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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 to production planning and operation process with cost management. For their survival, organizations and industrial units take steps toward their goals by recognizing the impact points of the challenges ahead. Economic dispatching attempts to determine the share of production capacity in a way that optimizes the overall performance of the system economically and improves 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, and 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 been implemented in power plants and a few gas companies and has provided acceptable results, the present study develops a new approach in Iran's oil industry field. Findings revealed that the industrial unit could lead its costs to better efficiency in implementing economic dispatching.

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

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illustrates the complexities of this industry (Hanga and Kovalchuk, 2019; Inkpen and Moffett, 2011). Therefore, it is necessary to use innovative approaches to reducing operating costs and increasing productivity (Hanga and Kovalchuk, 2019). For example, sensors and robots have been used to control the upstream sectors and ensure raw materials (Kong and Ohadi, 2010; Shukla and 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, heuristic and meta-heuristic algorithms are proposed to manage industrial costs, especially renewable energy sources and profit analysis (Khan et al., 2016). Sinha et al. (2009) proposed using multiple Particle swarm optimization (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 data organization in oil, gas, and petrochemicals areas. Algorithm-based tools' risk assessment and management are also 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 and Siarry, 2006). Because particle swarm optimization also begins with an initial random population matrix (R. Eberhart and Kennedy, 1995), it is similar to many other evolutionary algorithms, such as the continuous genetic algorithm and the colonial competition algorithm (Chatterjee and Siarry, 2006). In this method, exciting results are achieved in various functions using two stages of population mobility and convergence. The members of the answer population are directly related to each other and solve the problem by exchanging information with each other (Chatterjee and Siarry, 2006; R. C. Eberhart et al., 2001). In other algorithms, there is a population of individuals; the particle swarm optimization algorithm is similar to a bird flying school (J Kennedy and Eberhart, 1995). Therefore, particles tend to fly better and better toward the search area during the search process (Shi, 2004). In 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, inertial weight, to the principle of particle swarm optimization and simulation to show the significant influence of this new parameter in particle swarm optimization (J Kennedy and 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 introduced a different algorithm by simulating extended social behavior (Shi and Eberhart, 1998). Particle swarm adaptation is an optimization model that is the ability of human societies to process simulation knowledge (J Kennedy and Eberhart, 2001). Every particle in PSO decides to evolve using its own experience and the experiences of its neighbor. In other words, particles approach the best state through current velocity, previous experience, and the best experience of neighbors (James Kennedy, 1997). Particle swarm optimization 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 the PSO is used successfully.

Economic load distribution (ELD) is one of the crucial 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 and Mahor, 2013). Economic deployment optimization (ED) is the most critical 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, energy usage constraints comply with stability (Kaur and 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 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 implementing this article with the particle swarm optimization algorithm in other industrial units such as oil-related industries to have a clean production economically, 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, this project attempts 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 and data collection, and Section 3 introduces the modeling of the economic dispatching problem. Section 4 is devoted to implementing the PSO algorithm, and 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. Data collection regularly and correctly leads to fast and accurate data analysis. Because this research has once been conducted in the refinery environment to implement feasibility, the information in this article is close to the factual and field information of the refinery industrial units. 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. According to the available database and their classification, the method of data analysis in this article 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 announced the result.

3. Mathematical model for economic dispatch

Table 1 demonstrates the modeling of the economic dispatching problem to make it feasible and shows 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.

$$
\begin{aligned}
\mathrm{Min}C_{\mathrm{total}} &= \sum \mathrm{C}_i\mathrm{C}_i \\
&= \mathrm{f}(P_i) \\
&= a_{0i} + a_{1i}P_i \\
&+ a_{2i}(P_i)^2
\end{aligned}
\quad (1)
$$

$$P_i\,\mathrm{min} \quad \le P_i \le P_i\mathrm{max}$$

$$\sum P_i = P_L$$

The problem modeling information is described in Equation (1), and i indicates the producer power; the primary purpose of the proposed problem is to minimize the cost function. This problem is a constrained optimization. a_{0i} includes all fixed costs, including maintenance and repairs 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).

4. Particle swarm optimization algorithm

Particle group optimization is a global method 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 period. Over time, particles accelerate toward particles with a higher competency standard and are in the same communication group. The main advantages of the PSO algorithm are summarized as a simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithms and other heuristic optimization techniques. The flowchart of the particle swarm optimization algorithm is shown in Figure 1.

Table 1: 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	$[-0.2401 - 0.1894 \; - 0.2310 - 0.1168 - 0.2164 - 0.1742 - 0.1904] \times 1e - 4$
P_L	Production capacity	10000

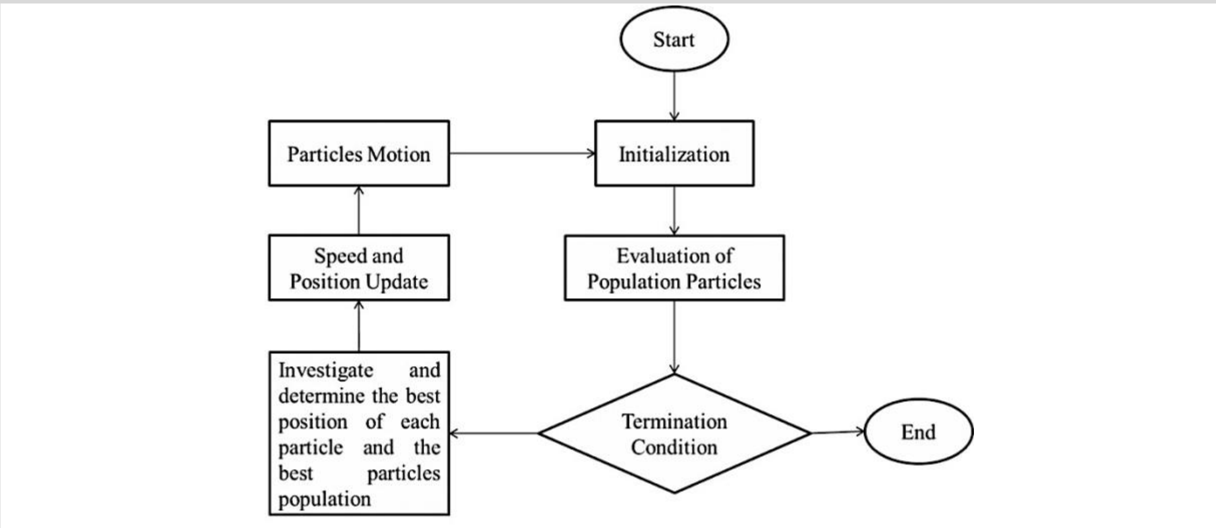

Figure 1. The research flowchart.

$$\begin{aligned} \mathrm{V}_i[\mathrm{t}+1] &= \mathrm{W}\, \mathrm{V}_{ij}[\mathrm{t}] + \mathrm{r}_1 c_1 \left(P_{ij}(\mathrm{t}) - X_{ij}(\mathrm{t})\right) \\ &+ \mathrm{r}_2 c_2 \left(\mathrm{gij}\ (\mathrm{t}) - X_{ij}(\mathrm{t})\right) X_{ij}(\mathrm{t}+1) \\ &= X_{ij}(\mathrm{t}) + \mathrm{V}_{ij}(\mathrm{t}+1) \end{aligned} \quad (2)$$

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

$$\begin{aligned} v(t+1) = v(t) + c_1 \times rand(t) \times \\ (pbest(t) - position(t) + c_2 \times \\ rand(t) \times \left(gbest(t) - position(t)\right) \end{aligned} \quad (3)$$

Equation (3) can be used to explain Equation (2) better. Equation (3) can be divided into three functional parts. The first part $v(t)$ can be described as the velocity that the particle is currently experiencing (current velocity), and the second part of Equation (3) is as follows ($c_1 \times randt \times pbestt - positiont$), the rate of change of the particle velocity and its rotation toward the best personal experience (best memory). For the third part, Equation (3) is as follows ($c_2 \times rand(t) \times (gbest(t) - position(t))$, 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, 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 toward 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.

$$\begin{aligned} 0 \le c_1 \le 2 \\ 0 \le c_2 \le 2 \end{aligned} \tag{4}$$

In Equation (4), c_1 is considered the coefficient of personal learning, and c_2 is the coefficient of social (collective) learning.

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

In Figures 2 and 3, *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 simultaneously 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 current best-found solution to be communicated to the particles more slowly, thereby 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 promising areas and receive feedback from the environment at each repetition. Synchronous updating is appropriate for the *gbest*-PSO algorithm, and asynchronous updating is appropriate for the *lbest*-PSO algorithm (Shay and Eberhart, 1998).

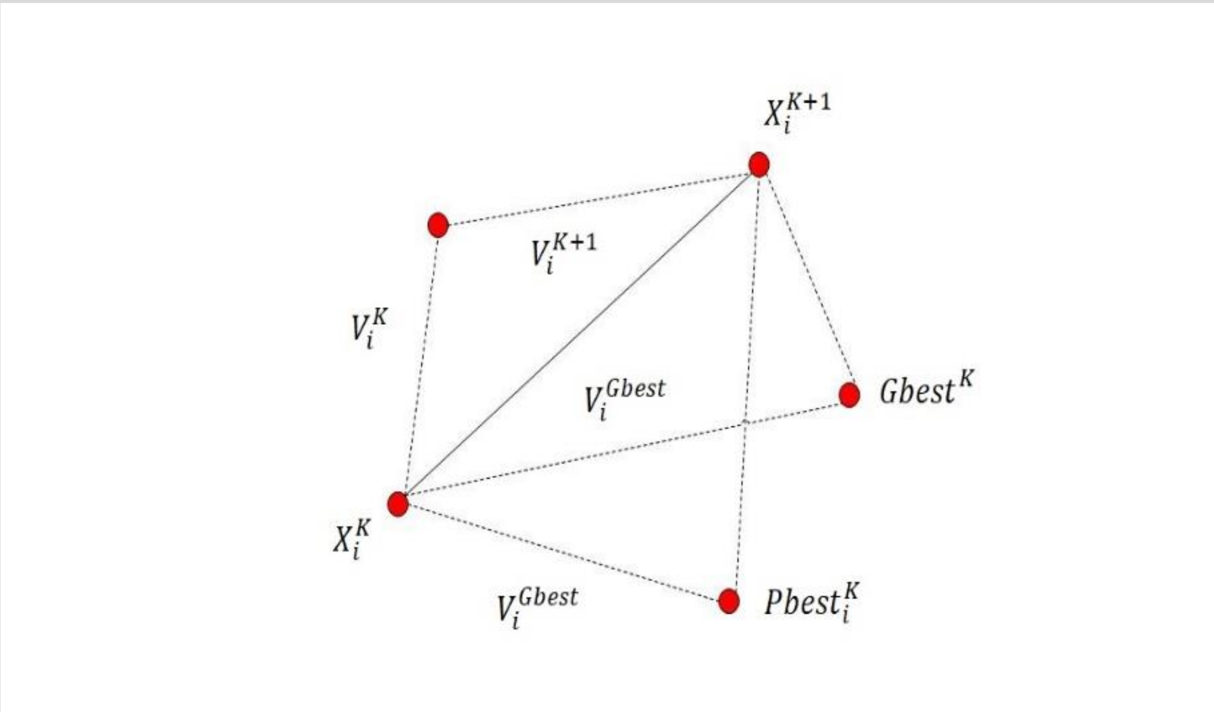

Figure 2: Representing *gbest* of PSO.

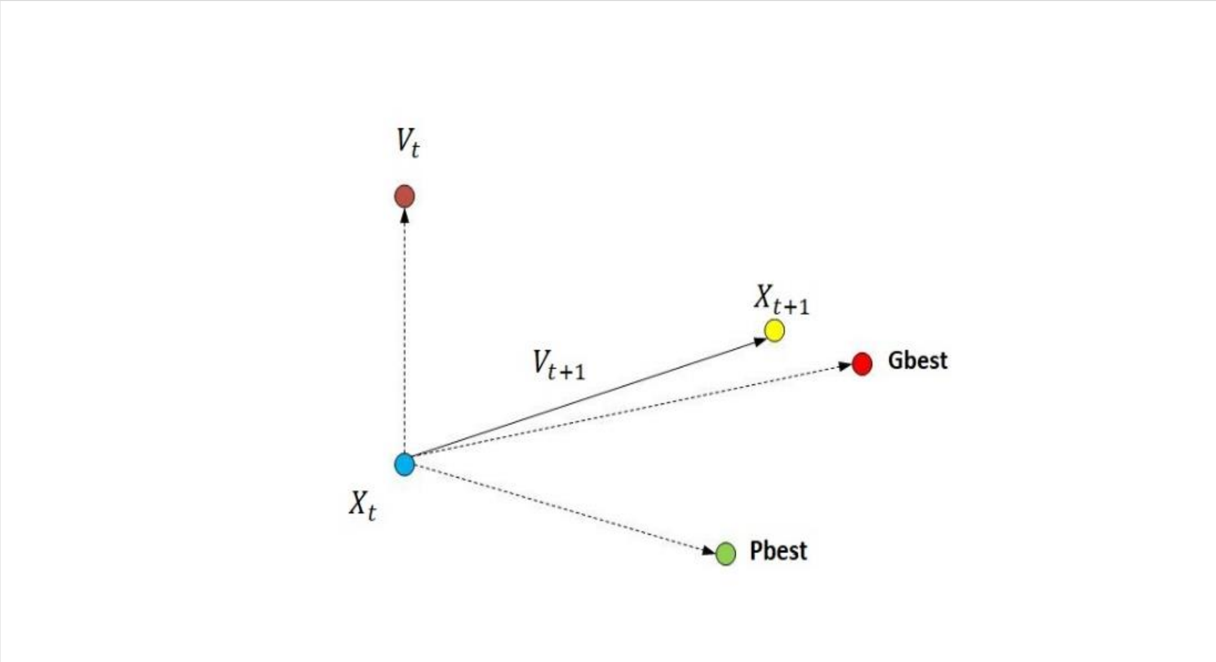

Figure 3: Representing *1best* of SO.

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

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 restricts the intended velocity to a certain level. This method differs from Equation (7) in the case of derivability.

$$\text{MinCtotal} = \sum C_i \quad (9)$$

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 one; the lower the inertia coefficient, the better it is. 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 crucial role in finding the best position is the velocity parameter, which calculates the velocity of objects to converge in the desired direction.

Table 2: Optimal response of software

nPop	nVar	VarSize	C1	C2	MaxIt	NFE	w	wdamp
40	7	[1 7]	2	2	1000	40040	4.3171×10^{-5}	0.99

5. Solutions to economic dispatching with particle swarm optimization algorithm

5.1. Global best solution

After modeling and programming in the 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. The relevant outputs are categorized and presented in the following tables .

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

Table 3: Global Best Solution, MATLAB output.

Global Best Position	$\mathbf{1.0}e+\mathbf{03}\ \times$ $\mathbf{2.0120}\quad \mathbf{1.2310}\quad \mathbf{0.7800}\quad \mathbf{1.9030}\quad \mathbf{1.4340}\quad \mathbf{1.9280}\quad \mathbf{0.7120}$
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. After calculating each power, the first row of the table is multiplied by 1.0×10^3 to show the real numbers. In terms of costs, it follows the above law precisely. The total costs in the initial table indicate that achieving a justified answer in future tables 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 by the problem model to optimize and study each component. At this level, the researcher seeks to find numbers between the lower and upper production limits to categorize and apply reasonable solutions. The solutions themselves in the form of matrices have a subset structure, and the following tables will refer to this.

5.2. Global best solution results

As mentioned in Table 4, in stochastic solutions, each component with an infrastructure that helps find the best possible answer is considered to optimize. This part of the answer is mentioned in programming to study and store the calculations performed for each year for the cost and distribution of its economic burden. The production capacity of the refinery, mentioned in the first line, indicates 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 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 generally searches 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 in the main answer is first created and published in this section. Paragraph charts, 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 can be seen, speed in the 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.

Table 4: The 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

5.3. Global best position

As presented in Table 5, the global best position tries to evaluate the best global (collective) position of the particle. The primary evaluation of the article is in this area and two sub-categories can be mentioned at 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. In other words, 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 product variety. These two rows have significantly improved compared to the refinery products and represent the best position. If we multiply the numbers of each best position by 1.0 × 10^3, 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, numbered 10,000 cubic meters. Now, can we see if the found answer has been able to meet the needs of the network with the same 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 equals the network requirement of 10,000.

Table 5: The 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

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. Further, the answers of the best collective position should be smaller and equal to the upper limit, which is equal to one in the number of sample sizes studied in the defined model. This allows the researcher to both verify the information obtained and to validate the modeling and input information.

According to Figure 4, a log–log diagram comparing several alternatives is demonstrated. Log–log (x, y) plots the x and y coordinates using the logarithmic scales on the x-axis and the y-axis. This chart shows the trend of the best cost number function elevation (NFE) and maximum repetition. The middle diagram shows the varmax effects, and the end chart depicts the number of varmin effects. Scatter (x, y) parabolic diagram shown in Figure 5 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 where the best point is located.

According to Figure 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.

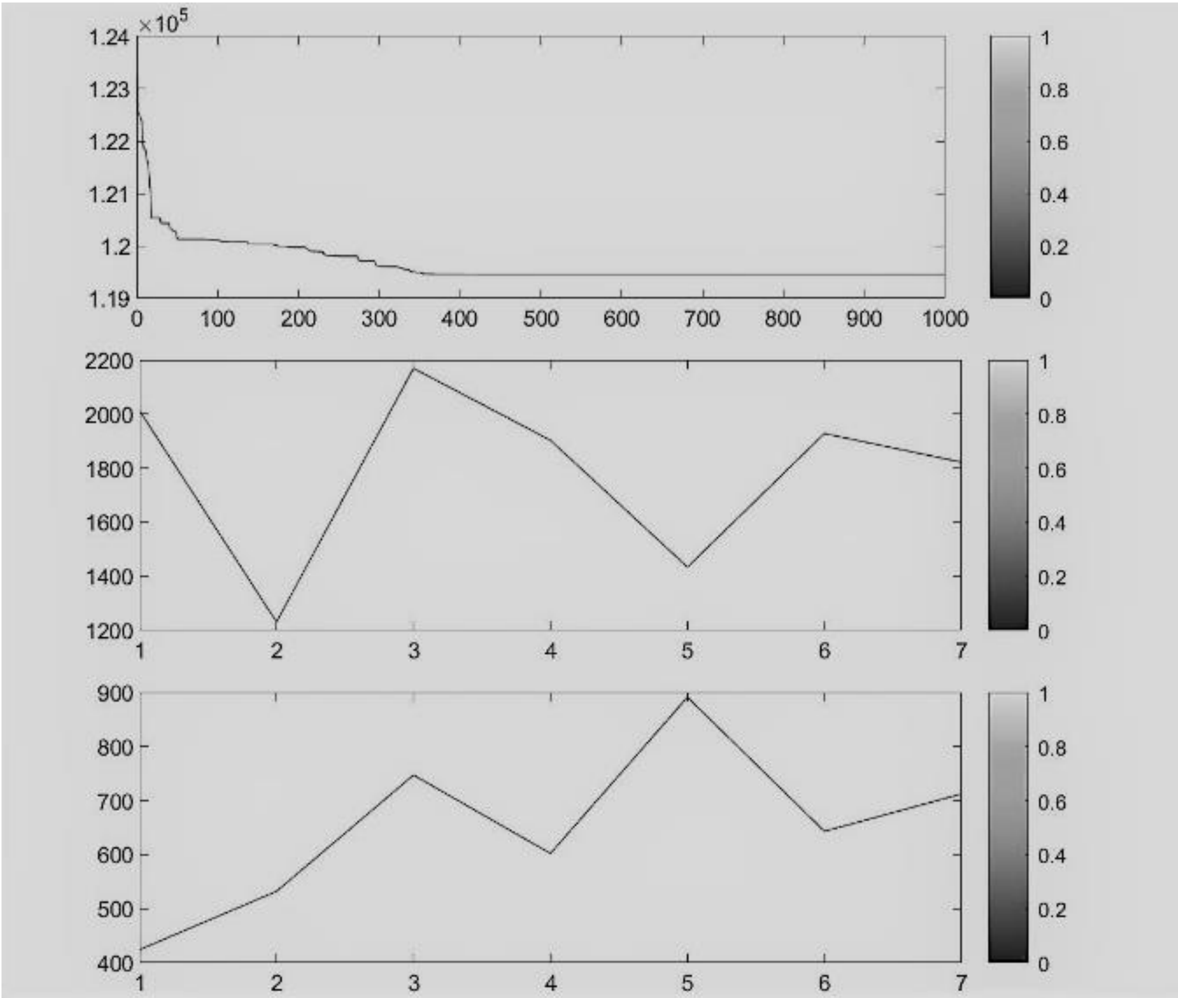

Figure 4: Represents log–log diagram comparing several alternatives.

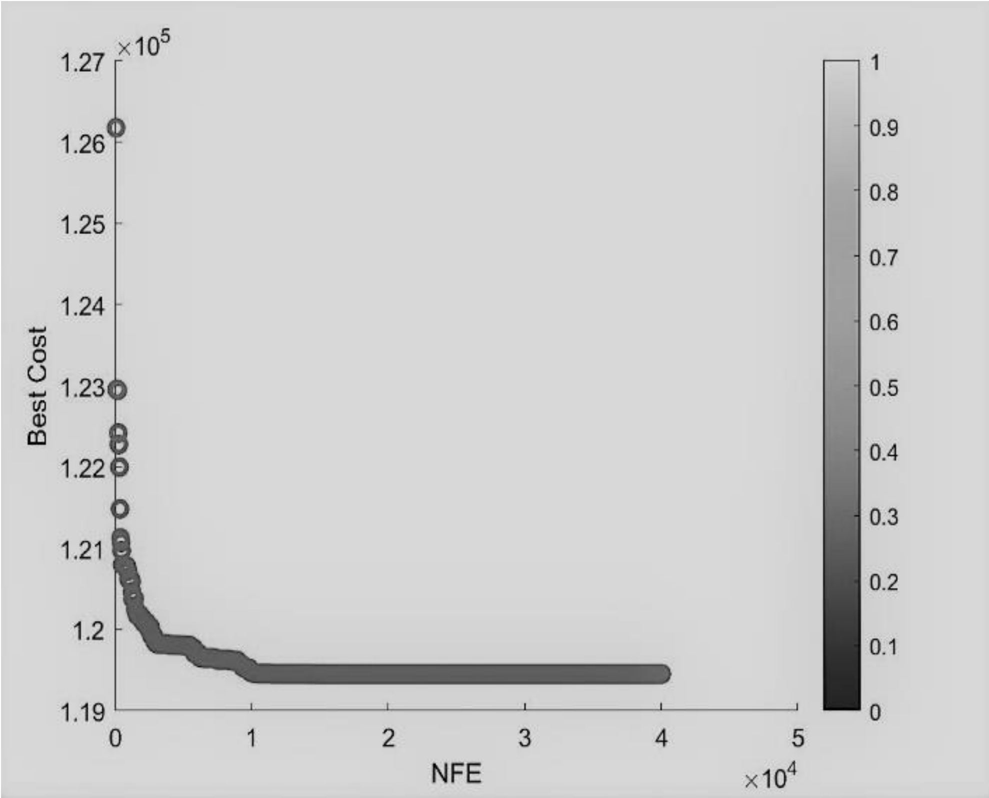

Figure 5: The scatter plot of position.

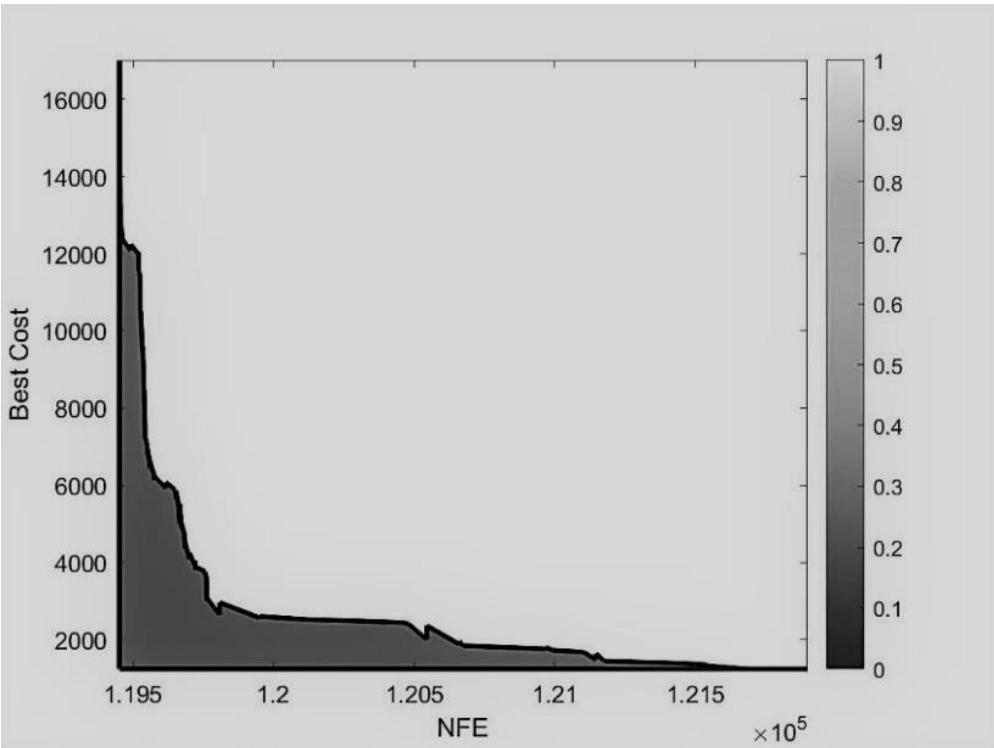

Figure 6: The best cost.

6. Conclusions

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 the MATLAB software environment has optimal answers that seek a justified answer due to the number of repetitions. 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 conducted before performing calculations related to economic dispatching with the approach of particle swarm optimization algorithm to increase the 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 the industrial unit must lead its costs to better efficiency to implement economic dispatching. This can be achieved by costing and distributing the economic burden according to the operations mentioned in the methodology section, presenting a new strategic plan for the industrial unit, and modifying medium-term plans.

After modeling and finding the ideal goals, the steps to answer this problem began to calculate the best global position solution. The software provides the solution of the best global situation to improve the initially extracted information by recognizing the affected points of the problem. Then, in the final table, it collects the relevant information. In the section of the best global situation, it has also 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 minimum, and researchers have taken steps to minimize and optimize the objective function. Finally, in each step and in the last three 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 seven years, the industrial unit (refinery) has an estimated cost of 28,432,911,220 Iranian 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 Iranian Rials. The refinery will reduce its costs by a total of 119,450.28459 Iranian Rials at the end of seven 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 optimized value is minimal. Of course, the industrial unit understudy can have no waste of costs of production and operations, and in the calculations performed, can 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 natural environment, we saw a significant reduction, which was able to balance the supply and demand and improve the costing system and production and refining;

Equation (10) implies:

$$\begin{aligned} Ctotal - MinC\ by\ ED = Best\ Cost \\ = 2{,}843{,}291{,}122 \\ - 11{,}945.28459 \\ = 2{,}843{,}279{,}177 \end{aligned} \tag{11}$$

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

7. Suggestions for future researchers

This article offers suggestions for researchers who intend to continue their studies on economic dispatching in other industrial units.

- It is suggested that this research be conducted in other communities, and the results be compared.
- It is suggested that modeling be performed by recognizing environmental factors in a natural context to remove the obstacles of industrial units.
- This research is about minimizing refinery costs; Researchers are advised to pursue future research to maximize sales and revenue.

- It is suggested that economic dispatching in production should be researched according to the alternatives in that field to create a new attitude.

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