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Majority–Dominant–Mixed Strategy Game Theory Model for Deregulated Generation Expansion Planning Problem

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Abstract: Obtaining an optimum solution in a deregulated generation expansion planning (GEP) using a mixed strategy game theory method has faced a computation problem. Therefore, this paper proposes a new method called the majority–dominant–mixed strategy (MDMS) game theory to obtain the optimum solution with an acceptable computation time. The MDMS is a social science optimization-based approach that combines a social science concept called the majority rule and the dominant strategy with the mixed strategy. The research results show that the MDMS saves computation time by reducing the matrix size, as shown in the reduced quadratic coefficient of the time complexity trend line. Compared with the mixed strategy, the MDMS obtains the optimum solution with a significant computation time reduction. The optimum solution of the levelized total cost obtained using the MDMS is similar to that obtained using the mixed strategy and lower than that of the improved genetic algorithm (IGA). The MDMS requires a computation time of 23.1 hours, while the mixed strategy requires nine days. The MDMS computation time only slightly differs from that of the IGA previously used in regulated GEP.

Keywords: Deregulated generation expansion planning; social science; game theory; majority dominant strategy; time complexity

1. Introduction

The electricity industry is shifting from a regulated to a deregulated market, which has prompted the research on generation expansion planning (GEP). Before the market change, the regulated electricity market is the basic model of the GEP. The shift to a deregulated market creates a new problem called deregulated GEP (DGEP) because the electricity industry is assumed to operate as a deregulated market[1].

In the conventional (regulated) GEP, the electricity market is a monopoly, which means a public utility owns all power plants. Therefore, there is no competition between power plants to obtain maximum profit. Because of the monopoly system, the electricity price is only defined by the utility. However, in the deregulated market, the electricity market is a competitive market, which means the power plants are owned by more than one generation company (Genco)[2]. Each Genco competes for its maximum payoff[3]. Under the deregulated market, the utility cannot define the electricity price because it is defined based on the Genco competition. Because of the market competition in the deregulated market, an optimization method representing the Genco competition mechanism is needed[4]. Game theory is one of the best optimization methods to solve the Genco competition problem[5]. In terms of solving the Genco competition, two factors should be considered in the game theory: the model's characteristics to get the optimal value and the computational burden.

Based on the game model, game theory can be classified into two types: cooperative game and non-cooperative game[6]. In the cooperative game model, the decision-making process of each Genco is based on not only personal rationality but also collective rationality and social optimality; these are combined to gain better profits. In this game, there is a possibility of cooperation between Gencos to realize increased profits. Examples of cooperative game implementation include the power retailers' competition in a spot market[7] and competition on building a distributed heating network[8]. An optimum solution in the cooperative game has been found using the Nash bargaining model[6].

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Unlike in the cooperative game model, the decision-making process in the non-cooperative game model is based solely on personal rationality to maximize personal profit without considering cooperation with other Gencos[6]. Examples of non-cooperative games have been modeled in [9] and [10]. In [9], a non-cooperative game strategy was used to model the competition between wind power plants in a deregulated market by considering the ramping rate factor. In [10], a non-cooperative game strategy was used to model the effect of dynamic pricing in a deregulated market.

An optimum solution in non-cooperative game models can be found by using different models, such as the Stackelberg model[11], the Cournot model[5], and a simultaneous quantity model[1]. The Stackelberg model is a sequential quantity leadership model that involves a sequential scheme movement of all companies[11]. For example, Company 1 moves first and is followed by Company 2. To find the optimum solution in the Stackelberg model, [12] used the Lagrangian function, while [13] used a combination of the particle swarm optimization algorithm and nonlinear programming to find the optimum solution.

The Cournot model is a simultaneous quantity model[5]. In this model, all companies are assumed to be moving simultaneously. Unlike in the Stackelberg, there is no order of company movement in the Cournot model. In [14], the optimum solution in the Cournot model was found using the determining-optimal-quantity algorithm, while in [15], the optimum solution was found using the generalized Nash equilibrium based on the Karush-Kuhn-Tucker conditions. In another research, the Gauss-Seidel iterative method was used to find the optimum solution[16].

Besides the Cournot model, there is another type of simultaneous model that does not use the Cournot mechanism, which is called the simultaneous quantity model. In this model, all companies simultaneously decide their strategy, and the optimum solution is found using a mixed strategy method[1]. In one study[1], a multi-objective function and a multi-period framework were combined into the game theory to optimize GEP in a deregulated market. The optimal solution in this model was found in the Nash equilibrium condition (NEC). To find the NEC, the research used a mixed strategy method. The computation time required in [1] was nine days due to the Nash equilibrium searching process.

In addition to [1], another study [17] has also shown the extended computation time to be the disadvantage of using the mixed strategy method. In [17], the computation time increased in proportion to the increasing number of players and strategies. This was caused by the searching mechanism of the mixed strategy method to find the optimum solution in the NEC. The mixed strategy used the greatest probability value of each strategy in each player to find the NEC. Increasing the number of players and strategies increased the probability value sought. The statement on computation time disadvantage is also supported by the result of [18], which shows that computation time is the main problem in DGEP. Because of the computation time problem, implementing DGEP in big power systems is difficult.

In [1] and [17], the computation time problem was caused by the Nash equilibrium searching process. A faster method to find the Nash equilibrium and consequently reduce the computation time is needed to solve the problem. Not only realizing a faster computation time but also keeping the optimum result is important. Therefore, this research focuses on developing a faster method to find the Nash equilibrium while maintaining the optimum result.

In the game theory model, especially in the non-cooperative model, a dominant strategy is important for finding the NEC. The dominant strategy is a player's strategy that gives the best payoff, even when the other players change their strategies[19]. Rationally, every player will choose the strategy that gives the best payoff[20]. The location of the strategy that gives the best payoff is the location of the NEC. However, a problem may arise from the dominant strategy if the player does not have a dominant strategy or has more than one dominant strategy. This will result in a lack of a unique solution. No unique solution means that there is no Nash equilibrium or more than one Nash equilibria[21], and this is the disadvantage of using the dominant strategy. Thus, [1] used a mixed strategy rather than the dominant strategy to find the Nash equilibrium. However, the current study did not use the mixed strategy because of its disadvantage related to computation time.

Branching into the social science field has helped to identify a solution to this problem. Social science involves an organized study of relationships between macro variables, such as culture and society, and micro variables, such as human interactions[22]. An example of a social science topic of study is the majority rule in a democratic system. In the context of the current research topic, the majority-rule game is a game in which the optimum strategy is chosen based on the majority-rule. In other words, the strategy chosen by more than half of the players will be the optimum solution[23]. The majority rule is derived from the decision-making process in a democratic system[24]. The majority-rule division game was proved in [25] to be the simplest equilibrium that resulted in less computation time.

By adopting this democratic concept, in the majority-rule game in [23], most players' strategy is set as an optimum solution. Another study [26] combined the majority rule with the bargaining set theory. The result of the combination was flexible majority rules[24]. The bargaining process can be used to decrease the game size[15]. The game size is proportional to the computation time.

On the other hand, another study has proved a sub-optimality in the majority-rule model, especially in a stochastically correlated environment[28]. In the study, the dominant strategy rule was better than the majority rule in the stochastically correlated environment.

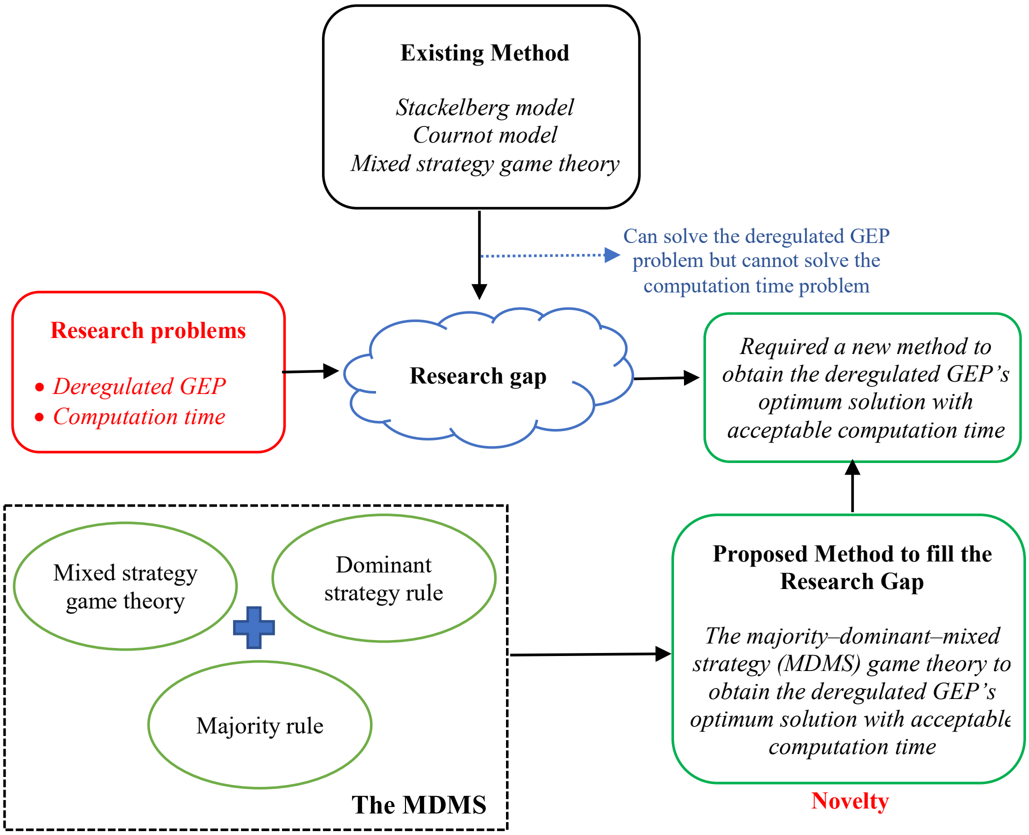

Figure 1. Novelty Offered by this Research

By considering the pros and cons of the majority rule and the characteristics of the dominant strategy in terms of the Nash equilibrium, the current research proposes a new method that combines the dominant strategy and the majority rule with the mixed strategy. The combination of the dominant strategy and the majority rule resolves the lack of a unique solution while realizing less computation time, while the mixed strategy is used to maintaining the optimum result. In this research, the combination is called the majority–dominant–mixed strategy

(MDMS) game theory rule. Using the MDMS, the optimum strategy is obtained based on the location of the dominant strategy chosen by the majority (hereafter referred to as "the majority dominant strategy"). The computation time is directly proportional to the algorithm's complexity related to the matrix size[29], which can be represented by the time complexity[30]. The effective method to analyze the time complexity of an algorithm is the big-O notation[31]. Therefore, this research uses the big-O notation to analyze and compare the time complexity between the proposed method and the game theory mixed strategy.

The purposes of this research are to create a new method to find the NEC based on a social science optimization-based approach, obtain the optimum solution, and solve the computation time problem in a deregulated market. The deregulated market is modeled as a non-cooperative game, and it is solved using a simultaneous quantity model. This research offers a novelty in creating a new method called the MDMS to obtain the deregulated GEP's optimum solution with acceptable computation time, as shown in Figure 1. The MDMS is proposed to fill the research gap on obtaining the deregulated GEP's optimum solution with acceptable computation time. It is hoped that by implementing this method, the optimum solution is obtained, and the computation time is reduced, making the game theory more viable for use on larger power systems.

The MDMS was implemented in two case studies. The first was to analyze the time complexity of the proposed method, and the second was to prove the effectiveness of the proposed method in DGEP. The first case study consists of different scenarios, whereby all scenarios equally have four existing power plants but different numbers of candidate power plants, from 3 to 16. The numbers of power plants were different to analyze the impact of the number of power plant strategies on the computation time. Based on the first case study results, the big-O notation can be obtained.

The second case study consists of 15 existing power plants and five candidate power plants. The case study has previously been considered in [32] and [1]. In [32], an improved genetic algorithm (IGA) was applied, considering a regulated market point of view. Later on, unlike in [32], a deregulated point of view was considered in [1], and a game theory mixed strategy was applied to solve the optimization problem. The effectiveness and validity of the method proposed in this research were assessed by comparing the obtained levelized total cost (LTC) and computation time with those of the game theory mixed strategy and IGA, as these methods considered similar case studies.

2. Notation

The notations used throughout the paper are stated below:

Indices:

i	the player number
J	the strategy number
N	the total number of players
X	the total combinations of power plant
x	the index of power plant combination
m	the total number of strategies for ith player
t	Years

Constants:

s	strategy
S_j	the number of dominant strategies in j
S_{-j}	the number of dominant strategies located outside of j
$\mu^i(\sigma)$	the player-i^{th} payoff (US dollar)
$\mu^i(\sigma^{(-i)}, s_j^i)$	the player-i^{th} payoff for each strategy-j^{th} without considering the player-i^{th} strategy probability (US dollar)

μ_j^i	the player-i[th] payoff in strategy-j[th] (US dollar)
∇	gradient function
∇^2	Hessian function
$\nabla \quad L(x,\lambda,\mu)$	the gradient of Lagrangian function
$\nabla^2 L(x,\lambda,\mu)$	the hessian of Lagrangian function
$LOLP$	loss of load probability index
β^i	the optimum payoff of player-i^{th} (US dollar)
σ_j^i	the strategy-j^{th} probability from player-i^{th}
$f(x)$	nonlinear function
$h(x)$, $g(x)$	constrains of nonlinear function
$L(x,\lambda,\mu)$	Lagrangian function
λ	the coefficient of h(x) in Lagrangian function
μ	the coefficient of g(x) in Lagrangian function
Loc_{dom}^i	the location of the i^{th} player dominant strategy
Loc_{major}	the location of the majority dominant strategy
P_x	the cumulative probability
T_x	the duration of loss of load
LTC	levelized total cost (US dollar)
$Investment_t$	investment cost in t^{th} year (US dollar)
$O\&M_t$	operation and maintenance cost in t^{th} year (US dollar)
$Fuel_t$	fuel cost in t^{th} year (US dollar)
r	discount rate (%)

3. Problem Formulation

The shift of GEP from a regulated market to a deregulated market creates a new problem known as the DGEP problem, which features a computation time challenge. Therefore, a method that can be implemented in DGEP to create an optimum solution with an acceptable computation time is needed. This research aims to create a new method based on a social science optimization-based approach that satisfactorily answers the defined problems.

In [32], an IGA is proposed to solve the regulated GEP problem. The results showed that the IGA performed well, with an LTC of USD 45,053 million and a computation time of 13.3 hours. However, the method was adopted for a regulated market, so it cannot be used in DGEP. Therefore, [1] proposed a game theory mixed strategy to solve the DGEP problem and compared the results with the IGA's results. The results showed that the mixed strategy performed satisfactorily. Compared with the IGA, the mixed strategy produced a lower LTC (USD 43,718 million), but its computation time (9 days) was much higher. This creates a computation time problem in DGEP. Therefore, the current study aims to create a new method based on a social science optimization-based approach to find the optimum solution in DGEP that requires a shorter computation time. To create this method, we combine the mixed strategy with a social science concept (majority rule) and a dominant strategy, forming a method we call the MDMS rule.

The MDMS was implemented in a case study with 15 existing power plants and five candidate power plants. The same case study was used in [32] and [1]. Thus, the proposed method's effectiveness and validity were assessed by comparing the LTC and computation time with those of the mixed strategy[32] and IGA[1].

The first step of the MDMS implementation is modeling the MDMS into a non-cooperative game theory. Based on the MDMS modeling, the possibility and the concept of the MDMS implementation can be known. The next step is modeling the optimization algorithm based on the MDMS. By using the optimization algorithm, the time complexity of the MDMS and the optimum solution of DGEP can be obtained with feasible computation time.

A. Modeling the MDMS into Non-Cooperative Game

In [1], a non-cooperative game theory problem was solved using a mixed strategy. In the non-cooperative game theory, the optimum solution is found in the NEC. Each player has the maximum payoff in the NEC, so they do not change their decision [17]. The mixed strategy is used to find the optimal strategy of each player in the NEC. Each strategy from each player is given a probability value. The optimal strategy is the strategy with the highest probability value.

The probability value is calculated based on the expected utility of each player. The expected utility is illustrated in Figure 2. To simplify the illustration, it is assumed that there are only two players in the game and that each player has only two strategies. The players represent power plants, i.e., a coal steam power plant and a gas turbine power plant, while strategies represent the investment decision of power plants (invest or not). The game represents the DGEP optimization process.

				Player B		Expected Utility Player 2
			Strategy	s1	s2	
			Probability	PB	1-PB	
	Strategy	Probability				
Player A	S1	PA		Solution 1 A11, B11	Solution 2 A12, B21	B11*PB + B21* (1-PB)
	S2	1-PA		Solution 3 A21, B12	Solution 4 A22, B22	B12*PB + B22* (1-PB)
Expected Utility Player A				A11*PA+A21* (1-PA)	A12*PA+A22* (1-PA)	

Figure 2. Illustration of the Expected Utility of Each Player[1]

As previously mentioned, there are two players: player A and player B. Player A has two strategies, i.e., S1 and S2, and player B has two strategies, i.e., s1 and s2. The probability of each strategy from each player has a specific value. PA is the probability of S1 chosen by player A, and $(1 - PA)$ is the probability of S2 chosen by player A. PB is the probability of s1 chosen by player B, and $(1 - PB)$ is the probability s2 chosen by player B. There are four alternative solutions in Figure 2 because there are two players, each of them having two strategies (22). Each of the alternative solutions has different payoffs for each power plant. Solution 1 has A11 as a payoff for player A, and B11 as a payoff for player B. Solution 2 has A12 as a payoff for player A, and B21 as a payoff player B. Solution 3 has A21 as a payoff for player A, and B12 as a payoff for player B. Solution 4 has A22 as a payoff for player A, and B22 as a payoff for player B.

Expected utility is used by players to analyze the game situation and make a decision under uncertainty. There are two uncertainties in Figure 2: the strategies of other players and their strategies. For example, player A does not know which strategy is chosen by player B and which one of its strategies can give the maximum payoff. Player A uses its expected utility to know which one of its strategies can give the maximum payoff. Player A has two expected utilities: the expected utility when player B chooses s1 $(A11 \times PA + A21 \times [1 - PA])$ and the expected utility when player B chooses s2 $(A12 \times PA + A22 \times [1 - PA])$. The strategy of player A that gives the maximum payoff is the strategy that has the largest probability. In the NEC, regardless of the strategy chosen by player B, player A does not change its strategy. This condition creates an optimum strategy for player A. The NEC is met when the two expected utilities from player A have the same value. Equation (1) shows the NEC of player A. For player B, the mechanism of choosing the optimum strategy is similar to that of player A. The NEC of player B is met when two expected utilities from player B have the same value. Equation (2) shows that the NEC of player B. Using (1) and (2), the optimum strategy of each player can be obtained.

$$B_{11} * P_B + B_{21} * (1 - P_B) - (B_{12} * P_B + B_{22} * (1 - P_B)) = 0 \quad (1)$$

$$A_{11} * P_A + A_{21} * (1 - P_A) - (A_{12} * P_A + A_{22} * (1 - P_A)) = 0 \quad (2)$$

This study considers a test system with 15 existing power plants and 13 candidate power plants; therefore, solving the expected utility equation is more complicated. The expected utility equation problem can be solved using sequential quadratic programming (SQP) combined with a quasi-Newton method (QNM)[17]. The SQP-QNM produces the probability value of each player's strategy. The optimum solution is the strategy that has the largest probability value for each player[1]. This method requires transforming the expected utility equation into a nonlinear function that can represent the NEC. The transformation is performed using (3), (4), (5), and (6).

$$min \sum_{i=1}^{N}(\beta^i - \mu^i(\sigma)) \quad (3)$$

$$\mu^i(\sigma^{-i}, s_j^i) - \beta^i \le 0 \quad (4)$$

$$\sum_{j=1}^{m}(\sigma_j^i - 1) = 0 \quad (5)$$

$$\sigma_j^i \ge 0 \quad (6)$$

Where

β^i = Player-ith optimum payoff

$\mu^i(\sigma)$ = Player-ith payoff

$\mu^i(\sigma^{-i}, s_j^i)$ = Player-ith payoff for each strategy-jth without considering the strategy probability of player-ith

σ_j^i = Probability of strategy-jth from player-ith

N = The number of all alternative strategies

The NEC is met when the player payoff ($\mu^i(\sigma)$) has a similar value with the optimum payoff of each player (β^i). Therefore, (3) minimizes the difference between the optimum payoff and the player payoff. Because the player payoff is similar to or slightly different from the optimum payoff, the player does not change its strategy.

Equations (4) and (6) show the inequality constraints. Equation (4) means that the optimum payoff of each player (β^i) is greater than each player's payoff for each strategy without considering the strategy probability of other players ($\mu^i(\sigma^{-i}, s_j^i)$). In other words, (4) creates a condition in which when a player changes its strategy, it does not produce a payoff greater than the optimum payoff, or when other players change their strategy, the optimum payoff of the player is not affected. Therefore, the player does not change its strategy. The other function of (4) prevents the optimum payoff from being negative, so the minimum value in equation (3) is zero. Equation (6) means that each player's probability must be a positive value. Equation (5) is an equality constraint that shows that the sum of each player's strategy probabilities is equal to one.

In [1], (3) to (6) are formed based on all the alternative strategies. The test system in [1] comprises 15 existing power plants that have only one strategy (invest) and 13 power plants that have two strategies (invest or not). The total number of all alternative strategies is 8192 (115 × 213 = 8192), and this resulted in a computation time of 9 days. To reduce the size of all alternative strategies, the current study uses the majority rule and the dominant strategy.

The first step of reducing the size of all alternative strategies is to find each player's dominant strategy using (7). The second step is to find the location of the dominant strategy using (8). The location is known from the index (j) on the dominant strategy. The dominant strategy and the location are sought for each player.

$$dominant\ strategy = max\ \mu_j^i \quad (7)$$

$$Loc_{dom}{}^i = j \quad (8)$$

Once the dominant strategy location of each player is known, the next step is to find the majority dominant strategy's location. There are two types of majority dominant strategies: absolute majority and the relative majority[33]. The absolute and relative majorities were calculated by (9) and (10), respectively. If more than half the players choose the j^{th} strategy, then the j^{th} strategy is the absolute majority. If most players choose the j^{th} strategy, but the number of players is less than or equal to half of the total number of players, then the j^{th} strategy is the relative majority. Once the strategy is identified as the majority dominant strategy, the strategy's location is obtained using (11).

$$absolute\ majority = S_j \mid S_j > \frac{N}{2} \tag{9}$$

$$relative\ majority = S_j \mid S_j > (N - S_{-j}) \tag{10}$$

$$Loc_{major} = j \tag{11}$$

In the majority dominant strategy, not all players agree to invest. In the deregulated market, the investment decision of Genco cannot be forced. Therefore, this research combines the mixed strategy with the majority dominant strategy. Players that agree to invest have one strategy (invest). Players that do not agree to invest have two strategies (invest or not). For example, the majority dominant strategy is strategy no. 5000 (the total number of strategies is 8192 (115 × 213 = 8192)). In strategy no. 5000, 24 players agree to invest, and four players refuse to invest. Therefore, all alternative strategies that are used in equations (3) to (6) total 16 (124 × 24 = 16). Compared with the mixed strategy method in [1], in which 8192 strategies are used, the majority dominant strategy uses 16 strategies. The number of strategies used shows that the majority dominant strategy's computational load is lighter than that in the mixed strategy.

After the reduction process using the majority rule and dominant strategy, the next step is to find the optimum payoff of each player (β^i) and the probability value of each player strategy (σ_j^i). The optimum payoff and the probability value are calculated using the SQP-QNM. The SQP solves a nonlinear optimization problem using Lagrangian[1]. The nonlinear optimization problem is shown in (12) [34].

$$Min\, f(x) \tag{12}$$

with constraints:

$$h(x) = 0$$

$$g(x) \geq 0$$

Equation (12) is similar to equations (3) to (6), which consist of objective function (min f(x)), inequality constraint (g(x)), and equality constraint (h(x)). The nonlinear optimization problem is solved using the Lagrangian method, as shown in (13).

$$L(x, \lambda, \mu) = f(x) - \lambda\, h(x) - \mu\, g(x) \tag{13}$$

The values of x, λ, and μ that produce the minimum L can be calculated using (13). The values are searched using the QNM. To update the values of x, λ, and μ, the QNM uses the Hessian and gradient[35]. Using the QNM in (13) requires (14) to find the minimum L. The minimum L is obtained when δx δx, δy, and $\delta\mu$ are equal to zero or less than the tolerance value.

$$\begin{bmatrix} \nabla^2 L(x,\lambda,\mu) & {N^T}_\lambda & {N^T}_\mu \\ {N^T}_h & 0 & 0 \\ {N^T}_g & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta x \\ \delta y \\ \delta \mu \end{bmatrix} = \begin{bmatrix} \nabla\ L(x,\lambda,\mu) \\ h(x) \\ g(x) \end{bmatrix} \tag{14}$$

where

NTh = ∇h(x)

NTg = ∇g(x)

B. Constraints and Objective Function

The constraints used in this research are energy production and loss of load probability (LOLP). The energy production constraint requires that the energy production is more than the energy demand and lower than the maximum production capacity of the power plants. The energy production constraint is shown in (15). The LOLP constraint relates to the reliability requirement of a power system. The LOLP index can be calculated using (16), while the LOLP constraint is shown in (17).

$$Max\ capacity\ factor \times Capacity\ x\ 8760 \geq Energy\ production \geq Energy\ demand \quad (15)$$

$$LOLP = \sum_{x=1}^{X} P_x\ .T_x \quad (16)$$

$$LOLP \leq LOLP\ standard \quad (17)$$

The objective function in this study is to find the minimum value of LTC which can be calculated using (18).

$$LTC = \sum_{t=0}^{n} \frac{Investment_t + O\&M_t + Fuel_t}{(1+r)^t} \quad (18)$$

The LTC is inversely proportional to the Genco's payoff. The minimum LTC creates the maximum Genco's payoff. In addition, (3) to (6) need a payoff from each Genco. Therefore, (18) needs to be modified so that it can represent the Genco's payoff. Because the LTC is inversely proportional to the Genco's payoff, the modification to represent the Genco's payoff is shown in (19). The small number is needed to avoid infinity. Infinity occurs when the Genco has an LTC of zero.

$$Payoff = \frac{1}{LTC + small\ number} \quad (19)$$

The relationship between the constraints and the objective function is modeled as a bi-level model (Figure 3). There are two levels in the bi-level optimization method; the first level is used for constraints checking, while the second level is used for optimizing the LTC objective function. The inputs in the first level are all of the alternative solutions. The checking process at this level uses the LOLP constraint. The aim of this level is to find the alternative solutions that are appropriate to the constraints criteria. The alternative solution that exceeds the constraints criteria is not used for the second level.

After the first level, the second level can be implemented using the LTC objective function. The inputs of this level are the outputs of the first level. The aim of this level is to find the solution that has the minimum LTC value and is set to be the optimum solution.

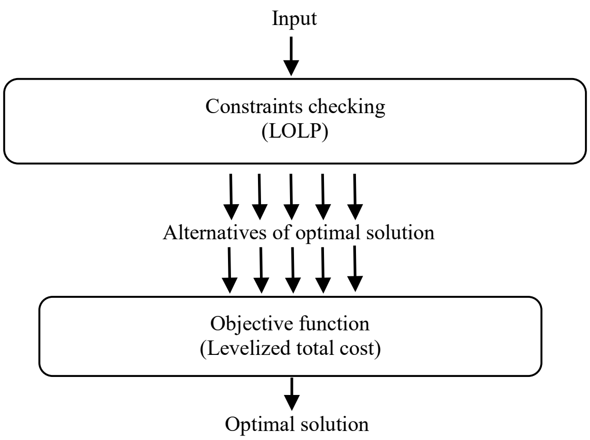

Figure 3. Bi-level model

C. *Design of Optimization Algorithm*

The optimization was completed by following the steps presented in the flowchart in Figure 4. The first step is to input the data and constraints, i.e., the existing power plants, candidate power plants, the techno-economic parameters of power plants, electricity demand, and LOLP constraint. Based on the entered data, the input data are read for the next processes, and m =1 and j = 1 are set for indexing purposes, with m and j representing alternative strategy and alternative solution index, respectively.

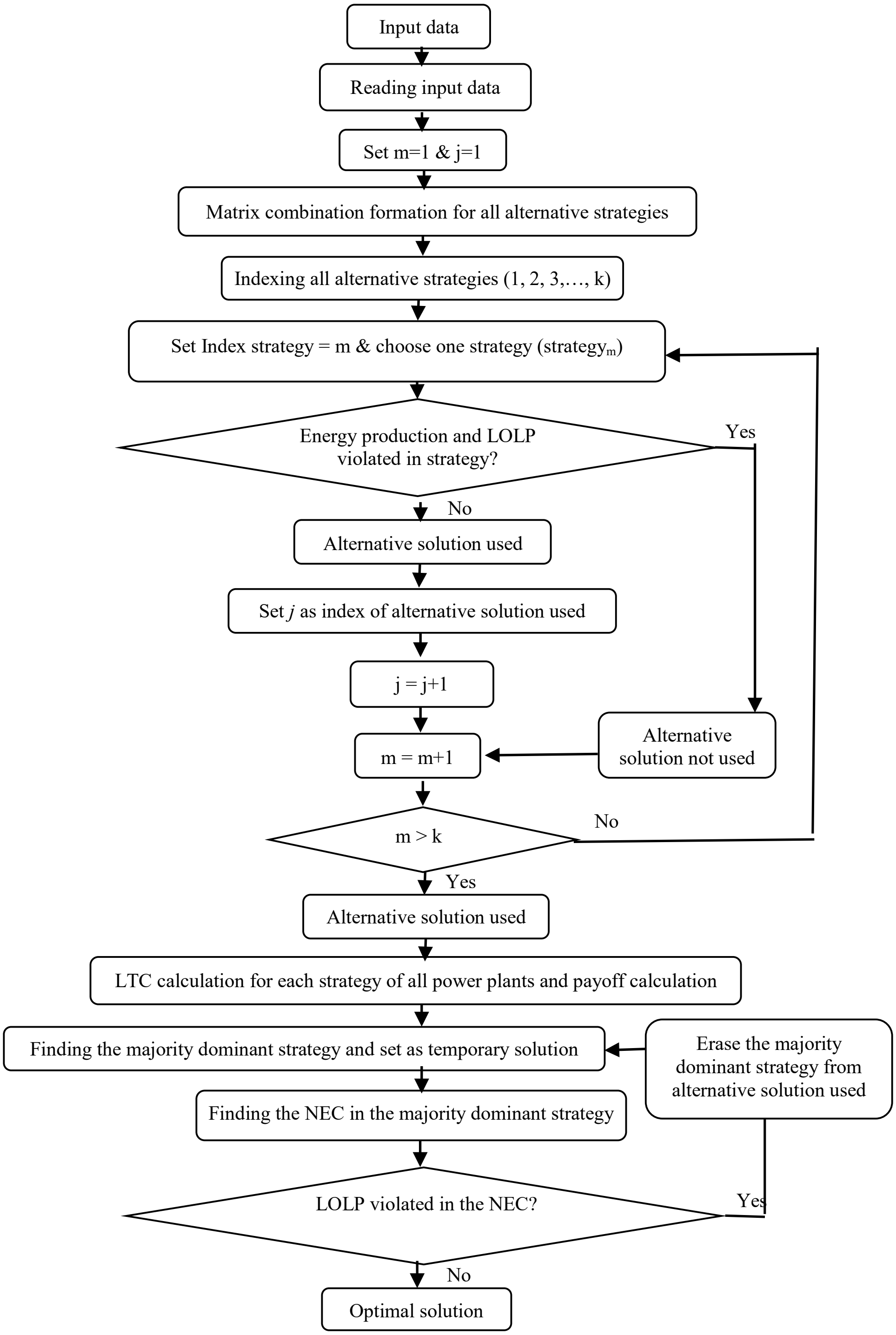

Figure 4. Design of optimization algorithm

The matrix combination formation for all alternative strategies is obtained from combining each power plant's strategy. For example, there are three existing power plants (E1 = 10 MW, E2 = 10 MW, and E3 = 10 MW) and four candidate power plants (C1 = 8 MW, C2 =8 MW, C3 = 8 MW, and C4 = 8 MW). Each existing power plant only has one strategy (invest), and each candidate power plant has two strategies (invest or not). Based on the existing and candidate power plants' strategies, the total number of alternative strategies is 16 (13 × 24 = 16), as shown in Table 1.

Table 1. Alternative strategies matrix

Alternative	The capacity of each power plant (MW)							Total (MW)
	E1	E2	E3	K1	K2	K3	K4	
1	10	10	10	0	0	0	0	30
2	10	10	10	0	0	0	8	38
3	10	10	10	0	0	8	0	38
4	10	10	10	0	0	8	8	46
5	10	10	10	0	8	0	0	38
6	10	10	10	0	8	0	8	46
7	10	10	10	0	8	8	0	46
8	10	10	10	0	8	8	8	54
9	10	10	10	8	0	0	0	38
10	10	10	10	8	0	0	8	46
11	10	10	10	8	0	8	0	46
12	10	10	10	8	0	8	8	54
13	10	10	10	8	8	0	0	46
14	10	10	10	8	8	0	8	54
15	10	10	10	8	8	8	0	54
16	10	10	10	8	8	8	8	62

Table 2. Alternative strategies index

Index (m)	Alternative	Total (MW)
1	1	30
2	2	38
3	3	38
4	4	46
5	5	38
6	6	46
7	7	46
8	8	54
9	9	38
10	10	46
11	11	46
12	12	54
13	13	46
14	14	54
15	15	54
16	16	62

The Genco role in the matrix formation is important because the number of Gencos and their strategy determine the number of alternatives. Suppose K1 changes its number of strategies from 2 to 1 (invest) and K2 changes its decision and cancels its participation; then, the matrix will have four alternative strategies (13 × 11 × 22 = 4).

After the Gencos submit their alternative strategies and the matrix is obtained, the government utility indexes all alternative strategies, as shown in Table 2. The strategies index (m) ranges from 1 to k, with k being the maximum index.

After the indexing process, the utility calculates and checks the LOLP of each alternative strategy using (15) and (16). If the LOLP of an alternative strategy is more than the pre-specified LOLP constraint, the utility moves the strategy to the unused strategy. If the LOLP of the alternative strategy is less than or equal to the LOLP constraint, the utility places the strategy in the alternative solution and assigns a new index (j). For example, from the 16 strategies in Table 2, there are five strategies (1, 2, 3, 5, and 9) that violate the LOLP constraint, as shown in Table 3. Therefore only 11 strategies are used by the utility as alternative solutions, and the strategies are assigned a new index, as shown in Table 4.

Table 3. LOLP checking of each alternative strategy

Index (m)	Alternative strategy	Total (MW)	LOLP violation
1	1	30	Yes
2	2	38	Yes
3	3	38	Yes
4	4	46	No
5	5	38	Yes
6	6	46	No
7	7	46	No
8	8	54	No
9	9	38	Yes
10	10	46	No
11	11	46	No
12	12	54	No
13	13	46	No
14	14	54	No
15	15	54	No
16	16	62	No

Table 4. Matrix combination of alternative solutions and their new index

New index (j)	Old index (m)	Alternative solution	The capacity of each power plant (MW)							Total (MW)
			E1	E2	E3	K1	K2	K3	K4	
1	4	4	10	10	10	0	0	8	8	46
2	6	6	10	10	10	0	8	0	8	46
3	7	7	10	10	10	0	8	8	0	46
4	8	8	10	10	10	0	8	8	8	54
5	10	10	10	10	10	8	0	0	8	46
6	11	11	10	10	10	8	0	8	0	46
7	12	12	10	10	10	8	0	8	8	54
8	13	13	10	10	10	8	8	0	0	46
9	14	14	10	10	10	8	8	0	8	54
10	15	15	10	10	10	8	8	8	0	54
11	16	16	10	10	10	8	8	8	8	62

By using the alternative solutions with their new indices, as shown in Table 4, the LTC calculation was performed using (17). The LTC calculation was performed for each power plant in every alternative solution. The LTC represents the total cost of each Genco, which is inversely proportional to the payoff. Therefore, each Genco tries to minimize this cost. This means that the minimum cost creates the maximum payoff. The LTC is reformed to represent a payoff of each power plant using (18). Table 5 shows the matrix combination of alternative solutions with payoff value.

Table 5. Matrix combination of alternative solutions with payoff value

New index (j)	The payoff of each Genco (MW)						
	Ea	Eb	Ec	Ka	Kb	Kc	Kd
1	CEa1	CEb1	CEc1	CKa1	CKb1	CKc1	CKc1
2	CEa2	CEb2	CEc2	CKa2	CKb2	CKc2	CKc2
3	CEa3	CEb3	CEc3	CKa3	CKb3	CKc3	CKc3
4	CEa4	CEb4	CEc4	CKa4	CKb4	CKc4	CKc4
5	CEa5	CEb5	CEc5	CKa5	CKb5	CKc5	CKc5
6	CEa6	CEb6	CEc6	CKa6	CKb6	CKc6	CKc6
7	CEa7	CEb7	CEc7	CKa7	CKb7	CKc7	CKc7
8	CEa8	CEb8	CEc8	CKa8	CKb8	CKc8	CKc8
9	CEa9	CEb9	CEc9	CKa9	CKb9	CKc9	CKc9
10	CEa10	CEb10	CEc10	CKa10	CKb10	CKc10	CKc10
11	CEa11	CEb11	CEc11	CKa11	CKb11	CKc11	CKc11

The majority dominant strategy was searched using (7) to (11) based on the value in Table 5. The payoffs of the alternative solutions for the Gencos are compared to determine the location of each Genco strategy that produces the maximum payoff. Suppose that the maximum payoff of Ea is in strategy 6 (CEa6), the maximum payoff of Eb is in strategy 6 (CEb6), the maximum payoff of Ec is in strategy 6 (CEc6), the maximum payoff of Ka is in strategy 3 (FKa3), the maximum payoff of Kb is in strategy 9 (FKb9), the maximum payoff of Kc is in strategy 6 (FKc6), and the maximum payoff of Kd is in strategy 6 (FKd6). By using (9), strategy 6 can be identified as the absolute majority dominant strategy. Table 6 shows the absolute majority dominant strategy.

Table 6. The absolute majority dominant strategy

New index (j)	Alternative solution	The capacity of each power plant (MW)							Total (MW)
		E1	E2	E3	K1	K2	K3	K4	
6	11	10	10	10	8	0	8	0	46

The utility informs each Genco of the absolute majority dominant strategy as a temporary optimum solution, and then, each Genco searches their optimum solution based on the absolute majority dominant strategy (strategy 6). The optimum solution of each Genco is found in the NEC based on strategy 6. The first step of searching the NEC is to create a matrix combination based on each Genco's decision regarding strategy 6. Five Gencos (E1, E2, E3, K1, and K3) agree to invest. Therefore, the five Gencos only have one strategy (invest) because they have obtained the maximum payoff. For the rest of Gencos that do not agree to invest, they have an opportunity to recalculate their strategy. Therefore, these Gencos have two strategies (invest or not). This situation creates 4 (14 × 22 = 4) alternative strategies, as shown in Table 7.

Table 7. The new matrix combination based on strategy 6

Alternative solution	The capacity of each power plant (MW)							Total (MW)
	E1	E2	E3	K1	K2	K3	K4	
1	10	10	10	8	0	8	0	46
2	10	10	10	8	0	8	8	54
3	10	10	10	8	8	8	0	54
4	10	10	10	8	8	8	8	62

Based on Table 7, the probability of each strategy for every GenCo is searched using the mixed strategy method (equations (3), (4), (5), (6), (12), (13), and (14)). Assume the mixed strategy method results show that E1, E2, E3, K1, K2, and K3 decide to invest and that K4 refuses to invest, then the utility checks the LOLP violation. If the LOLP is not violated, the results are set as the optimum solution. If the LOLP is violated, the utility erases strategy 6 from Table 5 and searches the new majority dominant strategy based on the new Table 5 (without strategy 6). After the new majority dominant strategy is found, the next processes are repeated to find the optimum solution using the mixed strategy method until the LOLP is not violated.

After the first-year optimum solution is obtained, all the processes to find the optimum solution are repeated until the planning period ends. The existing power plants in the $(y+1)^{th}$ year use the optimum solution in the y^{th} year, while the candidate power plants are the same.

D. Time Complexity Analysis

The time complexity was analyzed using the big-O notation. The big-O notation is an effective method to analyze the time complexity of an algorithm or method[31]. The big-O notation calculation can be implemented stepwise or by using a practical approach, i.e., running the method code using different test system sizes and making a graph of computation time vs. test system size[36], [37]. From the graph, the big-O notation for the method can be obtained.

Previous works have categorized the big-O notation into some classes, such as: O(1) = constant, O(log n) = logarithmic, O((log n)c) = polylogarithmic, O(n) = linear, O(n2) = quadratic, O(nc) = polynomial, and O(cn) = exponential[31], [37]–[39]. Figure 5 shows the illustration of a graph of computation time vs. test system size with the big-O notation.

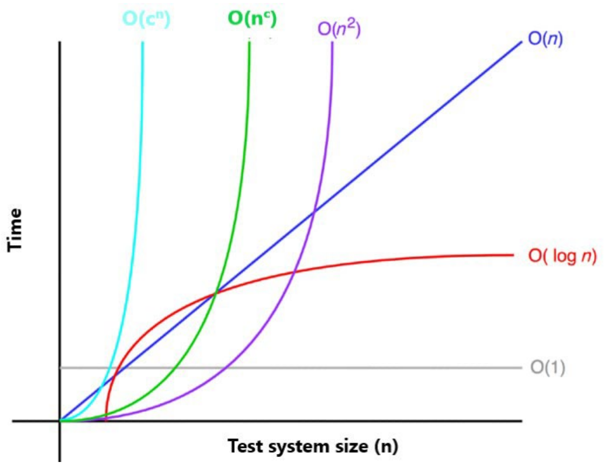

Figure 5. Illustration of a graph of computation time vs. test system size with the big-O notation[40]

This research uses the practical method to obtain the graph and the big-O notation. The proposed method (MDMS) was implemented using the first case study with various numbers of power plant strategies to obtain the graph of computation time vs. test system size. Based on the graph, the big-O notation of the MDMS can be obtained.

For comparison, the method in [1] was run using the first case study with various numbers of power plant strategies. The graph obtained from the method was compared with the MDMS graph. Based on the comparison, the effectiveness of MDMS to reduce the computation time can be proved.

4. Case Study

Two case studies were considered in this study. Each case study has its purpose. The first case study was used to analyze the time complexity of the proposed method. The second case study was used to prove the effectiveness of the proposed method in DGEP. The method was built and solved with MATLAB R2014A on a 3.5 GHz laptop with 4 GB RAM.

A. The First Case System

The first case study was used to analyze the time complexity of the proposed method. The case study consists of 14 scenarios, whereby all scenarios equally have four existing power plants but different numbers of candidate power plants, from 3 to 16. The first scenario, scenario 1, consists of four existing power plants and three candidate power plants. In contrast, the last scenario, scenario 14, consists of four existing power plants and 16 candidate power plants. The numbers of power plants were different to analyze the impact of the number of power plant strategies on the computation time.

The existing power plant data are shown in Table 8. The number and type of candidate power plants for each scenario are presented in Table 9, while the techno-economy parameters of the candidate power plants are listed in Table 10. The peak demand for the case system is 50 MW.

Table 8. Existing power plants of the first case study

Power plant	Capacity (MW)	FOR	Fixed costs (USD/kW)	Operational costs (USD/kWyr)
Diesel	5	0.09	35.34	704.18
Diesel	5	0.09	35.34	704.18
Diesel	16	0.09	35.34	704.18
Diesel	10	0.09	35.34	704.18

Table 9. The number and type of candidate power plants for each scenario

Scenario	Number of candidate power plants			Total candidate power plants
	Coal steam PP	Gas turbine PP	Biomass PP	
1	1	1	1	3
2	2	1	1	4
3	2	2	1	5
4	2	2	2	6
5	3	2	2	7
6	3	3	2	8
7	3	3	3	9
8	4	3	3	10
9	4	4	3	11
10	4	4	4	12
11	5	4	4	13
12	5	5	4	14
13	5	5	5	15
14	6	5	5	16

Table 10. The techno-economy parameters of the candidate power plants

Power Plant	Cap. (MW)	FOR	Fix Costs (USD/kW)	Operational Costs (USD/kWyr)	Investment Costs (USD/kW)	Lifetime (year)
Coal steam	25	0.05	31.32	118.02	1400	25
Gas turbine	15	0.023	11.64	196.87	1200	20
Biomass	7	0.05	31.32	17.52	1400	20

B. The Second Case System

The second case study was used to prove the effectiveness of the proposed method in DGEP. To prove the performance of the proposed model in terms of the computation time and the LTC, we present a case study similar to those in [32] and [1].

For the second test system, this study used the test system used in [1] and [32] with the data, as shown in Table 11, Table 12, and Figure 6. Table 11 presents the existing power plants and their techno-economic data. Table 12 shows the candidate power plants and their techno-economic data. Figure 5 shows the forecasted peak demand. The discount rate is 8.5%. The LOLP constraint is 0.01. The discount rate and LOLP constraint used in this research are similar with the discount rate and LOLP constraint value used in [32] and [1].

Table 11. Data of existing power plants [1], [32]

Power plant	Capacity (MW)	FOR	Fixed costs (USD/kW)	Operation costs (USD/kWyr)
Oil PP #1	200	0.07	27	210.24
Oil PP #2	200	0.068	27	236.52
Oil PP #3	150	0.06	25.56	262.8
LNG_GT PP #1	50	0.03	54.24	376.68
LNG_GT PP #2	50	0.03	54.24	376.68
LNG_GT PP #3	50	0.03	54.24	376.68
LNG_CC PP #1	400	0.1	19.56	332.88
LNG_CC PP #2	400	0.1	19.56	350.4
LNG_CC PP #3	450	0.11	24	306.6
Coal PP #1.1	250	0.15	79.8	201.48
Coal PP #1.2	250	15	79.8	201.48
Coal PP #2	500	9	33.72	166.44
Coal PP #3	500	8.5	33.72	131.4
Nuclear PP #1	1000	9	59.28	43.8
Nuclear PP #2	1000	8.8	55.56	43.8

Table 12. Data of candidate power plants [1], [32]

Power Plant	Cap. (MW)	FOR	Fixed Costs (USD/kW)	Operation Costs (USD/kWyr)	Investment Costs (USD/kW)	Lifetime (year)
OIL PP #1	200	0.07	26.4	183.96	812.5	25
OIL PP #2	200	0.07	26.4	183.96	812.5	25
OIL PP #3	200	0.07	26.4	183.96	812.5	25
LNG_CC PP #1	450	0.1	10.8	306.6	500	20
LNG_CC PP #2	450	0.1	10.8	306.6	500	20
LNG_CC PP #3	450	0.1	10.8	306.6	500	20
COAL PP #1	500	0.095	33	122.64	1,062	25
COAL PP #2	500	0.095	33	122.64	1,062	25
COAL PP #3	500	0.095	33	122.64	1,062	25
PWR PP #1	1000	0.09	55.2	35.04	1,625	25
PWR PP #2	1000	0.09	55.2	35.04	1,625	25
PHWR PP #1	700	0.07	66	26.28	1,625	25
PHWR PP #2	700	0.07	66	26.28	1,625	25

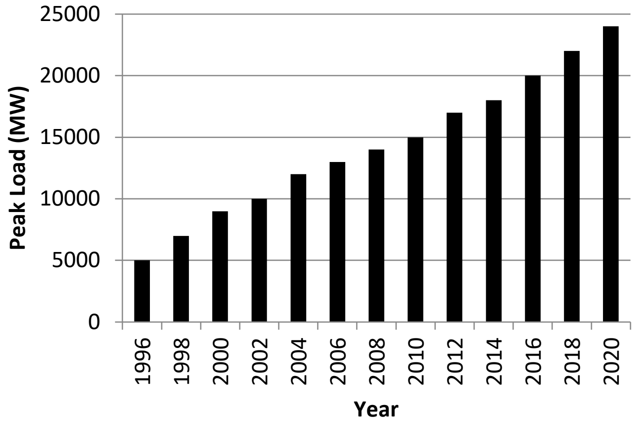

Figure 6. Forecasted peak demand [1], [32]

5. Results and Analysis

This research proposes a new method called the MDMS, which is based on a social science optimization-based approach to obtain the optimum solution and solve the computation time problem in a deregulated market. A time complexity analysis is needed to prove that the computation time problem is solved, and the MDMS implementation in DGEP is analyzed to obtain the effectiveness and performance of the MDMS.

A. Time Complexity

The time complexity was analyzed using the big-O notation, and the practical method was adopted to obtain the big-O notation. Using the results developed from the first scenario, the pattern of the proposed method computation time was obtained. Each scenario has a different number of power plants and a different number of strategies, as shown in Table 13.

Table 13. The matrix size and the total combination of all alternative strategies for each scenario

Scenario	Existing power plants		Candidate power plants		Total of all alternative strategies	The size of the all alternative strategies matrix	The total combination of all alternative strategies
	Number of units	Number of strategies	Number of units	Number of strategies			
1	4	1	3	2	8	7 × 8	56
2	4	1	4	2	16	8 × 16	128
3	4	1	5	2	32	9 × 32	288
4	4	1	6	2	64	10 × 64	640
5	4	1	7	2	128	11 × 128	1408
6	4	1	8	2	256	12 × 256	3072
7	4	1	9	2	512	13 × 512	6656
8	4	1	10	2	1024	14 × 1024	14336
9	4	1	11	2	2048	15 × 2048	30720
10	4	1	12	2	4096	16 × 4096	65536
11	4	1	13	2	8192	17 × 8192	139264
12	4	1	14	2	16384	18 × 16,384	294912
13	4	1	15	2	32768	19 × 32,768	622592
14	4	1	16	2	65536	20 × 65,536	1310720

From Table 13, the matrix size increases linearly with the number of scenarios. The number of power plants and strategies are the main contributors to the increasing matrix size and the total combination. The number of power plants affects the number of matrix rows, while the number of alternative strategies affects the number of matrix columns. The number of matrix columns is equal to m^n, where m is the number of strategies and n is the number of power plants. For example, scenario 2 has four existing power plants with one strategy on each existing power plant and four candidate power plants with two strategies on each candidate power plant. The number of matrix columns is 8 (4 existing power plants + 4 candidate power plants), and the number of matrix rows is 16 ($1^4 \times 2^4$).

The addition of the number of power plants and strategies has an impact on (increases) the matrix size of all the alternative strategies and the total combination. The increasing matrix size and the total combination cause the computation time to increase, as shown in Figure 7. Figure 7 not only shows the computation time of the proposed method (MDMS) but also compares it with that of a previous method, the game theory mixed strategy.

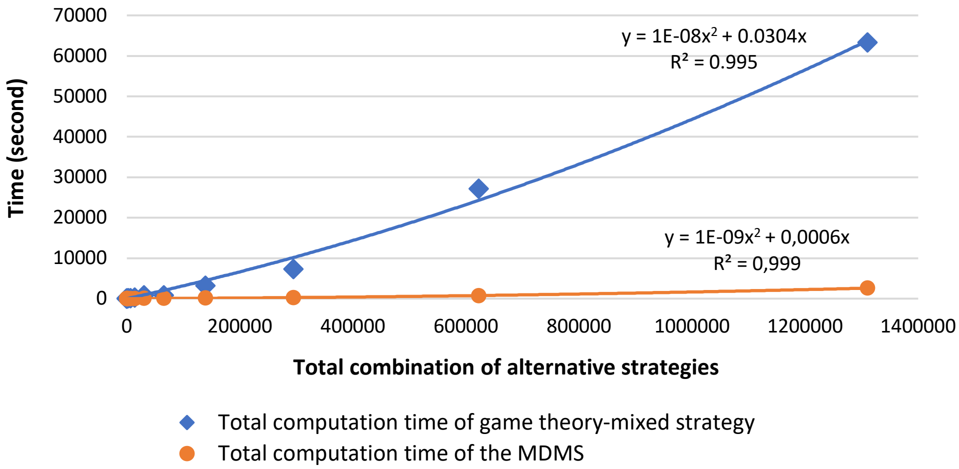

Figure 7. Computation time for each scenario

The computation time pattern of the MDMS, i.e., quadratic (x^2), is similar to that of the game theory mixed method. Therefore, the big-O notation for the MDMS and the game theory mixed strategy is $O(n^2)$. The MDMS and the game theory mixed strategy still have a similar time complexity (quadratic) because the MDMS also uses the mixed strategy to obtain the NEC after implementing the social science approach (majority dominant strategy rule). The implementation of the majority dominant strategy rule decreases the alternative strategy matrix size and the total combination. The reduction in the matrix size and the total combination significantly saves computation time, as shown in Figure 7.

The constant of x^2 in the MDMS is less than that in the game theory mixed strategy. This shows that the curve slope of the MDMS is lower than that of the game theory mixed strategy. The MDMS has a lower curve slope because, by the majority dominant strategy rule, the number of players and strategies can be reduced, which saves computation time. In this strategy, the optimization is performed based on the majority dominant strategy location, not using all alternative strategies. In contrast, in the mixed strategy, the optimization is performed using all alternative strategies. For example, using 15 power plants, with each of the power plants having two strategies (invest or not), 32,768 (2^{15}) alternative strategies are created. The mixed strategy requires using all the alternative strategies, while the MDMS requires about 16 alternative strategies and depends on the majority dominant strategy location.

By using the equation based on the total computation time curves in Figure 7, it can be calculated the total computation time of the MDMS and game theory-mixed strategy for a larger power system, as shown in Table 14. Table 14 shows that the MDMS reduces the computation time by about 90% compared to the game theory-mixed strategy. The MDMS's computation time reaches 17.3 hours (0.72 days) when the total power plant is 116 power plants (100 existing power plants and 16 candidate power plants). In contrast, the game theory-mixed strategy produces a computation time of 224.7 hours (9.36 days). When the total power plant is increased to 120 power plants (100 of existing power plants and 20 of candidate power plants), the MDMS produces the computation time of 4,419 hours (184.13 days), while the game theory-mixed strategy produces the computation time of 45,043 hours (1,876.79 days). This significant reduction proves that the MDMS is more superior to conduct the deregulated GEP than the game theory-mixed strategy. Therefore, the MDMS more feasible to be implemented in big power systems than the game theory-mixed strategy.

Table 14. The comparison of total computation time between the MDMS and game theory-mixed strategy

Existing power plants (unit)	Candidate power plants (unit)	The total combination of all alternative strategies	The total computation time	
			The MDMS (hour)	Game theory-mixed strategy (hour)
20	16	2,359,296	1.9	35.4
40	16	3,670,016	4.4	68.4
60	16	4,980,736	7.7	111.0
80	16	6,291,456	12.0	163.1
100	16	7,602,176	17.3	224.7
20	18	9,961,472	29.2	359.8
40	18	15,204,352	66.7	770.5
60	18	20,447,232	119.5	1,334.0
80	18	25,690,112	187.6	2,050.2
100	18	30,932,992	270.9	2,919.1
20	19	20,447,232	119.5	1,334.0
40	19	30,932,992	270.9	2,919.1
60	19	41,418,752	483.4	5,115.1
80	19	51,904,512	757.0	7,921.9
100	19	62,390,272	1,091.7	11,339.5
20	20	41,943,040	495.7	5,240.9
40	20	62,914,560	1,110.0	11,526.4
60	20	83,886,080	1,968.7	20,255.2
80	20	104,857,600	3,071.7	31,427.5
100	20	125,829,120	4,419.0	45,043.0

B. MDMS Implementation in DGEP

To measure the performance and effectiveness of the MDMS in DGEP, the MDMS was applied in the second case study. The second case study has been previously solved using the game theory mixed strategy[1] and IGA[32]. Therefore, the effectiveness and validity of the MDMS can be obtained by comparison with the game theory mixed strategy and IGA.

Figure 8 compares the optimization results of the MDMS, game theory mixed strategy, and IGA. In the figure, GT MDMS represents the MDMS, GT Mix represents the mixed strategy, and IGA represents IGA. The results of the MDMS and mixed strategy are similar in total capacity, while the IGA gives a significantly higher total capacity. The total capacity affects the LTC. From this, it can be determined that the MDMS produces a lower LTC than that of the IGA. Considering that the total capacity of the MDMS is similar to that of the mixed strategy and lower than that of the IGA, the MDMS is valid and produces more economical results.

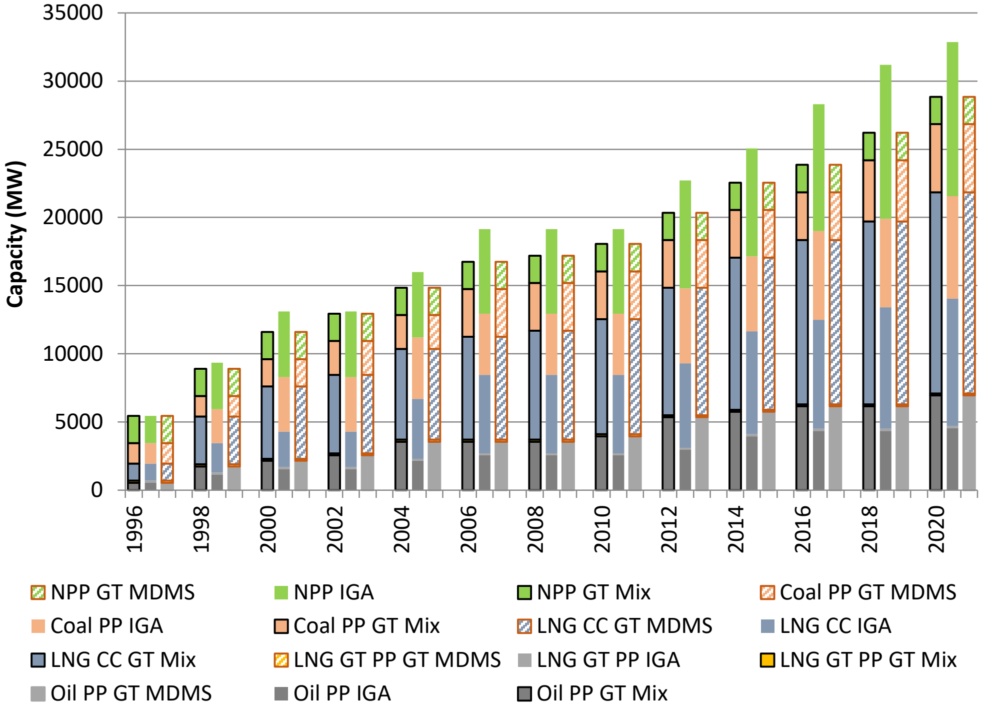

Figure 8. Comparison of the results of game theory majority with [1] and [32]

To determine the effectiveness of the MDMS, its LTC and computation time need to be compared with those of the mixed strategy and IGA. The LTC of the MDMS in the period of 1996–2020 is USD 43,718 million, and the computation time is 23.1 hours, while the mixed strategy generated an LTC of USD 43,718 million with a computation time of about nine days[1], and the IGA generated an LTC of 45,053 million with a computation time of about 13.3 hours[32]. Figure 9 and Figure 10 show comparisons of the LTC and computation time, respectively.

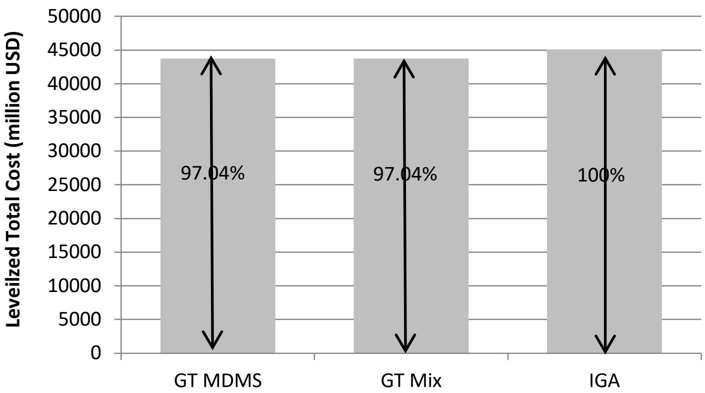

Figure 9. Levelized total cost comparison of the game theory dominant strategy, game theory mixed strategy, and IGA

If the IGA optimization result is used as the basis, the percentage of the LTC and computation time of the three methods can be obtained, as shown in Figure 9 and Figure 10. The MDMS generated better LTC than the IGA. The LTC of the MDMS is 2.96% lower than that of the IGA because the IGA uses a stochastic approach, while the MDMS seeks the optimal solution by using all combination alternative solutions. In addition, the MDMS LTC value is similar to that of the mixed strategy. This result shows that combining the majority rule and the dominant strategy with the mixed strategy yields economical results. The first aim of this research, the combination of the social science approach (majority rule and dominant strategy) with the mixed strategy gives economical results, is accomplished.

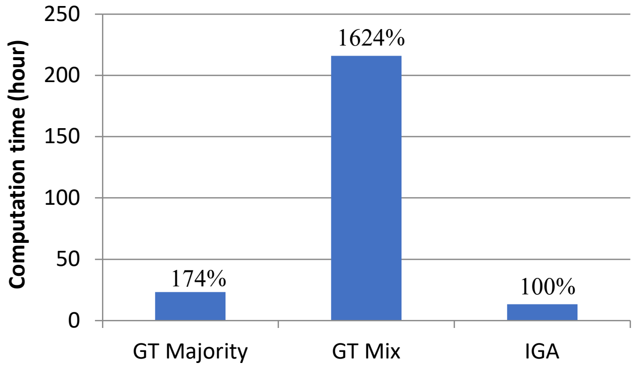

Figure 10. Computation time comparison of the game theory dominant strategy, game theory mixed strategy, and IGA

Besides affecting the LTC, the optimization mechanism of the three methods also affects the computation time. The IGA has the lightest computational load among the three methods because it uses a stochastic approach; therefore, it does not calculate the LTC for all alternative solutions. The mixed strategy has the heaviest computational load because of the probability searching process for each strategy. The computation time using the MDMS is longer (74%) than that of the IGA. Although the percentage increment appears high (74%), the computation time in the MDMS is acceptable (23.1 hours) and is much less than that of the mixed strategy. The computation time using the MDMS is only 10.69% of that required by the mixed strategy. This is due to the reduction process of the matrix combination size using the majority rule and dominant strategy. This computation time's reduction is in line with the results on the time complexity sub-section. In the time complexity sub-section, the MDMS reduces the game theory-mixed strategy's computation time by about 90%.

The LTC and computation time comparison shows that the MDMS presents economical results and can significantly speed up the computation time in DGEP. Thus, the MDMS is effective and feasible for solving the DGEP problem. By using the MDMS, the computation problem in [1] can be solved while maintaining optimal result. Therefore, the MDMS more viable to be implemented in big power systems.

The optimization results are validated by referring to the LOLP index. Figure 11 shows that the LOLP index of this research result is appropriate with the LOLP constraint (≤1%). Therefore, the result is valid.

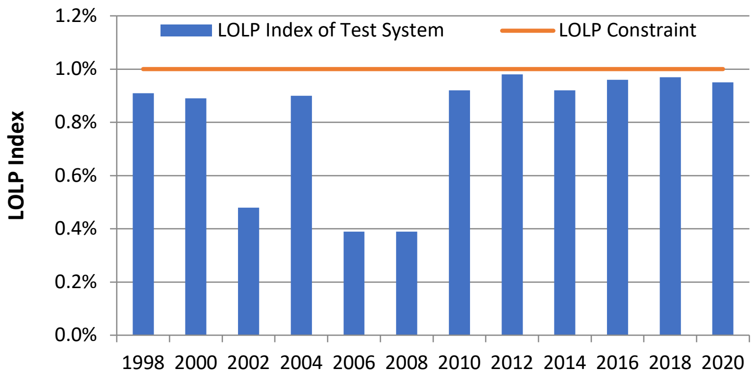

Figure 11. The LOLP index of the test system

6. Conclusion

This study proposes a novel social science optimization-based method, called the MDMS, to obtain the optimum solution and solve the computation problem in DGEP. The MDMS combines a social science concept called the majority rule and the dominant strategy with the mixed strategy method. The MDMS finds the NEC by adopting the democratic concept of the majority rule. By adopting the democratic concept, the optimum solution in DGEP can be achieved with a faster computation time.

Implementing the democratic concept of the majority rule saved significant computation time. The MDMS saved the computation time by reducing the matrix size of all the alternative strategies and the total combination, as shown in the reduced quadratic coefficient of the time complexity trend line.

The MDMS was successfully implemented in DGEP. It created an optimum solution similar to that of the mixed strategy but with a faster computation time. The LTC obtained using the MDMS (USD 43,718 million) was less than that of the IGA (USD 45,053 million). The mixed strategy also generated an LTC of USD 43,718 million, but with a computation time of 9 days, while the MDMS required only 23.1 hours. The MDMS computation time was only slightly higher than that of the IGA (13.3 hours) when the latter was used in regulated GEP with the same case study used in this research.

The results of the MDMS in both case studies show that the method is effective and feasible to solve the DGEP problem. The MDMS reduces the game theory-mixed strategy's computation time by about 90% in the small power system with seven power plants and in the big power system with 120 power plants. Therefore, the problem of DGEP implementation in big power systems can be solved by using the MDMS,

7. Acknowledgment

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8. References

[1] Sarjiya, R. F. S. Budi, and S. P. Hadi, “Game theory for multi-objective and multi-period framework generation expansion planning in deregulated markets,” Energy, vol. 174, pp. 323–330, 2019.

[2] A. Gautam, P. R. Sharma, and Y. Kumar, “Sensitivity Based Congestion Management in a Deregulated Power System by Optimal Allocation & Parameter Setting of TCSC using Grey Wolf Optimization,” *Int. J. Electr. Eng. Informatics*, vol. 12, no. 4, pp. 890–911, 2020.

[3] N. Hariyanto, M. Nurdin, Y. Haroen, and C. Machbub, “Decentralized and simultaneous generation and transmission expansion planning through cooperative game theory,” *Int. J. Electr. Eng. Informatics,* vol. 1, no. 2, pp. 149–164, 2009.
[4] R. F. S. Budi, Sarjiya, and Sasongko Pramono Hadi, “A review of potential method for optimization of power plant expansion planning in Jawa-Madura-Bali electricity system,” *Commun. Sci. Technol*., vol. 2, no. 1, pp. 29–36, 2017.
[5] S. Safarzadeh and M. Rasti-Barzoki, “A game theoretic approach for pricing policies in a duopolistic supply chain considering energy productivity, industrial rebound effect, and government policies,” Energy, vol. 167, pp. 92–105, 2019.
[6] X. Zhang *et al.*, “Game-theoretic planning for integrated energy system with independent participants considering ancillary services of power-to-gas stations,” Energy, vol. 176, pp. 249–264, 2019.
[7] X. Peng and X. Tao, “Cooperative game of electricity retailers in China’s spot electricity market,” Energy, vol. 145, pp. 152–170, 2018.
[8] Q. Wu, H. Ren, W. Gao, and J. Ren, “Benefit allocation for distributed energy network participants applying game theory based solutions,” Energy, vol. 119, pp. 384–391, 2017.
[9] Y. Qi, Y. Liu, and Q. Wu, “Non-cooperative regulation coordination based on game theory for wind farm clusters during ramping events,” Energy, vol. 132, pp. 136–146, 2017.
[10] D. Srinivasan, S. Rajgarhia, B. M. Radhakrishnan, A. Sharma, and H. P. Khincha, “Game-Theory based dynamic pricing strategies for demand side management in smart grids,” Energy, vol. 126, pp. 132–143, 2017.
[11] M. Andoni, V. Robu, W. G. Früh, and D. Flynn, “Game-theoretic modeling of curtailment rules and network investments with distributed generation,” Appl. Energy, vol. 201, pp. 174–187, 2017.
[12] F. Wei, Z. X. Jing, P. Z. Wu, and Q. H. Wu, “A Stackelberg game approach for multiple energies trading in integrated energy systems,” Appl. Energy, vol. 200, pp. 315–329, 2017.
[13] Q. Lu, S. Lü, and Y. Leng, “A Nash-Stackelberg game approach in regional energy market considering users’ integrated demand response,” Energy, vol. 175, pp. 456–470, 2019.
[14] Y. Zhang, C. Gu, J. Yan, and F. Li, “Cournot Game Based Multi-Supplier Local Energy Trading,” Energy Procedia, vol. 158, pp. 3528–3533, 2019.
[15] P. I. Helgesen and A. Tomasgard, “An equilibrium market power model for power markets and tradable green certificates, including Kirchhoff’s Laws and Nash-Cournot competition,” Energy Econ., vol. 70, pp. 270–288, 2018.
[16] Q. Chen *et al.*, “A Nash-Cournot approach to assessing flexible ramping products,” Appl. Energy, vol. 206, pp. 42–50, 2017.
[17] B. Chatterjee, “An optimization formulation to compute Nash equilibrium in finite games,” in *2009 Proceeding of International Conference on Methods and Models in Computer Science (ICM2CS)*, 2009.
[18] C. Daskalakis, P. W. Goldberg, and C. H. Papadimitriou, “The Complexity of Computing a Nash Equilibrium,” SIAM J. Comput., vol. 39, no. 195–269, 2008.
[19] J. A. Schwartz and Q. Wen, “A Characterization for Dominant Strategy Implementation,” Front. Econ. China, vol. 8, no. 1, pp. 1–18, 2013.
[20] R. M. Harstad, “Dominant strategy adoption and bidders’ experience with pricing rules,” Exp. Econ., vol. 3, no. 3, pp. 261–280, 2000.
[21] N. Najjar, “Game Theory Portfolio : A Computational Exploration of the Nash Equilibrium,” 2009.
[22] D. Adhikari, “Exploring the differences between social and behavioral science.,” Behav. Dev. Bull., vol. 21, no. 2, pp. 128–135, 2016.
[23] J. J. Buckley and T. E. Westen, “The majority rule game,” Int. J. Game Theory, vol. 4, no. 2, pp. 105–112, 1975.
[24] H. Gersbach, “Flexible Majority Rules in democracyville : A guided tour,” Math. Soc. Sci., vol. 85, pp. 37–43, 2017.
[25] D. Baron and E. Kalai, “The simplest equilibrium of a majority-rule division game,”

Journal of Economic Theory, vol. 61, no. 2. pp. 290–301, 1993.
[26] J. J. Buckley and T. E. Westen, "Bargaining Set Theory and Majority Rule," J. Conflict Resolut., vol. 20, no. 3, pp. 481–496, 1976.
[27] M. Montero and J. J. Vidal-puga, "Games and Economic Behavior Demand bargaining and proportional payoffs in majority games," Games Econ. Behav., vol. 71, no. 2, pp. 395–408, 2011.
[28] P. W. Schmitz and T. Tröger, "The (sub-)optimality of the majority rule," Games Econ. Behav., vol. 74, no. 2, pp. 651–665, 2012.
[29] H. Férée, "Journal of Computer and System Sciences Game semantics approach to higher-order complexity," J. Comput. Syst. Sci., vol. 87, pp. 1–15, 2017.
[30] S. Baichoo and C. A. Ouzounis, "Computational complexity of algorithms for sequence comparison , short-read assembly and genome alignment," BioSystems, vol. 156–157, pp. 72–85, 2017.
[31] S. Gayathri Devi, K. Selvam, and S. P. Rajagopalan, "An abstract to calculate big o factors of time and space complexity of machine code," in IET Conference Publications, 2011, pp. 844–847.
[32] J.-B. Park, Y.-M. Park, J.-R. Won, and K. Y. Lee, "An improved genetic algorithm for generation expansion planning," IEEE Trans. Power Syst., vol. 15, no. 3, pp. 916–22, 2000.
[33] A. Rubinstein, "Stability of Decision Systems under Majority Rule," J. Econ. Theory, vol. 23, pp. 150–159, 1980.
[34] J. L. Morales, J. Nocedal, and Y. Wu, "A Sequential Quadratic Programming Algorithm with an Additional Equality Constrained Phase," IMA J. Numer. Anal., vol. 32, no. 2, pp. 553–579, 2012.
[35] L. Vandenberghe, "Quasi-Newton Methods," 2016.
[36] S. Farhana, M. M. Billah, Z. M. Yusof, and K. Kadir, "An Optimal Algorithm to Resolve the Impact of Big Data in IoT Application using Bayesian Network," Procedia Comput. Sci., vol. 163, pp. 603–608, 2019.
[37] H. Liu, J. Cai, Y. S. Ong, and Y. Wang, "Understanding and comparing scalable Gaussian process regression for big data," Knowledge-Based Syst., vol. 164, pp. 324–335, 2019.
[38] Á. Arnaiz-González, J. F. Díez-Pastor, J. J. Rodríguez, and C. García-Osorio, "Instance selection of linear complexity for big data," Knowledge-Based Syst., vol. 107, pp. 83–95, 2016.
[39] MIT, "Big O notation." p. 9, 2020.
[40] B. Bundi, "Understanding Big-O Notation With JavaScript," Dev Community, 2020. [Online]. Available: https://dev.to/b0nbon1/understanding-big-o-notation-with-javascript-25mc.

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