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Efficient optimization of static economic load dispatch in electrical power systems using the teaching–learning based optimization algorithm

Introduction. Power grids are considered one of the most critical energy infrastructures in modern societies, and their economic exploitation plays an important role in reducing the costs of generating electrical energy and increasing the efficiency of generation systems. In the meantime, power generation plants are responsible for providing the required power to the grid, and the optimal distribution of power among them has a direct impact on the final cost of energy generation. For this reason, the economic load dispatch (ELD) problem has been raised as one of the fundamental issues in the optimal operation of power systems. **Problem.** The static economic load dispatch problem is defined with the aim of determining the amount of power generated by each generator unit in such a way that the total cost of energy generation is minimized, while all operational constraints of the power system, including power balance constraints, transmission network losses, generator production constraints, power rate of change constraints, and prohibited areas, are met. The presence of features such as nonlinear cost function, valve-point effect and nonconvex search space makes solving this problem with classical mathematical methods face serious challenges. **Goal.** To develop an efficient method for solving the ELD problem and to achieve an optimal production schedule for power system generators with minimum production cost. **Methodology.** In this study, the metaheuristic algorithm teaching–learning based optimization (TLBO) has been used to solve the ELD problem. The performance evaluation of the algorithm has been carried out on a standard 6-unit power system. **Results.** The optimization results show that the TLBO algorithm is able to provide an optimal production schedule by observing all system constraints, in which the total production cost reaches \$15452.06. To evaluate the performance quality, the results of TLBO were compared with seven well-known metaheuristic algorithms, and the simulation results showed that TLBO provided the best performance by achieving first rank in terms of objective function value, average cost, and performance stability. **Scientific novelty.** The innovation of this research lies in the effective application of the TLBO algorithm to solve the ELD problem by considering a complete set of operational constraints and providing a comprehensive comparative analysis with several metaheuristic algorithms. **Practical value.** The findings of this study indicate that the TLBO algorithm can be used as an efficient, stable, and reliable method for solving operation optimization problems in power systems and help reduce the cost of energy generation and increase the economic efficiency of power grids. References 29, tables 4, figures 2.

Key words: economic load dispatch, power system optimization, generation cost minimization, electrical power system operation, valve-point effect, metaheuristic algorithms, teaching–learning based optimization.

Вступ. Енергетичні мережі вважаються однією з найважливіших інфраструктур енергопостачання в сучасному суспільстві, і їхня економічна експлуатація відіграє важливу роль у зниженні витрат на виробництво електроенергії та підвищенні ефективності систем генерації. У той же час електростанції відповідають за забезпечення мережі необхідною потужністю, і оптимальне розподілення потужності між ними безпосередньо впливає на кінцеву вартість виробництва енергії. З цієї причини завдання економічного розподілу навантаження (ELD) було поставлено як одну з фундаментальних проблем оптимальної роботи енергосистем. **Проблема.** Статичне завдання економічного розподілу навантаження визначається з метою визначення кількості електроенергії, що виробляється кожним генераторним блоком, таким чином, щоб мінімізувати загальну вартість виробництва енергії, при цьому дотримувалися всі експлуатаційні обмеження енергосистеми, включаючи обмеження балансу потужності, втрати в передавальній мережі, обмеження на виробництво електроенергії генераторами. Наявність таких особливостей, як нелінійна функція вартості, ефект точки включення та невипуклий простір пошуку робить рішення цього завдання класичними математичними методами серйозною проблемою. **Мета.** Розробка ефективного методу розв'язання ELD задач та досягнення оптимального графіка виробництва для генераторів енергосистеми з мінімальними виробничими витратами. **Методика.** У цьому дослідженні для розв'язання задачі ELD використовувався метаевристичний алгоритм оптимізації на основі навчання та викладання (TLBO). Оцінка продуктивності алгоритму проводилася на стандартній шестиблочній енергосистемі. **Результати** оптимізації показують, що алгоритм TLBO здатний забезпечити оптимальний графік виробництва з урахуванням усіх системних обмежень, при цьому загальні виробничі витрати сягають \$15452,06. Для оцінки якості роботи результати TLBO порівнювалися з сімома відомими метаевристичними алгоритмами, і результати моделювання показали, що TLBO забезпечує найкращу продуктивність, займаючи перше місце за значенням цільової функції, середньої вартості та стабільності роботи. **Наукова новизна.** Інновація даного дослідження полягає в ефективному застосуванні алгоритму TLBO для вирішення задачі ELD з урахуванням повного набору експлуатаційних обмежень та надання всебічного порівняльного аналізу з декількома метаевристичними алгоритмами. **Практична значимість.** Результати цього дослідження показують, що алгоритм TLBO може бути використаний як ефективний, стабільний і надійний метод для вирішення завдань оптимізації роботи енергосистем, сприяючи зниженню собівартості виробництва енергії та підвищенню економічної ефективності електромереж. Бібл. 29, табл. 4, рис. 2.

Ключові слова: економічний розподіл навантаження, оптимізація енергосистеми, мінімізація собівартості генерації, експлуатація електроенергетичної системи, ефект перемикавання клапанів, метаевристичні алгоритми, оптимізація на основі навчання та викладання.

Introduction. Electric power networks are recognized as one of the most important critical infrastructures in modern societies and play a fundamental role in providing energy to various industrial, commercial and domestic sectors. The rapid growth in demand for electrical energy, the development of industries and the increasing dependence of societies on electrical systems have made economical, safe and reliable exploitation of power networks one of the most important concerns of engineers and power system planners. In the meantime,

electric power generation plants, as the main production components in power networks, are responsible for providing the power needed by consumers. Given the high costs of electric power generation, the way power is distributed among generating units has a direct impact on the final cost of energy production and the economic efficiency of the power system. Therefore, the development of efficient methods for optimal allocation of generated power among power plant units is of particular importance.

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One of the fundamental problems in the economic operation of power systems is the economic load dispatch (ELD) problem. The main goal of this problem is to determine the amount of power generated by each generator unit in such a way that the total cost of generating electrical energy is minimized while at the same time observing all operational constraints of the power system [1]. These constraints include power balance constraints, transmission network losses, generator generation constraints, power rate of change constraints, and also prohibited areas of operation. The ELD problem is actually one of the most important optimization problems in the field of power system operation, and its accurate solution can lead to significant reduction in energy production costs and increased power plant efficiency [2].

Among the different variants of this problem, static economic load dispatch (SELD) refers to a case where the power system conditions are assumed to be constant over a short period of time – usually 1 hour – and the goal is to optimally distribute the generated power among the power plant units [3]. Although the SELD model seems simpler than its dynamic version, in practice it is still a complex, nonlinear and nonconvex optimization problem. The presence of factors such as the valve point loading effect on the cost function of generators, the consideration of transmission network losses, power rate constraints and prohibited operation areas causes the search space of this problem to have multi-peaked and discontinuous characteristics [4]. For this reason, despite the successful performance of classical mathematical methods in solving many problems [5, 6], the use of classical gradient-based optimization methods or mathematical programming in many cases encounters problems such as poor convergence or getting stuck in local optima [7].

In recent decades, the use of metaheuristic algorithms as powerful tools for solving complex optimization problems has attracted widespread attention from researchers. These algorithms, which are often inspired by natural phenomena, biological behaviors, or social processes, are able to effectively explore the response space without the need for gradient information and using population search, and provide high-quality answers to complex optimization problems [8, 9]. Features such as global search ability, high flexibility, and the ability to solve nonlinear and nonconvex problems have led to these algorithms being widely used in various engineering fields, including power system optimization [10–13].

Numerous studies have also been conducted in the field of ELD problem using metaheuristic algorithms. For example, in one of the early studies in this field, an adaptive particle swarm optimization method was proposed to solve the ELD problem, which was able to consider constraints such as network losses, dynamic constraints, and prohibited areas of operation, and the results showed that this method performed well compared to conventional methods in terms of convergence speed and response quality [14]. In another study, the ELD problem was modeled as a dynamic programming problem by considering the spinning reserve constraint, and an efficient algorithm was presented to solve the sequence of load dispatch problems in different time intervals [15].

In recent years, various approaches based on advanced metaheuristic algorithms have been developed

to solve the ELD problem. For example, a hybrid method based on slime mould algorithm and genetic algorithm has been proposed to solve the ELD problem in microgrids, which has been able to provide better performance than several known algorithms by increasing the population diversity in the early stages of the search and enhancing the exploitation power in the final stages [16]. Also, newer algorithms such as osprey optimization algorithm have been used to solve ELD and SELD problems, and their results have shown that these algorithms have a good ability to reduce the production cost and improve the stability of the responses [17].

In addition, some research has investigated hybrid and more advanced approaches. For example, the use of metaheuristic algorithms in combined economic emission dispatch planning has been studied considering renewable energy sources and demand side management [18]. In another study, a new crowd-learning-based algorithm called achieving and refining knowledge-based optimization was introduced to solve the SELD problem, which uses the crowd-learning process in the population to improve the search performance [19]. Also, advanced parameter less algorithms such as self-adaptive multi-population quadratic approximation guided Jaya have been used to solve ELD problems in power systems with different numbers of generating units, which have been able to significantly reduce the production cost compared to previous methods [20].

Along with these studies, the use of hybrid metaheuristic algorithms has also been considered. For example, a meme version of salp swarm algorithm has been developed to solve ELD problems with strong constraints, in which the combination of the global search of the population algorithm with the local search of the improver has led to increased accuracy and convergence speed in finding optimal solutions [21].

Despite significant advances in this area, there are still several challenges in solving the ELD problem. The high complexity of the search space, the existence of multiple operational constraints, the nonlinear and multi-peaked behavior of the cost function, as well as the need to achieve stable and reliable responses in limited computational time are among the factors that necessitate the development of more efficient optimization methods. In addition, many metaheuristic algorithms require fine tuning of control parameters and their performance can be highly dependent on the choice of these parameters. This issue causes that in some practical applications, the use of these algorithms is associated with additional complexities.

In the meantime, the teaching–learning based optimization (TLBO) algorithm has been proposed as one of the effective metaheuristic algorithms that are inspired by the learning process in educational environments. This algorithm operates based on two main stages teacher phase and student phase and tries to gradually improve the quality level of responses by using the interaction between population members. One of the important features of TLBO is that, unlike many metaheuristic algorithms, it does not require complex control parameters and can be implemented using only the population size and number of iterations. This feature makes its implementation and use process relatively simple and has good stability in solving complex optimization problems.

The goal of this work is to develop an efficient method for solving the ELD problem and to achieve an optimal production schedule for power system generators with minimum production cost.

In this study, the ELD problem is modeled by considering a set of operational constraints including power balance constraint, transmission network losses, generator generation constraints, power rate of change constraints, and prohibited operation areas. Then, the TLBO algorithm is used as an optimization tool to minimize the total cost of electrical energy generation.

The main innovations and contributions of this research can be summarized as follows:

- investigating the SELD problem in a power system considering a complete set of real operating constraints;
- providing an accurate mathematical model of the ELD problem including the generation cost objective function and the power system operating constraints;
- using the TLBO algorithm as an efficient optimization method for solving the ELD problem;
- conducting simulation studies on a standard 6-unit power system to evaluate the performance of the algorithm;
- conducting a comprehensive comparative analysis between the performance of TLBO and seven well-known metaheuristic algorithms in order to development the quality of responses, performance stability, and convergence speed.

The obtained results show that the TLBO algorithm is able to provide an optimal generation schedule for generators by observing all power system constraints and shows very competitive and stable performance compared to several well-known metaheuristic algorithms.

Problem statement and mathematical modeling.

The ELD problem is one of the fundamental problems in the optimal operation of power systems. The main objective in this problem is to determine the amount of power generated by each generator unit in such a way that the total cost of generating electrical energy is minimized, while all operating constraints of the power system are met.

In the static version of this problem, known as SELD, the operating time period is usually considered to be a short period such as 1 hour. In this framework, it is assumed that the system conditions are constant during this time period and the goal is to distribute the generated power among the operating units in an optimal manner. At the same time, it must be ensured that the system load demand is met and the technical constraints of the generators such as generation limits, power rate limit and prohibited operation areas are observed.

In general, the mathematical model of the ELD problem consists of a production cost objective function and a set of physical and operational constraints, which are presented below.

Objective function. In many power system studies, the fuel cost of the generating units can be approximated by a quadratic function of the generator output power. Accordingly, the objective function of the problem is expressed as the minimization of the total production cost:

$$\text{Minimize} : F = \sum_{i=1}^{N_G} f_i(P_i), \quad (1)$$

where F is the total production cost of the system; N_G is the number of generating units in operation; P_i is the

actual output power of generator i (MW); $f_i(P_i)$ is the production cost function of generator i .

The cost function of each generator is modeled as:

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i, \quad (2)$$

where the coefficients a_i , b_i , c_i are the cost coefficients related to the generating unit i .

In some power plants, due to the valve point loading effect, the cost function has a nonsmooth and oscillating behavior. In this case, the cost function is modified as:

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin \left(f_i \left(P_i^{\min} - P_i \right) \right) \right|, \quad (3)$$

where e_i , f_i are the coefficients related to the valve point loading effect and cause discontinuity and multi-peaking of the cost function. The existence of these features makes the ELD problem a nonlinear and nonconvex optimization problem.

Power balance constraint. The most important constraint in the ELD problem is the power balance constraint. According to this constraint, the total power generated by the generators must be equal to the sum of the system load demand and the power losses in the network. This relationship is expressed as:

$$\sum_{i=1}^{N_G} P_i = P_D + P_L, \quad (4)$$

where P_D is the system load demand power; P_L is the power losses in the transmission network

Power losses are usually calculated using B -factors as:

$$P_L = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{0i} P_i + B_{00}, \quad (5)$$

where B_{ij} , B_{0i} , B_{00} are the network loss factors.

Generator production limits. Each generating unit has a minimum and maximum power that can be produced, which is determined by the technical limitations of the equipment. Therefore, the output power of each generator must be within its allowed range:

$$P_i^{\min} \leq P_i \leq P_i^{\max}, \quad (6)$$

where P_i^{\min} is the minimum power output of generator i ; P_i^{\max} is the maximum power output of generator i .

Power rate limit. In practical power plant operation conditions, generators are not able to change their output power suddenly. For this reason, the rate of increase or decrease in their power is limited, which is called ramp rate limit.

If the generated power increases:

$$P_i^t - P_i^{t-1} \leq UR_i, \quad (7)$$

And if the generated power decreases:

$$P_i^{t-1} - P_i^t \leq DR_i, \quad (8)$$

where P_i^{t-1} is the generated power of unit i in the previous time period; UR_i is the upper limit of the power increase rate; DR_i is the lower limit of the power decrease rate.

As a result, the generator operating range is modified by considering these limitations as:

$$\max(P_i^{\min}, P_i^{t-1} - DR_i) \leq P_i^t \leq \min(P_i^{\max}, P_i^{t-1} + UR_i). \quad (9)$$

Prohibited operating zones. In some generators, there are ranges of generated power in which operation is not allowed due to mechanical limitations or instability phenomena. These areas, known as prohibited operating zones, may be caused by factors such as shaft vibrations, steam valve problems or mechanical limitations of the equipment. Therefore, the generator output power must be outside these areas. Symbolically for unit i :

$$P_i \leq P_{i,k}^{lower} \quad \text{or} \quad P_i \geq P_{i,k}^{upper}, \quad (10)$$

where $P_{i,k}^{lower}$, $P_{i,k}^{upper}$ are the lower and upper bounds of the forbidden region k for generator i , respectively.

If the minimum or maximum generator output limits fall within a forbidden region, these limits must be modified to prevent the generator operating point from falling within the forbidden region.

Problem solving method. Due to the presence of nonlinear, discontinuous, and multi-peaked cost function as well as numerous operational constraints, the SELD problem becomes a complex optimization problem that is difficult to solve with classical mathematical methods in many cases. For this reason, in recent years, the use of metaheuristic algorithms to solve this problem has received widespread attention.

In this paper, the TLBO algorithm is used to solve the SELD problem. Inspired by the learning process in educational environments, this algorithm is able to provide high-quality answers to complex optimization problems by creating an appropriate balance between global search and local search. In the following, the structure and steps of the TLBO algorithm are introduced and how it is applied to solve the ELD problem in the power system will be explained.

The TLBO algorithm is one of the efficient metaheuristic algorithms in the field of optimization, which was first introduced by Rao R. V. et al [22]. The main idea of this algorithm is inspired by the learning process in educational environments. In an educational environment, the knowledge and scientific level of students are improved through two main processes: first learning from the teacher and then learning from interaction with other students.

The TLBO algorithm, by modeling these two steps, gradually guides a population of possible answers towards the optimal answer. In this algorithm, each member of the population is considered as a learner and the best member of the population plays the role of teacher. During the optimization process, students try to improve their knowledge level by learning from the teacher and also by interacting with each other.

One of the important features of TLBO is that, unlike many metaheuristic algorithms, it does not require complex control parameters and operates only using the population size and the number of iterations. This feature makes it simple to implement and has good stability in solving complex optimization problems.

In the framework of optimization problems, each student represents an answer vector and the value of the objective function will indicate the knowledge level or quality of the answer of that student. In the following, the mathematical model of the TLBO algorithm is presented in two main phases, namely teacher phase and student phase.

Representation of answers and initializing the population. Suppose that the optimization problem has D decision variables. In the TLBO algorithm, an initial population of N students is randomly generated in the search space. Each student is represented as a vector as:

$$X_i = [x_{i,1}, x_{i,2}, \dots, x_{i,D}], \quad i = 1, 2, \dots, N, \quad (11)$$

where X_i is the position of student i in the search space. After generating the initial population, the value of the objective

function is calculated for all individuals and the best individual in the population is selected as the class teacher.

Teacher phase. In an educational class, the teacher tries to increase the knowledge level of the entire class. In the TLBO algorithm, the teacher also tries to bring the average knowledge of the class closer to his knowledge level.

First, the population mean is calculated as:

$$M = \frac{1}{N} \sum_{i=1}^N X_i. \quad (12)$$

Then the position of each student is updated using the following relationship:

$$X_i^{new} = X_i + r_i \cdot (X_{teacher} - TF \cdot M), \quad (13)$$

where $X_{teacher}$ is the best individual in the population (teacher); r_i is the random number in the interval $[0, 1]$; TF is the teaching factor, which is usually randomly set to 1 or 2, i.e., $TF \in \{1, 2\}$.

After calculating the new position, if the objective function value for X_i^{new} is better than X_i , the student's position is updated to the new value.

Learner phase. In educational environments, students learn from interacting and exchanging information with other students in addition to learning from the teacher. In the TLBO algorithm, this concept is modeled in the form of the learner phase.

In this step, for each student X_i , another student X_j is randomly selected $i \neq j$. Then, based on the comparison of the objective function values of these 2 students, the new position is calculated as:

$$X_i^{new} = \begin{cases} X_i + r_i \cdot (X_i - X_j), & \text{if } f(X_i) < f(X_j) \\ X_i + r_i \cdot (X_j - X_i), & \text{else,} \end{cases}, \quad (14)$$

where r is the random number in the interval $[0, 1]$.

After calculating the new position, if the objective function value is better for the new response, the student's position is updated. This process increases the diversity of the population and improves the search power of the algorithm.

Application of TLBO in solving the ELD problem.

Given the nonlinear, nonconvex and multiple-constrained nature of the ELD problem, the use of classical methods in many cases encounters convergence problems and getting stuck in local optima. The TLBO algorithm is considered a suitable option for solving such optimization problems due to its simple structure, appropriate search ability, and no need to adjust complex parameters.

In this study, each student in the TLBO algorithm represents a generator power vector in the ELD problem, and the objective function will be the total system production cost as defined in the previous section. During the optimization process, the TLBO algorithm tries to minimize the value of the objective function by gradually updating the power vectors and at the same time satisfy all the constraints of the power system.

In the next section of the article, the modeling and implementation of the TLBO algorithm for solving the SELD problem will be presented in detail and the results of the optimization will be examined.

Simulation studies and results analysis. In this section, the performance of the TLBO algorithm in solving the SELD problem is investigated and evaluated. The main objective of these simulation studies is to development the ability of the TLBO algorithm to

determine the optimal generation schedule of power plants in order to minimize the total cost of electrical energy production in a real power system, taking into account all operational constraints.

Due to the nonlinear, nonconvex, and multi-peaked nature of the ELD problem – especially in the presence of the valve point loading effect, power rate limitation, and forbidden operation zones – solving this problem using classical optimization methods is very difficult. Hence, the use of advanced metaheuristic algorithms can be an effective solution to achieve high-quality answers.

In this regard, in this section, the ELD problem is investigated using the TLBO algorithm. First, the case study and data of the power system used are introduced. Then, the results obtained from implementing the TLBO algorithm on this problem are presented and analyzed. In the following, comparative studies between TLBO and several well-known metaheuristic algorithms are conducted to accurately evaluate the performance quality of this algorithm.

Introduction to the studied system and its data. In order to evaluate the performance of the proposed algorithm, the ELD problem is investigated on a power system consisting of 6 generating units (generators). This system is used as a standard case study in many power system optimization studies and includes a set of realistic operational constraints including network losses, power rate of change constraints, and prohibited operation areas.

In this system, the total network load demand is equal to $P_D = 1263$ MW. And the goal is to distribute the generated power among the 6 generators in such a way that the total cost of production is minimized while at the same time respecting all system constraints.

The transmission network losses in this system are modeled using the B coefficient matrix, which is defined as:

$$B = \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0 & -0.1 & -0.6 \\ -0.1 & 0.1 & 0 & 0.24 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.1 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15 \end{bmatrix} \times 10^{-5}.$$

Also, the coefficient vector and the loss constant are defined as:

$$B_{0i} = [-0.3908, -0.1297, 0.7047, 0.0591, 0.2161, -0.6635] \times 10^{-5};$$

$$B_{00} = 0.0056 \cdot 10^{-2}.$$

The technical characteristics of the generating units, including minimum and maximum generation power, cost function coefficients, and valve-point effect coefficients, are presented in Table 1. These data model the actual behavior of the power plant units and create a nonlinear and discontinuous cost function.

Also, information related to initial generation power, power increase and decrease rate constraints, and forbidden operation areas is reported in Table 2. The existence of these constraints complicates the search space of the problem and turns it into an optimization problem with multiple constraints and discrete response space.

Consequently, finding an optimal generation schedule for this system requires the use of a powerful optimization algorithm with the ability to search efficiently in the response space.

Table 1

Unit	P_{\min} , MW	P_{\max} , MW	a , \$/MW ²	b , \$/MW	c , \$	e	f
1	100	500	0.007	7	240	300	0.035
2	50	200	0.0095	10	200	200	0.042
3	80	300	0.009	8.5	220	150	0.042
4	50	150	0.009	11	200	120	0.063
5	50	200	0.008	10.5	220	150	0.063
6	50	120	0.0075	12	190	100	0.063

Table 2

Unit	P_0 , MW	UR, MW/h	DR, MW/h	Zone 1 min	Zone 1 max	Zone 2 min	Zone 2 max
1	440	80	120	210	240	350	380
2	170	50	90	90	110	140	160
3	200	65	100	150	170	210	240
4	150	50	90	80	90	110	120
5	190	50	90	90	110	140	150
6	150	50	90	75	85	100	105

Optimization of the ELD problem using TLBO.

In this section, the TLBO algorithm is implemented to solve the ELD problem of the studied system. In the framework of this algorithm, each student represents a vector containing the generation power of 6 generators: $X = [P_1, P_2, P_3, P_4, P_5, P_6]$. And the value of the objective function is equal to the total production cost of the system, which must be minimized.

The results obtained from the implementation of the TLBO algorithm are presented in Table 3, which shows the optimal generation schedule for each of the power plant units.

Table 3

Gen. 1	452.7068 MW
Gen. 2	171.6543 MW
Gen. 3	254.0167 MW
Gen. 4	135.0149 MW
Gen. 5	155.2349 MW
Gen. 6	106.9519 MW
Generation	1275.58 MW
Demand	1263 MW
Loss	12.58 MW
Objective function	\$15452.06

Based on these results:

- total power generated: 1275.58 MW;
- system demand load: 1263 MW;
- network losses: 12.58 MW;
- total production cost: \$15452.06.

It is observed that the total power generated by the generators is equal to the sum of demand load and network losses, which indicates exact implementation of the power balance constraint in the optimal response.

In order to examine the convergence behavior of the algorithm, the TLBO convergence curve is shown in Fig. 1.

Analysis of this curve shows that the TLBO algorithm experiences a very rapid decrease in the value of the objective function in the initial stages of the search. This indicates the high ability of the algorithm in Exploration of the search space. After the first few iterations, the objective function decreases gradually and the algorithm enters the Exploitation phase, during which the answers gradually converge around the best answer.

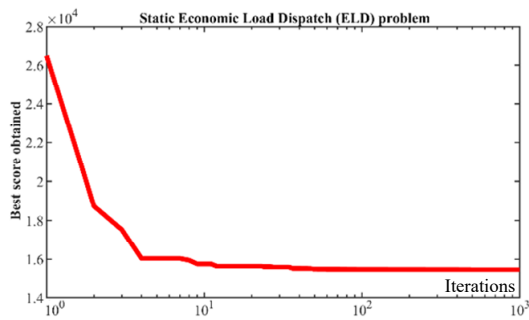


Fig. 1. TLBO convergence curve in solving the ELD problem

Around the middle iterations, the objective function value approaches a nearly constant value and very small fluctuations are observed. This behavior indicates that the algorithm has been able to achieve a stable optimal region in the search space.

Overall, the convergence curve shows that the TLBO algorithm has a suitable convergence speed and high stability in solving the ELD problem.

Comparative studies with competing algorithms. In order to accurately evaluate the performance quality of the TLBO algorithm, the results obtained have been compared with the performance of seven well-known metaheuristic algorithms: genetic algorithm (GA) [23], particle swarm optimization (PSO) [24], gravitational search algorithm (GSA) [25], whale optimization algorithm (WOA) [26], multi-verse optimizer (MVO) [27], tunicate swarm algorithm (TSA) [28] and grey wolf optimizer (GWO) [29]. The statistical results obtained from the implementation of these algorithms are presented in Table 4. Examining the mean objective function value shows that TLBO, with a value of 15467.22, has the lowest average production cost among all the algorithms. This indicates the high stability of the TLBO algorithm in multiple implementations.

Table 4
Statistical results of TLBO and competitor algorithms applied to the ELD problem

SI	TLBO	GA	PSO	GSA
Mean	15467.22	22037.65	15535.48	189616.1
Best	15452.06	15615.83	15486.05	145612.4
Worst	15484	40320.06	15599.81	234290
Std	14.69466	12196.11	48.77296	36358.59
Median	15466.4	16107.36	15528.04	189281
Rank	1	7	5	8
SI	MVO	WOA	GWO	TSA
Mean	15502.55	15589.42	15504.69	15509.38
Best	15472.31	15457.59	15469.45	15485.58
Worst	15557.81	15725.69	15524.75	15520.32
Std	38.14957	125.157	25.18478	16.01018
Median	15490.04	15587.2	15512.27	15515.8
Rank	2	6	3	4

In terms of best value, TLBO also performed very competitively with a value of 15452.06 and in many cases better than other algorithms.

Also, the standard deviation (std) for TLBO is 14.69, which is a very small value compared to most other algorithms. This shows that the TLBO algorithm has very stable and reliable behavior in different implementations.

In contrast, algorithms such as GA and GSA have very large standard deviations, which indicate lack of stability and high sensitivity to initial conditions.

Finally, the ranking presented in Table 4 shows that TLBO has achieved the 1st rank among all algorithms.

To provide a visual analysis of the results, Boxplot graphs related to the performance of the algorithms are displayed in Fig. 2.

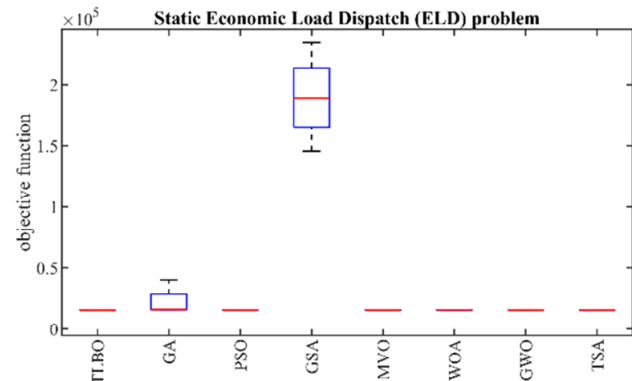


Fig. 2. Boxplot diagram of the performance of the algorithms on the ELD problem

Analysis of these diagrams shows that:

- TLBO has the lowest dispersion of results;
- the range of changes in the responses in TLBO is very limited;
- the median value in TLBO is very close to the optimal value.

These features indicate that TLBO is able to achieve responses very close to the optimal response in most implementations.

Discussion. The results of simulation studies show that the TLBO algorithm exhibits very effective performance in solving the SELD problem. This algorithm has been able to provide an optimal generation schedule for generators, which leads to minimizing the total cost of energy production, while respecting all power system constraints.

Comparative studies also show that TLBO has superior performance compared to known metaheuristic algorithms. In particular, this algorithm has achieved the lowest objective function value, lowest standard deviation, and best performance rank among the algorithms studied.

One of the most important advantages of TLBO is the no need for complex control parameters. Unlike many metaheuristic algorithms such as GA or PSO that require fine-tuning of parameters such as mutation rate, crossover rate, or acceleration coefficients, TLBO operates only using the population size and number of iterations. This feature makes its implementation and use process much simpler and more reliable.

In addition, the two-stage structure of TLBO including teacher phase and student phase creates a good balance between global search and local search in the response space. This feature plays an important role in preventing the algorithm from getting stuck in local optima.

Despite these advantages, the use of TLBO also has some limitations. For example, in very large-scale problems, the convergence speed of the algorithm may decrease. Also, in some problems with very complex search spaces, there may be a need to combine TLBO with other improvement techniques.

However, the results of this study show that TLBO is an efficient, stable, and reliable method for solving the ELD problem in power systems.

Finally, the most important finding of this study is that the TLBO algorithm is able to provide high-quality answers to the SELD problem with appropriate convergence speed and high stability and has superior performance compared to many known metaheuristic algorithms. This indicates that TLBO can be used as an effective tool in power system operation optimization problems.

Conclusions. Power systems, as one of the vital infrastructures of modern societies, play a fundamental role in providing the electrical energy needed by the industrial, commercial and domestic sectors. The economic and reliable operation of these systems largely depends on the proper operation of power generation plants and the optimal distribution of generated power among them. In the meantime, the ELD problem has been raised as one of the fundamental problems in the operation of power networks, the main goal of which is to determine the optimal generation schedule of power plant units in such a way that the total cost of electrical energy generation is minimized while all system operating constraints are met.

Due to the nonlinear, nonconvex and multi-peaked characteristics of the ELD problem – especially in the presence of valve point loading effect, power rate constraints and prohibited operation areas – solving this problem using classical mathematical methods has faced serious challenges in many cases. For this reason, in recent years, the use of metaheuristic algorithms as powerful tools for solving complex optimization problems in power systems has received widespread attention from researchers.

In this study, the SELD problem was investigated in a power system consisting of 6 generating units, and the TLBO algorithm was used as a problem-solving method. In this framework, each member of the TLBO algorithm population was considered to represent a generator power vector in the power system, and the objective function was defined as minimizing the total cost of energy production. Also, all system operating constraints, including power balance constraints, transmission network losses, generator generation constraints, power rate of change constraints, and prohibited operation areas were included in the optimization model.

Simulation studies were conducted on a 6-unit power system in which the total network load demand was considered to be 1263 MW. The optimization results showed that the TLBO algorithm was able to provide an optimal generation schedule for the generators such that the total generated power was 1275.58 MW and after considering 12.58 MW of network losses, the system power balance constraint was accurately established. The total generation cost obtained was also reported to be \$15452.06, which indicates the appropriate performance of the algorithm in achieving quality responses.

In order to accurately evaluate the performance quality of the TLBO algorithm, the results obtained from this algorithm were compared with the performance of seven well-known metaheuristic algorithms GA, PSO, GSA, WOA, MVO, TSA, and GWO. The results of the comparative studies showed that the TLBO algorithm was

able to provide the best performance among all the algorithms studied. Specifically, this algorithm achieved the lowest objective function value, the lowest average production cost, and the lowest standard deviation in different runs. Based on the presented statistical results, TLBO was introduced as the most efficient method for solving the ELD problem in this study, ranking first among the eight algorithms studied.

The analysis of the simulation results also showed that the TLBO algorithm has appropriate convergence speed, high stability in multiple runs, and effective ability to search the response space. One of the most important advantages of this algorithm is the lack of need to adjust complex control parameters, which simplifies its implementation and increases its reliability in practical applications. In addition, the two-stage structure of the algorithm, including teacher phase and student phase, creates an effective balance between global search and local search and reduces the possibility of getting stuck in local optima.

Based on the results obtained, the findings of this study showed that the TLBO algorithm is an efficient, stable and competitive method for solving the ELD problem in power systems and can be used as a suitable tool in power grid operation optimization problems. The use of this algorithm can lead to reducing the cost of electric energy generation, increasing the efficiency of power plants and improving the economic performance of the power system.

Despite the successful results obtained in this study, there are still several areas for the development and expansion of this study in future research. Some of the most important research suggestions for future work include:

1. Developing the proposed model for solving the ELD problem, in which time variations of the load and dynamic constraints of the power system are considered.
2. Investigating the performance of the TLBO algorithm in large-scale power systems with a larger number of generators and comparing it with other advanced metaheuristic algorithms.
3. Combining the TLBO algorithm with other optimization methods or artificial intelligence techniques to create hybrid algorithms with stronger search capabilities and higher convergence speed.
4. Extending the ELD problem model by considering renewable energy sources such as wind and solar power plants and investigating the impact of the uncertainty of the production of these sources on the optimization process.
5. Development of multi-objective versions of the TLBO algorithm to solve power system operation problems in which, in addition to the production cost, indicators such as pollutant emissions, system reliability, and network stability are simultaneously optimized.

Overall, the results of this research showed that using the TLBO algorithm can be an effective approach to solving complex optimization problems in power systems and provide a suitable path for the development of future research in the field of economic operation of power networks.

Conflict of interest. The authors declare that they have no conflicts of interest.

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