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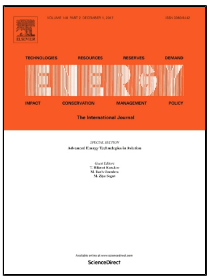

Optimizing a Hybrid Wind-PV-Battery System Using GA-PSO and MOPSO for Reducing Cost and Increasing Reliability

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Highlights

- ✓ A photovoltaic/wind turbine/battery system is simulated and optimized in Tehran.
- ✓ The cost-reliability optimization is carried out by the GAPSO method.
- ✓ Net present cost of the hybrid system is 300200 $ for 2% loss of power supply.
- ✓ The levelized cost of energy for hybrid unit is obtained as 0.502.

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Optimizing a Hybrid Wind-PV-Battery System Using GA-PSO and MOPSO for Reducing Cost and Increasing Reliability

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Abstract

In this paper, a hybrid genetic algorithm with particle swarm optimization (GA-PSO) is applied for the optimal sizing of an off-grid house with photovoltaic panels, wind turbines, and battery. The GA-PSO is one of the most powerful single-objective optimization algorithms. In the other hand, the multi-objective PSO (MOPSO) can solve the optimization problems considering all objectives without transforming them. Minimizing the total present cost including initial cost, operation and maintenance cost, and replacement cost with satisfying the load demand is the main goal of this study. In this optimization problem, the considered reliability factor is a loss of power supply probability, which specifies the subtraction of the load power and generated power. The wind velocity, solar irradiance, and load demand are simulated in 12 months of a year by the HOMER software for a suburbs of Tehran. Then, the optimal size of PV and WT are obtained with both GA-PSO and MOPSO methods, and compared with the HOMER results. At last, the strengths and weaknesses of each method are explained. The results show that the proposed approach with 0.502 of the levelized cost of energy for the PV/WT/BAT system has the best result through the compared methods.

Keywords: Optimization; wind; photovoltaic; battery; GA-PSO; MOPSO.

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Nomenclature

A	Wind turbine rotor swept area (m^2)	$P_{BAT}(t)$	Battery charge at t(kW)
C	Power coefficient of wind turbine	P_{in}	Power injected by PV and WT (kW)
c	Constant weighting parameter	$P_{Load}(t)$	Load demand at t (kW)
C_{BAT}	Per unit cost of battery ($)	P_{PV}	PV panel capacity (kW)
C_{INV}	Per unit cost of inverter ($)	$P_{PV}(t)$	PV power at t (kW)
$C_{M,BAT}$	Maintenance cost of batteries ($/kWh)	$P_{PV\,rated}$	PV rated power for G=1000 w/m^2
$C_{M,PV}$	Maintenance cost of PV panel ($/kW)	P_{WT}	Wind turbine capacity (kW)
$C_{M,WT}$	Maintenance cost of wind turbine ($/kW)	$P_{WT}(t)$	Wind turbine power at t (kW)
C_{PV}	Per unit cost of PV panel ($/kW)	$P_{WT\,rated}$	Wind turbine rated power
C_{WT}	Per unit cost of wind turbine ($/kW)	PF	Penalty factor
CI	Initial cost ($)	R	Random parameter
CM	Maintenance cost ($)	T	Life cycle of system
		TC	Terminal criterion
CR	Replacement cost ($)	V	Wind speed (m/s)
CT	Total cost	V	Particle speed vector
E_t	Total energy generated by the system in one year	V_{Ci}	Cut-in wind speed (m/s)
G	solar radiation at the PV surface (w/m^2)	V_{Co}	Cut-out wind speed(m/s)
gbest	Global best position	W	Weighting parameter
pbest	Particle best position	X	Particle position
H	Height (m)	ρ	Air density
$InfR$	Inflation rate	α	Hellman coefficient

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$IntR$	Interest rate	σ	Battery self-discharge rate
LPS	Loss of power supply	η_{mppt}	PV module efficiency
LPSP	Probability of loss of power supply	η_{REC}	Rectifier efficiency
LCE	Levelized cost of energy ($/kWh)	η_{BAT}	Charge efficiency of battery system
N_{BAT}	Number of batteries	η_{CON}	Converter efficiency
N_{INV}	Number of inverters	η_{INV}	Inverter efficiency
N_{PV}	Number of PV panels	GA	genetic algorithm
N_{PV}^{fail}	Number of failed PV panels	EMS	Energy management system
N_{WT}	Number of wind turbines	PSO	Particle swarm optimization
N_{WT}^{fail}	Number of failed WT	GA-PSO	Genetic algorithm particle swarm optimization
NPC	Net present cost	MOPSO	Multi-objective particle swarm optimization
OF	Objective function		
$P_{BAT}(t)$	Battery charge at t	WT	Wind turbine

1. Introduction

The technology development, population growth and increasing energy demand and consequently increasing the cost and greenhouse gas emissions, all resulted from fossil fuels, have led to more attention to renewable energy resources. The wind and solar energies are the most accessible and important renewable resources which can be integrated together to construct a hybrid energy system with higher quality and reliability than the single resources [1-3]. In fact, the wind and solar energies are the base resources in a hybrid energy system. The batteries energy storage, fuel cells (FC) and diesel generators can be applied to hybrid systems to increase the efficiency and remove the shortcomings. In fact, when the wind speed or solar radiation decreases or a peak demand occurs, the existence of these storage units becomes essential [4, 5]. Hybrid energy

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systems can operate both stand-alone and grid-connected, and also, a control unit can be added for connecting the hybrid system to the power generation circuit at any particular time. The design optimizing and effective sizing of hybrid energy systems are essential to increase the performance and reliability, meet the external load demand, reduce the energy cost and net present cost (NPC), and minimize the greenhouse gas emissions [6]. Therefore, designing a hybrid energy system, which is economically and technically justified, requires the multi-objective optimization stages. In general, the sizing methodologies for the optimal designing of hybrid PV/WT generating systems can be divided into four categories including probabilistic, analytical, iterative, and hybrid methods [6]. The literature study indicates that these methods have been developed, as single-objective and multi-objective, in the form of numerical, analytical and optimization means or through different commercial software.

The studies show that in different single objective problems the total cost is the most applied cost function. Yang et al. [7] optimized the design variables (number of the PV modules, number of wind turbines, number of batteries, the PV module slope angle, and the wind turbine installation height) of a hybrid Solar/Wind/Battery system to achieve the desired loss of power supply probability (LPSP) with minimum annualized cost of system (ACS) concepts through the GA. Kornelakis and Marinakis [8] used PSO as a single objective optimization algorithm for optimizing different design parameters of PV grid-connected systems, such as the PV modules number, in order to achieve to the maximum net economic benefit during the period of the system usage. Khoury et al. [9] designed a PV/Battery system as a backup during the power outage times in a residential building and minimized the cost of the unit via the GA and PSO optimization algorithms. Maleki et al. [10] investigated different optimization algorithms in order to optimize the size of a PV/WT/FC hybrid system for achieving the minimal total annual cost.

Also, the literature survey shows that the HOMER program, for the use of optimization algorithms and the ability to analyze the sensitivity of stand-alone and grid-connected hybrid systems, is the most common software in this field. Kamel and Dahl [11] compared the economic potential and greenhouse gas emissions reduction of the use of a stand-alone hybrid Solar/Wind/Diesel generator case with an alone-diesel generator, using a hybrid optimization model in the HOMER software. After that, Bernal-Agustín et al. [12] investigated the Strength Pareto Evolutionary Algorithm using the HOMER program to the optimal design of a PV/WT/Diesel system for reducing the total cost and greenhouse gas emissions. Also Hafez and Bhattacharya [13] investigated and compared

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several cases containing a diesel-only, a fully renewable-based, a diesel renewable mixed, and an external grid-connected microgrid configuration by the HOMER software in terms of economy and emissions for optimizing the system design parameters and minimizing the life cycle cost. Bhattacharjee and Acharya [14] carried out a techno-economic analysis by the HOMER software for a PV/WT hybrid unit in an educational building located in the north-east Indian with a low wind topography. Baghdadi [15] evaluated the possibility of a PV/WT/Diesel/Battery hybrid unit under the climate of southern Algeria and optimized it by the HOMER software taking into account renewable resources potential and energy demand; while maximizing renewable electricity use and fuel saving are the purpose Singh et al. [16] performed a detailed simulation by HOMER considering manufacturing cost and efficiency for optimizing the size and location of a PV/WT/Battery system. This optimal hybrid unit was able to provide some advantages like lower emission, lower cost of energy and elimination of dummy load over the existing system. Amrollahi et al. [17] investigated the ability of demand response programming in the case of component size optimization of hybrid PV/WT/Battery system in a stand-alone micro-grid. For this purpose, in order to reduce the number of required batteries, the required inverter and the photovoltaic cells capacity, the optimization program was performed by the HOMER software together with the GAMS software via the CPLEX solver. Mohammadi et al. [18] provided an optimal planning approach, by examining different scenarios, in order to select a hybrid power generation system based on 100% renewable energy system (RES) for a residential house located in Tehran, Iran. This study, by using HOMER software, aimed to reduce the energy supply cost and increase the reliability. Halabi et al. [19] studied and compared the use of different power generation systems including all possible standalone diesel generators, hybrid PV/diesel/battery, and 100% PV/battery scenarios for two decentralized power stations in Sabah, Malaysia by HOMER. Recently, Hemmati [20] has already conducted an economic study for home energy management system (HEMS), by applying wind turbine and battery energy storage. The results show that installing wind turbine with battery storage allows home to make profit through selling energy to the grid, when the energy price is high.

The studies on the use of various optimization algorithms for optimization of hybrid energy systems indicate that minimizing the costs of energy are common objectives in the multi-objective optimization. Bilal et al. [21] optimized a hybrid Solar/Wind/Battery system by multi-objective GA for an isolated site, located in the northern coast of Senegal, and investigated the influence of

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the load profiles on the optimal configuration. The objective functions (OF) in this study were minimization of the annualized cost and minimization of LPSP. Also, in another study, Bilal et al. [22] optimized the size of a hybrid PV/WT/Diesel/Battery unit through different data such as wind speed, air temperature, and solar radiation. They conducted the optimization for the Levelized Cost of Energy (LCE) and CO_2 emission by using the Multi-Objectives GA approach. Daud et al. [23] presented a backup control unit for a grid-connected hybrid PV/battery system and optimized the control parameters through the input data of Malaysia for mitigating PV farm output power fluctuations by the GA-based multi-objective optimization. Dufo-López et al. [24] optimized a PV/WT/Diesel/Battery unit in for minimizing the energy cost and CO_2 emissions using a multi-objective optimization. The analysis of different Pareto fronts revealed that applying the diesel generator to the hybrid system is better than gasoline generator, in aspects of the economy and reducing CO_2 emissions. Also, the best Pareto fronts showed that the PV panel is necessary for reducing the emissions and also the wind system without PV panel is not optimal. Tahani et al. [25] applied a hybrid FPA/SA (Flower Pollination Algorithm and Simulated Annealing algorithm) algorithm as a new optimization technique to maximize the reliability and minimize the costs of a hybrid PV/WT/Battery unit for a three-floor building, located in Tehran. Mohamed et al. [26] applied an Artificial Bee Colony algorithm (ABC) to maximize the output power and minimize the life cycle cost of a PV system including photovoltaic, a battery bank, a battery charger controller, and inverter. The ABC algorithm results for the Helwan city (Egypt) were compared with the results of the use of GA for another case in the Zagazig city, and it was found that the ABC was more efficient than the GA. Clarke et al. [27] analyzed a stand-alone desalination renewable energy system with the aim of sizing and power management, by comparing the MOPSO and the HOMER results. Finally, it was found that the optimization by MOPSO showed better results in reducing the NPC and CO_2 emissions. Baghaee et al. [28] have designed a hybrid PV/WT/FC generating system and presented a MOPSO algorithm to minimize the three objective functions namely the annualized cost of the system, the loss of load expected and the loss of energy expected, with maximum reliability. The results reveal that the cost and reliability are under the direct effect of three main components of the unit including a wind turbine, PV array, and AC/DC converter.

In this paper, the main objectives are minimizing the total present cost and maximizing the reliability of a hybrid PV-wind turbine system with energy management (EMS) or battery bank,

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for a place in Tehran, Iran. Based on the literature, this is the first time that such an optimization is conducted. In this work, the hybrid method of GA-PSO is applied as the single-objective algorithm; while the MOPSO is utilized as the multi-objective algorithm for the optimal system sizing. Since the GA-PSO is a single-objective algorithm, and cost is the main objective in the single-objective optimizations, therefore the reliability factor is converted to cost by an optional penalty factor. Then, in order to achieve satisfying load demand, the sizing results of these two methods are compared, and their strengths and weaknesses are determined.

2. Methodology

This paper aims at providing an optimal cost/reliability sizing for a PV/WT/Battery system. The variables in this optimization method are the power of PVs, the wind turbines power, and the batteries capacity. Table 1 shows the estimated cost of the components. It shall be notified that since the problem is solved for a small scale of residential application, the maintenance cost of a wind turbine would be higher than the large-scale turbines [29].The total cost includes all the costs throughout the useful life of the system (20 years), which are translated to the initial moment of the investment

Insert Table 1

2.1. System modeling

The system consists of a wind turbine, a PV source and a battery for energy storage (Fig. 1). There are many different configurations for an electrical generator, but the generator which can be used in a wind power system is the Permanent Magnet DC Generator or PMDC Generator. The same PMDC machine may be driven electrically as a motor to move a mechanical load, or it may be driven mechanically as a simple generator to generate an output voltage. This case makes the PMDC generator ideal to be used as a simple wind turbine generator. The load profile, solar radiation, and wind speed data are simulated by the HOMER for 8760 h in a year. The PV and wind turbine supply the load power. If there is extra power, it must be stored in the battery bank and, in the case of lacking generated power; the batteries must supply the power shortage. A charge regulator regulates the voltage and current going to the batteries and keeps them from

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overcharging. Since electrical devices mostly need AC power to work, the inverter converts the DC to the AC so that the renewable system can supply the electrical load demand.

Insert Fig. 1

- Photovoltaic array

The power, generated by a PV, depends on the cell temperature and solar radiation. The power generation of a PV array is shown by Eq. 1:

$$P_{PV} = P_{PV\,rated} \times \frac{G}{1000} \times \eta_{mppt} \tag{1}$$

where G is solar radiation at the PV surface (w/m^2), $P_{PV\,rated}$ is the PV rated power for G=1000w/m^2, and η_{mppt} is the module efficiency. Usually, the PV generation stays around maximum power point, because of a charge controller which uses the maximum power point tracking system [30].

- Wind turbine generator

The wind turbine generates power when the wind velocity (wind speed) is within the cut-in and cut-out velocity, and it depends on the wind velocity, air density, and windmill area. The power, generated by a wind turbine, is shown by Eqs. (2.a) and (2.b) [30-32].

$$P_{WT} = \begin{cases} 0 & V < V_{Ci}, V > V_{Co} \\ \frac{1}{2}\rho C A V^3 & V_{Ci} \le V \le V_{Co} \end{cases} \tag{2.a}$$

where, ρ is the air density (Kg/m^3), A is the windmill area perpendicular to the wind (m^2), C is the power coefficient of the wind turbine, and V is the wind velocity (m/s) at the height of turbine hub, which is calculated according to:

$$\frac{V_2}{V_1} = \left(\frac{H_2}{H_1}\right)^{\alpha} \tag{2.b}$$

Having V1 as the wind velocity at a reference height denoted by H1, and α is the Hellman coefficient. In this study, $\rho = 1.08$, C=0.42, α=0.25, H_1=10 m and H_2=40 m.

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- Battery energy storage system

Energy management system is widely used for renewable energy generators, especially in PV and WTs, because of the unpredictable nature of the wind and solar irradiation. The extra electricity, generated by PV and WT, is stored in the battery bank and, in the case of electricity deficiency; it supplies the required load demand. The power of the battery in charge and discharge state is obtained by Eq. (3) [33]:

$$P_{BAT}(t) = P_{BAT}(t-1) \times (1-\sigma) + \left[\left(N_{PV} \times P_{PV}(t) \times \eta_{CON} + N_{WT} \times P_{WT}(t) \times \eta_{REC}\right) - \frac{P_{Load}(t)}{\eta_{INV}}\right] \times \eta_{BAT} \quad (3)$$

where $P_{BAT}(t)$ is the battery charge at time,t, and $P_{BAT}(t-1)$represents the charge amount at time $t-1$. Also, σ is the battery self-discharge rate, η_{CON} is the converter efficiency, η_{REC} is the rectifier efficiency, $\eta_{INV}$is the inverter efficiency, η_{BAT} is the charge efficiency of the battery system, and $P_{Load}(t)$is the load demand. N_{PV} and N_{WT} are the numbers of PV panels and wind turbines.

If the generated power by renewable resources is less than the power demand, discharging begins. In this paper, the discharge efficiency is supposed to be unity. Then, the power of the battery in the discharge state is shown by Eq. (4) [30]:

$$P_{BAT}(t) = P_{BAT}(t-1) \times (1-\sigma) - \left[\frac{P_{Load}(t)}{\eta_{INV}} - \left(N_{PV} \times P_{PV}(t) \times \eta_{CON} + N_{WT} \times P_{WT}(t) \times \eta_{REC}\right)\right] \Big/ \eta_{BAT} \quad (4)$$

- Energy management strategy

The PV power and wind power depend on the solar radiation, wind velocity, and temperature, so these are uncertain and changed hour by hour. The load demand also varies according to the user energy demand. The power injected by PV and WT is defined by Eq. (5) [34]:

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$$P_{in}\left(N_{PV}^{fail},N_{WT}^{fail}\right) = \left(N_{PV} - N_{PV}^{fail}\right) \times P_{PV} + \left(N_{WT} - N_{WT}^{fail}\right) \times P_{WT} \quad (5)$$

where, N_{PV} and N_{WT} are the total installed PV panels, and WTs, N_{PV}^{fail}, and N_{WT}^{fail} are the failed PV panels and WTs; the failures indicate the unavailability of power sources. Then, the output power is distributed between the load and the battery storage system through the following strategy:

- If $\boldsymbol{P_{in}}$ is equal to the power demand, all the load demand is supplied by the power sources, and there is no storage and extraction from the batteries.
- If $\boldsymbol{P_{in}}$ is higher than the required power demand, all the load demand is fulfilled by the power sources, and the excess power is stored by the storage system. If the excess power is more than the batteries rated power, a portion of the power will be lost.
- If $\boldsymbol{P_{in}}$ is less than the required power demand, the storage system supplies the shortage power. If the shortage power is more than the batteries rated power, a part of the load will be lost.

2.2. The system cost and reliability model

The total cost (CT) of the system includes the initial cost (CI), maintenance cost (CM) and replacement cost (CR), which are obtained from equations (6-9) [35-37]:

$$CT = CI + CM + CR \quad (6)$$

$$CI = \left(N_{PV}C_{PV}\right) + \left(N_{WT}C_{WT}\right) + \left(N_{BAT}C_{BAT}\right) + \left(N_{INV}C_{INV}\right) \quad (7)$$

Where, C_i is per unit cost of $the\ i^{th}$ component and N_i is the number of ith component.

$$CM = (N_{PV}C_{M,PV} + N_{WT}C_{M,WT} + N_{Bat}C_{M,BAT})\sum_{t=1}^{T}\left(\frac{1+InfR}{1+IntR}\right)^{t} \quad (8)$$

where, $C_{M,i}$ is per unit maintenance cost of $the\ i^{th}$ component, $InfR$ is the inflation rate, $IntR$ is the interest rate, and t is the life cycle of the components which is 20 years.

In this study, it is assumed that only batteries and inverter need replacement, so the replacement cost is obtained by:

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$$CM = (N_{BAT}C_{BAT} + N_{INV}C_{INV})\sum_{t=1}^{T}\left(\frac{1+InfR}{1+IntR}\right)^{t} \quad (9)$$

The subtraction of the load power at each hour and the generated power from the renewables, expressed by the loss of power supply (LPS) and LPSP, would the probability of the LPS's occurrence in a complete year (8760h), as shown in Eqs. (10.a,b):

$$\mathrm{LPS} = \sum_{t=1}^{8760}\left[P_{Load}(t) - \left(P_{PV}(t) + P_{WT}(t) + P_{BAT}(t)\right)\right] \quad (10.a)$$

where $P_i(t)$ is the power quantity of ith resource at time t.

$$\mathrm{LPSP} = \frac{\sum_{t=1}^{8760}\mathrm{LPS_t}}{\sum_{t=1}^{8760}\mathrm{P_{Load}(t)}} \quad (10.b)$$

where $\mathrm{LPS_k}$ is the loss of power supply at each hour, and $\mathrm{P_{Load}(t)}$ is the load demand at each hour.

2.3. Optimization algorithms

- Particle swarm optimization (PSO)

PSO is a population-based stochastic approach for solving continuous and discrete optimization problems which arose from swarming behaviors were observed in schools of fish, flocks of birds, a swarm of bees and even human social behavior [38-40]. In PSO, a population of particles moves in the search space of an optimization problem. The position of a particle represents a candidate solution to the optimization problem at hand. Each particle searches for better positions in the search space according to its local best position and global best position [41, 42]:

$$\mathrm{v_k(i+1) = w(i) \times v_k(i) + c_1 \times r_1\left(pbest_k(i) - x_k(i)\right) + c_2 \times r_2\left(gbest(i) - x_k(i)\right)} \quad (11)$$

$$\mathrm{x_k(i+1) = v_k(i+1) + x_k(i)} \quad (12)$$

$\mathrm{k = 1,2,\ldots,N_p}$ and $\mathrm{i = 1,2,\ldots,i_{max}}$

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where, x_k and v_k represent the particle's position and velocity, k is the particle's index, i is the iteration number, $r_1$and $r_2$are the randomly generated numbers between 0 and 1 and $c_1$and c_2 are learning factors.

First of all, the PSO generates a random population and a random initial velocity for each particle in the search space. Then, the algorithm calculates the objective function for all particles. Here, pbest is the best experience of each particle, and gbest is the best experience of all particles in the population. The position and value of the objective function for gbest and pbest must be stored after each iteration, and after the initial evaluation, the iterative loop begins. The algorithm calculates the objective function for all particles and updates the pbest and gbest. If the termination criterion (TC) is satisfied, the optimal solution is gbest, and the algorithm is ended, otherwise the loop repeats. In this study, TC is the specific number of iterations (100 iteration). Also, a population size of 50 particles is defined for PSO approach. Each particle has three variables as the PV power capacity, WT power capacity and battery energy storage capacity. The search space for the variables is 0 to 1000 kW for the PV and WT, and 0 to 1000 kWh for the battery. In the initialization step, random positions are assigned to each particle. Then, in the next 100 iterations, the positions and velocities are updated according to Eq. 11 and Eq. 12 to obtain the lowest cost function.

- Genetic algorithm

The genetic algorithm is a method, inspired by natural selection, to find the solution for optimization problems [43]. As Tomassini summarized [44], the idea is to adapt a population to environmental conditions like what happens for genes in nature. Each individual of the population has its own characteristic, and in this technique, the bad and ineffective traits must be eliminated, while the helpful behaviors must be improved. The genetic algorithm is an evolutionary algorithm with evolution strategies and evolutionary genetic programming. The solutions, found by this way, are similar to the real populations that are adapted to the natural environment. The algorithm starts with a randomly-generated individual. In this study, 50 randomly initialized individuals are considered as the population. Each individual has three variables with a search space similar to the proposed PSO approach. In each iteration, new populations are generated by applying certain stochastic operators through a loop, called the generation. These operators are as crossover and mutation. Crossover is the process of taking two parents and producing two children solution from

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them. The crossover rate of 0.8 assigns the number of parents which are included in the crossover operation, and it means that in each iteration, 40 parents are taken in order to generate 40 children. The other operator, called mutation, is a randomly change in one gene value of an individual from its initial state. Mutation is a kind of error, and if the mutation rate is set low, it may lead GA to a better solution. Here, the mutation rate is 0.1 which means five individuals meet mutation operation in each iteration. After the generation, 50 best solutions are selected to continue the algorithm for 100 iterations.

This iterative process can be summarized as followings [44]:

I. *Iteration = 0*
II. *Seed population*
III. ***While** not (termination condition) **do***
IV. *Iteration= Iteration+1*
V. *Calculate fitness*
VI. *Selection*
VII. *Crossover*
VIII. *Mutation*
IX. ***End while***

Fig. 2 shows the optimization and simulations algorithm. The process of optimization by the GA-PSO algorithm is described at the GA-PSO algorithm subsection in the following.

Insert Fig. 2

- GA-PSO algorithm

In this study, a hybrid GA-PSO method is proposed which executes the genetic algorithm and particle swarm optimization simultaneously, selects the best-evaluated population from the GA, and optimizes it by the PSO in any iteration [40]. The first step is initializing the GA and PSO subsystems. Then, both algorithms are executed simultaneously, and the best solution is memorized. After executing a specified number of iterations (termination criterion), the program running stops and the best solution are announced as the final solution. In this paper, the percentage

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of using GA and PSO in the hybrid system is equal. Fig. 2 shows the GA-PSO flowchart, and the GA-PSO algorithm processes are summarized as followings [36]:

Step-1: Set population size ($2*P_s$), maximum number of generations (Mg), the probability of crossover (P_C), the probability of mutation (P_m) and the bounds of decision variables.

Step-2: Set $t = 0$. [t presents the generation/iteration number]

Step-3: Initialize the chromosomes/particles of the population P(t).

Step-4: Compute the fitness function for each chromosome of P(t).

Step-5: Find the global best chromosome/particles (P_g) having the best fitness value.

Step-6: Divide the chromosome/particles into two groups, viz. $P_{GA}(t)$ and $P_{PSO}(t)$ with equal population size.

Step-7: Repeat the following until the termination criterion is satisfied:

i. Increase the value of t by unity.

ii. Apply GA for population $P_{GA}(t)$.

iii. Apply crossover & mutation operators on $P_{GA}(t)$ to produce new population $P_{GA}(t)$.

iv. Find the best chromosome (P'_g) from the current population $P_{GA}(t)$.

v. Compare P'_g with earlier best chromosome P_g and store better one in P'_g.

vi. Set $t = t + 1$.

vii. Select the population $P_{GA}(t)$ from the population $P_{GA}(t-1)$ of $(t-1)$- th generation using tournament selection.

viii. Apply PSO for $P_{PSO}(t)$.

ix. Improve the best position of each particle by comparing the position of all chromosomes of $P_{GA}(t)$.

x. Compute the velocity of each particle.

xi. Obtain the new position of each particle.

xii. Improve the position of each particle and also find the global best particle (P_g).

Step-8: Print the position and fitness of global best particle.

Step-9: End.

The parameters of the algorithms used in this paper are summarized as follows:

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PSO : N=50 ; c1= 2 ; c2 = 2; β = 0.99 ; w =1; maximum iteration = 100;

GA: N=50; Mutation rate = 0.1; crossover rate = 0.8 maximum iterations = 100;

The search space for variables is 0 to 1000kW for PV and WT and 0 to 1000kWh for battery. Since the GA-PSO is a single objective algorithm and the cost function is the final objective, the reliability factor must be converted to cost. The weighted summation method counts the primary cost function in addition to weighted cost, obtained from LPS, multiplied by an optional penalty factor. The total cost of the components plus the capacity shortage penalty factor, yield in the total net present cost (NPC). In this study, the penalty is considered as 5.6$ / kWh, which is an average capacity shortage penalty [29].

$$NPC = CT + PF \times LPS \quad (\$) \tag{13}$$

Moreover, the levelized cost of energy (LCE) term is used to find the cost of the generated unit of energy. This term is the ratio of the total yearly cost of the system components to the total yearly energy provided by the system [45]. The LCE can be calculated as:

$$LCE = \frac{NPC}{E_t} \ (\$/\text{kWh}) \tag{14}$$

where E_t (kWh/year) is the total energy, generated by the system in one year.

In this study, the cost optimization has been implemented for 2%, 5% and 10% of the maximum LPSP. The $P_{PV\,rated}$, $P_{WT\,rated}$ and the number of batteries are the first positions in the PSO. So that, after few iterations, the optimal cost of these variables are obtained. Also, the minimum and maximum bounds for the PV panels and wind turbines are 0 to 200, while these are 0 to 300 for the batteries. Three different scenarios are considered for the simulation:

- PV and battery bank system
- WT and battery bank system
- PV, WT and battery bank system

- Multi-objective particle swarm optimization (MOPSO)

Many real world problems have two or more objectives to be obtained. In these problems, objectives may be in conflict, and a tradeoff between possible solutions is the optimal point [46-48]. In this study, the system cost and risk are the objectives. The PSO algorithm is an inherent

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single-objective optimizer while, in multi-objective problems, an absolute global optimum does not often exist. Thus, to make the PSO algorithm capable of dealing with multi-objective optimization problems, some modifications become necessary. The personal best performance (pbest) of each individual particle is replaced with the new solution, if and only if, it dominates the former pbest. Also, two major issues should be considered in the updating process of the global best performance (gbest).

Firstly, the fitness assignment and selection should be addressed, such that a search can move towards the Pareto optimal set. Fitness is proportional to the dominance rank of solutions. The MOPSO, which is used in this study, is a dominance-based method.

Secondly, the diversity of the swarm should be maintained to prevent premature convergence and obtain an evenly distributed Pareto optimal front [28]. In this paper, an archiving mechanism was employed to form a repository, which may contain only a limited number of solutions. Compared to the conventional archiving, this approach shows a better performance in terms of both diversity and optimality and less complexity.

3. Results and discussion

3.1 Irradiance/wind/ load data

The simulated radiation for a house in Tehran by the HOMER software is shown in Fig.3. The latitude and the longitude are considered as *35°* 6892' S and *51°* 3890'E, respectively. As expected, the solar radiation varies in each hour, day and month. The average solar radiation for Tehran is 5.2$kWh/(m^2/day)$ and the maximum occurs in June with nearly 7.5 $kWh/m^2/day$. Also, the month with minimum solar radiation is December with nearly 2.5$kWh/(m^2/day)$. Fig. 3(a,b) shows the monthly radiations and the distribution of solar radiation in hours for one day in each month, respectively.

Insert Fig. 3

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The wind velocity (v) data, obtained from the Renewable Energy Organization of Iran`s anemometric stations, is shown in Fig. 4(a,b). The average wind speed in Tehran is 7.5 m/s which can lead to generate power at nights, unlike solar radiation.

Insert Fig. 4

The load demand is simulated by the HOMER for a residential section with an average demand of 210 kWh per day. As shown in Fig. 5(a, b), the electricity consumption in summer is more than other seasons. Two peaks occur in the load demands between 12 to 18 and 18 to 24 in summer. Also, the load demand in August and February is maximum and minimum, respectively.

Insert Fig. 5

3.2 The GA-PSO Results

The GA-PSO was the first algorithm which was used to optimize the problem, and the simulation results of GA-PSO are shown in Figs. 6 to 8. The algorithm starts with an initial evaluation and continues until the termination criterion (TC) is satisfied. The LPSP with three levels of 2%, 5%, and 10% is considered to have wider choices. Since the using a hybrid renewable energy system has a capital cost more than using PVs or wind turbines individually, the optimization is done for three different systems. The WT/Battery is considered as the first system and Fig.6 (a, b, c) shows the optimization results for the first system with three different levels of LPSP. As Fig. 6 (a, b, c) shows, the optimization is done for 100000 numbers of function evaluations (NFE). Approximately after 20 iterations, the optimal point for 2% and 5% of LPSP is obtained. For 10% of the LPSP, the optimal point is obtained after nearly 100 iterations. The detailed information is reported in Table 2(a).

Insert Fig. 6

Insert Fig. 7

Insert Fig. 8

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Fig. 8 (a,b,c) shows the optimization results for three different levels of the LPSP for this case. As Fig. 9 shows, nearly after 20000 NFEs, the optimal point for 2% and 5% of LPSP is obtained. For 10% of the LPSP, the optimal point is obtained after about 100 iterations. The detailed information is represented in Table 2(c).

The first system with WT and battery cannot use suitable solar irradiance of the area, and the second system with PV and battery needs too much storage for the night since PV is not able to provide electricity to meet the load demand. The third system, with employing PV, WT, and battery, applies all the energy production capacity and obtains the minimum total cost.

The results of cost, power, and the capacity of the components are summarized in Table 2 (a,b,c). The total cost includes the investment cost, the operation and maintenance (O&M) and replacement cost of PVs, also the costs of WTs, inverter, and batteries for 20 years, plus minor items like charge controller and installation costs.

Insert Table 2

3.3 The MOPSO Results

In the last section, the optimum cost function is evaluated for three systems with different penalty factors. In this part, both reliability and cost objectives are considered simultaneously. It is obvious that each point with lower cost and higher reliability (lower risk) is a better point than the others, but some points have lower cost and higher risk, while some points are vice-versa. Since there is no advantage for any objective, all points that make a curve combined with the best costs and reliabilities, are considered as the best points. This method's name is the none-dominated sorting optimization, and the curve's name is the Pareto front.

The red stars in Fig.10are the Pareto front points and the black circles are the non-optimum points which are dominated by the Pareto front. Similar to the single objective optimization, three scenarios are considered and simulated. It is evident that the optimum results of the single objective optimization are procurable from the multi-objective optimization. The blue rectangles are the optimum points with 2%, 5%, and 10% of LPSP, which are obtained from single objective optimization too.

The multi-objective optimization, compared to the single objective optimization method, gives a wider choice of optimal point. By this method, it is possible to have the cost of the system for any

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value of LPSP. For the first hybrid system, consisting PV/WT/Battery with 0% of LPSP, the total cost is nearly 800000$. If a lower cost is desired, the lower values of LPSP must be chosen, and there would be a tradeoff between the cost and the LPSP. For example, for 20% of LPSP, the total cost is 250000$, and it is about one-third of the previous choice, as shown in Fig. 9. Figs. 10 and 11 show the other scenarios' results. The black circles are the initial population, and the red stars indicate the Pareto front in Figs. 9 to 11. Also, the 2%, 5% and 10% of LPSP are marked with blue rectangles.

Insert Fig. 9

The MOPSO method was also applied to the hybrid WT/Battery system, and the Pareto front was obtained. If the loss of the load is not acceptable (LPSP=0), the total cost would be nearly 1400000$, so 20% of the LPSP costs 500000$.

Insert Fig. 10

Fig.11 represents the Pareto front of the hybrid PV/Battery system. The costs of this case are less than that of the WT/Battery system. For 0% of LPSP, it costs 1100000$, and the total cost for 20% of LPSP is 300000$. As expected from the GA-PSO results, the hybrid PV/WT/Battery has a lower cost compared to the other two systems.

Insert Fig. 11

3.4. Comparison of the results

For evaluating the validity of the proposed approach, the LCE factor is considered. Based on the average solar radiation and wind speed maps, the techno-economically optimized systems are designed by simulating the behavior of various combinations of renewable energy systems with different sizing. This is the same method by which, the HOMER software obtains the optimal sizing. As shown in Table3, the GA-PSO results have been compared with the HOMER software. Also, with two cities of ref. [29], the comparison has been done for the LCE factor (shown in Table 4). The researchers in [29], have applied an optimization in four different cities, among those, the Moaleman and Nikouye cities have earned the best results for the hybrid PV/WT/battery

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unit, and the maximum LPSP of 2%. It is shown that the cost of components is the same with [29]; nevertheless, the load data is different. For the proposed approach, ref. [29] and the HOMER optimization average daily loads are 210 kWh, 220kwh, 400kwh, for the GA-PSO method, HOMER optimization, and ref. [29]. The Nikouye and Moaleman cities are 5.2 kWh/m^2/day, 5.2kwh/m^2/day, 5 kWh/m^2/day, and 5.77 kWh/m^2/day, respectively. The average wind velocity for the GA-PSO method and HOMER optimization is 7.5 m/s; this velocity is 7.2 m/s and 6.1 m/s for ref. [29]. As shown in Table 3, even though the wind and solar resources in the GA-PSO and HOMER are exactly equal and approximately equal to ref. [29], the GA-PSO has the best result among different methods. The deviation percentage between the proposed method's LCE and the LCE of [29] for Moaleman and Nikouye is 6% and 10%, respectively. The difference between the algorithms like GAPSO and the HOMER optimization is that the HOMER must calculate all modes of variables without any history of variables` best global and personal results. It is actually like a try and error process. But, in the GAPSO method, the relationship between the variables cause more convergence rate and better result.

Insert Table 3

Insert Table 4

To show the impact of cost function, from the electrical load data, the LCE for different load data are also plotted in Fig.12

Insert Fig. 12

As shown in Fig.12 for different electrical load data between 150 (kWh/d) to 350 (kWh/d), the LCE is about 0.5 to 0.7 ($/kWh). The red foursquare is the load data, considered for simulations in this paper (210kWh/d).

4. Conclusion

In this paper, a hybrid PV-WT generating unit with a battery bank for storing extra electricity, generated by PV and WT, was designed and the load profile, solar radiation, and wind speed data were simulated by the HOMER for 8760 h in a year in an off-grid house in Tehran, Iran. The GA-

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PSO and MOPSO methods were applied for the optimal system sizing with two objectives including maximizing the system reliability and minimizing the total present cost. Then, the sizing results were compared to achieve the satisfying load demand. Three different scenarios were considered for the simulation, including PV panel and battery bank system, wind turbine and battery bank, and PV panel-wind turbine with battery bank system. In the optimization through GA-PSO, as a single objective algorithm, the LPSP was considered as the reliability factor, and 5.6 $/kWh penalty factor was determined for the capacity shortage.

The results show that the PV/WT/BAT system has lower cost, compared to the PV/BAT and WT/BAT systems in all three levels of LPSP. So, the PV/WT/BAT system is the best choice for this case. The best-obtained NPC for the PV/WT/BAT system was 787193$ for 2% of the maximum LPSP which is 42.17% less than the WT/BAT system and 17.17% less than the PV/BAT system. For 5% of the maximum LPSP, the total NPC of 644235$ is obtained as the best result for the PV/WT/BAT system; which is 29.91% less than the WT/BAT, and 16.68% less than the PV/BAT system. For 10% of the maximum LPSP, the best total NPC was 508540$ for the PV/WT/BAT system; which is 28.24% less than the WT/BAT and 20.22% less than the PV/BAT system. Through the MOPSO, the cost and reliability are optimized simultaneously, as the two objectives. Also, three Pareto fronts are obtained for the three systems, which can be used in order to find the sizing strategy with the lowest cost in every level of maximum LPSP. The comparison results show that the proposed approach with 0.508 of LCE, represents a deviation between 7% and 10%.

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Table1. Cost of the components [29]

Item	PV Panel	Wind Turbine	Battery Bank	Inverter, Charge Regulator
Rated power	1 (kW)	1 (kW)	1 (kWh)	1(kW)
Lifetime (year)	20	20	5	10
Investment cost ($)	2000	3200	100	700
Maintenance Cost ($/year)	33	100	5	0

Table 2. The optimum cost of components for PV/WT/Battery (a), WT/Battery (b), and PV/Battery (c)

A.

MAX LPSP	PV (kW)	WT (kW)	Battery (KWh)	Inverter (kW)	Total NPC ($)
2%	82	25	190	33	787193
5%	62	25	148	33	644235
10%	47	25	98	33	508540

B.

MAX LPSP	PV (kW)	WT (kW)	Battery (KWh)	Inverter (kW)	Total NPC ($)

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2%	0	166	370	33	1361403
5%	0	120	230	33	919202
10%	0	92	150	33	708695

C.

MAX LPSP	PV (kW)	WT (kW)	Battery (KWh)	Inverter (kW)	Total NPC ($)
2%	144	0	241	33	950412
5%	104	0	224	33	773241
10%	81	0	192	33	637476

Table 3. Comparison with HOMER software

Method	PV (kW)	WT (kW)	BAT (kWh)	Wind Vel.	Irradiance ($kWh/m^2/d$)	Inverter (kW)	LCE ($/kWh)	NPC ($)	LPSP
GA-PSO	82	25	190	7.5	5.2	33	0.508	787193	0.02
HOMER	165	54	350	7.5	5.2	65	0.511	1652300	0.02

Table 4. Comparison results

Method	PV(kW)	WT(kW)	BAT(kWh)	Wind Vel.	Irradiance	LCE
GA-PSO	82	25	190	7.5	5.2	0.508
***[29]* Moaleman**	61	22	434	6.1	5.8	0.540

[29] **Nikouye**	35	30	360	7.2	5	0.560

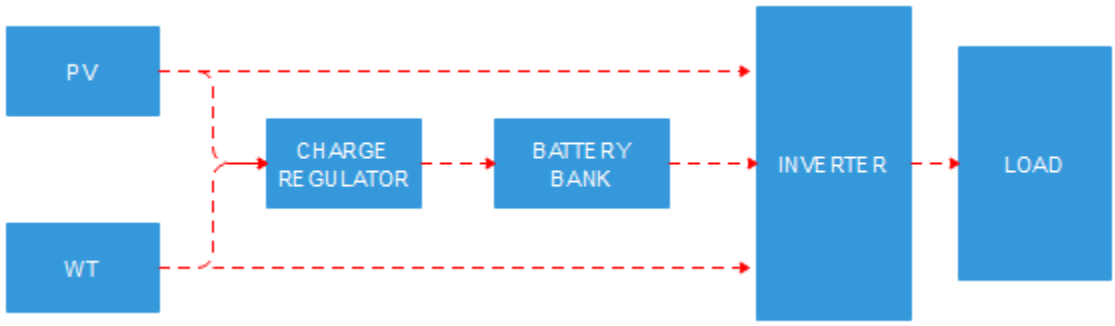

Fig.1. Simple diagram of the PV/WT/Battery system

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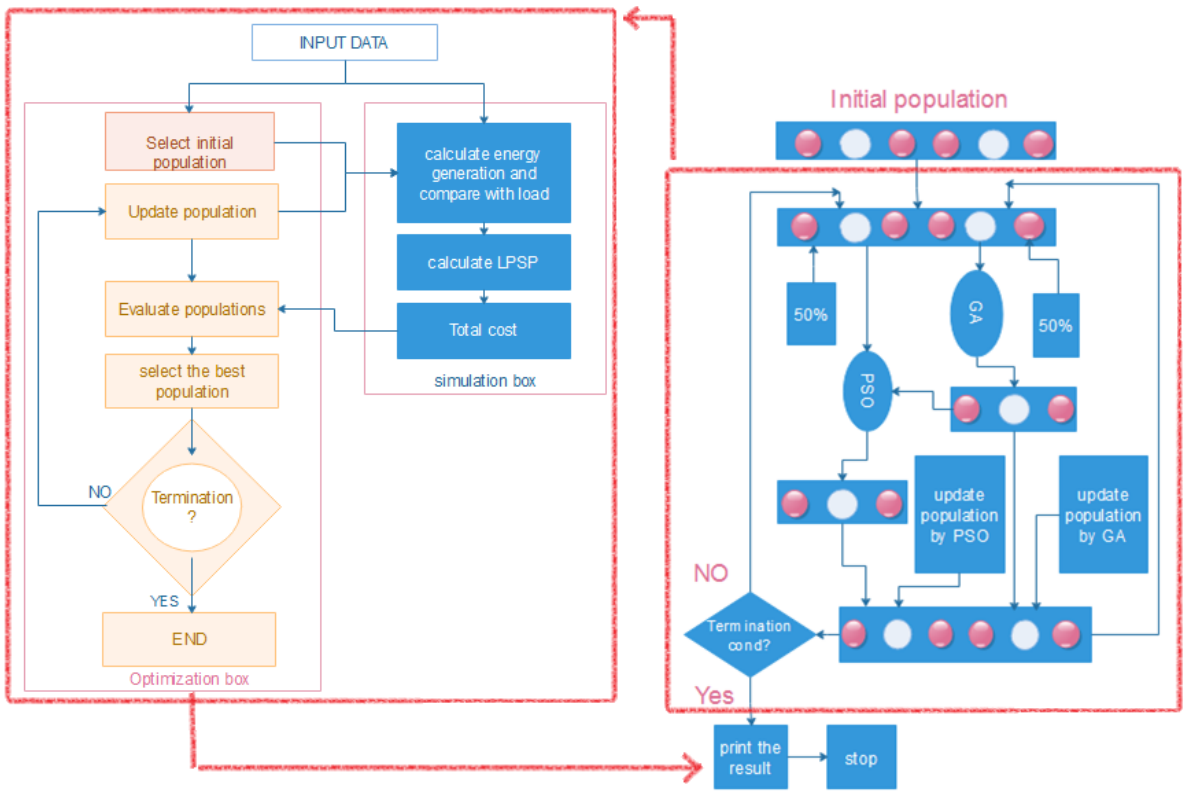
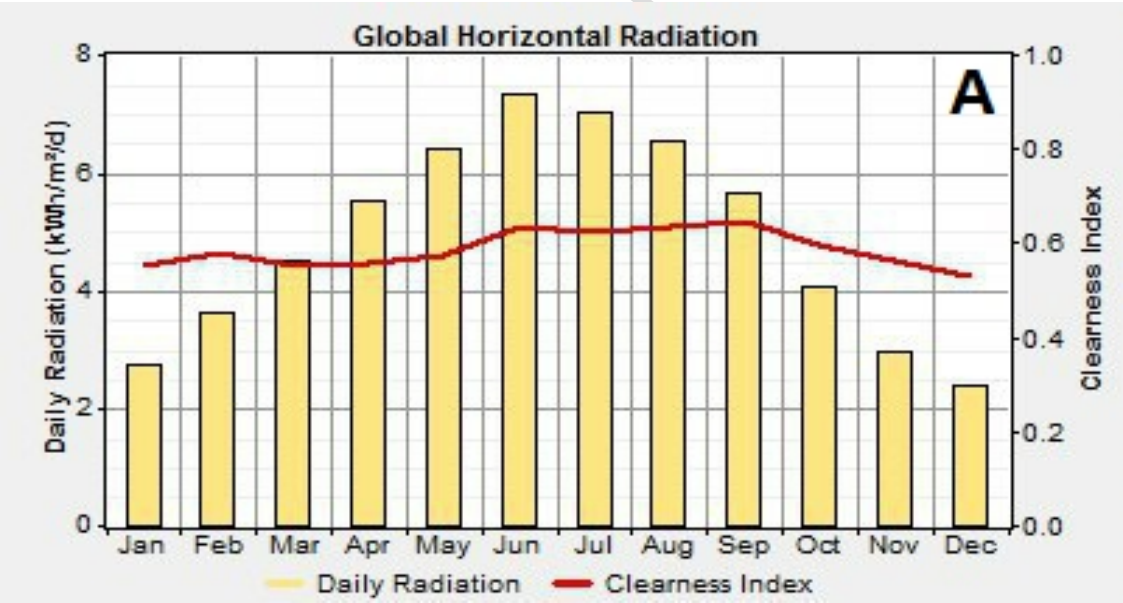


Fig. 2. Optimization and simulation flowchart



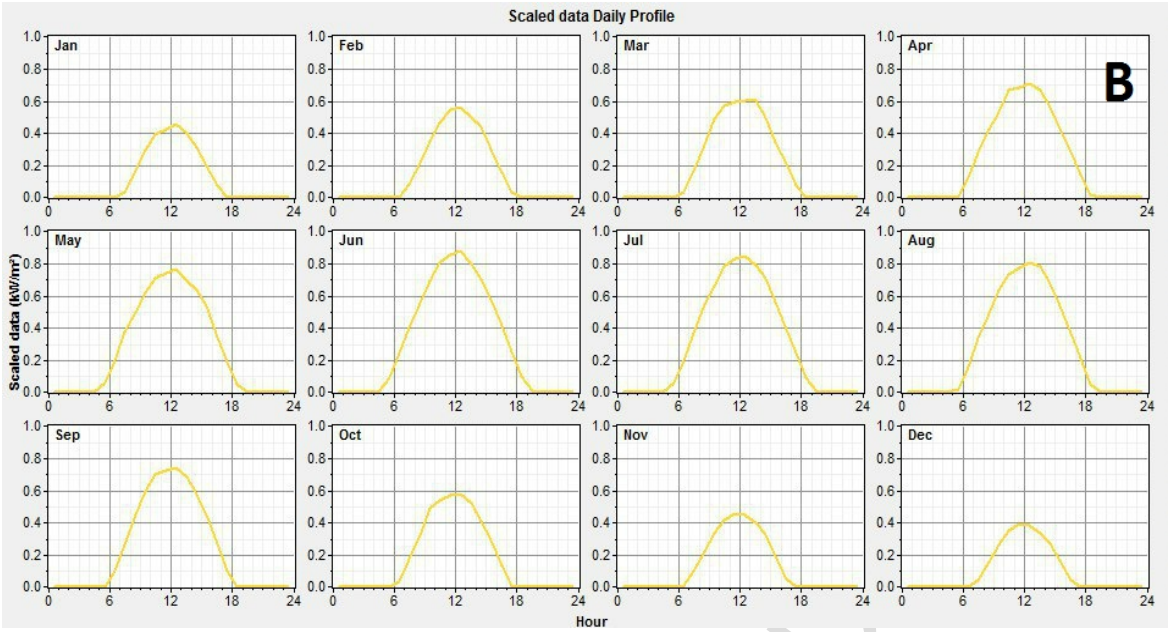


Fig. 3. The mean monthly (a) and hourly (b) solar radiation in one year in Tehran, Iran

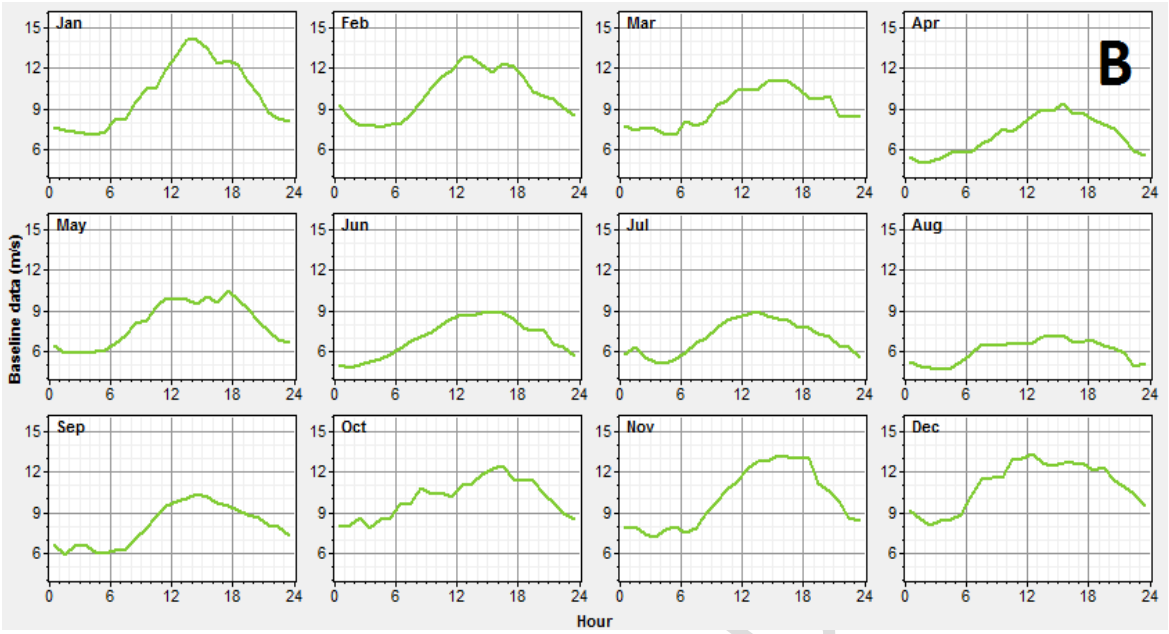
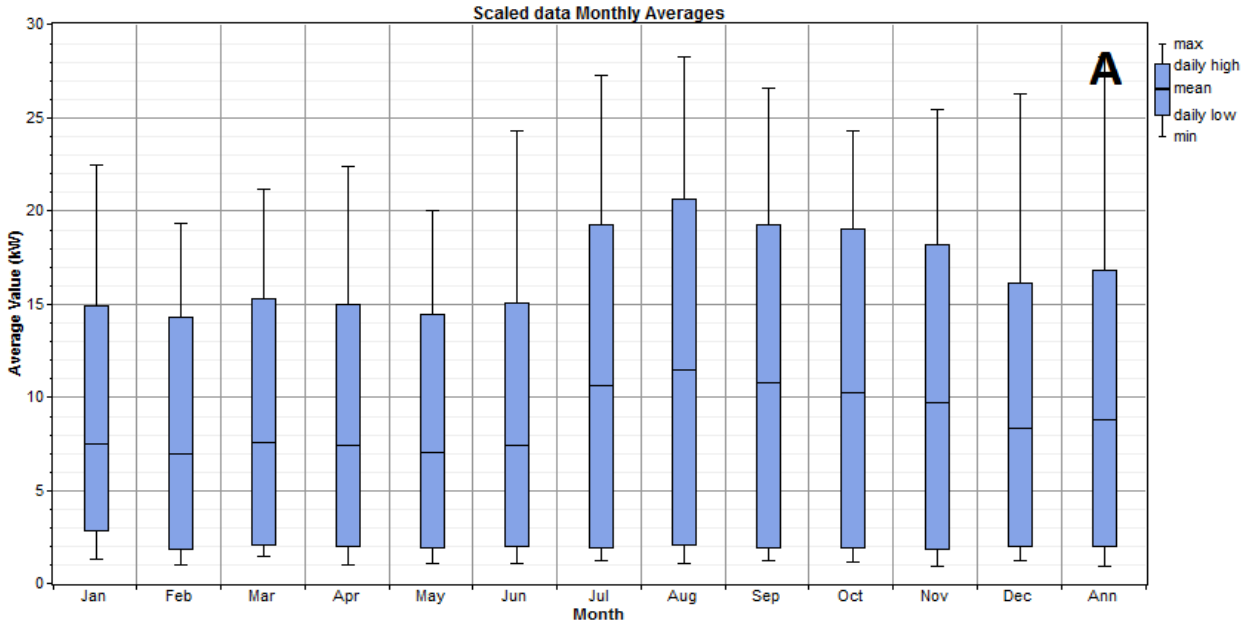


Fig. 4. The mean monthly (a) and hourly (b) wind velocity [48]



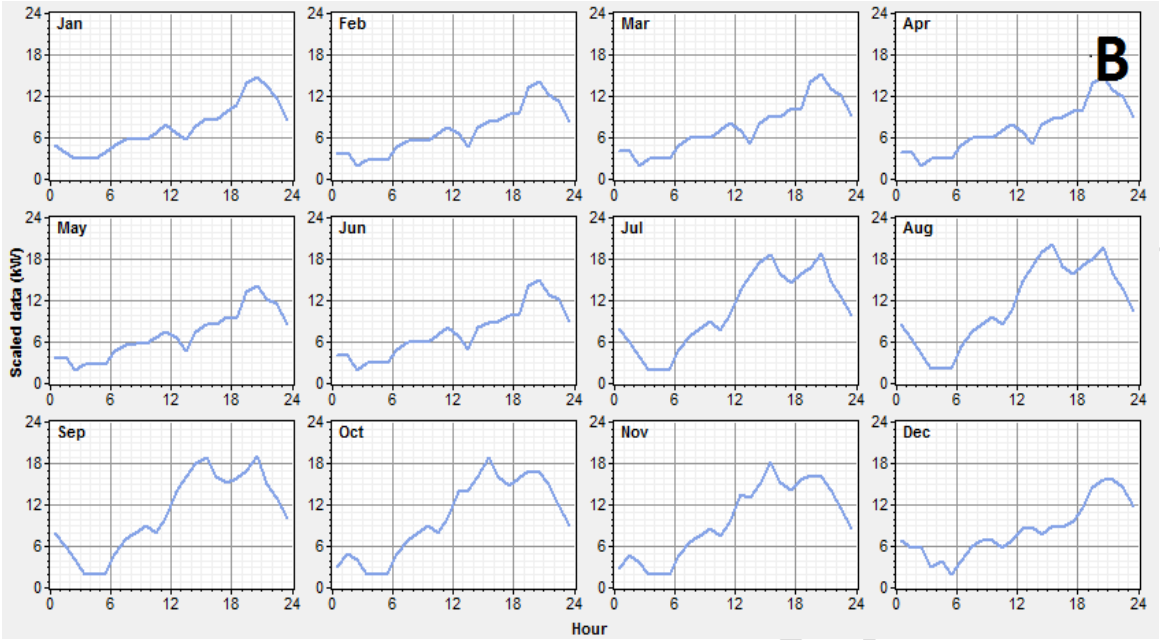
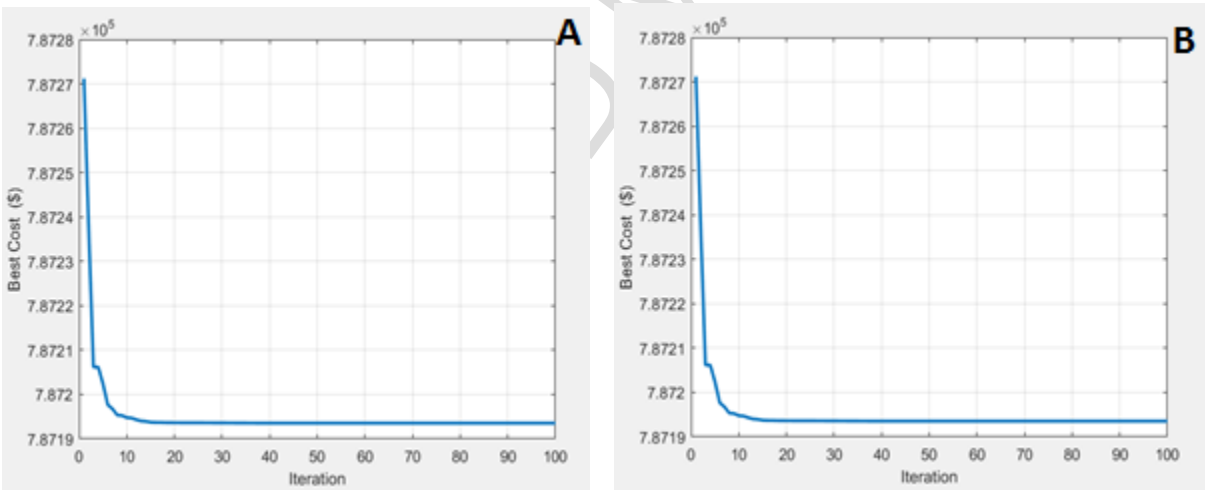


Fig. 5. Monthly (a) and hourly (b) load demand diagram for a residential section



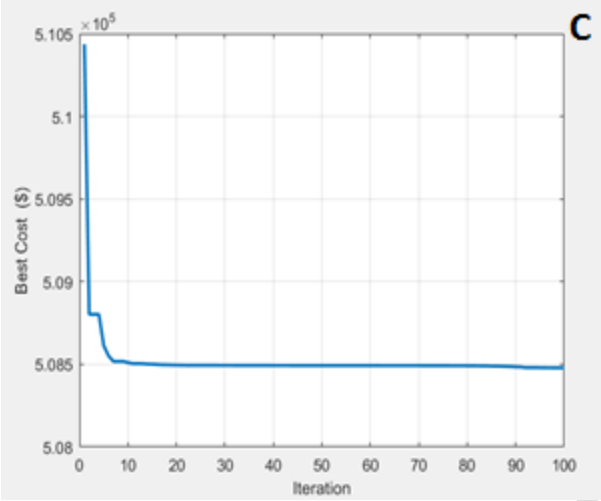
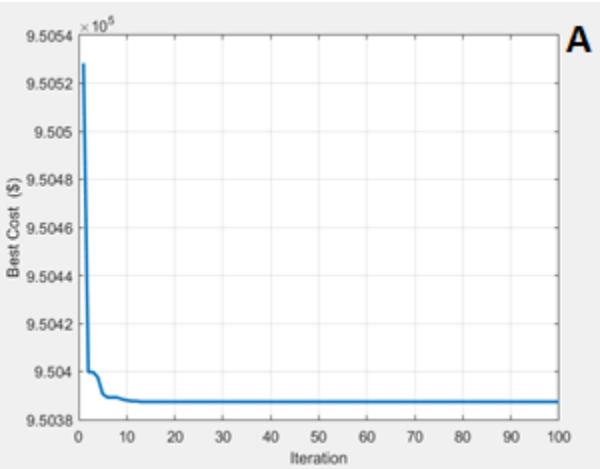
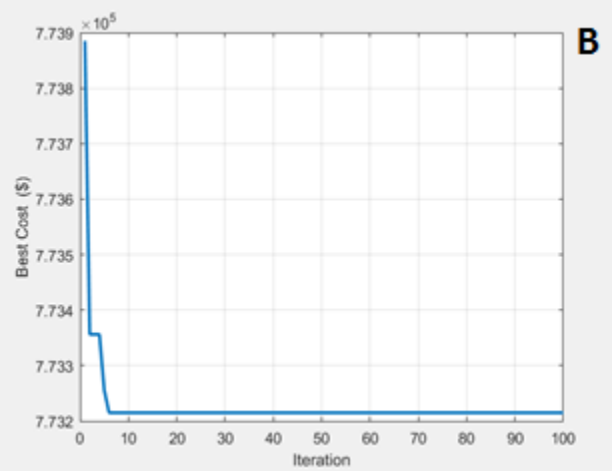


Fig. 6. Single objective optimum solution for the hybrid PV/WT/Battery system with 2% (a), 5% (b), and 10% (c) of LPSP





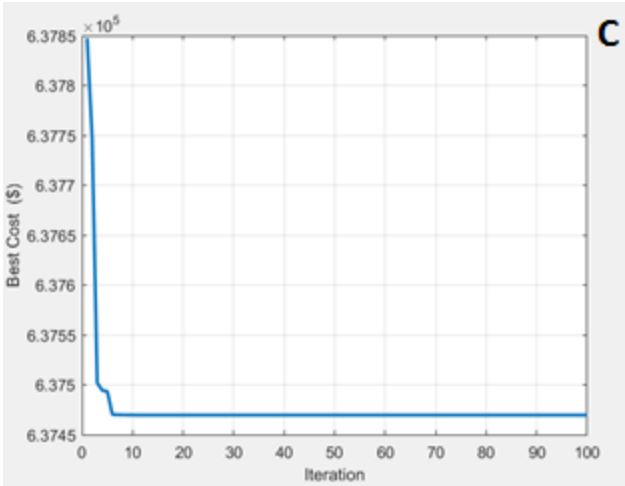
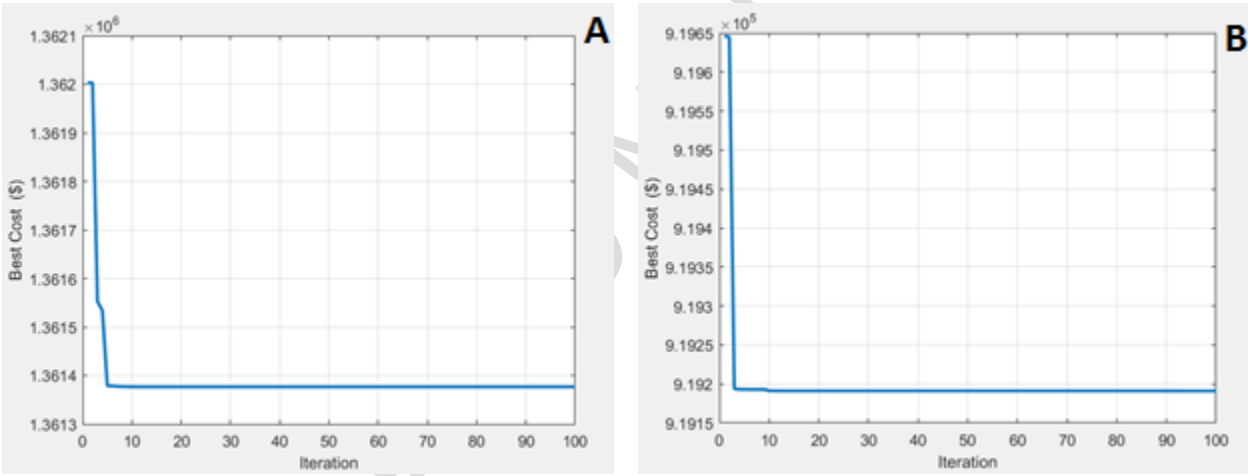


Fig. 7. Single objective optimum solution for the hybrid PV/Battery system with 2% (a), 5% (b), and 10% (c) of LPSP



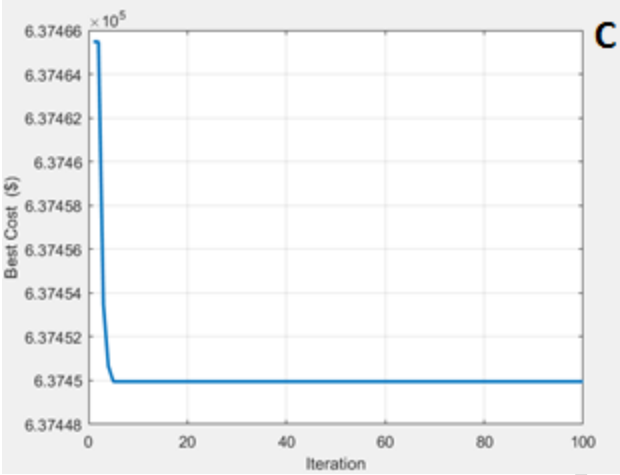


Fig. 8. Single objective optimum solution for the hybrid WT/Battery system with 2% (a), 5% (b), and 10% (c) of LPSP

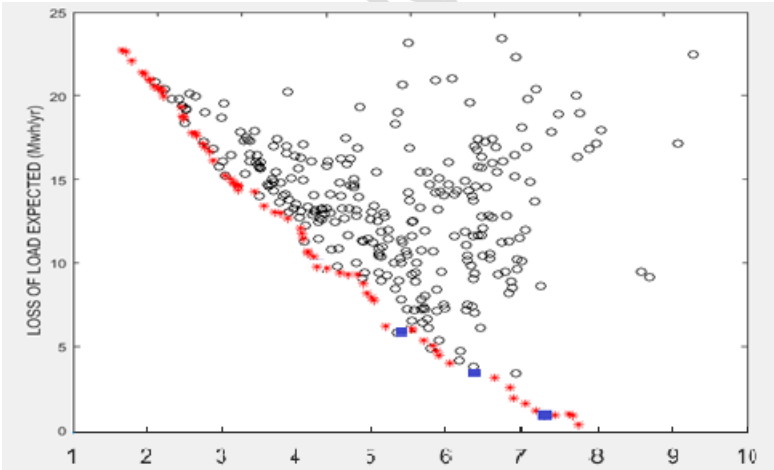


Fig.9. MOPSO simulation results for hybrid PV/WT/Battery system

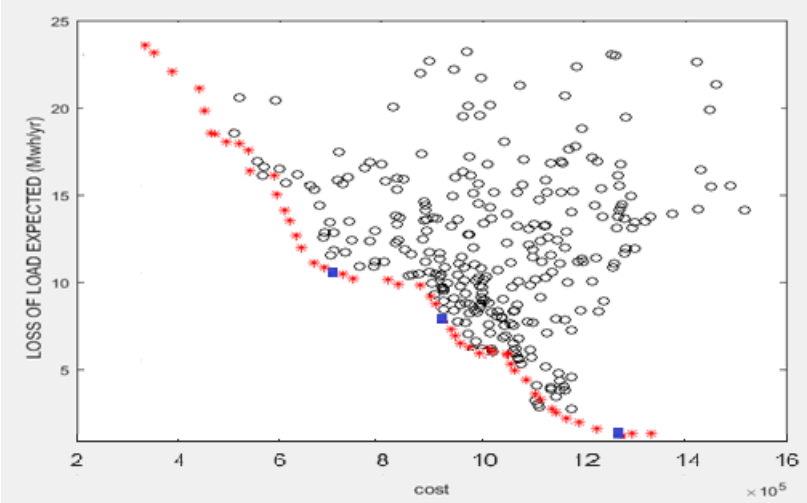


Fig. 10. MOPSO simulation results for hybrid WT/Battery system

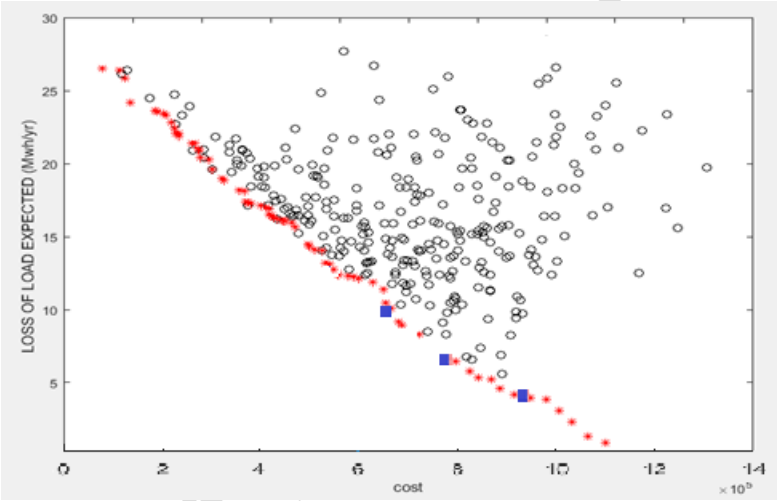


Fig.11. MOPSO simulation results for hybrid PV /Battery system

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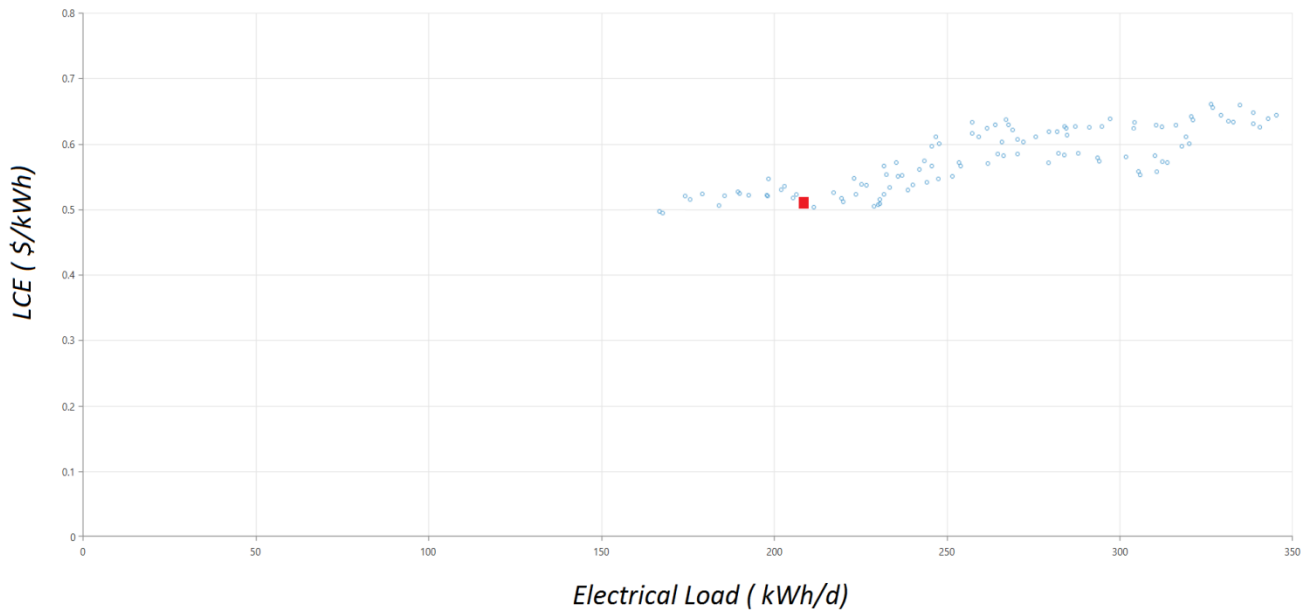

Fig. 12 LCE for different electrical loads

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