Energy Management Optimization for Micro-grids, using a Chaotic Symbiotic Organism Search Algorithm

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Abstract: This paper presents an efficient approach, that is centered on a chaotic symbiotic organism search (CSOS) algorithm, for solving the energy management optimization (EMO) problem in Micro-grids (MG) containing diverse distributed generation resources (DGR) besides energy storage systems. The proposed approach is equipped with a chaotic map to guarantee a wider coverage of the search space and rapid time for convergence when searching solutions for the EMO problem under the various exploiting constraints. The CSOS approach is examined on a practical microgrid linked to public services. The effectiveness of CSOS is proven through a comparison of the obtained solutions, in terms of operating costs, with those of other scalable algorithms, such as, GA and PSO.

Keywords: Micro Grids; Energy Management Optimization; Distributed Generation Resources, Chaotic Symbiotic Organism search algorithm

1 Introduction

Over the past two decades, the electric power sector suffered from rapidly rising fossil fuel prices and global climate change, and researchers had to help in adopting an accepted response to save this industry from vanishing. This trend pushed the concept of clusters in this field; hence, the "Micro-grid" can be viewed as a cluster of distributed energy resources, energy storage, and local loads, managed by a smart energy management system [1] [2].

The Micro-grids (MGs) offer much superiority over traditional distribution systems, in terms of reducing energy losses due to the proximity between DGs and loads, improving reliability, it offers the ability to work in the island, to combat system failures by dividing the horizon, and added value appears as relief of transmission and distribution lines, the latter is achieved by the said energy management to reduce or by completely import the energy from the healthy grids. Whereas these benefits come with extra cost, the heavy integration of DGs will manifest as complex challenges for the MG's operation control. Therefore, for the energy management optimization (EMO) problem there is a strong need for adequate planning and location of energy sources and energy storage devices in MGs while observing satisfaction of all objectives and constraints [2].

The problem themselves is usually highly nonlinear, involving continuous and discrete variables under complex constraints, which cannot be solved by classical methods. The drawbacks from existing classical methods have shown the importance to rely on more advanced algorithms which are more adequate. Hence, the evolutionary algorithms come in terms of the solution for the drawbacks found on existing classical methods.

Recently, many evolutionary algorithms attracted intense consideration from the scientific community and formed interesting tools for solving many optimizations problem in different areas of science and industry. The main motivations towards these algorithms are due to their inherent nonlinear mapping, implementation simplicity, and powerful search capabilities [3-9].

The EMO problem in MGs consists of finding the optimal (or near-optimal) unit commitment and dispatch of available energy sources and storage devices so that certain selected criteria are met [10] [11] For this purpose, a growing number of scientific works have been developed by researchers to address and solve the problems attributed to EMO in the deterministic and probabilistic formulations. In the deterministic formulation of the EMO, it is assumed that the output variables of the DG ressource, the loads, and the market prices, are equal to their predicted values [12]. However, the uncertainty of these variables leads to a probabilistic formulation of the problem [13].

To solve the optimal power dispatch problem of interconnected MGs, while maintaining a minimum operating cost, and considering load uncertainties and generated power, Nikmehr and Ravadanegh used a PSO solution [12]. A probabilistic approach to the EOM of renewable microgrids under undefined environments is proposed in reference [13]. Hatziargyriou et al. [14] investigated the outcome of using a Microgrid Central Controller (MGCC) to ensure the coordinated operation of various DG units, storage devices, and controllable loads to avoid power losses within the local network and present the potential economic benefits. A smart energy management system, based on the matrix real-coded genetic algorithm (GA), to optimize the operation of the MG is presented in [15]. An improved PSO algorithm combined with Monte Carlo simulation is used to solve the dynamic economic dispatch of an MG system with both renewable and nonrenewable energy sources, this work has been presented in [16].

Mohan and al. in [17] proposed a stochastic weight trade-off PSO-based backward–forward sweep OPF method to obtain the online optimal schedules of DGs in MG considering renewable energy, grid power trade, and demand-side response. Chakraborty, Weiss, and Simoes proposed a linear programming algorithm to optimize the operating cost of the MG and the states of charge of the battery [18]. Tsikalakis and Hatziargyriou used centralized control of multiple MGs combined with optimizing the production of the local DGs versus power exchanges with the main distribution grid [19]. A method based on an optimal power flow and a PSO algorithm is suggested by Sortome et al to study two MGs [20]. In the paper of Mohamed et al [21], an adaptive direct mesh search algorithm is employed to minimize the cost function of MG, taking into account the cost of emissions.

An expert multi-objective Adaptive Modified Particle Swarm Optimization algorithm (AMPSO) is developed and implemented in the work of Moghaddam et al [22] to optimize the operation of a typical micro-grid with renewable energy sources accompanied by backup hybrid power sources, in this paper the problem is formulated as a multi-objective optimization problem with nonlinear constraints to simultaneously minimize the total operating cost and the net gas emission.

Mohamed and Koivo [23] applied GA for solving the EMO problem which is modeled as a nonlinear constrained multi-objective optimization, where the fitness function includes the costs of the emissions added to the start-up costs, as well as all incurring operation and maintenance costs. In the publication of Tomoiaga et al., a new heuristic approach is proposed for the energy management on stand-alone micrograds, which avoids the waste of the existing renewable potential at each time interval [24]. Nikmehr and Ravadanegh used an imperialist competitive algorithm (ICA) to solve the optimal power dispatch problem of interconnected MGs with minimum operating cost considering load uncertainties and limits of the generated power [25].

Radosavljevic´ et al. [26] presented an efficient algorithm based on PSO to tackle the EMO in an MG including different DG units and energy storage devices. Liu et al. developed an economic scheduling model of MG in grid-connected mode with the consideration of the storage battery lifetime [27].

A day-ahead optimal energy management strategy for the economic operation of industrial microgrids with high-penetration renewables under both isolated and grid-connected operation modes is well studied in the work of Han et al. [28]. The non-dominated sorting GA II is employed for optimal EMO of a grid-connected MG in the paper authored by Karuppasamypandiyan et al. [29]. To schedule power in a microgrid, the dual decomposition method was utilized in Zhang et al. [30].

The above gives a state of the art of this research field. We noticed that most of the developed approaches, by the scientific community, are based on more or less complex metaheuristics in terms of internal control parameters and random initialization. Therefore, this usually leads these approaches to a premature convergence or to get stuck in local optima.

To tackle these drawbacks, we propose a chaotic symbiotic organism search-based approach to solve the EMO problem in this paper. the performances of this approach will be evaluated and compared with some other well-known evolutionary algorithms described previously by multiple researchers [13] [22] [26].

The remainder of this paper is structured as follows: in Section 2, the constrained energy management optimization (EMO) problem is formulated. Then, the chaotic SOS (CSOS) is presented in Section 3. The case study, simulation results, and comparisons are shown in Section 4. Finally, the conclusions and future work are presented in Section 5.

2 Mathematical Formulation of the Energy Management Optimization Problem

For a practical low-voltage (LV) grid-connected MG (as shown in Figure 1) the optimization procedure depends strongly on the market policy adopted in the MG operation. In this paper, we have considered that the EMO problem is defined according to the first market policy presented in the references [14] [19] [26]. Therefore, in a typical MG, the EMO problem aims to minimize the total operating cost of the microgrid through optimal adjustment of the DG's power generation while satisfying various system operating constraints.

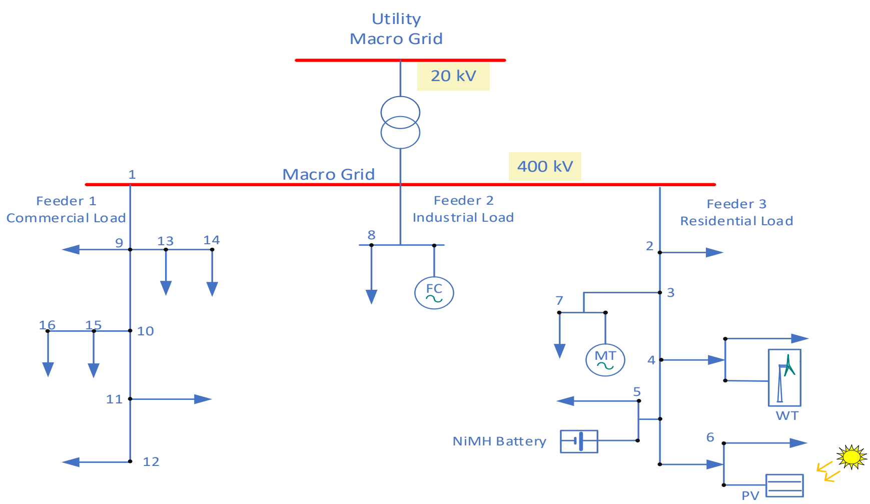

Figure 1

A typical low voltage microgrid [20]

2.1 Formulation of the EMO Objective Function

The total cost of operating the micro-grid includes the DG's offers and market prices for the exchange of electricity between the micro-grids and utilities. So, the mathematical model of such a problem concerns the minimization of the total operating cost as an objective function which can be expressed as follows:

$$Min\, F(P) = Min(\sum_{t=1}^{NT} cost^t) = \mathrm{Min}\left(\sum_{t=1}^{NT}\sum_{i=1}^{N_g}\langle B_{Gi}(P_{Gi}^t) + MP^t.P_{Grid}^t\rangle\right) \quad (1)$$

Where,

$F(P)$ is the objective function;

$P = [P^1\ P^2\ ...\ P^t\ ...\ P^{NT}]$ is a vector of candidate solution and P^t are variable-state scalar vectors including the active power of the generation and storage units within the MG, and can be described as follows:

$$P^t = \left[P_{G1}^t\ P_{G2}^t\ ...\ P_{GN_g}^t\right] \quad (2)$$

Where,

NT and is the total number of hours;

N_g is the total number of DG including storage units;

P_{Gi}^t is the real power outputs of the i^{th}DG;

$B_{Gi}(P_{Gi}^t)$is the bid of the i^{th} DG unit as a function of its active power at time t;

P_{Grid}^t is the active power which is bought (sold) from (to) the utility at time t, and MP^t is the market price of power exchange between the microgrid and the utility at time t.

2.2 Formulation of Microgrid and Unit Constraint Functions

The objective (or fitness) function formulated above is subject to the constraints due to the limits of its components: the grid power transfer limits, energy storage units' capacity and operational limits, dispatchable DGs' power limit, and all other micro-grid technical limitations and requirements.

2.2.1 Power Balance

Grid balance is guaranteed through the following considerations: for each time interval t , the combined output power of the energy storage devices of the DGs and the utility has to meet the total load demand in the micro-grid without any loss of power. Hence, the constraint of the power balance can be written as follows:

$$\sum_{i=1}^{N_g} P_{Gi}^t + P_{Grid}^t = \sum_{D=1}^{N_D} P_{L_D}^t \quad (3)$$

Where P_{L_D} is the amount of the D^{th} load level, and N_D is the total number of load levels.

2.2.2 Real Power Generation Capacity

The real power output of each unit in the microgrid, including the utility, will ensure stable operation if it is restricted by minimum and maximum power limits as follows:

$$P_{GiMin}^t \leq P_{Gi}^t \leq P_{GiMax}^t \tag{4}$$

$$P_{GridMin}^t \leq P_{Grid}^t \leq P_{GridMax}^t \tag{5}$$

Where, P_{GiMin}^t and $P_{GridMin}^t$ are the minimum active power of the i^{th} DG, and the utility at time t;

P_{GiMax}^t and $P_{GridMax}^t$ are the maximum active powers of the i^{th} DG, and the utility at time t;

2.2.3 Spinning Reserve

The detected power fluctuations of renewables and load fluctuations will degrade the reliability of the system, consequently, it is necessary to adopt the spinning reserve to increase the system's reliability. The spinning reserve is met if the following inequality condition is satisfied [16] [26]:

$$\sum_{i=1}^{N_g} P_{GiMax}^t + P_{GridMax}^t \geq \sum_{D=1}^{N_D} P_{L_D}^t + P_{\mathrm{SSR}}^t \tag{6}$$

Where P_{SSR}^t is the scheduled spinning reserve at time t. In a microgrid, the spinning reserve constraint is considered by adding an extra value to the total power demand, which should be supplied by the DG units.

2.2.4 Energy Storage Limits

Since there are some limitations on charge and discharge rates of storage devices during each time interval, the following equation of constraints can be expressed for a typical battery as follows [22] [26]:

$$W_{ess,t} = W_{ess,t-1} + \eta_{charge}.P_{charge}.\Delta t - \frac{1}{\eta_{discharge}}.P_{discharge}.\Delta t \tag{7}$$

$$\begin{cases} W_{ess,min} \leq W_{ess,t} \leq W_{ess,max} \\ P_{charge,t} \leq P_{charge,max}; \;\; P_{discharge,t} \leq P_{discharge,max} \end{cases} \tag{8}$$

Where

$W_{ess,t}$ and $W_{ess,t-1}$ are the amount of energy storage inside the battery at hour t and $(t-1)$, respectively,

$P_{charge}(P_{discharge})$ is the permitted rate of charge (discharge) during a definite period of time (t),

$\eta_{charge}(\eta_{discharge})$ is the efficiency of the battery during the charge/discharge process and $W_{ess,min}$ and $W_{ess,max}$ are the lower and upper limits on the amount of energy storage inside the battery, respectively, and $P_{charge,max}(P_{discharge,max})$ is the maximum rate of battery charge (discharge) during each time interval (Δt).

2.2.5 Calculation of the Active Power from (to) the Utility

Considering the active power from (to) the utility as a dependent variable will consequently reinforce the active power balance constraint depicted in Equation (3). Hence the value of grid power is evaluated using the following equation:

$$\left\{P_{Grid}^{t} = \sum_{D=1}^{N_D} P_{L_D}^{t} - \sum_{i=1}^{N_g} P_{Gi}^{t} \right. \tag{9}$$

The obtained P_{Grid}^{t} either satisfies the restriction defined in Equation (10) or not. Therefore, the variable $P_{Grid,lim}^{t}$ is calculated depending on P_{Grid}^{t}:

$$P_{Grid,lim}^{t} = \begin{cases} P_{Grid,min}^{t} \; if \; P_{Grid}^{t} < P_{Grid,min}^{t} \\ P_{Grid,max}^{t} \; if \; P_{Grid}^{t} > P_{Grid,max}^{t} \\ P_{Grid}^{t} \; if \; P_{Grid,min}^{t} \leq P_{Grid}^{t} \leq P_{Grid,max}^{t} \end{cases} \tag{10}$$

The control variables are said to be self-constrained, whereas the dependent variable P_{Grid}^{t}, is a relevant term in the objective function, it is considered as a quadratic penalty term. This is evaluated as a penalty factor multiplied by the square of the difference between the actual value and the limiting value of the dependent variable, which must be included in the objective function, then, all unfeasible solutions obtained during the optimization process are ignored [21]. The new extended objective function to be minimized develops to:

$$Min\, F_{\rho}(P) = Min\left(\sum_{t=1}^{NT}\sum_{i=1}^{N_g}\langle B_{Gi}(P_{Gi}^{t}) + MP^{t}.P_{Grid}^{t}\rangle + \sum_{t=1}^{NT}\alpha_p\left(P_{Grid}^{t} - P_{Grid,lim}^{t}\right)^2\right) \tag{11}$$

Where, α_p is the penalty factor.

In the above equation, the DG bids (B_{Gi}) are considered quadratic to the cost function of the units [21] [34]. They can be determined utilizing the following:

$$B_{Gi} = a_i(P_{Gi}^{t})^2 + b_i P_{Gi}^{t} + c_i \tag{12}$$

3 The Chaotic SOS Algorithm (CSOS)

The SOS algorithm is one of the most powerful optimization techniques mimicking the biological interactions between two life forms in the ecosystem, to establish a new solution for practical optimization problems. The SOS algorithm is based on three idealized phases, namely; mutualism, commensalism, and parasitism as is illustrated in Figure 2. To solve any optimization problem, the SOS iteratively uses a population of candidate solutions to explore and exploit the promising areas of the search space as presented in reference [31].

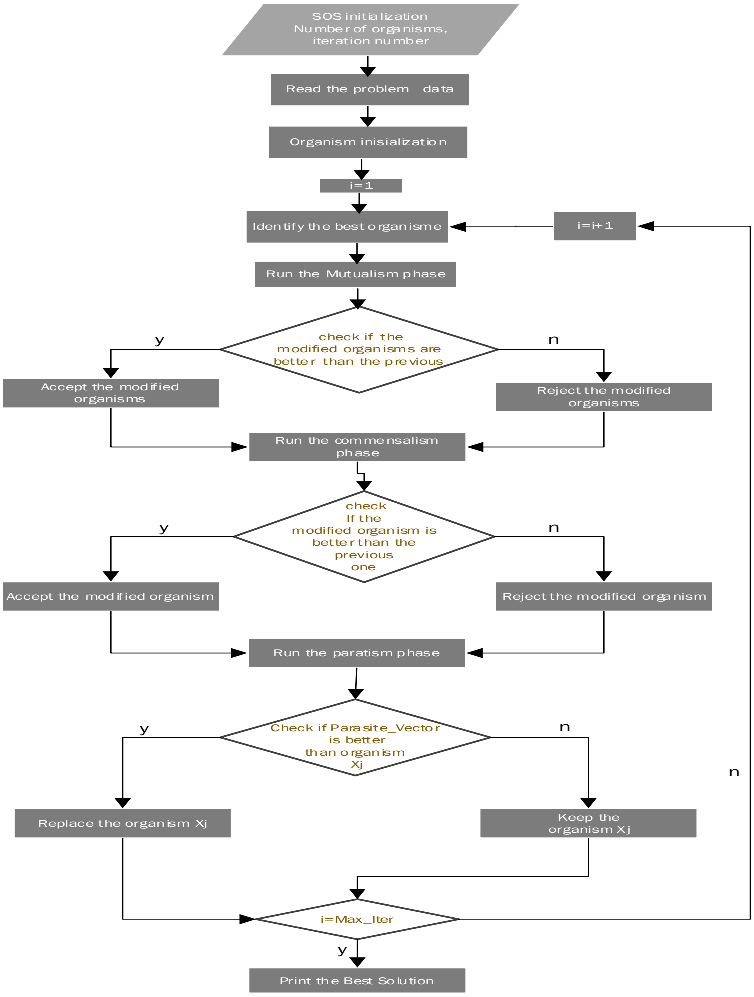

Figure 2
Schematic flowchart of SOS algorithm

1. Define input variables, objective function, and searching boundaries
% Organism size (orgsize), maximum iterations (maxiter), variables upper bound and lower bound.
2. Initialize population of organisms using the logistic map given by equation (13)
3. Identify the best organism in the initial population (X_{best})
while iter<maxiter

for i=1:orgsize

4. Mutualism Phase

Select organisms X_i and X_j ($X_i \neq X_j$)

Calculate Beneficial Factor (BF_1 & BF_2) using

$BF_1 = 1$ +round(rand(0,1))

$BF_2 = 1$ +round(rand(0,1))

Calculate Mutual Vector (MV) using: MV= ($X_i + X_j$)/2

Generate new organisms (X_{inew}, X_{jnew}) using equations:

$X_{inew} = X_i + \text{rand}(0,1)\times(X_{best} - MV \times BF_1)$

$X_{jnew} = X_j + \text{rand}(0,1)\times(X_{best} - MV \times BF_2)$

Check constraints using equations (3-10)

Evaluate fitness value and replace predecessor if the fitness of the new organism is better

5. Commensalism Phase

Select organism X_j randomly ($X_i \neq X_j$)

Generate new organism Xinew using

$X_{inew} = X_i + \text{rand}(-1,1)\times(X_{best} - X_j)$

Check constraints using equations (3-10)

Evaluate fitness value and replace predecessor if the fitness of the new organism is better

6. Parasitism Phase

Select organism X_j randomly ($X_i \neq X_j$)

Generate Parasite Vector (PV) by modifying X_i and

Check constraints using equations (3-10)

Evaluate fitness value and replace X_j with PV if the fitness of PV is better

end for

7. Update best organism (X_{best}) of the current population

end while

8. Print the best organism (X_{best}) and the Best cost

Figure 3
Pseudo-code of CSOS algorithm

Unfortunately, the standard SOS uses a random initial population of the organism, which yields a negative impact on the efficiency of the calculation and the results. The disadvantages of this approach are its slow convergence and its tendency to be trapped in local optima due to the low diversity of the starting organism.

To improve the diversity of the initial population, many chaotic maps have been developed for the existing evolutionary algorithms [32]. In the present work, we have adopted the logistic map as an initialization strategy. This later is one of the simplest chaotic maps. Moreover, it provides initial populations that are more diversity than the random selection which ensures smarter coverage of the search space hence, it offers a lower probability of premature convergence [32] [35]. This map is given by the following equation:

$$X_{i+1} = \eta X_i(1 - X_i), 0 \le X_0 \le 1 \qquad (13)$$

Where, X_i is the logistic chaotic value for the i[th] organism;

X_0 is used for generating the initial population of CSOS, $X_0 \in (0,1)$ and η is set to 4

The pseudo-code of the proposed CSOS algorithm is presented in Figure 3

4 Case Study

In this part of the work we implemented and examined the above described CSOS to find optimal global (or near-optimal) solutions of the deterministic EMO problem defined by the augmented objective function (11) and the constraints functions (3-10).

4.1 Microgrid Dataset

The system used for the case study, as shown in Figure 1, is a typical microgrid consisting of a DG unit. These DG's are a microturbine (MT), fuel cell (FC), wind turbine (WT), photovoltaic PV, and energy storage device (NiMH battery).

We assume that all DG sources deliver active power with a unity power factor. Additionally, there is a tie between the utility and the microgrid to trade energy during a day. This link will ensure power exchange as described before. For a typical day, the load demand in the microgrid consists of: a primarily residential area, an industrial feeder serving a small workshop, and a feeder for light commercial shops, with the total energy demand of 1695 kWh is the requirement for this typical day [22][26].

The test system data in terms of the supply coefficients and operating power limits of each DG unit is given in Table 1. In addition, the forecasted daily energy prices, load curve, WT, and PV power generation are presented in Figure 4

Table 1

The power limits and coefficients of bid functions of the installed DG units

Type	Min (kW)	Max (kW)	a_i (€ct/kW h2)	b_i (€ct/kW h)	c_i(€ct/ h)	Star/Shut Cost (€ct)
MT	6	30	0	0.457	0	0.96
FC	3	30	0	0.294	0	1.65

PV	0	25	0	2.584	0	0
WT	0	15	0	1.073	0	0
Battery	-30	30	0	0.38	0	0
Utility	-30	30	-	-	-	-

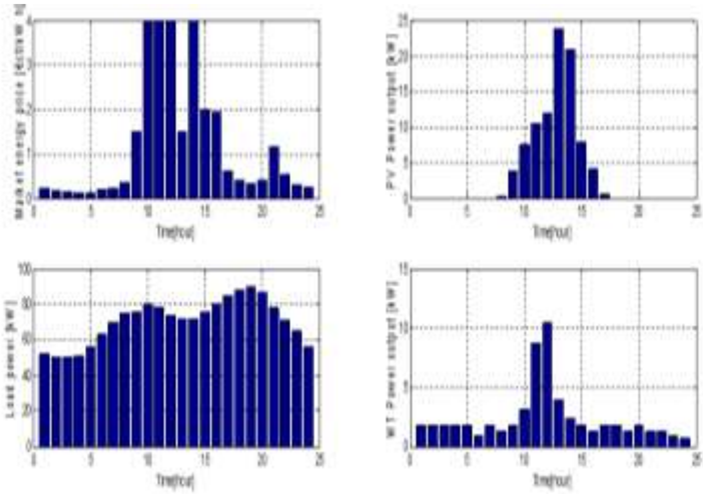

Figure 4
Daily energy market price(a), load curve(b), WT(c) and PV(d) power outputs

4.2 Simulation Results and Comparisons

To test the performance CSOS for solving EMO, initially, we have examined it for three possible operating scenarios of the considered microgrid (MG).

Then, we have conducted a comparison study of the proposed CSOS with some scalable algorithms existing in the literature. For simulations It must be noted that the developed code of CSOS for EMO is run 20 times using MATLAB R2014a software on Core i5@ 2.20 GHz, 4 GB RAM machine. Moreover, the maximum number of iterations is set at 200 with a population size of 30, and the best results are reported for each considered operating scenario.

- Scenario S1: In this scenario, we assume that both renewable energy sources (WT and PV) act at their available maximum power outputs during each hour of the day, while the remaining DGs, including MT, FC, battery, and the distribution grid (utility), operate just at their power limits yet satisfying the set constraints. All DGs above produce the electricity needed by the microgrid, however, the extra energy inside the grid is exchanged with the utility. The obtained results are presented in Figure 5.1 and Figure 5.2

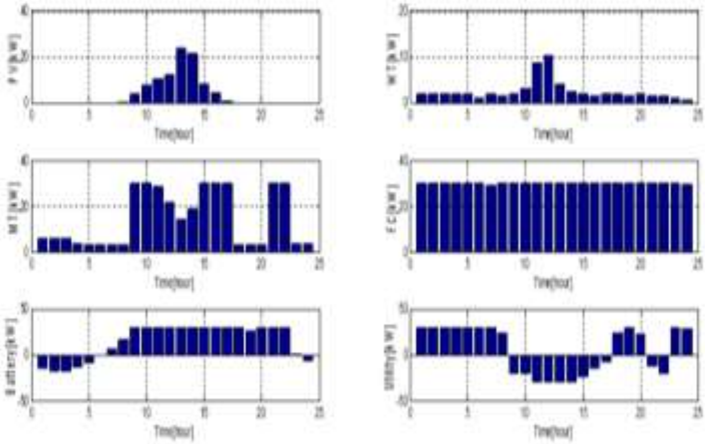

Figure 5.1
Best obtained EMO solutions using CSOS for Scenario S1

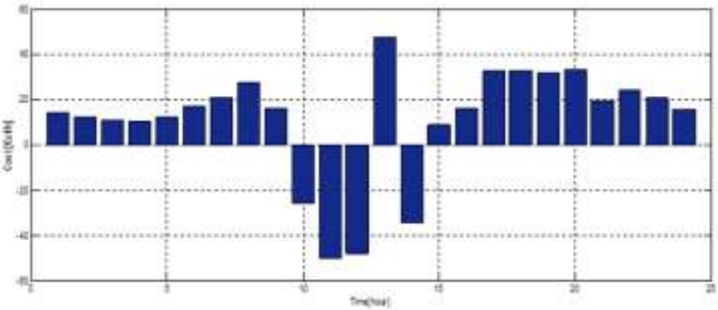

Figure 5.2
Microgrid operating cost for Scenario S1

The results of Figure 5.1 and Figure 5.2, clearly show a large part of the load is mainly supplied by the FC and the utility during the periods (1 a.m. to 8 a.m. and from 11 p.m. to midnight); obviously, this is justified by the supremacy of these 2 unites' offers compared to those of other units during the same period examined. We also notice that the excess energy is exported from the MG to the utility during the period where the prices market are much higher (from 9 a.m. to 5 p.m. and from 9 p.m. to 10 p.m.). However, the battery is charged only during the hours of the day when market prices are low.

- Scenario S2: In this scenario, we assume all the DGs and the utility operating just at their power limits yet satisfying the set constraints. The obtained results are presented in Figure 6.1 and Figure 6.2

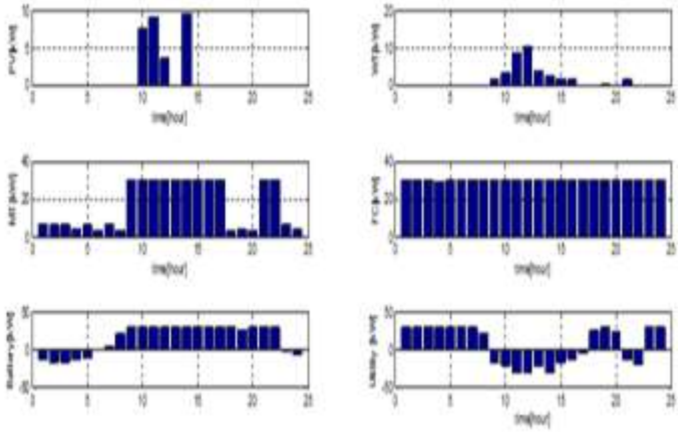

Figure 6.1

Best obtained EMO solutions using CSOS for Scenario S2

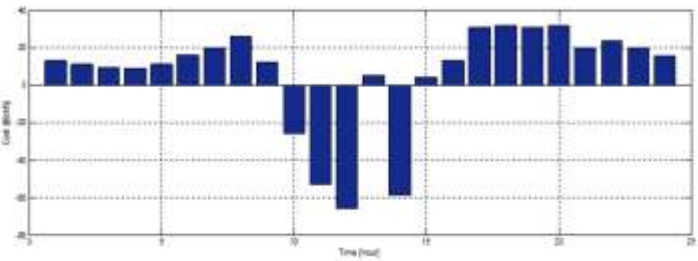

Figure 6.2

Microgrid operating cost for Scenario S2

In the second scenario, Figure 6.1 and Figure 6.2 show that the operating cost of the microgrid decreases considerably (153.98507 [€ct/day]) compared to the first scenario (268.44724 [€ct/day]). This is largely due to the significantly lower participation of WT and PV (they have much higher bids than the other DGs). The output power of FC has a maximum value throughout the day, while the MT offers change depending on the market prices. The battery charging still happens during periods of low market prices, and the extra energy is exchanged from the utility to the microgrid during the same periods.

- Scenario S3: In this scenario, we suppose that the utility behaves as an unconstrained unit and exchanges energy with the microgrid without any limitations, while the rest of the DGs act as described in the second scenario (S2). The found solutions are presented in Figure 7.1 and Figure 7.2

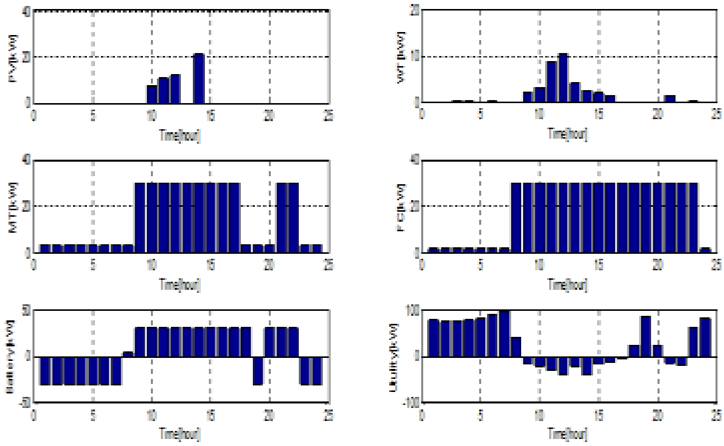

Figure 7.1
Best obtained EMO solutions using CSOS for Scenario S3

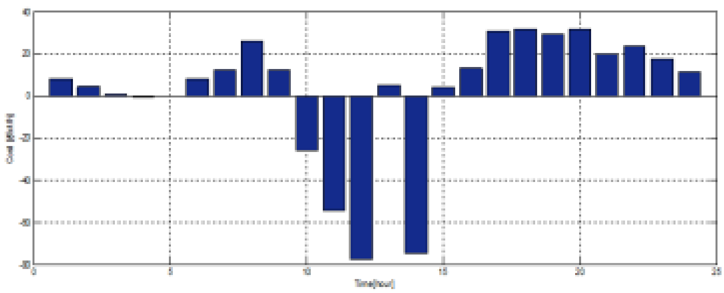

Figure 7.2
Microgrid operating cost for Scenario S3

In this scenario, the PV and the WT will start offering when a shortage of electricity production occurs inside the microgrid or when it is necessary to export more energy to the utility. Similarly, the FC, MT, and battery adjust their generation levels according to the load levels at each hour of the day.

In this situation of unlimited electricity exchange, the obtained results show a clear reduction of the microgrid operating costs (59.69627 €ct/day) compared to the first and second scenarios.

The convergent characteristics for all the scenarios considered are presented in Figure 8. So, this figure allows us to state that the CSOS exhibits a characteristic of rapid convergence and it can reach the minimum cost after a few iterations.

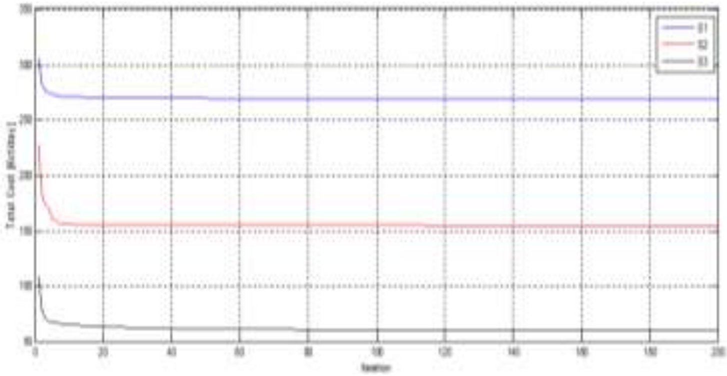

Figure 8

Convergence characteristics of CSOS for the operation scenarios

4.3 CSOS Comparisons with other Evolutionary Algorithms

While using the same test system, control variable limits, and constraints, the obtained results for EMO after deploying the proposed CSOS approach are compared to some other well-known evolutionary algorithms deployment results briefly described in the introduction with their corresponding references. The comparison results are presented in Table 2.

The comparison of results when sorted from best and worst cost, clearly shows that the suggested approach reveals a better performance with the other considered evolutionary algorithm and the standard SOS for all considered scenarios.

Concerning the execution speed, the total execution time of the CSOS is 44.02 seconds. Although it is very hard to compare execution time with other research in literature without enough information about their execution times, it can still be noticed that CSOS may be a successful candidate when it comes to execution speed as it only used 120 iterations to achieve better results in comparison with 1500 iterations for PSO, AMPSO-L, GSA, and GSA as indicated in [13] [22]. Moreover, the standard deviation confirms well another advantage of the CSOS in the optimization process. Hence, we are taking the number of iterations as a measure to say that this a better candidate.

Table 2

Best obtained solutions for EMO using CSOS over other metaheuristics

Scenarios	Method	Study reference	STD	Best cost	Worst cost
S1	GA	[22]	13.4421	277.7444	304.5889
	PSO	[22]	10.1821	277.3237	303.3791
	AMPSO-T	[22]	0.321	274.5507	275.0905
	AMPSO-L	[22]	0.0921	274.4317	274.7318

	GSA	[13]	2.9283	275.5369	282.1743
	SGSA	[13]	0	269.76	269.76
	PSO	[26]	0	269.75999	269.75999
	SOS		**0**	**269.75977**	**269.75977**
	CSOS		**0**	**268.44724**	**268.44724**
S2	GA	[22]	24.5125	162.9469	198.5314
	PSO	[22]	12.6034	162.0038	180.2282
	AMPSO-T	[22]	0.3427	159.9244	160.4091
	AMPSO-L	[22]	0.0963	159.3628	159.6813
	PSO	[26]	0	155.01333	155.01333
	SOS		**0**	**155.01324**	**155.01324**
	CSOS		**0**	**153.98507**	**153.98507**
S3	GA	[22]	13.4005	91.3293	127.7625
	PSO	[22]	10.8689	90.7629	112.8628
	AMPSO-T	[22]	0.4457	89.9917	90.6221
	AMPSO-L	[22]	0.0921	89.972	90.0431
	PSO	[26]	0	68.17626	68.17626
	SOS		**0**	**68.17626**	**68.17626**
	CSOS		**0**	**59.69627**	**59.69627**

Conclusions

This paper introduces a chaotic symbiotic search algorithm, for solving energy optimization management problems, under different operational conditions, for microgrids. In this regard, the suggested CSOS approach includes a chaotic map to improve the approach's search capabilities and ensure better convergence in terms of finding the optimal results and time for convergence.

The effectiveness of the suggested approach was examined under three different operating conditions (scenarios) and compared with other well-known population-based evolutionary algorithms, that were described previously, by other researchers. The results achieved using the CSOS are very interesting, in terms of performance and rapid convergence. Furthermore, the recommended approach doesn’t require any internal control parameter. This study was limited to the deterministic case of EMO, thus, we plan to extend it, to the probabilistic case, when the outputs of DGs and the load demand, are both variable over time and difficult to predict.

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