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ORIGINAL RESEARCH

A stochastic multi-objective model for energy efficiency and renewable resource planning in energy communities: A sustainably cost-effective trade-off

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The integration of energy efficiency programs and renewable resources in energy communities (EC) incorporating smart microgrids might be the future development of sustainable cities. Cooperation among EC with high penetration of renewable energy resources will support energy procurement. Mutual energy efficiency programs in EC associated with deploying renewable resources can guarantee sustainable development significantly. This paper proposes a new sustainability index (SI) influenced by the loss of load reduction while increasing the penetration of renewable energies. A multi-objective optimization method is used to determine the optimal size and location of renewable resources incorporating energy efficiency programs. The objective functions, that is, the total cost and SI, are based upon social, economic, environmental, and technical (SEET) considerations. Since the outputs of renewable energies are uncertain, it may increase the loss of load probability. Therefore, this paper introduces a model that can handle the uncertainties of renewable energies. A new method so-called adaptive multi-objective crow search algorithm (AMCSA) is developed for the trade-off between cost and sustainability in the optimization problem. The proposed methodology cannot only minimize the total cost in EC but also will maximize the SI. Simulation studies and results analysis indicates the effectiveness of the proposed methodology for the development of sustainability and renewable energies in the smart grid.

1 | INTRODUCTION

Sustainable energy procurement especially in smart cities will enhance the level of welfare of their residents. Supplying reliable as well as flexible energy may facilitate a better life competency as a crucial issue in sustainable cities. Energy is sustainable if it meets the needs of the present without compromising the ability of future generations to meet their own energy needs [1]. Sustainable energy includes considerations of environmental aspects such as greenhouse gas emissions as well as social and economic aspects. It also meets the goals of energy communities (EC) such as reducing payment to electricity with minimum blackouts while increasing sustainability. Renewable energy production has become one of the most important components of sustainable development strategies around the world [2]. In a smart and sustainable city, EC are established based on social, environmental, economic, and technical (SEET) considerations. The structure of multi-EC can be facilitated by cooperation in energy procurement through local renewable generation and energy saving that will also guarantee energy efficiency. On the other hand, the energy efficiency programs will be based upon employing renewable energies associated with new energy storage technologies.

For the sake of sustainability, EC could be coordinated to exchange their energy production as well as participating in the energy efficiency programs in a collaborative scheme. Energy efficiency is a long-term strategy to reduce energy consumption via participating energy clients without reducing the level of access to such an important service to facilitate sustainability [3]. Incorporating renewable power plants (RPPs) as well as energy efficiency programs associated with smart facilities in energy procurement will support sustainability in EC.

Increasing the sustainability and reducing various costs of the smart grid are among the most important objectives of the smart grid operators. The integration and planning of renewable energy resources and using energy efficiency programs to achieve these goals can be important and effective. For this purpose, multi-objective methods are suitable for solving the planning problem by considering both the mentioned objectives. The main question of this research has been what is the impact of energy efficiency programs and renewable energy resources' planning on the sustainable development of the smart grid? The aim of this paper is to show the impact of renewable energy resources' planning and energy efficiency programs on the sustainability index (SI) and total cost of the smart grid by the adaptive multi-objective crow search algorithm (AMCSA).

1.1 | Literature review

ECs including local renewable energy resources may meet their energy needs independently from the upstream power distribution network. A smart EC could be considered an eco-friendly and sustainable alternative to the classical configuration [4]. A pool-based model for a local energy community in a power distribution system has been presented in [5], where an energy management system (EMS) for each smart home is considered. An approach for energy management of the ECs based on the transactive energy concept has been presented in [6]; in which the impact of demand response programs on the electricity bill is investigated. A reliability evaluation method for community-based energy systems in a power distribution network has been reported in [7], where a fault incidence matrix has been defined to show the impact of components' failure on the energy supply. In [8], a transactive energy scheduling based on the game theory using flexible demand in the energy communities has been discussed to provide fair payoff distribution schemes for energy participants. An optimization algorithm to investigate the impact of improving flexibility on the cost of a real energy community has been investigated in [9]. A framework for defining and designing electric services for local EC in the presence of RPPs has been proposed in [10]. The cooperation among energy supply participants in a community based on a cheating equilibrium-based solution is studied in [11], in which a Nash bargaining-based benefit-sharing model for determining the payment of energy sharing is employed. In [12], an electricity market model for an energy community where the participants can share their energy locally has been developed. An energy management scheme for an energy community in the presence of small-scale battery storage to handle the uncertainty in RPPs has been reported in [13]. One of the most important goals in energy communities is to support sustainable energy, especially in smart microgrids. Sustainability is a concept based on SEET aspects that might be ensured using renewable energy technologies [14].

Energy management of smart buildings in energy communities is considered as a practical and attractive applied research. Real-time energy management for a smart residential building including energy storage systems and distributed energy resources is presented in [15], in which a multi-objective method for the energy management of prosumers is developed. An energy scheduling framework for smart buildings consisting of the non-identical occupant has been proposed in [16], where it aims to optimize the whole buildings' demand in the presence of the uncertainties of PV production as well as market prices. A decentralized energy management method for exchanging energy among prosumers in the presence of the electric vehicle has been discussed in [17], by using an application of the P2P approach based on the concept of the zero-energy building.

Some studies introduced new indicators for assessing the state of the network in the scenarios before and after the installation of RPPs with small-scale capacities in smart grids. An expansion planning model for an isolated system with the aim of reducing the total costs in the presence of increasing the penetration of renewable resources has been proposed in [18]. A two-stage planning framework to increase the penetration of renewable energies in microgrids is investigated in [19]. The selected representative operating periods have been presented as the basis of the framework. In [20], the planning of an integrated energy system in the presence of renewable energy sources such as solar and biogas has been optimized. The energy efficiency program is one of the demand-side programs to reduce energy consumption. There are many studies that have investigated the energy efficiency. For instance, the impacts of energy efficiency programs on reducing costs, emission, and energy consumption in an industrial system have been investigated in [21]. In [22], the effects of energy efficiency have been investigated in reducing energy costs for a residential building by introducing an incentive for energy efficiency programs. In [23], an approach for reducing the interruptible demand in residential buildings by energy efficiency programs, changing the energy technology, and using smart meters' information has been proposed.

1.2 | Research gap and contribution

Based on the literature review, the following limitations can be found in previous research. Given the centrality of the studies conducted in the field of sustainable development for EC, it can be easily seen that:

- To the best of our knowledge, there is a lack of a comprehensive model for the sustainability of EC based on social, economic, environmental, and technical (SEET) considerations.
- In a smart grid, we seek to apply as little pressure as possible to the upstream grid during peak load conditions. Therefore, it is necessary to develop renewable energies locally and provide a structure for the participation of the consumers

in demand-side management such as energy efficiency programs. In the past articles, this point of view has not been raised with the trade-off between the cost and sustainability of the smart grid.

To bridge these research gaps, in this paper, a comprehensive sustainable development along with energy-saving technologies for multi-EC is presented. The proposed framework of this paper is implemented in multi-EC. Here a SI is introduced to measure the performance of EC incorporating energy efficiency programs. The results have been compared in different scenarios; before and after employing RPPs associated with uncertainties in the generation of renewable energy resources. The goal is to maximize the reliability and efficiency of the multi-EC while minimizing the total costs for the sake of boosting energy sustainability.

In this paper, the concept of energy efficiency in multi-energy communities to reduce payment costs with higher reliability is presented. A new SI is proposed and then optimized to reduce the multi-EC' losses as well as electric power consumption. Moreover, an AMCSA is proposed to find the optimal size and location of RPPs based on SEET considerations.

1.3 | Paper organization

The outline of the paper is as follows. Section 2 is about the approach overview, while problem formulation and introducing SI and the objective function are discussed in Section 3. The optimization method is proposed in Section 4. Simulation and numerical results are driven in Section 5, while concluding remarks are presented in Section 6.

2 | APPROACH OVERVIEW

The energy-saving programs such as energy efficiency programs and the use of clean energy as much as possible can be used for the sustainable development of EC that have a practical and real application. This paper has considered the penetration of renewable energy resources in the EC and has investigated the effect of energy efficiency programs in the proposed sustainability index.

An overview of the proposed approach is depicted in Figure 1. The structure of multi-energy communities is such that it combines a multi-objective obtimization with proposed models for the uncertainties of solar irradiance and wind speed, which simultaneously minimizes the total cost and maximizes the sustainability index. The problem is to determine the size/location of RPPs in the multi-EC based on SEET considerations. Each energy community has a manager that will participate in energy efficiency programs for the sake of sustainability. The multi-EC' manager optimizes the energy efficiency as well as the proposed sustainability index.

Depending on the size and location of the renewable energy resources that are installed in the smart grid, the amount of transmission lines' current and buses' voltage will change. As a result, with the change of the amount of transmission lines' current, transmission lines' loss will change, and the cost of transmission lines' loss will also change. On the other hand, the energy not supplied (ENS) of the system will also change with the change of the transmission lines' current. As a result, the ENS cost will also change. Also, the investment cost of renewable energy resources depends on the size of them. On the other hand, with the integration of renewable energy resources in the smart grid, the SI will also increase because its value depends on the capacity of renewable energy resources. In addition, with the optimal installation of renewable energy resources and the reduction of the transmission lines' loss and ENS, the SI will also increase.

3 | MATHEMATICAL MODEL

3.1 | Objective functions

The first objective function is the total costs of the multi-energy communities that should be minimized as Equation (1).

$$f_1 = \text{Min.}\left\{Cost_{total} = C_{fix} + C_{ENS} + C_{Loss} + C_{inc_{EE}}\right\} \tag{1}$$

where C_{fix}, C_{ENS}, C_{Loss} and $C_{inc_{EE}}$ are the fixed cost of return on capital costs, the costs of ENS, the cost of power loss and the incentive payments for energy efficiency programs, respectively.

The second objective function shown by Equation (2) is the proposed SI that should be maximized. The proposed SI includes the solar and wind power plants and does not contain other RES power plants.

$$f_2 = \text{Max.}\left\{SI = \frac{\sum_{k=1}^{N_w} P_{\text{wind}}(k) + \sum_{s=1}^{N_s} P_{\text{solar}}(s)}{\sum_{i=1}^{N_{br}} PL(i) + \sum_{j=1}^{N_l} P_{EE}(j)}\right\} \tag{2}$$

where P_{wind} and P_{solar} are the active power capacity of wind power plants and active power capacity of solar power plants, respectively. PL is the active power losses and P_{EE} is the modified total load after implementing energy efficiency programs. The energy efficiency programs are applied as policies for energy-saving programs. N_w and N_s are the number of wind and solar power plants, respectively. N_{br} and N_l are the number of branches and the number of load points of the multi-energy communities, respectively. The value of SI in the best condition of the system is equal to 1. The upstream grid power can affect costs, but the use of renewable energy resources can lead to sustainable development of the smart grid. In fact, in the SI, it is important to know how much is the share of the renewable energy resources in providing the total required power.

In fact, sustainability is a concept based on using renewable energies in the generation section and using energy-saving facilities in an energy community [18]. The SI shows the effects of energy-saving programs such as energy efficiency programs and

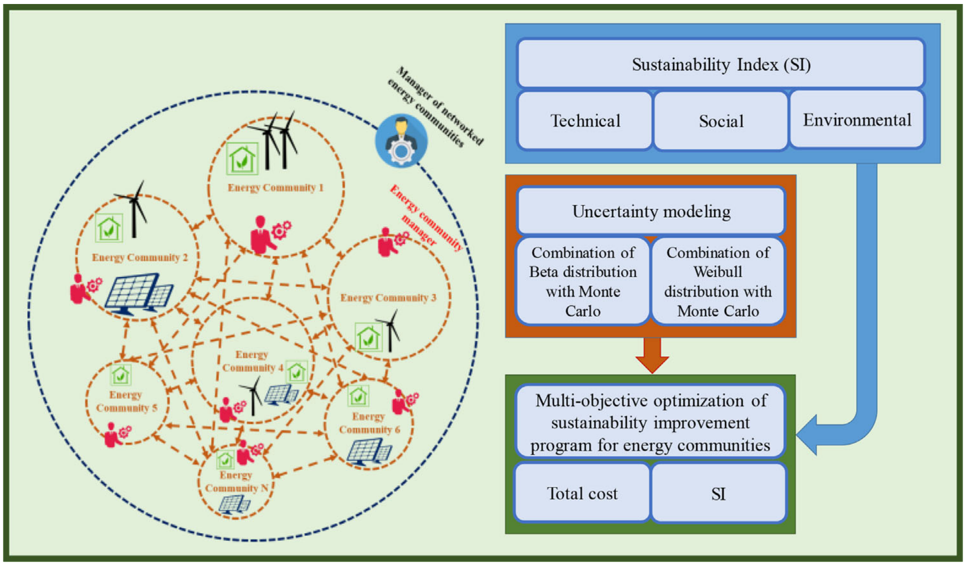

FIGURE 1 The schematic of the proposed approach

penetration of RPPs on reducing energy consumption while reducing power losses and lesser electricity shortage. In the literature, sustainability is introduced mainly via a socio and economic aspects, but here SI is defined via a socio, environmental, economic, and technical considerations, the so-called SEET aspects. In this way, the greater the share of renewable resources; that do not produce any pollutant; and the lower the system losses as well as energy saving will boost sustainability. Moreover, the effect of energy efficiency programs in reducing system loads is considered. The more the consumers' participation in demand-side programs in cooperative energy communities implies, the more sustainability will be.

3.2 | System indices

Several indices are formulated for investigating the renewable resource planning in the multi-energy communities. Active power loss depends on the line current and network that can be obtained by Equation (3).

$$PL = \sum_{k=1}^{N_{br}} |I_k|^2 \cdot R_k \tag{3}$$

where I_k is the current, R_k is the resistance of the kth line.

Similarly, reactive power loss can be obtained by Equation (4).

$$QL = \sum_{k=1}^{N_{br}} |I_k|^2 \cdot X_k \tag{4}$$

where X_k is the impedance of the kth line.

ENS can be obtained as follows:

$$ENS = \alpha \cdot \sum_{k=1}^{N_{br}} d_k \cdot \lambda_k \cdot \left|I_{kp}\right| \cdot V_{rated} \tag{5}$$

where I_{kp} is the line current of peak load, $\lambda_k$is the failure rate of the kth line and V_{rated} is the rated voltage of the system. α and d are load factor and repair duration, respectively.

Reliability of the system after implementing energy efficiency programs depends on the ENS and total load of the system that can be obtained as follows [24]:

$$R_{EE} = \left(1 - \frac{\sum_{i=1}^{N_{br}} ENS(i)}{\sum_{j=1}^{N_l} P_{EE}(j)}\right) \tag{6}$$

where$P_{EE}$is the total load of the system after energy efficiency programs.

The fixed cost of return on capital for the system is obtained as follows. Investment cost as a fixed cost of return on capital costs includes the cost related to feeders' lines and RES installation.

$$C_{fix} = g\left(\begin{array}{l} \sum_{k=1}^{N_w} C_s \cdot P_{\text{wind}}(k) + \sum_{s=1}^{N_s} C_w \cdot P_{\text{solar}}(s) \\ + \sum_{k=1}^{N_{br}} C_k \end{array}\right) \tag{7}$$

where C_s is the investment cost per 1 MW solar power plant, and C_w is the investment cost per 1 MW wind power plant, and C_k is the investment cost of the line k of the main feeder. g is the annual return rate of fixed cost.

The cost of ENS is calculated as follows:

$$C_{ENS} = c_i \cdot ENS \tag{8}$$

where c_i is the cost of the ith line.

The cost of energy losses is calculated as follows:

$$C_{Loss} = 8760 \times c_l \cdot \beta \cdot \sum_{k=1}^{N_{br}} |I_k|^2 \cdot R_k \tag{9}$$

where c_l is the cost of line (for all the lines is considered the same) and β is the loss factor of line. I_k and R_k are the current and resistance of line k, respectively. The value of β can be calculated as follows [25]:

$$\beta = 0.15\alpha + 0.85\alpha^2 \tag{10}$$

where α is the load factor.

The incentive payment for energy efficiency programs is obtained as follows. The energy efficiency programs mean the use of any advanced technology (such as using energy-saving lamps) to reduce energy consumption without reducing the level of service and access to electricity [24].

$$C_{inc_{EE}} = c_{EE} \cdot (P_D - P_{EE}) \tag{11}$$

where c_{EE} is the incentive payment per MWh and P_{EE} is the total system load after implementing energy efficiency program.

In this paper, the power-flow constraints introduced in [25] are considered. The energy production of wind and solar power plants depends on their model and source. The model of the wind and solar power plants generations is defined in [25–27]. In more detail, the generation of solar power plants depends on the nominal and actual solar radiation on the modules, the nominal and actual modules' temperature, the nominal open circuit voltage and short circuit current of the PV modules, and the fill factor of PV modules [25, 26]; also, the generation of wind power plants depends on the wind speeds, the cut-in, cut-out and nominal speeds of the wind turbines, the average wind speed, and the rated output power of wind turbines [27].

Since the generation of wind speed and solar irradiance is associated with uncertainty, so the combination of beta distribution with the Monte Carlo simulation sampling and the combination of Weibull distribution with Monte Carlo simulation sampling are applied for the solar irradiance and wind speed uncertainty modelling, respectively.

4 | THE PROPOSED SOLUTION APPROACH

4.1 | Adaptive multi-objective crow search algorithm (AMCSA)

Crow search algorithm is a population-based optimization method that is inspired by flocks of crows [28]. A crow can remember faces and warn other crows when an unfamiliar one approaches. Crows follow other birds and find out the place that other birds hide their food. Then they steal the food when the owners leave their hiding places. This paper presents a new AMCSA which converges and explores the results in a better order than the base algorithm 1.

Figure 2 shows the pseudo code of the proposed AMCSA. The proposed AMCSA has two advantages compared to the base algorithm: First, AMCSA does more exploration in search space as fl and AP have large values at low iterations and are near fl_{max} and AP_{max}, respectively. Second, the possibility of achieving higher quality results will be more as fl and AP have small values at high iterations and are near fl_{min} and AP_{min}, respectively.

The proposed algorithm considers fl a decreasing number varies with iteration in order to find results with higher quality (exploitation) and also search more points from the search space (exploration). In this way that in first, fl has a large value and reduces gradually; this causes the optimization algorithm to do more exploration at low iterations in order to prevent hasty convergence and jump from local optimum and go to higher exploitation at high iterations. In the other words, whatever crow to be more experienced and revert to his memory, the crow tends from the exploration of hidden places to finding out higher quality food sources. On the other hand, the proposed algorithm also considers AP a decreasing number varies with time (iteration). Whatever the awareness probability of crow to

ALGORITHM 1 AMCSA method

Randomly initialize the position of a flock of N_c crows in the search space
Evaluate the first fitness function for the position of the crows
Evaluate the second fitness function for the position of the crows
Sort the population of crows positions by the ranking method
Initialize the memory of each crow
while iter $< iter_{max}$
for i $= 1 : N_c$ (*all N_c crows of the flock*)
Randomly choose one of the crows to follow (for example j)
Update the flight length and the awareness probability as follows:
$fl^{i,iter+1} = fl_{max} - \frac{fl_{max} - fl_{min}}{iter_{max}} \times iter$ $AP^{j,iter+1} = AP_{max} - \frac{AP_{max} - AP_{min}}{iter_{max}} \times iter$
if $r_j \geq AP^{j,iter}$
$x^{i,iter+1} = x^{i,iter} + r_i \times fl \times (m^{j,iter} - x^{i,iter})$
Else
$x^{i,iter+1} =$ *a random position of search space*
end if
end for
Check the feasibility of new positions
Evaluate the first fitness function for the new position of the crows
Evaluate the second fitness function for the new position of the crows
Sort the population of crows positions by the ranking method and delete duplicate crows' positions
Update the memory of crows
end while

AMCSA Method

1: *Randomly initialize the position of a flock of N_c crows in the search space*
2: *Evaluate the first fitness function for the position of the crows*
3: *Evaluate the second fitness function for the position of the crows*
4: *Sort the population of crows positions by the ranking method*
5: *Initialize the memory of each crow*
6: **while** $iter < iter_{max}$
7: **for** $i = 1{:}N_c$ (*all N_c crows of the flock*)
8: *Randomly choose one of the crows to follow* (*for example* j)
9: *Update the flight length and the awareness probability as follows:*

$$fl^{i,iter+1} = fl_{max} - \frac{fl_{max} - fl_{min}}{iter_{max}} \times iter$$

$$AP^{j,iter+1} = AP_{max} - \frac{AP_{max} - AP_{min}}{iter_{max}} \times iter$$

10: **if** $r_j \geq AP^{j,iter}$
11: $x^{i,iter+1} = x^{i,iter} + r_i \times fl \times (m^{j,iter} - x^{i,iter})$
12: **else**
13: $x^{i,iter+1} =$ *a random position of search space*
14: **end if**
15: **end for**
16: *Check the feasibility of new positions*
17: *Evaluate the first fitness function for the new position of the crows*
18: *Evaluate the second fitness function for the new position of the crows*
19: *Sort the population of crows positions by the ranking* method and delete duplicate crows' positions
20: *Update the memory of crows*
21: **end while**

FIGURE 2 The pseudo code of the proposed AMCSA. AMCSA, adaptive multi-objective crow search algorithm.

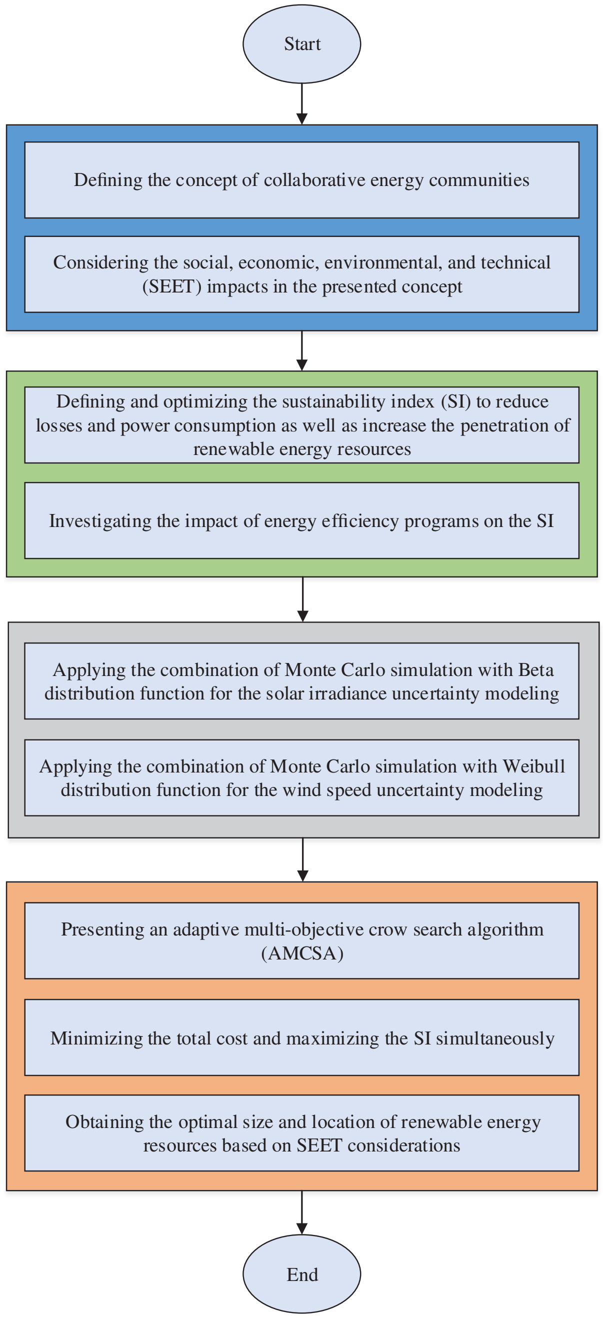

FIGURE 3 The proposed hierarchy to solve the problem

be more, crow tends to do exploration rather than exploitation and will fool the follower crow by going to another place in search space. Whatever the Awareness probability of crow to be less, crow tends to do exploitation rather than exploration and will lead the follower crow to go to the goal place in search space. Therefore, AP has a large value at low iteration and a small value at high iteration.

4.2 | Proposed hierarchal flow diagram

The proposed hierarchy is to determine the size and location of RPPs in the multi-energy communities based on SEET considerations presented in Figure 3.

According to Figure 3, the concept of multi-energy communities has been defined based on SEET impacts. The SI is then optimized to reduce losses and power consumption as well as increasing the penetration of renewable energy resources in the energy communities. Moreover, the impacts of energy efficiency programs on the SI are derived. The combination Monte Carlo simulation sampling with the beta distribution and Weibull distribution are applied for the solar irradiance and wind speed uncertainty modelling, respectively. Finally, the proposed AMCSA is applied to obtain the optimal size and location of RPPs in the energy communities based on SEET to minimize the total costs while maximizing SI.

5 | CASE STUDY

The proposed method for determining the size and location of RPPs is evaluated in different scenarios. In this section, simulation results for the studied multi-energy communities are

TABLE 1 Problem scenarios for optimal sitting and sizing of RPPs

Scenario	Number of wind PPs	Number of solar PPs	First fitness function	Second fitness function
1	1	2	Min. Cost	Max. *SI*
2	2	1	Min. Cost	Max. *SI*

TABLE 2 The parameters of the AMCSA method

Method	Maximum number of iterations ($iter_{max}$)	The number of crows (N)	Flight length (fl)	Awareness probability (AP)
AMCSA	400	10	$fl_{max} = 2.5$ $fl_{min} = 1.5$	$AP_{max} = 0.2$ $AP_{min} = 0$

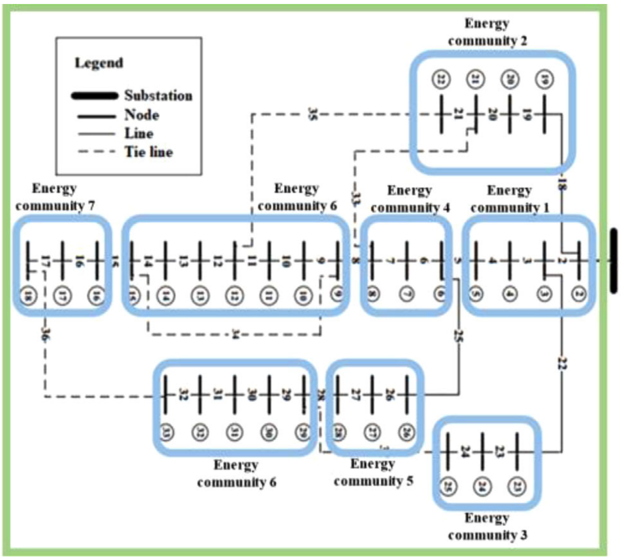

FIGURE 4 The studied multi-energy communities

presented. The optimization is implemented by using AMCSA to determine the size and location of wind and solar power plants generation, considering the uncertainty. The objective functions are analyzed in two different scenarios for optimal RPPs in the multi-energy communities that are shown in Table 1.

5.1 | Data and assumptions

The parameters used to solve the proposed model by AMCSA are presented in Table 2.

The studied system is the multi-energy communities shown in Figure 4. The data of active and reactive loads, nodes, and lines are taken from [30]. The active and reactive power losses can be calculated by (3) and (4) That are 129.4 kW and 86.1 kVAr, respectively. The ENS for this multi-energy communities using Equation (5) is equal to 126.3 kW.

TABLE 3 The parameters of the wind PPs

Parameter	Value
Rated output power (P_{rated}) [MW]	0.1
Cut-in speed ($v_{cut\text{-}in}$) [m/s]	4
Rated wind Speed (v_n) [m/s]	16
Cut-out speed ($v_{cut\text{-}out}$) [m/s]	20

TABLE 4 The parameters of the solar PPs

Parameter	Value
The maximum output power of one module (P_{max}) [W]	100
Rated solar radiation of one module (G_N) [W/m^2]	1000
Open circuit voltage of one module (V_{Noc}) [V]	21
Short circuit current of one module (I_{Nsc}) [A]	6.5
Series resistant of one module (R_{se}) [Ω]	0.012
Rating temperature of the solar cell (T_N) [°C]	25

Network parameters related to wind and solar PPs are taken from [29]. Some of the parameters of wind turbines are dependent on different wind speeds and are presented in Table 3, and some of the parameters of solar arrays are dependent on solar radiation and temperature and are presented in Table 4. The capital cost of both solar and wind farm is considered $1 million per 1 MW. The price of power in 24 h is assumed to be $22.5 per MW and the incentive payment to customers for energy efficiency programs is $30 per MW [2].

The weather data for the wind speeds and solar radiations are related to the Milwaukee city in the state of Wisconsin, United States [29]. The hourly data is reported for 1 year, with an average of 365 days per 24 h a day. Wind speeds and solar radiations are different for all nodes. First, the data is categorized in such a way that effective data is retained, and duplicate data is removed. Then the data normalization and shuffling operations are performed. The data are classified into two parts: training data and test data. The learning process is performed on the training data and then compared with the test data. Finally, the forecasting error is evaluated. 65% of the data, that is, the number of 5694 data are considered as training data and 35% of the data, that is, the number of 3066 data are considered as test data. Thirty epochs have been used to estimate the solar radiation and wind speed. Information related to the production of solar and wind power plants is needed during peak times in order to solve the problem. The load of IEEE systems is based on the peak time. Therefore, we have to estimate the wind speed and solar radiation for a short-term period and then calculate the production of solar and wind power plants.

Figure 5 shows the annual average solar radiation modelled by the beta distribution using the Monte Carlo simulation sampling for all hours of a day taking into account the uncertainty [27]. Figure 6 shows the annual average wind speed modelled by the Weibull distribution using the Monte Carlo simulation sampling for all hours of a day taking into account the uncertainty [27].

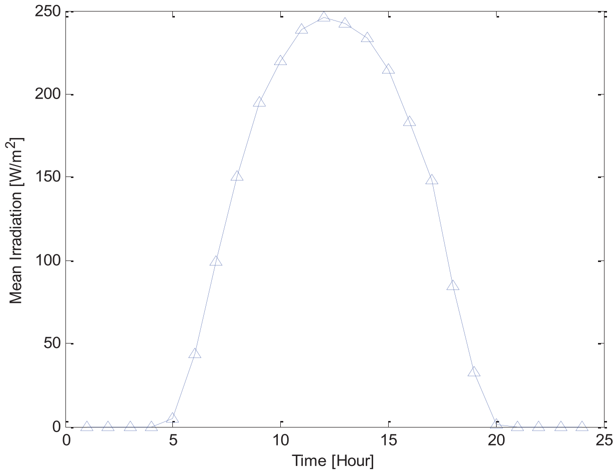

FIGURE 5 The annual average solar radiation for 24 h

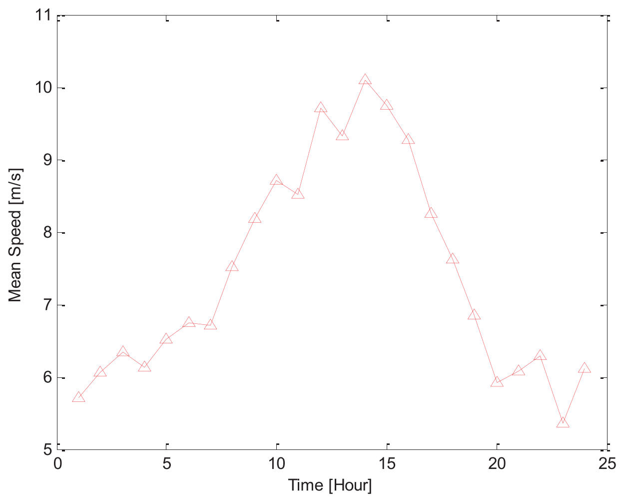

FIGURE 6 The annual average wind speed for 24 h

In this paper, the value of the solar and wind RPPs' generation obtained based on weather parameters, corresponding to the peak load hour, will be used to solve the problem because the system load in the problem is the annual average daily peak load.

5.2 | Numerical results and discussion

The proposed AMCSA method is compared with other methods in the supplementary material. In this section, the size and location of RPPs have been determined. The optimal size and location of RPPs considering the uncertainty of their generations as well as the values of objective functions in different scenarios for the multi-energy communities are presented in Table 5. According to Table 5, the average SI in Scenario 2 (0.865) is higher than the average SI in Scenario1 (0.564), while the average of total costs in Scenario 2 (\$2050224) is less than the average of total costs in Scenario 1 (\$2051497).

The problem is multi-objective and a front of optimal results is reported in which the multi-energy communities' operator chooses one of the results depending on his preferences. In fact, the choice of the optimal results is given to the multi-energy communities' operator.

The active power loss index (PLI) can be defined as $PLI = \frac{PL_{RPP}}{PL_{NO-RPP}}$, where PL_{RPP} is the active power loss in the presence of RPP and PL_{NO-RPP} is the active power loss in the absence of RPP. On the other hand, the reactive power loss index (QLI) can be defined as $QLI = \frac{QL_{RPP}}{QL_{NO-RPP}}$, where QL_{RPP} is the reactive power loss in the presence of RPP and QL_{NO-RPP} is the reactive power loss in the absence of RPP.

The voltage profile of a system can be used to determine the weak and strong points of the system, transmission line loading, etc. The voltage profile after the installation of RPPs should be improved compared to before the installation of RPPs, and the lower the voltage deviation, the better the system status. The voltage deviation index is measured relative to the reference voltage V_{reff}. The voltage deviation index can be calculated by $VDI = \max_{j=2:n} (\frac{V_{reff} - V_{RPP_j}}{V_{reff}})$, where n is the total number of nodes. The reference voltage is equal to $V_{reff} = 1$ p.u., and V_{RPPj} is the voltage of node j after installation of RPP.

The amount of active and reactive power loss and minimum voltage of the multi-energy communities before and after of RPPs installation in different scenarios as well as the amount of VDI, PLI, and QLI considering the uncertainties of wind and solar power plants generations are presented in Table 6. According to Table 6, the active and reactive power losses of the multi-energy communities after RPPs optimal installation are decreased compared to before RPPs installation in all scenarios; also, the minimum voltage of the multi-energy communities after RPPs optimal installation is improved compared to before RPPs installation in all scenarios.

When installing RPPs, it is important to improve the voltages' profile of buses and ensure the stability of the power network. Based on the mentioned reason, the value of the VDI index has been calculated and reported in order to evaluate the deviation of buses' voltage from the nominal voltage (reference voltage) in the states before and after the installation of RPPs in different scenarios. Also, PLI and QLI have been analyzed to show the improvement ratio of active and reactive power losses, respectively. To analyze the PLI and QLI, the ratio of active power losses and the ratio of reactive power losses after the installation of RPPs to before their installation are calculated, respectively. In addition to the mentioned ratios, the amount of active and reactive power losses and the minimum voltage among all buses are also reported in different scenarios. It is noteworthy that the amount of active and reactive power losses also affects both objective functions.

The costs of ENS, the cost of active power loss, the fixed cost, and the total cost of different scenarios for the multi-energy communities, taking into account the uncertainty, are presented in Table 7.

The multi-energy communities' reliability before and after RPPs installation after energy efficiency programs, the multi-energy communities demand before and after energy efficiency programs and the ENS before and after RPPs installation after energy efficiency programs are presented in Table 8. According

TABLE 5 The optimal size and location of RPPs for different scenarios

Scenario	First fitness function	Second fitness function	Location and size RPP_{PV1}	Location and size RPP_{PV2}	Location and size RPP_{Wind}	Active power RPP_{PV1} [kW]	Active power RPP_{PV2} [kW]	Active power RPP_{Wind} [kW]
First scenario	Total cost [$]	SI						
Result 1	2,055,378	0.586210	22 (4×19 cells)	11 (19×16 cells)	23 (1 turbine)	17.721	17.528	697.483
Result 2	2,049,444	0.547146	26 (24×23 cells)	22 (3×30 cells)	8 (1 turbine)	221.518	115.189	688.087
Result 3	2,050,006	0.551124	27 (6×2 cells)	28 (15×22 cells)	4 (1 turbine)	19.937	62.025	692.161
Result 4	2,051,158	0.574153	32 (12×16 cells)	17 (7×24 cells)	26 (1 turbine)	17.728	104.440	685.836
Second Scenario	**Total cost [$]**	**SI**	**Location and size RPP_{PV1}**	**Location and size RPP_{Wind1}**	**Location and size RPP_{Wind2}**	**Active power RPP_{PV1} [kW]**	**Active power RPP_{Wind1} [kW]**	**Active power RPP_{Wind2} [kW]**
Result 1	2,051,592	0.967345	6 (3×7 cells)	5 (2 turbines)	30 (2 turbines)	8.769	1385.05	686.862
Result 2	2,047,788	0.735664	10 (21×27 cells)	2 (2 turbines)	9 (1 turbine)	192.911	680.593	673.141
Result 3	2,049,363	0.946715	10 (22×29 cells)	2 (1 turbine)	20 (2 turbines)	192.911	680.593	679.496
Result 4	2,047,536	0.687918	14 (7×6 cells)	24 (1 turbine)	5 (1 turbine)	232.981	678.685	692.525
Result 5	2,054,843	0.985857	23 (2×12 cells)	26 (2 turbines)	19 (1 turbine)	7.753	1340.095	663.333

TABLE 6 The value of the multi-energy communities' indicators

Scenario	VDI	PLI	QLI	P_{Loss}^{NoRPP} [kW]	P_{Loss}^{RPP} [kW]	Q_{Loss}^{NoRPP} [kVAr]	Q_{Loss}^{RPP} [kVAr]	V_{min}^{NoRPP} [p.u.]	V_{min}^{RPP} [p.u.]
First scenario									
Result 1	0.044564	0.505733	0.526627	129.398	65.441	86.098	0.045342	0.93933	0.955436
Result 2	0.030674	0.284881	0.287882	129.398	36.863	86.098	0.024786	0.93933	0.969326
Result 3	0.042343	0.454637	0.485277	129.398	58.829	86.098	0.041782	0.93933	0.957657
Result 4	0.030549	0.304774	0.316992	129.398	39.437	86.098	0.027292	0.93933	0.969451
Second scenario									
Result 1	0.025757	0.173979	0.215480	129.398	22.513	86.098	18.553	0.93933	0.974243
Result 2	0.028601	0.274304	0.276374	129.398	35.494	86.098	23.795	0.93933	0.971399
Result 3	0.040416	0.500821	0.508039	129.398	64.805	86.098	43.741	0.93933	0.959584
Result 4	0.029349	0.239415	0.276181	129.398	30.980	86.098	23.779	0.93933	0.970651
Result 5	0.028360	0.228647	0.260212	129.398	29.587	86.098	22.404	0.93933	0.971640

to Table 8, the ENS, and the multi-energy communities demand is decreased and the reliability of the multi-energy communities is improved after RPPs optimal installation in all scenarios.

The amount of ENS index also affects both objective functions, and the reliability of a system has an inverse relationship with the ENS. The noteworthy point is that by performing energy efficiency programs, the system load is reduced. As a result, it shows its effect in reducing ENS and increasing reliability, as well as reducing total cost and increasing the sustainability of the power system.

Figure 7 shows the results of the voltage profile of the nodes before and after the installation of wind and solar PPs in the first scenario. The studied system consists of several bus and a number is assigned to each of them. The term 'Bus number' specifies where the system buses/nodes are placed. As can be seen in Figure 7, the minimum voltage of nodes before RPPs

TABLE 7 The costs of the multi-energy communities in different scenarios

Scenario	Cost of ENS [$]	Cost of active power loss [$]	Fixed cost [$]	Total cost [$]
First scenario				
Result 1	229.89	13661.19	2,041,487	2,055,378
Result 2	171.99	7785.14	2,041,487	2,049,444
Result 3	180.81	8337.52	2,041,487	2,050,006
Result 4	195.02	9475.33	2,041,487	2,051,158
Second scenario				
Result 1	185.84	9918.85	2,041,487	2,051,592
Result 2	154.16	6146.17	2,041,487	2,047,788
Result 3	170.00	7706.12	2,041,487	2,049,363
Result 4	152.47	5896.30	2,041,487	2,047,536
Result 5	205.06	13150.51	2,041,487	2,054,843

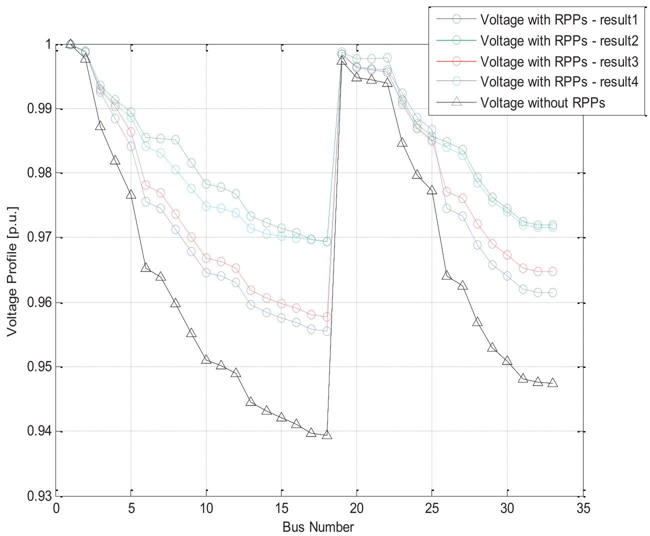

FIGURE 7 Voltage profiles in Scenario 1

installation is about 0.939 p.u and after the RPPs installation it is about 0.95 to 0.96 in the first scenario.

Figure 8 shows the results of the line loading before and after the installation of wind and solar PPs in the first scenario. Line loadings are decreased after RPPs installation in the first scenario compared to before RPPs installation and only for a few lines, the line loading is increased, while the average of active and reactive power losses is reduced significantly.

Figure 9 shows the Pareto optimal results in the first and second scenarios. Although all of these results are optimal, the multi-energy communities' operator should solve a decision-making problem to choose one of the Pareto-efficient results. A good approximation to the social welfare and smart grid sustainability could be achieved by the optimal Pareto-efficient results.

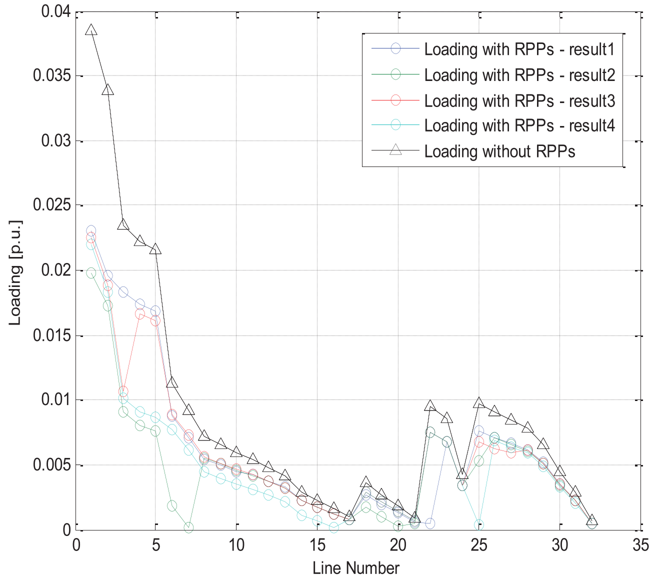

FIGURE 8 Line loading in Scenario 1

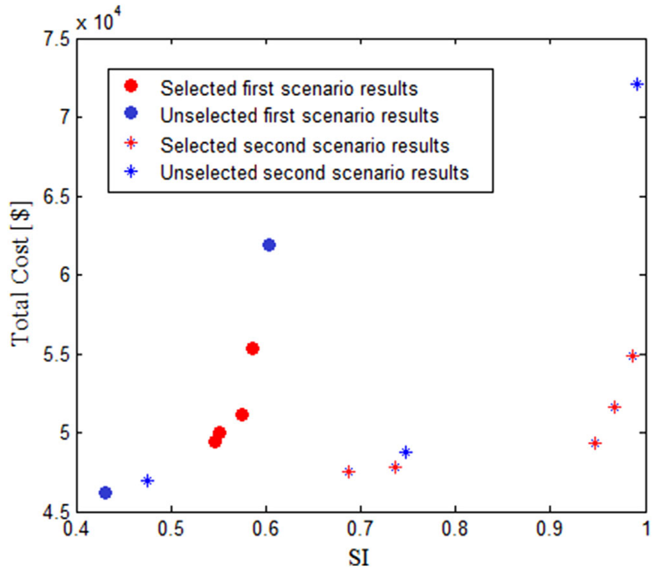

FIGURE 9 The Pareto optimal results in the first and second scenarios

Figure 10 shows the results of voltage profile of the nodes. As can be seen from Figure 10, the minimum voltage of nodes before RPPs installation is about 0.939 p.u. and after the RPPs optimal installation it is about 0.95 to 0.97 in the second scenario. Figure 11 shows the results of the line loadings in the second scenario compared to before RPPs installation.

Figure 12 shows the effects of the long-term energy efficiency programs on the short term, that is, peak hour, for all scenarios. According to Figure 12, the demand of the multi-energy communities has been reduced at almost hours by energy efficiency programs using energy-saving technologies.

The numerical results show that the installation of wind power plants in the studied area could reduce the cost and increase the SI more than installation of solar power plants. As

TABLE 8 The reliability index and ENS and demand in different scenarios

Scenario	Reliability index before RPPs and after energy efficiency programs	Reliability index after RPPs and after energy efficiency programs	Demand before energy efficiency programs [kW]	Demand after energy efficiency programs [kW]	ENS before RPPs and after energy efficiency programs [kW]	ENS after RPPs and after energy efficiency programs [kW]
First scenario						
Result 1	0.957503	0.975865	3720	2972	101.656	71.728
Result 2	0.957503	0.981393	3720	2972	101.656	55.299
Result 3	0.957503	0.976367	3720	2972	101.656	70.237
Result 4	0.957503	0.980629	3720	2972	101.656	57.57
Second scenario						
Result 1	0.957503	0.986253	3720	2972	101.656	40.856
Result 2	0.957503	0.98167	3720	2972	101.656	54.477
Result 3	0.957503	0.976419	3720	2972	101.656	70.082
Result 4	0.957503	0.983708	3720	2972	101.656	48.419
Result 5	0.957503	0.98244	3720	2972	101.656	52.187

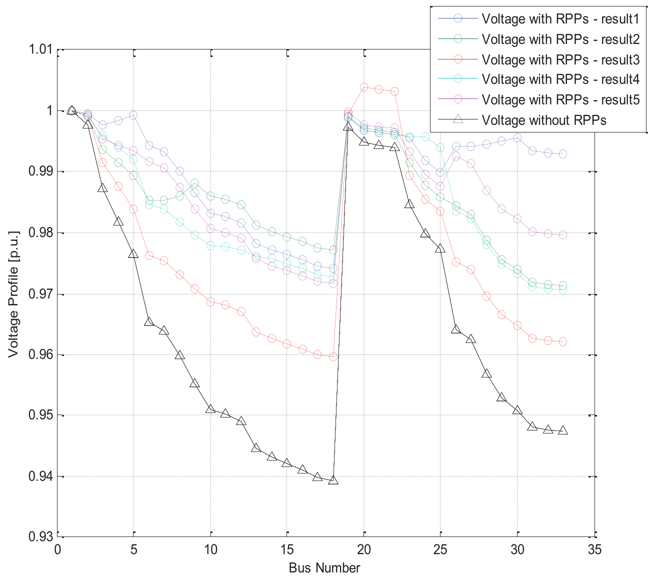

FIGURE 10 Voltage profiles in Scenario 2

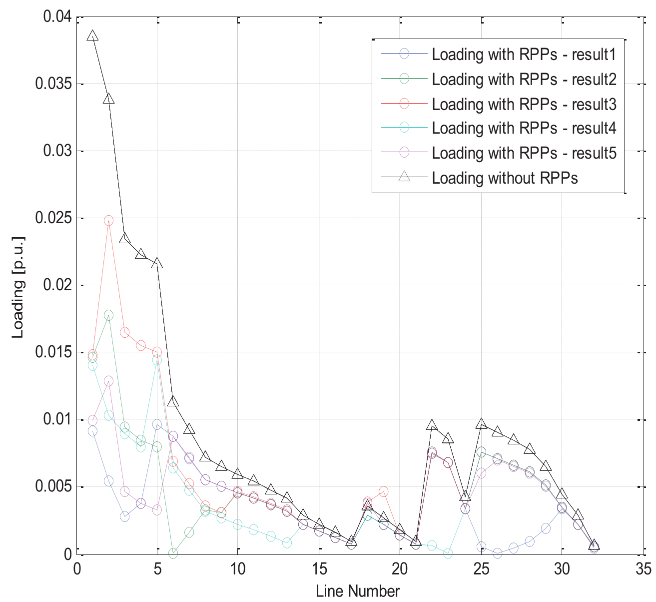

FIGURE 11 Line loading in Scenario 2

an important policy implication, the total cost of the smart grid could be dramatically reduced by the optimal placement of the renewable energy power plants and performing the energy efficiency programs in the smart grid. The infrastructure design of the installation of the renewable energy power plants in the energy communities should be in a way that they have the ability to supply the energy of their energy community independently of the upstream grid.

All the results obtained by the multi-objective algorithm are optimal, but the network operator should decide to choose one of the results depending on whether the cost is more important for him/her or the sustainability of the power system. For example, if reducing cost is much more important than increasing sustainability for the system operator, then he/she will choose the result that leads to the lowest cost.

In the case where reducing cost is more important than increasing sustainability for the system operator, the results of proposed AMCSA are compared with basic CSA in Table 9.

According to Table 9, the proposed AMCSA has achieved a lower total cost ($2,049,444 in the first scenario and $2,047,536 in the second scenario) than basic CSA ($2,051,024 in the first scenario and $2,049,267 in the second scenario) in both scenarios. It should be noted that in this case, reducing cost is more important than increasing sustainability for the system operator.

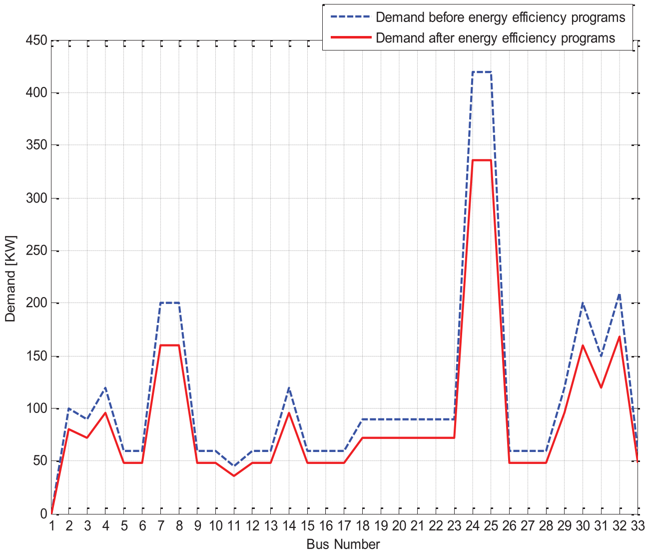

FIGURE 12 Demand profile before and after energy saving

TABLE 9 The comparison of proposed AMSCA method with basic CSA if reducing cost is more important than increasing the SI for the system operator

Method	CSA	AMCSA
First scenario		
Total cost [$]	2,051,024	**2,049,444**
SI	0.564031	0.547146
Second scenario		
Total cost [$]	2,049,267	**2,047,536**
SI	0.938084	0.687918

TABLE 10 The comparison of proposed AMSCA method with basic CSA if increasing the SI is more important than reducing cost for the system operator

Method	CSA	AMCSA
First scenario		
Total cost [$]	2,052,646	2,055,378
SI	0.569508	**0.586210**
Second scenario		
Total cost [$]	2,050,330	2,054,843
SI	0.962152	**0.985857**

In the case where increasing sustainability is more important than reducing cost for the system operator, the results of proposed AMCSA are compared with basic CSA in Table 10.

According to Table 10, the proposed AMCSA has achieved a higher SI value (0.586210 in the first scenario and 0.985857 in the second scenario) than basic CSA (0.569508 in the first scenario and 0.962152 in the second scenario) in both scenarios. It should be noted that in this case, increasing sustainability is more important than reducing cost for the system operator.

6 | CONCLUSION

In this paper, the sustainable development problem based on determining the size and location of RPPs was solved for the multi-energy communities. The results of this paper showed that the higher penetration of renewable energy resources in energy communities and the participation of consumers in energy efficiency programs could increase the development of energy communities. Although the use of green energy resources could increase energy efficiency in energy communities, but because green energy resources are associated with uncertainty, it should not switch towards them completely. In the study, the upstream grid was considered to avoid this complete switch to green energy resources to some extent. The results showed that the proposed AMCSA method has reached the appropriate quality results in different scenarios. In the first scenario, two solar PPs and one wind PP were optimally sized and placed in the multi-energy communities; also, in the second scenario, two wind PPs and one solar PP were optimally sized and placed in the multi-energy communities. In each scenario, objective functions, that is, cost and the SI, and different indicators were compared before and after the installation of RPPs. As a policy implication, the results obtained to determine the size and location of RPPs based on SEET considerations by the proposed algorithm significantly improved the different indicators of the multi-energy communities compared to before RPPs installation. The results showed that the smart grid planners through the optimal installation of RPPs along with energy efficiency programs could significantly reduce cost and improve the sustainability of the energy communities.

NOMENCLATURES

PL	active power loss
PLI	active power loss index
QL	reactive power loss
QLI	reactive power loss index
I_k	current of kth transmission line
R_k	resistance of kth transmission line
N_{br}	total number of branches
PL_{RPP}	active power loss with renewable energy power plant (RPP)
PL_{NO-RPP}	active power loss without RPP
X_k	reactance of kth transmission line
QL_{RPP}	reactive power loss with RPP
QL_{NO-RPP}	reactive power loss without RPP
V_{reff}	reference voltage of the system
V_{RPPj}	system voltage value with RPP
VDI	voltage deviation index
ENS	energy not supplied
I_{kp}	branch current at peak load
λ_k	failure rate of kth transmission line
V_{rated}	rated voltage of system
α	load factor
d_k	repair duration of kth transmission line
$\text{Cost}_{\text{total}}$	total cost of system
C_{fix}	fixed cost

C_k	cost of line k of the main feeder
C_s	investment cost of solar power plant (PPs)
C_w	investment cost of wind PPs
g	yearly return rate of fixed cost
C_{ENS}	cost of energy not supplied
C_{Loss}	cost of energy losses
β	loss factor
P_{wind}	power generation of wind PPs with uncertainty
P_{solar}	power generation of solar PPs with uncertainty
P_{RPP_i}	active power of ith RPP
Q_{RPP_i}	reactive power of ith RPP
I_i^k	current of bus i at kth iteration
J_i^k	current of transmission line i at kth iteration
V_i^k	voltage of bus i at kth iteration
$iter$	iteration
$iter_{\max}$	maximum iteration
r_i	a random number with a uniform distribution between 0 and 1 is specific to the crow i
$fl^{i,iter}$	the flight length of the crow i at iteration $iter$
$fl_{\max}$	maximum flight length
$fl_{\min}$	minimum flight length
$AP^{j,iter}$	awareness probability of crow j at iteration $iter$
$AP_{\max}$	maximum awareness probability
$AP_{\min}$	minimum awareness probability
N	the number of crows
$x^{i,iter}$	position of crow i at iteration $iter$
$m^{i,iter}$	memory of crow i at iteration $iter$
SI	sustainability index
R_{EE}	system reliability after energy efficiency programs

AUTHOR CONTRIBUTIONS

Peyman Afzali: Conceptualization; Formal analysis; Methodology; Software; Validation; Writing – original draft. Masoud Rashidinejad: Investigation; Project administration; Supervision; Validation; Visualization. Amir Abdollahi: Investigation; Supervision; Validation; Visualization. Mohammad Reza Salehizadeh: Investigation; Supervision; Validation; Visualization; Writing – review & editing. Hossein Farahmand: Investigation; Supervision; Validation; Visualization; Writing – review & editing.

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CONFLICT OF INTEREST

Any COI to declare?: No

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

1. Junejo, F., Saeed, A., Hameed, S.: Energy management in ocean energy systems. Comprehensive Energy Syst. 5, 778–807 (2018)
2. Hejeejo, R., Qiu, J., Brinsmead, T.S., Reedman, L.J.: Sustainable energy system planning for the management of MGS: A case study in New South Wales, Australia. IET Renew. Power Gener. 11(2), 228–238 (2017)
3. Dorahaki, S., Rashidinejad, M., Abdollahi, A., Mollahassani-pour, M.: A novel two-stage structure for coordination of energy efficiency and demand response in the smart grid environment. Int. J. Electr. Power Energy Syst. 97, 353–362 (2018)
4. Roncero-Clemente, C., Vilhena, N., Delgado-Gomes, V., Romero-Cadaval, E., Martins, J.F.: Control and operation of a three-phase local energy router for prosumers in a smart community. IET Renew. Power Gener. 14(4), 560–570 (2020)
5. Javadi, M.S., Gough, M., Nezhad, A.E., Santos, S.F., Shafie-khah, M., Catalão, J.P.S.: Pool trading model within a local energy community considering flexible loads, photovoltaic generation and energy storage systems. Sustain. Cities Soc. 79, 103747 (2022)
6. Bokkisam, H.R., Acharya, R.M., Selvan, M.P.: Framework of transactive energy market pool for community energy trading and demand response management using an auction-theoretic approach. Int. J. Electr. Power Energy Syst. 137, 107719 (2021)
7. Zhao, J. et al.: Reliability evaluation of community integrated energy systems based on fault incidence matrix. Sustain. Cities Soc.80, 103769 (2022)
8. Hou, X., Wang, J., Huang, T., Wang, T., Wang, P.: Smart Home energy management optimization method considering energy storage and electric vehicle. IEEE Access. 7, 144010–144020 (2019)
9. Feng, C., Wen, F., You, S., Li, Z., Shahnia, F., Shahidehpour, M.: Coalitional game-based transactive energy management in local energy communities. IEEE Trans. Power Syst. 35(3), 1729–1740 (2020)
10. Tomar, A., Shafiullah, D.S., Nguyen, P.H., Eijgelaar, M.: An integrated FLEXIBILITY optimizer for economic gains of local energy communities — a case study for a university campus. Sustain. Energy Grids Netw. 27, 100518 (2021)
11. Piazza, G., Bracco, S., Delfino, F., Siri, S.: Optimal design of electric mobility services for a local energy community. Sustain. Energy Grids Netw. 26, 100440 (2021)
12. Cui, S., Wang, Y.-W., Shi, Y., Xiao, J.-W.: Community energy cooperation with the presence of cheating behaviors. IEEE Trans. Smart Grid. 12(1), 561–573 (2021)
13. Crespo-Vazquez, J.-L., AlSkaif, T.; González-Rueda, Á.-M., Gibescu, M.: A community-based energy market design using decentralized decision-making under uncertainty. IEEE Trans. Smart Grid. 12(2), 1782–1793 (2021)
14. Jo, H.-C., Byeon, G., Kim, J.-Y., Kim, S.-K.: Optimal scheduling for a zero net energy community microgrid with customer-owned energy storage systems. IEEE Trans. Power Syst. 36(3), 2273–2280 (2021)
15. Paul, S., Padhy, N.P.: Real-time energy management for smart homes. IEEE Syst. J. 15(3), 4177–4188 (2021)
16. Paul, S., Padhy, N.P.: Real-time bilevel energy management of smart residential apartment building. IEEE Trans. Ind. Inf. 16(6), 3708–3720 (2020)
17. Lyu, C., Jia, Y., Xu, Z.: Fully decentralized peer-to-peer energy sharing framework for smart buildings with local battery system and aggregated electric vehicles. Appl. Energy. 299, 117243 (2021)
18. Torul Yürek, Y., Bulut, M., Özyörük, B., Özcan, E.: Evaluation of the hybrid renewable energy sources using sustainability index under uncertainty. Sustain. Energy Grids Netw. 28, 100527 (2021)
19. Silva, A.R., Estanqueiro, A.: Optimal planning of isolated power systems with near 100% of renewable energy. IEEE Trans. Power Syst. 35(2), 1274–1283 (2019)

20. Shahidehpour, M., Li, C., Wang, X., Huang, W., Nengling, T.: Two-stage full-data processing for microgrid planning with high penetrations of renewable energy sources. IEEE Trans. Sustain. Energy. 12(4), 2042–2052 (2021)
21. Li, C., Yang, H., Shahidehpour, M., Xu, Z., Zhou, B., Cao, Y., Zeng, L.: Optimal planning of islanded integrated energy system with solar-biogas energy supply. IEEE Trans. Sustain. Energy. 11(4), 2437–2448 (2020)
22. Malinauskaite, J., Jouhara, H., Ahmad, L., Milani, M., Montorsi, L., Venturelli, M.: Energy efficiency in industry: EU and national policies in Italy and the UK. Energy. 172, 255–269 (2019)
23. Pride, D., Little, J., Mueller-Stoffels, M.: The value of residential energy efficiency in interior Alaska: A hedonic pricing analysis. Energy Policy. 123, 450–460 (2018)
24. Liang, H., Ma, J., Sun, R., Du, Y.: A data-driven approach for targeting residential customers for energy efficiency programs. IEEE Trans. Smart Grid. 11(2), 1229–1238 (2020)
25. Bohre, A.K., Agnihotri, G., Dubey, M.: Optimal sizing and sitting of DG with load models using soft computing techniques in practical distribution system. IET Gener. Transm. Distrib. 10(11), 2606–2621 (2016)
26. Kayal, P., Chanda, C.K.: Placement of wind and solar based DGs in distribution system for power loss minimization and voltage stability improvement. Int. J. Electr. Power Energy Syst. 53, 795–809 (2013)
27. Afzali, P., Anjom Shoa, N., Rashidinejad, M., Bakhshai, A.: Techno-economic study driven based on available efficiency index for optimal operation of a smart grid in the presence of energy storage system. J. Energy Storage 32, 101853 (2020)
28. Askarzadeh, A.: A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. Comput. Struct. 169, 1–12 (2016)
29. Weather historical data from the state of Milwaukee, (n.d.). Retrieved from: https://www.meteoblue.com/en/weather/archive/export/milwaukee_united-states_5263045.
30. Moradi, M.H., Abedini, M.: A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. Int. J. Electr. Power Energy Syst. 34(1), 66–74 (2012)

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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