Research Article

Optimal cost and feasible design for grid-connected microgrid on campus area using the robust-intelligence method

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Abstract

In this paper, a robust optimization and sustainable investigation are undertaken to find a feasible design for a microgrid in a campus area at minimum cost. The campus microgrid needs to be optimized with further investigation, especially to reduce the cost while considering feasibility in ensuring the continuity of energy supply. A modified combination of genetic algorithm and particle swarm optimization (MGAPSO) is applied to minimize the cost while considering the feasibility of a grid-connected photovoltaic/battery/diesel system. Then, a sustainable energy-management system is also defined to analyse the characteristics of the microgrid. The optimization results show that the MGAPSO method produces a better solution with better convergence and lower costs than conventional methods. The MGAPSO optimization reduces the system cost by up to 11.99% compared with the conventional methods. In the rest of the paper, the components that have been optimized are adjusted in a realistic scheme to discuss the energy profile and allocation characteristics. Further investigation has shown that MGAPSO can optimize the campus microgrid to be self-sustained by enhancing renewable-energy utilization.

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Graphical Abstract

Keywords: distributed energy and smart grid; renewable-energy system optimization; MGAPSO algorithm

Introduction

Investment in renewable energy (RE) has become popular and almost reached a total of $2.6 trillion from 2010 through to the end of 2019 worldwide [1]. It happened because of the role of the UN’s Sustainable Energy for All partnership that aims to double the global share of RE from 18% in 2010 to 36% by 2030 [2]. To support these ambitions, the International Renewable Energy Agency has mapped the potential RE resources around the world. Based on its mapping, Southeast Asia, which is a predominantly tropical region, has very high RE potential, but it has not been optimally utilized. The members of the Association of Southeast Asian Nations have agreed to target 23% of RE in their total energy mix in 2025 to respond to this situation [3]. Indonesia, the largest country and most populated in Southeast Asia, is joining India and China as an energy hot spot. The energy demand in Indonesia is expected to double in the next 10 years while Indonesia still relies on fossil fuels that are rapidly decreasing [4]. The Indonesian government has begun to maximize RE utilization by setting up investment funding up to $36.9 billion for hydro and micro-hydro, solar, wind and bioenergy power generation [5].

The RE-utilization trend provides a great opportunity to develop a microgrid based on the renewable-energy system (RES) to support the government’s ambition. It can maximize the potential RE resources in a specific region. The RES can be implemented in a stand-alone scenario to supply isolated regions or remote islands [6] and also can be combined with the existing conventional grid to supply the load demand in various sites, such as residential, urban, commercial, industrial and educational areas [7-9]. Among various sites, the educational area (such as the campus area) has become an ideal site to be chosen for RES development. A campus is a suitable place for test-bed experiments, with many academics who have high enthusiasm for research. Moreover, the load profile in the campus also has high potential for RES implementation because the major energy use in the campus is during the daytime and a RES can supply these needs. Suitable RE, such as solar energy, has full potential during the daytime when there is a high level of solar global horizontal irradiance (GHI). The solar power-generation system is the most widely used in the campus area, since solar-energy utilization through photovoltaic (PV) technology is the most accessible and has very high availability to be integrated with the campus microgrid [10]. The PV system can also be implemented as building-attached PV (BAPV) or building-integrated PV (BIPV) to save land use in campus areas [11]. Campus-load characteristics are different from residential energy needs. A residential-based RES usually prioritizes
the produced energy to be stored in batteries and exported to the grid. The stored energy will be used in the nighttime when most of the family members are doing their activities at home.

Indonesia as a tropical region has 297.8 gigawatts (GW) of potential solar energy, but has only utilized ~0.14 GW, or ~0.07% [12]. That condition is a great opportunity for the campus in Indonesia to increase renewable-energy utilization, especially solar energy through the PV system. On the other hand, uncertainties and variabilities of solar energy become the main challenge in using PV as the main energy supplier [13]. As mentioned before, PV performance depends on the solar-GHI level. So, lower solar GHI becomes a disadvantage for a PV system because it cannot produce energy optimally [14]. Moreover, the PV system that sustains the RES must ensure continuity with fluctuating resources, because the busy activity on campus requires a continuous energy supply. Therefore, battery storage is usually applied in campus microgrids to ensure the continuity of energy supply and to increase the feasibility of the system [15]. However, more complicated conditions can occur. For example, if the PV system cannot operate at maximum power and the battery is not fully charged yet, sufficient electricity will not be available. In that situation, the campus needs a power supply that can cover the load that is not dependent on the PV system and the grid. As usual, the diesel generator (DG) is deployed to mitigate this situation [16].

The grid-connected RES design faces more complex problems because multiple considerations must be involved, such as system-performance indices, economics, and certain scenarios [17, 18]. To resolve the problems, RES-planning software has been developed to help researchers. Well-known software, such as Hybrid Optimization of Multiple Energy Resources (HOMER), H2RES, PVsyst, PV*Solu, System Advisor Model by NREL, etc., have been widely used to design RES systems in various cases [19, 20]. However, the designing software has limitations in scenarios and design modifications. The limitations make it difficult to find the optimal RES in non-general cases.

Therefore, researchers have used various intelligence algorithms to provide a wider scenario and ease of modification. Such algorithms also can be combined with software methods to evaluate the performance. Kumar et al. [7] made the integrated assessment using a multi-criteria decision-making algorithm to conduct a sustainable remote microgrid with technical, economic, social and environmental aspects. Then, Kumar et al. used the HOMER software to evaluate their best model for specific cases. Subiyanto et al. [13] used fuzzy analytic hierarchy process (AHP) methods to design a grid-connected PV/battery/diesel system in a campus area. Subiyanto et al. also used HOMER to simulate and assess the electrical and economic performance of the system.

Metaheuristic algorithms also have been developed for solving more complex RES-optimization problems to improve the results. The algorithms that have been used are as follows: genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing, tabu, search, etc. Twaha et al. [21] and Lian et al. [17] reviewed the recent RES-optimization methods. Their reviews show that combining metaheuristic algorithms can effectively improve the accuracy, optimize results and make the algorithm more adaptive in solving complex cases. Suresh et al. [22] also proved that the combination or hybrid algorithm can provide better solutions in RES optimization.

GA and PSO have become the most widely used in RES optimization. The previous studies showed that both GA and PSO have advantages and disadvantages. GA was more flexible to be transferred into various optimization models [23]. On the other hand, the poor fitness function could cause the optimization process to become stuck at local optima rather than finding the global optimum [24], whereas PSO is not more flexible than GA. However, the mathematical fitness function of PSO is simpler than that of GA. The PSO algorithm has shown faster convergence [21]. Torres-Madroñero et al. [25] showed that GA and PSO algorithms were very flexible to solve the various RES-optimization cases. He et al. [26] took advantage of each algorithm to make a better hybrid GA–PSO algorithm. Hybrid GA–PSO provided flexible modelling, more effectively and with faster convergence [27]. Ghobani et al. [28] compared GA–PSO and HOMER optimization results for optimizing stand-alone wind/PV/battery systems. The results showed that GA–PSO was better than HOMER for optimization. Ali et al. [29] also proved that the hybrid GA–PSO algorithm was better than standard PSO in large-scale optimization cases.

Based on the previous research, RES design becomes more complex because of the involvement of various considerations. Moreover, a high potential site, such as a RES in the campus area, must be designed using a robust method with further investigation. The investigation is needed to ensure that a feasible RES design can satisfy the load demand in the campus area at minimum cost. Therefore, this paper presents the robust optimization and sustainable investigation of campus RES implementation. This study aims to find a feasible design of RES at a reasonable minimum cost. A well-known combination of modified GA and particle swarm optimization (MGAPSO) is applied to minimize cost while considering the feasibility of a grid-connected PV/battery/diesel system. The MGAPSO optimization takes advantage of GA and PSO algorithms. The PSO operates to improve and evaluate the initial random population with the vector operators while GA is used to modify the population using genetic operators to conduct better optimization results. Then, a sustainable energy-management system is also determined to investigate the characteristics of the system on the campus. The optimization results are compared with the conventional GA and PSO methods. HOMER software is also used to benchmark the results of the algorithm method. In the rest of the paper, cost and feasibility investigation is discussed.
1 Methodology

A two-level framework has been developed to find the optimal design of the grid-connected PV/battery/diesel system at minimum cost on the campus as shown in Fig. 1.

Level 1 consists of pre-processing and optimization steps. This stage begins with gathering meteorological profiles in the study location. Then, the RES components are modelled in a mathematical model and simulated in a sustainable energy-management system. The MGAPSO will find the optimal size of the components of a feasible RES design at the lowest cost possible. If satisfactory optimization results have been obtained, then MGAPSO proceeds to the next stage.

Level 2 is the evaluation stage. This stage presents the optimization comparison using various methods. The convergence curve and best solution will be compared to each other. Then, the cost and feasibility analysis is also presented to investigate the robustness of the MGAPSO in optimizing RES on the campus.

1.1 Study location

This study is located in the Faculty of Engineering, Universitas Negeri Semarang, Indonesia. The campus has a tropical climate with a 7.05° south latitude, 110.40° east

![Diagram of Methodology](https://example.com/diagram.png)

**Fig. 1:** Framework for RES optimization.
longitude and elevation 187 metres above sea level. Fig. 2 shows the study location.

This site has a potential solar-GHI profile in the range of 4.0–6.9 kWh/m² with an average of 4.8 kWh/m². The tropical climate means that the solar-GHI level during the day is consistent over the year, as shown in Fig. 3. It makes this site a potential place for solar energy generation through RES technology.

The campus has 8 departments and 13 buildings. Each building has a different energy consumption. Pradita [30] has reported the daily energy consumption in kilowatt-hour (kWh), as shown in Table 1.

From the daily energy consumption in Table 1, the annual energy consumption \( P_{\text{annual}} \) in kWh can be obtained using Equation (1):

\[
P_{\text{annual}} = (P_{\text{daily}} \times \text{weekdays}) + (0.15 \times P_{\text{daily}} \times \text{weekends})
\]

\( P_{\text{daily}} \) is calculated from Table 1. The energy consumption at the weekend is assumed to be 15% of \( P_{\text{daily}} \). This site has 5 days of work. So, a year consists of 260 weekdays and 105 weekends. The annual energy consumption has been scaled using the HOMER software platform [31] to define the load profile as shown in Fig. 4.

The typical load profile in the campus area is almost the same throughout the year. The load demand will start to rise in the morning and will be relatively constant during the day within work hours. The load will start to decrease in the afternoon. At night, the campus only needs electricity to supply the lights, computer servers, internet devices and security systems.

### 1.2 RES modelling and sustainable energy-management system

The RES is designed to operate in both grid-connected and stand-alone modes to supply campus-load demand. The schematic diagram in Fig. 5 illustrates the designed campus RES. The RES mainly consists of a PV system as the main energy supplier, battery for energy storage, DG for the backup, power conditioning unit and power grid. The mathematical models of the components are presented in the following sections.

#### 1.2.1 Solar power generation

Solar power generation generates energy based on a PV system that depends on the solar GHI and temperature level. The power generated by PV is carried out using Equation (2) [32]:

\[
P_{\text{PV}} = N_{\text{PV}} \times \left( \frac{R}{R_{\text{STC}}} \right) \times \left[ 1 + \alpha_T (T - T_{\text{STC}}) \right]
\]

where \( N_{\text{PV}} \) is a power-rated PV in kW, \( R \) is solar GHI in W/m², \( R_{\text{STC}} \) is solar GHI in Standard Test Condition (STC) = 1000 W/m², \( T \) is temperature, \( T_{\text{STC}} \) is a solar module temperature in STC = 25°C [33] and \( \alpha_T \) is the temperature coefficient.

The PV system usually uses the maximum power point tracking (MPPT) converter to make the output power stay around the maximum power point, so the temperature effect of the PV can be replaced with MPPT efficiency \( \eta_{\text{MPPT}} \) as in Equation (3) [28]:

\[
P_{\text{PV}} = N_{\text{PV}} \times \left( \frac{R}{1000} \right) \times \eta_{\text{MPPT}}
\]
This paper assumed that the discharging efficiency is similar to the charging efficiency. So, the discharging state \( P_{\text{disch}}(t) \) is shown as Equation (5):

\[
P_{\text{disch}}(t) = \left[ \frac{P_{\text{load}}(t)}{\eta_{\text{conv}}} - \frac{P_{\text{PV}}(t) \times \eta_{\text{MPPT}}}{\eta_{\text{conv}}} \right] / \eta_{\text{BESS}}
\]

where \( \eta_{\text{conv}} \) is the converter efficiency and \( \eta_{\text{BESS}} \) is the BESS efficiency. The load demand in time, \( t \), is represented by \( P_{\text{load}}(t) \).

The charging and discharging states make the available energy in the BESS change with time in the simulation, depending on the charge quantity (\( P_{\text{ch}} \) or \( P_{\text{disch}} \)). So, the available BESS energy in time, \( t \), in the charging state is calculated using Equation (6):

\[
P_{\text{BESS}}(t) = P_{\text{BESS}}(t-1) \times (1 - \sigma) + (P_{\text{ch}}(t))
\]

The available BESS energy in time, \( t \), in the discharging state is calculated using Equation (7):

\[
P_{\text{BESS}}(t) = P_{\text{BESS}}(t-1) \times (1 - \sigma) - (P_{\text{disch}}(t))
\]

where \( P_{\text{BESS}}(t) \) and \( P_{\text{BESS}}(t-1) \) are the quantities of the battery at \( t \) and \( t-1 \) time in the simulation and \( \sigma \) is the hourly self-discharge rate. The self-discharge rate is ignored.

The BESS must be available when the PV system needs support. So, \( P_{\text{BESS,min}} \) and \( P_{\text{BESS,max}} \) are defined as 20% and 100%, respectively, to make sure that the capacity is not empty or overcharged. The BESS capacity in time, \( P_{\text{BESS}}(t) \), should follow the constraint as shown in Equation (8):

\[
P_{\text{BESS,min}} \leq P_{\text{BESS}}(t) \leq P_{\text{BESS,max}}
\]

One more important thing in determining the BESS is to consider battery autonomy. Battery autonomy is the specific time period (in minutes or hours) that a BESS will last in case of the unavailability of PV energy [36]. The battery autonomy \( A_{\text{BESS}} \) in hours can be calculated using Equation (9):

\[
A_{\text{BESS}} = \text{hours}
\]
\[ A_{\text{BESS}} = \frac{P_{\text{BESS}} \times V_{\text{BESS}} \times \eta_{\text{BESS}} \times \text{DoD}}{N_{\text{BESS}}} \]  

(9)

where \( V_{\text{BESS}} \) is the nominal DC voltage, DoD is a depth of discharge that is determined as \( P_{\text{BESS,min}} \) in the previous section.

The BESS needs a converter to regulate AC/DC power. This study needs the converter for converting DC power to AC power when the battery is supplying the electrical load. The size of the inverter \( N_{\text{inv}} \) used is not allowed to be less than the peak load and the battery maximum discharge power to ensure that the load can be supplied properly and to anticipate the condition when the battery is discharged at maximum power.

### 1.2.3 Conventional grid

The conventional grid is modelled as an infinite power supply whenever the PV and BESS power outputs are insufficient to supply the load. The grid power output is shown in Equation (10) [37]:

\[ P_{\text{GRID}}(t) = \delta_{\text{GRID}}(t) \times P_{\text{GRID}}(t) \]  

(10)

where \( \delta_{\text{GRID}}(t) \) is the grid availability in time, \( t \). If the grid is available to supply the load, \( \delta_{\text{GRID}}(t) = 1 \) and, in blackout conditions, \( \delta_{\text{GRID}}(t) = 0 \). The grid output is assumed as \( \infty \leq P_{\text{GRID}}(t) \leq \infty \).

The grid regulation allows the user to export and import energy through an export–import (EXIM) kWh-meter.
The import tariff from the grid for 1.7 mega-volt amperes grid power rated is 0.093 $/kWh [38]. Meanwhile, the export tariff to the grid regarding the regulation is 65% of the import tariff. And there is a regulation that ±10% of the energy produced by the PV system must be exported to the grid [39].

2.2.4 DG
The DG is used as a backup power system under grid-blackout conditions. The advantage of the DG is that it can be used at any time when needed. The DG provides constant power output [40]. This study has used the installed DGs in the site location as shown in Table 2.

The import tariff from the grid for 1.7 mega-volt amperes grid power rated is 0.093 $/kWh [38]. Meanwhile, the export tariff to the grid regarding the regulation is 65% of the import tariff. And there is a regulation that ±10% of the energy produced by the PV system must be exported to the grid [39].

\[ P_{DC} = \delta_{DC}(t) \times N_{DC} \]

where \( \delta_{DC}(t) \) is the on/off condition in time, t. If the DG is in the ‘on’ condition, \( \delta_{DC}(t) = 1 \), and if it is in the ‘off’ condition, \( \delta_{DC}(t) = 0 \). The \( P_{DC} \) must be bigger than \( P_{oad} \) when the blackout occurs. Then, the DG fuel consumption, \( F_{DC} \), depends on the output power and operation time, as shown in Equation (12) [16]:

\[ F_{DC}(t) = F_c \left( AP_{DC}(t) + BP_{DC}(t) + C \right) \]

where \( P_{DC} \) is the DG output power in kW, \( F_c \) represents the fuel price in $/L and generator coefficients (A, B and C) are adopted from previous research in [41, 42]: \( A = 0.24 \) L/kW·h, \( B = 0.08 \) L/kWh and \( C = 0.42 \).

1.2.5 Energy-management system
The component models are used to construct a self-sustainable energy-management system as shown in Fig. 6. This flowchart explains the relation between the equations in the previous section. The energy-management system is designed to regulate energy generation and allocation when operating in both grid-connected and standalone modes. The system in this study increases solar-energy usability instead of using a conventional grid to supply the load. The main reference in energy management is \( P_{pv} \), which depends on the solar GHI. It makes the behaviour of the RES change hour by hour.

The flowchart will simulate RES to operate in the following cases.

First case. Sufficient energy is being generated by the PV system to cover the load demand \( (P_{load}) \). If there is no excess energy generated \( (P_{ex}) \), then there is no energy injected into the grid \( (P_{grid}) \) and the BESS. The system prioritizes solar-energy utilization to supply the load directly when there is high solar GHI. That is why the RES on the campus needs the major energy supply during the daytime when the campus is in working hours.

Second case. The PV system produces more energy than the load demand. The excess energy will be prioritized to charge the BESS. So, the BESS will operate in charging-state mode. If the capacity meets the allowable maximum capacity \( (P_{BESt}) \), then the excess energy will be injected into the grid. The amount of energy injected into the grid is just to meet the regulation. In this study, the regulation requires ±10% of the total PV energy to be exported to the grid.

Third case. The power generated by the PV system is insufficient to cover the load. The system will check the available BESS capacity. If the capacity is sufficient to cover the lack of energy \( (P_{load}) \), then the BESS will switch to the discharging state. The BESS stops covering the lack of energy when the capacity reaches the allowable minimum capacity \( (P_{BESt}) \).

Fourth case. The power generated by the PV system and the energy stored in the BESS are insufficient to satisfy the load. The system will check the grid availability. If the grid is available, the lack of energy will be covered by the grid. The system will reduce grid imports to ensure that the designed RES is not dependent on the conventional grid. Then, the system will back up the lack of energy if the grid is not available (blackout). The grid-blackout condition is assumed to be 15 hours a year based on the average grid-blackout time in Indonesia [43].

1.3 Conventional optimization
The conventional GA and PSO methods are discussed first before presenting MGAPSO optimization. The conventional methods are used to measure MGAPSO robustness. HOMER optimization is also executed to validate and benchmark the algorithm-method results.

1.3.1 Conventional GA method
The GA is easy to be transferred into various models so it has become the most widely used algorithm in the intelligence system. The concept of the GA is to transfer the optimization case model into the natural system process, which is required for evolution to find the best individual based on the fitness function [27]. A fitness function is used to evaluate the individual cases and select the best one. A fitness function becomes crucial in the GA-optimization process because an improper fitness function can trap the result in a local optimum rather than finding a global optimum [44].

Table 2: The installed diesel generator in study location [13]

| No. | Merk and type | kVA/kW base rate | Voltage |
|-----|---------------|------------------|---------|
| 1.  | Stamford X11K452404 | 140/112 | 220 – 1 phase @ 50 Hz380 – 3 phase @ 50 Hz |
| 2.  | Stamford X170171431 | 45/36 | 220 – 1 phase @ 50 Hz380 – 3 phase @ 50 Hz |
The first step in the GA is generating the initial random population. In this work, 100 individual cases are randomly generated as the initial population. Each individual has PV, battery, inverter and DG variables (in GA, variables are called genes). The search space is 0–1000 kW for PV, inverter and DG variables, and 0–1000 kWh for the battery variable. Each individual consists of genes that represent the optimization variables. The gene consists of a random size of each component in the search space. The GA process generates a better population from new parents by applying genetic operators that consist of: selection, recombination, mutation and elitism. The process will iterate until the maximum number of iterations is reached. The GA-optimization process is shown in Table 3.

### 1.3.2 Conventional PSO method

The PSO method is inspired by the social behaviour of animals in a swarm, such as birds, fishes and bees; or even sometimes the social behaviour of humans. The principle of the PSO is similar to GA in terms of generating a random population (defined as a swarm in PSO) that consists of particles, as random solutions, and searching for global optima in n generations. In PSO, the particles move through the search space following the current optimum particles until the global optimum solution is obtained. The operation rules in PSO are simpler than in GA, which means that PSO has high precision and fast convergence. However, some complex optimization cases are difficult to be transferred into the PSO-algorithm model [17, 45].
The initial step in PSO is generating random particles and the initial velocity of each particle in the search space. In this case, a swarm consists of 100 particles. Then, the fitness value of each particle is evaluated. The particle consists of PV, battery, inverter and DG variables. The search space is 0–1000 kW for PV, inverter and DG, and 0–1000 kWh for the battery. The position in PSO represents a nominee solution for the optimization case. Each particle moves for a better position based on its personal best position ($P_{best}$) and global best position ($G_{best}$). Equations (13) and (14) shows the PSO operators [28, 45]. Then, the PSO updates the optimization vector until the maximum number of iterations is reached. The PSO-optimization process is summarized in Table 4.

$$v_{k+1} = w \cdot v_k + c_1 \cdot r_1 \left( P_{best_k} - x_k \right) + c_2 \cdot r_2 \left( G_{best_k} - x_k \right) \quad (13)$$

$$x_{k+1} = x_k + v_{k+1} \quad (14)$$

### 1.3.3 HOMER optimization

HOMER software is the global standard in microgrid-optimization design, from a common sector (such as a village, residential, etc.) to a specific sector (such as grid-connected campus, remote island, etc.) [31]. Since the algorithms need to be validated using a common-use method, this study has used HOMER to benchmark the results. HOMER was employed because of its strength in three aspects: simulation, optimization and sensitivity analysis. In this paper, HOMER finds the optimal size of each component of the grid-connected PV/battery/diesel system with the lowest net present cost (NPC) in a certain scenario. The RES was simulated in load-following and cycle-charging dispatch modes. The optimization is set for 100 iterations with 2% NPC precision. Fig. 7 shows a simulation diagram of RES optimization in HOMER.

#### 1.3.4 A modified combination method

This paper applies the MGAPSO method to find the optimal size of the grid-connected PV/battery/diesel components with the lowest cost but which can feasibly supply the load demand in the campus area. The flowchart of MGAPSO optimization is shown in Fig. 8 and the detailed process of MGAPSO-method implementation is described in the following.

**1.3.4.1 Fitness function**

The main optimization goal is to minimize system costs. The total cost of the system ($CT$) represents the cost of the RES components in their project time. The $CT$ calculation involves investment cost ($CI$), maintenance cost ($CM$), component replacement cost ($CR$), fuel cost ($CF$) and grid cost ($CG$), as shown in Equation (15) [16, 28]:

$$CT = CI + CM + CR + CF + CG \quad (15)$$

The investment cost represents the number of costs that must be incurred by the user before building a RES. The maintenance and replacement costs are operational components of a system that must be considered to ensure the system works properly in several lifetimes. The fuel cost is obtained from Equation 12. In this study, the replacement cost is ignored because the simulation only takes a year of project time. Meanwhile, the grid cost calculates the amount of export and import energy from the grid. $CI$, $CM$ and $CG$ are obtained from the calculations in Equations 16–18:

$$CI = (N_{PV} \cdot C_{PV}) + (N_{BESS} \cdot C_{BESS}) + (N_{DG} \cdot C_{DG}) + (N_{INV} \cdot C_{INV}) \quad (16)$$

![Fig. 7: HOMER simulation diagram. This figure was used with permission from [31].](https://academic.oup.com/ce/article-lookup/6/1/823/6471931)
\[ CM = \left[ \frac{(N_{PV} C_{M,PV}) + (N_{BESS} C_{M,BESS})}{(N_{DG} C_{M,DG}) + (N_{INV} C_{M,INV})} \right] \left( \frac{1 + \text{infR}}{1 + \text{intR}} \right) \]  

(17)

\[ CG = (P_{GRID} \times \text{grid tariff}) - (P_{GRID,IN} \times \text{sellback tariff}) \]  

(18)

where \( C_x \) is the cost per unit and \( C_{M,x} \) is the maintenance cost/unit of the \( x \) component (where \( x \) can represent PV, DG, BESS or INV) and \( N_x \) is the number of components installed. The inflation rate (\( \text{infR} \)) = 1.55\% and the interest rate (\( \text{intR} \)) = 3.75\% [46, 47].
The salvage value is also considered. The salvage value represents the remaining value of each component at the end of the project time. The salvage value (SV) can be obtained using Equation (19) [48]:

$$SV = (N_{PV}C_{PV})(\frac{R_{TPV}}{L_{TPV}}) + (N_{P攻坚}C_{P攻坚})(\frac{R_{TP攻坚}}{L_{TP攻坚}}) + (N_{DG}C_{DG})(\frac{R_{TDG}}{L_{TDG}}) + (N_{INV}C_{INV})(\frac{R_{TINV}}{L_{TINV}})$$  (19)

where $R_{x,t}$ is the remaining lifetime of each component at the end of the project time. Then, $L_{x,t}$ is a component lifetime that has been determined. This project assumes a 1-year project time. The PV has a 30-year lifetime, the battery has a 10-year lifetime, the inverter has a 15-year lifetime and the DG has an ~15 000-hour lifetime.

After the cost function is determined, the system-feasibility function is also defined. The feasibility is quantified by the loss of power supply (LPS), which represents the loss from energy generation by the RES. The LPS must be minimized. The LPS is obtained from the subtraction of the load demand at each hour and the generated power from the RES, as shown in Equation 20 [35]:

$$LPS = \sum_{t=1}^{T} [P_{load}(t) - (P_{INV})]$$  (20)

$P_{INV}$ consists of the energy from the PV system as the main energy supplier, battery and DG output and grid.

The LPS is constrained by the maximum LPS probability (LPSP), which is specified by the user. The LPSP is the probability that the power supply is unable to satisfy the load demand [20]. The LPSP calculation is shown in Equation (21):

$$LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} P_{load}(t)}$$  (21)

where $P_{x,t}$ is power by each component at time, $t$, and LPS($t$) is the loss of power supply at time, $t$. The optimization takes 2% and 5% of the maximum allowable LPS (LPSP$_{max}$). Two constraints are taken to investigate the algorithm consistency in solving optimization cases.

Since MGAPSO is a single-objective optimization, the cost and feasibility functions must be combined in a single equation model. A combined function can be represented in the NPC. The NPC is obtained from the summation of the total cost including the SV and the weighted cost, as shown in Equation (22). The weighted cost can be obtained from the reliability factor. In this case, the reliability factor is represented as the LPS multiplied by the capacity shortage penalty factor ($p_f$) as 5.6 $$/kWh [28, 49]:

$$NPC = (CT - SV) + (p_f \times LPS)$$  (22)

From the equations above, the fitness function can be obtained as shown in Equation (23):

$$fitness \ F(\ x) = minimize \ NPC \ (N_{PV},N_{P攻坚},N_{DG},N_{INV}) = (CT - SV) + (p_f \times LPS)$$  (23)

Furthermore, the cost of energy (COE) is also used to evaluate the system in several studies. The calculation of the COE is separate from the fitness evaluation. The COE is calculated from the NPC divided by the yearly energy produced ($P_{year}$) by the RES, as shown in Equation (24):

$$COE = \frac{NPC}{P_{year}} (\$/kWh)$$  (24)

### 1.3.4.2 MGAPSO process

The first step is to initialize the optimization and algorithm parameters. The MGAPSO will find the optimal $N_{PV}$, $N_{P攻坚}$, $N_{DG}$ and $N_{INV}$ in a certain search space. The search space is 0–1000 kW for PV, inverter and DG variables, and 0–1000 kWh for the battery variable. Table 5 shows the assumptions of the cost per variable or component used, which are taken from previous works and datasheets.

The MGAPSO method generates 100 individuals and optimizes the problem within 100 iterations. The PSO takes parameters as follows: learning factor: $c_1 = 2$; $c_2 = 2$; inertia weight: $w_{min} = 0.4$ and $w_{max} = 0.9$. The GA takes parameters as follows: $R_e = 0.6$; $R_m = 0.1$.

The PSO operators play an initial role to generate a random particle swarm as an initial population. For each particle, the PSO operator will generate the random initial position and velocity. The PSO operators are simpler than the GA operators. So, the MGAPSO algorithm can provide a good population from the beginning. After getting the position and velocity vectors, the particles will be evaluated using the fitness evaluation function that has been formulated in the previous section. Then, the algorithm stores the values of $P_{best}$ and $G_{best}$. The best particles are stored for further optimization using genetic operators.

The GA adopts the best particles in the PSO swarm as the population. The genetic operators modify the genes of each individual for a better solution in the generation. The genetic operator performs the selection process using a roulette-wheel selection scheme. The selected

| Variable    | PV       | BESS     | Inverter | Grid       | Diesel    |
|-------------|----------|----------|----------|------------|-----------|
| Investment cost | 650 $/kW | 492.5 $/kWh | 114.9 $/kW | –          | 316.2 $/kW |
| Maintenance cost | 71.9 $/year | 35.8 $/year | 35.8 $/year | –          | –         |
| Operation cost | –        | –        | –        | –          | 0.06 $/op. hrs |
| Fuel cost     | –        | –        | –        | –          | 0.64 $/L   |
| Grid tariff   | –        | –        | –        | 0.093 $/kWh | –         |
| Sell-back tariff | –       | –        | –        | 0.06 $/kWh  | –         |
individuals will become the parents in the crossover process to produce the offspring. The crossover rate is 0.6, which means that 60 parents and 60 children will be involved. The mutation rate is 0.1, which means 6 of the 60 individuals will be mutated in each iteration. Then, the children are evaluated using the fitness evaluation function. The best solution is sorted by the elitism operator. After the best solution is obtained, the solution is evaluated again by PSO operators.

The PSO operators update the new position and velocity within a certain bound. The position and velocity boundary are used to restrict the particles from moving in non-converging directions. Then, the algorithm updates P_best and G_best. The algorithm will store a set of better solutions. The process will iterate until the maximum number of iterations is reached. The MGAPSO-optimization process is summarized in pseudocode as presented in Table 6.

| Table 6: Pseudocode of MGAPSO optimization |
|--------------------------------------------|
| 1. Define fitness function: f(x)          |
| 2. Determine optimization parameters      |
| 3. Determine algorithm parameters: learning factor (c₁ and c₂), inertia weight (w_{min} and w_{max}), crossover rate (R_c), mutation rate (R_m), maximum iteration and number of population |
| 4. Generate initial population            |
| 5. Generate the initial position and velocity of each particle in a random population |
| 6. Calculate the fitness value of each particle |
| 7. Find P_best and G_best                 |
| 8. Store best-known particles             |
| 9. Do                                     |
| 10. Iteration = \(\text{Iteration} + 1\) |
| 11. Generate population based on best-known particles |
| 12. Apply roulette-wheel selection        |
| 13. Apply recombination                    |
| 14. If \(R_c > \text{rand}\), end recombination |
| 15. Apply mutation                        |
| 16. If \(R_m > \text{rand}\), end mutation |
| 17. Apply elitism                         |
| 18. Update particle vector                |
| 19. Update P_best and G_best              |
| 20. Accept if a set of solutions is better|
| 21. Sort the best solution for next iteration |
| 22. While maximum iteration is reached    |

2.1 Optimization result

The optimal size and system cost that have been determined by the MGAPSO optimization are shown in Table 7. The optimization is carried out considering two constraints: 2% and 5% maximum LPSP.

Table 7 shows that 2% or 5% maximum LPSP makes no significant difference in component size. The PV size obtained by both 2% and 5% calculations is similar while the BESS is a bit higher in the 5% LPSP case. It means that the lower LPSP makes the calculation more optimal because the 2% LPSP system is capable of satisfying the load with the same PV size and smaller BESS capacity. The 2% LPSP obtains the best NPC with the sum of $163 378, which is 3.8% lower than the 5% LPSP one. As expected, the lower constraint will make the calculation better.

The MGAPSO-optimization process is shown in Fig. 9 to analyse the consistency of the algorithm in solving optimization cases.

Fig. 9 shows that the MGAPSO has a good convergence curve. The results always lead to a lower value in each iteration until reaching the lowest NPC in 35–40 iterations. A similar curve between 2% and 5% maximum LPSP shows that MGAPSO is consistent to optimize these cases with different constraints. It means the user can consider another maximum LPSP that fits in the user's budget.

Table 7: MGAPSO-optimization result

| Constraint | PV (kW) | BESS (kWh) | Inverter (kW) | Diesel (kW) | NPC ($) |
|------------|---------|------------|---------------|-------------|--------|
| 2%         | 586     | 755        | 135           | 140         | 163 378|
| 5%         | 583     | 880        | 137           | 140         | 169 839|

2 Result and Discussion

In this section, the discussion is divided into two parts. The first section shows the algorithm-performance comparison between MGAPSO and the conventional method. The second section discusses the cost and feasibility analysis.
The MGAPSO-optimization process curve is compared to the conventional algorithms, GA and PSO, as shown in Fig. 10. The comparison is used to measure the robustness of the MGAPSO algorithm in solving optimization cases in this study.

The PSO has a simpler process than those of MGAPSO and GA. PSO is the fastest algorithm to reach the best solution. The PSO has obtained the best cost at 30 iterations while MGAPSO and GA have obtained the best cost at 35 and 45 iterations, respectively. However, the final result shows that MGAPSO and GA can offer a lower cost compared to PSO. The MGAPSO results in the lowest NPC with the result of $163\,378. The GA is a little higher at ~$167\,757 and the PSO has the highest at $180\,684.

The MGAPSO curve is similar to that of the PSO in that it did not become stuck in a local optimum like the curve in the GA process, which found a local optimum at 10–20 iterations before converging to a global optimum. It can be concluded that the MGAPSO method is successful to adopt the PSO advantages of speed and a good convergence curve. The MGAPSO can also improve the best solution through GA operators.

2.2 Cost and feasibility analysis

Table 8 shows the detailed optimization result for MGAPSO, GA and PSO methods. The HOMER optimization is used as a reference in the cost-saving calculation because HOMER predicts the highest NPC. Table 8 indicates that the intelligence algorithm method can improve the best solution in terms of the system cost in this study. The PSO and GA results are 2.69% and 9.64% lower than those of HOMER, respectively. Then, MGAPSO has the lowest NPC at 11.99% lower that HOMER, which also means the highest cost-saving percentage.
The components that have been optimized need to be adjusted in a realistic scheme to further analyze the feasibility of the system. The total size in a realistic scheme could be a bit smaller or higher than the optimization result depending on the available sizes of system components in the market. In this realistic scheme, the size is chosen to be higher than the optimization result to keep the RES supplying load demand properly. Moreover, a slightly higher PV size will not be wasted; it can be stored in the BESS or exported to the grid. Then, the higher inverter capacity also ensures that the energy conversion runs well. Sometimes, the peak power in the real system can be higher than the peak power in the simulation system. Fig. 11 shows a realistic scheme containing commercial specifications and the connection of each component is based on the MGAPSO results.

The 586-kW solar PV generation needs 1240 modules of Sunpower XPR-X22-480, which is divided into four sub-arrays. Each sub-array is composed of 310 modules in 5 series and 62 parallel configurations. The solar power generation is $P_{\text{max}} = 592$ kW with a corresponding $V_{\text{max}} = 395$ V. To store the excess energy of the PV generation, 56 Tesla Powerwall batteries with 13.5-kWh capacity have been implemented. To ensure AC/DC energy conversion, four modules of PV-powered PV35-600 inverters have been arranged to match the PV and battery specification. As a backup process, the 140-kW DG block has been deployed. The DG consists of two Stamford DG models with power ratings of 112 and 36 kW.

Since the energy-management system allows the RES to supply load in several ways, the analysis must break down the energy production and allocation in each component. Fig. 12 shows the PV energy-production comparison between the MGAPSO system and the systems determined using the GA and PSO methods. It can be seen that the MGAPSO system has the smallest PV size in Table 7. The MGAPSO system produces less energy than the other systems. Fig. 12 shows that the MGAPSO system produces 348 447 kWh/year, which is 0.55% and 0.75% lower than the GA and PSO systems, respectively. On the other hand, the MGAPSO has a higher BESS capacity than the GA and is much smaller than the PSO. Despite the PV size in the MGAPSO result being smaller than those of the GA and PSO, the optimal ratio between the PV and the BESS makes the energy allocation better, as shown in Table 9.

It can be seen that the MGAPSO system has the lowest PV-to-grid percentage. It indicates that the energy produced by the MGAPSO system successfully prioritizes supplying the load directly and storing it in the BESS. A higher amount of energy injected into the grid indicates a higher amount of excess energy. The excess energy becomes dumb energy in a stand-alone RES. From this analysis, it can be concluded that more excess energy does not make system costs cheaper. Keep in mind that the sell-back tariff is only 60% of the grid tariff. Hence, the optimal amount of energy injected into the grid is just to comply with the regulation. The MGAPSO system can suppress the PV-to-grid energy so that it is close to 10%. The MGAPSO process succeeded in designing a RES on the campus that prioritizes direct energy utilization rather than selling the energy to the conventional grid.

Furthermore, Table 10 presents a comparison of energy in and out through the BESS. The simulations use a similar BESS specification, so the efficiency and hours of autonomy are also similar.

### Table 8: MGAPSO-optimization result

| Method   | PV (kW) | BESS (kWh) | Inverter (kW) | Diesel (kW) | NPC($) |
|----------|---------|------------|---------------|-------------|--------|
| MGAPSO   | 586     | 755        | 135           | 140         | 163 378|
| GA       | 636     | 723        | 170           | 140         | 167 757|
| PSO      | 667     | 896        | 188           | 140         | 180 684|
| HOMER    | 812     | 646        | 250           | 140         | 185 655|

**Fig. 11:** Realistic scheme of designed RES.

**Fig. 12:** shows the PV energy-production comparison...
The system also has a period when the PV and BESS cannot satisfy the load. In this study, the lack of energy can be served by the grid. Also, the RES has DGs to back up when a grid blackout occurs. Fig. 13 shows the comparison between grid import and diesel output to cover the lack of energy.

In this case, the grid import shows the lack of energy that cannot be covered by the PV and BESS systems. The DG outputs are similar since the simulation assumes the same grid-blackout period in a year. From Fig. 13, it can be seen that the MGAPSO has the lowest amount of energy imported from the grid. It indicates that the MGAPSO optimization makes RES more self-sustained and less dependent on the conventional grid.

From the different optimization algorithms, Fig. 14 presents the amount of energy used to supply the load from each RES component.

As discussed before, the MGAPSO system makes the energy from PV more focused to supply the load directly and store the excess energy through the BESS. Then, the MGAPSO system can also reduce imported energy from the grid. These things become advantages for RES in the campus area, because the major energy use is in the daytime and the RES can supply that energy at the same time. So, Fig. 12 justifies that the MGAPSO can optimize the RES better than the other methods.

The different system characteristics that comprise the system are different for each algorithm, which results in different COE values, as shown in Table 10. The COE represents the price to be paid per kWh of energy produced by
the RES. The lower COE implies that the RES is more feasible to deploy. Table 11 shows that MGAPSO optimization obtains the lowest COE at 0.524 $/kWh. It means that the MGAPSO system is feasible to supply the campus load demand at minimum cost.

3 Conclusion
In this paper, robust optimization and further investigation of a campus RES have been implemented. The RES model consists of PV as the main energy supplier, BESS as the storage, inverter as the power conditioning unit and a DG as backup during the grid-blackout condition. The RES components were represented in the mathematical model simulated in a sustainable energy-management system. The energy-management system manages the energy generation and allocation based on the system behaviour in grid-connected and stand-alone modes.

A feasible design at the minimum cost for a grid-connected PV/battery/diesel system has been conducted using the MGAPSO method. In this study, an 881.8-kWh/day load campus profile was simulated in a year-long project time. The optimal component sizes determined by MGAPSO optimization are 586 kW of the PV system with 755 kWh of the BESS to store the energy. The optimal RES needs 135 kW of the inverter to condition AC/DC power. The RES also needs 140 kW of DGs to back up when grid blackout occurs.

The MGAPSO optimization utilizes two constraints for consideration. The convergence curve has been presented, showing that MGAPSO is consistent to optimize this case. The MGAPSO method has determined the best NPC at $163 378 in 2% maximum LPSP with COE at 0.524 $/kWh. The MGAPSO optimization can save up to 2–11% of cost as compared to conventional optimization methods. Further investigation also has been carried out. The system characteristic analysis has shown that the MGAPSO method has designed a self-sustained RES in the campus area at minimum cost by enhancing renewable-energy utilization.

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Conflict of interest statement
None declared.

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