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New symbolic model for multi-compressor operation based on multi-objective Jaya optimization for life/energy saving

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ABSTRACT

Compressors can be considered as one of the most important utilities in industrial processes. Around 10–14 percent of the electricity consumption in industry was used to produce compressed air. So, in industrial facilities, compressors are the largest energy-consuming equipment. Therefore, energy saving in multi-compressor systems (MCS) is very challenging. In this paper, a new symbolic model based on multi objective Jaya algorithm for the MCS is proposed. The proposed model considered an optimal electrical power consumption (EPC) as well as optimal life span while maintaining the demanded compressed air flow during load change. The proposed model selected compressors that would meet the demanded air flow by adjusting their partial load ratio (PLR) for each changeable variable speed drive compressor (VSDC). This study has optimized the operating period for each compressor based on the optimal power consumption of MCS as well as optimal life span of each compressor. Evolutionary multi-objective Jaya algorithm is proposed to solve the optimization problem. Furthermore, Grey Wolf optimizer has been used and its results have been compared to show that MO-Jaya showed better performance with the proposed problem. Different practical cases of study have been considered and analyzed showing that the multi-objective optimization model could dramatically reduce consumption costs and increase machine's life span. Besides, the maintenance schedule of each compressor could be predicted and planned based on the MCS schedule. Variant air flow has been applied to test the effectiveness of the proposed model.

1. Introduction

Energy saving became a basic necessity in national economic development. Energy consumption in all sectors like: households, industry, buildings and transportation was inefficient according to key performance indicators [1]. Therefore, energy efficiency is an area of increased importance due to the high cost of energy [2]. The tendency is now to increase the electricity production, especially through renewable resources due to their high reliability and low cost. For instance; autonomous hybrid grid composed of wind turbines, hydrokinetic turbines, photovoltaic (PV) systems, energy storage systems and diesel generator [3].

Recently, there are worldwide studies aimed at reducing energy consumption as a result of unexpected increase in energy consumption [4]. There were many research works that have been represented in energy saving in various fields such as smart homes for more convenience and industrial processes which lead to more profits in the competitive market. Various Metaheuristic optimization algorithms have been used to solve optimal EPC problem [5]. Metaheuristic algorithms are inspired by nature which mostly based on swarm intelligence. Such as Grey Wolf Algorithm (GWO) was presented in the year 2014 which used for optimizing electrical consumption of a smart home around the year [6]. Electricity demand is rising because of the population growth and economic development. Causing a gap between energy production and demand. So, an optimization-based energy management framework is proposed for consumers' power usage scheduling based on a hybrid Genetic Ant Colony algorithm [7]. Furthermore, some research work aim at developing poor-efficiency algorithms for more accurate results. So, due to the poor-efficiency of traditional particle swarm optimization (PSO) algorithm, improved PSO was proposed for optimal energy consumption of office buildings in cold area [8]. As a result of rapid increasing in electrical energy consumption, there was a need to match this increase by increasing the production of electricity either by integrating PV panels, electrical energy storages in smart home to increase power generation using GA, PSO, Whale Optimization Algorithm (WOA) and Sine Cosine Algorithm (SCA) for scheduling appliances of single

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Nomenclature

Abbreviations

AFR	Average Flow Rate
AI	Artificial intelligence
EPC	Electrical Power Consumption
FR	Flow Rate
FSC	Fixed speed compressors
GWO	Grey Wolf
Hr	Hours
LS	life Span
MCS	multi compressors system
MO-Jaya	multi objective Jaya
n1	the number of standalone compressors
n2	the number of dependent compressors
n3	the number of changeable VSD compressors
OEPC	Optimal Electrical Power Consumption
P_d	dependent compressor power
P_{SF}	standalone fixed compressor power
PLR	partial load ratio
Q_d	dependent compressor flow rate
Q_m	mixed compressors flow rate
Q_{Sch}	standalone changeable compressors flow rate
Q_{SF}	standalone fixed compressor flow rate
T	the overall operation time
t_m	the operating period of mixed compressors
t_{Sch}	the operating period of each standalone changeable compressor
t_{SF}	the operating period of each standalone fixed compressor
TEPC	Total Electrical Power Consumption
VSDC	Variable speed drive compressors
τ_m	the number of operating hours before maintenance

and multiple homes. These research achieved the user's maximum possible comfort extended to social welfare where consumers could use all appliances with a reasonable electricity bill [9].

As a result of continuous increase of electricity prices, industry had been forced to re-evaluate its energy systems and process controls. The energy consumption varies significantly with respect to the various industries. So, reduced energy consumption is currently driving research efforts towards an increase in industrial applications [10]. For example, in China, according to the National Bureau of Statistics in 2018, the total power consumption has increased by 3.2% compared to 2017. The important energy consumer of overall energy consumption was the building sector. Hence, radiant cooling (RC) systems have been used as preferred technology to reduce building energy consumption. So, RC system have saved the energy by 41% in comparison to an air conditioner [11]. So, improving the cooling system efficiency has attracted much attention as the reduction of cooling system EPC. The existing optimization methods currently, can be classified into data-based approaches and system-model-based. This system model was used to optimize the energy consumption and operation cost in each iteration of the optimization computing [12].

Due to cooling demand uncertainty robust optimization is introduced for uncertainty modeling [5]. In order to obtain optimal energy consumption of each chiller within satisfying demand and excessive cooling avoiding. Equilibrium Optimizer (EO) algorithm is proposed to solve the OCL problem of multiple chiller system [13].

As explained, single objective metaheuristic optimization algorithms have a high effectiveness in solving various energy saving problems. But, industrial processes produce many products and services required for society. As each industry faces various challenges from different perspectives, multi objective optimization algorithms are developed to obtain profitable, productive, controllable, safe and sustainable processes [14]. Multi-objective optimization algorithms have proved their effectiveness in design, operation and control of such processes. In order to assess the system performance including different metrics and evaluate the trade-offs between the objectives in conflict [15]. There are many applications of multi objective optimization in industrial processes and each application has its own challenges [16,17]. As, a multi-objective optimization is very important tool for the operation, design, control and optimization of industrial processes such as Life-Cycle Assessment, Product Development, Water Networks, Energy Production, Storage, Distribution Systems and Supply Chain Networks [14]. Also, multi objective optimization algorithms are used for assembly line rebalancing processes which described by multi objective functions [18].

In some industrial processes, air compressors have avital role as many manufacture processes depend on compressed air. As industrial air compressors are the most energy consumer [19]. Generally, about 10%-14% of the electricity consumption cost in industry is used to produce compressed air [1,20]. So, in industrial facilities compressors are the largest energy-consuming equipment [21]. Therefore, an adaptive optimization matching method is developed of the air supply in order maintain the high-efficiency operation of the system based on (GA) and centrifugal air compressor model are developed [22]. Also, a combined operation model of the air cooler and compressor based on optimization of the switching scheme of compressors and air coolers, which can extremely reduce the production energy consumption of the pipeline system. genetic algorithm (GA), simulated annealing (SA) and particle swarm optimization (PSO) that are used to solve the optimization model [23]. In order to, minimize compressors energy consumption. As the compressed air systems are often very expensive and inefficient industrial systems. A real time ambient sensing are combined with Artificial Intelligence and knowledge management to automatically minimize energy consumption for air compressors. Based on real-time manufacturing conditions [24]. Also, in [24] Artificial Intelligence will understand that data and automatically act. Knowledge Management will simplify the processing of information to advise operators on actions. In order to minimize energy consumption and maintain productivity. The aim is to develop new intelligent techniques to optimize energy in compressed air systems. Moreover, electrical load profile of compressed air systems has been predicted based on Artificial Neural Network. Which is worthy to industry practitioners as well as software providers in developing better practice and tools for load management and look-ahead scheduling programs [20].

As shown, single-objective and multi-objective metaheuristic optimization algorithms have a high effectiveness in solving various energy saving problems and various industrial applications. There are many works have discussed the EPC problem in smart homes and their different applications as well as EPC control Challenge in industrial processes. Furthermore, the most of works have discussed the optimal EPC problem of multi-chillers system in refrigeration systems. But there are few works have studied the problem of optimal EPC of MCS. unfortunately, the methodology of researches which discussed the optimal EPC they will not be effective for solving the problem of optimal EPC of MCS. As they have some gaps as follows: only variable speed drive (VSD) machines were discussed whether compressors or chillers. VSD machines have been loaded at a different load ratio for the same operating period, which negatively affects the LS of each equipment. As a result, it will be difficult to determine the machines that could meet the demand independently. Furthermore, There is a difficulty for system's maintenance planning. Besides, there is no developed generalized mathematical model for MCS power consumption control.

In this paper, a mathematical model for MCS was developed. Based on it, MCS could be defined in terms of the type of each compressor by its rated power, and rated flow rate. In addition, the operating duration of each compressor has been added to that model to calculate the EPC of each compressor. Based on the proposed mathematical model, it became possible to apply artificial intelligence optimization algorithms on MCS. In order to obtain the optimal consumption of MCS as well as optimal LS of each compressor. Hence, a new symbolic model based on a multi objective Jaya algorithm for the MCS is proposed. In order to obtain optimal EPC in MCS as well as optimal LS of each compressor for fixed speed compressors (FSC) and VSDC. According to the previous explanation, the main contributions of the proposed paper is briefly presented as follow:

- The study has been based on a real-life problem in one of the biggest cooking appliances factories near to Cairo - Egypt. The power consumption recordings have been gathered and a multi objective optimization have been proposed. A min–max objective functions are optimized.
- The study considered not only cost reduction but also low power consumption and lifetime extension of MCS.
- The study considered different air-flow rates during day/night shifts.
- Different scenarios for the MCS problem have been proposed.
- A comparison based on different optimization algorithms has been studied and compared.

This paper is organized as follows: Section 2 presented problem formulation of optimal compressors consumption in-detail. In Section 3 multi-objective algorithms are explained, especially, MO-Jaya algorithm. Section 4 discusses research results for a real case study, while the research conclusions are presented in Section 5.

2. Optimal EPC problem of MCS

Air compressors are vastly used in various industries. Whether large, small and medium enterprises (SMEs) [21]. As, in the manufacturing industry a necessary form of energy used is stored as a compressed air (CA) [25]. Compressed air is widely used in operating cylinders, pneumatic valves, cleaning, testing of products and transporting products [14]. In industrial applications. Inlet fresh air is compressed by compressors to the required pressure at sufficient FR according to compressors rate. Then, compressed air is dried by air dryers to be usable in order to preserve the equipment from internal damage as shown in Fig. 1.

2.1. Structure of MCS

Fig. 2 illustrates the structure of MCS. Which consists of multiple compressors, compressed air receiver, multiple dryers. In proposed case study MCS consists of three compressors which classified into two types: FSC which operates at a constant and regular speed. This produces a fixed air flow of compressed air per minute [27] and VSDC in which the compressor's operating speed is automatically adjusted according to demand [28]. A brief description of compressors data is provided in Table 1.

2.2. Optimal EPC problem formulation

High EPC and it's corresponding high cost is our main research problem. which caused due to trial and random operation based on an unknown factory demand of air FR. Furthermore, some compressors are being loaded for longer than others. Which negatively affects the lifespan of each compressor and increase the number of maintenance times for them. Which entails an additional high cost. As, in every maintenance, filters and oil are changed. The high and unstable EPC of multi compressors system is shown in Fig. 3.

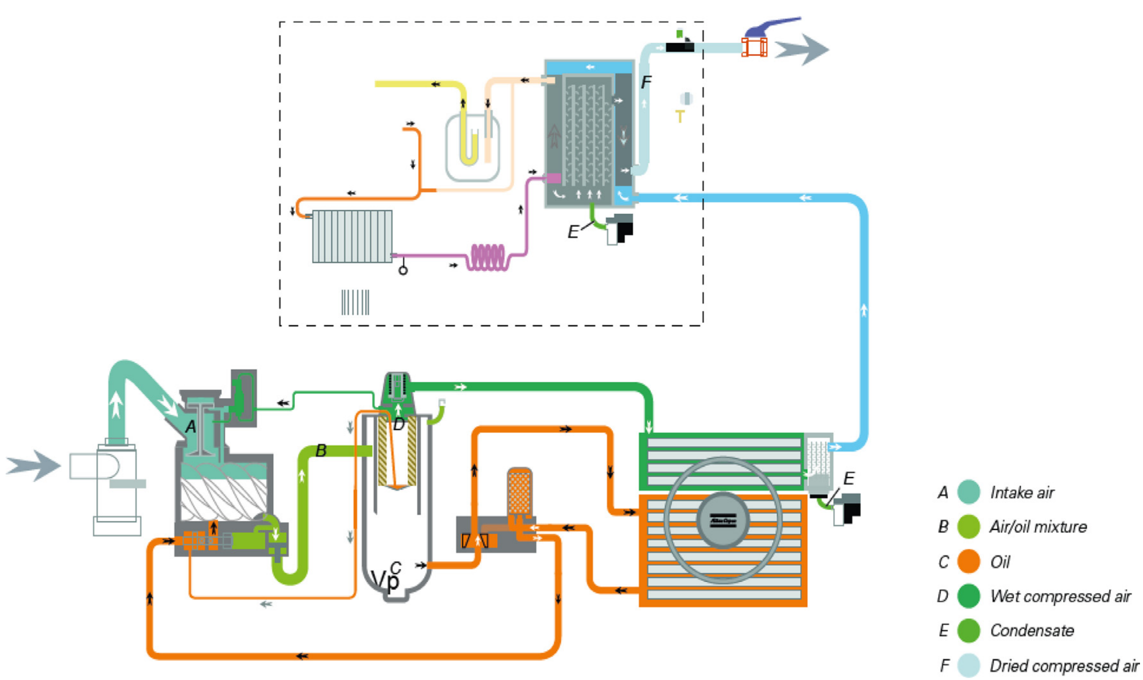

Fig. 1. The adopted compressor operation cycle [26].

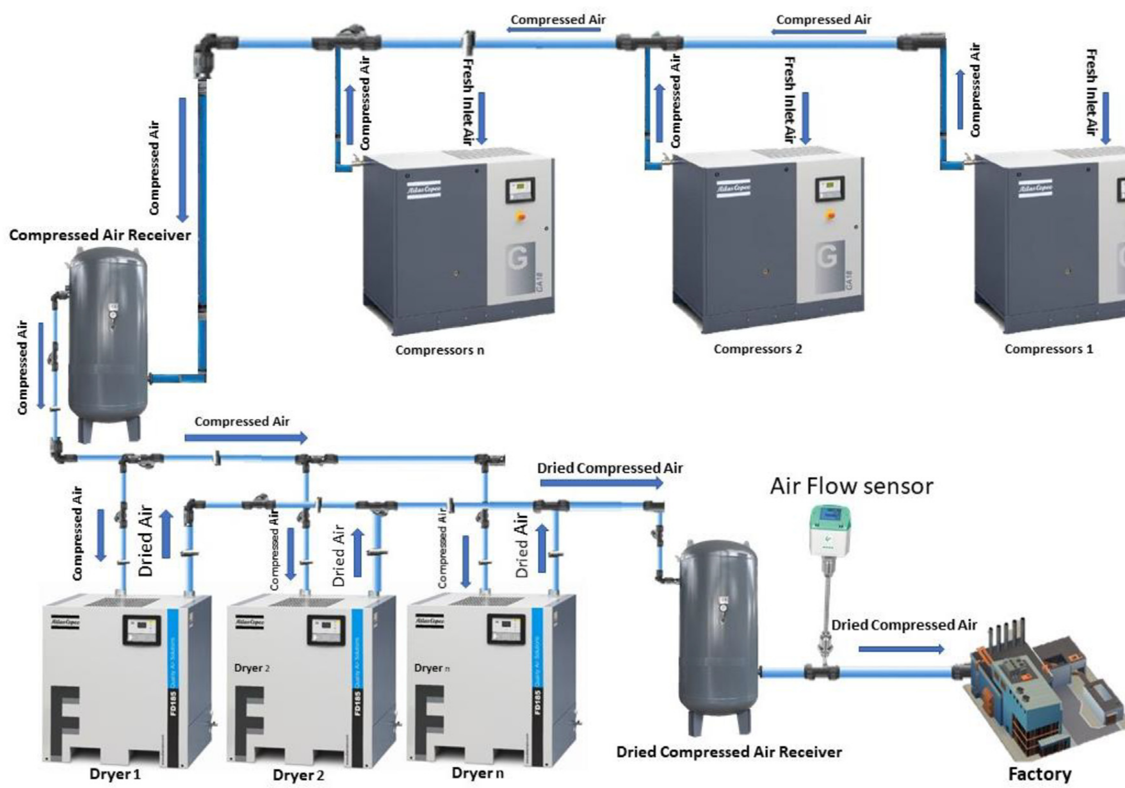

Fig. 2. The MCS architecture in the proposed case study.

2.2.1. Compressors classification

To determine the factory's actual demand of compressed air during different loading conditions. An air flowmeter has been installed. According to the demand of compressed air FR, multi compressors system can be classified as follows:

The standalone fixed speed compressors which can provide the demand alone are selected based on the following Eq. (1):

$$\sum\nolimits_{i=1}^{n1} Q_{SF} \geq Q_{req} \tag{1}$$

The standalone changeable compressors which can provide the demand alone are selected based on the following Eq. (2):

$$\sum_{i=1}^{n1} Q_{Sch} \geq Q_{req} \tag{2}$$

And their PLR are determined based on the following Eq. (3):

$$PLR_{Sch} = Q_{Sch}/Q_{req} \tag{3}$$

The fixed compressors which can't meet the demand alone. In this case the changeable compressors which can be loaded with them. In order to, be able to meet the demand are selected and they have been called mixed compressors and PLR of changeable compressors are determined based on following Eq. (4):

Table 1
Multi compressors system data.

Compressors Rated Power	FR (m^3/min)	Type
37 kW	6.1	Fixed Speed
45 kW	9.4	Variable Speed Drive
75 kW	12.6	Fixed Speed
90 kW	17.6	Variable Speed Drive

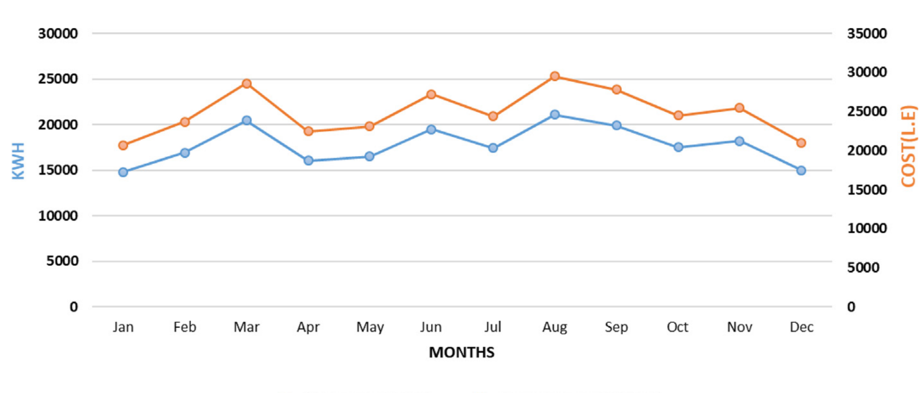

Fig. 3. Compressors EPC and it's corresponding cost for year 2021.

$$PLR_{mch} = (Q_{req} - Q_d)/Q_{mch} \tag{4}$$

2.2.2. Optimal operating period based on a multi objective Jaya optimization algorithm

In order to, achieve optimal electricity consumption for multi compressors systems. The optimal operating period for each compressor should be determined based on a multi objective Jaya optimization algorithm. It is possible to select the compressor with the lowest electrical rated power. In order to run for the longest period more than other compressors, but this will inevitably negatively affect the LS of this compressor and increase the number of maintenance times. Also, it will lead to an additional cost. So, the LS of each compressor must be considered by increasing the period in which it reaches the number of operating hours. At which maintenance is carried out. So, single objective optimization will not be effective for our problem. Therefore, it was intended to use multi objective algorithms for their effectiveness in solving conflicting objectives. Hence, our research problem can be formulated as two objective functions. Which constrained with equality and inequality constraints as shown in Fig. 4. First objective is to maintain optimal TEPC for MCS by obtaining the minimum of the following Eq. (5):

$$\mathrm{TEPC} = \mathrm{Min}\left(\sum_{i=1}^{n1}[P_{SF\,i} * t_{SFi}] + [\sum_{j=1}^{n2} P_{DF\,j} + \min\sum_{k=1}^{n3}(PLR_{mch\ i,j} * P_{mch\,k})] * t_{mj} + \sum_{y=1}^{n3} PLR_{Sch\,y} * P_{Sch\,y} * t_{Sch\,y}\right) \tag{5}$$

And the second objective is to maintain optimal LS of compressors by maximize the period before pre-maintenance operating hours as presented in the following Eq.6:

$$\mathrm{LS} = \mathrm{Max}\left(\sum_{i=1}^{n1}[\tau_m/t_{SF\,i}] + \sum_{j=1}^{n2}[\tau_m/t_{m\,j}] + \sum_{y=1}^{n3}[\tau_m/t_{Sch\,y}]\right) \tag{6}$$

And these objectives will be solved subject to the following constraints:

$$PLR_{mch} \leq 1 \tag{7}$$

$$PLR_{Sch} \leq 1 \tag{8}$$

$$\sum_{i=1}^{n1} t_{SF\,i} + \sum_{j=1}^{n2} t_{mj} + \sum_{y=1}^{n3} t_{Schy} = T \tag{9}$$

$$Lifespan_{(SF,m,Sch)} \leq \alpha\tau_m \tag{10}$$

Where the TEPC is total power consumption,τ_m number of operating hours before maintenance it will be equal 2000 h in this proposed case study,P_{SF} is the power of standalone FSC which should meet the desired air flow alone, P_d is the power of dependent compressor which can't meet the desired air flow alone,P_{Sch} is the power of standalone changeable compressor which meet the desired air flow alone, P_{mch} is the power of changeable VSDC which supports the dependent compressor to meet the demand air flow, $n1$ is the number of standalone compressors, $n2$ is the number of dependent compressors, $n3$ is the number of VSDC,t_{SF} is the operating period of each standalone compressor, t_m is the operating period of mixed compressors (dependent and changeable), t_{Sch} is the operating period of each standalone changeable compressors, Q_{SF} is FR of standalone compressors, Q_d is the FR of dependent compressors, Q_m is the FR of mixed compressors (dependent and changeable), Q_{Sch} is the FR of standalone changeable compressors, T is the overall operation time will be equal 9 h for day shift and 8 h for night shift and α is the maintenance duration factor which depends on the actual FR and number of operated compressors during the shift and determines the period after which the maintenance process will be carried out.

3. Metaheuristics optimization algorithms (MOA)

Optimization is one of the widely discussed subjects that has many algorithms [6].For simple function, derivative and deterministic techniques are used for solving an optimization problem. For complex and highly nonlinear optimization problems these deterministic techniques aren't effective for solving such types of problems. So, Metaheuristics algorithms are developed [29].Which used for solving optimization problems through searching optimal solutions to a specific problem of interest using many agents. Which create a system of developing solutions using a set of mathematical equations during multiple iterations until the best solution is selected when system is reached a converged state [30]. Metaheuristic optimization techniques perhaps classified into main four types, namely, physics-based algorithms, human-based algorithms, evolutionary algorithms and swarm-based algorithms [31]. The selective of this meta-heuristic algorithm based on the algorithm behavior, time limitation, availability of resources, issue type, and required accuracy [32]. In science and engineering fields multiple conflicting objectives for optimization arise. So, multi-objective meta-heuristic algorithms are developed to maximize or minimize many conflicting objective functions simultaneously [33].

3.1. Multi-objective optimization

Multi-objective optimization has been used in various engineering problems where a set of conditions must be met to provide an optimal solution for successful application [34]. A multi-

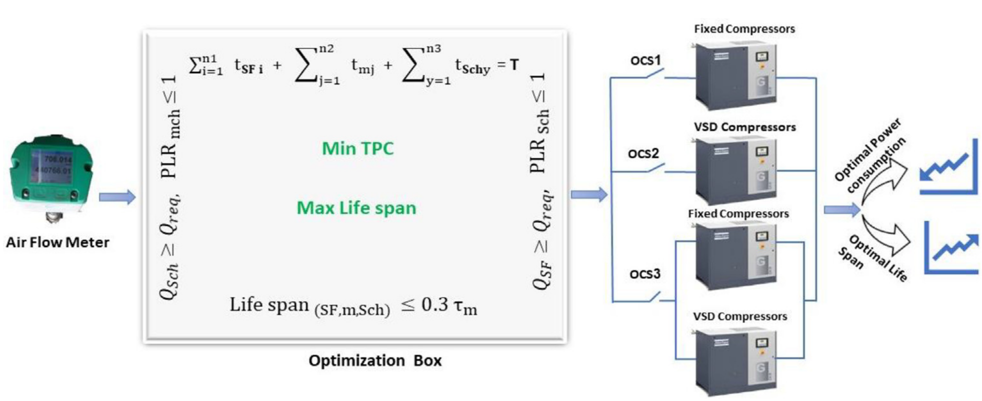

Fig. 4. The proposed multi-objective constrained system.

objective optimization problem includes a several objective functions which are to be maximized or minimized and they may be conflicting functions. The multi-objective optimization problem may subject to some constraints must satisfy as in a single-objective optimization problem. Multi objective optimization problem can be formulated in a general form as:

Maximize/Minimize $F_m(x)$, m = 1,2,. . ..,M;

Subject to $g_i(x) \geq 0$, i = 1,2,. . ..,I;

$h_y(x) = 0$, y = 1, 2,. . ..,Y;

$\chi_L^{lb} \leq x_l \leq \chi_L^{ub}$, L = 1,2,. . ..,l;

$F_m(x)$ is the objective functions, $g_i(x)$ is inequality constraints, $h_y(x)$ is equality constraints and χ_L^{lb}, χ_L^{ub} are lower and upper boundary respectively. For each solution × in the decision variable space, if the solution $x^{(1)}$ isn't worse than $x^{(2)}$ in each objective and it is strictly better than $x^{(2)}$ in at least one objective, the solution $x^{(1)}$ is said to dominate the other solution $x^{(2)}$. So, if one point dominates the other can be confirmed. All points which are not dominated by any another point of the set are called the non-dominated points. For non-dominated points one property of any other such points is a gain in an objective from one point to the other [35–37]. The dominated and non-dominated points for different types of objective functions are shown in the Figs. 5 to 7.

3.1.1. Multi-objective Jaya algorithm (MO-Jaya)

Jaya algorithm is a *meta*-heuristics algorithm proposed by R. Venkata Rao in 2016. The inspiration of Jaya algorithm originates from obtaining a solution for a given problem should move towards the best solution through positive thinking. Also, should avoid the worst solution by avoiding the negative thinking as shown in Fig. 8. Jaya algorithm does not require any algorithm-specific parameters. It requires only common controlling parameters like population size and number of generations for its working [38].

Then, for solving the multi-objective optimization problems MO-Jaya algorithm is developed in 2017. It is a modified version of Jaya algorithm to be able to solve multiple objectives effectively [39]. The performance of MO-Jaya algorithm is tested on non-quadratic unconstrained multi-objective benchmark functionof CEC2009. The MO-Jaya algorithm was compared with various algorithms such as GA, NSGA, NSTLBO, BBO, NSGA-II, SQP, PSO and Monte Carlo simulations. The results had shown the better performance of the MO-Jaya algorithm [40].

Jaya algorithm begins with a random initial population at first iteration according to the populations size. Then selects the best and the worst solutions at every iteration. Next, each solution moves forward searching the best solution in the population and moves away from the worst solution according the following Eq. (11):

$$\boldsymbol{X_{new,i}} = \boldsymbol{X_{old,i}} + \boldsymbol{r}_1 \times (\boldsymbol{X_{best,i}} - |\boldsymbol{X_{old,i}}|) - \boldsymbol{r}_2 \times (\boldsymbol{X_{worst,i}} - |\boldsymbol{X_{old,i}}|) \quad (11)$$

where $\boldsymbol{X_{new}}$ and $\boldsymbol{X_{old}}$ are the variable values for the updated solution and the current solution respectively. $\boldsymbol{X_{best}}$ and $\boldsymbol{X_{worst}}$ are defined as the best solution and the worst solution respectively.

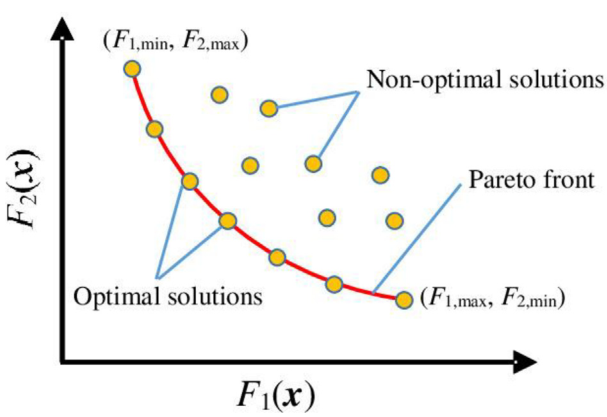

Fig. 5. Min-Min objective functions space [35].

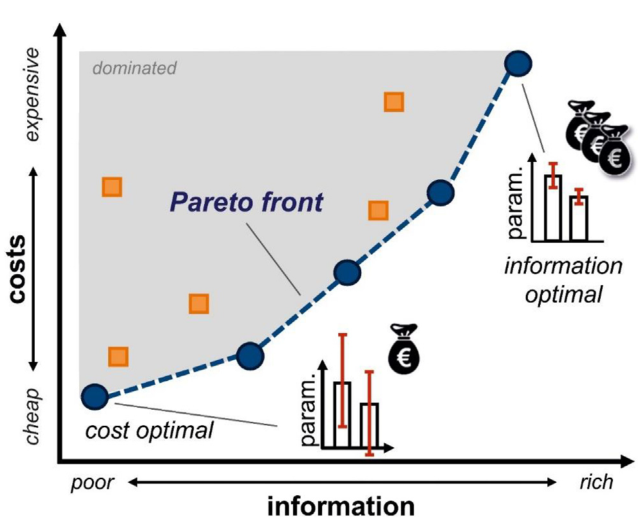

Fig. 6. Min-Max objective functions space [36].

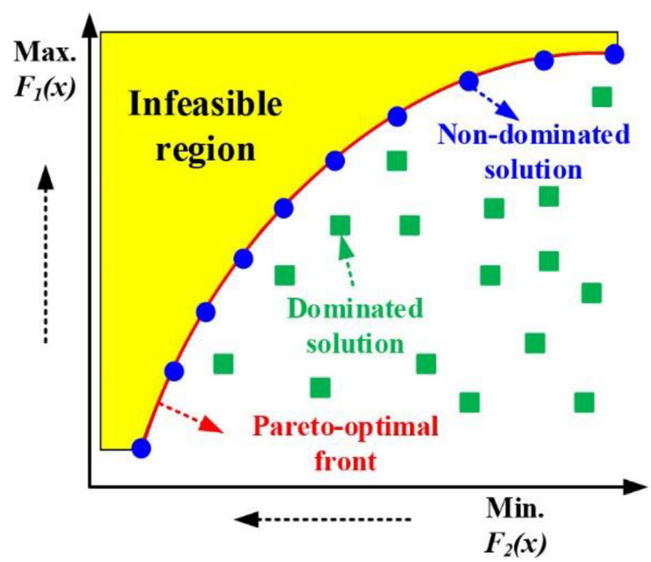

Fig. 7. Max-Min objective functions space [37].

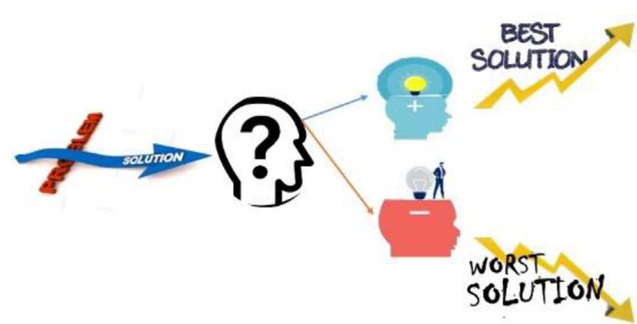

Fig. 8. Jaya algorithm positive/negative thinking.

$\boldsymbol{r}_1$ and $\boldsymbol{r}_2$ are two random values between [0, 1]. In Eq.11,the expression $\boldsymbol{r}_1 \times (\boldsymbol{X}_{best,i} - |\boldsymbol{X}_{old,i}|)$ shows that the current solution goes closer to the best solution and the expression -$\boldsymbol{r}_1 \times (\boldsymbol{X}_{worst,i} - |\boldsymbol{X}_{old,i}|)$ shows that the current solution goes away from the worst solution [41].The Jaya algorithm steps are explained in the following flow chart as shown in Fig. 9.

4. Results on cases study

4.1. Experiment data

An air flowmeter has been installed to monitor the factory's demand of compressed air, in order to select the compressors that should be loaded to meet the demand as mentioned in Section 2.2.1. Table 2 shows the average factory consumption of compressed air for 5 months during day and night shifts. Two Scenarios are simulated to test and confirm the effectiveness of the proposed model.

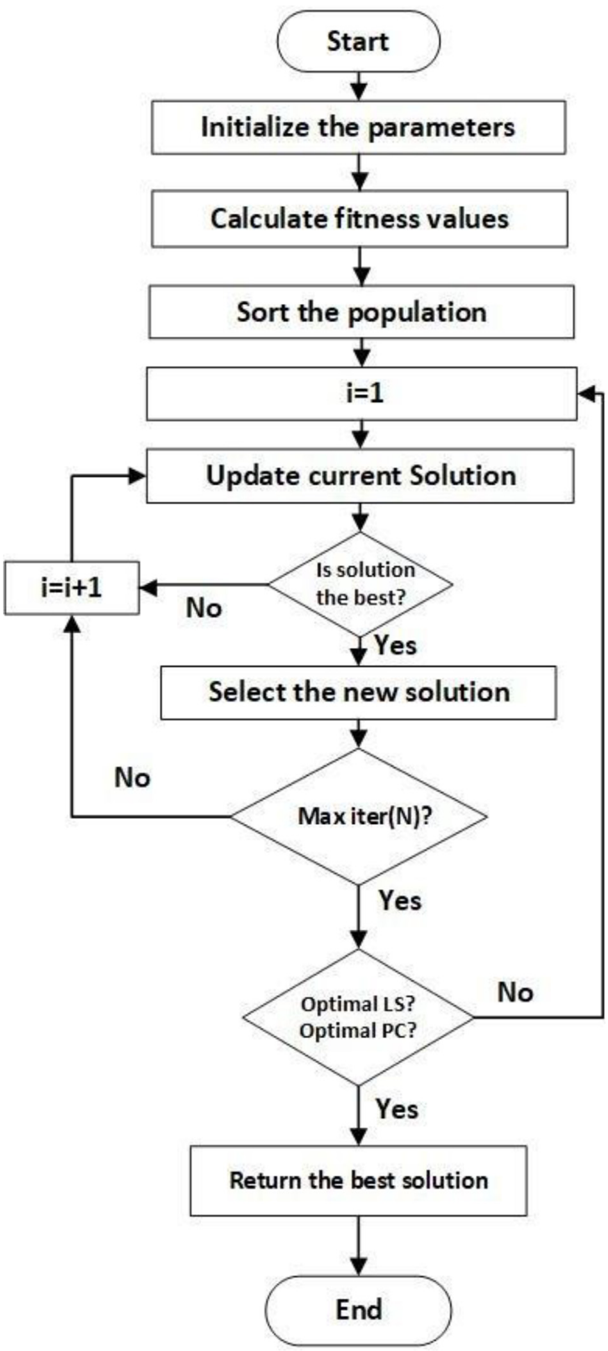

Fig. 9. The MCS proposed algorithm flowchart based on Jaya.

4.1.1. Scenario 1

In this scenario, MCS consists of two fixed compressors 37, 75 kW and only one changeable VSD compressor of 45 kW, as presented in Table 1. Each compressor will be loaded based on the proposed model to obtain the optimal EPC as well as the optimal LS.

4.1.2. Scenario 2

In this scenario, the MCS consists of two fixed compressors 37, 75 kW and two changeable VSD compressors 45, 90 kW as in Table 1. The 90-kW compressor has a more power and flow rate than other compressors. Adding this specific compressor to the system has the advantage of operating as a standalone compressor in case of high/low FR maintaining optimal PLR to obtain better EPC as well as LS.

4.2. Experiment environment

The simulation experiments is implemented on laptop, CPU: Intel(R) Core (TM) i5-10210U CPU @ 1.60 GHz 2.11 GHz, RAM: 8.00 GB, OS: Windows 10. Moreover, Multi-Objective Jaya algorithm is coded in MATLAB(R2018b) software environment for simulation experiments.

4.3. Parameter setting of Multi-objective algorithms

The parameters of multi-objective algorithms, are set as:

- Number of particles = 100.
- Maximum iteration = 100.

4.4. Experimental results and discussion

Through the proposed model, the compressors that should be loaded to meet the factory's demand of compressed air have been determined. In addition, the optimal PLR for each VSDC as well as the optimal operating duration for each compressor were calculated. Accordingly, the optimal EPC is maintained, as well as, the optimal period of operating hours before maintenance is due, which was recommended by the manufacturer to extend the LS of each compressor.

The MO-Jaya algorithm will be compared to another well-known GWO algorithm keeping the same multi-objective functions.

4.4.1. Results of scenario 1

Table 3 shows the optimal standalone compressors that could meet the air flow demand during day shift as proposed in Table 2. According to AFR of the day shift during March, the 75-kW FSC could meet the air flow demand alone for 3.35 Hr/day. Optimal EPC will be obtained based on the proposed model. Optimal period will be 596 days before periodic maintenance.

Fixed compressors that could not meet the demand alone will operate in parallel with the optimal PLR of VSD compressor, as mixed compressors. As shown in Table 4, for March AFR demand, compressor 37 kW can't meet the demand alone. Based on the proposed model, it will operate with a VSD compressor at PLR 43.74% to meet the demand for 5.64 Hr/day. Optimal EPC based on the proposed model will be achieved. Optimal period of 354 days prior to periodic maintenance, and so on for other months. The standalone

Table 2
A Day/night shift AFR for 5 consecutive months.

	March		April		May		June		July	
Shift	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
AFR (m^3/m)	10.088	2.29	10.32	0.94	10.20	1.06	8.76	0.945	8.99	1.57

Table 3
Scenario 1: Standalone compressors during day shift.

Months	Compressors (kW)	Operating duration (Hr /Day)	Optimal PLR	Optimal LS (day)
March	75	3.35	–	596
April	75	3.54	–	564
May	75	3.42	–	584
June	75	2.03	-	985.2
	45	4.72	96.2%	
July	75	2.00	-	1000
	45	4.95	98.7%	

Table 4
Scenario 1: Mixed compressors during day shift.

Months	Compressors (kW)	Operating duration (Hr/day)	**Optimal PLR**	**Optimal LS (day)**
March	37	5.64	-	354
	45		43.74%	
April	37	5.44	-	367
	45		46.26%	
May	37	5.60	-	357
	45		45.05%	
June	37	2.24	-	888.9
	45		20%	
July	37	2.06	-	967.11
	45		31.7%	

Table 5
Scenario 1: Optimal selected compressors during night shift.

Months	Compressors (kW)	Operating duration (Hr/day)	Optimal PLR	Optimal LS (day)
March	45	8	25.16%	250
April	45	8	8%	250
May	45	8	11.5%	250
June	45	8	20%	250
July	45	8	17.3%	250

compressors and mixed compressors will be operated in parallel for high demand of FR.

During the night shift according to very low FR, as in Table 2, only VSD will operate with its optimal PLR based on the proposed model to achieve the optimal EPC. As shown in Table 5 according to AFR demand, compressor 45 kW will operate with its optimal PLR 25.16%, in order to obtain the optimal EPC as well as the optimal period before pre-maintenance operating hours will be 250 days, and so on for other months. The switching process between compressors and operation duration of each compressor at AFR of March will be shown in Fig. 10. and the load power profile of operated compressors are shown in Fig. 11 for monitoring the current EPC at each operation duration.

In Fig. 12, the optimal EPC (kWh/Month) based on the proposed model and its corresponding cost will be Compared with EPC and its corresponding cost in case of random operation. As shown, the operating based on the proposed model led to a 30.89 % reduction in the average EPC, as well as the average cost of EPC per 5 months compared to random operation.

As proposed, the model constraints are achieved as: the total day shift operating period doesn't exceed 9 h and the total night shift operating period doesn't exceed 8 h. The LS of each compressor doesn't exceed the α of τ_m which adjusted at 0.3 for first 3 months and 0.5 for last 2 months according to the actual FR and the number of operated compressors during the shift, as well as the optimal period before pre-maintenance operating hours is achieved.

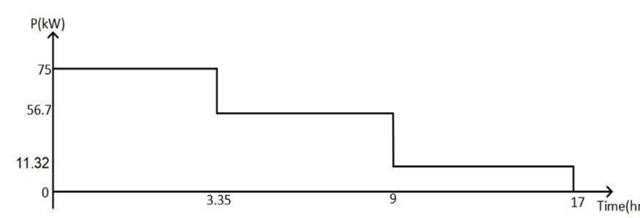

Fig. 11. Scenario 1: Compressors power profile at AFR in March.

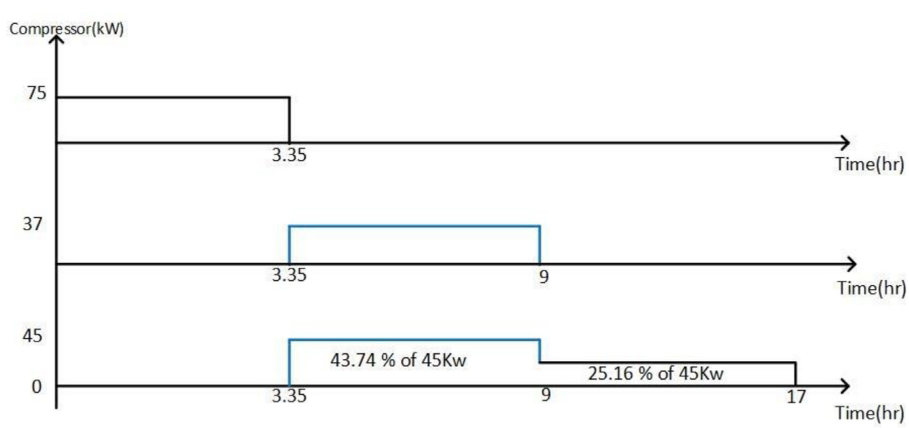

Fig. 10. Scenario 1: Compressors switching and operating duration at AFR in March.

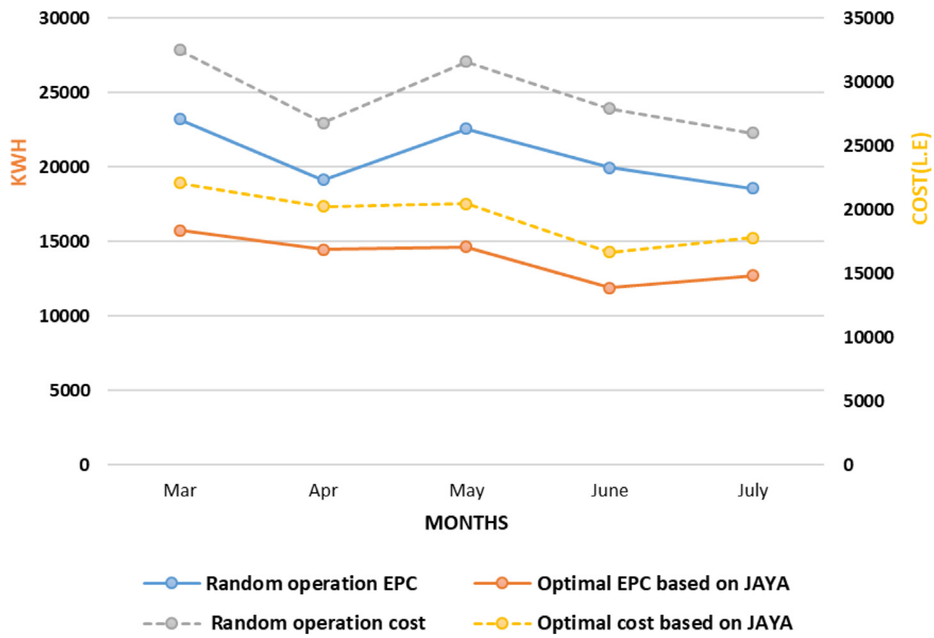

Fig. 12. Scenario 1: Optimal Vs random operation of compressors for 5 months indicating EPC/cost.

The dominated and non-dominated points for two conflicting objective functions min EPC-max LS are shown in Fig. 13.

The MO-Jaya algorithm has been compared to a well-known GWO algorithm on the MCS problem using the same multi-objective functions. The results had shown a better performance for MO-Jaya algorithm as listed in Table 6 and Fig. 14.

4.4.2. Results of scenario 2

As explained in section 4.1.2 of scenario 2, the VSD compressor 90 kW has a maximum power and FR more than other compressors. So, it can be operated as a standalone compressor in case of a high and low FR at the optimal PLR, in order to obtain more optimal EPC as well as optimal LS. Table 7 shows that, For March the FSC 75 kW can be operated with the optimal PLR 57% of the VSD 90 kW alternately for 2.07 and 4.87 Hr/day respectively to obtain optimal EPC based on the proposed model as well as the optimal period before pre-maintenance operating hours will be 967.14 and 411.07 days for 75 kW and 90 kW compressors respectively. And so on for other months.

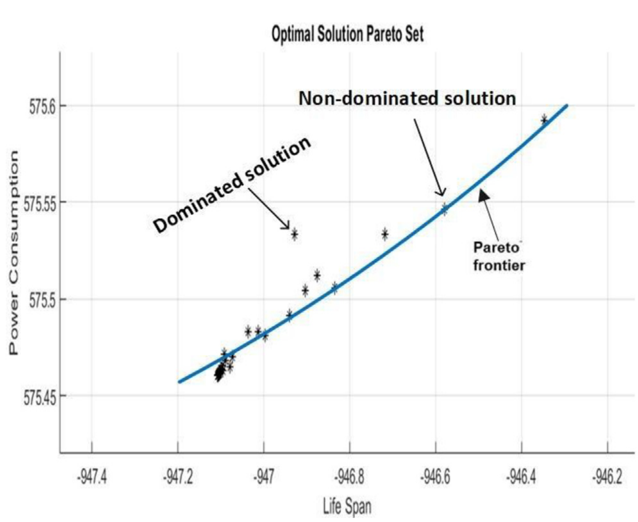

Fig. 13. Scenario 1: Pareto front for the proposed min–max EPC/LS objective functions.

The FSC which can't meet the demand alone will be able to operate in parallel with the optimal PLR of VSD compressor as mixed compressors. As shown in Table 8, for March according to demand compressor 37 kW can't meet the demand alone. So, based on the proposed model, it will operate with the PLR 43% of VSD compressor to be able to meet the demand for 2.076 h/day to obtain optimal EPC based on the proposed model as well as the optimal period before pre-maintenance operating hours will be 354 days, and so on for other months.

During the night shift according to very low FR as shown in Table 2, only VSD compressors will operate with its optimal PLR based on proposed model as shown in Table 9 in order to obtain the optimal EPC as well as LS. So, for March 45 kW will operate with optimal PLR 25.16% alternately with VSD 90 kW with optimal PLR 13.01% for 4.63 and 3.37 Hr/day respectively. The switching process between compressors and operation duration of each compressor at AFR of March will be shown in Fig. 15. and the load power profile of operated compressors are shown in Fig. 16 for monitoring the current EPC at each operation duration.

In Fig. 17, the optimal EPC (kWh/Month) based on the proposed model and its corresponding cost will be Compared with EPC and its corresponding cost in case of random operation. As shown, the operating based on the proposed model led to a 36% reduction

Table 6
Scenario 1: Comparison between MO-Jaya and MO-GWO.

Months	GWO EPC (kWh)	GWO LS (Day)	Jaya EPC (kWh)	Jaya LS (Day)
March	16,260.88	900.56	13,691.4	950
April	16,174.86	858.96	14,448.3	931
May	16,026.58	924	14,616.2	941
June	14,736.5	1,960.53	11,885.2	2,270
July	14,234.24	1,888.51	12,695.3	2,371

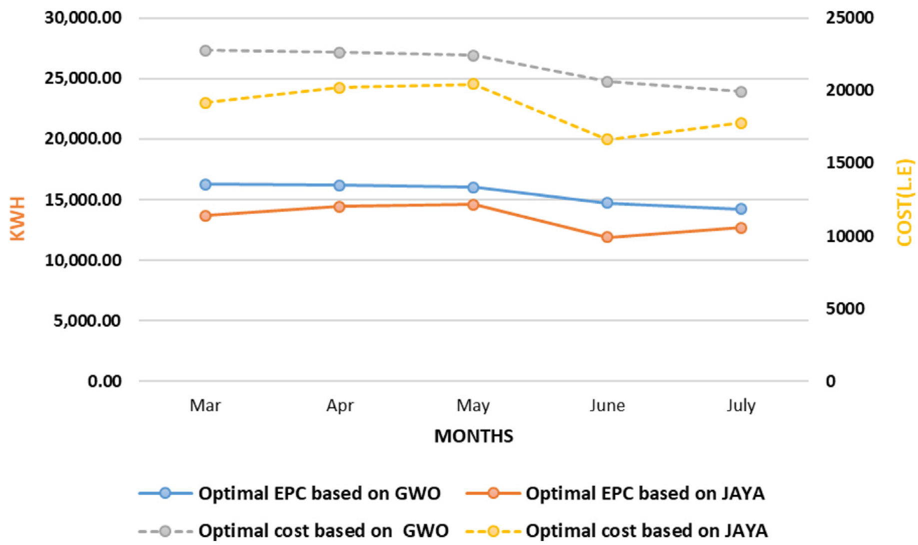

Fig. 14. Scenario 1: Optimal EPC/cost based on MO-JAYA compared with MO-GWO.

Table 7
Scenario 2: Standalone compressors during day shift.

Months	Compressors (kW)	Operating duration (Hr /Day)	Optimal PLR	Optimal LS (days)
March	75	2.07	-	967.16
	90	4.87	57%	411.07
April	75	2.03	-	987.38
	90	4.90	58.6%	408.08
May	75	2.07	-	967.16
	90	4.87	57.9%	411.07
June	75	1.45	-	1374.75
	45	4.57	96%	437.73
	90	1.49	49.7%	1338.34
July	75	1.17	-	1714.16
	45	3.34	98.7%	597.95
	90	3.06	51%	654.02

Table 8
Scenario 2: Mixed compressors during day shift.

Months	Compressors (kW)	Operating duration (Hr/day)	Optimal PLR	Optimal LS (days)
March	37	2.076	-	963.07
	45		43%	
April	37	2.079	-	961.89
	45		46%	
May	37	2.076	-	963.07
	45		45%	
June	37	1.48	-	1343.67
	45		29.23%	
July	37	1.51	-	1324.75
	45		31.76%	

in the average EPC, as well as the average cost of EPC per 5 months compared to random operation.

In Fig. 18 the optimal EPC (kWh/Month) based on Scenario 1 and its corresponding cost will be Compared with the optimal EPC (kWh/Month) based on Scenario 2 and its corresponding cost.

The MO-Jaya algorithm has been compared to a well-known GWO algorithm on the MCS problem using the same multi-objective functions. The results had shown a better performance for MO-Jaya algorithm. The comparison between MO-Jaya algorithm and MO-GWO has been illustrated in Fig. 19 and listed in Table 10.

Table 9
Scenario 2: Optimal selected compressors during night shift.

Months	Compressors (kW)	Operating duration (Hr/day)	Optimal PLR %	Optimal LS (days)
March	45	4.63	25.16	431.67
	90	3.37	13.01	593.85
April	45	5.31	10.34	376.63
	90	2.69	5.34	743.50
May	45	6.15	11.54	325.11
	90	1.85	5.97	1080.67
June	45	6.23	10.38	319.55
	90	1.74	5.37	1146.33
July	45	6.32	17.29	316.40
	90	1.69	8.94	1186.23

5. Conclusion

In this paper, the random operation of MSC problem has been studied. This unoptimized operation causes a high EPC, moreover, negatively affects the LS of each compressor. A new symbolic model based on a MO-Jaya algorithm has been developed for the MCS. The proposed symbolic model offered optimal EPC besides optimal LS while maintaining the demanded compressed air flow during load change. To meet the factory's compressed air flow demand, the proposed model optimally selects either the FSC that could operate on as a standalone, or selects the VSDC with its corresponding PLR. Alternatively, it selects dependent FSC that operates synchronously with VSDC with an optimal PLR as mixed compressors. This model optimized the operating period for each compressor based on the optimal EPC of MCS as well as the optimal LS of each compressor. Different scenarios have been considered and analyzed showing that the multi-objective optimization model could dramatically reduce consumption costs and increase machine's life span. The overall cost reduction in scenarios 1 and 2 are 30.89 and 36 %, respectively. A recent well-known optimizer GWO has been tested/compared for the same objectives to ensure that Jaya was a better choice for the MSC problem. Jaya optimizer showed better results of up to 15% reduction in EPC and up to 33%

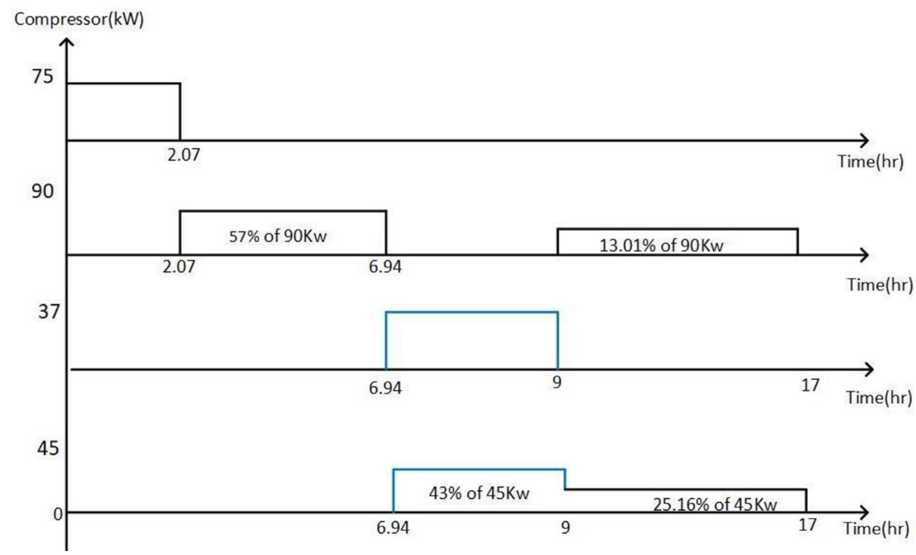

Fig. 15. Scenario 2: compressors switching and operating duration at AFR in March.

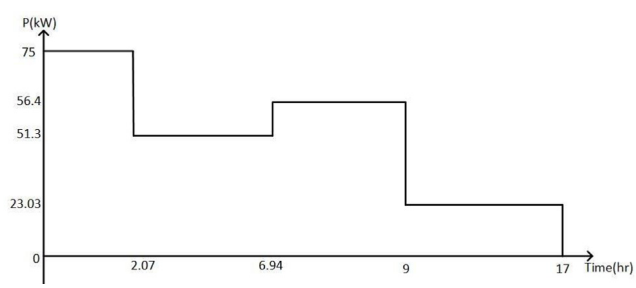

Fig. 16. Scenario 2: Compressors power profile at AFR in March.

Table 10
Scenario 2: Comparison between MO-Jaya and MO-GWO.

Months	GWO EPC (kWh)	GWO LS (days)	Jaya EPC (kWh)	Jaya LS (days)
March	16,019.54	1,748.17	13,735.94	2,341.3
April	14,756.74	2,231.65	13,889.478	2,357.35
May	14,510.076	2,004.34	13,821.74	2,341.3
June	12,596.78	3,839.94	12,079.989	4,494.498
July	12,653.32	4,068.45	12202.892	4,290.88

increase in LS. In addition, optimal operation of compressors allow a better periodic maintenance planning for each compressor.

The future recommendations, is to modify the proposed model to accommodate variable tariff system to achieve a generalized and efficient model. Furthermore, survey production line operation/ scheduling to develop a processes scheduling model based on multi-objective algorithms to gain higher productivity and minimum power consumption.

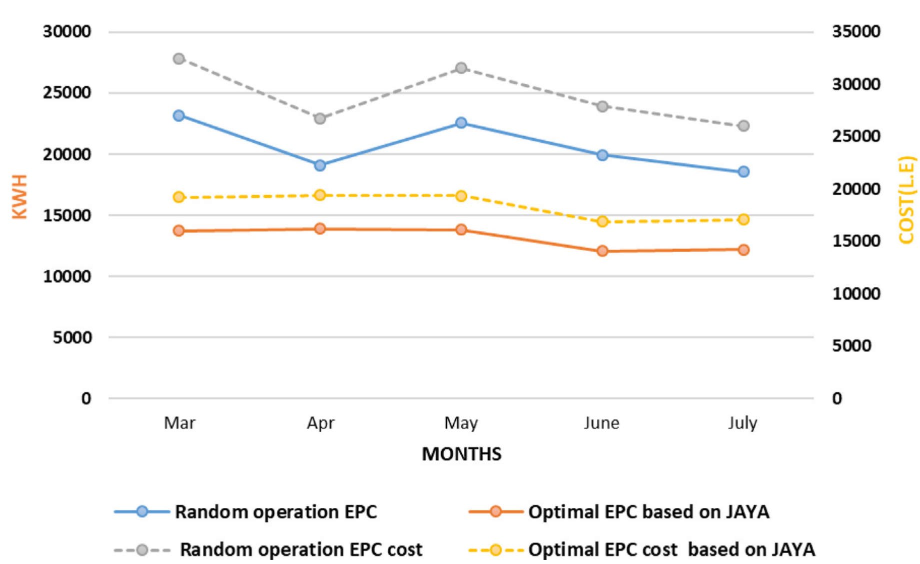

Fig. 17. Scenario 2: Optimal Vs random operation of compressors for 5 months indicating EPC/cost.

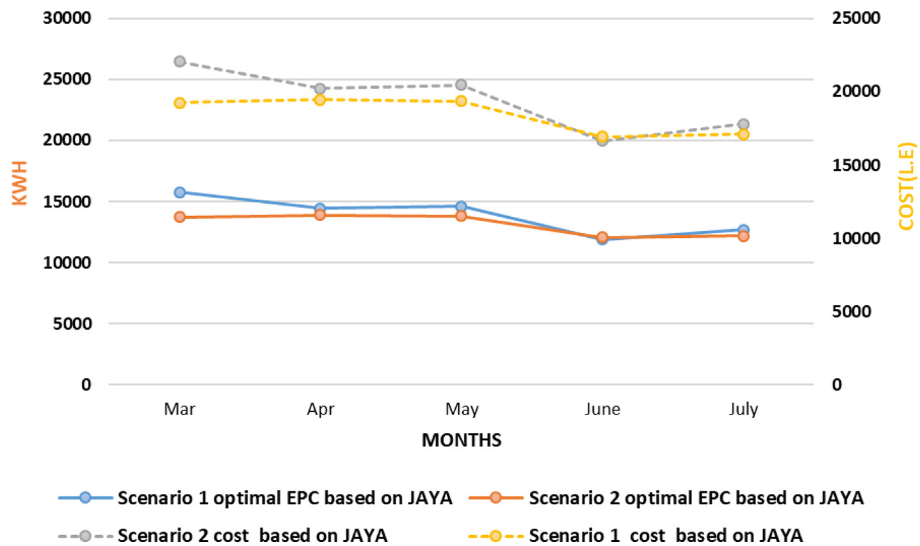

Fig. 18. Optimal EPC/cost based on Jaya for Scenario 1 compared to Scenario 2.

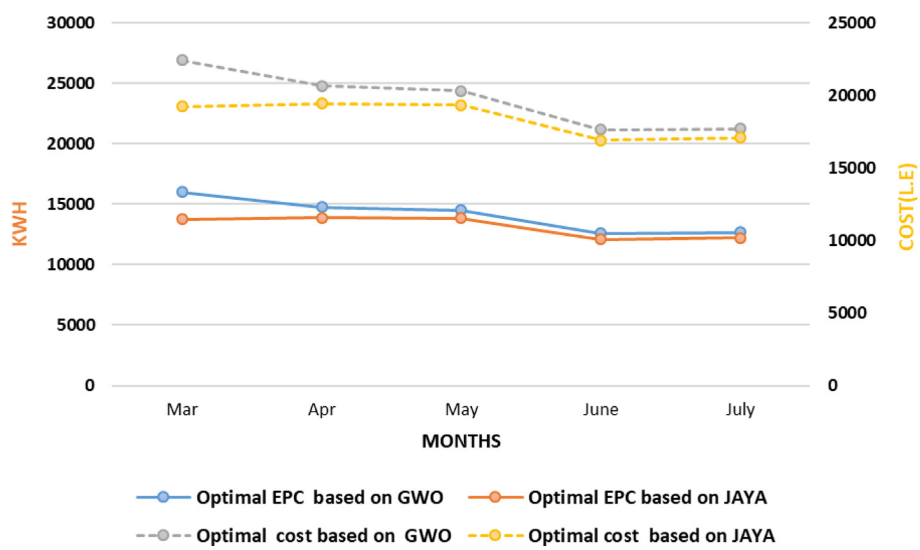

Fig. 19. Scenario 2: Optimal EPC/cost based on MO-JAYA compared with MO-GWO.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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