Multi-objective operation of a microgrid in the presence of renewable generation and thermal block

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In this paper, the Combined Heat and Power (CHP) generation concerning distribution networks is investigated. Using the distributed generation based on CHP generation is an important breakthrough in dividing distribution networks into microgrids as the building blocks of smart systems. Therefore, it is necessary to study and evaluate the distributed generation performance together with the CHP generation in microgrids and their operations considering electric and thermal energy storage. In this study, considering the CHP generation units with thermal energy storages, the behavior of a CHP unit is provided and the problem of optimal multi-objective operation of the microgrid is formulated using the evolutionary firefly algorithm (FA). Objective functions of interest consist of microgrid operating costs, grid losses, and voltage deviation of buses from the nominal value. To solve the optimization problem, the evolutionary firefly algorithm is used due to its robustness and effectiveness in this area. The study network has 69 busbars, including several distributed generation units, as well as the CHP generation resources. The obtained results show the effectiveness of multi-objective operation planning of microgrids using thermal loads. By achieving the optimal daily curve of active and thermal power of distributed generation and storage, the proposed scheme can improve economic and operation situation of the network simultaneously; in other words, it can minimize the operating cost of the microgrid, energy loss, and voltage deviations functions simultaneously.

keywords: *Combined heat and power (CHP), heat storage, multi-objective operation planning, Firefly algorithm (FA)*

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NOMENCLATURE

Variables

T Set of hourly time intervals.

$E_{turbine}$ Power produced by gas turbines in per-unit (p.u.).

$Gastotal$ Total gas in Combined Heat and Power (CHP) in p.u.

G_{RHheat} Gas used in the boiler heat recovery sector in CHP (p.u.)

$G_{turbine}$ Gas required to achieve the intended electricity (p.u.)

h Available heat in thermal storage (p.u.)

H_{gen} Heat generated by CHP units (p.u.)

$\bar{H}_{load}$ Thermal charge power in thermal storage (p.u.)

H_{mn} Stored thermal energy of storage (p.u.)

$\bar{H}_{unld}$ Thermal discharge power in thermal storage (p.u.)

I Electric current of the microgrid branch (p.u.)

$\bar{P}_{Bat}$ Battery power (p.u.)

$\bar{P}_{CHP}$ Active power generated by CHP units (p.u.)

$\bar{P}_{MT}$ Production active power for all microturbines (p.u.)

POP Decision variables matrix

P_{PV} Active power of photovoltaic (p.u.)

P_{sub} Active power received from the network (p.u.)

P_{WT} Active power of wind turbine (p.u.)

Q_{EGheat} Heat supplied by the turbine exhaust (p.u.)

q^{load} Charging heat power in thermal storage (p.u.)

Q_{Texh} Heat produced by the turbine exhaust gases (p.u.)

q^{ltotal} Total thermal load of the network (p.u.)

q^{unld} Discharging heat power in thermal storage (p.u.)

$\bar{S}$ Charging and discharging state of thermal storage

vol Voltage magnitude (p.u.)

$W_{turbine}$ Maximum loading limit of turbines (p.u.)

$\gamma^{load}, \gamma^{unld}$ Auxiliary variables

Parameters

C_{gas} Natural gas purchase cost ((\$)/MWh)

C_{heat} Thermal energy sales price ((\$)/MWh)

C_{MT} Energy purchase price from microturbines ((\$)/MWh)

C_{PV} Energy purchase price from photovoltaics((\$)/MWh)

C_{sub} Market price ((\$)/MWh)

C_{WT} Energy purchase price from wind turbines((\$)/MWh)

$E^{max}_{turbine}$, $H^{min}_{turbine}$ Minimum and maximum active power of CHP (p.u.)

H^{max} Size of thermal storage (p.u.)

H^{min}_{load}, E^{max}_{load} Minimum and maximum charging heat power of thermal storage (p.u.)

H_{rq} Thermal load required by the microgrid (p.u.)

H^{min}_{unld}, E^{max}_{unld} Minimum and maximum discharging heat power of thermal storage (p.u.)

HV_{gas} Natural gas thermal capacity (kWh/m3)

LF Ratio of the turbine real exhaust to the capacity peak

n Number of decision-making variables

N_{BAT} Total number of batteries

N_{br} Total number of microgrid branches

N_{bus} Total number of microgrid buses

N_{CHP} Total number of CHPs

N_{MT} Total number of micro-turbines

N_{POP} Population size

N_{PV} Total number of photovoltaics

N_{ST} Total number of thermal storage

N_{WT} Total number of wind turbines

P^{min}_{MT}, P^{max}_{MT} Minimum and maximum active power of micro-turbine (p.u.)

P^{min}_{PV}, P^{max}_{PV} Minimum and maximum active power of photo-voltaic (p.u.) (p.u.)

P^{min}_{WT}, P^{max}_{WT} Minimum and maximum active power of wind turbine (p.u.)

Q_{heat} Total network heat load(p.u.)

Q^{min}_{EGheat}, Q^{max}_{EGheat} Minimum and maximum thermal power recovered by the boiler (p.u.)

Q^{min}_{Texh}, Q^{max}_{Texh} Minimum and maximum thermal power re-covered by the boiler (p.u.)

q^{net}_t Thermal load related to the heat consumers (p.u.)

R Resistance of the microgrid branche (p.u.)

vol^{nom} Voltage magnitude in slack bus (p.u.)

R Dissipated heat in storage

β^{load} Loss of the charging process in thermal storage

β^{unld} Loss of the discharging process in thermal storage

η^{boiler} Boiler efficiency in CHP

η^{loss} Turbine thermal loss

$\eta^{HRboiler}$ Heat recovery efficiency

$\eta^{turbine}$ Gas-to-electricity efficiency

Indices

t Operation time index

br Microgrid branch index

bus Microgrid bus index

1. INTRODUCTION

Heating and cooling practices consume the main portion of energy. The dissipated heating energy from the distributed generation systems can also be utilized for this purpose. Therefore, in addition to decreasing the energy demand from the network, the efficiency of the distributed generation systems is increased by the CHP generation [1]. Today, there are concerns about changes in the price of the electricity market and energy efficiency, as well as the emissions increase which can be lowered via the CHP generation [2]. These factors have enhanced the utilization of the CHP generation systems. CHP generation systems are applicable in residential, industrial, and commercial sectors to decrease the energy consumers' payment cost [3]. On the other hand, system operation depends on its flexibility under different conditions of electrical, heat-related, and cooling-related loads available in the network. Adding electrical and thermal energy storage can increase the system flexibility so that generated energy can be stored when the electrical and/or thermal energy demand is low, and it is injected into the system at load peak times when the energy price grows. According to the aforementioned reasons, using the distributed generation based on the CHP generation is a great achievement in dividing distribution networks into microgrids as the building blocks of smart systems. Hence, it is required to investigate the distributed generation performance, along with the CHP in microgrids and their operation concerning electric and thermal energy storage. Microgrids operation with CHP generation units, as well as the behavior of CHP units and thermal storages have been examined in various research. In [4], using boilers and thermal storages to increase the CHP system flexibility along with wind turbines has been investigated. In [5], CHP units have been introduced as one of the restrictor factors for wind turbines in the network. In [6], two linear models have been provided to plan for the CHP generation accompanied by energy storage coordinated with wind turbines. In [7], a model has been proposed for the optimal operation of CHP units in a restructured system environment. In this model, the variation of the thermal-to-electrical load ratio is adjusted dynamically. In [8], the model of the CHP units in microgrids has been provided. Using heat energy generation systems to supply thermal energy in microgrids can play an important role in supplying customers' demand and frequency regulation in microgrids, as well as enhancing the energy generation efficiency of the network. Hence, in [8], the frequency regulation in microgrids based on steady-state frequency deviation regulation has been evaluated using the dynamic model of CHP behavior. In [9], a model of the optimal generation allocation for an integrated energy system with cooling, heating, and power units has been applied. The model considers a modeled natural gas system and the network security constraints in the optimal allocated model. In [10], the problem of multi-objective location and determination of the optimal size of CHP units are studied in power networks containing thermal loads and natural gas. In [11], the problem of CHP units, together with thermal energy storage, has been investigated in a case study in Italy, and the effect of initial drives on the CHP system has been examined. In [12], the presence of electrical and thermal loads has been proposed as a requirement for studying microgrids, and thermal loads have been investigated in terms of hot water and suitable temperature for buildings. In [13], the load response planning for CHP units has been discussed by predicting controllable thermal loads. In [14], the problem of the optimal microgrid operation with CHP units and load response planning in the presence of uncertainties has been addressed. In [15], the mathematical modeling of microgrid operation, together with thermal loads and CHP units, has been provided. In [16], microgrid energy management in the presence of CHP and photovoltaic units has been studied. In [17], the optimal usage of distributed generation units in microgrids, including the identification of location, capacity, and type of units has been proposed. In [19], the optimal location of CHP units based on electricity, water, and natural gas systems has been evaluated. In [20] and [21], the problem of the combined load dispatch of electricity, gas, and heat systems has been proposed by introducing an energy hub. A hybrid stochastic/robust coordinated power management strategy (CPMS) is proposed [22] to enhance flexibility, reliability, and security indices of a microgrid with electric vehicles (EVs), energy storage system (ESS), distributed generation (DG)/CHP, and demand response programming (DRP). The main problem that attempts to minimize the cost difference between operation and reliability of the microgrid is modeled, while presenting flexibility and security advantages and taking into account the constraints of optimal power flow. [23] models the operating cost and pollutant emission using a two-objective optimization problem. To solve the problem, the hybrid non-dominated sorting genetic algorithm (NSGA) is employed together with the co-evolution theory and the beetle antennae search algorithm. The authors in [24] consider the thermal inertia of concentrated buildings as it helps improve the flexibility of operation of wind turbines. To this end, a day-ahead scheduling method is utilized. Also, the paper exploited a CHP to enhance the flexibility of a power system considering wind power uncertainty. One approach to enhance technical and economic indices of a system and improve the efficiency is to utilize a combination of various power sources, storage systems, and responsive loads [26]. Energy hub (EH) is among such combined systems. To optimize the operation of EHs in combined electrical, gas, and heating systems, a new optimization model is employed in [27]. To improve the flexibility of an EH with renewables, a CHP, the paper adopts an energy storage system and an incentive-based demand response program (IDRP). The overall operating cost, reliability, and flexibility of energy networks with EHs are minimized in the form of an optimization problem subject to optimal power flow (OPF) equations, the reliability needs of the networks, and the model of EHs than contains ESS and IDRP. [28] coordinates the energy of EHs in multiple networks using the cooperation of EHs in a day-ahead market. The model integrates electrical, gas, and thermal network while taking into account electricity and gas as the inputs to the EH and electricity and thermal energy as the outputs. The literature [29] describes the energy management of EHs connected to the main grid, where EHs coordinates distributed generation units and ESSs. Uncertainties of load, energy price, renewables, and demand of mobile storage systems are the constraints of the problem. Moreover, the suggested design has a mixed-integer nonlinear programming (MINLP) nature. To model the uncertainties, the paper utilizes an adaptive robust optimization method formed according to a hybrid metaheuristic algorithm as the problem is nonlinear and non-convex. In [30], the authors formulates an approach that uses particle swarm optimization (PSO) to achieve the optimal location of a CHP that considers the maximum allowable capacity with the aim of improving network operation induces such as reducing losses, improving the voltage profile and reliability of microgrids considering networks loading condition. Based on the literature review, CHP appears in the electrical sector as a flexible source in the microgrid with a renewable source. Nonetheless, since its thermal power will depend on its active power, it does not have independent control in the thermal sector. This reduces the microgrid flexibility in the thermal sector. However, this is solved by using a thermal storage alongside the CHP. Also, in most literature, one or two economic or technical indices as the criteria have been considered in the objective function. It must be said that the improvement of one index does not guarantee the improvement of another. For example, to reduce the operating cost of a microgrid, local resources need to inject high reactive power into the network. This issue causes overvoltage in the network. Therefore, in order to eliminate these research gaps, in this paper, the multi-objective operation of microgrids with renewable sources, microturbine, and CHP and storage system is described. In this scheme, in order to simultaneously improve the efficiency and economic indices, the problem is described in the form of optimization of three objectives, including minimizing the operating cost of the network and the mentioned elements, minimizing energy losses, and minimizing the deviation function. Voltage is expressed in three separate functions. It is also subject to network power loss constraints, network operation limitations, and operating model of the mentioned elements. Since this problem is nonlinear, the firefly algorithm has been used to achieve the optimal solution. Finally, the contributions of the proposed design include the following:

– Using the model of combined system of CHP and thermal storage to formulate in the presence of a flexible resource in the microgrid, and

– Simultaneous improvement of technical and economic indices such as energy cost, energy loss, and voltage profile using the multi-objective model for microgrid operation problem.

2. MODELING OF CHP UNITS AND THERMAL ENERGY STORAGE

In this paper, the modeling is performed based on the behavior of a CHP assuming two substantial hypotheses:

– The temperature of gas output from the turbine and heat recovery are assumed to be constant.

– The system efficiency during the system operation is assumed to be constant.

The first function of the problem studied is related to the microgrid operating costs, namely supplying the electrical load, thermal load, and electrical and thermal power amounts exchanged with electrical and thermal energy storages and the mild-pressure network.

A. Operating cost of CHP Units

The operating cost of CHP units involves gas purchase to produce electrical and thermal energy. The amount of power produced by gas turbines is a function of the turbine loading and the maximum loading limit, which is formulated as follows:

$$E_{turbine} = LF \times W_{turbine} \quad \textbf{(1)}$$

LF is the ratio of the turbine real exhaust to the capacity peak and $W_{turbine}$ is the maximum loading limit.
By dividing the figure by gas into electricity conversion efficiency and natural gas heat capacity, the gas amount required to achieve the intended electricity is calculated [31].

$$G_{turbine} = \frac{E_{turbine}}{\eta_{turbine} \times HV_{gas}} \tag{2}$$

$\eta_{turbine}$ is the gas-to-electricity efficiency in the turbine, and HV_{gas} is the natural gas thermal capacity (kWh/m^3).

The heat output of CHP generation units is calculated by multiplying the units output power and the non-converted gas-to-power energy ratio. The heat converted into power is also obtained from deducting the efficiency of the turbine gas-to-power ratio and system thermal efficiency [31].

$$Q_{Texh} = \frac{E_{turbine} \times (1 - \eta_{turbine} - \eta_{loss})}{\eta_{turbine}} \tag{3}$$

η_{loss} is the turbine thermal loss, and Q_{Texh} is the heat produced by the turbine exhaust gas. The heat supplied by the turbine exhaust is calculated from the product of the turbine exhaust heat and the boiler heat recovery efficiency.

$$Q_{EGheat} = Q_{Texh} \times \eta_{HRboiler} \tag{4}$$

$\eta_{HRboiler}$ shows the heat recovery efficiency.

The gas required to enter the heat recovery boiler to supply the load that is not provided by the turbine exhaust heat is calculated by dividing the supplied heat by the product of boiler efficiency and the gas heat capacity.

$$G_{RHheat} = \frac{Q_{heat} - Q_{EGheat}}{\eta_{bioler} \times HV_{gas}} \tag{5}$$

$Q_{heat}$is the total network heat load, and G_{RHheat} is the gas used in the boiler heat recovery sector to supply the heat energy surplus for the heat load.

$$Gastotal = G_{turbine} + G_{RHheat} \tag{6}$$

This figure is utilized to calculate the function of microgrid operating cost. Another important issue in studying the behavior of CHP units is their manner of interaction with thermal energy storage, which is discussed in the following sections.

B. Formulation of the Interaction of CHP Units and Thermal Energy Storages

Thermal energy storages are installations that store thermal energy in the form of hot water. The charge and discharge of storage are defined by an increase and decrease in the water volume in the storage reservoir, respectively. It is worth mentioning that both charge and discharge have losses. Also, some of the stored water heat is dissipated by the radiation which must be considered in storage modeling at the first step. If at the time interval t no charge and discharge is performed in the storage, the relation between the stored heat at times t and t-1 will be as follows [32].

$$h_t = (1 - \alpha)h_{t-1} \tag{7}$$

h_t is the available heat at the time t, $h_{t-1}$is the available heat in the storage at the time $t-1$, and α is the dissipated heat at the time interval t ranging from 1 to 24 [32]. The variable t indicates both time interval and time duration. On the other hand, the time interval t always falls between $t-1$ and t. Accordingly, it can be claimed that there are 24 equations for heat balance. Now, it is assumed that at the time interval t, the heat load q_t^{load} is received from the heat supplier system and is used to charge the thermal storage. If β^{laod} is the loss of the charging process $(1-\beta^{laod})q_t^{load}$ will be added to the stored thermal energy [32]. Some of the thermal energy is dissipated even in the lack of system charge and discharge. Therefore, to complete the energy stored in the storages system, both mentioned cases must be included simultaneously, and the result will be as follows [32]:

$$\begin{aligned} h_t &= (1-\alpha)h_{t-1} + (1-\beta^{laod})q_t^{load} - 0.5\alpha(1-\beta^{laod})q_t^{load} \Rightarrow \\ h_t &= (1-\alpha)h_{t-1} + (1-0.5\alpha)(1-\beta^{laod})q_t^{load} \end{aligned} \tag{8}$$

The parameter γ^{unld} is defined to facilitate the composition:

$$\gamma^{load} = (1-0.5\alpha)(1-\beta^{laod}) \tag{9}$$

However, in terms of discharge, if the system delivers the heat amount of q_t^{unld} to the system at the time interval t, namely during discharge, the heat discharge from the system storage set will be equal to $(1+\beta^{unld})q_t^{unld}$. If the loss portion during storage discharge is significant, the figure must be subtracted from the system output $0.5\alpha(1+\beta^{unld})q_t^{unld}$. Thus, in the discharge condition, the thermal energy balance relation for the storage is written as follows [32]:

$$\begin{aligned} h_t &= (1-\alpha)h_{t-1} - (1+\beta^{unld})q_t^{unld} + 0.5\alpha(1+\beta^{unld})q_t^{unld} \Rightarrow \\ h_t &= (1-\alpha)h_{t-1} - (1-0.5\alpha)(1+\beta^{unld})q_t^{unld} \end{aligned} \tag{10}$$

Similarly, it can be defined that

$$\gamma^{unld} = (1-0.5\alpha)(1+\beta^{unld}) \tag{11}$$

By combining the equations related to the system charge and discharge, the following relation will be given:

$$h_t = (1-\alpha)h_{t-1} + \gamma^{load}q_t^{load} - \gamma^{unld}q_t^{unld} \tag{12}$$

Thus, given the charge and discharge in thermal energy storages, the stored energy for the consequent times, as well as the total network thermal load needed to be supplied by the CHP units and/or natural gas can be determined. Generally, the total network thermal load in any hour of the day can be obtained as follows:

$$q_t^{total} = q_t^{net} + q_t^{load} - q_t^{unld} \tag{13}$$

Signs in the relation are determined according to the charge and discharge condition of the thermal energy storage. q_t^{total} is the total network thermal load at the time t, and q_t^{total} is the thermal load related to the heat consumers throughout the network

3. FORMULATION OF THE OPTIMAL OPERATION PROBLEM

A. Control Parameters of the Optimization Problem

Control variables in an optimization problem are the quantities dedicated to the operator, and by changing their values in the permissible range, the objective function values can be changed. For the problem being studied in this paper, the variables are defined as follows.

$$
\begin{aligned}
&POP = [\overline{P}_{MT}, \overline{P}_{CHP}, \overline{\mathrm{H}}_{\mathrm{load}}, \overline{\mathrm{H}}_{\mathrm{unld}}, \overline{S}, \overline{\mathrm{P}}_{Bat}]_{N_{pop}\times n}\\
&\overline{P}_{MT} = [\overline{P}_{MT,1}, \overline{P}_{MT,2}, ..., \overline{P}_{MT,N_{MT}}]_{N_{pop}\times(N_{MT}\times 24)}\\
&\overline{P}_{MT,i} = [P^1_{MT,i}, P^2_{MT,i}, ..., P^T_{MT,i}]_{1\times T} \quad T = 24,\ i = 1,2,...,N_{MT}\\
&\overline{P}_{\mathrm{CHP}} = [\overline{P}_{\mathrm{CHP},1}, \overline{P}_{\mathrm{CHP},2}, ..., \overline{P}_{\mathrm{CHP},N_{\mathrm{CHP}}}]_{N_{pop}\times(N_{\mathrm{CHP}}\times 24)}\\
&\overline{P}_{CHP,i} = [P^1_{CHP,i}, P^2_{CHP,i}, ..., P^T_{CHP,i}]_{1\times T} \quad T = 24,\ i = 1,2,...,N_{\mathrm{CHP}}\\
&\overline{\mathrm{H}}_{\mathrm{load}} = [\overline{\mathrm{H}}_{\mathrm{load},1}, \overline{\mathrm{H}}_{\mathrm{load},2}, ..., \overline{\mathrm{H}}_{\mathrm{load},\mathrm{N_{ST}}}]_{N_{pop}\times(N_{\mathrm{ST}}\times 24)}\\
&\overline{\mathrm{H}}_{\mathrm{load,i}} = [\mathrm{H}^1_{load,i}, \mathrm{H}^2_{load,i}, ..., \mathrm{H}^T_{load,i}]_{1\times T} \quad T = 24,\ i = 1,2,...,N_{\mathrm{ST}}\\
&\overline{\mathrm{H}}_{\mathrm{unld}} = [\overline{\mathrm{H}}_{\mathrm{unld},1}, \overline{\mathrm{H}}_{\mathrm{unld},2}, ..., \overline{\mathrm{H}}_{\mathrm{unld},\mathrm{N_{ST}}}]_{N_{pop}\times(N_{\mathrm{ST}}\times 24)}\\
&\overline{\mathrm{H}}_{\mathrm{unld,i}} = [\mathrm{H}^1_{unld,i}, \mathrm{H}^2_{unld,i}, ..., \mathrm{H}^T_{unld,i}]_{1\times T} \quad T = 24,\ i = 1,2,...,N_{\mathrm{ST}}\\
&\overline{S} = [\overline{S}_{1\_2,1}, \overline{S}_{1\_2,2}, ..., \overline{S}_{1\_2,\mathrm{N_{ST}}}]_{N_{pop}\times(2N_{\mathrm{ST}}\times 24)}\\
&\overline{S}_{1\_2,i} = [S^1_{1,i}, S^1_{2,i}, S^2_{1,i}, S^2_{2,i}, ..., S^T_{1,i}, S^T_{2,i}] \quad T = 24,\ i = 1,2,...,N_{\mathrm{ST}}\\
&\overline{\mathrm{P}}_{\mathrm{BAT}} = [\overline{\mathrm{P}}_{\mathrm{Bat},1}, \overline{\mathrm{P}}_{\mathrm{Bat},2}, ..., \overline{\mathrm{P}}_{\mathrm{Bat},\mathrm{N_{BAT}}}]_{N_{pop}\times(N_{\mathrm{BAT}}\times 24)}\\
&\overline{\mathrm{P}}_{\mathrm{BAT,i}} = [P^1_{BAT,i}, P^2_{BAT,i}, ..., P^{\mathrm{T}}_{BAT,i}]_{1\times T} \quad T = 24,\ i = 1,2,...,N_{\mathrm{BAT}}
\end{aligned}
\tag{14}
$$

POP is the initial population vector $\overline{P}_{MT}$ is the production power for all of the microturbines throughout the day. The vector sign above the variables indicates a control variable state throughout the day related to the equipment of the variable in the network. For instance, if there are three microturbines in the network, the mentioned vector will comprise three microturbines states in 24 hours. According to the description, it can be said that $\overline{P}_{CHP}$, $\overline{H}_{load}$, $\overline{H}_{unld}$, $\overline{S}$ and are the vectors pertaining to the power generated by CHP units, thermal storages charge, energy storages discharge, and the indicative vector of charge and discharge states of energy storages units, respectively. $\overline{P}_{MT,1}$ is the vector for determining the initial state of the microturbine unit in 24 hours. Consequently, these vectors are defined in the number of microturbine units (N_{MT}). According to the description, it can be said that $\overline{P}_{\mathrm{CHP},1}$, $\overline{\mathrm{H}}_{\mathrm{load},1}$, $\overline{\mathrm{H}}_{\mathrm{unld},1}$, and $\overline{S}_{1\_2,1}$ are the vectors containing the state of power generated by the first CHP unit: the first thermal storage charge, the first thermal energy storage discharge, and the first energy storage charge and discharge states during 24 hours. These vectors are repeated in the number of CHP units (N_{CHP}) and in the number of thermal energy storages (N_{ST}), respectively. $P^1_{MT,i}$ is the power generated by the ith microturbine unit in the first hour of the day, and the value is determined for all hours of a day in 24 values. Hence, it can be said that $P^1_{CHP,i}$, $\mathrm{H}^1_{load,i}$, $\mathrm{H}^1_{unld,i}$, and $S^1_{1,i}$, $S^1_{2,i}$ are the power generated by the first CHP in the first hour, the first energy storage charge, the first thermal energy storage discharge, the variables determined in the first hour, the first energy storage to be charged and or discharged. $\overline{\mathrm{P}}_{\mathrm{Bat},1}$ shows the power exchanged with the first battery during the day. $P^1_{BAT,i}$ indicates the power exchanged with the ith battery in the first hour of the day.

B. Objective Functions of the Optimization Problem

The objective functions to be formulated in this paper are microgrid's operating costs in presence of CHP units and thermal storages, the network losses, and the network voltage deviations described in the following

B.1. Objective Functions of the Microgrid's Operating Costs

According to the aforementioned issues, the objective function of the microgrid's operating costs can be formulated as follows:

$$
\begin{aligned}
Cost1 = {} & P_{sub} \times C_{sub} + \\
& Gastotal \times C_{gas} \times \eta_{bioler} \times HV_{gas} \\
& - C_{heat} \times Heat_{total} + \sum_{i=1}^{N_{MT}} P_{MT} \times C_{MT} \\
& + \sum_{i=1}^{N_{PV}} P_{PV} \times C_{PV} + \sum_{i=1}^{N_{WT}} P_{WT} \times C_{WT}
\end{aligned}
\tag{15}
$$

It must be noted that P_{sub} is the power received from the network, C_{sub} is the energy purchase cost from the network or market price, C_{gas} is the natural gas purchase cost, C_{heat} is the thermal energy sales price for consumers, P_{MT} is the power received from microturbine units, N_{MT} is the number of microturbine units installed in the network, C_{MT} is the energy purchase price from the microturbine units, and P_{PV} is the power received from photovoltaic units. Also, P_{WT} is the power received from the wind turbine units, N_{WT} is the number of wind turbine units installed in the network, and C_{WT} is the energy purchase price from the wind turbine units. In EqEq. (23), the heat sold to the network is the sum of the thermal loads in the microgrid and the energy exchanged by the storage and can be formulated as follows.

$$
Heat_{total} = H_{gen} - (H_{rq} + S_1 H_{load} - S_2 H_{unld}) \tag{16}
$$

H_{gen} is the heat generated by the CHP units or the heat directly produced by the boilers. H_{rq} is the thermal load required by the microgrid. On the other hand, thermal energy storage can exist as either a load or a thermal energy generator in planning. The thermal energy is added to the load during charge, and it is subtracted from the load during discharge. The variables of the storage charge (H_{load}) and storage discharge (H_{unld}) controller are $S1$ and $S2$ which cannot be equal to unity simultaneously. It should be noted that the cost of electrical energy generated by the CHP generation units is taken into account in the above equations, and there is no need to calculate again.

B.2. Objective Function of the Decrease in the Network Loss

The objective functions of the microgrid losses and voltage deviations should be considered in the microgrid operation problem and are formulated as follows:

$$
Cost2 = \sum_{br=1}^{N_{br}} \sum_{t=1}^{24} R_{br} I_{br}^2 \tag{17}
$$

R_{br} is the ohmic resistance of the microgrid branches, N_{br} is the number of microgrid branches, and I_{br} is the electric current of the microgrid branches.

B.3. Objective Function of the Decrease in the Bus Voltage Deviation from the Nominal Value

If the nominal values of bus voltages are assumed equal to 1 per unit (p.u.), the voltage deviation from the nominal value can be formulated as an objective function as follows.

$$
Cost3 = \sum_{bus=1}^{N_{bus}} \sum_{t=1}^{24} \left| \frac{vol_{bus}^{nom} - vol_{bus}^{t}}{vol_{bus}^{nom}} \right| \tag{18}
$$

B.4. Multi-Objective Function of the Decrease in Microgrid's Operating Costs, Network Losses, and Bus Voltage Deviation from Nominal Value

The multi-objective problem holds when several objective functions are defined so that optimizing one objective function deteriorates the others [33–35]. In this case, a single solution cannot be found for the problem, thereby all objective functions are optimized simultaneously. Therefore, the principle of relativity emerges. That is, a solution should be sought with the capability of providing the optimal condition for each objective function to some extent. One of the various types of solution methods for multi-objective problems is to use a fuzzy interaction method as follows.

$$\mu_z(X) = \max_{i=1,\ldots,m} (\mu_{ref_i} - \mu_{of_i}(X))$$
$$best\_sol = \min(\mu_z(X)) = \min < \max_{i=1,\ldots,m} (\mu_{ref_i} - \mu_{of_i}(X)) > \quad (19)$$

μ_{ref_i} and μ_{of_i} are the reference values for the fuzzy one of each objective function and that of the ith objective function, respectively, and m is the number of objective functions. It is worth mentioning that converting the multi-objective function into a single-objective function is based on the Pareto optimization. The method has different approaches to integrate all objective functions. One approach is called weight coefficient-based Pareto optimization. In this method, the single-objective function of the problem is equal to the sum of the product of different objective functions with appropriate weight coefficients. Then, by determining various values of weight coefficients, different optimal points are obtained for the new problem. The number demonstrating different objective functions values is called Pareto front. In addition to this method, the epsilon-constraint method has many applications. In the epsilon-constraint method, the single-objective function of the problem is equal to one of the functions of the multi-objective problem, and other objective functions emerge as constraints in the single-objective problem. It should be noted that these objective functions are introduced as constraints in the single-objective problem and their maximum values are equal to ε. As ε values change, different values are obtained for objective functions. Now, the number demonstrating different objective functions values is called the Pareto front. The fuzzy decision-making method for multi-objective problems determines the interaction point among different objective functions of the problem. On the other hand, by using the fuzzy decision-making method, a point is extracted from different points of the Pareto front and is defined as the optimal point of the problem. In this method, a fuzzy membership function is assigned to each solution in the Pareto front and the fuzzy membership range is [0,1]. There are different ways to propose the membership function; however, the simplest way is to use linear fuzzy membership functions. Such functions can be obtained using the following equation for the proposed objective functions of the problem.

$$\hat{f} = \begin{cases} 1 & f \leq f^{\min} \\ \frac{f - f^{\max}}{f^{\min} - f^{\max}} & f^{\min} \leq f \leq f^{\max} \\ 0 & f \geq f^{\max} \end{cases} \quad (20)$$

The fuzzy decision-making method obtains the best comprised solution among the objective functions of the problem based on values of the membership functions for each function. The best comprising solution can be given using the min-max method. The steps are as follows [36–38]:

1. The values of membership functions for different objective functions are calculated based on EqEq. (19).
2. The minimum value among the membership objective functions is calculated. That is, the term $\min(\hat{f}_1, \hat{f}_2)$ is calculated for both objective functions $f1$ and $f2$ of the proposed problem.
3. The maximum value in step 2 is determined. The corresponding solution related to this step will be the best comprising point among the objective functions.

C. Optimization Problem Constraints

The defined optimization problem has several constraints discussed in the following.

– The active power of CHP units is limited as follows:

$$E^{\min}_{turbine} \leq E^t_{turbine} \leq E^{\max}_{turbine} \quad (21)$$

Superscripts max and min indicate the maximum and minimum power generation by the unit, respectively.

– The thermal power limit of CHP units:

$$Q^{\min}_{Texh} \leq Q^t_{Texh} \leq Q^{\max}_{Texh} \quad (22)$$

– The limit of thermal power recovered by the boiler:

$$Q^{\min}_{EGheat} \leq Q^t_{EGheat} \leq Q^{\max}_{EGheat} \quad (23)$$

– The limits of energy storage charge and discharge:

$$H^{\min}_{load} \leq H^t_{load} \leq H^{\max}_{load} \quad (24)$$
$$H^{\min}_{unld} \leq H^t_{unld} \leq H^{\max}_{unld} \quad (25)$$

– - The limit of the heat stored in the energy storage:

$$H^t_{rmn} \leq H^{\max} \quad (26)$$

H^t_{rmn} is the thermal energy stored in the energy storage at time t.

– Lack of simultaneous charge and discharge in the energy storage [39]:

As per EqEq. (27), the two variables $S1$ and $S2$ indicate the storage charge and discharge states that must satisfy the following equations.

$$\begin{aligned} S_1 + S_2 &= 1 \\ S_1 &= 0\, or\, 1 \\ S_2 &= 0\, or\, 1 \end{aligned} \quad (27)$$

– - The limit of power generated by the photovoltaic and wind turbine units [40]:

$$P^{t,\min}_{PV(WT)} \leq P^t_{PV(WT)} \leq P^{t,\max}_{PV(WT)} \quad (28)$$

– The limit of power generated by the microturbine units [41]:

$$P^{t,\min}_{MT} \leq P^t_{MT} \leq P^{t,\max}_{MT} \quad (29)$$

Given the distributed generation units' power, as well as the power generated by CHP units, the current transferred by the lines and the network losses are acquired. Consequently, the energy losses in the network are determined. Also, after the load dispatch on the network, different bus voltages are identified, and the gap between bus voltages and the voltage of one p.u. can be calculated as the objective function of network voltage deviations.

4. REVOLUTIONARY FIREFLY ALGORITHM OPTIMIZATION

The operation model of microgrid is non-linear. Hence, to achieve reliable optimal solution, this paper uses firefly algorithm to solve this problem. It is strong algorithm to solve complex engineering optimization problems [42]. The algorithm seeks the optimal solution to the problem by modeling the behavior of a set of fireflies and allocating a value related to the location fit of each firefly as a model for the pigments amounts, as well as updating the flies location with algorithm successive iterations. In fact, the two main phases of the algorithm in each iteration are the pigment update and movement. The fireflies move to the others with more pigments in the neighborhood. Therefore, the set approaches the better solution during successive iterations [42]. The algorithm pertains to the stochastic algorithms group, meaning that a kind of stochastic search is used to achieve a set of solutions. At its lowest level, the firefly algorithm focuses on the solution production within a search space and chooses the best solution to survive. The stochastic search puts an obstacle to falling into local optimization traps. The firefly algorithm is based on an initial population. The details of this algorithm is presented in [42]. In this algorithm, the values of decision-making variables, given in EqEq. (14), are determined using the algorithm based on their permissible range. Then, dependent variables such as voltage, active power, and reactive power of distribution lines, etc. are specified by equality constraints. In this section, the power flow constraints of the network are solved using the forward-backward method [43], and other equality constraints will be solved using the Newton-Raphson method. The penalty function is used to estimate inequality constraints. In this method, the fitness function is equal to the sum of the objective function of the problem and penalty functions of inequality constraints. The penalty function for a constraint $a \leq b$ is $\lambda max(0, a-b)$, presented as represents the Lagrangian multiplier and its value is determined similar to decision-making variables using the firefly algorithm [44]. Eventually, the problem-solving procedure is depicted as a flowchart shown in Fig. 1.

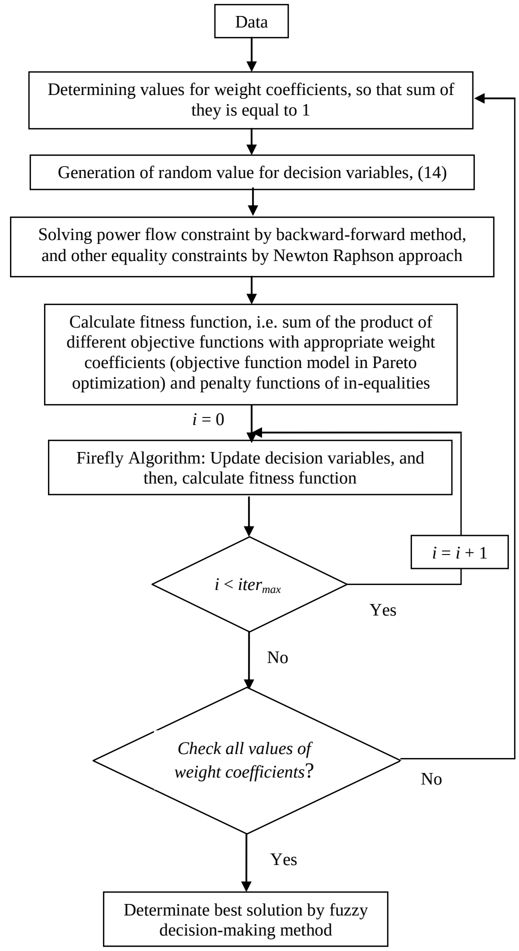

Fig. 1. Flowchart of solving the proposed problem

5. SIMULATION RESULTS

A. The Network Under Study

The test network is the standard IEEE 69-bus network [26]. The basic load is equivalent to 3802 kW and 2694 $kVAR$. To study the model proposed in this paper with the mentioned network, several distributed generation units and CHP units are installed on the network. These units consist of three wind turbines, three CHP units, three photovoltaic units, three microturbine units, and two energy storage units. The maximum capacity of the energy storage units is 100 kW with charge/discharge rates of both 30 kWh. The power generated by photovoltaic units and wind turbines is portrayed in Figs. 2 and 3 [28].

The other required information is as follows:
Gas to power efficiency: 24%
Thermal loss coefficient: 0.08
The thermal capacity of 1 m3 of gas (kWh/m3): 7856.74
Absorption chiller efficiency: 85%
Absorption chiller performance coefficient: 1.2
Heat recovery boiler efficiency: 77.6%
Boiler efficiency: 85%
To study the behavior of the proposed problem, different states have been considered and discussed, along with results in the following.

B. The considered Cases

B.1. Case I: Single-Objective Problem to Decrease the Cost

In this case, the network operation problem is solved to reduce the operating cost. It is expected that the results are obtained so that costly units and units with high energy prices become the minimum. The obtained results, in this case, are illustrated in Figs. 4-6. The power of CHP units is also shown in Figs. 7,8,9. The charge and discharge of the thermal energy storages are depicted in Figs. 10(a)-10(c).

It can be seen from the results that due to the low cost of the power generated by CHP units, the units mostly use their maximum capacity. Next, the power generated by microturbine units has a lower price compared to the energy market. In this situation, one can assure that the network thermal loads power is fully supplied by the CHP units. Considering the high power generation of CHP units, the thermal energy storages behavior can be predicted, which can be discharged in the initial hours and cannot be charged unless the required situations prevent the dissipating of thermal energy.

B.2. Case II: Single-Objective Problem to Decrease the Losses

It is expected that the power generation profile coordinates with the network load. The investigation of the results shows that most of the generation units are at their maximum generation

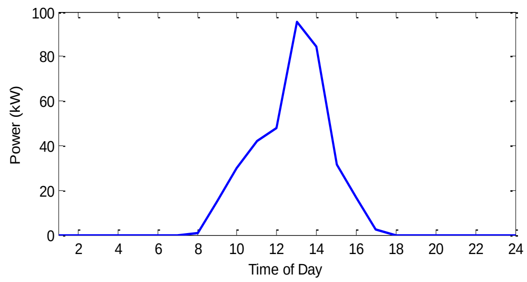

Fig. 2. Daily variations of photovoltaic power [28]

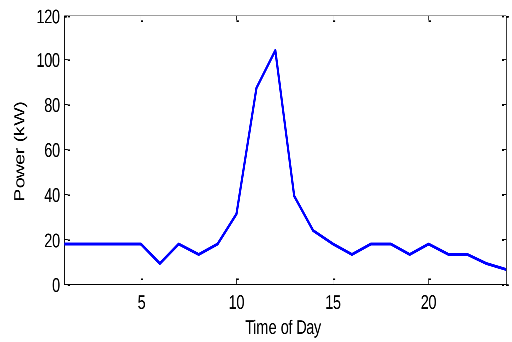

Fig. 3. Daily wind turbine power changes [?]

threshold to help decrease network losses by supplying power. High power generation by CHP units removes the need for thermal energy storage, and the units can be useless until the last hours of the day after an initial discharge. The charge and discharge of the thermal energy storages are shown in Figs. 11(a)-11(c). The convergence trend of the optimization algorithm for the objective function is depicted in Fig. 12.

B.3. Case III: Single-Objective Problem to Decrease Voltage Deviations

Considering the high network load, the optimal point selected by the revolutionary algorithm is the same as the loss objective function. In other words, the high network load requires the distributed generation network to produce high power so that it can compensate for the voltage decline in the network feeders. The thermal energy storages behavior in the situation is in accordance with the loss objective function. The charge and discharge of the thermal energy storages are presented in Figs. reff13(b)-13(c). The convergence trend of the algorithm, in this case, is revealed in Fig. 14.

B.4. Case IV: Multi-Objective Problem to Decrease the Operating Costs, Losses, and Voltage Deviations

The control variables of the problem are summarized in Table 1, and the charge and discharge of the thermal energy storages are shown in Figs. 15(a)-15(c).

The positive and negative values show charge and discharge, respectively. As it can be seen, the discharge occurs when the power related to other units decreases. The convergence trend of the algorithm for the objective function is shown in Fig. 16. Finally, the convergence results of the proposed design obtained from the firefly algorithm (FA), krill herd optimization (KHO) [45], training and learning-based optimization (TLBO) [46], particle swarm optimization (PSO) [44], and genetics algorithm (GA) [44] are presented in Table 2. In this section, population

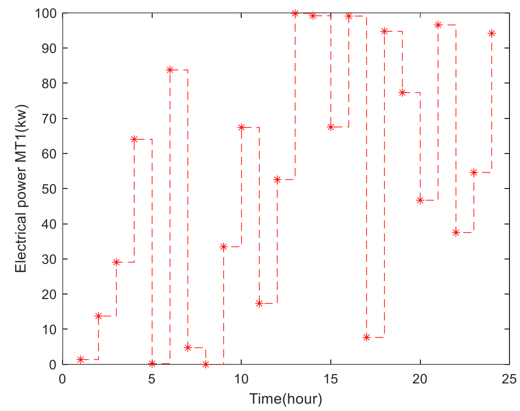

Fig. 4. The power output of the first microturbine unit

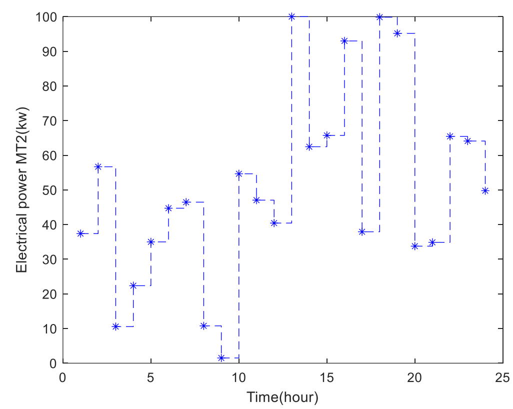

Fig. 5. The power output of the second microturbine unit

size and maximum number of convergence iterations for the mentioned algorithms are set 80 and 3000, respectively. Also, other setting parameters of each algorithm were determined based on [42],[44],[45],[46]. In this section, to calculate statistical indices such as standard deviation (SD) of final response, each algorithm solves the proposed problem 20 times. However, Table 2 presents the results of the last iteration. Based on this table, it can be seen that the FA algorithm was able to find the minimum values for the proposed objective functions compared to the KHO, TLBO, PSO, and GA solvers at the least number of convergence iteration (CI) with minimum computational time (CT). It also has the lowest SD value. These cases show that the FA algorithm has a good ability to achieve the optimal solution with the least standard deviation in the response and the highest convergence speed.

6. CONCLUSION

In this paper, thermal and electrical energy storages were modeled and their equations were used for charge and discharge. Also, the microgrid operation in the presence of thermal loads was evaluated as a problem with the goal of a decrease in operating costs, losses, and voltage deviations. In this situation, the operation problem was examined by using the firefly optimization algorithm. The objective functions were studied in individual and combined forms, and the results were obtained. Determining the optimal capacity is of great importance to power genera-

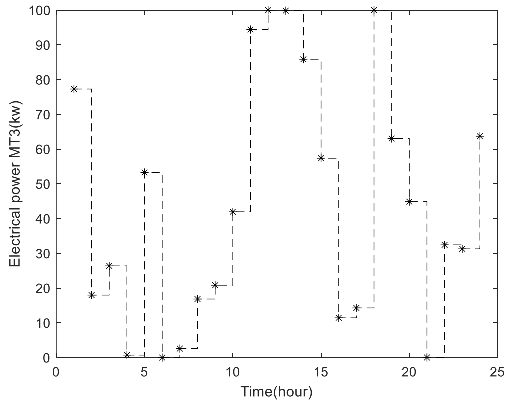

Fig. 6. The power output of the third microturbine unit

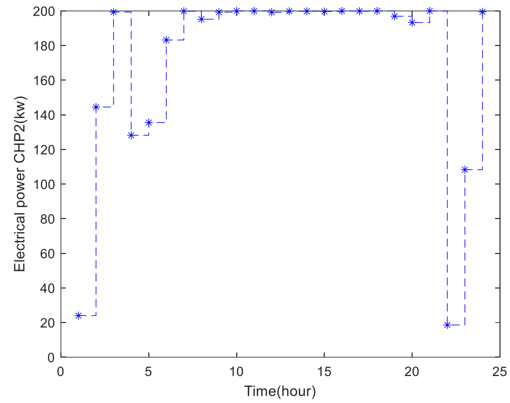

Fig. 8. The power output of the second CHP unit

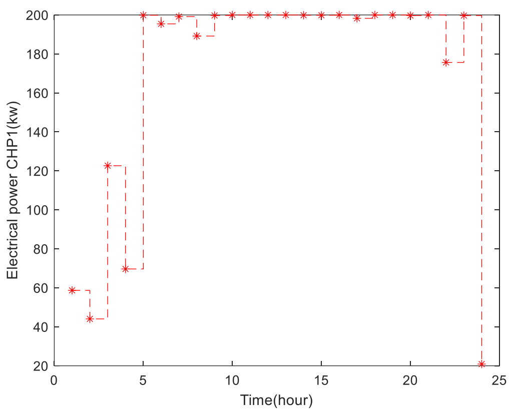

Fig. 7. The power output of the first CHP unit

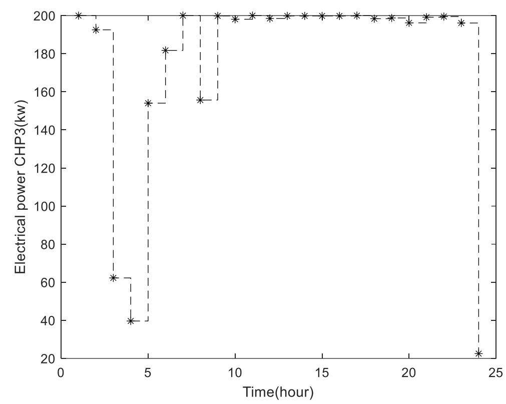

Fig. 9. The power output of the third CHP unit

tion units, CHP units, and thermal and power storage. Utilizing the distributed generation capacity depends upon both the optimization algorithm and the type of objective function. The objective function considers operating costs of power generation resources based on the energy supply price and the purchases from the lowest price. Here, there are two other issues: first, using distributed generation based on their energy price causes voltage issues in the network, and second, supplying the thermal loads is challenging. In the objective function, the usage of thermal energy storage was not considerable because of utilizing CHP power capacity, generating thermal energy, and supplying thermal heat. Regarding the function, the objective of achieving the optimal capacity of the equipment installed on the network is essential. Concerning the two other objective functions, i.e. losses and voltage deviations, only the technical aspect of the microgrid operation was taken into account. In these two functions, the installation location of power generation units is highly important. Installing the units in locations with voltage issues increases the network losses. In the two objective functions, the thermal and power energy storages play a more significant role. Eventually, based on the obtained numerical results, the proposed scheme can obtain the optimal daily curve of active and thermal power of distributed generation and energy storage. This result is proportional to the simultaneous improvement of economic and operation conditions of the microgrid, where the energy loss, energy cost, and voltage deviations functions are simultaneously minimized. Moreover, the firefly algorithm is able to find the optimal solution with high convergence speed a lower standard deviation in the final response of the suggested scheme. Note that the proposed scheme employs a deterministic model. However, power generation of wind and photovoltaic systems and the demand are uncertainties. Hence, it requires stochastic or robust modeling, which will be addressed in the future works.

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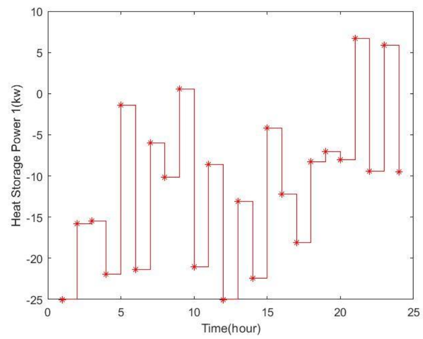

Fig 10(a). Charge and discharge rate of the first thermal energy storage

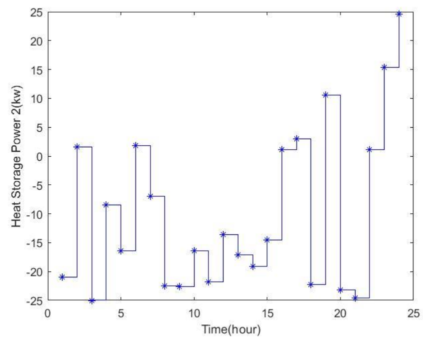

Fig 10(b). Charge and discharge rate of the second thermal energy storage

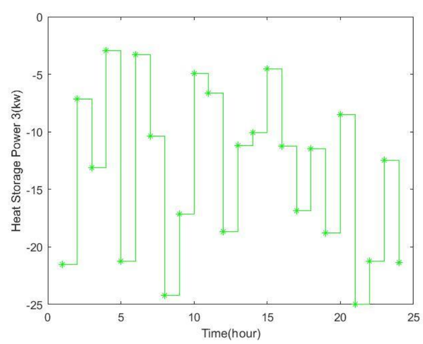

Fig. 10. (c) Charge and discharge rate of the third thermal energy storage

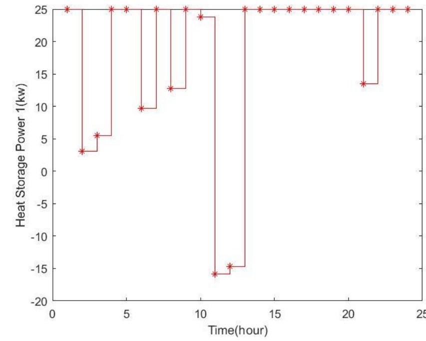

Fig 11(a). Charge and discharge rate of the first thermal energy storage

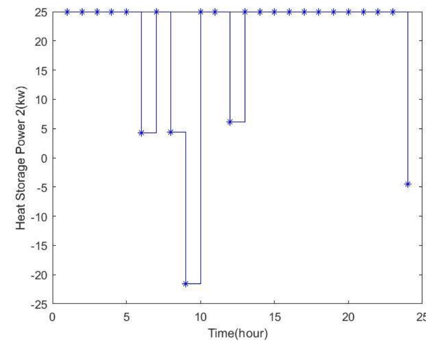

Fig 11(b). Charge and discharge rate of the second thermal energy storag

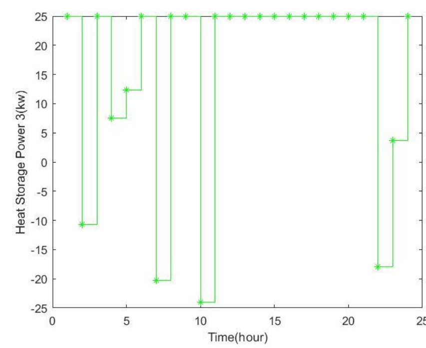

Fig. 11. (c) Charge and discharge rate of the third thermal energy storage

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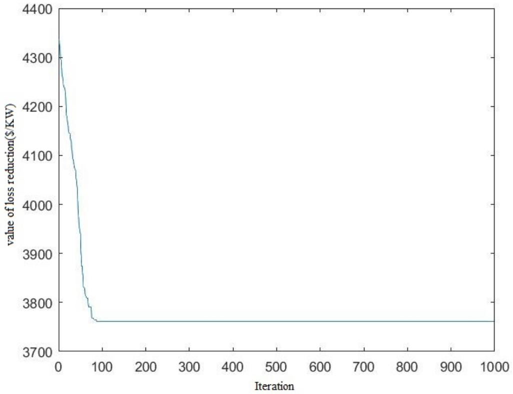

Fig. 12. The convergence process of an evolutionary algorithm for loss reduction

Table 1. Multi-objective problem control variables

Time	CHP1	CHP2	CHP3	MT1	MT2	MT3
1	199.94	200.00	199.94	100.00	99.94	100.00
2	199.94	31.29	200.00	32.83	99.93	100.00
3	200.00	199.94	200.00	99.94	100.00	7.46
4	199.94	199.94	199.94	39.16	99.94	99.94
5	199.94	197.46	200.00	52.38	57.75	14.89
6	199.94	199.94	199.94	100.00	99.94	100.00
7	198.59	137.97	199.94	100.00	52.83	98.31
8	200.00	199.94	200.00	12.99	99.94	99.94
9	200.00	200.00	200.00	51.57	99.89	99.94
10	199.94	199.94	200.00	100.00	99.94	76.28
11	200.00	199.94	200.00	100.00	100.00	99.94
12	199.94	199.94	199.94	98.25	99.94	99.94
13	199.94	200.00	199.94	99.94	100.00	99.94
14	199.94	200.00	200.00	99.94	99.94	53.53
15	200.00	200.00	199.94	13.56	100.00	99.94
16	199.94	199.94	200.00	100.00	6.59	78.53
17	200.00	200.00	199.94	99.94	99.94	99.94
18	200.00	200.00	200.00	100.00	100.00	99.94
19	199.94	199.94	200.00	100.00	100.00	99.94
20	199.94	200.00	199.94	98.06	99.99	99.81
21	167.42	199.06	200.00	50.91	99.18	65.47
22	197.87	199.94	199.94	100.00	100.00	100.00
23	199.94	71.63	200.00	100.00	99.94	100.00
24	200.00	200.00	97.51	52.86	99.94	99.94

Table 2. Convergence results of the proposed scheme obtained by different solvers

Solver	CI	CT (s)	SD (%)	Cost1 ($)	Cost2 (kW)	Cost3 (p.u)
FA	981	108	0.98	4136	3852	30.22
KHO	1122	145	1.11	4337	3947	31.02
TLBO	1353	154	1.57	4407	3962	31.16
PSO	1911	164	2.06	4724	4083	32.19
GA	2037	183	2.75	4975	4133	32.87

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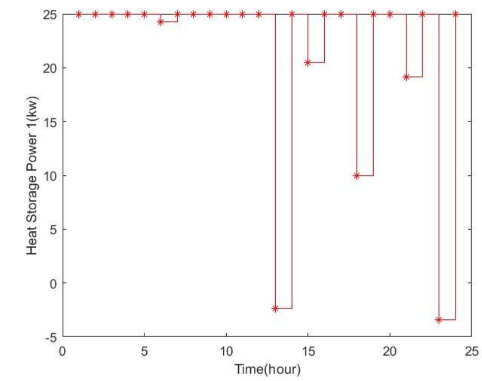

Fig 13(a). Charge and discharge rate of the first thermal energy storage

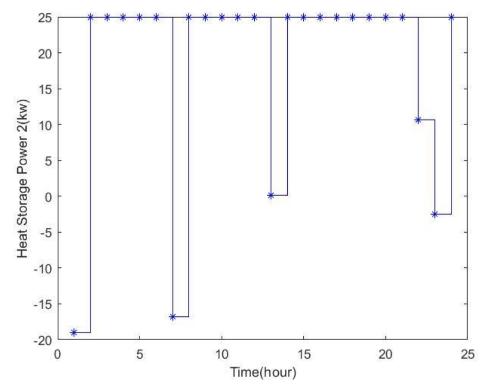

Fig 13(b). Charge and discharge rate of the second thermal energy storage

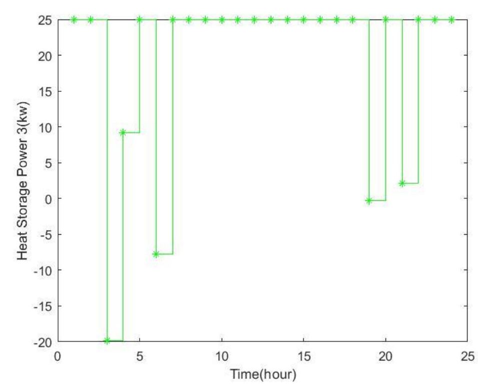

Fig. 13. (c) Charge and discharge rate of the third thermal energy storage

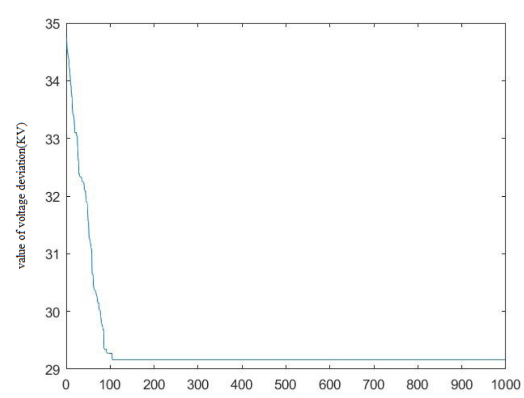

Fig. 14. Evolutionary algorithm convergence process for voltage deviation

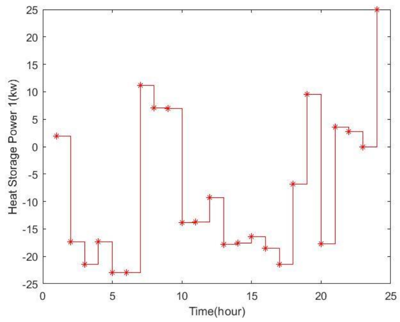

Fig 15(a). Charge and discharge rate of the first thermal energy storage

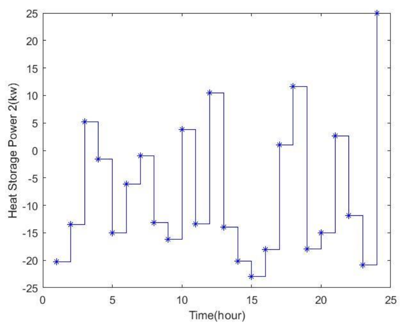

Fig 15(b). Charge and discharge rate of the second thermal energy storage

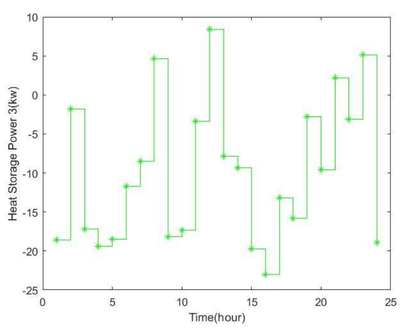

Fig. 15. (c) Charge and discharge rate of the third thermal energy storage

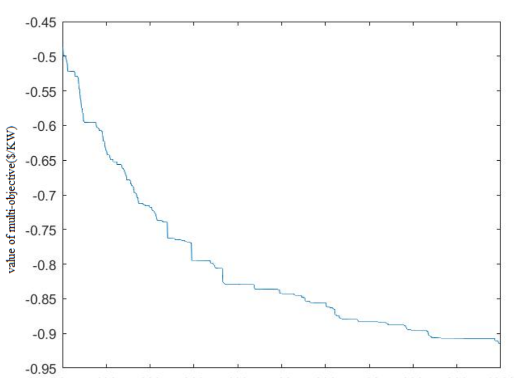

Fig. 16. Convergence Process of Multi-Objective Optimization Algorithm