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Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost of microgrid

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Abstract: Nowadays, optimal operational planning of micro-grid (MG) with regard to energy costs minimisation of MG and better utilisation of renewable energy sources (RES) such as solar and wind energy systems, has become the head of concern of modern power grids and energy management systems. Due to large integration of RES into the MG, the necessity of battery energy storage (BES) has increased rapidly. Size of BES plays an important role in the operation cost minimisation of MG. A cost-based formulation has been performed in this study to determine the optimal size of BES in the operation cost minimisation problem of MG under various constraints, such as power capacity of distributed generators (DGs), power and energy capacity of BES, charge/discharge efficiency of BES, operating reserve and load demand satisfaction. A recently developed optimisation technique known as grey wolf optimisation (GWO) has been applied here to solve the problem. The proposed algorithm is tested on a typical MG. Simulation results establish that the proposed approach outperforms several existing optimisation techniques such as genetic algorithm, particle swarm optimisation, tabu search, differential evolution, biogeography-based optimisation, teaching–learning-based optimisation, bat algorithm (BA) and improved BA in terms of quality of solution obtained and computational efficiency.

Nomenclature

Indices

PV, WT	photo-voltaic (PV) and wind turbine (WT) indices, respectively
FC, MT	fuel cell (FC) and micro-turbine (MT) indices, respectively
BES, grid	battery energy storage (BES) and grid indices, respectively
t	time index
iter	iteration index of the GWO algorithm

Constants

$B_{\text{grid},t}$, $B_{\text{BES},t}$, $B_{\text{MT},t}$, $B_{\text{FC},t}$, $B_{\text{PV},t}$, $B_{\text{WT},t}$	bid of utility, BES, MT, FC, PV, WT at time t, respectively (€ct/kWh)
FC_{BES}, MC_{BES}	fixed and maintenance cost for BES, respectively (€ct/kWh)
IR	interest rate for financing the installed BES
LT	lifetime of the installed BES (year)
T	operation time horizon (h)
OR_t	minutes operating reserve requirements (kW)
OM_{DG}	fixed operation and maintenance cost of distributed generators (DGs) (€ct)
OM_{MT}, OM_{FC}, OM_{PV}, OM_{WT}	fixed operation and maintenance cost of MT, FC, PV and WT, respectively (€ct/kWh)
$P_{\text{grid,max}}$, $P_{\text{grid,min}}$	maximum/minimum limits of power production for the utility, respectively (kW)
$P_{\text{D},t}$	electrical load demand at time t (kW)
$P_{\text{MT,max}}$, $P_{\text{FC,max}}$, $P_{\text{PV},t\,\text{max}}$, $P_{\text{WT},t\,\text{max}}$, $P_{\text{BES,max}}$	maximum producible power of MT, FC, PV, WT and BES respectively (kW)
$P_{\text{MT,min}}$, $P_{\text{FC,min}}$, $P_{\text{PV},t\,\text{min}}$, $P_{\text{WT},t\,\text{min}}$, $P_{\text{BES,min}}$	minimum producible power of MT, FC, PV, WT and BES respectively (kW)
SD_{MT}, SD_{FC}	shut-down cost coefficient for MT and FC, respectively (€ct)
SU_{MT}, SU_{FC}	start-up cost coefficient for MT and FC, respectively (€ct)
tax	tax rate of utility power grid
Δt	time interval duration
η_d, η_c	discharge and charge efficiency of BES, respectively
Iter_max	maximum number of iteration for the GWO algorithm

Variables

$C_{\text{BES,min}}$, $C_{\text{BES,max}}$	minimum and maximum size of BES (kWh)
$C_{\text{BES},t}$	energy stored in the BES at time t (kWh)
$\text{Cost}_{\text{grid},t}$	cost of trade with the up-stream grid at time t (€ct)
$\text{Cost}_{\text{DG},t}$, $\text{Cost}_{\text{BES},t}$	cost of fuel and operating power of DGs and BES at time t, respectively (€ct)
X	control variable
F	total costs (€ct)
$P_{\text{grid,t}}$, $P_{\text{BES},t}$, $P_{\text{MT},t}$, $P_{\text{FC},t}$ $P_{\text{PV},t}$, $P_{\text{WT},t}$	power of utility, BES, MT, FC, PV and WT, respectively (kW)
$\overline{P}_{\text{BES},t}$, $\underline{P}_{\text{BES},t}$	maximum discharge and charge rates of BES at time t, respectively (kW)
$\text{SDC}_{\text{MT},t}$, $\text{SDC}_{\text{FC},t}$	shut-down cost for MT and FC at time t, respectively (€ct)
$\text{SUC}_{\text{MT},t}$, $\text{SUC}_{\text{FC},t}$	start-up cost for MT and FC at time t, respectively (€ct)
TCPD_{BES}	total cost per day of BES (€ct)
$u_{\text{BES},t}$, $u_{\text{MT},t}$, $u_{\text{FC},t}$	status (on or off) of BES, MT and FC at time t, respectively
$\boldsymbol{X}$	position vector of a grey wolf in GWO algorithm

X_P position vector of the prey in GWO algorithm

tt current iteration of GWO algorithm

Subscript

t tth time step (h)

1 Introduction

A micro-grid (MG) provides an effective means to integrate small-scale distributed generation sources (DGs) into the bulk electric power grid to meet the increasing load growth. MG is defined as an aggregation of electrical loads and DGs (mainly renewable resources such as wind and solar) along with the energy storage devices operating as a single system providing both power and heat. MG combined with renewable energy sources (RESs) and small scale DGs can be a preferable solution to the raised energy crisis as well as a complement to the centralised modern power grids [1]. Nowadays, due to the increasing concerns and challenges about the fluctuation and intermittency of wind turbine (WT) and photo-voltaic (PV) units as RESs in the MG system, the MG central controller (MGCC) feels the urge to implement battery energy storage (BES) within the MG system for storing excess energy throughout the times of high availability and to inject it to the MG during a power shortage. So, determination of appropriate capacity or size of BES plays an important role for an optimised operation cost minimisation problem of MG.

The operation cost minimisation problem of MG is one of the backbone optimisation tools for smart grid manager or MGCC in which the optimal power output of BES and DGs are determined while satisfying all equality and inequality constraints, to minimise the operation cost of MG. Many research works have been done in the field of operation cost minimisation of MG, considering the impact of optimum size of BES on operation cost minimisation problem, some of which are discussed here. Mitra [2] described an analytical approach to determine the size of backup storage unit to meet a specified reliability target. Ekren and Banu Y. Ekren [3] presented simulated annealing algorithm to optimise the size of a PV/wind integrated hybrid energy system with battery storage to minimise the total cost of the hybrid energy system. Kaldellis *et al.* [4] developed a complete methodology able to define the dimensions of an autonomous electricity generation system based on the maximum available solar energy at minimum electricity generation cost by selecting the most cost efficient energy storage configuration. Mohammadi *et al.* [5] presented a genetic algorithm (GA)-based optimisation method to obtain optimum power and price of MG consisting of PV array, fuel Cell (FC) and battery bank with multiple DG units under hybrid electricity market to maximise net present worth of the MG. Chen *et al.* [6] presented a mixed linear integer problem solved in a modelling language for mathematical programming which was based on the cost-benefit analysis for optional sizing of an energy storage system in MG. Jia *et al.* [7] proposed a statistical model based on Monte–Carlo simulation to determine the capacity of battery-super capacitor hybrid energy storage system in autonomous MG. Bahmani-Firouzi and Azizipanah-Abarghooee [8] proposed an improved bat algorithm (IBA) to minimise total operation cost of MG and to determine optimal size of BES. Abbassi and Chebbi [9] developed and simulated supervisory algorithms for optimum operation of a DG-coupled wind/photovoltaic hybrid system equipped with BES system.

Although a large number of research works focused on the operation cost minimisation problem without considering the impact of optimum sizing of BES on the MG operation. Chakraborty *et al.* [10] used linear programming method to minimise operation cost of MG and to optimise the charge states of BES. Sortomme and El-Sharkawi applied particle swarm optimisation (PSO) algorithm to the operation cost minimisation of MG in [11]. Mohamed and Koivo [12] presented mesh adaptive direct search algorithm to determine the optimal operating strategy and cost minimisation scheme for MG. Moghaddam *et al.* [13] proposed an adaptive modified PSO for optimal operation of a typical MG with RESs accompanied by a micro-turbine (MT), FC and BES over 24 h time horizon to minimise the total operating cost and the net emission simultaneously. Taher Niknam *et al.* presented a multi-objective honey bee mating optimisation algorithm in [14] for multi-objective operation cost minimisation of MG including FC, WT and PV neglecting the BES technology to minimise the active power losses, the voltage deviations, total electrical energy costs and the total emissions of RESs and substations. A fuzzy self-adaptive PSO algorithm was proposed by Moghaddam *et al.* [15] to optimise a multi-objective operation cost minimisation problem of MG considering economy and emission as competitive objectives. Niknam *et al.* [16] presented improved teaching–learning-based optimisation to minimise the operation cost and emission of MG simultaneously. Marrouchi and Saber [17] presented a comparative study between a strategy based on hybrid gradient-GA method and two strategies based on meta-heuristic methods, fuzzy logic and GA, in order to predict the combinations and the unit commitment scheduling of each production unit of IEEE 14 bus system and to minimise the total production cost of the system.

In this paper grey wolf optimisation (GWO) has been applied to solve the operation cost minimisation problem of MG. GWO algorithm [18] is mimicked from the leadership hierarchy and hunting mechanism of grey wolves in nature and is able to provide very competitive results of different benchmark functions compared with other well-known meta-heuristic techniques. Moreover the exploration and exploitation ability of GWO algorithm is much improved compared with many previously developed optimisation techniques. The improved performance of GWO algorithm has motivated the present authors to apply this algorithm to minimise the total operation costs of MG considering optimum size of BES. To show the effectiveness and superiority, the results obtained with GWO algorithm has been compared with many other popular optimisation techniques such as GA, PSO, bat algorithm (BA) [8], IBA [8], Tabu search (TS), differential evolution (DE), biogeography-based optimisation (BBO) and TLBO. Recently GWO algorithm has been applied to solve different power system optimisation problems. In [19] Sulaimana, *et al*. applied GWO to solve optimal reactive power dispatch problem to minimise loss and voltage deviation of power system network. Mahdad and Srairi [20] introduced a flexible and reliable power system planning strategy by the application of GWO coordinated with pattern search algorithm for solving the security smart grid power system management under critical situations.

Section 2 of the paper provides a brief description and mathematical formulation of the operation cost minimisation problem of MG. Section 3 describes the GWO shortly and the application of GWO algorithm to solve operation cost minimisation problem of MG. Simulation results are presented and discussed in Section 4. The conclusion is drawn in Section 5.

2 Mathematical formulation of operation cost minimisation problem of micro-grid

The mathematical formulation of the present operation cost minimisation problem can be described as follows:

2.1 Objective function

The objective function is to minimise the total costs of MG and may be written as follows [6, 8, 21]

$$\text{Min } F(X) = \sum_{t=1}^{T} f_t + \text{OM}_{\text{DG}} + \text{TCPD}_{\text{BES}} \tag{1}$$

where

$$f_t = \mathrm{Cost}_{\mathrm{grid},t} + \mathrm{Cost}_{\mathrm{DG},t} + \mathrm{Cost}_{\mathrm{BES},t} + \mathrm{SUC}_{\mathrm{MT},t} + \mathrm{SUC}_{\mathrm{FC},t} + \mathrm{SDC}_{\mathrm{MT},t} + \mathrm{SDC}_{\mathrm{FC},t} \quad (2)$$

$$\mathrm{Cost}_{\mathrm{grid},t} = \begin{cases} B_{\mathrm{grid},t} P_{\mathrm{grid},t} & \text{if } P_{\mathrm{grid},t} > 0 \\ (1-\mathrm{tax}) B_{\mathrm{grid},t} P_{\mathrm{grid},t} & \text{if } P_{\mathrm{grid},t} < 0 \\ 0 & \text{if } P_{\mathrm{grid},t} = 0 \end{cases} \quad (3)$$

$$\mathrm{Cost}_{\mathrm{DG},t} = B_{\mathrm{MT},t} P_{\mathrm{MT},t} u_{\mathrm{MT},t} + B_{\mathrm{FC},t} P_{\mathrm{FC},t} u_{\mathrm{FC},t} + P_{\mathrm{PV},t} B_{\mathrm{PV},t} + P_{\mathrm{WT},t} B_{\mathrm{WT},t} \quad (4)$$

$$\mathrm{Cost}_{\mathrm{BES},t} = B_{\mathrm{BES},t} P_{\mathrm{BES},t} u_{\mathrm{BES},t} \quad (5)$$

$$\mathrm{SUC}_{\mathrm{MT},t} = \mathrm{SU}_{\mathrm{MT}} \times \max(0, u_{\mathrm{MT},t} - u_{\mathrm{MT},t-1}) \quad (6)$$

$$\mathrm{SUC}_{\mathrm{FC},t} = \mathrm{SU}_{\mathrm{FC}} \times \max(0, u_{\mathrm{FC},t} - u_{\mathrm{FC},t-1}) \quad (7)$$

$$\mathrm{SDC}_{\mathrm{MT},t} = \mathrm{SD}_{\mathrm{MT}} \times \max(0, u_{\mathrm{MT},t-1} - u_{\mathrm{MT},t}) \quad (8)$$

$$\mathrm{SDC}_{\mathrm{FC},t} = \mathrm{SD}_{\mathrm{FC}} \times \max(0, u_{\mathrm{FC},t-1} - u_{\mathrm{FC},t}) \quad (9)$$

$$\mathrm{OM}_{\mathrm{DG}} = (\mathrm{OM}_{\mathrm{MT}} + \mathrm{OM}_{\mathrm{FC}} + \mathrm{OM}_{\mathrm{PV}} + \mathrm{OM}_{\mathrm{WT}}) \times T \quad (10)$$

The total energy and operating cost of the MG consists of the operation cost of utility, operation cost of BES, fuel costs of DGs, operation and maintenance cost of DGs, start-up/shut-down costs of MT and FC as well as total cost per day of BES ($\mathrm{TCPD_{BES}}$). The cost of BES contains the one time fixed cost ($\mathrm{FC_{BES}}$) which arises from the purchase of small battery blocks to make up BES and the annual Maintenance Cost ($\mathrm{MC_{BES}}$) which is a variable cost and is proportional to the size of BES. If $C_{\mathrm{BES,max}}$ is the size of BES, then the total cost of battery is $(\mathrm{FC_{BES}} + \mathrm{MC_{BES}}) \times \mathrm{C_{BES,max}}$. The time horizon considered here is one day and the operation is calculated over 24 h. If the interest rate for financing the installed BES and its lifetime are considered as IR and LT, then the $\mathrm{TCPD_{BES}}$ installed in €ct/day can be formulated as follows [6, 8]

$$\mathrm{TCPD_{BES}} = \frac{\mathrm{C_{BES,max}}}{365} \left(\frac{\mathrm{IR}(1+\mathrm{IR})^{\mathrm{LT}}}{(1+\mathrm{IR})^{\mathrm{LT}} - 1} \mathrm{FC_{BES}} + \mathrm{MC_{BES}} \right) \quad (11)$$

2.2 Constraints

The above mentioned operation cost minimisation problem is subjected to the following constraints:

2.2.1 Electrical load demand balance constraint: Electrical load demand $P_{\mathrm{D},t}$ at time t, should be equal to the summation of total generated power of MT, FC, PV and WT and total absorbed or injected power to BES and utility. Thus the electrical load demand balance operation [13] can be expressed as:

$$P_{\mathrm{MT},t} u_{\mathrm{MT},t} + P_{\mathrm{FC},t} u_{\mathrm{FC},t} + P_{\mathrm{PV},t} + P_{\mathrm{WT},t} + P_{\mathrm{BES},t} u_{\mathrm{BES},t} + P_{\mathrm{grid},t} = P_{\mathrm{D},t} \quad t = 1, 2, \ldots, T \quad (12)$$

2.2.2 Active power constraints of DG units: The operating output of each DG unit should be within its minimum and maximum limits [15]. The generating capacity constraints are written as

$$P_{\mathrm{MT,min}} \le P_{\mathrm{MT},t} \le P_{\mathrm{MT,max}} \quad t = 1, \ldots, T \quad (13)$$

$$P_{\mathrm{FC,min}} \le P_{\mathrm{FC},t} \le P_{\mathrm{FC,max}} \quad t = 1, \ldots, T \quad (14)$$

$$P_{\mathrm{PV},t\,\mathrm{min}} \le P_{\mathrm{PV},t} \le P_{\mathrm{PV},t\,\mathrm{max}} \quad t = 1, \ldots, T \quad (15)$$

$$P_{\mathrm{WT},t\,\mathrm{min}} \le P_{\mathrm{WT},t} \le P_{\mathrm{WT},t\,\mathrm{max}} \quad t = 1, \ldots, T \quad (16)$$

2.2.3 Constraints for BES: In this study the lithium-ion BES has been used in the MG. It has several advantages and benefits such as no memory effect, the highest energy density among other types of the BESs and a slow loss of charge when not in use [6, 8]. It is also considered globally as the major energy storage device for defence, automotive, and aerospace applications in terms of high energy density [8, 22].

Discharging mode:

$$C_{\mathrm{BES},t+1} = \max\left\{ \left(\frac{C_{\mathrm{BES},t} - \Delta t P_{\mathrm{BES},t}}{\eta_d} \right), C_{\mathrm{BES,min}} \right\} \quad t = 1, \ldots, T \quad (17)$$

where

$$\underline{P}_{\mathrm{BES},t} \le P_{\mathrm{BES},t} \le \overline{P}_{\mathrm{BES},t} \quad t = 1, \ldots, T \quad (18)$$

Charging mode:

$$C_{\mathrm{BES},t+1} = \min\{ (C_{\mathrm{BES},t} - \Delta t P_{\mathrm{BES},t} \eta_c), C_{\mathrm{BES,max}} \} \quad t = 1, \ldots, T \quad (19)$$

where

$$\underline{P}_{\mathrm{BES},t} \le P_{\mathrm{BES},t} \le \overline{P}_{\mathrm{BES},t} \quad t = 1, \ldots, T \quad (20)$$

where

$$\overline{P}_{\mathrm{BES},t} = \min\left\{ P_{\mathrm{BES,max}}, \frac{(C_{\mathrm{BES},t} - C_{\mathrm{BES,min}})\,\eta_{\mathrm{d}}}{\Delta t} \right\} \quad t = 1, \ldots, T \quad (21)$$

$$\underline{P}_{\mathrm{BES},t} = \max\left\{ P_{\mathrm{BES,min}}, \frac{(C_{\mathrm{BES},t} - C_{\mathrm{BES,max}})}{(\eta_{\mathrm{c}} \Delta t)} \right\} \quad t = 1, \ldots, T \quad (22)$$

Constraints (17) and (18) mentioned above are the limitations of released energy from the BES and power discharged by the BES, respectively. Moreover the restrictions on the stored energy in the BES and power charged by the grid to the BES are expressed as (19) and (20), respectively. The maximum and minimum charging/discharging rates are determined using (21) and (22), respectively.

2.2.4 Grid constraint: Power supplied by utility should be within its minimum and maximum limits in each time step and is given by:

$$P_{\mathrm{grid,min}} \le P_{\mathrm{grid},t} \le P_{\mathrm{grid,max}} \quad t = 1, \ldots, T \quad (23)$$

2.2.5 Operating reserve (OR) constraint: OR is the sum of reserved electrical power generation capacity of turned on MT, FC, utility and BES in each time step [8]. It can be injected to the MG in less than 10 min and formulated as follows

$$P_{\mathrm{MT,max}} u_{\mathrm{MT},t} + P_{\mathrm{FC,max}} u_{\mathrm{FC},t} + P_{\mathrm{grid,max}} + \overline{P}_{\mathrm{BES},t} u_{\mathrm{BES},t} \ge \mathrm{OR}_t + P_{\mathrm{D},t} \quad t = 1, \ldots, T \quad (24)$$

where, OR_t is the 10 min OR requirement at time t.

3 Optimal operation management of MG using GWO

This paper presents GWO algorithm for solving optimal operation management of MG.

3.1 Overview of GWO algorithm

GWO is proposed by Mirjalili *et al.*[18]. The mathematical model of GWO is inspired by the hunting technique and the social hierarchy of

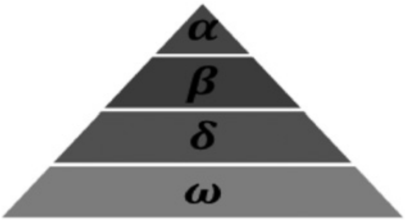

Fig. 1 *Social hierarchy of grey wolf*

grey wolves that belong to Canidae family. Fig. 1 shows the social hierarchy of grey wolves. The leader of the social hierarchy of grey wolves is called alpha and the group follows his or her instructions. The second level of the hierarchy is called beta wolves and they assist the alpha in making decisions. Omegas are the lowest ranking grey wolves of the hierarchy and they have to submit to all other dominant wolves. Delta wolves come in the hierarchy next to the alphas and betas but they lead the omega. To mathematically model the social hierarchy of grey wolves, first the fitness solutions are determined and the best fitness solution is regarded as alpha (α), the second and third best solutions are considered as beta (β) and delta (δ), while the rests of the fitness solutions are regarded as omega (ω) wolves. In addition to the social hierarchy of wolves, group hunting is another important social activity of grey wolves. The steps for group hunting of grey wolves are shown in Fig. 2 and also discussed in the following sections.

3.1.1 Encircling prey: Grey wolves encircle prey during the hunt. In this process, a grey wolf can update its position inside the space around the prey in any random location by using (25) and (26).

The encircling behaviour of grey wolves can be represented as [18]

$$\boldsymbol{D} = \left|\boldsymbol{C}\cdot\boldsymbol{X}_{\mathrm{P}}(tt) - \boldsymbol{X}(tt)\right| \tag{25}$$

$$\boldsymbol{X}(tt+1) = \boldsymbol{X}_{\mathrm{P}}(tt) - \boldsymbol{A}\cdot\boldsymbol{D} \tag{26}$$

$\boldsymbol{A}$ and $\boldsymbol{C}$ are the coefficient vectors which are calculated using the following equations

$$\boldsymbol{A} = 2\boldsymbol{a}\cdot\boldsymbol{r}_1 - \boldsymbol{a} \tag{27}$$

$$\boldsymbol{C} = 2\cdot\boldsymbol{r}_2 \tag{28}$$

The components of $\boldsymbol{a}$ are linearly decreased from 2 to 0 over the course of iterations and $\boldsymbol{r}_1$ and $\boldsymbol{r}_2$ are random vectors between [0, 1].

3.1.2 Hunting: The hunt is guided by the alpha wolf. The beta and delta wolves participate in hunting occasionally. To mathematically represent the hunting behaviour of grey wolves, it is considered that the alpha, beta and delta wolves have superior knowledge about the potential location of prey. Hence, the first three best solutions achieved are saved and the other search agents are forced to update their positions according to the location of the best search agents [18]. The following equations can be used in this regard.

$$\boldsymbol{D}_\alpha = \left|\boldsymbol{C}_1\cdot\boldsymbol{X}_\alpha - \boldsymbol{X}\right| \tag{29}$$

$$\boldsymbol{D}_\beta = \left|\boldsymbol{C}_2\cdot\boldsymbol{X}_\beta - \boldsymbol{X}\right| \tag{30}$$

$$\boldsymbol{D}_\delta = \left|\boldsymbol{C}_3\cdot\boldsymbol{X}_\delta - \boldsymbol{X}\right| \tag{31}$$

$$\boldsymbol{X}_1 = \boldsymbol{X}_\alpha - \boldsymbol{A}_1\cdot(\boldsymbol{D}_\alpha) \tag{32}$$

$$\boldsymbol{X}_2 = \boldsymbol{X}_\beta - \boldsymbol{A}_2\cdot(\boldsymbol{D}_\beta) \tag{33}$$

$$\boldsymbol{X}_3 = \boldsymbol{X}_\delta - \boldsymbol{A}_3\cdot(\boldsymbol{D}_\delta) \tag{34}$$

$$\boldsymbol{X}(tt+1) = \frac{\boldsymbol{X}_1 + \boldsymbol{X}_2 + \boldsymbol{X}_3}{3} \tag{35}$$

3.1.3 Attacking prey (exploitation): The grey wolves finish their hunting process by attacking the prey when it stops moving. To mathematically represent the approaching of grey wolves towards the prey, the value of $\boldsymbol{a}$ is gradually reduced from 2 to 0 and thereby the fluctuation range of $\boldsymbol{A}$ is also decreased. When $\boldsymbol{A}$ has random values in the range [−1, 1], then the search agent's next location will be in any place between its current position and

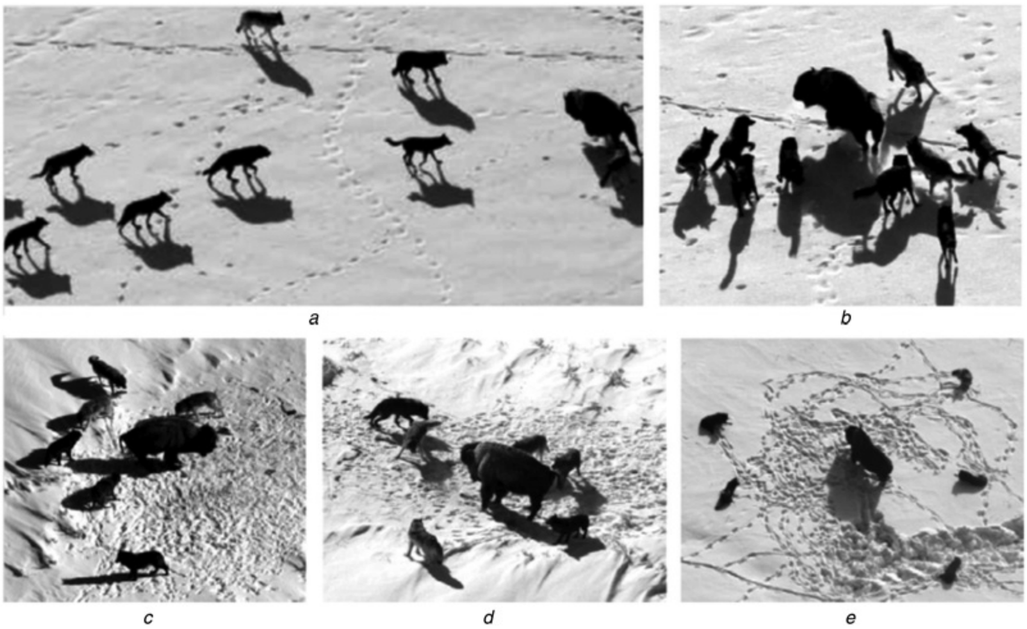

Fig. 2 *Hunting behaviour of grey wolves*

a Chasing, approaching, and tracking prey
b–d Pursuing, harassing, and encircling prey
e Stationary situation and attack

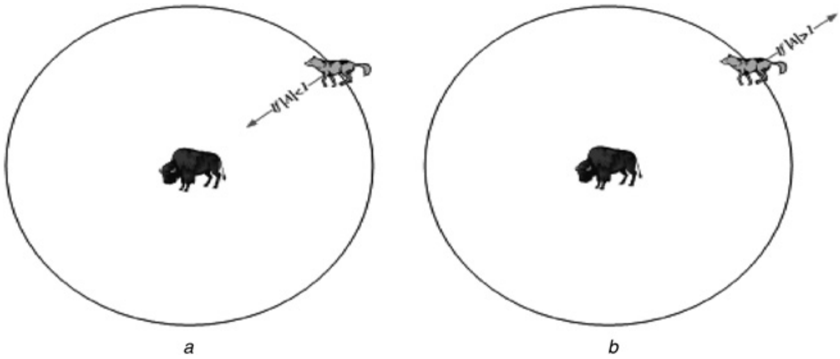

Fig. 3 *Exploitation and exploration characteristics of grey wolf*

a Attacking prey (exploitation)
b Searching for prey (exploration)

the position of the prey [18]. When $|A| < 1$, the grey wolves attack the prey, which is shown in Fig. 3*a*.

3.1.4 Search for prey (exploration): To search for a fitter prey, grey wolves diverge from each other. To mathematically model the divergence characteristics of grey wolves, $\boldsymbol{A}$ is employed with random values greater than 1 or less than −1 to force the search agent to diverge from the prey. This put emphasis on exploration characteristics and allows the GWO algorithm to explore globally. Fig. 3*b* shows that when $|A| > 1$, the grey wolves diverge from the prey to find a fitter prey [18].

3.2 Application of GWO algorithm to solve operation cost minimisation problem of MG

Different steps for applying GWO algorithm to minimise total operation cost of MG, by finding optimum size of BES and optimum output power of DGs, BES and upstream power grid are given below.

Step 1: Initially define all necessary input data, that is, bid-rate of all DGs and BES, operation and maintenance cost and generation capacity of each DG, power output of WT and PV, minimum and maximum injectable or absorbable power limit of grid and BES, bid-rate of grid and utility, limits of BES size, interest rate and lifetime of BES, fixed and maintenance cost of BES, charge and discharge efficiency of BES, electrical load demand, operating reserve capacity, start-up and shut-down cost data for MT and FC etc.
Step 2: Initialise the number of search agents (N) in grey wolf population matrix ($\boldsymbol{X}$) and also initialise maximum numbers of iterations ($\text{iter}_{\max}$).
Step 3: Initialisation of grey wolf population matrix ($\boldsymbol{X}$):

In grey wolf population matrix ($\boldsymbol{X}$), each population set represents the position of a search agent. From the optimisation point of view, position of a search agent signifies one of the possible solutions for the operation cost minimisation problem of MG. In the present operation cost minimisation problem of MG, position of each search agent consists of the maximum size of BES, output power of MT, FC, PV, WT, absorption/injection power of BES and utility, status of MT, FC, PV, WT, BES and utility in the operation horizon (T). Each element of the position of search agent is initialised within the effective operating size limit of BES, real power output limits of MT, FC, PV, WT, BES and utility and on/off status of MT, FC, PV, WT, BES and utility (1 for 'on' condition and 0 for 'off' condition) and may be determined as follows

$$x_{m,j} = x_{m,j}^{\min} + rand(0,1) * (x_{m,j}^{\max} - x_{m,j}^{\min}) \tag{36}$$

where $x_{m,j}$ is the jth element of mth search agent position. Here $m = 1, 2,\dots, N$ and $j = 1, 2,\dots, D$.

Here N is the number of search-agents and D is the number of variables in the problem.

If the MG under study has k number of MT, n number of FC, p number of PV, q number of WT and s number of BES, then the position of mth search agent (X_m) can be defined as follows: (see equation (37) at bottom of the next page)

Now complete initial grey wolf population matrix ($\boldsymbol{X}$) is represented in the form of the following matrix:

Grey wolf population matrix,

$$\boldsymbol{X} = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_m \\ \cdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \cdots & & & \\ x_{m,1} & x_{m,2} & \cdots & x_{m,D} \\ \cdots & & & \\ x_{N,1} & x_{N,2} & \cdots & x_{N,D} \end{bmatrix} \tag{38}$$

Here to get highest benefit of various resources, assume the ON/OFF status of PV, WT and utility as 1, that is, ON state in all the three cases. Each population set, that is, position of each search agent should satisfy the constraints such as load demand balance constraint, DGs output power limit constraints, charging/discharging limits of BES, grid output power limit and operating reserve constraint mentioned in (12)–(24).

Step 4: If constraints limits for position of each search agent of grey wolf population matrix are satisfied, then go to the next step, otherwise again generate the initial population matrix and repeat the step 3, until all the constraints are satisfied.
Step 5: Initialise $\boldsymbol{a}$, $\boldsymbol{A}$, $\boldsymbol{C}$ using (27) and (28).
Step 6: Evaluate the fitness function value of each search agent.
Step 7: Calculate the minimum value of fitness function and the corresponding position of search agent is regarded as X_α. The position representing second and third minimum values of fitness function are considered X_β and $X_\delta$respectively.
Step 8: Set iteration number $iter = 1$.
Step 9: Update the position of each search agent using (29)–(35).
Step 10: Update the values of $\boldsymbol{a}$, $\boldsymbol{A}$, $\boldsymbol{C}$ using (27) and (28).
Step 11: Check the limits of output power of MT, FC, PV, WT, BES and utility. Moreover check all the equality and inequality constraints mentioned in (12)–(24) with the new position of each search agent.
Step 12: If constraints limits are satisfied, then go to the next step, otherwise go to step 9 again and repeat steps 9–12.
Step 13: Evaluate the fitness function value of each updated search agent and determine the minimum value of fitness function.
Step 14: Set the position of search agent corresponding to minimum fitness function value as X_α. Moreover set the position corresponding

to second and third minimum values of fitness function as X_β and X_δ respectively.

Step 15: Increase iteration (*iter*) number by 1, that is, $iter = iter + 1$.

Step 16: Check the convergence criterion. If the maximum number of iterations is reached, terminate the iterative process and store the objective function value corresponding to X_α as the best solution of the optimisation problem**,** else repeat steps 9–16.

The flow-chart of operation cost minimisation of MG using GWO algorithm is depicted in Fig. 4.

4 Simulation results and discussions

In this paper GWO algorithm has been applied to solve operation cost minimisation problem of MG. To assess the validity and effectiveness of the algorithm, it is tested on a typical low voltage MG system which is depicted in [8].

4.1 Description of the MG test system

The MG under study is comprised of different DGs such as the MT, FC, PV, WT and also Li-ion BES. All coefficients and production limits which are utilised in the operation cost minimisation of MG are listed in Table 1 [8]. The forecasted PV and WT power outputs for 24 h time horizon are shown in Table 2, whereas forecasted load demand and market energy prices within the MG for 24 h time horizon are depicted in Figs. 5 and 6 [6, 8, 13, 21]. In all case studies, it is assumed that all the DGs generate active power at unity power factor, neither requesting nor generating reactive power. The operating reserve requirement is set to the 5% of the load demand in each time step. The fixed and maintenance cost for installation and operation of BES are assumed as 465 (€ct/kWh) and 15 (€ct/kWh). The lifetime and interest rate for financing the installed BES are considered as 3 and 0.06 respectively. The tax is selected as 10% in this study. The charge rate and discharge rate of BES are the same and set at 90%. The full capacity of BES is fixed at 500 kWh and the minimum capacity is set to 10% of the full capacity. It means that maximum size of BES, that is, $C_{\mathrm{BES,max}}$ is a variable and it should be optimised in the range of [50, 500]. The case studies on operation cost minimisation are performed for a time horizon of one day with hourly time step [6, 8, 13, 21].

The proposed GWO algorithm for operation cost minimisation of MG has been implemented using MATLAB software and executed on a personal computer with 2.4 GHz CPU and 1 GB RAM. During simulation, the values of parameters used in GWO are: number of search-agents = 100 and maximum number of iteration = 1000. To verify the performance of GWO algorithm, the results obtained in this paper has been compared with the results obtained by applying other algorithms such as GA [8], PSO [8], BA [8] and IBA [8], TS, DE, BBO and TLBO. In the present paper three different cases have been considered to determine the validity of GWO algorithm for operation cost minimisation of MG. The cases are as follows:

Case A: Operation of MG without BES.
Case B: Operation of MG including BES without any initial charge.
Case C: Operation of MG including BES with initial charge equal to the size of BES.

4.1.1 Case A: In this case study it is considered that the MG is operating without the presence of BES and all the DGs either RESs or non-RESs should satisfy the forecasted load demand during the examined period. The operation cost of MG obtained for Case A by applying GWO algorithm has been compared with the results of other algorithms such as GA [8], PSO [8], BA [8], IBA [8], TS, DE, BBO and TLBO**.** The results are presented in Table 3. The table shows the best, average and worst values of operation cost of MG for 30 trail runs. Mean simulation time to carry out the simulation with all the above mentioned algorithms are also listed in the same table. From the results obtained it is clear that, GWO algorithm gives lower operation cost of MG (816.3751 €ct/day) compared with other algorithms. Moreover mean simulation time required with GWO algorithm (0.0896 min) is less compared with other algorithms. Table 3 also shows the median and standard deviation values of operation cost of MG for Case A after 30 trail runs for each algorithm. From the results it is observed that the values of median and standard deviation of operation cost of MG for case A are 816.3751 and 0.1249 respectively obtained by applying GWO algorithm, which are much less compared with those obtained with other algorithms.

The available operating reserve capacity by dispatchable DGs, that is, MT and FC and upstream network for Case A is presented in Table 4. As no BES is considered in the MG in this case study, the available power output of the DGs and utility must be greater than the power demand of MG as operating reserve, to ensure stable system operation. Table 5 shows the numerical results of the optimal power dispatch of different DGs and utility and their corresponding status under the operation of MG using GWO algorithm. In this case study, the operation cost of MG obtained by applying GWO algorithm is 816.3751 €ct/day which is less than the results obtained using GA [8], PSO [8], BA [8], IBA [8], TS, DE, BBO and TLBO algorithms and the comparison is shown in Table 3. As BES is not considered in the operation of MG, the MGCC should purchase power from the utility power grid in most of the hours of the day. From the results obtained, it is clear that due to the lower bid of FC compared with MT, the MGCC purchases more power from the FC. The convergence characteristics for MG operation cost minimisation using different

$$X_m = \left[x_{m,1}\, x_{m,2}\, \ldots\, x_{m,D}\right]$$
$$= \left[\begin{array}{l} C_{\mathrm{BES\,max},1},\, C_{\mathrm{BES\,max},2},\, \ldots,\, C_{\mathrm{BES\,max},s},\, P^m_{\mathrm{MT},1,1},\, P^m_{\mathrm{MT},1,2},\, \ldots,\, P^m_{\mathrm{MT},1,T}, \\ P^m_{\mathrm{MT},2,1},\, P^m_{\mathrm{MT},2,2},\, \ldots,\, P^m_{\mathrm{MT},2,T},\, \ldots,\, P^m_{\mathrm{MT},k,1},\, P^m_{\mathrm{MT},k,2},\, \ldots,\, P^m_{\mathrm{MT},k,T}, \\ P^m_{\mathrm{FC},1,1},\, P^m_{\mathrm{FC},1,2},\, \ldots,\, P^m_{\mathrm{FC},1,T},\, P^m_{\mathrm{FC},2,1},\, P^m_{\mathrm{FC},2,2},\, \ldots,\, P^m_{\mathrm{FC},2,T},\, \ldots,\, P^m_{\mathrm{FC},n,1},\, P^m_{\mathrm{FC},n,2},\, \ldots,\, P^m_{\mathrm{FC},n,T}, \\ P^m_{\mathrm{PV},1,1},\, P^m_{\mathrm{PV},1,2},\, \ldots,\, P^m_{\mathrm{PV},1,T},\, P^m_{\mathrm{PV},2,1},\, P^m_{\mathrm{PV},2,2},\, \ldots,\, P^m_{\mathrm{PV},2,T},\, \ldots,\, P^m_{\mathrm{PV},p,1},\, P^m_{\mathrm{PV},p,2},\, \ldots,\, P^m_{\mathrm{PV},p,T}, \\ P^m_{\mathrm{WT},1,1},\, P^m_{\mathrm{WT},1,2},\, \ldots,\, P^m_{\mathrm{WT},1,T},\, P^m_{\mathrm{WT},2,1},\, P^m_{\mathrm{WT},2,2},\, \ldots,\, P^m_{\mathrm{WT},2,T},\, \ldots,\, P^m_{\mathrm{WT},q,1},\, P^m_{\mathrm{WT},q,2},\, \ldots,\, P^m_{\mathrm{WT},q,T}, \\ P^m_{\mathrm{BES},1,1},\, P^m_{\mathrm{BES},1,2},\, \ldots,\, P^m_{\mathrm{BES},1,T},\, P^m_{\mathrm{BES},2,1},\, P^m_{\mathrm{BES},2,2},\, \ldots,\, P^m_{\mathrm{BES},2,T},\, \ldots,\, P^m_{\mathrm{BES},s,1},\, P^m_{\mathrm{BES},s,2},\, \ldots,\, P^m_{\mathrm{BES},s,T}, \\ P^m_{\mathrm{grid},1},\, P^m_{\mathrm{grid},2},\, \ldots,\, P^m_{\mathrm{grid},T},\, u^m_{\mathrm{MT},1,1},\, u^m_{\mathrm{MT},1,2},\, \ldots,\, u^m_{\mathrm{MT},1,T},\, u^m_{\mathrm{MT},2,1},\, u^m_{\mathrm{MT},2,2},\, \ldots, \\ u^m_{\mathrm{MT},2,T},\, \ldots,\, u^m_{\mathrm{MT},k,1},\, u^m_{\mathrm{MT},k,2},\, \ldots,\, u^m_{\mathrm{MT},k,T}, \\ u^m_{\mathrm{FC},1,1},\, u^m_{\mathrm{FC},1,2},\, \ldots,\, u^m_{\mathrm{FC},1,T},\, u^m_{\mathrm{FC},2,1},\, u^m_{\mathrm{FC},2,2},\, \ldots,\, u^m_{\mathrm{FC},2,T},\, \ldots,\, u^m_{\mathrm{FC},n,1},\, u^m_{\mathrm{FC},n,2},\, \ldots,\, u^m_{\mathrm{FC},n,T}, \\ u^m_{\mathrm{PV},1,1},\, u^m_{\mathrm{PV},1,2},\, \ldots,\, u^m_{\mathrm{PV},1,T},\, u^m_{\mathrm{PV},2,1},\, u^m_{\mathrm{PV},2,2},\, \ldots,\, u^m_{\mathrm{PV},2,T},\, \ldots,\, u^m_{\mathrm{PV},p,1},\, u^m_{\mathrm{PV},p,2},\, \ldots,\, u^m_{\mathrm{PV},p,T}, \\ u^m_{\mathrm{WT},1,1},\, u^m_{\mathrm{WT},1,2},\, \ldots,\, u^m_{\mathrm{WT},1,T},\, u^m_{\mathrm{WT},2,1},\, u^m_{\mathrm{WT},2,2},\, \ldots,\, u^m_{\mathrm{WT},2,T},\, \ldots,\, u^m_{\mathrm{WT},q,1},\, u^m_{\mathrm{WT},q,2},\, \ldots,\, u^m_{\mathrm{WT},q,T}, \\ u^m_{\mathrm{BES},1,1},\, u^m_{\mathrm{BES},1,2},\, \cdots,\, u^m_{\mathrm{BES},1,T},\, u^m_{\mathrm{BES},2,1},\, u^m_{\mathrm{BES},2,2},\, \ldots,\, u^m_{\mathrm{BES},2,T},\, \ldots, \\ u^m_{\mathrm{BES},s,1},\, u^m_{\mathrm{BES},s,2},\, \ldots,\, u^m_{\mathrm{BES},s,T},\, u^m_{\mathrm{grid},1},\, u^m_{\mathrm{grid},2},\, \ldots,\, u^m_{\mathrm{grid},T} \end{array}\right] \tag{37}$$

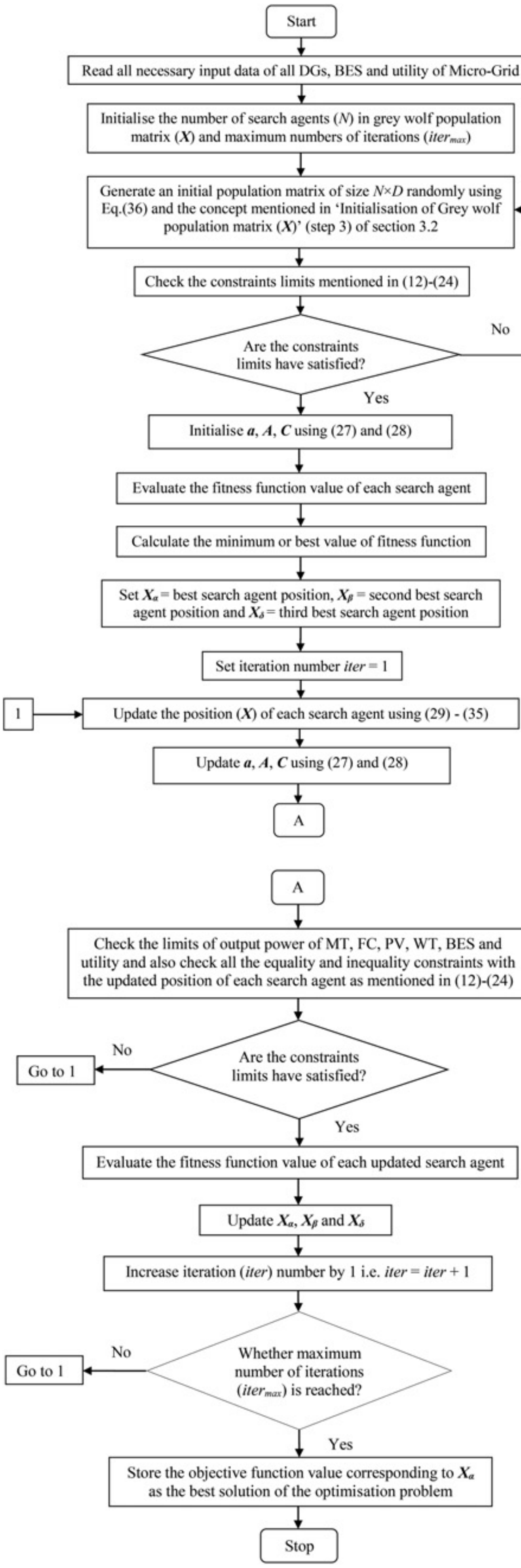

Fig. 4 *Flowchart of operation cost minimisation of MG using GWO algorithm*

algorithms for Case A, are shown in Fig. 7. From the Fig. 7 it is observed that with TS, DE, BBO, TLBO and GWO algorithms, the optimum solutions are reached at 962, 948, 938, 786 and 398th iterations respectively. It establishes that GWO algorithm converges faster than other optimisation techniques as shown in Fig. 7.

Table 1 Limits and bids of the DGs, Utility and BES

Type	Min. power, kW	Max. Power, kW	Bid, €ct/kWh	Operation and Maintenance (OM) cost, €ct/kWh	Start-up/shut-down cost, €ct
MT	6	30	0.457	0.0446	0.96
FC	3	30	0.294	0.08618	1.65
PV	0	25	2.584	0.2082	0
WT	0	15	1.073	0.5250	0
BES	–30	30	0.380	–	0
Utility	–30	30	–	–	–

Table 2 Forecasted output power of WT and PV

Hour, h	WT output power, kW	PV output power, kW
1	1.785	0
2	1.785	0
3	1.785	0
4	1.785	0
5	1.785	0
6	0.915	0
7	1.785	0
8	1.305	0.2
9	1.785	3.75
10	3.09	7.525
11	8.775	10.45
12	10.41	11.95
13	3.915	23.9
14	2.37	21.05
15	1.785	7.875
16	1.305	4.225
17	1.785	0.55
18	1.785	0
19	1.302	0
20	1.785	0
21	1.3005	0
22	1.3005	0
23	0.915	0
24	0.615	0

4.1.2 Case B: In this case Li-ion BES is added to the MG test system. The main benefit of BES in MG is to maintain stability, facilitate integration of the RESs, improve power quality etc., [1, 8, 23, 24]. The Li-ion BES starts the time period without any initial charge, so discharging action of BES in each step of the day is restricted to how much it is charged in previous hours. The full capacity of BES is fixed to 500 kWh and the minimum capacity of BES is taken as 10% of the full capacity. In this case study, in order to investigate the efficiency of selecting a BES with suitable and optimal capacity, the maximum size of battery ($C_{\mathrm{BES,max}}$) is considered as one of the control variable which should be optimised in the range of [50, 500]. This means that the energy stored in BES is under [$C_{\mathrm{BES,min}}$, $C_{\mathrm{BES,max}}$] limits. Considering all these parameters, the operation cost minimisation problem has been solved for the MG test system using GA, TS, PSO, DE, BBO, TLBO and GWO algorithms to optimise total operation costs, in order to find the optimal size of BES and corresponding output power of the utility, MT, FC, PV, WT, and BES. Table 6 shows the best, average and worst values of operation cost of MG obtained for Case B after 30 trail runs by applying different algorithms. In this case study, the operation cost of MG obtained by GWO algorithm is 470.4718 €ct/day, which is much lower than the costs obtained by other algorithms. The value of operation cost of MG obtained in this case study by applying GWO algorithm is much lower than the operation cost for Case A, that is, 816.3751 €ct/day in which the BES is not considered. In this case study, the optimal size of BES obtained by applying GWO algorithm is 78.85 kWh. The comparison of results obtained by GWO algorithm for Case A and Case B shows that the installation of a BES of optimal size 78.85 kWh without any initial charge, reduces the operation cost of MG by (816.3751–470.4718) = 345.9033 €ct per day. Table 6 also shows that mean simulation time required with GWO algorithm (0.0912 min) is much less compared with other algorithms. The median and standard deviation values of operation cost of MG obtained by applying different algorithms for Case B are also shown in Table 6. From the results it is observed that the values of median and standard deviation of operation cost of MG for Case B by applying GWO algorithm are 470.4718 and 0.2973 respectively, which are much less compared with those obtained by other algorithms. The numerical results for optimal output power available from DGs, BES and utility and their corresponding status obtained by GWO algorithm are tabulated in Table 7.

The available operating reserve by dispatchable DGs, that is, MT, FC, BES and upstream network for Case B obtained by applying GWO algorithm is shown in Table 4. In this case BES can supply the operating reserve which was previously supplied by MT and FC and upstream network in Case A. Fig. 8 shows the convergence characteristics for MG operation cost minimisation using different algorithms for Case B. From the Fig. 8 it is observed that with GA, TS, PSO, DE, BBO, TLBO and GWO algorithms, the optimum solutions are reached at 988, 982, 978, 976, 972, 970 and 801th iterations respectively. Therefore it may be concluded here that convergence speed of GWO algorithm is better than other algorithms as shown in Fig. 8.

4.1.3 Case C: In this case BES is included in the MG with the initial charge equal to the size of BES. Table 8 shows the comparison of operation cost of MG obtained for Case C after 30 trail runs by applying different algorithms. In this case study, the operation cost of MG obtained by applying GWO algorithm is 298.4217 €ct/day, which is much lower than the costs obtained by other algorithms. Table 8 also shows that mean simulation time required with GWO algorithm (0.0920 min) is much less compared with other algorithms. The median and standard deviation values of operation cost of MG for case C obtained by different algorithms are also shown in Table 8. From the results it is observed that with

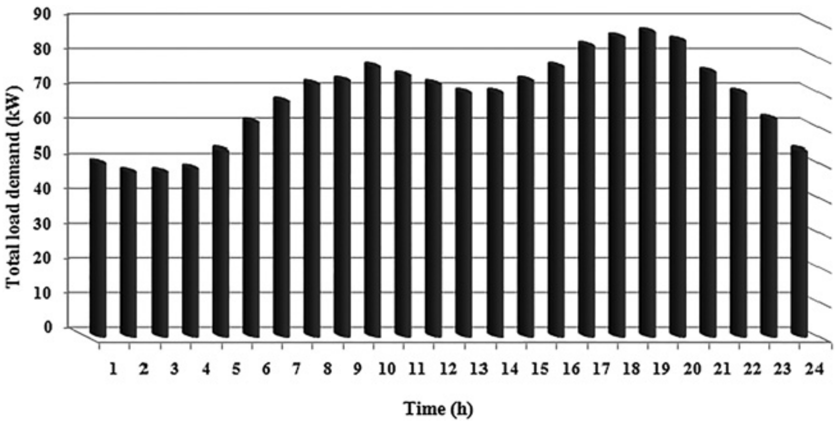

Fig. 5 *Forecasted values for load demand*

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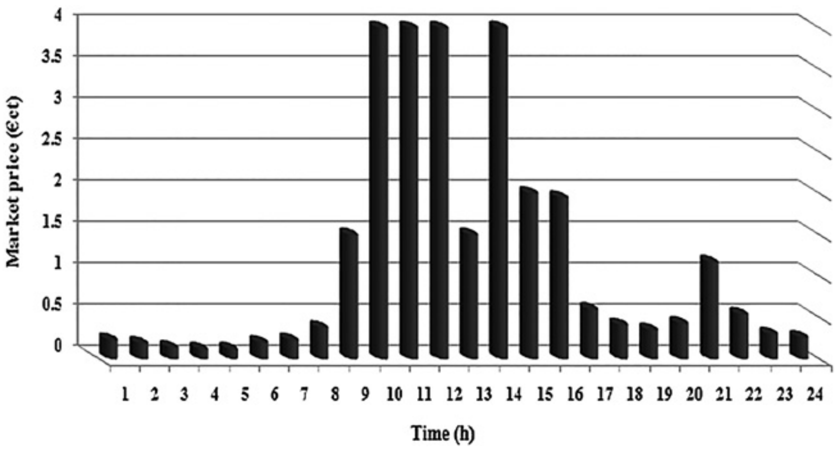

Fig. 6 *Forecasted values for market energy prices*

Table 3 Comparison of operation cost of MG and simulation time obtained using various optimisation techniques, after 30 trial runs for Case A

Solution methodology	Best solution, €ct	Average solution, €ct	Worst solution, €ct	Mean simulation time, min	No. of hits to optimum solution	Median	Standard deviation
GA [8]	1041.8376	1196.3251	1361.2437	0.417	–	1041.8376	162.07185
PSO [8]	968.0190	1081.8351	1241.7459	0.330	–	968.0190	136.3906
BA [8]	933.8145	989.3718	1106.9860	0.289	–	–	–
IBA [8]	825.8849	825.8849	825.8849	0.104	–	–	–
TS	999.6174	1094.1898	1283.3345	0.365	20	999.6174	136.0319
DE	852.1207	858.2814	875.2234	0.125	22	852.1207	10.3911
BBO	840.2262	845.9575	864.7888	0.0996	23	840.2262	10.5664
TLBO	837.6402	843.0257	864.5677	0.0987	24	837.6402	10.9551
GWO	816.3751	816.4079	816.8674	0.0896	28	816.3751	0.1249

GWO algorithm, the values of median and standard deviation of operation cost of MG are 298.4217 and 0.6910 respectively which are much less compared with those obtained with other algorithms. Table 9 shows output power of DGs, BES and upstream power grid in the MG and their corresponding status obtained by GWO algorithm under this case study. Optimal size of BES obtained in this case study is 83.34 kWh. Considering the MG with BES of optimal size 83.34 kWh with initial charge of 83.34 kWh, the operation cost of the system is 298.4217 €ct/day, that is, total operation cost is reduced by (470.4718–298.4217) = 172.0501 €ct in one day compared with the cost obtained in Case B (operation of MG including BES without any initial charge). The available operating reserve by dispatchable DGs, that is, MT, FC, BES and upstream network obtained by GWO algorithm under this case study is presented in Table 4. The convergence characteristics for MG operation cost minimisation using different algorithms under this case study are depicted in Fig. 9. From the Fig. 9 it is observed that with GA, TS, PSO, DE, BBO, TLBO and GWO algorithms, the optimum solutions are reached at 985, 981, 976, 968, 963, 960 and 386th iterations respectively. Therefore it may be concluded here that convergence speed of GWO algorithm is better than other algorithms as shown in Fig. 9.

Table 4 Operating reserve amounts of 24 h time horizon for Case A, Case B and Case C obtained using GWO algorithm

Time, h	Operating reserve capacity for Case A	Operating reserve capacity for Case B	Operating reserve capacity for Case C
1	11.785	41.785	11.785
2	14.285	44.285	14.285
3	14.285	44.285	14.285
4	13.285	67.4663	13.285
5	8.285	62.4663	8.285
6	29.415	53.5963	29.415
7	24.285	48.4663	24.285
8	19.005	43.1863	49.005
9	22.035	46.2163	52.035
10	23.115	47.2963	53.115
11	34.225	58.4063	64.225
12	39.86	64.0413	69.86
13	47.815	71.9963	77.815
14	43.42	67.6013	73.42
15	26.16	50.3413	56.16
16	18.03	42.2113	48.03
17	8.835	33.0163	38.835
18	5.785	29.9663	35.785
19	4.302	28.4833	34.302
20	6.785	30.9663	36.785
21	15.3	39.4813	45.3
22	21.3	45.4813	51.3
23	28.415	52.5963	28.415
24	37.115	31.2963	37.115

4.2 Effect of search agents on GWO algorithm

In GWO algorithm search agent is a control parameter. It is observed that change in search agent number affects the performance of the GWO algorithm. In this paper tests are carried out by varying search agent numbers from 10 to 200. Tests are carried out 30 times for each case with 1000 iteration numbers. Table 10 shows the performance of GWO algorithm for different search agent numbers for operation cost minimisation problem of MG under Case A. From the results, it is observed that search-agent number 100 gives better results for all the three case studies mentioned in this paper. Furthermore, the mean simulation time for search-agent number 100 is much less (for Case A, mean simulation time is 0.0896 min with search-agent number 100 as shown in Table 10).

4.3 Comparative study

4.3.1 Solution quality: Table 11 shows the statistical analysis of GA, TS, PSO, DE, BBO, TLBO and GWO algorithms. To perform multiple comparisons among various algorithms, different statistical analysis methods are available in literature [25, 26]. Among these methods, Friedman test has been used to compare the performance

Table 5 Optimal output power and corresponding status of each DG and utility power grid obtained by GWO algorithm for Case A (total cost = 816.3751 €ct)

Time, h	DG sources and outputs					Status				
	MT, kW	FC, kW	PV, kW	WT, kW	Utility, kW	MT	FC	PV	WT	Utility
1	0	20.0000	0	0	30.0000	0	1	1	1	1
2	0	17.5000	0	0	30.0000	0	1	1	1	1
3	0	17.5000	0	0	30.0000	0	1	1	1	1
4	0	18.5000	0	0	30.0000	0	1	1	1	1
5	0	23.5000	0	0	30.0000	0	1	1	1	1
6	6.0000	25.5000	0	0	30.0000	1	1	1	1	1
7	7.5000	30.0000	0	0	30.0000	1	1	1	1	1
8	12.5000	30.0000	0	0	30.0000	1	1	1	1	1
9	30.0000	30.0000	0	0	13.5000	1	1	1	1	1
10	30.0000	30.0000	7.5250	3.0900	6.8850	1	1	1	1	1
11	30.0000	30.0000	10.4500	8.7750	−4.2250	1	1	1	1	1
12	30.0000	30.0000	11.9500	10.4100	−9.8600	1	1	1	1	1
13	30.0000	30.0000	0	0	10.0000	1	1	1	1	1
14	30.0000	30.0000	21.0500	2.3700	−13.4200	1	1	1	1	1
15	30.0000	30.0000	0	1.7850	11.7150	1	1	1	1	1
16	30.0000	30.0000	0	1.3050	16.1950	1	1	1	1	1
17	30.0000	30.0000	0	0	23.5000	1	1	1	1	1
18	26.0000	30.0000	0	0	30.0000	1	1	1	1	1
19	27.0000	30.0000	0	0	30.0000	1	1	1	1	1
20	25.0000	30.0000	0	0	30.0000	1	1	1	1	1
21	30.0000	30.0000	0	0	16.0000	1	1	1	1	1
22	30.0000	30.0000	0	0	10.0000	1	1	1	1	1
23	6.0000	26.0000	0	0	30.0000	1	1	1	1	1
24	6.0000	17.5000	0	0	30.0000	1	1	1	1	1

of GWO with few other optimisation techniques for all the three case studies and the results are tabulated in Table 11. Table 11 shows that Friedman Statistic value or Chi-square value is 18 here, which is greater than critical value of Chi-square (critical value of Chi-square are 12.592 and 16.81 at 5% and 1% significance level) [26]. The p-value obtained here is also much less compared with the p-value for 5% or 1% significance level. These results show that there is significant difference among the algorithms. Depending on the values of average errors, all the algorithms have been ranked and average ranks are shown in Table 11, which is calculated by applying the procedure mentioned in [25]. Table 11 shows that GWO achieves the minimum value of average rank.

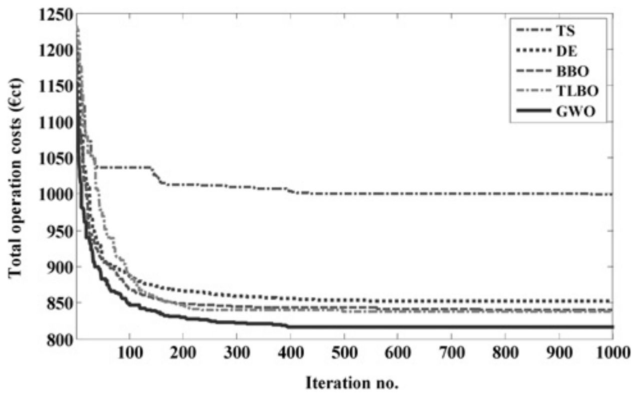

Fig. 7 *Convergence characteristics of GWO algorithm for Case A*

Hence it may be concluded that the performance of GWO algorithm is better in terms of quality of solutions obtained, compared with above-mentioned other algorithms.

Table 3 shows the comparison of total operation cost of MG for Case A obtained by using GWO algorithm with the results obtained using other algorithms such as GA, PSO, BA, IBA [8], TS, DE, BBO and TLBO. From the results it is observed that the value of operation cost of MG for Case A is 816.3751 €ct/day with GWO algorithm, whereas with GA [8], PSO [8], BA [8], IBA [8], TS, DE, BBO and TLBO algorithms the values of operation costs obtained are 1041.8376 €ct/day, 968.0190 €ct/day, 933.8145 €ct/day, 825.8849 €ct/day, 999.6174 €ct/day, 852.1207 €ct/day, 840.2262 €ct/day and 837.6402 €ct/day respectively. Similarly for Case B and Case C, the operation costs of MG obtained using GWO algorithm are 470.4718 €ct/day and 298.4217 €ct/day respectively, which are much less than the costs obtained by other algorithms. From the results it is clear that GWO algorithm gives lower operation cost of MG compared with other algorithms.

4.3.2 Computational efficiency: Table 3 shows the mean simulation time required for Case A with all algorithms. From the results obtained it is observed that the mean simulation time taken by GWO algorithm to reach to the minimum operation cost of MG for Case A is 0.0896 min, whereas the time taken by GA, PSO, BA, IBA, TS, DE, BBO and TLBO algorithms are 0.417 [8], 0.330 [8], 0.289 [8], 0.104 [8], 0.365, 0.125, 0.0996 and 0.0987 min respectively. Hence it is clear that the time taken by GWO algorithm is quite less compared with other algorithms. Similarly, Tables 6 and 8 also show that for Case B and Case C the simulation times taken by GWO algorithm are quite less compared with other

Table 6 Comparison of operation cost of MG and simulation time obtained using various optimisation techniques, after 30 trial runs for Case B

Solution methodology	Best solution, €ct	Average solution, €ct	Worst solution, €ct	Mean simulation time, min	No. of hits to optimum solution	Median	Standard deviation
IBA [8]	497.0082	–	–	–	–	–	–
GA	615.9034	623.4835	638.6436	0.398	20	615.9034	10.9031
TS	583.7757	589.5775	605.5325	0.357	22	583.7757	9.7857
PSO	567.5185	575.1266	592.8787	0.312	21	567.5185	11.8202
DE	559.7946	567.1353	587.3222	0.144	22	559.7946	12.3813
BBO	547.3977	553.6488	574.1879	0.108	23	547.3977	11.5247
TLBO	545.7281	551.1160	572.6678	0.103	24	545.7281	10.9601
GWO	470.4718	470.5499	471.6435	0.0912	28	470.4718	0.2973

Table 7 Optimal output power and corresponding status of each DG, BES and utility power grid obtained by GWO algorithm for Case B (total cost = 470.4718 €ct)

Time, h	DG sources and outputs						Status					
	MT, kW	FC, kW	PV, kW	WT, kW	BES, kW	Utility, kW	MT	FC	PV	WT	BES	Utility
1	21.9505	29.7895	0	0.7387	−30.0000	27.5212	1	1	1	1	1	1
2	24.1010	19.6597	0	0	−25.4090	29.1484	1	1	1	1	1	1
3	30.0000	18.6237	0	0	−30.0000	28.8763	1	1	1	1	1	1
4	6.0000	13.3051	0	0	0.2967	28.8983	1	1	1	1	1	1
5	6.0000	11.9972	0	0.1171	8.1957	27.1900	1	1	1	1	1	1
6	6.0000	30.0000	0	0.3070	2.2637	22.9294	1	1	1	1	1	1
7	6.0000	29.5045	0	0	3.0423	28.9532	1	1	1	1	1	1
8	6.0000	30.0000	0.0120	0	15.3371	21.1509	1	1	1	1	1	1
9	30.0000	29.6165	0.0435	1.7850	24.1813	−12.1263	1	1	1	1	1	1
10	30.0000	29.9951	7.4870	3.0473	24.1813	−17.2106	1	1	1	1	1	1
11	29.9976	30.0000	10.4220	8.6749	23.8992	−27.9938	1	1	1	1	1	1
12	30.0000	28.5325	10.2590	10.2608	23.1227	−29.6750	1	1	1	1	1	1
13	30.0000	30.0000	0.0373	0	24.1813	−14.2186	1	1	1	1	1	1
14	30.0000	30.0000	16.8308	2.3700	20.4854	−29.6861	1	1	1	1	1	1
15	30.0000	29.9738	0.2363	0.9766	24.1813	−11.8680	1	1	1	1	1	1
16	29.6778	29.9375	0.5883	1.0364	24.1813	−7.9213	1	1	1	1	1	1
17	30.0000	29.6893	0.0188	0	15.6078	8.1840	1	1	1	1	1	1
18	23.9174	29.4057	0	0.1864	10.3192	22.1713	1	1	1	1	1	1
19	30.0000	27.1031	0	0.0527	15.4648	14.3794	1	1	1	1	1	1
20	8.8145	29.6493	0	0	24.1813	22.3548	1	1	1	1	1	1
21	29.4512	29.9080	0	0	24.1813	−7.5405	1	1	1	1	1	1
22	20.6158	29.6182	0	0	24.1813	−4.4153	1	1	1	1	1	1
23	6.0000	30.0000	0	0	2.1967	24.3033	1	1	1	1	1	1
24	0	18.8387	0	0.2478	5.1725	29.2410	0	1	1	1	1	1

optimisation techniques. The convergence characteristics shown in Figs. 7–9 also depict that the convergence speed of GWO algorithm is better compared with other algorithms. Moreover comparing the convergence characteristics with GWO algorithm for Case C with the convergence characteristics obtained with IBA and BA algorithm as shown in [8], it is clear that though more iteration number is required for GWO algorithm to reach to the optimum solution, but the simulation time per iteration is less with GWO algorithm compared with other algorithms mentioned in [8]. As a result mean simulation time with GWO algorithm is also less than other algorithms. This proves significantly better computational efficiency of GWO algorithm to solve the operation cost minimisation problem of MG.

4.3.3 Robustness: Performance of GWO algorithm has been analysed for 30 trail runs in each case study. Tables 3, 6 and 8 show that for all the three cases numbers of hits to optimum solution is 28 out of 30 trails using GWO algorithm. Hence with GWO algorithm the success rate is 93.33% to solve the operation cost minimisation problem of MG, whereas success rate of other algorithms applied to solve same problem as shown in the tables, are less. From Table 3 it is also observed that for Case A, numbers of hits to optimum solution is 30 out of 30 trails using IBA algorithm [8], but average operation cost of MG for Case A is less with GWO algorithm than the cost obtained by IBA algorithm. Hence overall performance of GWO algorithm is better.

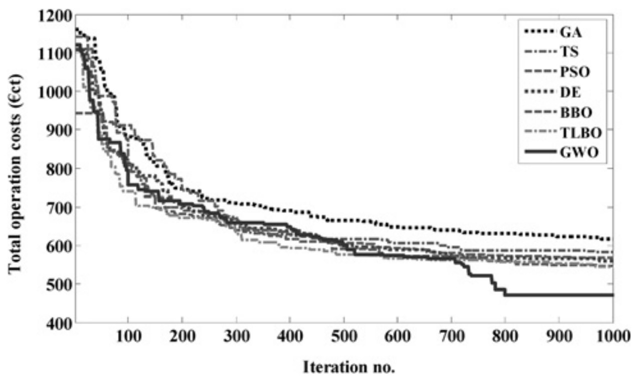

Fig. 8 *Convergence characteristics of GWO algorithm for Case B*

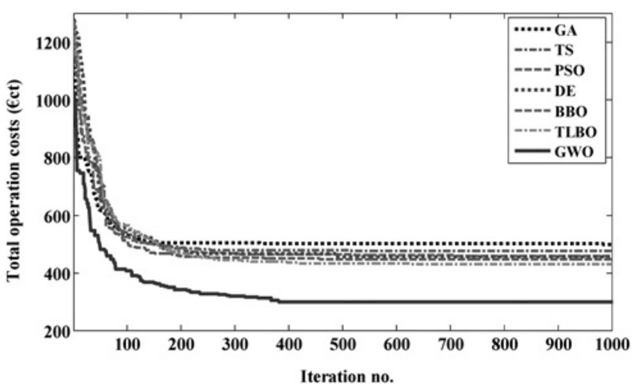

Fig. 9 *Convergence characteristics of GWO algorithm for Case C*

Table 8 Comparison of operation cost of MG and simulation time obtained using various optimisation techniques, after 30 trial runs for Case C

Solution methodology	Best solution, €ct	Average solution, €ct	Worst solution, €ct	Mean simulation time, min	No. of hits to optimum solution	Median	Standard deviation
IBA [8]	424.1339	–	–	–	–	–	–
GA	499.0665	506.4029	523.5212	0.401	21	499.0665	11.3981
TS	474.8817	480.3977	495.5668	0.362	22	474.8817	9.3037
PSO	459.8236	466.6086	485.2675	0.316	22	459.8236	11.4441
DE	454.7765	460.3783	478.7842	0.151	23	454.7765	10.3277
BBO	447.4127	452.3732	472.2154	0.115	24	447.4127	10.0907
TLBO	430.0397	435.3635	456.6587	0.108	24	430.0397	10.8296
GWO	298.4217	298.6033	301.1454	0.0920	28	298.4217	0.6910

Table 9 Optimal output power and corresponding status of each DG, BES and Utility power Grid obtained by GWO algorithm for Case C (total cost = 298.4217 €ct)

Time, h	DG sources and outputs						Status					
	MT, kW	FC, kW	PV, kW	WT, kW	BES, kW	Utility, kW	MT	FC	PV	WT	BES	Utility
1	0	0	0	0	20.0268	29.9732	0	0	1	1	1	1
2	0	0	0	0.0009	17.5066	29.9925	0	0	1	1	1	1
3	0	0	0	0	17.5076	29.9924	0	0	1	1	1	1
4	0	0	0	0	18.5118	29.9882	0	0	1	1	1	1
5	0	0	0	0	23.5153	29.9847	0	0	1	1	1	1
6	0	13.0111	0	0	18.4965	29.9924	0	1	1	1	1	1
7	0	26.0555	0	0.0010	11.4577	29.9857	0	1	1	1	1	1
8	6.0006	20.0532	0	0.0013	24.3658	22.0791	1	1	1	1	1	1
9	29.9989	29.9975	0	0.0107	29.9987	−16.5058	1	1	1	1	1	1
10	29.9996	30.0000	7.5247	3.0863	30.0000	−23.1105	1	1	1	1	1	1
11	29.9999	30.0000	6.2251	8.7750	29.9995	−29.9994	1	1	1	1	1	1
12	29.9998	30.0000	2.0882	10.4100	30.0000	−29.9980	1	1	1	1	1	1
13	29.9961	30.0000	0.0047	0	29.9988	−19.9996	1	1	1	1	1	1
14	30.0000	30.0000	7.6267	2.3692	29.9995	−29.9954	1	1	1	1	1	1
15	30.0000	29.9976	0.0012	1.7850	29.9933	−18.2771	1	1	1	1	1	1
16	29.9989	30.0000	0	1.3050	29.9976	−13.8015	1	1	1	1	1	1
17	30.0000	29.9607	0.0015	0.0019	29.9905	−6.4545	1	1	1	1	1	1
18	6.0255	29.9919	0	0	29.8848	20.0978	1	1	1	1	1	1
19	6.0000	26.7663	0	0.0013	24.3693	29.8631	1	1	1	1	1	1
20	6.0000	30.0000	0	0.0006	30.0000	18.9994	1	1	1	1	1	1
21	29.9979	30.0000	0	0	29.9972	−13.9951	1	1	1	1	1	1
22	9.9097	29.9877	0	0.0002	29.9853	0.1171	1	1	1	1	1	1
23	0	3.0000	0	0	29.5771	29.9229	0	1	1	1	1	1
24	0	3.0000	0	0.0017	20.6035	29.8949	0	1	1	1	1	1

Table 10 Effect of search-agent number on minimum objective function value for Case A using GWO algorithm (for 1000 iterations)

Search-agent no.	No. of hits to optimum solution, out of 30 trail runs	Mean simulation time, min	Overall objective function, *f*		
			Minimum	Maximum	Average
10	24	0.0745	819.4576	821.4232	819.8507
20	25	0.0787	819.0342	820.5674	819.2897
40	27	0.0803	818.5465	819.7212	818.6640
60	26	0.0825	818.1455	819.2766	818.2963
80	25	0.0858	817.3452	818.5223	817.5414
100	28	0.0896	816.3751	816.8674	816.4079
120	26	0.0925	816.8905	817.7544	817.0057
150	27	0.0966	816.6576	817.5234	816.7442
200	25	0.122	816.7564	817.9545	816.9561

Table 11 Statistical analysis: Friedman test

Solution methodology	Average error			Average rank	Friedman Statistic value, Chi-square	*p*-value
	Case A	Case B	Case C			
GA	379.9500	153.0117	207.9812	7		
TS	277.8147	119.1057	181.9760	6		
PSO	265.460	104.6548	168.1869	5		
DE	41.9063	96.6635	161.9566	4	18	0.0062
BBO	29.58240	83.1770	153.9515	3		
TLBO	26.6506	80.6442	136.9418	2		
GWO	0.0328	0.0781	0.1816	1		

Therefore, the above results establish the enhanced ability of GWO algorithm to achieve superior quality solutions, in a computationally efficient and robust manner.

5 Conclusion

This paper presents GWO algorithm to solve operation cost minimisation problem of MG. The introduction of BES of optimum size also led to superior performance of MG operation studies. The effectiveness of the proposed algorithm is tested over a day in a typical MG operation cost minimisation. Analyses of the simulation results reveal that the performance of GWO algorithm in all respect is better in comparison with the previously developed several optimisation techniques. The comparison of the results for case study A, B and C reveal the superiority of GWO algorithm, in terms of the computational effort, convergence speed and performance of the solutions. Case B and Case C show that considering a BES of optimal size for the MG may decrease the operation cost of the MG, as BES can store surplus powers of RESs and re-dispatch them appropriately. Therefore, GWO algorithm may be considered as one of the strongest algorithm to solve different operation cost minimisation related optimisation problems of MG.

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