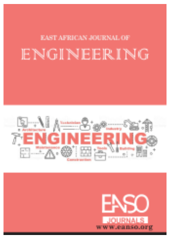

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Original Article

Critical Investigation of Sizing Methods for Renewable Energy Systems Microgrid.

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ABSTRACT

In this work, relevant literature with regards to sizing and designing renewable energy systems microgrid have been analysed and discussed. These sizing methods were found to have been categorised mainly as intuitive, numerical, artificial intelligence, and hybrid methods. However, from preliminary investigation performed via simulation in MATLAB, using three simple numerical sizing methods from existing literature, justified the validity for the inclusion of an active energy management strategy to enhance the reliability of hybrid energy storage systems while limiting the use of non-renewable sources. In conclusion, the sizing of hybrid energy storage systems' assets alone was shown to be inadequate to cater for uncertainty and intermittent renewable energy sources, an underpinning element in the design of reliable microgrid.

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INTRODUCTION

Several research studies [1, 2] have underscored the importance of hybrid energy systems in contrast to conventional standalone power systems as they are more cost-effective and reliable due to the use of multiple sources of electricity generation. Nevertheless, adequate sizing of the hybrid energy systems components and devices has often been a challenge largely due to the influence of capital and operating costs. Therefore, various empirical models have been proposed by researchers in literature aimed at sizing components of the standalone renewable energy systems microgrid (RES-MG) at minimum cost while considering environmental impact and the full utilisation of the assets to guarantee reliability [3]. Nevertheless, these sizing methods are often utilised as fit and forget, with little or no consideration for the energy management strategy (EMS) which is crucial to the optimal operation of the RES-MG.

This paper seeks to critically review and analyse existing sizing methods, and the findings presented which have been validated via simulation, rationalises the need for an advanced energy management strategy for optimal performance to be achieved.

LITERATURE REVIEW

According to [3, 4], the existing sizing methods which were reviewed are classed generically as intuitive, numerical, artificial intelligence and hybrid methods.

Intuitive Sizing Method

In the intuitive processes, the required number of PV panels and energy storage capacity is determined by simple mathematical calculation. The net energy balance calculation (which is based on the net summation of the power demand, load demand and power generation) is used iteratively at every sampling instance over a 24h period. More specifically, the data profile of the residential annual average power demand typical meteorological wind velocity and solar insolation to deduce the capacity of the battery storage. Thereafter, the energy storage capacity in the RE microgrid is based on the load and RE instantaneous power, which is scaled up by an autonomy factor. In addition, a DSL is used as a redundant energy source, in the event of an emergency, where the energy generated by the wind/solar is insufficient as is usually the case in a real-life situation. This method was used for sizing a standalone hybrid with configuration WTS/PV/BAT micro-grid in [5]. In [6], the WTS-DSL hybrid configurations are sized using a similar approach.

In [7], a generalized methodology for sizing RE systems was presented. The solar radiation on the inclined surface of the PV is used to derive the global diffused and direct radiation indices according to the model presented by Collare-Pereira and Rabl in [8], while the total irradiance is based on Hay's anisotropic model [9]. Thereafter a daily energy balance derived from the PV and the daily load demand profile is used to determine the PV array capacity based on multivariate linear regression via optimization using radiation information.

The mathematical equation for the energy balance of a typical wind/PV battery standalone topology sampled hourly for a year is given as follows in Eq. 1:

Net Energy, $E(t) = \sum_{k=1}^{8760}((n_{PV}P_{PV}(k)P_{PV}(k) + n_{WTS}P_{WTS}(k)) - P_L(k))\Delta k$ (1)

where, n_{PV} and n_{WTS} are the numbers of PV panels and wind turbine systems respectively. ΔK and k are the hourly sampling interval and hour in a year, respectively. $P_L(k)$ is the instantaneous load demand. $P_{PV}(k)$ and $P_{WTS}(k)$ are the generated instantaneous power for PV and WTS to available wind and solar insolation at a given time (k). Positive and negative values of E(k) denote availability and deficiency of energy generation.

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The total energy deficiency of the system is thereafter used to determine the size of the BAT as presented in Eq. 2;

$$C_{BAT} = DE/(DOD * \eta_{BAT}) * At \quad (2)$$

where, *DOD* is the depth of discharge of Battery (BAT) at 80%, *DE* is deficit energy (KWh) battery, η_{BAT} is the efficiency of the battery, *At* is the autonomy factor of the battery storage asset and C_{BAT} is the required capacity of the battery (KWh).

$$N_{BAT} \geq C_{BAT}/E_{BAT} * DOD \quad (3)$$

where, N_{BAT} as presented in Eq. 3, is the number of battery units required and E_{BAT} is the rated capacity of each battery.

Additionally, in [10] three simple methods for determining the minimum surface area of a stand-alone photovoltaic (SAPV) system to cater for the annual consumer load demand and any associated losses. The mathematical equations for the three methods; A_1, A_2 and A_3 are as presented in Eq. 4-6:

$$A_1 = \left(\sum_1^{12}(L_{dm} + L_{nm}/\eta_b)(\eta_w\eta_T\eta_{vr}\eta_c)\right)\left(\sum_1^{12} H_{k,m}\eta_i\eta_d\right)^{-1} \quad (4)$$

$$A_2 = \left(\left(L_{dp} + L_{np}/\eta_b\right)(\eta_w\eta_T\eta_{vr}\eta_c)\right) * \left(1/12\sum_1^{12} H_{k,m}\eta_i\eta_d\right)^{-1} \quad (5)$$

$$A_3 = \left((L_{dm} + L_{nm}/\eta_b)(\eta_w\eta_T\eta_{vr}\eta_c)\right) * \left(H_{k,mw}\eta_i\eta_d\right)^{-1} \quad (6)$$

where, L_{dm} and L_{nm} are the day and night time monthly average load respectively. L_{dp} and L_{np} are the day and night time annual peak load respectively. η_b, η_w, η_T, η_{vr} and η_c are efficiencies for BAT, PV wiring, maximum power-point tracking, voltage regulator, battery and cabling, respectively. η_i and η_d are the average hourly PV efficiency and factor of degradation respectively. $H_{k,m}$ is the monthly average of the daily insolation and $H_{k,mw}$ is the monthly average of the daily insolation on the worst month.

The PV surface area derived from A_1 is as a function of the ratio between L_{dm}, L_{nm}, and $H_{k,m}$. Furthermore, in A_2 the average night and day time monthly average load are replaced with L_{dp} and L_{np}, thus, A_2 results in a smaller area than A_1. While A_3 is similar to A_2, $H_{k,m}$ is replaced with $H_{k,mw}$. Thus, it is obvious that using method A_2 will result in the PV having a smaller surface area than A_3. However, A_3 will have a smaller surface area compared to A_1 since A_3 makes use of L_{dp} and L_{np} which will be ideally smaller than L_{dm} and L_{nm}.

The methods; A_1, A_2 and A_3 are evaluated as a function of the unserved energy and the loss of load probability (LOLP) expressed mathematically in Eq. 7:

$$LOLP = \sum_{k=1}^{8760} DE(k)/\sum_{k=1}^{8760} LD(k) \quad (7)$$

where, *LD*(*k*) is the hourly load demand.

This sizing method suffers certain shortcomings peculiar to a deterministic approach, which does not account for intermittent solar radiation. Therefore, decreased reliability associated with under-sizing or increased operational and maintenance costs as a consequence of oversizing is bound to occur.

Numerical Sizing Method

This method employs the use of linear or quadratic optimisation techniques to minimise an objective function which may comprise the total annual cost of the system and environmental impact factor. The most suitable combination of the system components such as how large the size of the PV/WTS or BAT ES capacity should be determined and solved by an optimisation algorithm aimed at minimising objective cost function [5, 11]. Typically, the sizing problem is to find the optimum combination with a minimum cost that satisfies the

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net energy balance constraint is formalised using an optimisation objective function.

The objective cost function is usually composed of the summation of the annualised cost of owing the PV/WTS/Battery and the balance of system cost as well as the environmental impact factor.

In [12] hybrid optimisation model for electric renewables (HOMER) was used as a pre-feasibility study optimisation and sizing tool for HESS assets with hydrogen energy carrier, for an application in Newfoundland, Canada. The study revealed that the most feasible hybrid energy systems configuration, which resulted in the least cost at the time was the WTS-BAT-DSL hybrid system which comprised a WTS, battery and DSL. Nevertheless, with a future reduction in FC cost, a superior configuration would be the WTS-FC architecture. In [13] a simple algorithm was developed to size the components of a standalone hybrid microgrid. The optimal size of the hybrid MG components; the number of PV, WTS, and BAT were determined such that the load demand is satisfied with a zero-load rejection criterion while maximising the life cycle cost of the assets. However, the work assumed that the state of charge of the BAT will periodically remain invariant without due consideration for daily or seasonal variation, which is far-fetched from reality.

In [14] chance-constrained optimisation probabilistic approach is adopted in contrast to a deterministic approach to size PV-DSL hybrid energy systems under resources uncertainty. And similarly, in [15], the chance-constrained approach was realized within the Power Pinch Analysis (PoPA) framework for sizing the area of a PV, after that validated via a Monte Carlo simulation.

Artificial Intelligence Optimisation Method

Artificial intelligence optimisation techniques such as an artificial neural network (ANN), genetic algorithm (GA), particle swarm optimisation (PSO) have been proposed by several authors [3, 15, 16, 17] to determine the PV asset sizing ratio in a standalone grid. These methods have the advantage of finding the global optimal value for a multi-objective cost function while considering the intermittency of the meteorological data. The PSO is therefore used to minimise cost, Carbon IV Oxide emission, life cycle cost, and loss of power probability while predicting the size and number of PV, Battery, and Diesel generators.

In addition, [18] PSO, was compared to the result from HOMER software for the concurrent sizing of a standalone HESS which included water desalination by reverse osmosis. The optimisation objective was to minimize a multi-objective function such as the total net present cost NPC, which comprised the capital, maintenance and replacement cost; and the overall CO2 emission cost, estimated over 25 years while meeting water and electrical load demands. The PSO was found to have a lower NPC compared to the solution rendered by HOMER software [19–21].

In [22] AI based on adaptive neural fuzzy inference system (ANFIS) and artificial neural network (ANN) were compared to the optimal PV system component sizing and tilt angle prediction of a PV/BAT/DSL hybrid system. The AI sizing approach which did not require meteorological data and employed different load demands in 34 different remote locations in India, was validated to have a LOLP less than 0.01. The approach utilised 80% of the entire data set for training, while 20% was used for validation. The prediction performance indices based on mean square error showed that the ANFIS performed better than the ANN for the standalone grid component sizing.

The significance of BAT capacity to the operational cost of the microgrid is emphasized in [23]. Thus, the grey wolf optimisation (GWO), is formulated to determine the BAT size that best minimises the operational cost while satisfying operational constraints such as power capacity of distributed generators (DGs), power and energy capacity of

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BAT, charge/discharge efficiency of BAT, in service reserves and consumer load demand.

Interestingly, the GWO outperformed other popular algorithms such as the GA, PSO, Bat, Differential Evaluation, Tabu search, teaching-learning based optimisation with regards to computational efficiency and quality of the solution in the sizing of the MG asset.

Hybrid Evolutionary Optimisation Techniques

Hybrid configuration of several evolutionary, Swarm Intelligence Teaching Learning-based optimisation methods have also been explored to harness the advantages inherent in these metaheuristic methods. In [24], six metaheuristic AI algorithms; Fire-Fly, PSO, Teaching Learning-based Optimization TLBO, the Whale optimisation WO, Differential Evaluation and GA, are comprehensively reviewed, in a bid to aid engineers and researchers better solving smart microgrid optimisation problems concerning the economic cost and operational constraint. The TLBO was found to have a better performance in comparison to the aforementioned methods. Also, TLBO had a faster convergence with the capability to explore a much wider search space with the GA and PSO having better performance compared to the WO and FF.

Nineteen hybrid metaheuristic methods comprising several combinations of PSO, modified PSO, improved PSO, PSO with constriction, inertia weight and repulsion factor, bee swarm optimization, harmony search, simulated annealing, chaotic search, and Tabu search algorithm were investigated in [25]. The objective was to minimise the total life cycle cost and a loss of power supply reliability index for sizing the components of a hybrid renewable energy system which comprised a WTS-PV-BAT architecture, reverse osmosis desalination asset. The hybrid configuration of the evolutionary algorithms which yielded the best and worst performance index were the improved harmony search-based chaotic simulated annealing and the artificial bee swarm optimisation respectively. The metaheuristic methods were found to have the advantage of searching for both global and local optima, better accuracy with a faster convergence rate.

Furthermore, in [26], hybridization of the analytical and numerical methods is presented. The hourly intermittency of the RES and Load profile are studied for loss of load probability. Afterwards, the life cycle cost of the system is minimized by an adaptive feedback iterative numerical optimisation to obtain the optimally sized components of the SAPV microgrid. In [27] incorporated the use of mathematical optimisation in parallel with ANN and thereafter with the GA technique. More specifically, ANN with longitude, latitude and altitude information was used to predict thirty possible PV sizing values which are further optimised using the GA technique for faster convergence while minimising the capital cost of the systems.

In [28] the design and sizing of hybrid Power system HPS is based on a mathematical superstructure model which incorporates chance-constrained programming which considers uncertainty introduced by intermittent RES and consumer load. Thus, the optimal generation and storage capacities of the assets are determined such that a specified level of minimum systems reliability is achieved. Thereafter, fuzzy optimisation is incorporated to resolve a multi-objective trade-off concerning economic, environmental and parametric uncertainties in the HPS design. The approach was validated using a Monte Carlo simulation and is similar to ref. [15].

Power Pinch Analysis Sizing, Design and Planning Methods for Microgrids

The PoPA is a process integration technique that evolved from the original Pinch Analysis for heat exchange networks [29] to sophisticated tools [30,

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44] that permit the investigation of complex energy systems based on the identification of insights that indicates promising design and operating decisions [31]. PoPA has been considered by a number of researchers for the sizing and design of electric power systems. The grand composite curve was created by integrating energy demand and supply over time in [32, 15], and it was then utilized to appropriately size an isolated power production plant. In addition, for optimal size of the hybrid power system, the PoPA was used in [33] as a combination of both the graphical and numerical approaches with the help of the power cascade analysis and storage cascade table. [34] suggested the expanded Power Pinch analysis (EPoPA) as an upgrade to the PoPA for optimally designing renewable energy systems with battery-hydrogen assets and a DSL. The EPoPA was used to calculate the required external electricity to be dispatched, as well as the wasted energy that cannot be stored in the BAT but could be stored in the form of hydrogen in a normal operating year. Following that, the HT and DSL sizes were established by minimizing the overall annualized cost. The investigations on PoPA for sizing MG assets were conducted without using uncertainty, with the exception of [15], which employed chance-constrained programming to attain technical viability.

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SIMULATION RESULTS AND DISCUSSION

The simulation results utilising the net energy modelling concept for hierarchical energy management strategy (EMS) in a renewable MG comprising a PV, BAT, consumer load and a backup diesel generator are presented in this section. For all time instances, the EMS ensures the BAT is charged with excess energy in the event the PV power exceeds the load power. To avoid overcharging, the fully charged battery ($SOAcc_{BAT}$>90%) is disconnected from the MG, while the load is sustained by the energy from the PV. During periods of unavailability of power from the PV, the load demand is satisfied by discharging the BAT as long as the *SOAcc* of the BAT is not less than 30% (i.e. $SOAcc_{BAT}$<30%). The diesel generator is activated if the $SOAcc_{BAT}$ is below 30% and the power from the PV is less than the load (i.e. $P_{PV} < P_L$). The BAT is sized for the average consumer load energy per day, the autonomy of 2 days for safety factor as well as the allowable depth of discharge. While the PV surface area is sized using the three methods presented in [10].

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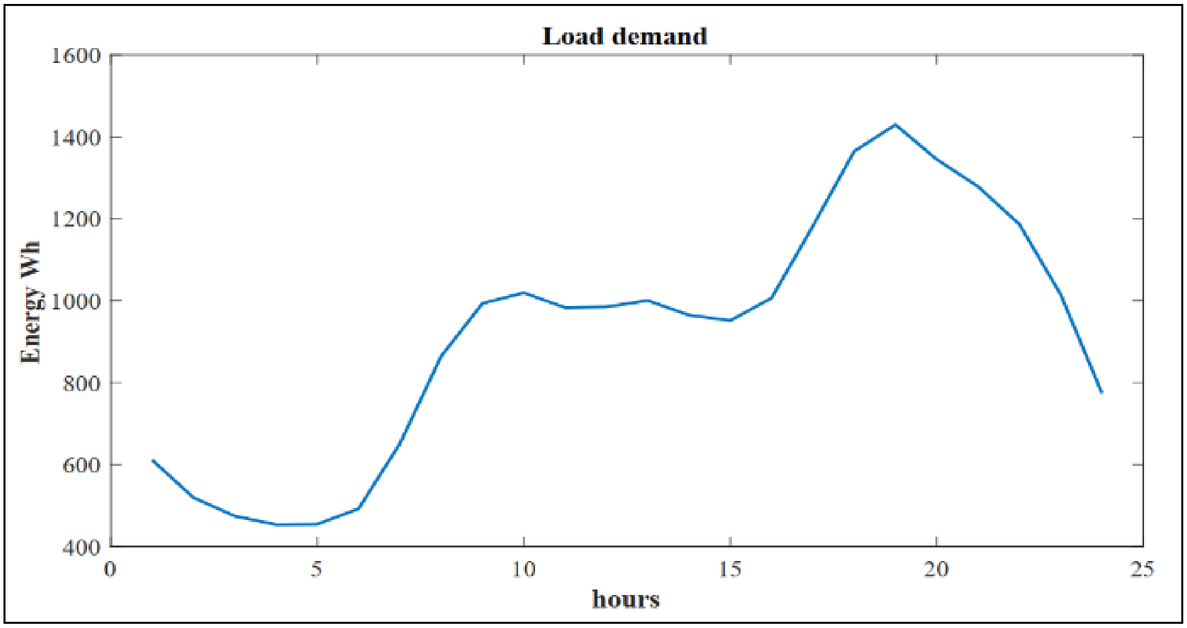
Figure 1: Typical residential load demand profile [35].



A typical deterministic residential consumer load profile characterised by dual peaks in the morning (1.2KW) and evening (1.5KW) is shown in *Figure 1* [35]. Figure 2, show the response of the MG with subplots (a) explicitly showing the PV power response [36], the battery's *SOAcc* and Net Energy for 8760 h, (b) 1st of January for PV sizing Method 1.

Figure 2(a): 8760h MG response

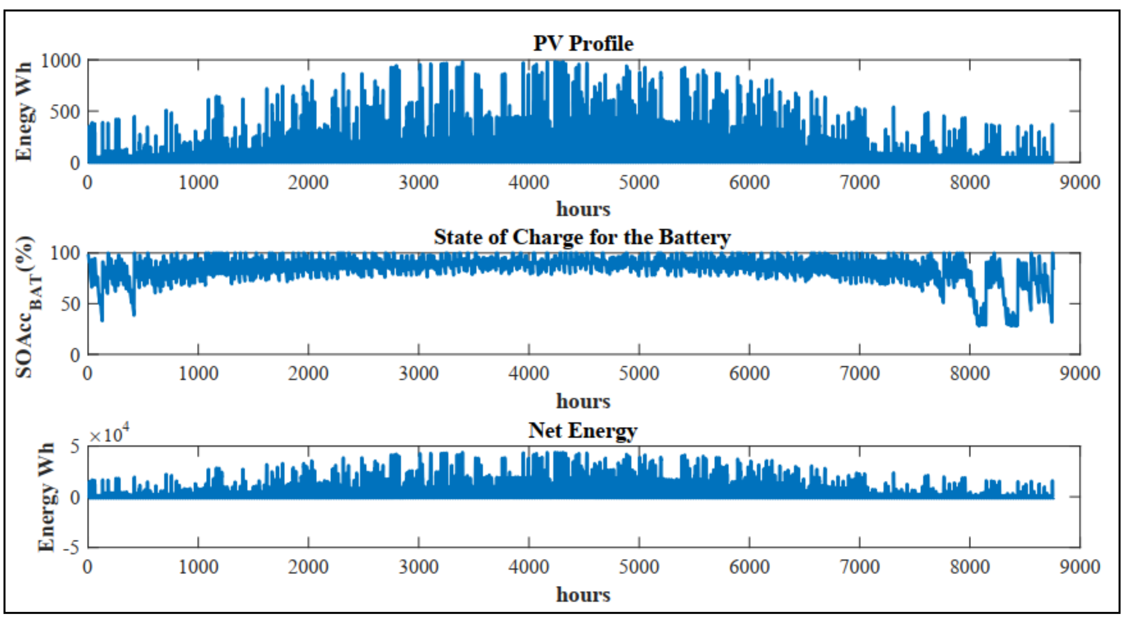


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Figure 2(b): 72h MG response (1st January)

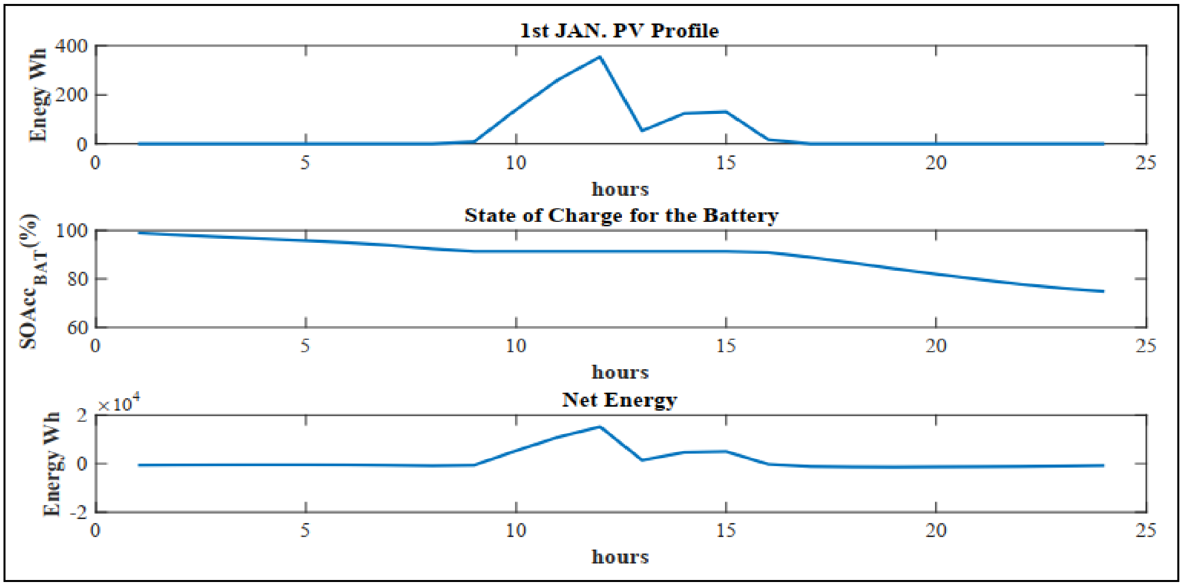

Table 1, shows the performance indices of the methods employed when a diesel generator serving as backup is absent and present. Method 1 is easily seen to be more reliable as it has a level of autonomy of 0.9758 and 0.9935 and LOLP of 0.5006 and 0.5055 when the backup generator is absent and present respectively. With the LOLP a 0 means the load demand will always be satisfied while a one connotes it will never be satisfied. However, the level of Autonomy increases as it approaches 1. The Diesel generator does not improve the LOLP significantly of the Microgrid sized by Method 1. The battery is also overcharged despite having the least failure due to lack of advanced control incorporated. The second sizing method has the least level of autonomy as it does not proffer any form of reliability; this improves drastically with the integration of a diesel generator. The third method has a better performance than the second method; however, it is not reliable as the diesel generator is needed to improve it. Also, method 1 has the most excess energy occurrence, which indicates oversizing, while method 2 has the least excess energy, which also shows under-sizing. This underscores the problem of correctly sizing the MG assets, as the PV intermittent introduces offsets in the energy targets.

Table 1: Performance indices for the PV sizing methods

Reliability Indices	Method 1	Method 2	Method 3
Battery Failure with DSL	57	4238	2098
Battery Failure NO DSL	212	8717	5488
Battery Overcharged with DSL	3817	8	471
Battery Overcharged No DSL	3804	8	437
Battery Deactivated	1058	0	1836
LOLP with DSL	0.5006	0.3286	0.4312
LOLP no Diesel	0.5055	0.8305	0.6421
Level of Autonomy with diesel	0.9935	0.5162	0.7904
Level of Autonomy NO diesel	0.9758	0.0049	0.3735

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CONCLUSION

This paper showed that proper sizing of an MG is critical to its dependability nonetheless difficult to achieve. Therefore, the significance of decision-making in terms of optimal energy distribution and control, as well as other parts of HESS, cannot be overstated. More so, active control utilising advanced energy management strategy (EMS) techniques such as those based on model predictive control as opposed to a logic-based EMS is indeed justified and required to absorb excess energy and supply deficit energy in advance adequately.

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