Identifying Effective Alternatives to Economic Dispatching with the Particle Swarm Optimization Algorithm Approach in the Oil Industry

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ABSTRACT

Nowadays, oil industries management needs a new approach in the realm of production planning and operations process with a cost management approach. For their survival, organizations and industrial units, by recognizing the impact points of the challenges ahead, take steps towards their goals. Economic dispatching attempts to determine the share of production capacity in a way that optimizes the overall performance of the system economically and improve system performance, including: production and process planning, supply and demand balance, cost management, productivity growth, optimal allocation of resources according to the capacity of tanks, formulation of production and operational strategies, the impact on the strategic vision document. Identifying points of influence and collecting field information from the industrial unit and employing quantitative calculations, mathematical modeling and related formulas in MATLAB environment, this article aims to implement economic dispatching employing particle swarm optimization algorithm and hypothetical information to measure the feasibility of implementation and its impact on the overall performance of the system. Given that economic dispatching has so far been implemented in the field of power plants and a few gas companies and has provided acceptable results, present study developed a new approach in the field of oil industry in Iran. Finding revealed that the industrial unit can lead its costs to a better degree of efficiency in order to implement economic dispatching.

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1. Introduction

The oil and gas industry is one of the world's leading industries and provides one third of the world's total energy consumption (Schiffer et al., 2018). The dynamic nature of the oil and gas industry on the one hand and the increasing demand for energy and related petrochemical products on the other hand, fully illustrates the complexities of this industry (Hanga & Kovalchuk, 2019; Inkpen & Moffett, 2011). Therefore, it is necessary to use innovative approaches to reduce operating costs and increase productivity (Hanga & Kovalchuk, 2019). For example, in recent years, sensors and robots have been used to control the upstream sectors and ensure raw materials (Kong & Ohadi, 2010; Shukla & Karki, 2016). With the proliferation of applied technologies and the resulting output data, there is a logical need for the right tools for data processing and management, and this is one of the reasons for the introduction of artificial intelligence and machine learning in this field of science (Wooldridge, 2009). In this regard, the use of heuristic and meta-heuristic algorithms is proposed in the management of industrial costs and especially renewable energy sources and profit analysis (Khan et al., 2016). Sinha et al. (2009) proposed the use of multiple PSO algorithms in the supply chain management of the petrochemical industry. Cherepovitsyn et al., (2018) applied decision algorithms in rational investment in exploration. The application of algorithms in the field of oil and gas is still growing. Ajao et al., (2019) introduced algorithms in the field of data organization in oil, gas and petrochemicals areas. Also, risk assessment and risk management by algorithm-based tools is growing in this industry (Karami et al., 2020).

Particle swarm optimization was first proposed as a non-deterministic search method for functional optimization. This algorithm is inspired by the mass movement of food-seeking birds (Chatterjee & Siarry, 2006); because particle swarm optimization also begins with an initial random population matrix (R. Eberhart & Kennedy, 1995). PSO is similar to many other evolutionary algorithms such as the continuous genetic algorithm and the colonial competition algorithm (Chatterjee & Siarry, 2006). In this method, using two stages of population mobility and convergence, interesting results are achieved in a variety of functions. The members of the answer population are directly related to each other and solve the problem by exchanging information with each other (Chatterjee & Siarry, 2006; R. C. Eberhart et al., 2001). In other algorithms, there is a population of individuals; this

particle swarm optimization algorithm is similar to a bird flying school (J Kennedy & Eberhart, 1995). Therefore, particles tend to fly better and better towards the search area during the search process (Shi, 2004). In a particle swarm optimization, instead of using genetic agents, these individuals improve their situation through "evolved" generation by cooperating and competing with each other.

The aim is to introduce a new parameter, called inertial weight, to the principle of particle swarm optimization and simulation to show the significant and effective influence of this new parameter in particle swarm optimization (J Kennedy & Eberhart, 1995). Evolutionary computation techniques, genetic algorithms, evolutionary strategy, and genetic programming are manipulated by Population motivation from the evolution of human nature, which encodes the solution to the problem according to the survival of the fittest through "genetic" operations, such as mutation, crossover, and reproduction. The best solution is through evolution. Compared to the evolutionary computation method, Eberhart and Kennedy introduce a different algorithm by simulating extended social behavior (Shi & Eberhart, 1998). Particle swarm adaptation is an optimization model that is the ability of human societies to process simulation knowledge (J Kennedy & Eberhart, 2001). Every particle in PSO makes its decision to evolve using its own experience and the experiences of its neighbor. That is, particles approach the best state through current velocity, previous experience, and the best experience of neighbors (James Kennedy, 1997). Particle swarm optimization (PSO) is also an effective and reliable evolution-based approach. It has become popular for many optimization problems due to its higher quality solutions including mathematical simplicity, fast convergence and robustness. There are several areas of the power system in which PSO is used successfully.

Economic Load Distribution (ELD) is one of the important tasks that provide the economic conditions of the electricity system. This is a method for determining the most efficient, low-cost and reliable performance of a power system by sending the existing power generation sources to supply the load in the system (Sharma & Mahor, 2013). Economic deployment optimization (ED) is the most important issue to consider in power systems. The problem of ED in power systems is raised in such a way that for each dedicated generator unit, program the amount of power output in such a way that its operating cost is minimized and at the same time, with load demand, with load demand, energy usage constraints comply with stability (Kaur & Kumar, 2014). According

to the studies, most of the dispatching and PSO researches are in the field of non-oil industries and renewable resources, and considering all the cases mentioned in the introduction (above), the need to manage cost loss in complex industries related to Fossil fuels are strongly felt through innovative methods. Necessities are created in this stage, by feasibility of implementing this article with the approach of particle swarm optimization algorithm in other industrial units such as oil-related industries, to have a clean production economically and effective organizational process and performance to optimize the system economically.

Achieving this will have a direct impact on the strategic vision document of industrial units. This study seeks to apply the PSO algorithm to optimize the costs of oil and gas related industries. To the best of our knowledge and research, no economic dispatching has taken place in this area. Therefore, in this project, an attempt is made to design the relevant and required model and evaluate its feasibility in a case study. The results obtained from different comparison criteria demonstrate the high quality of the proposed solution methods in terms of speed and accuracy in finding optimal solutions.

The remainder of this paper is as follows. Section 2 explains the research process as well as data collection. Section 3 introduces the modeling of economic dispatching problem. Section 4 is devoted to implementation of PSO algorithm. Section 5 discusses solutions to economic dispatching with particle swarm optimization algorithm and findings, Section 6 presents the conclusion and Section 7 is devoted to suggestions for future researchers.

2. Methodology

One of the main parts of any research work is data collection. A data collection in a regular and correct manner leads to the fast and accurate data analysis. Due to the fact that this research has once been conducted in the refinery environment to implement feasibility, the information in this article is close to the real and field information of the refinery industrial unit in the present study, the data collection tools used are as follows: interviewing experts and identifying points of influence

and collecting field information from the industrial unit. This can align the issue, study the implementation aspects and extract the required information. The method of data analysis in this article, according to the available database and their classification, through scientific theory and using quantitative calculations and related formulas in MATLAB software (R2020a) environment, examined the effectiveness of the article in the refinery industrial unit and announces the result.

3.Mathematical model for economic dispatch

The table 1 demonstrates the modeling of economic dispatching problem in order to make it feasible and shows what the purpose of the problem. In this table, modeling is divided into seven parts based on the needs of the problem. Each section is described separately. The number of samples studied in this article is seven-year production capacity and total costs of the industrial unit (refinery). To evaluate the number of samples, production capacity information with low and high limits of the refinery production by information that each year is needed. This can be introduced as one of the most important tools for evaluating this issue.

$$\text{Min}C_{\text{total}} = \sum C_i$$
$$C_i = f(P_i) = a_{0i} + a_{1i}P_i + a_{2i}(P_i)^2 \tag{1}$$
$$P_i\text{min} \leq P_i \leq P_i\text{max}$$
$$\sum P_i = P_L$$

The problem modeling information described as being in relation to (1) the producer power (i) and the main purpose of proposed problem is to minimize the cost function. This problem is a constrained optimization. a_{0i} includes all fixed costs, including maintenance and repairs, etc. of the industrial unit (refinery). a_{1i} and a_{2i} are both coefficients for P_i, which require variable and semi-variable costs to calculate and find the total cost of an industrial unit (refinery).

Table1: Model of Economic Dispatch

N	Number of samples (years of production capacity and total costs of the refinery)	7
$pmin$	Minimum of production capacity	[424 532 747 602 891 643 712]
$pmax$	Maximum of production capacity	[2012 1231 2169 1903 1434 1928 1822]
a_0	fixed costs	[6422 5935 8651 8329 7368 9114 6299]
a_1	P_i coefficients	[7 6 8 6 6 7 9]
a_2	P_i coefficients	$[-0.2401 - 0.1894 - 0.2310 - 0.1168 - 0.2164 - 0.1742 - 0.1904] * 1e - 4$
P_L	Production capacity	10000

4. Particle swarm optimization algorithm

Particle group optimization is a global optimization method that can be employed to deal with problems whose answer is a point or surface in n-dimensional space. In such an environment, hypotheses are put forward for consideration, an initial velocity is assigned to the particles and communication channels between particles are also considered. These particles then move in the response space, and the results are calculated based on a "competency criterion" after each time period. Over time, particles accelerate toward particles that have a higher competency standard and are in the same communication group. The main advantages of the PSO algorithm are summarized as: simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques. The flowchart of particle swarm optimization algorithm is shown in figure 1.
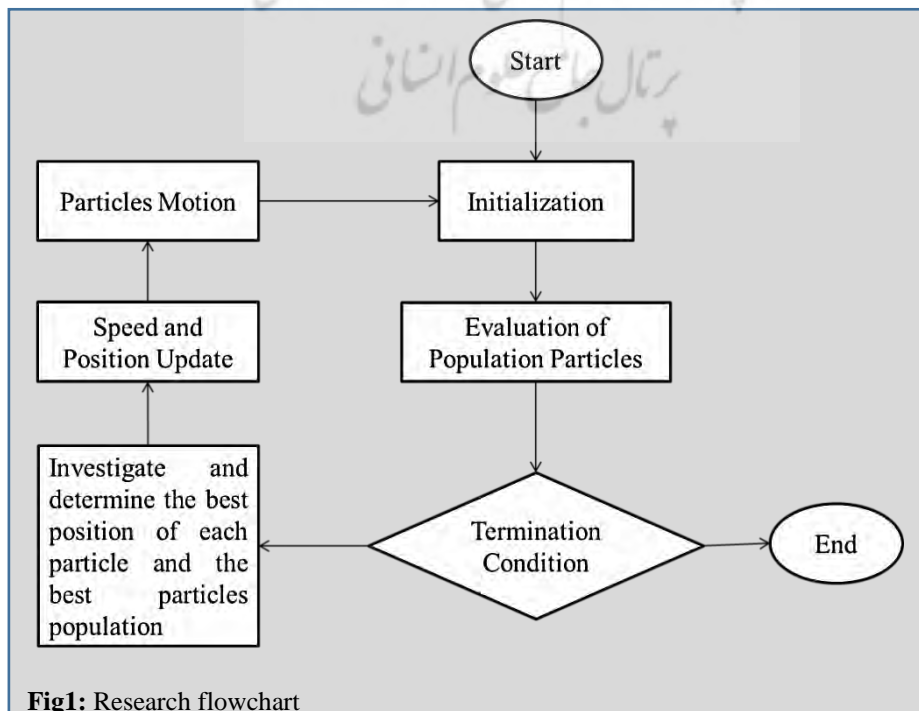

Fig1: Research flowchart

$$+ r_2 c_2 \ (gij\ (t) - X_{ij}(t))$$
$$X_{ij}(t + 1) \ = \ X_{ij}(t)$$
$$+ V_{ij}(t$$
$$+ 1)$$

(2)

Equation (2) represents the calculation of the best experienced individual situation and the best collective experienced situation that occurs at a certain speed. Where V (i) is the swarm velocity and x (i) is the position of the particle. In Equation (2), r_1 and r_2 are both random numbers with a uniform distribution, and C_1 and C_2 are position and velocity adjustment coefficients.

$$v(t + 1) = v(t) +$$
$$c_1 * rand(t) *$$
$$(pbest(t) -$$
$$position(t) + c_2 *$$
$$rand(t) *$$
$$\big(gbest(t) -$$
$$position(t)\big)$$

(3)

Equation (3) can be used to better explain Equation (2). Equation (3) can be divided into 3 functional parts. The first part $v(t)$ which can be described as the velocity that the particle is currently experiencing (current velocity), the second part of Equation (3) is as follows $(c1*randt*pbestt-positiont$, the rate of change of the particle velocity and its rotation towards the best personal experience (best memory), And for the third part, relation (3) is as follows $(c2*rand(t)*(gbest(t)-position(t))$, which is the accumulation of the best group experience (collective intelligence). If the first part of this relationship is ignored, the velocity of the particles is determined only according to the current position و the best particle experience and the best group experience (collective intelligence); in practice, the effect of current speed and speed barriers are reduced or eliminated.

Thus, the best particle in the group remains in place and the other particles move towards that particle. In fact, the mass movement of particles without the first part of Equation (3) will be a process during which the search space gradually becomes smaller, and a local search for the best particle is formed. In contrast, if only the first part of Equation (3) is considered, the particles travel their normal path to reach the boundary of the range to perform a kind of global search.

$$0 \ \leq \ c_1 \ \leq \ 2$$
$$0 \ \leq \ c_2 \ \leq \ 2$$

(4)

In relation (4), c1 is considered the coefficient of personal learning and c2 is the coefficient of social (collective) learning.

The result of PSO algorithm is influenced by a number of control parameters, the number of particles, The result of PSO algorithm is influenced by a number of control parameters, the number of particles, the acceleration coefficients, inertia weight, and number of iterations, the initial temperature and the temperature reduction factor. According to the considerable effect of parameter adjusting on the results of the proposed algorithm, we have used Taguchi design for tuning the algorithm parameters by considering five levels for each parameter value.

In Figure2 and Figure3, gbest PSO and lbest PSO can update the particle velocity equation synchronously or asynchronously. If all the particles update their position and the best met position at the same time and then the best met position of the whole group is updated, this is called simultaneous or synchronous updating. The synchronous update in PSO provides the perfect information concerning the particles, thus allowing the swarm to choose a better neighbor and exploit the information provided by this neighbor, but asynchronous updates help to a shorter execution time (Xue et al., 2009). Imperfect information due to asynchronous updates causes the information of the current best found solution to be communicated to the particles more slowly, thus encouraging more exploration. Asynchronous updating has the advantage that the particles become aware of good areas very quickly at runtime, in contrast, in the synchronous method, the particles are informed of good areas and receive feedback from the environment at each repetition. Synchronous updating is appropriate for the gbestPSO algorithm and asynchronous updating is appropriate for the lbestPSO algorithm (Shay and Eberhart, 1998).
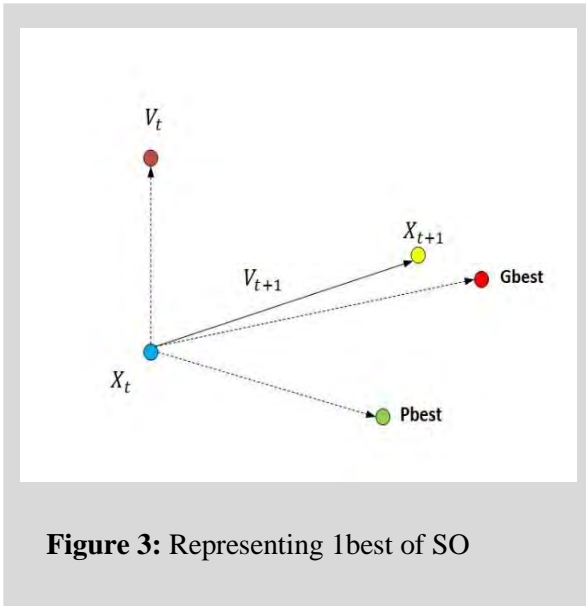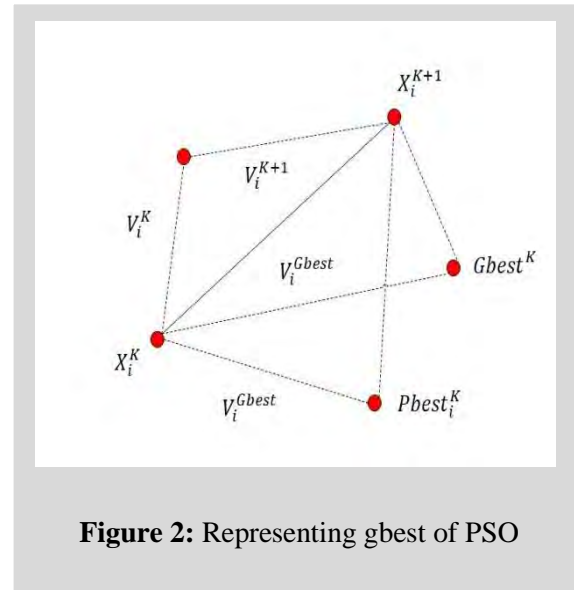
Figure 3: Representing 1best of SO

Figure 2: Representing gbest of PSO

$$x(0) = xmin + rand(xmax - xmin) \quad (5)$$

Initialization is done through Equation (5).

$$v(0) = 0 \quad (6)$$

The initial velocity to be considered, as in Equation (6), is zero.

$$v'(t+1) = \begin{cases} v(t+1) & v(t+1) < vmax \\ vmax & v(t+1) \geq vmax \end{cases} \quad (7)$$

In Equation (7), to prevent over-acceleration, a velocity is defined as the maximum velocity, until the calculated velocity exceeds the maximum velocity, and cut the calculated velocity.

$$v'ij(t+1) = \tanh\left(\frac{vij(t+1)}{vmaxj}\right)vmaxj(t) \quad (8)$$

A hyperbolic tangent function can be seen in Equation (8), which is used to restrict the intended velocity to a certain level. This method differs from Equation (7) in the case of derivability.

$$MinCtotal = \sum C_i \quad (9)$$

Equation (9) shows the main reason for the goal that the problem starts on its own (minimizing the total cost).

$$Ctotal - MinC \ by \ ED = Best \ Cost \quad (10)$$

To calculate the optimality of the response extracted from the software with the actual response, Equation (10) is used.

Table (2) shows the basic information of the problem. The coefficient of inertia in physics is defined as the tendency of objects to maintain a state; inertia should be less than 1; the lower the inertia coefficient, the better. In this paper, the role of the inertia coefficient is the tendency of the industrial unit to move from the current point to the best community of optimal points of production and costing. To minimize the coefficient of inertia, a tool called "wdamp" is used to reduce the coefficient of inertia with each repetition. Another factor in this formula that plays a key role in finding the best position is the velocity parameter, which calculates the velocity of objects to converge in the desired direction.

Table2: Optimal response of software

nPop	nVar	VarSize	C1	C2	MaxIt	NFE	w	wdamp
40	7	[1 7]	2	2	1000	40040	4.3171e-05	0.99

5.Solutions to economic dispatching with particle swarm optimization algorithm

5.1. Global Best. Sol

After modeling and programming in MATLAB software environment, according to the need of the problem and the use of basic information, the dispatching problem is solved through the particle swarm optimization algorithm and the relevant outputs are categorized and presented in the following tables .

First, considering that the article pursues the problem in terms of costing, and the main purpose of the article is to distribute the optimal economic load of the industrial unit (refinery), optimize the costs during the refinery, continuous improvement, increase capacity (operational-production) and improve refinery performance.

Table3: Global Best.Solution, MATLAB output.

	$1.0e + 03$ *						
GlobalBest.Position	2.0120	1.2310	0.7800	1.9030	1.4340	1.9280	0.7120
Global Best.Sol.pTotal	10000						
Global Best.Sol.c	1.0e+04 * 2.0409 1.3292 1.4877 1.9705 1.5928 2.2545 1.2697						
Global Best.Sol.z	1.1945e+05						
Global Best.Sol.v	0						

In the first step, seven years of production capacity and total production capacity were calculated separately. The first row of the table, after calculating each power, is multiplied by $1.0e + 03$ * to show the real numbers. In terms of costs, it follows exactly the above law. The total costs in the initial table indicate that in order to achieve a justified answer in future tables, it is possible to optimize, which will be mentioned. Speed is a sensitive alternative in economic distribution that acts as a sensitivity analysis; the closer it is to zero, the more efficient and effective it is. Finally, (z) tests the cost function to find the equality of the answers of each part and analyze the optimal answer.

Random solutions are created inspired by the problem model for optimization and study each component. At this level, the researcher seeks to find numbers that are between the lower and upper limits of production to categorize and apply reasonable solutions. The solutions themselves in the form of matrices have a subset structure and in the following tables will be referred to this.

5.2. Global Best. Sol. Results

As mentioned in the Table4, stochastic solutions, in order to optimization, each component that has an infrastructure that helps to find the best possible answer is considered. This part of the answer is mentioned in programming in order to study and store the calculations that are performed for each year for the cost and distribution of its economic burden.

Table4: Indicates Results							
p	[2.0120e+03 1.2310e+03 780.0000 1903 1.4340e+03 1.9280e+03 712]						
P_Total	10000						
c	2.0409e+04	1.3292e+04	1.4877e+04	1.9705e+04	1.5928e+04	2.2545e+04	1.2697e+04
C_Total	1.1945e+05						
v	0						
z	1.1945e+05						

The production capacity of the refinery, which is mentioned in the first line, means each year, which has been selected in random solutions to improve it as much as possible. Finally, total production capacity must be equal to the sum of the particle swarm and the amount of capacity required by the network, which shows the importance of the correctness of the answers again.

The costs recorded separately for each year, like the production capacity, are found in a random solution with the highest number of MaxIt, which, in general, search for optimal costs. The total cost is the same as the optimal cost mentioned in the main answer in the table above. In fact, the sum of the total optimal cost that is in the main answer is first created and published in this section. Paragraph charts, which will be mentioned in the appendix, represent the expressive area of the answer separately for each point and the number of repetitions according to the population of the answers. The closer the velocity alternative is to zero, the lower the perturbations and lower velocity variables. As you can see, speed in the most ideal conditions has provided the most justified cost to the researcher. Finally, (z) tests the cost function to find the equality of the answers of each part and to analyze the optimal answer, which in this part is used as a reliable function to attach to the final table.

5.3.   Global Best Position

As can be seen in Table (5), it tries to evaluate the best global (collective) position of the particle. The main evaluation of the article is in this area and two sub-categories can be mentioned in the heart of the main answer. The main answer is the global best position of the particle, which is assigned to the position in the first row of the table and the best collective position in the second row; That is, according to the information received by the industrial unit (refinery) based on production capacity and high and low production limit of this industrial unit during seven years, the study of economic dispatching feasibility with particle swarm optimization algorithm can be considered the best collective position each year in terms of cubic meters of total refinery production and in terms of product variety. These two rows have significantly improved compared to the refinery products and represent the best position that if we multiply the numbers of each best position by $1.0e + 03 *$ we can find the position of each particle.

The bottom three lines of Table (5) are for reviewing the answers found. As mentioned in the dispatching modeling table, the alternative was listed as the amount of production capacity required by the network, which

was numbered 10,000 cubic meters. Now, are we able to see if the found answer has been able to meet the needs of the network with the same amount of cubic meters at a more efficient cost? It is important to note that the sum of the best particle positions in the particle swarm optimization algorithm is equal to the network requirement of 10,000.

Finally, to verify the answers and to find out if the answers are in the upper and lower limits of production, the best collective position responses which are greater than and equal to the lower limit should be defined in the model equal to one, in the number of sample sizes studied. Also, the answers of the best collective position should be smaller and equal to the upper limit, which in the defined model is equal to one in the number of sample sizes studied. This allows the researcher to both verify the information obtained and to validate the modeling and input information. Finally, he ensures the possibility of implementing the plan.Finally, to verify the answers and to find out if the answers are in the upper and lower limits of production, the best collective position responses which are greater than and equal to the lower limit should be defined in the model equal to one, in the number of sample sizes studied. Also, the answers of the best collective position should be smaller and equal to the upper limit, which in the defined model is equal to one in the number of sample sizes studied. This allows the researcher to both verify the information obtained and to validate the modeling and input information. Finally, he ensures the possibility of implementing the plan.

Table5: Indicates Global best position**.**

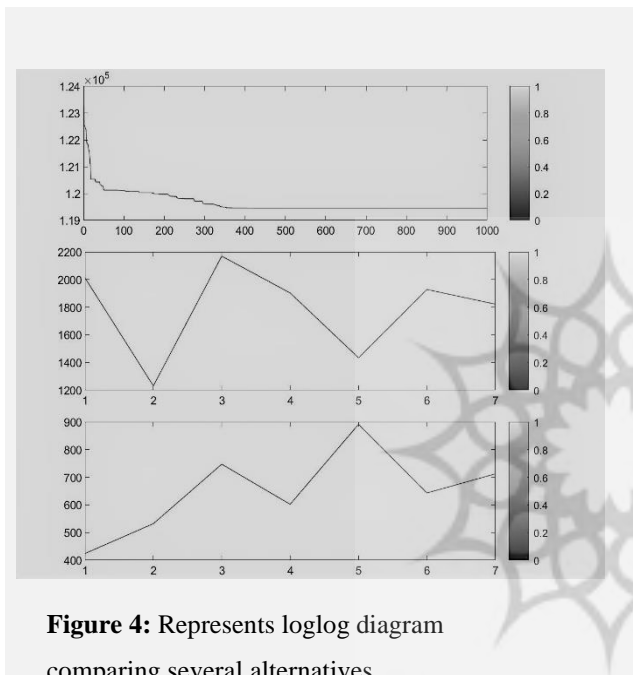| Position	[2.0120e+03 1.2310e+03 780.0000 1903 1.4340e+03 1.9280e+03 712]
Global Best.Position	1.0e+03 * 2.0120 1.2310 0.7800 1.9030 1.4340 1.9280 0.7120
Cost	1.1945e+05
Sol	[1×1 struct]
BestCost	11945.28459
Sum(GlobalBest.Position)	10000
Global Best.Position>=model.pmin	1 1 1 1 1 1 1
Global Best.Position<=model.pmax	1 1 1 1 1 1 1

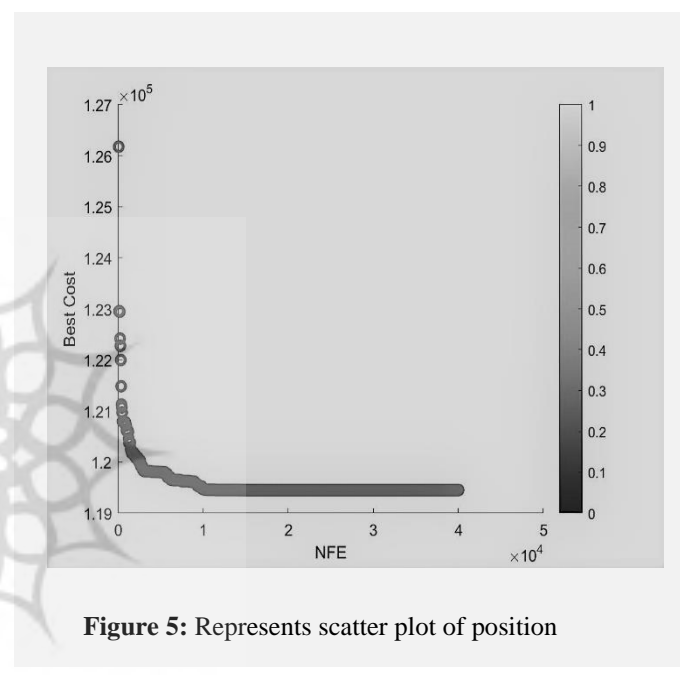**Figure 4:** Represents loglog diagram comparing several alternatives

Figure 5: Represents scatter plot of position

According to Figure.4, a loglog diagram comparing several alternatives is demonstrated. Loglog (x, y) plots the -x and y coordinates using the logarithmic scales on the x-axis and the y-axis. In this chart, the trend of the best cost Number Function Elevation (NFE) and maximum repetition are showed. The middle diagram shows the varmax effects and the end chart shows the amount of varmin effects. Scatter parabolic diagram as shown in Fig.5, Scatter (x, y) creates a scatter plot with circles at the locations specified by the x and y vectors. This type of diagram is also known as a bubble design. The answer is shown in points, how the stock position works in the best cost and NFE intervals and in which area the best point is located.

According to Fig.6, a diagram shows the area of the elements in Y as one or more curves and fills the area below each curve. When Y is a matrix, the curves are stacked, representing the relative contribution of each row element to the total height of the curve in each x interval. Area (y) plots the vector Y or plots each column in the Y matrix separately and stacks the curves. The x-axis automatically scales to 1: size (Y, 1). The values in Y can be numeric or duration values.
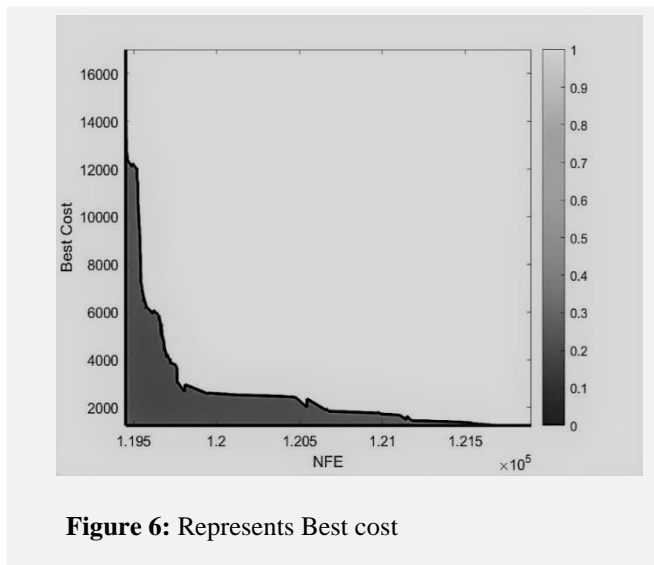
Figure 6: Represents Best cost

6. Conclusion

Given that economic dispatching has so far been implemented in the field of power plants and a few gas companies and has provided acceptable results, this research has created a new approach in the field of other industrial units. The problem of economic dispatching in MATLAB software environment has optimal answers that due to the number of repetitions, seeks to achieve a justified answer. It is suggested that for projects that do not have the default information of the operation process, simulation and data mining in the relevant software be done before performing calculations related to economic dispatching with the approach of particle swarm optimization algorithm, to increase the amount of accuracy in the calculations to an acceptable value using the perturbation matrix and other tools. According to the information extracted from MATLAB software, the answers indicate that it is important that the industrial unit can lead its costs to a better degree of efficiency in order to implement economic dispatching. This can be achieved by costing and distributing the economic burden according to the operations mentioned in the methodology section and presenting a new strategic plan for the industrial unit and modifying medium-term plans.

The steps to answer this problem, first, after modeling and finding the ideal goals, began to calculate the best global position solution. The software provides the solution of the best global situation in order to improve the initially extracted information by recognizing the

affected points of the problem. Then, in the final table, it collects the relevant information and in the section of the best global situation, it has been able to provide the optimal answer in justified points to provide the necessary decisions for economic dispatching to the researcher. All the relationships and operational answers are performed by programming in MATLAB software. The proposed problem is a minimum problem and researchers have taken steps to minimize and optimize the objective function. Finally, in each step and in the last 3 lines in Table (5), all the answers of the dispatching model are evaluated and validated; Moreover, graphs show the justified area of the answer separately for each point and the number of repetitions according to the population of answers.

According to the total estimated costs during 7 years, the industrial unit (refinery) has an estimated cost of 28,432,911,220 Rilas. If economic dispatching is implemented in the industrial unit, the total cost of the refinery after the optimization operation will be equal to 28,432,791,770 Rials; the refinery will reduce its costs by a total of 119,450.28459 at the end of 7 years, or by the total of each year, if it implements economic dispatching.

In this paper, due to the hypothetical information of the industrial unit, the value that was optimized is very small; Of course, the industrial unit under study can have no waste of costs of production and operations, and in the calculations performed, be placed at the head-to-head point, to assure managers that the roadmap and production process they have chosen is at its best. In the studies conducted before this article, in the real environment, we saw a significant reduction, which was

able to balance the supply and demand, improve the costing system and production and refining;

Relation (10) implies:

$$Ctotal - MinC\ by\ ED = Best\ Cost \qquad (11)$$

$$2{,}843{,}291{,}122 - 11{,}945.28459 = 2{,}843{,}279{,}177$$

In the parent industrial units, costs can be clustered in different ways, such as: spatial constraints, time constraints, the amount of manpower required according to specialization, construction of newly established units, maintenance and repairs, Costs from sales, resource allocation costs, shipping costs, etc. In order for us to be able to reduce costs and at the point of comfort and optimization, the industrial unit should be put in a state of cost freezing, according to optimal production so that it can control and respond to the needs of domestic and international networks. The industrial unit (refinery) with its system costing has been able to optimize the existing costs in this area to some extent, but according to the economic dispatching model, it indicates that these costs can be optimized to the scale of the currency have. The industrial unit can put the implementation of economic dispatching on its agenda with acceptable confidence

7. Suggestions for Future Researchers

The researchers in this article offer suggestions for researchers who intend to continue their studies on economic dispatching in other industrial units.

1) It is suggested that this research be conducted in other communities and the results be compared with each other.

2) It is suggested that modeling be done by recognizing environmental factors in a real context in order to remove the obstacles of the industrial unit.

3) This research is about minimizing refinery costs; Researchers are advised to pursue their research in future research to maximize sales and revenue function.

4) It is suggested that in order to create a new attitude, economic dispatching in the field of production should be researched according to the alternatives in that field.

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