration applications. Electric vehicles (EVs) are another significant complimentary area where BSS technologies are being used [11], and they are increasing in popularity [12]. Besides, short-medium-long-term BSSs can be also classified into...
Nomenclature

\( A_t \) \quad \text{Age vector value}
\( b_t \) \quad \text{The hth energy price ($/kWh)}
\( b_t^{\text{WT}} \) \quad \text{The hth WT bid price}
\( b_t^{\text{PV}} \) \quad \text{The hth PV bid price}
\( B_t \) \quad \text{Lifecycles of the batteries}
\( B_t^{\text{dis}} \) \quad \text{Operational cost of the grid}
\( B_t^{\text{grid}} \) \quad \text{Unit costs of the energy capacity of the BSSs}
\( B_t^{\text{Power}} \) \quad \text{Capital cost of the battery}
\( C_t^{\text{PV}} \) \quad \text{Total PV costs ($/kWh)}
\( C_t^{\text{WT}} \) \quad \text{Total WT costs ($/kWh)}
\( C_t^{\text{NaS-BSS}} \) \quad \text{Daily total cost of NaS-BSS usage ($/day)}
\( D \) \quad \text{Total number of days of operation per year}
\( D_t^{\text{loss}} \) \quad \text{Total active power losses}
\( E_t \) \quad \text{Energy capacity of the battery}
\( E_{g,h} \) \quad \text{Actual RESs energy generated at } \ h \text{ and the}
\( E_{\text{rated}} \) \quad \text{Rated RESs energy that can be generated at}
\( e \) \quad \text{Battery efficiency}
\( e \) \quad \text{Inverter efficiency of the PV system}
\( G \) \quad \text{Global solar irradiance}
\( G_0 \) \quad \text{Standard solar irradiance}
\( H \) \quad \text{Day horizon}
\( HIP \) \quad \text{Herd immunity population}
\( HIS \) \quad \text{Herd immunity capacity}
\( i_t \) \quad \text{Interest rate}
\( I_{\text{rms}} \) \quad \text{Total rms branch current}
\( I_{\text{max}}^{\text{rms}} \) \quad \text{Maximum branch current}
\( k_{\text{NaS}}(h,e) \) \quad \text{Cycles completed given as a function of } h \text{ and the day of}
\( \text{operation (e)} \)
\( \text{MaxAge} \) \quad \text{Maximum infected cases age}
\( \text{MaxAge}_{\text{str}} \) \quad \text{Maximum iteration number}
\( N_b \) \quad \text{Number of branches in the microgrid}
\( N_{PV} \) \quad \text{Number of PV units connected}
\( p_t^{\text{Power}} \) \quad \text{Power capacity of the battery}
\( p_t^{\text{charge,h}} \) \quad \text{Charging power of the NaS battery}
\( p_t^{\text{max-charge,h}} \) \quad \text{Maximum charging capacity of the NaS batteries at } h
\( p_t^{\text{discharge,h}} \) \quad \text{Discharging power of the NaS battery}
\( p_t^{\text{max-discharge,h}} \) \quad \text{Maximum discharging capacity of the NaS batteries at } h
\( p_{\text{grid},h} \) \quad \text{The hth output (delivered) grid power}
\( p_t \) \quad \text{Total power demand}
\( p_t^{\text{PV}} \) \quad \text{The hth output power of the PV}
\( p_t^{\text{dis,max}} \) \quad \text{Maximum PV generated power limit}
\( p_t^{\text{PV, h,min}} \) \quad \text{Minimum PV generated power limit}
\( p_t^{\text{rated}} \) \quad \text{Hourly nominal power of the PV}
\( p_{\text{WT},h} \) \quad \text{The hth output power of the WTs}
\( p_{\text{WT, h,max}} \) \quad \text{Maximum WT generated power limit}
\( p_{\text{WT, h,min}} \) \quad \text{Minimum WT generated power limit}
\( p_t^{\text{losses}, h} \) \quad \text{The hth branch active power loss}
\( p_{\text{WT, rated}} \) \quad \text{Rated power of the WTs}
\( S \) \quad \text{Status vector}
\( SoC \) \quad \text{State of charge}
\( SoC_{\text{h}} \) \quad \text{The hth state of charge}
\( SoC_{\text{max}} \) \quad \text{Maximum soc of NaS batteries ath}
\( SoC_{h, \text{min}} \) \quad \text{Minimum soc of NaS batteries ath}
\( SoC_{\text{in}} \) \quad \text{Initial state of charge}
\( t_{\text{h,i}} \) \quad \text{A binary, 0/1, variable that indicates the battery at } h \text{ and}
\( e \)
\( T_{\text{off}} \) \quad \text{Temperature-based coefficient}
\( T_{\text{amb}} \) \quad \text{Ambient temperature}
\( \mu_{\text{WT, cut-in}} \) \quad \text{Cut-in speed of the WTs}
\( \mu_{\text{WT, cut-out}} \) \quad \text{Cut-out speed of the WTs}
\( \mu_{\text{WT, h}} \) \quad \text{Hourly wind speed at hour } h
\( V_{\text{bus}}^{\text{max}} \) \quad \text{Maximum voltage limit}
\( V_{\text{bus}}^{\text{min}} \) \quad \text{Minimum voltage limit}
\( \mu_{\text{WT, rated}} \) \quad \text{Rated speed of the WTs}
\( Y(X) \) \quad \text{Self-consumption rate of all the RESs hosted on the } \mu_{g} \text{ }
\( Z \) \quad \text{Project lifetime

three categories relying on the discharge length – short- (seconds to minutes), medium- (minutes to hours), and long-term (hours to days) [13]. For end-use energy and auxiliary applications in power utilities, short-term and medium-term discharge periods are applicable, but long-term discharge periods are more appropriate for bulk and RESs integration applications. BSSs capabilities can be employed at various voltage levels by generating systems and end-users because they have important effects on the various utilization stages of power grids, like security, serving peak demands, power quality (PQ), stability, reliability, hosting capacity (HC), and others [14,15]. However, sodium-sulfur (NaS) BSS (NaS-BSS) technology has its own set of advantages. Fig. 1 explores the applications and benefits of NaS-BSS technology in power networks, μGs, and nano grids.

Overall, energy storage (ES) has been touted as a way to solve RESs issues, efficiently arrange self-consumption, and paving the route to significant growth in RESs penetration into the overall production share [16,17]. In addition to enhancing PQ performance and reliability, energy storage systems can also minimize power losses, overcome uncertainty concerns related to RESs, improve system stability, reduce power import during peak periods by feeding the peak demands, and reduce overall operating costs of power system networks [18,19].

Considering the influence of the storage facility's optimal allocation on the system performance, many studies have been done for evaluating the optimal allocation of the storage system and energy management strategies to enhance the μGs techno-economic competencies [20]. In [21], Nayak et al. planned optimal location and sizing of ES with WT penetrations for unbalanced distribution network utilizing an inherited competitive swarm algorithm, in which the approach developed had been examined on IEEE 37-bus distorted radial distribution scheme and the results obtained show the improvement of different performance metrics of the distribution system. Pontes et al. [22] proposed a technique for optimum allocation of ES in distribution networks with the integration of RESs. That approach assigned ES’s optimal allocated locations and sizing of ES with WT penetrations for unbalanced economic competencies [20]. In [21], Nayak et al. planned optimal allocation of ES in distribution networks with the integration of RESs. That approach assigned ES’s optimal allocated
of RESs. Xu et al. [24] proposed ESS's optimal allocation to enhance the voltage fluctuations in distribution networks with high RESs penetration. That approach has utilized a bi-level optimization technique of ES capacity allocation concerning cost (life cycle based) and the profit of dropping power losses. Mahmoud et al. [25] proposed a model to find the ES's global capacity. The main objective is to boost the profitable deployment of ESs and maintain safe and secure operations.

In [26], Feng et al. introduced an optimal procedure of multi-feature technique for finding optimal sizes of hybrid ES systems in order to make use of their complementary features. As part of the optimization procedure, the optimization problem formulation involves both standalone and grid-connected μG operating modes. Minimizing the cost of operation was the goal in grid-connected mode while improving the μG’s reliability was the goal in the isolated mode.

Rawa et al. [27] proposed the application of the Harris hawks search algorithm to enhance the performance of the IEEE 33-bus with high penetration of RESs. That approach presented two objectives – optimum planning of ESs to improve the RESs's ScR and the grid-connected μG's HC to reduce the μG’s total operating costs. Minimizing the cost of operation was the goal in grid-connected mode while improving the μG's reliability was the goal in the isolated mode.

Nojavan et al. in [28] developed a mixed-integer non-linear program to get the ES's optimum allocation regarding the optimal demand response. To reduce the overall investment and operating costs as well as load expectation loss, multi-targets functions were implemented in that approach. Chen and Duan [29] settled an optimization technique built on the genetic approach for ES' and distributed generators’ optimum allocation with economic considerations taken into account. The capacity of the distributed generators and ES systems have been controlled by dealing with different cost functions in order to protect the μG and satisfy the client demands. Qiu et al. [30] proposed a bi-level forecasting model for ES's allocation in a μG, taking controllable loads into account. A study of cost-benefits was evaluated to establish the best allocation decisions and economic consideration of the ES scheme. However, the majority of previous studies have not looked at the effects of ESs on multi-criteria metrics such as the ScR of the RESs, power losses, voltage profile, ES features, and optimal energy management (OEM) of the μGs [31–34].

Furthermore, at peak times, the substation transformer feeding the power system or the μG may be overloaded due to the restricted transformer capacity [35]. The usual key is supporting the transformer – reinforce its capacity. However, application of the appropriate key subjects to the presence of a standby transformer or the availability of a suitable budget [36]. Therefore, the peak loads should be removed or moved to off-peak times to reduce the transformer load rate – demand-side management or extreme load shedding [37]. In this context, the decision of the optimum location and size of the BSS and the OEM of the produced by the BSS, renewables, and the main grid according to the load demands, and climatic conditions is not only related to the reliability of the power basis of the whole scheme or PQ measures but seriously spreads to economic considerations and scheme’s reliability [35].

In this work, an optimization framework is proposed to enhance a grid-connected μG performance in three stages. The first stage epitomizes maximization of the ScR of the highly-penetrated RESs hosted in the μG considered (adapted 33-node system that operates as a μG with highly-penetrated RESs) via sodium sulfur (NaS) batteries allocation (number, location, and size).

![Fig. 1. Applications of NaS batteries in power networks and μGs.](image-url)
Up to three NaS batteries are allowed in the problem formulation. The load flow methodology used relies on building matrices – (i) matrix of the bus_injection to branch_current, (ii) matrix of the branch_current to bus_voltage, and (iii) their multiplication matrix to get OLF results. This methodology is often fast, effective, and efficient in solving OLF problems in power systems [38,39].

The second stage epitomizes the minimization of the active power losses. The third stage epitomizes the calculation of the OEL relying on minimizing the overall operating cost of the μG based on the optimal findings of the earlier two stages. The coronavirus herd immunity optimization (CHIO) algorithm, which is a new optimization approach settled by Al-Betar et al. in [40], is employed to solve the problem investigated in this work. Numerous linear and nonlinear constraints have been taken into account, including the charging–discharge balance, power balance, allowable voltage profile limits, number, capacity, and location of the NaS batteries, and the technical performance limits of the μG and its elements.

This work’s core contributions are briefed as follows:

1. Investigating the ScR of RESs and reducing the power loss of (μGs), when NaS batteries are allocated.
2. Highlighting the promising potential of using NaS batteries in grid-connected systems in detail.
3. Minimizing the overall operating cost of the μG with high-penetrated RESs while addressing the NaS battery – location, capacity, and number impacts on the solutions obtained.
4. Evaluating the effects of optimally allocated NaS batteries on the transformer’s capacity that powers the μG and releasing a significant amount of its capacity.
5. Applying a recent metaheuristic optimization algorithm to resolve the multi-stage problem expressed in this paper.

The remainder of the paper is systematized as follows. Configuration of the studied microgrid (μG) is given in Section 2. The optimization problem is mathematically expressed in detail in Section 3. The optimization algorithm employed in this work, CHIO, is explained in Section 4. The findings obtained are introduced and discussed in Section 5. Finally, Section 6 is dedicated to present a review of the study’s findings, work limitations and future endeavors to be addressed.

2. Configuration of the studied microgrid (μG)

The grid-connected μG considered in this work, shown in Fig. 2, includes the main μG central controller (μGCC), main transformer (Tr), 5 PVs, and 5 WTs. The μGCC facilitates the optimal energy management (OEM) of the μG, in addition to the charging/discharging processes of NaS batteries to attain the minimum daily change of the operation (Cost) of the μG. The PVs and WTs data, primarily obtained from [27], are presented in Table 1.

2.1 Photovoltaics (PVs)

The PVs’ output power (P_{op}) relies on the weather conditions – solar irradiation, real-measured temperature and cloud coverage, as expressed in Eq. (1) [41–43].

\[
P_{op} = N_{PV} \cdot P_{rated} \cdot \left( \frac{G}{G_0} \right) (1 - T_{col} \cdot (T_{amb} - 25)) \eta_i \eta_R
\]  

where \(P_{op}^*, P_{rated}^*,\) and \(N_{PV}\) denote \(P_{op}\) and the hourly nominal power of the PV, and the number of PV units connected, respectively. \(G\) and \(G_0\) denote the global solar irradiance and the standard solar irradiance. \(T_{col}\) and \(T_{amb}\) denote the temperature-based coefficient and the ambient temperature, respectively. \(\eta_i\) and \(\eta_R\) denote the inverter’s efficiency and the relative efficiency of the PV system, respectively [44].

2.2 Wind turbine (WTs)

The hourly \(P_{op}\) of wind turbines (WTs) relies on the wind speed (site-based) and the WT’s speed-power curve (provided by WTs manufacturer data). It is typically expressed as given in Eq. (2), in which the wind speed per hour is assessed using the Weibull probability distribution function using the statistics obtained from [27].

\[
P_{WT} = \begin{cases} \frac{0 \cdot P_{WT} \cdot (v_{WT}^{\text{in}})}{V_{WT}^{\text{rated}}}, & v_{WT}^{\text{in}} < V_{WT}^{\text{rated}} \\ \frac{P_{WT}^{\text{rated}} \cdot (v_{WT}^{\text{in}})/(v_{WT}^{\text{cut-in}})}, & V_{WT}^{\text{in}} < v_{WT}^{\text{rated}} < v_{WT}^{\text{cut-out}} \\ \frac{0 \cdot P_{WT} \cdot (v_{WT}^{\text{cut-out}})}, & v_{WT}^{\text{in}} > V_{WT}^{\text{cut-out}} \end{cases}
\]  

where \(P_{WT}\) and \(P_{WT}^{\text{rated}}\) are the output and rated powers of the WTs, respectively. \(v_{WT}^{\text{in}}, v_{WT}^{\text{rated}}, v_{WT}^{\text{cut-in}},\) and \(v_{WT}^{\text{cut-out}}\) denote the hourly wind speed at hour \(h\), rated, cut-in, and cut-out speeds of the WTs.

2.3 Cost of grid operation

The operating cost of the grid (Cost_{grid}) relies on the hth output (delivered) grid power \(P_{grid}^{\text{delivered}}\) at and its corresponding hth energy bid \(b_{grid}^{\text{h}}\) in (S/kW), as given in Eq. (3).

\[
\text{Cost}_{\text{grid}}^h = b_{\text{grid}}^h \cdot P_{\text{grid}}^{\text{delivered}} \cdot \forall h
\]  

Fig. 2. Configuration of the studied microgrid.
2.4. Sodium sulfur (NaS) battery storage system (NaS-BSS)

There are different types of batteries with multiple cost and technical properties, such as NaS, lead acid (LA), lithium-ion, cadmium nickel (NiCd), and other batteries. Each battery has particular merits that may positively affect the electrical grid and its stability, and OEM of the μGs. In this context, the NaS battery was the first molten sodium battery to be investigated and developed in the late 1960s [45,46]. It is one of the most installed batteries in the world. During electrochemical cycling of the batteries, the NaS battery oxidizes (discharges) and reduces (charges) sodium, based on the reversible reduction (discharge) and oxidation (charge) of molten sulfur. Normal discharge reactions occur when the anode oxidized Na⁺ passes through the ion-conducting ceramic separator and interacts with the cathode’s reduced molten sulfur (or polysulfides). These polysulfides (e.g., Na₂S₅) can be electrochemically cycled as a byproduct of this process, as expressed in Eq. (4) [45,46].

$$S + 2Na \leftrightarrow Na₂S_x, x \in \{3, 4, 5\}$$

Fig. 3 shows a tubular NaS batteries architecture and theory of operation. The NaS battery has an advantage of a molten sodium anode and a ceramic sodium-ion conducting solid-state separator, most frequently β-alumina, where the sodium anode is held inside a ceramic separator tube, while its sulfur cathode is located outside. An elongated cell is used to seal and package the entire system, together with all of the current collectors. Many cells are then grouped into a module to be assembled in larger containers later. They are then placed and controlled by the external power conversion system. Assembling and operating batteries is easier with these designs, which also provide high power density [47].

Nowadays, NaS and sodium-nickel chloride (Na-NiCl₂) systems are the only grid-scale technologies that are commercially mature [48–50]. Both technologies can store energy from a few kilowatt-hours (kWh) to tens megawatt-hours (MWh) of energy.

Table 2 summarizes the key metrics for these batteries. As noted in Table 2, NaS systems have a high energy density, scalability, rapid reaction times (less than 1 s), and good round-trip energy efficiency. Over 10–15 years, they are robust, self-contained systems, and maintenance-free with 4000–4500 total cycles (DOD expectation of 80%). The core disadvantages of NaS batteries are to preserve the high temperature required for their operation as well as the corrosive nature of sodium polysulfides.

In this context, the cost and technical parameters of different battery storage systems (BSSs) – NaS, Li-ion, LA, and NiCd have been presented in Table 3 for different ES technologies, where it should be noted that Li-ion has a higher capital (investment) cost than the other battery types. NiCd has low efficiency, a short lifetime, and a high cost. LA battery is not highly efficient and has a short lifetime. The NaS battery is highly efficient and has a long lifetime. $C_{\text{Power}}$ and $C_{\text{Energy}}$ denote the unit costs of the power and energy capacities of the BSSs.

Some research works in the literature have examined the economic analysis and costs framework of different energy storage systems. In [16], the authors have provided a detailed cost model of energy storage systems reinforced by in-market insight – short, medium, and long terms storage technologies. It was demonstrated that the NaS battery offers the lowest cost due to its (a) high efficiency, (b) long lifetime, and (c) low replacement costs. Fig. 4 shows the values of the annualized life cycle cost of storage ($LCCOS$) estimated for seven BSSs – hydrogen energy storage (HES), LA, NiCd, NaS, vanadium-redox (VR), zinc-bromine (ZnBr), and Li-ion, which validates the reasons of selection of NaS batteries in this work.

Finally, the capital cost ($B_{\text{capital}}$) of the battery relies on the power ($P^b$) and energy ($E^b$) capacities as given in Eq. (5).

$$B_{\text{capital}} = (C_{\text{Power}} \times P^b) + (C_{\text{Energy}} \times E^b)$$

3. Formulation of the problem

This section introduces the invention of the three optimization stages to get the optimally-allocated NaS-BSSs to epitomize maximization of the $ScR$ of the highly-penetrated RESs hosted in the μG
considered, then to epitomize the minimization of the active power losses, and finally to epitomize the calculation of the OEM relying on diminishing the overall operating cost of the \( \mu \mathrm{G} \) based on the optimal findings of the earlier two stages. The investigated problem’s formulation is expressed mathematically as follows:

### 3.1. Objective functions (OFs)

#### OF1

\[
\text{OF}_1 = \max \ ScR(x) = \max Y(x) = \sum_{h=1}^{H} \left( \frac{E_{h,h}}{E_{h,h}^{\text{rated}}} \right)
\]

#### OF2

\[
\text{OF}_2 = \min \ \Delta P_{\text{loss}}(x) = \sum_{b=1}^{N_b} P_{\text{loss},b,h}, \forall h \in H, \forall b \in N_b
\]

#### OF3

\[
\text{OF}_3 = \min \ \text{Cost}(x)
\]

\[
= \sum_{h=1}^{H} \left( \text{Cost}_{h}^{\text{grid}} + \text{Cost}_{h}^{\text{WT}} + \text{Cost}_{h}^{\text{PV}} + \text{Cost}_{\text{NaS-BSS}} \right)
\]

So that:

\[
\text{Cost}_{h}^{\text{WT}} = b_{h}^{\text{WT}} p_{h}^{\text{WT}}, \forall h \in H
\]

\[
\text{Cost}_{h}^{\text{PV}} = b_{h}^{\text{PV}} p_{h}^{\text{PV}}, \forall h \in H
\]

where \( Y(x) \) signifies the ScR of all the RESs hosted on the \( \mu \mathrm{G} \) as a function in the decision variables \( x \). \( E_{h,h} \) and \( E_{h,h}^{\text{rated}} \) denote the actual RESs energy generated at \( h \) and the rated RESs energy that can be generated at \( h \), respectively, in which \( H \) expresses the day horizon (\( H = 24 \)). \( \Delta P_{\text{loss}}(x) \) denotes the total active power losses, in which \( P_{\text{loss},b,h} \) and \( N_b \) represents the \( b \)th branch active power loss and the number of branches in the \( \mu \mathrm{G} \), respectively. \( \text{Cost}(x) \) denotes the cost of operation of the \( \mu \mathrm{G} \) in ($/kWh), \( \text{Cost}_{h}^{\text{grid}} \) denotes the total WT costs in ($/kWh), and \( \text{Cost}_{h}^{\text{PV}} \) denotes the total PV costs in ($/kWh). All are expressed at \( h \). \( p_{h}^{\text{grid}}, p_{h}^{\text{WT}}, \) and \( p_{h}^{\text{PV}} \) denote the \( h \)th grid, WTs, and PVs, respectively. 

Table 2 shows the numerical values of PV and WT bids.

### Table 2

| Battery | Energy density (Wh/L) | Expected life cycle (cycles)* | Expected operational lifetime (years) | Operating temperature (°C) | Discharge duration (h)** | Round-trip efficiency (%) |
|---------|------------------------|-------------------------------|---------------------------------------|----------------------------|--------------------------|---------------------------|
| NaS     | 300–400                | 4000–4500                     | 15                                    | 300–350                    | 6–7                      | 80                        |
| Na-Nicl2| 150–190                | 3500–4500                     | 20                                    | 270–300                    | 2–4                      | 80–85                     |

* Cycles at 80% depth of discharge (DoD).

** Discharge duration is estimated at rated power.

### Table 3

| BSS     | Capital cost ($) | \( \epsilon_{\text{power}}^{\text{grid}} ($/kW) \) | \( \epsilon_{\text{energy}}^{\text{grid}} ($/kWh) \) | Life cycles (cycles) | Lifetime (years) |
|---------|-----------------|----------------|----------------|---------------------|---------------------|
| NaS     | 350             | 300            | 0.95            | 4000                | 15                  |
| Li-ion  | 900             | 600            | 0.98            | 3000                | 10                  |
| Li-ion  | 200             | 200            | 0.70            | 350                 | 7                   |
| NiCd    | 500             | 400            | 0.85            | 500                 | 9                   |

Fig. 4. Cost elements basis versus LCCOS for seven BSSs.
rate \( (i_e) \), and lifecycles \( (B_{\text{lifecycles}}) \) of the batteries. It can be calculated as follows:

\[
\text{Cost}_{\text{NaS-BSS}} = \frac{1}{D} \left( \sum_{e=1}^{D} k_{\text{NaS}}(h, e) \right) B_{\text{lifecycles}} \frac{Z}{B_{\text{lifecycles}}} \quad (11)
\]

where \( B_{\text{lifecycles}} \) denotes the total number of NaS-BSS cycles performed and is expressed in Eqs. (12) and (13).

\[
B_{\text{lifecycles}} = \sum_{e=1}^{D} \sum_{h=1}^{H} k_{\text{NaS}}(h, e) \quad (12)
\]

\[
k_{\text{NaS}}(h, e) = (t_{e}(h) - t_{e(h-1)}) V_{\text{HAnd}}(e) \quad (13)
\]

\( k_{\text{NaS}}(h, e) \) denotes the cycles completed given as a function of \( h \) and the day of operation \( (e) \), \( D \) denotes the total number of days of operation per year \( (i.e., D = 365) \), \( t_{e(h)} \) is a binary, \( 0/1 \), variable that indicates the battery at \( h \) and \( e \). When the NaS battery is discharging \( (P_{\text{NaS}}^{\text{dis}}) \), \( t_e \) equals \( 0 \), and it equals \( 1 \) when the NaS battery is charging \( (P_{\text{NaS}}^{\text{charge}}) \). Features of the NaS-BSS \( (95\% \text{ efficient}) \) used in this work are given as follows: \( C_{\text{power}} = 3500 \text{ kWe}, C_{\text{energy}} = 3300 \text{ kWe}, \) and \( B_{\text{lifecycles}} = 4500 \text{ cycles} \). In addition, the batteries’ lifetime has been set to 15 years.

### 3.2. Problem constraints

The problem formulated is subjected to two different sets of constraints – (i) the system constraints, and (ii) the battery constraints. The first set of constraints is represented by Eqs. (14)–(18), and the second set of constraints is expressed by Eqs. (19)–(24).

\[
p_{\text{grid}}^{\text{h}} + P_{\text{PV}}^{\text{h}} + P_{\text{NaS}}^{\text{dis}} = P_{\text{ch}}^{\text{h}} + P_{\text{NaS}}^{\text{charge}} \quad (14)
\]

\[
p_{\text{WT}, \text{min}}^{\text{h}} \leq p_{\text{WT}}^{\text{h}} \leq p_{\text{WT}, \text{max}}^{\text{h}} \quad (15)
\]

\[
p_{\text{PV}, \text{min}}^{\text{h}} \leq p_{\text{PV}}^{\text{h}} \leq p_{\text{PV}, \text{max}}^{\text{h}} \quad (16)
\]

\[
V_{\text{bus}, \text{min}}^{\text{h}} \leq V_{\text{bus}}^{\text{h}} \leq V_{\text{bus}, \text{max}}^{\text{h}} \quad (17)
\]

\[
l_{\text{b}, \text{min}}^{\text{h}} \leq l_{\text{b}}^{\text{h}} \leq l_{\text{b}, \text{max}}^{\text{h}} \quad (18)
\]

Eq. (14) expresses the balance of power condition, where \( P_{\text{grid}}^{\text{h}}, P_{\text{PV}}^{\text{h}}, P_{\text{NaS}}^{\text{dis}}, P_{\text{NaS}}^{\text{charge}}, P_{\text{ch}}^{\text{h}} \) denote the total power demand, Eqs. (15) and (16) express the WT and PV power limits, where \( p_{\text{WT}, \text{min}}^{\text{h}}, p_{\text{WT}, \text{max}}^{\text{h}}, p_{\text{PV}, \text{min}}^{\text{h}}, p_{\text{PV}, \text{max}}^{\text{h}} \) are the minimum and maximum WT and PV generated power limits. Eq. (17) represents the bus voltage limits, where \( V_{\text{bus}, \text{min}}^{\text{h}}, V_{\text{bus}, \text{max}}^{\text{h}} \) denote the minimum and maximum voltage limits, respectively. They are given 95% and 105%, respectively. Finally, Eq. (18) expresses the loading capacity limit, where \( l_{\text{b}, \text{min}}^{\text{h}}, l_{\text{b}, \text{max}}^{\text{h}} \) denote the total rms branch current and the maximum branch current, respectively.

\[
p_{\text{NaS}}^{\text{charge}} \leq p_{\text{NaS}, \text{max}}^{\text{charge}} \quad (19)
\]

\[
p_{\text{NaS}}^{\text{dis}} \leq p_{\text{NaS}, \text{max}}^{\text{dis}} \quad (20)
\]

\[
\text{SoC}_{\text{min}}^{\text{h}} \leq \text{SoC}^{\text{h}} \leq \text{SoC}_{\text{max}}^{\text{h}} \quad (21)
\]

| Table 4 |
|---|
| RES | Bids (kWh) |
| WT | 1.72 |
| PV | 2.80 |

The concept of herd immunity is mathematically represented in [40] to help establish the CHIO algorithm. According to this strategy, society defends itself against infection by converting the majority of non-infected people from vulnerable to immune. This means that even those who are most vulnerable would not be harmed since the immune population will no longer spread the virus. Herd immunity (HI) populations may be divided into three types – resistant, susceptible, and infectious. As seen in Fig. 5, population-based HI forms the basis for the CHIO formulation.

In the implementation approach of the CHIO algorithm, the improvement methodology is generated from vulnerable, contaminated, and immunized individuals. As a result of the CHIO algorithm, social distance is defined as the separation distance between a person and the community that may be sensitive, infected, or immunized between them. The CHIO optimization approach is used to create HI. As a result, the method has been established in six primary phases. The implementation stages are outlined as follows:

**Stage #1: Initialize CHIO parameters** – The target function of CHIO is represented as follows:

\[
\min_{X} f(X), X \in [lb, ub] \quad (25)
\]

where \( X = x_1, x_2, \ldots, x_n \) represents the target function for all the individuals, in which \( x_i \) denotes the decision variables. The subscripted variable with \( i \) and \( n \) denote the gene quantity. CHIO only requires two main control parameters – maximum infected cases \( (\text{MaxInf}) \) and the fundamental reproduction rate \( (R_0) \). In addition, four additional factors are required – \( C_0 \) (set to 1), \( \text{MaxInf} \) that denotes the maximum iteration number, \( \text{HIS} \) that denotes the HI capacity, and \( n \) that denotes the dimension.

**Stage #2: Produce HI population (HIP)** – Several HIS such as individuals are generated heuristically by the CHIO. The HIP is a bi-dimensional matrix that keeps track of the generated persons as follows:

\[
\text{HIP} = \left[ \begin{array}{ccc} X_1^1 & \cdots & X_n^1 \\ \vdots & \ddots & \vdots \\ X_1^{\text{HIS}} & \cdots & X_n^{\text{HIS}} \end{array} \right] \quad (26)
\]
Using Eq. (25), the optimum solution is determined for each individual. As with the status vector \( \mathbf{S} \), all people in the HIP are assigned a value of 1 or 0. It can be noted that \( \mathbf{S} \) numbers are randomly assigned from \( C_0 \).

**Stage #3: Evolution of HI** – The CHIO’s primary upgrading mechanism is set. According to the \( BR_r \), each gene has the same impact or a socially varied effect based on the following three principles:

\[
X_j(t+1) = \begin{cases} 
X_j(t), & r \geq BR_r \\
C(X_j(t)), & r < \frac{1}{2} BR_r \text{(Infected)} \\
N(X_j(t)), & r < \frac{1}{2} BR_r \text{(Susceptible)} \\
R(X_j(t)), & r < BR_r \text{(Immuned)} 
\end{cases}
\]

where \( r \) stands for a random number ranges between 0 and 1. The infected case has a value between 0 and \( 0.333BR_r \). There are several variations between a patient’s sick gene and the new one that reduces its value, including:

\[
X_j(t+1) = C(X_j(t)) 
\]

\[
C(X_j(t)) = X_j(t) + r(X_j(t) - X_j(t)) 
\]

Similarly, the susceptible case ranges between \( 0.033BR_r \) and \( 0.67BR_r \). In addition, the immune case ranges between \( 0.67BR_r \) and \( BR_r \).

**Stage #4: Population update** – The immunity rate is evaluated for each generated case; however, the current solution will only be substituted by the generated case if \( f(x'(t+1)) < f(x'(t)) \). If the \( S_j \) value is equal to 1, the age vector value \( A_j \) will increase to 1. The values of \( S_j \) are altered by the subsequent equation during each cycle, following the immunological threshold of the herd.

\[
S_j = \begin{cases} 
1, & f(x'(t+1)) < \frac{f(x'(t+1))}{\text{is_Corona}(x'(t+1))} \wedge S_j = 0 \wedge \text{is_Corona}(x'(t+1)) \\
2, & f(x'(t+1)) < \frac{f(x'(t+1))}{\text{is_Corona}(x'(t+1))} \wedge S_j = 1 
\end{cases}
\]

where \( \text{is_Corona}(x'(t+1)) \) is equal to one. If an infected case is used to create a new one, the binary value will be 1.

**Stage #5: Casualty cases** – \( \text{MaxAge} \) specifies if the immunity rate of the current affected case could not be determined for the necessary iteration, then this process is declared dead. It is then stimulated from the scraped applying \( X_j(t+1) = l_{bi} + (u_{bi} - l_{bi})U(0, 1) \). In addition, the values of \( S_j \) and \( S_i \) are set to be 0. It might encourage the present population to grow and, as a result, avoid local solutions.

**Stage #6: Stopping status** – The CHIO is carried out in stages 3 to 5 until the stopping criterion has been met, generally according to the maximum number of iterations \( \text{Max_Itr} \). The total number of immune and vulnerable patients dominates the population. As well, the contaminated casing will be removed. Fig. 6 shows the flowchart of the CHIO algorithm.

5. Results obtained and discussions

5.1. NaS batteries allocation

The optimal allocation of the NaS batteries is determined, in which one NaS-BSS was firstly planned (named as Scenario 1), then two NaS-BSSs were secondly planned (named as Scenario 2), and finally, three NaS-BSSs were planned (named as Scenario 3). The results attained for the three scenarios are organized in Table 5.
After realizing the optimal size and location of the NaS-BSSs, $\Delta P_{\text{loss}}$ of the $\mu$G all over a typical day are calculated and analyzed in the three scenarios, as illustrated in Fig. 7.

It is clear that the connection of the NaS-BSSs positively affects the total active power losses of the $\mu$G. However, the relation between the number of BSSs and $\Delta P_{\text{loss}}$ is not linear. For illustration, $\Delta P_{\text{loss}}$ of the $\mu$G (around 1.51 MW) during the day in scenario 3 (three NaS-BSSs connected) is greater than $\Delta P_{\text{loss}}$ of the $\mu$G (around 1.48 MW) during the day in scenario 2 (two NaS-BSSs connected). This means that NaS-BSSs allocation may adversely affect $\Delta P_{\text{loss}}$, if not correctly planned. To generalize, when the number of batteries used increases, it is not necessary to reduce $\Delta P_{\text{loss}}$ in $\mu$Gs. In this regard, Fig. 8 shows the hourly variation of the power losses over the day for Scenario 2 and the base system.

It is obvious that the NaS-BSSs are charging in periods characterized by low energy price (e.g., $h=1 \text{ to } h=6$), and the SoC of the batteries is rising, as illustrated in Fig. 9. Then, the SoC remains constant till $h=12$, which corresponds to the constant hourly $P_{\text{loss}}$ from $h=7$ to $h=12$. After that, the hourly $P_{\text{loss}}$ and SoC declines in the compensated system: Scenario 2 because of the discharging of the batteries.

### 5.2. ScR levels after NaS batteries allocation

Fig. 10 explores the hourly the ScR of the WTs and PVs in the base system with no NaS batteries connected. Remarkably, the ScR of the WTs and PVs is not equal to 1 at all hours of the day, in which the ScR of the WTs is 0.97 at $h=7$ and is in the range of 0.88 to 0.95 from $h=3$ to $h=5$. Also, the ScR of the PVs ranges between 0.32 and 0.71 from $h=13$ to $h=14$.

After merging two NaS batteries, the ScRs of the WTs and PVs are equal to 1 at all hours of the day. In this domain, the NaS-BSSs certainly improve the ScR of the RESs. This means that RESs can be more efficient as commoditized alternatives for green energy utilization in $\mu$Gs.

### 5.3. Voltage profile after NaS batteries allocation

Fig. 11 illustrates the voltage profile of the $\mu$G at two different hours – $h=4$, and $h=14$. Based on the loading profile, the loading levels at these hours are 0.51, and 0.88, respectively. One can see in Fig. 11 that the $\mu$G's bus voltage values are within the allowable limits. For instance, at $h=4$ and $h=14$ – half-load and shoulder loading. The bus voltages were high (almost 1p.u.) with no NaS-BSSs connected. After the NaS batteries connection into the system, the bus voltages profile has been declined as the batteries were charging; but still within allowable limits. On the contrary, when the NaS-batteries are discharging, the bus voltages profile increases to be better than the base case, but also still within the allowable limits.

### 5.4. Loading profile before and after RESs and NaS batteries connection

Fig. 12 explores the total RESs output power estimated, total loading before and after RESs connection, the hourly difference between the loading and RESs production, and the capacity delivered from the grid represented by the rated active power delivered from the substation transformer. All are given per hour.

Remarkably, when the generation of the output power from the RESs increases, the output power delivered by the main grid to the $\mu$G decreases. Besides, the back feed power (reverse power) can take place when the difference between the total generated RESs power exceeds the total load power, as highlighted in yellow in Fig. 12, for example at $h=12 \text{ to } h=14$. Also, overloads of the transformer may occur when total RESs power is low (low-RESs generation periods) and total load is high (high-demand periods). It should be mentioned that the rated capacity and active power of the transformer supplying the studied $\mu$Gs are 3.5 MVA and

### Table 5

Optimal allocation of the NaS-BSSs: Stage 1.

| Scenario | Bus | $P^b$(kW) | $P^d$(MWh) |
|----------|-----|-----------|------------|
| 1        | 6   | 2,170     | 13.02      |
| 2        | 29  | 1,010     | 6.06       |
| 3        | 14  | 640       | 3.84       |
| 3        | 3   | 1,720     | 10.32      |
| 3        | 14  | 559       | 3.35       |
| 3        | 30  | 780       | 4.68       |

Fig. 6. Flowchart of the CHIO algorithm [40].
2.97 MW, respectively. Fig. 13 explores the hourly loading of the transformer before and after one/two NaS-BSSs connections.

Evidently, no overloading occurs after batteries’ connection to the μG, particularly in Scenario 2 when 2 NaS-BSSs are connected. Therefore, NaS-BSSs can relieve the capacity of the supply transformer and defer its reinforcement plans.

5.5. OEM after RESs and NaS batteries connection

μG’s economic analysis was also investigated in this work once the best allocation of NaS batteries has been determined. The costs of the NaS batteries are involved in the economic analysis as a part of the μG’s costs.
Capital and replacement costs of the NaS-BSSs over the project’s lifespan have been included in the overall daily cost calculation, in which the total operating cost per day in the base system (No NaS-BSS connected) equals $193,310.8/day and $160,674.5/day in Scenario 2 in case of two NaS-BSSs connected. This means that the total operating cost of the μG declines by 16.80% percent when two NaS-BSSs are added to the μG under consideration, which validates the positive impacts of using the NaS batteries.

Fig. 14 explores the optimum hourly output powers of the grid, PVs, WTs, and NaS-BSSs in Scenario 2, when two BS units were allocated in the μG. The charging process of the two NaS-BSSs takes place when the demand is not high and the energy price is low, e.g. from \( h = 1 \) to \( h = 7 \). On the contrary, the discharging process of the two NaS-BSSs takes place during high-priced energy market hours to decrease μG’s cost of operation.

6. Conclusions

In this work, an optimization framework is proposed to enhance a grid-connected μG performance in three stages – maximization of the ScR of the highly-penetrated RESs hosted in the μG considered via NaS batteries allocation, minimization of the active power losses, and calculation of the OEM relying on minimizing the overall operating cost of the μG based on the optimal battery findings.
Also, the effects of optimally allocated NaS batteries on the loading capacity of the transformer that powers the μG were investigated.

It was clear that the connection of the NaS-BSSs positively affects the total active power losses of the μG. However, the relation between the number of BSSs and the active power losses is not linear, i.e., when the number of batteries used increases, it is not necessary to guarantee an adequate power loss reduction in the μGs. Also, the NaS-BSS positively enhances the ScR of the RESs. This means that RESs can be more efficient as alternatives for green energy utilization in μGs. Besides, NaS-BSSs can relieve the capacity of the supply transformer and defer its reinforcement plans.

Finally, the results obtained of the allocation of the NaS batteries in the μG validate the effectiveness of the proposed solution and the algorithm used, in addition to the techno-economic benefits that can be guaranteed.

One of the study limitations is the investigation of the direct impacts of connecting batteries to the μG. However, possible future works include the long-term investigation of the performance of the μG, the use of other recent optimization techniques to solve the problem, the use of different battery storage systems as well as enhancement of the μG performance by adding different active/reactive power compensators.
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.

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