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Economic load spreading by considering the presence of electric vehicles in order to reduce pollution particles and to consider demand response

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ABSTRACT

The evolution of power networks has introduced a highly competitive landscape for electricity production and consumption, particularly with the integration of renewable energy sources. Solar energy, as an example, offers significant advantages by reducing fuel dependency and lowering long-term electricity production costs, requiring only an upfront capital investment. This study centers on the economic dispatch of energy within the network, with the dual objectives of minimizing environmental pollution and reducing energy production costs. The problem at hand is inherently non-linear, making it unsuitable for linear modeling approaches. To address this, the research employs a range of tools and methodologies. A key strategy involves utilizing solar energy sources and energy storage systems to redistribute a portion of the load from peak demand periods to off-peak hours. For instance, electric vehicles are leveraged as flexible load-shifting agents. To optimize the operational schedule of electric vehicles and determine the output of each power generation unit, the particle swarm optimization (PSO) algorithm is applied. Additionally, this research incorporates specific constraints to ensure the optimal utilization of power generation units. These constraints and their implications are discussed in detail in subsequent sections.

1. INTRODUCTION

Energy supply remains one of humanity's most pressing challenges [1–4]. As a cornerstone of economic infrastructure, energy plays a pivotal role, with electricity standing out as the most versatile and valuable form of energy. In today's world, electricity production and consumption are recognized as key indicators of economic growth and development. However, the depletion of finite oil and gas reserves, coupled with rising global energy demands, has spurred researchers and scientists to focus on increasing the efficiency and productivity of power plants while minimizing energy losses.

To meet consumer demands for high-quality, reliable energy and to protect the environment, optimizing energy production and transmission within power grids is imperative [3–4]. Beyond fulfilling industrial energy demands,

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the electricity sector also bears the responsibility of minimizing the environmental impact of human activities. In this context, environmental considerations have become integral to energy planning, and the adoption of smart grids offers a promising solution to these challenges.

Smart grids offer a dual advantage: they empower consumers to intelligently manage their energy consumption—allowing them to save costs during peak hours when energy prices are higher—and provide environmental benefits by integrating technologies that mitigate climate change and reduce carbon emissions. These networks represent a paradigm shift in energy management, promoting both sustainability and efficiency. For stakeholders in the electrical industry, smart grids provide tools for informed decision-making and a clearer understanding of the network's status [5].

One practical step toward achieving sustainability goals is the adoption of electric vehicles (EVs) powered by grid-supplied electricity or batteries. This, combined with on-site energy generation and combined heat and power (CHP) systems, represents a significant advancement in energy efficiency. Such strategies have garnered significant attention in developed countries like the United States and Japan, while emerging economies like China and India have also made notable strides in this area.

However, in some nations, the low cost of fossil fuels has historically led to overconsumption. For instance, daily gasoline consumption in one region reaches an alarming 80 million liters. This overreliance on fossil fuels is further exacerbated by limited oil resources, the high cost of gasoline production, and the prevalence of aging, inefficient vehicles that remain in operation far beyond their intended lifespans. Addressing these challenges requires aligning with global trends by advancing EV technology and reducing dependence on fossil fuels [6].

Renewable energy sources, such as wind and solar power, play a pivotal role in reducing fossil fuel dependence and mitigating air pollution. These clean energy solutions are especially attractive to developing countries, offering a sustainable path to economic growth. International initiatives, including those led by the United Nations, are critical in promoting renewable energy adoption to achieve global sustainability goals.

Notable among these initiatives is the 2009 Low Carbon Transition Plan, which mandates an 80% reduction in carbon dioxide emissions by 2050. The United States, for example, has set a target to generate 20% of its electricity from wind energy by 2030. Similarly, China has achieved remarkable progress, increasing its wind power capacity from 2,000 MW to 52,580 MW in just six years. With its rapidly expanding wind energy sector, China is projected to reach a production capacity of 200,000 MW by 2020, making wind power a cornerstone of its electricity generation strategy.

The global transition toward sustainable energy systems is an urgent necessity. By adopting smart grids, promoting renewable energy sources, and integrating technologies such as electric vehicles, nations can effectively balance economic growth, energy security, and environmental sustainability. International collaboration and policy implementation are crucial in achieving these transformative objectives, ensuring a cleaner and more resilient energy future for all.

2. RESEARCH BACKGROUND

Numerous articles have analyzed the impact of electric vehicles on power systems from various perspectives. In a report, the National New Energy Organization (NREL) analyzed the changes in air pollution resulting from different car charging scenarios. The report demonstrated that the use of hybrid electric cars leads to a significant reduction in CO2 emissions [8,9]. In recent decades, several statistical search methods, such as genetic algorithms, evolutionary algorithms, and particle swarm optimization, have been developed. Among these methods, the particle swarm algorithm has attracted the attention of researchers due to its high speed and ability to produce high-quality solutions[10]. In their studies [11], the authors utilized the vehicle-to-grid (V2G) capability in electric vehicles as a reserve source to modify and adjust the load curve. Sood [12] investigated the impact of hybrid electric vehicles on the network load curve, production capacity, and fuel cost [13]. studied the changes in distribution network losses and the lifetime of its equipment [14]. employed an intelligent method for economic load distribution using hybrid electric vehicles and electric vehicles.

3. PARTICLE OPTIMIZATION (PSO)

The PSO algorithm is a social search algorithm modeled on the social behavior of flocks of birds. Initially, it was used to discover the patterns governing the simultaneous flight of birds, sudden changes in their paths, and the optimal shape of the flock. In PSO, particles move through the search space, and their location is influenced by their own and their neighbors' experience and knowledge. Thus, particle crowding affects the search for a particle. Modeling this social behavior results in particles tending towards successful areas. They learn from each other and move towards their best neighbors based on the knowledge obtained. The foundation of PSO work is rooted in the principle that, at any given moment, each particle finds its position in the search space based on the best location it has previously occupied and the best location within the entire neighborhood. This behavior of each particle within the community can be modeled using a simple vector. Boyd and Richardson conducted research on the human decision-making process and discovered the concept of cultural learning. Their research identified two types of important data used in decision-making: personal experiences and the desire for improvement. Individuals evaluate their past choices to inform their current decisions and strive to make better choices in the future. The second factor influencing decision-making is the experiences of others. The second factor influencing decision-making is the experiences of others. This means that people around an individual may have valuable insights into the best decisions for their society in a particular case. The second factor influencing decision-making is the experiences of others. Therefore, it can be concluded that every individual's decision-making process is influenced by their own experiences and the experiences of those around them [6].

The PSO algorithm for bird migration in two-dimensional space was developed by Kennedy and Eberhart, based on the theory presented by Kwang et al. in 2008[6].

Each particle's position is determined by its coordinates on the x and y axes, and its speed is determined by V_x,V_y Optimization of a specific objective function is necessary for bird migration. Each particle stores its best location so far in pbest and remembers the coordinates of this point. This information is based on the individual experiences of each particle. Additionally, each particle is aware of its optimal position within the group and stores it in gbest. It is important to note that gbest is a value among the pbests, and this information serves as a reference for the knowledge of particles. This knowledge helps particles understand how to progress and move towards their defined goals [6]. Each particle updates its position by considering its current position (x,y), current velocity(V_x,V_y), distance to personal best (pbest), and distance to global best (gbest). This change can be better represented by the concept of speed. The speed of each particle is updated using the following formula[6]:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest - s_i^k\right) \tag{1}$$

The formula includes the following variables v_i^k for the speed of particle i in the k th iteration, w for the inertial coefficient that indicates the effect of the previous speed vector on the current speed vector, c_1 and c_2 for the parameters of local acceleration and global acceleration, respectively. rand is a random number between 0 and 1, s_i^k for the current position of particle i in the kth iteration, pbest for the best position of the particle so far, and gbest for the best position obtained by the group. The formula demonstrates that the speed of each particle can be altered using three vectors, with a maximum limit typically imposed. This formula is known as the gbest model in PSO. The inertia coefficient (w) used in the formula is determined by the following equation[6].

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{2}$$

In this formulaw_{max} is the initial inertia coefficient, $w_{min}$is the final inertia coefficient, $iter_{max}$is the maximum iteration number of the current iteration of the PSO algorithm in which the above formulas are used, it is called inertia coefficient method (IWA) [6].

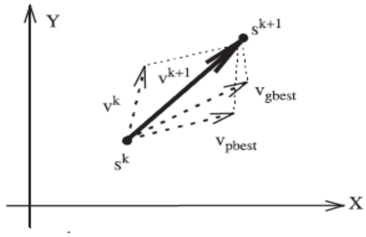

Fig. 1. The concept of updating the position of a particle in the search space

The main relationship of PSO is defined by the first formula, which consists of three vectors. The main relationship of PSO is defined by the first formula, which consists of three vectors. Each vector is considered a factor in the relationship. The first factor is the particle's previous speed, while the second and third factors are used to adjust the particle's speed. If we exclude the second and third factors, the particle will continue to move in the same direction as the initial velocity vector until the end of migration, reaching its determined boundary conditions. The first factor causes diversity in the search as the particle attempts to discover new areas. However, if the first factor is excluded, the particle's flight speed is solely determined by its current position and the best position in its memory. This means that the particle attempts to converge to either its personal best or global best. The second and third factors accelerate the convergence to reach these targets. As shown in the example, the values of w_{max} and w_{min} are set to 0.9 and 0.4, respectively. Initially, a large value of w is used to increase the search range and provide more variety. Towards the end, a small value of w is used to improve the accuracy of convergence in the search [6]. The particle's current position in the solution space is determined by the following equation [6]:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{3}$$

Figure 1: illustrates the process of updating a search point in the problem-solving space using the PSO algorithm. Figure 2 depicts the process of searching in the solution space. Each particle updates its current position by integrating the vectors shown in Figure 2[6].

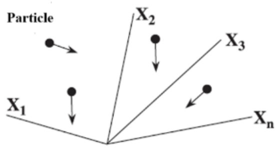

Fig. 2. The concept of searching by particles in the problem solving space by PSO[6].

At the start of the algorithm, the position vector of the particles is randomly selected within the upper and lower limits of the variables. Each particle has the same number of variables as the number of power plants. The target function value is calculated for each particle using the mentioned relations for the cost of fuel and pollution of thermal power plants, as well as the cost function for wind power plants. Step 3: The particle velocity vector is updated using Global Best (Gbest) and Individual Best (Pbest) values. The particle position vector is then updated based on the updated velocity vector. These calculations are repeated until the exit conditions are satisfied and the algorithm returns the minimum value for the cost function [6].

4. RESEARCH METHOD

This section presents the simulation results obtained using MATLAB. The system was constructed and optimized by implementing existing equations. The results are presented graphically. The simulation included 19 energy producing units, consisting of 6 fossil fuel power plants and 13 solar power plants. Electric vehicles are used to save energy by transferring peak load hours to low load hours. Load transfer is done first, followed by optimization using the desired algorithm and constraints identified in this research. Two scenarios were considered to evaluate the performance and cost of energy production required by the network. The first scenario involves the use of triangular fuzzy constraints to ensure equality between power production and consumption, while the second scenario uses trapezoidal constraints to manage the difference between production and consumption. The triangular constraint only allows for equality at one point, and the probability of production and consumption being equal becomes one only when the energy produced equals the energy consumed. In the model chosen for this research, based on the reference article, six fossil fuel power plant units and thirteen photovoltaic units were considered. In each scenario, the solar units reduced the cost of power generation required to meet the system load. [6].

4.1. Fuzzy modelling of economic load distribution

In economic load distribution, there are a number of generators, each of which has its own cost function. Economic load distribution should be such that the final cost of power production is minimized. The total cost function is expressed as follows[6]:

$$F_{Fuel\,Cost} = min(\,f_1(p_1) + f_2(p_2)+\ldots+f_n(p_n)) \tag{4}$$

where fi is the cost function of the i-th power plant, which is a function based on the amount of power produced[6].
There is also an equality condition that the energy produced and the energy consumed must be the same. This adverb is as follows[6]:

$$\sum P_{G_i} = \sum P_{L_i} + \sum P_{Loss} \tag{5}$$

where the power of the *i* generator is the $P_{G_i}$and the power consumption of the *i* load is the P_{L_i}.The system error is the difference between the amount of energy produced and the amount of energy consumed, which is presented as follows[6]:

$$ER = \sum P_{G_i} - \sum P_{L_i} - \sum P_{Loss} = 0 \tag{6}$$

$$ER_{p.u.} = \frac{\sum P_{G_i} - \sum P_{L_i} - \sum P_{Loss}}{\sum P_{G_i}} \tag{7}$$

The error in this function reaches zero only when production matches both the system losses and the required load. In all other scenarios, the error takes on a non-zero value. For improved clarity and interpretation, it is advisable to express this error either as a percentage or using electrical units, such as per-units [6]. The per-unit error can be determined using the following formula [6]:

In explaining this formula, it is important to note that the error introduced was in the form of a unit. Therefore, after calculating the system error, the value was divided by the total power output from different units to obtain the per-unit value of this error [6].

This section proposes the condition of equality between production and consumption using a membership function. The function is presented in two scenarios: a triangle or a trapezoid. Equality condition using triangular membership function [6]:

$$\mu_1 = \begin{cases} 1 & \left|\dfrac{P_{Demand} - P_{Generated}}{P_{Demand}}\right| = 0 \\[2ex] 1 - \left|\dfrac{P_{Demand} - P_{Generated}}{P_{Demand}}\right| & 0 < \left|\dfrac{P_{Demand} - P_{Generated}}{P_{Demand}}\right| \le 5\% \\[2ex] 0 & \left|\dfrac{P_{Demand} - P_{Generated}}{P_{Demand}}\right| > 5\% \end{cases} \tag{8}$$

As evident from the above function, the probability of being equal to 1 only occurs when the difference between production and consumption reaches zero. It is important to note that this definition differs slightly from the trapezoidal membership function. Due to the difference between production and consumption in the equality function of the triangular state with a constant slope, the probability of achieving 100% equality or a value of one on this graph begins to decrease and continues to do so gradually. To ensure a different scenario for analyzing totality and consumption, we assume that a 1% difference between production and consumption is acceptable. If production and consumption differ by only 1%, they are still considered equal. Therefore, we create another equality function called the trapezoidal function. The tolerance band for the trapezoidal function is one percent on each side of the difference. The expression on each side of the dispute indicates whether production exceeds consumption or vice versa. The resulting trapezoidal function is then applied to the system using the following formulation [6].

$$\mu_1 = \begin{cases} 1 & \left| \dfrac{P_{Demand} - P_{Generated}}{P_{Demand}} \right| \leq 1\% \\ 1 - \left| \dfrac{P_{Demand} - P_{Generated}}{P_{Demand}} \right| & 1\% < \left| \dfrac{P_{Demand} - P_{Generated}}{P_{Demand}} \right| \leq 5\% \\ 0 & \left| \dfrac{P_{Demand} - P_{Generated}}{P_{Demand}} \right| > 5\% \end{cases} \tag{9}$$

Based on the explanations provided above and formulations (9) and (8), the primary issue of production and consumption equality has been resolved in this research. The following sections will discuss the implementation of electric cars in this study. Therefore, it is essential to formulate this issue and incorporate it into the simulation and presentation of results[6].

4.2. Specifications of system generators

In this research, the power system that is considered as a model has 6 power plants whose information is given in Table 1 [6]. And in Table 1, the load information is also given during 24 hours[6].

Table 1. Information about energy cost coefficients and power plant capacity (Khan, 2015)

Machine NO.	a($/MW²h)	b($/MW²h)	c($/MW²h)	P_{min} (MW)	$P_{max(MW)}$
1	0.152	38.53	756.79	10	**150**
2	0.105	46.15	451.32	10	**175**
3	0.028	40.39	1049.32	40	**250**
4	0.035	38.30	1243.5	35	**250**
5	0.021	36.32	1658.5	130	**375**
6	0.018	38.27	1356.21	125	**365**

4.3. system load specifications and optimization without considering the equality constraints of production and consumption

At first, in order to obtain the normal load in the system, the load histogram of the system is drawn to find the load that has the most repetition in this system, and it is very likely that this load will be the average and desired load for the production of the system[6]. System load histogram chart in 24 hours a day:

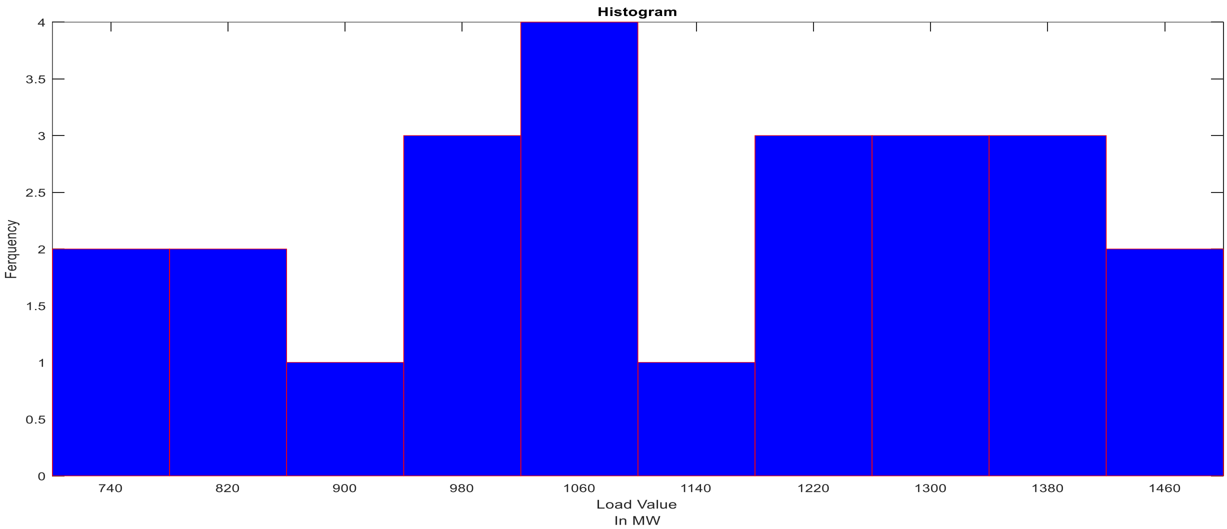

Fig. 3. System load histogram in 24 hours a day[6].

Based on the diagram, it can be inferred that the system's average load should be 1060 MW. Therefore, in this simulation, electric vehicles are incorporated into the normal load system when the system load is below 1060 MW, which is the production amount of generators and solar cells. At the same time, some of the energy produced is surplus. Electric vehicles can enter the circuit and consume this surplus energy as a load, storing it in their battery. During periods of high system load, electric vehicles are utilized as a source of energy production by injecting the energy stored in their batteries into the system. This compensates for any lack of power from production units. It is important to note that this only occurs during times of high demand. All subsequent concepts will be focused on economic solutions to address this main load. The system load diagram prior to the introduction of electric vehicles is presented below. This section includes the main load diagram of the system without electric vehicles.

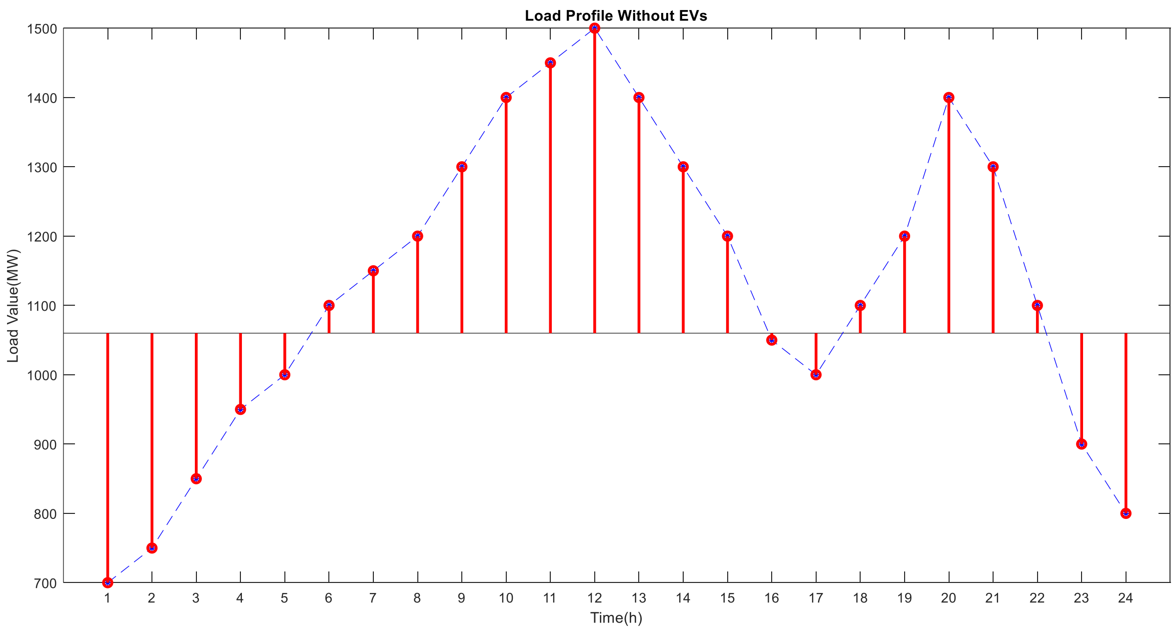

Fig. 4. System load curve without electric vehicles[6].

The load information table for Figure 4 is given in Table 2.

Table 2. Load information before the presence of electric vehicles

Time	1	2	3	4	5	6	7	8	9	10	11	12
Demand (MW)	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Time	13	14	15	16	17	18	19	20	21	22	23	24
Demand (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

As can be seen from this table, unbalanced loads are drawn from the system at different hours, and after the optimization of these loads, they are modified by the presence of electric vehicles, and as a result, the voltage profile diagram will move toward flattening[6].

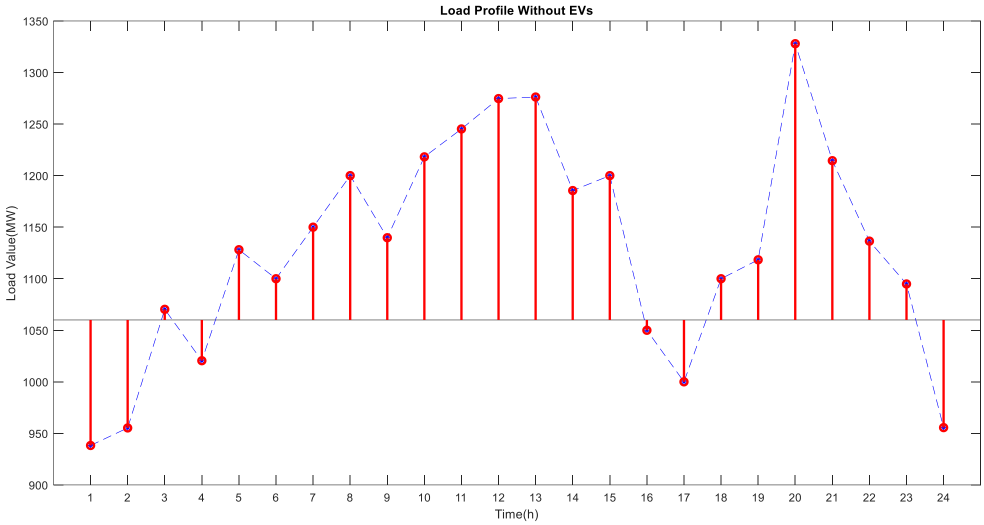

Fig. 5. System load curve after the presence of 150 thousand electric cars

The figure clearly shows that the load values have improved significantly before and after the introduction of electric vehicles. As a result, the system experiences less load, leading to economic savings. It has been observed that the presence of these cars on the network has been checked twice this season. The research examined 150,000 electric cars, while considering 90,000 cars in a previous study. The article did not have enough space to include the details of the previous study[6].

Table 3. Load information after the presence of 150 thousand electric cars

Time	1	2	3	4	5	6	7	8	9	10	11	12
Load in MW	938	955	1070	1020	1128	1100	1150	1200	1140	1218	1245	1275
Time	13	14	15	16	17	18	19	20	21	22	23	24
Load in MW	1276	1186	1200	1050	1000	1100	1118	1328	1214	1136	1095	956

Table 2 provides the load information for Figure 4. The table has been modified multiple times at different intervals due to the presence of electric cars, which act as a storage element in the system. This device draws electricity from the grid and stores it during off-peak hours, then releases it during peak hours. This reduces the overall load on the network, allowing power plants to operate more efficiently and consume less energy to meet demand. This section presents the results of the presence of 90,000 electric cars to provide an accurate reference for comparison[6].

Table 4. Load information after the presence of 90 thousand electric cars[6].

Time	1	2	3	4	5	6	7	8	9	10	11	12
Load in MW	823	899	976	996	1039	1100	1150	1200	1240	1292	1320	1371
Time	13	14	15	16	17	18	19	20	21	22	23	24
Load in MW	1031	1262	1200	1050	1000	1100	1188	1278	1246	1100	1031	936

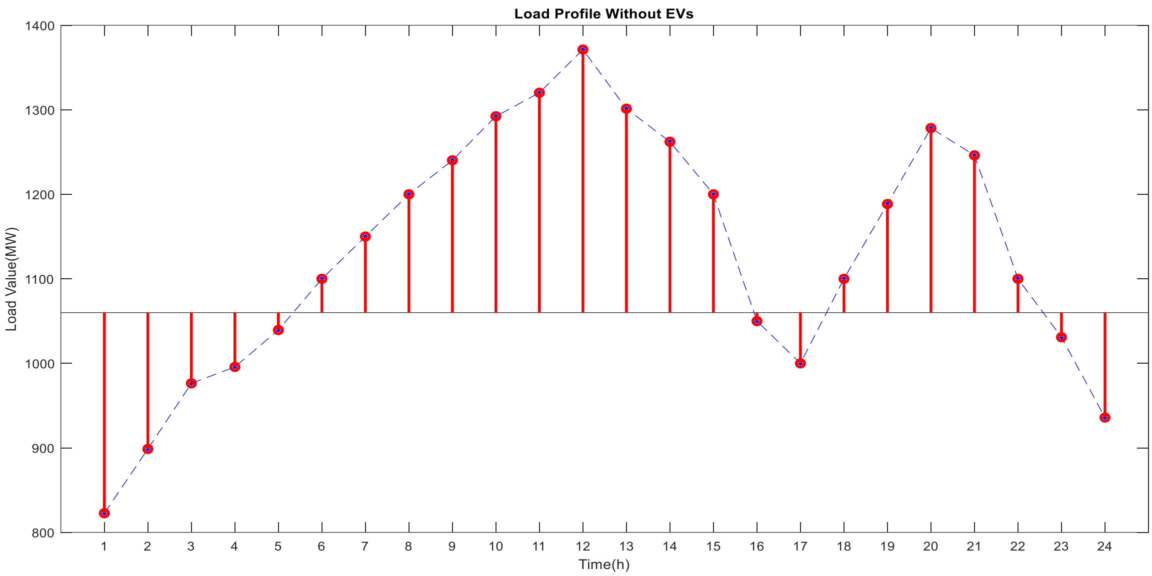

Fig. 6. System load curve before the presence of 90 thousand electric cars[6].

4.4. Minimization of pollution particles entering the environment

This section establishes that the presence of electric vehicles significantly reduces fuel consumption in the researched system. It is demonstrated that the use of electric cars minimizes fuel usage and, consequently, reduces the amount of pollution particles released into the environment[6].

4.5. The analyses presented in this research

This section presents reviews with varying loads, each accompanied by two charts. The first chart displays the reduction in fuel consumption, resulting in cost and pollution reduction. The second chart shows the probability of equality between production and consumption, determined by adding the phase adverb 'trapezoidal' or 'triangular' in each part. The first graph shows a downward trend in both pollution and cost reduction, while the second graph shows an upward trend in increasing the probability of equality. The following section presents these explanations for different time periods. The scenario is presented under the title of 'trapezoidal adverb', which specifies the scenario[6].

4.6. The first scenario of the trapezoidal membership function

4.6.1. Initial inspection of 900 MW

The analysis begins by implementing the trapezoidal membership function in the code. Then, the particle swarm algorithm is executed twice. The first execution considers production 5% less than consumption, resulting in the first cost (F1). The second execution considers production 5% more than consumption, resulting in the second cost (F2). At this stage of implementing the particle swarm algorithm, it is important to allocate power to the six fuel power plants and thirteen solar power plants in the system, as explained in the previous chapter. Therefore, the cost of fossil fuel power plants needs to be calculated using an appropriate method.This section discusses the response of the load over a 24-hour period using both solar and wind power, as outlined in the reference article. In this analysis, as well as in other analyses of this research, the algorithm was implemented twice with 5% more production than the network demand and the resulting costs were obtained. In the next stage, the formulation for the triangular or trapezoid condition of the equality condition in coding was implemented using these two costs, and the parameter of the difference between production and consumption was found as a percentage. In this scenario, the F1 and F2 coefficients are obtained by considering a 5% tolerance above and below the required power generation value. These coefficients are then used in the next part of the simulation, where the goal is to first reduce and then maximize again. During the reduction stage, the focus is on minimizing fuel consumption and pollution. In the subsequent maximization stage, the focus is on equalizing production and consumption. In this and other analyses, the goal of the study has been objectively achieved, as demonstrated by the two accompanying graphs. The results are currently being considered[6]. The convergence diagram for this implementation is shown in Figure 7:

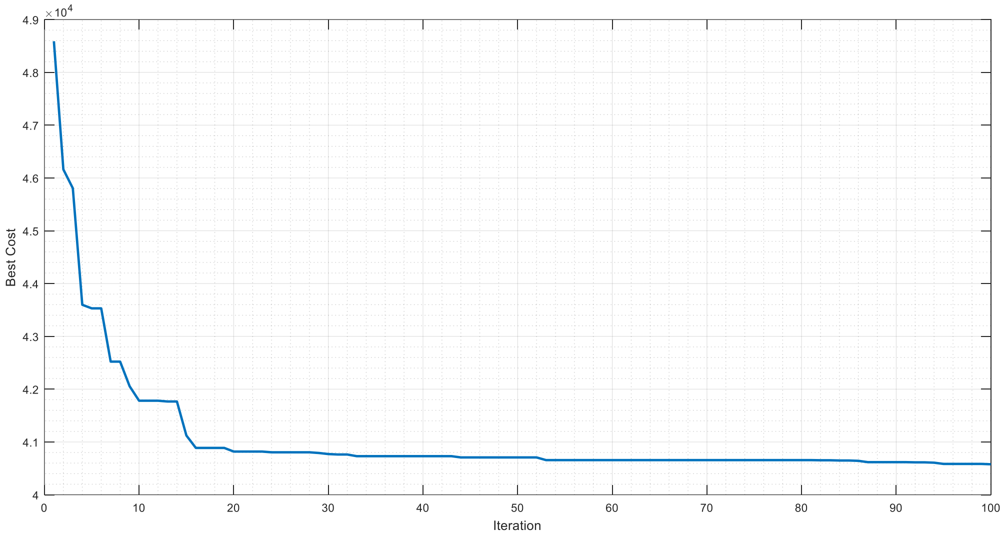

Fig. 7. Convergence considering production is 5% less than consumption at 900 MW load[6].

The figure shows the convergence diagram for the load of 900 MW when the production is 5% more than the consumption.

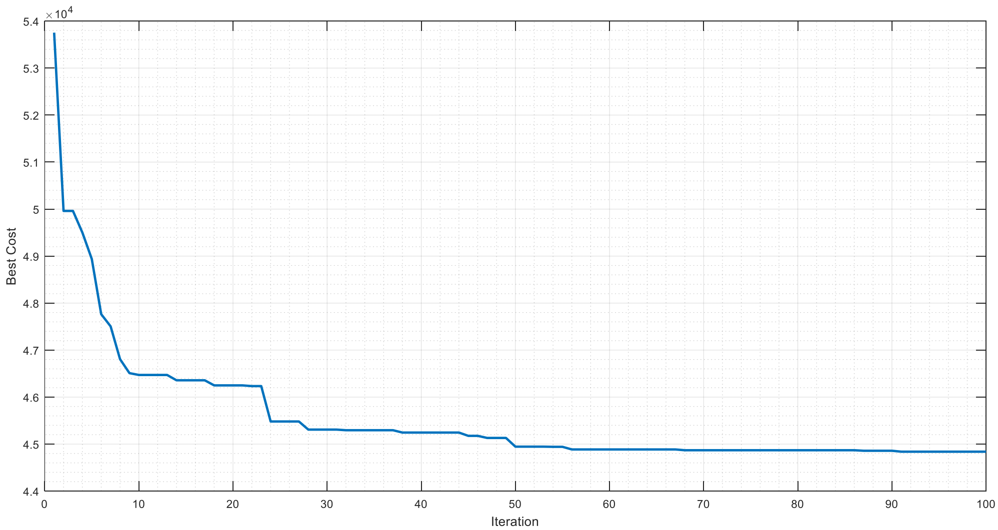

Fig. 8. Convergence considering production is 5% more than consumption at 900 MW load[6].

After determining the cost for energy production with values 5% higher and lower than the original value, the original value was reached. The convergence diagram shows that the production cost in the lowest state is 40577 dollars, which is the required amount of energy. The production of each power plant unit is also announced. The amount of energy produced by each of the six generating units in the system is:

Table 5. Values of generators in the system for the first scenario[6].

Generator 1	Generator 2	Generator 3	Generator 4	Generator 5	Generator 6
100	50	143	155	190	131

The amount of energy production through the thirteen solar power plants in the studied system is obtained as follows:

Table 6. Production value of thirteen solar energy producing units[6].

13	12	11	10	9	8	7	6	5	4	3	2	1
5	14	11	10	11	12	20	16	7	0	12	5	**0**

Due to the presence of scattered solar production sources in the investigated system, production and consumption have been completely equalized and the difference between production and consumption has reached less than 5%.

4.6.2. Second check of 1000 MW load

The analysis begins by implementing the trapezoidal membership function in the code. Then, the particle swarm algorithm is executed twice. The first execution considers production 5% less than consumption, resulting in the first cost (F1). The second execution considers production 5% more than consumption, resulting in the second cost (F2). At this stage of implementing the particle swarm algorithm, it is important to allocate power to the six fuel power plants and thirteen solar power plants in the system, as explained in the previous chapter. Therefore, the cost of fossil fuel power plants needs to be calculated using an appropriate method. This section discusses the response of the load over a 24-hour period using both solar and wind power, as outlined in the reference article. In this analysis, as well as in other analyses of this research, the algorithm was implemented twice with 5% more production than the network demand and the resulting costs were obtained. In the next stage, the formulation for the triangular or trapezoid condition of the equality condition in coding was implemented using these two costs, and the parameter of the difference between production and consumption was found as a percentage. In this scenario, the F1 and F2 coefficients are obtained by considering a 5% tolerance above and below the required power generation value. These coefficients are then used in the next part of the simulation, where the goal is to first reduce and then maximize again. During the reduction stage, the focus is on minimizing fuel consumption and pollution. In the subsequent maximization stage, the focus is on equalizing production and consumption. In this and other analyses, the goal of the study has been objectively achieved, as demonstrated by the two accompanying graphs. The results are currently being considered[6].

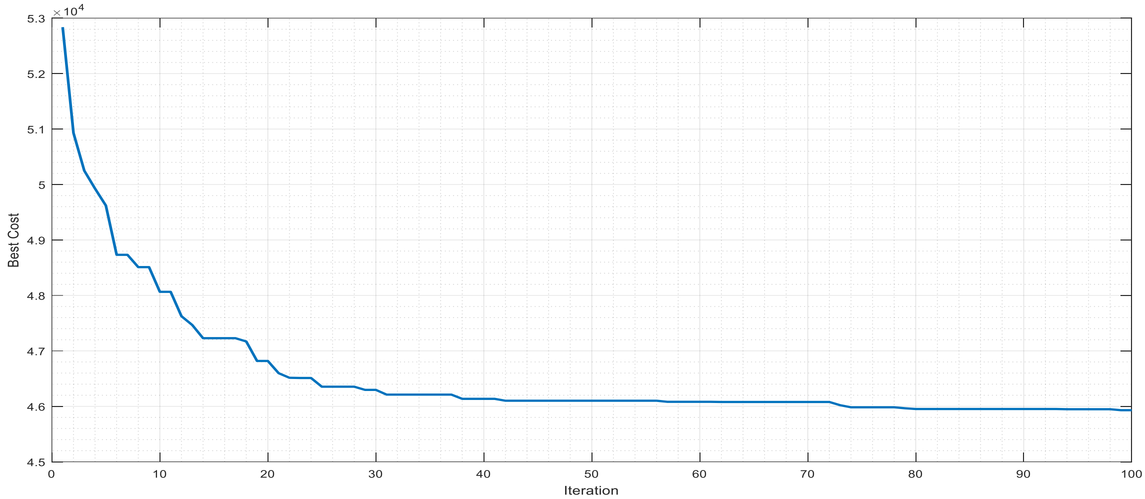

Fig. 9. Convergence considering production is 5% less than consumption at a load of 1000 MW[6].

Figure 10 shows the convergence diagram for a load of 1000 MW when production is 5% more than consumption.

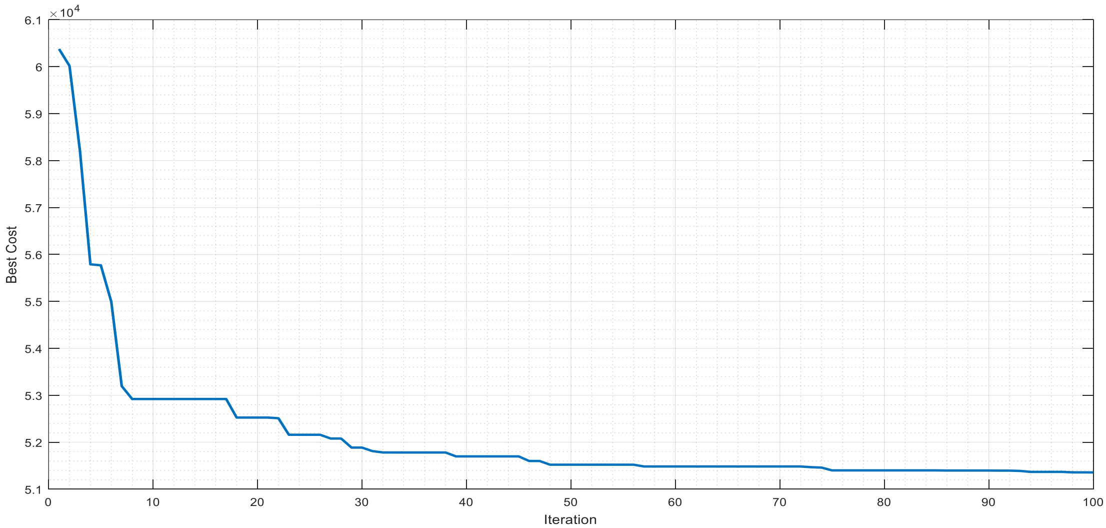

Fig. 10. Convergence considering production is 5% more than consumption at 1000 MW load[6].

In this part, after determining the cost for energy production with two values 5% higher and lower than the original value, it goes to the original value and the convergence diagram is presented: the value of the production cost in the lowest state of this diagram is $45909.3215, which for the value Energy is required and the amount of production of each power plant unit is also announced. The amount of energy produced by each of the six generating units in the system:

Table 7. Values of generators in the system for the first scenario[6].

Generator 1	Generator 2	Generator 3	Generator 4	Generator 5	Generator 6
100	71	211	173	198	119

The amount of energy production through the thirteen solar power plants in the studied system is obtained as follows:

Table 8. Production amount of thirteen solar energy producing units[6].

13	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
5	14	11	10	11	12	20	16	7	5	12	5	**0**

Due to the presence of scattered solar production sources in the investigated system, production and consumption have been completely equalized and the difference between production and consumption has reached less than 5%.

4.6.3. Third inspection of 1100 MW load

The analysis begins by implementing the trapezoidal membership function in the code. Then, the particle swarm algorithm is executed twice. The first execution considers production 5% less than consumption, resulting in the first cost (F1). The second execution considers production 5% more than consumption, resulting in the second cost (F2). At this stage of implementing the particle swarm algorithm, it is important to allocate power to the six fuel power plants and thirteen solar power plants in the system, as explained in the previous chapter. Therefore, the cost of fossil fuel power plants needs to be calculated using an appropriate method. This section discusses the response of the load over a 24-hour period using both solar and wind power, as outlined in the reference article. In this analysis, as well as in other analyses of this research, the algorithm was implemented twice with 5% more production than the network demand and the resulting costs were obtained. In the next stage, the formulation for the triangular or trapezoid condition of the equality condition in coding was implemented using these two costs, and the parameter of the difference between production and consumption was found as a percentage. In this scenario, the F1 and F2 coefficients are obtained by considering a 5% tolerance above and below the required power generation value. These coefficients are then used in the next part of the simulation, where the goal is to first reduce and then maximize again. During the reduction stage, the focus is on minimizing fuel consumption and pollution. In the subsequent maximization stage, the focus is on equalizing production and consumption. In this and other analyses, the goal of the study has been objectively achieved, as demonstrated by the two accompanying graphs[6].

The convergence diagram for this implementation is shown below, taking into account a 5% reduction in production compared to consumption[6].

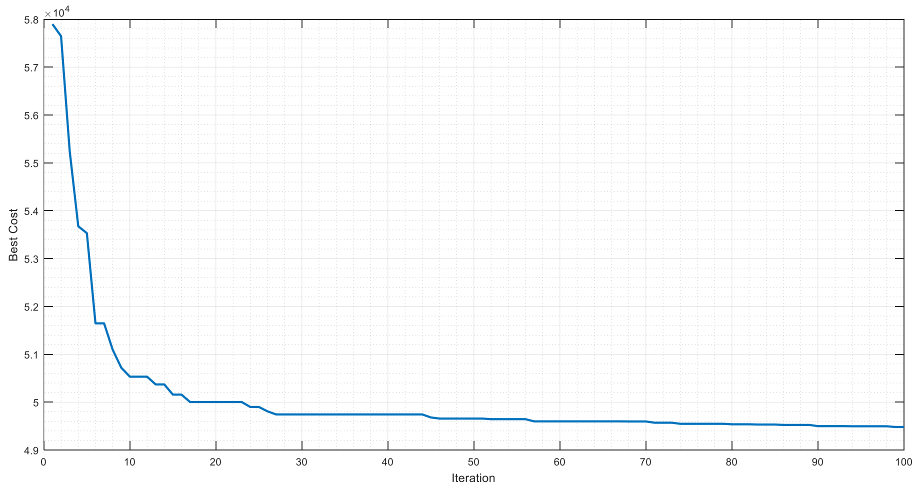

Fig. 11. Convergence considering production is 5% less than consumption at 1100 MW load[6].

The figure shows the convergence diagram for the load of 1100 MW when the production is 5% more than the consumption.

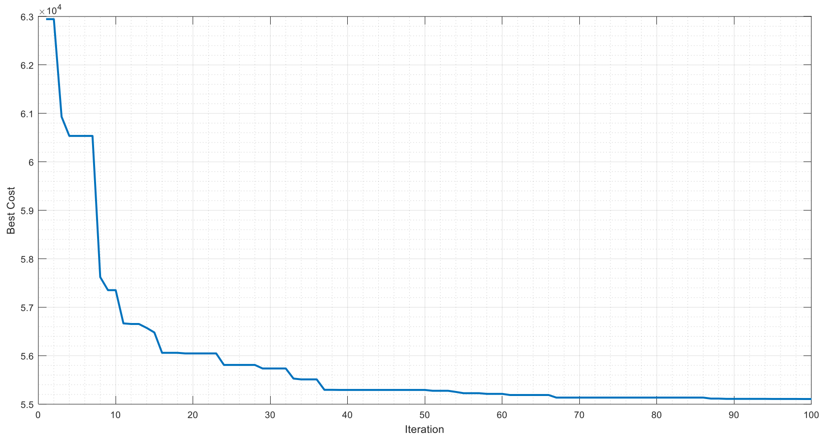

Fig. 12. Convergence considering production is 5% more than consumption at 1100 MW load[6].

After determining the cost for energy production with values 5% higher and lower than the original value, the original cost value of $49541.8741 is reached. The convergence diagram is presented, along with the required energy value and the production amount for each power plant unit. The amount of energy produced by each of the six generating units in the system is also provided.

Table 9. Values of generators in the system for the first scenario[6].

Generator 1	Generator 2	Generator 3	Generator 4	Generator 5	Generator 6
100	71	211	173	198	119

The amount of energy production through the thirteen solar power plants in the studied system is obtained as follows:

Table 10. Production value of thirteen solar energy generating units[6].

13	12	11	10	9	8	7	6	5	4	3	2	1
5	14	11	10	11	12	20	16	7	5	12	5	**2**

Due to the presence of scattered solar production sources in the investigated system, production and consumption have been completely equalized and the difference between production and consumption has reached less than 5%.

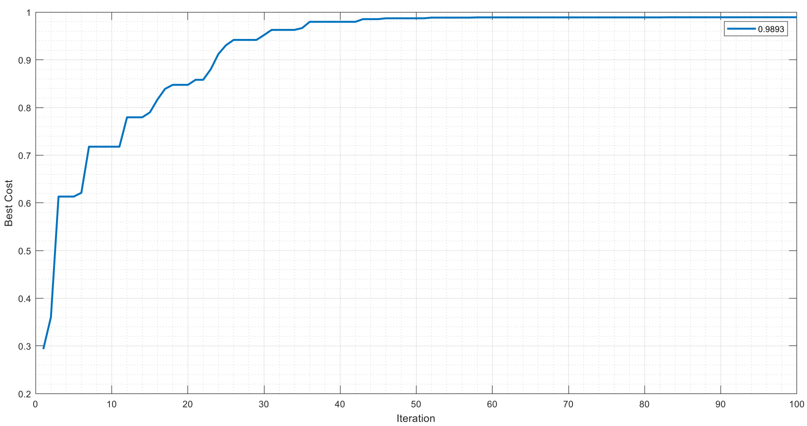

Fig. 13. Maximization of the mu coefficient related to the third review[6].

4.6.4. Fourth Inspection Of 1200 MW Load

The analysis begins by implementing the trapezoidal membership function in the code. Then, the particle swarm algorithm is executed twice. The first execution considers production 5% less than consumption, resulting in the first cost (F1). The second execution considers production 5% more than consumption, resulting in the second cost (F2). At this stage of implementing the particle swarm algorithm, it is important to allocate power to the six fuel power plants and thirteen solar power plants in the system, as explained in the previous chapter. Therefore, the cost of fossil fuel power plants needs to be calculated using an appropriate method. This section discusses the response of the load over a 24-hour period using both solar and wind power, as outlined in the reference article. In this analysis, as well as in other analyses of this research, the algorithm was implemented twice with 5% more production than the network demand and the resulting costs were obtained. In the next stage, the formulation for the triangular or trapezoid condition of the equality condition in coding was implemented using these two costs, and the parameter of the difference between production and consumption was found as a percentage. In this scenario, the F1 and F2 coefficients are obtained by considering a 5% tolerance above and below the required power generation value. These coefficients are then used in the next part of the simulation, where the goal is to first reduce and then maximize again. During the reduction stage, the focus is on minimizing fuel consumption and pollution. In the subsequent maximization stage, the focus is on equalizing production and consumption. In this and other analyses, the goal has been achieved. This is demonstrated in two graphs. The results, considering the production is 5% less than the consumption: the convergence diagram for this implementation is shown in Figure 14[6]:

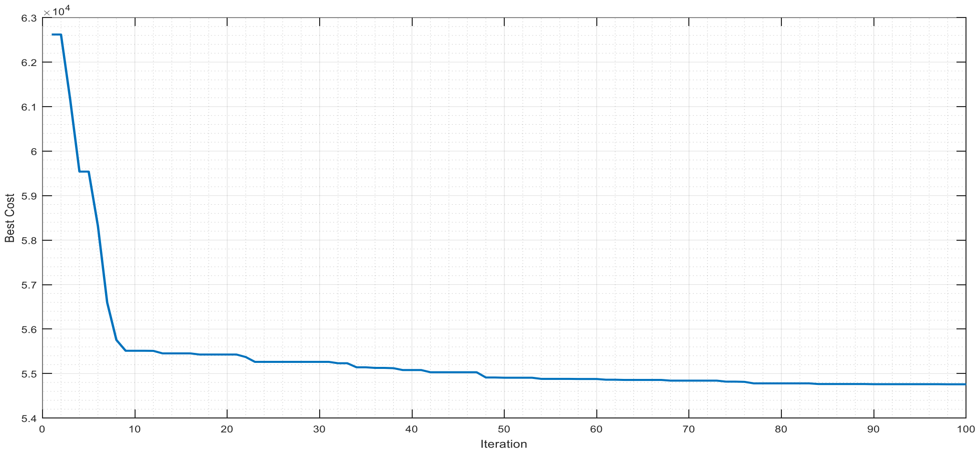

Fig. 14. Convergence considering production is 5% less than consumption at 1200 MW load[6].

Figure 15 shows the convergence diagram for the load of 1100 MW when the production is 5% more than the consumption.

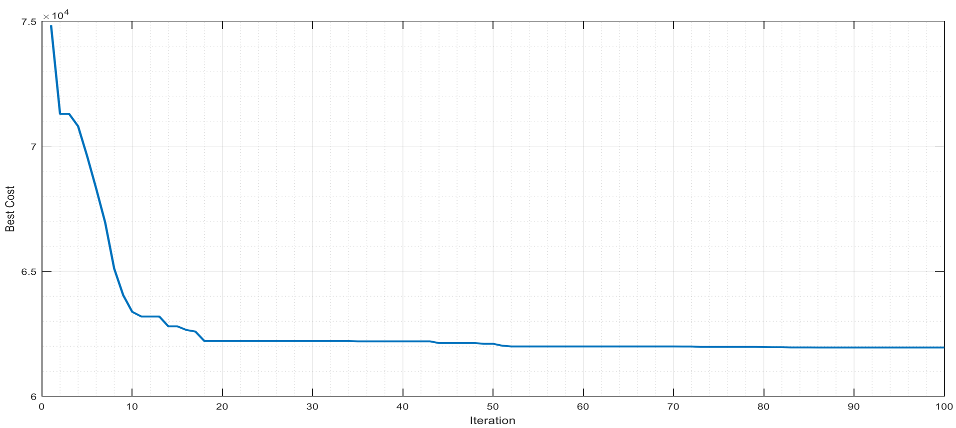

Fig. 15. Convergence considering production is 5% more than consumption at 1200 MW load[6].

After determining the cost for energy production with values 5% higher and lower than the original value, the original value was reached. The convergence diagram shows that the production cost in the lowest state of this diagram is $54853.2393. The required energy value and the amount of production for each power plant unit are also provided. The following is the amount of energy produced by each of the six generating units in the system:

Table 11. Values of generators in the system for the first scenario[6].

Generator 1	Generator 2	Generator 3	Generator 4	Generator 5	Generator 6
100	63	266	200	250	180

The amount of energy production through the thirteen solar power plants in the studied system is obtained as follows:

Table 12. Production amount of thirteen solar energy producing units

13	12	11	10	9	8	7	6	5	4	3	2	1
5	14	11	10	11	12	20	16	7	5	12	5	**2**

Due to the presence of scattered solar production sources in the investigated system, production and consumption have been completely equalized and the difference between production and consumption has reached less than 5%.

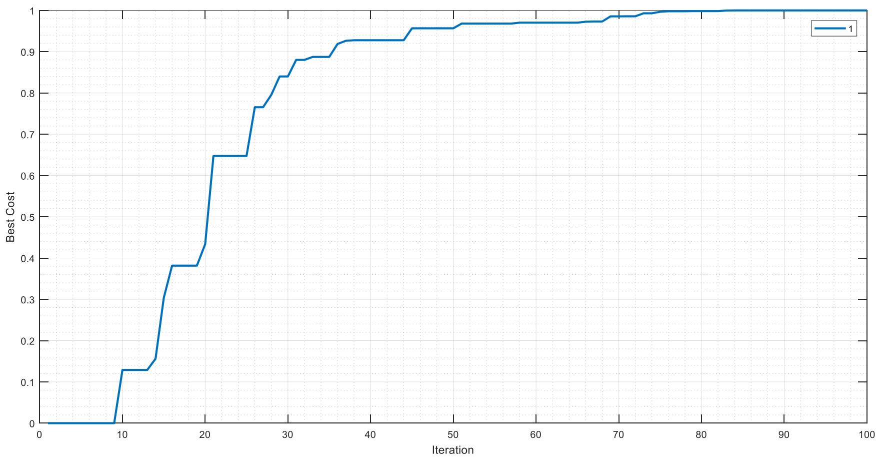

Fig. 16. Maximization of the mu coefficient related to the fourth review[6].

5. CONCLUSION

This research investigates the solution to the economic dispatching of cargo problem. In all power systems, traditional methods provide part of the system's energy, while the other part is provided using scattered productions and renewable energies. The investigated system comprises 13 solar power plants and 6 fossil fuel power plants. The aim of load response is to decrease fuel consumption and costs, thereby reducing environmental pollution. This study utilizes a meta-heuristic algorithm, specifically the particle swarm algorithm, to achieve this goal. This study utilizes a meta-heuristic algorithm, specifically the particle swarm algorithm, to achieve this goal. This study utilizes a meta-heuristic algorithm, specifically the particle swarm algorithm, to achieve this goal. The algorithm has been optimized for multiple objectives, resulting in a system with a multi-objective function. The primary objective of this research is to allocate appropriate production to fuel power plants based on the coefficients used to determine the cost of energy production by each unit. The algorithm has been designed to allocate the optimal amount of production to each unit. The secondary objective is to identify the optimal hours for electric vehicles to be present in the system as a storage device. The following section aims to decrease fuel consumption, thereby reducing both pollution and cost. Subsequently, the algorithm was utilized to increase the likelihood of equality between production and consumption. Finally, this section analyzes the system's performance over a 24-hour period to evaluate the effectiveness of the optimization results obtained in this study. This section presents the diagram and numerical results of the analysis. The subsequent section will discuss the total.

6. SUGGESTIONS

In other studies, to introduce innovation in these systems, the system can be modeled using Markov space and solved through unsupervised learning methods. This approach allows for real-time optimization in the event of system changes.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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