Maintenance Scheduling Optimization For Electrical Grid Using Binary Gray Wolf Optimization Technique

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***Abstract*— Power grid maintenance scheduling is one of the most important task for engineer and technician at the time of distributing electrical power. The time consumed to maintain specific parts will make the difference in efficient power delivery to the customer. In addition, the cost spent in maintaining and repairing these parts can be very expensive when the part fails. This research uses Gray Wolf Optimization to obtain the best maintenance schedule, such that, it finds the best time slots to maintenance different parts of electrical grid before reaching failure. The paper uses Weibull model to simulate part wear out against time. The main target is to minimize the cost spent in maintenance to keep the part in operation prior to its failure. In order to test this approach, the research takes a simplified Erbil City grid as a case study for demonstration the proposed technique.**

Keywords-Maintenance Scheduling; Optimization; Power Grid; Gray Wolf Optimization.

I. INTRODUCTION

Most industrial organizations deal with system reliability with great importance and concern. These systems can directly relate to human's daily life needs, such as electrical power stations, railroad and others, in which, keeping these systems in operation mode is a crucial task. Effective maintenance is essential for the safe and long operation of these systems. In order to achieve, the system must be monitored, inspected, tested, assessed and maintained to ensure that it will operate correctly and safely. There are various maintenance concepts can be used to form a maintenance strategy. The task of maintaining any system is highly depended on its schedule, in which; any actions must not interfere with periods when the system in an active state.

In general, Preventive Maintenance can be defined as planned and scheduled maintenance actions that should be taken to prevent breakdowns and failures of system components [1]. The main idea behind PM is to stop or prevent the failure of system equipment or subsystems before it actually occurs. It is designed to keep the system within a save level of operation by replacing any warn out parts before it fails, thus enhancing and preserving its reliability. Planned maintenance deals with different maintenance periods per machine or component [2]. The maintenance is applied according to an arranged schedule or pre-planned maintenance periods. The planned maintenance actions are directly related to resource availability and expenditure. The resources management for a system, to be kept failure free and reduces the system downtime, depends on managing effectively the repair crew and the availability of spare parts. In addition, a planned maintenance objective is not only reducing system downtime and breakage; it leads to total maintenance costs reduction of the system by reducing the effect of a damaged component on other components or system operation schedule [3].This planned maintenance scheduling is in the scope of this research.

II. RELATED WORKS

Metaheuristic optimization is heuristic algorithms, which use random guess and evolving solutions with each cycle to reach a solution or best solution. Their basic idea is built on simulating a real-life system behavior of natural evolving as a solution to complex problems. The use of metaheuristic algorithm in solving complex maintenance and stochastic processes proved to be genuine and efficient [4].

The introduction to genetic algorithms made a good and fast impact in maintenance, especially in PM by providing better solution for more complex system with objective functions for single machine [5], or optimizing multi-objective maintenance function with Pareto search [6], or PM included in condition based maintenance to find the optimal system maintenance actions and strategies by minimizing different maintenance cost subject to constraints [7]. With metaheuristic optimization was an introduction of the new swarm based algorithms, provided a good base for improving existing results such as Ant colony system [8], or through particle swarm optimization in non-periodic PM schedule by optimizing the probabilistic maintenance model [9], or using discrete particle swarm optimizing the productivity and PM schedule of a single machine [10]. Eventually, PM optimization adapted hybrid metaheuristic optimization, which used to deal with a more complicated maintenance schedule [11]. Hybrid optimization was used by combining simulated annealing and genetic algorithm to solve PM schedule for job shops [12], or a hybrid ant colony and genetic algorithm for solving a large variable maintenance schedule which cannot provide a reasonable solution using any of the two algorithms alone [13]. That leads to the conclusion that more complex systems require more effective solution, which can be provided by a hybrid algorithm.

Gray Wolf optimization algorithm was used in many optimization problems because it can search or improvise a better solution than GA and other heuristic algorithms [14]. Moreover, It was found to be the fastest global optimization algorithm for small-scale problems with limited variables [15]. Therefore, it is suitable for maintenance optimization problems since the numbers of variables are small and finding the better solution is required [16].

In this research, Gray Wolf optimization is used for maintenance cost and schedule optimization. Two scenarios are used for finding the best maintenance schedule. The first scenario covers finding the best maintenance schedule when no repair task is performed on the components of the power grid. While, in the second scenario, the repair task is performed in the failed component of the power grid. Maintaining the Integrity of the Specifications

III. MAINTENANCE COST OPTIMIZATION FRAME WORK

The main objective of this research is to obtain the best system components maintenance times while minimizing the overall maintenance cost. The requirement and data are modeled into a cost optimization problem to reflect the effect of actions (no maintenance, maintenance and repair) performed on the components and the cost of these actions. This model is used to find the most appropriate schedule and task using Gray Wolf optimization technique as shown in Fig. 1.

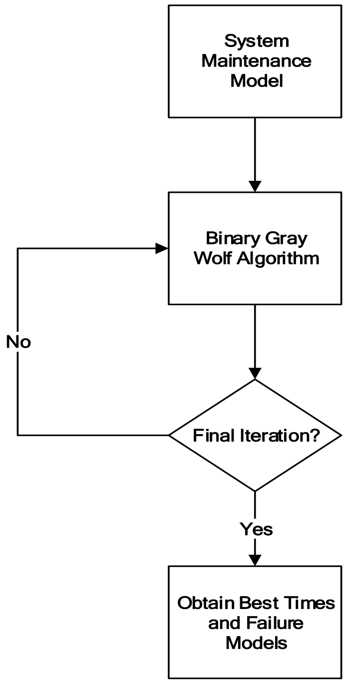


Figure 1: Proposed Maintenance Schedule Optimization System.

A.Maintenance Model

Maintenance modeling depends on defining and inspecting all the components that require maintenance [2]. The main condition to consider a component in a maintenance schedule is to have an increasing failure rate as shown in Fig. 2. In many systems, the component failure may occur even if the maintenance is applied due to unknown cause [3]. Therefore, the model should contain failure cost to give a better problem formulation. To give an optimum maintenance schedule, sudden failure must be considered. Moreover, the optimization model derivation may consider other factors, such as, system degradation after each maintenance process or repair, component availability, maintenance crew for maintaining each component. In this research, two models are used which addresses the problem of maintenance. The cost optimization is considered under certain maintenance policy which is scheduling component maintenance without component replacement.

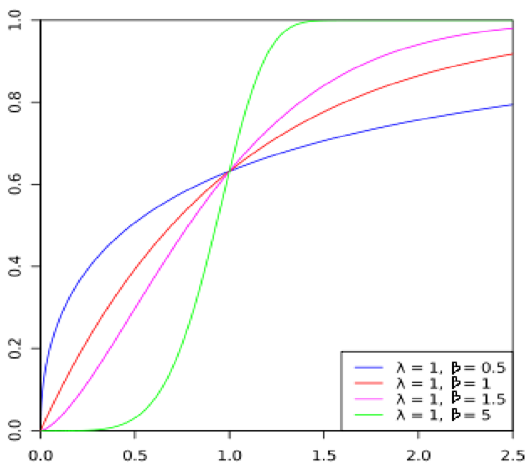


Figure 2: Component failure rate with different distribution.

In order to drive the maintenance model, consider a series system which consists of *N* components with wear out condition over a long working period. Each component ***i*** is assumed to have an increasing failure probability p_f over time ***t***, where ***t* >0**. The failure probability, which is derived from Weibull distribution, is increasing with time according to [3].

To formulate a model for preventive maintenance, a cost function is considered as a risk problem with expected risk R based on [17]. The risk cost function consists of two terms. The first term represents the risk acquired from failure occurrence FR, and the second term represents the risk obtained from applying maintenance to the system components. Hence, the risk cost can be expressed as,

$$R=FR+MR \qquad (1)$$

Where FR represent the failure risk and MR represent the maintenance risk. The failure risk FR represents the loss when an expected failure occurs. This risk consists of two terms: failure dependent loss and failure independent loss. The failure dependent loss represents the inflected loss caused by replacing the failed component. Failure independent loss represents the failure fixed cost spent during inspection work, diagnosis, starting and warming up of the system. The failure independent cost consists of two terms, the system fixed failure cost FF and the union of cumulative failure probabilities CP of system components. While, the failure dependent cost is the sum of expected cumulative failure costs of each component.

For simple calculation, the system components are considered non-repairable. Therefore, FR can be expressed as,

$$FR = FF \times \bigcup_{i=1}^{N} CP_{i,T} + \sum_{i=1}^{N} CP_{i,T} \times F_i \tag{2}$$

The cumulative failure rate for a component i at time T depends on all maintenance times at the end of the period, and is found by:

$$CP_{i,T(m)} = CP_{i,T(m-1)}(1 + P_{i,T(m)}), m > 1 \tag{3}$$

Where $P_{i,T(m)}$ is the probability of failure for component i at period T. After each maintenance action performed on the system components, the probability of failure is changed. The probability after maintenance P_{fm} is obtained either from formulation depending on failure probability before applying the maintenance action P_{fo} or from data obtained from similar machines. Therefore, the probability of failure is found by,

$$P_{i,t} = \begin{cases} P_{fo} & no-maintenance \\ P_{fm} & maintenance-applied \end{cases} \tag{4}$$

With failure probability P_{fm} is found by:

$$P(x,\beta,\lambda) = \frac{\beta}{\lambda}\left(\frac{x}{\lambda}\right)^{\beta-1} e^{-\left(\frac{x}{\lambda}\right)^{\beta}} \tag{5}$$

Where β is the component shape parameter and λ is the scale parameter. To obtain the failure rate before maintenance, the increment factor is applied to the failure rate after maintenance in Eq. (5) as follows,

$$P_{fo} = \min(1, P_{fm} + incr) \tag{6}$$

To find the maintenance risk MR, Consider $X_{i,t}$ to be the action applied to component $\boldsymbol{i}$ at time $\boldsymbol{t}$. The maintenance risk MR is obtained similarly to failure risk to have maintenance independent risk and maintenance dependent risk. The independent loss represents costs maintained from actions applied during maintenance such as stopping the system, disassembling, assembling, startup, etc. The dependent loss represents the cost of the maintenance. Therefore, the maintenance risk will be expressed as,

$$MR = FM \times \sum_{t=0}^{N} \left[1 - \bigcup_{i=1}^{N} (X_{i,t} \times CP_{i,t}) \min(1, \sum_{i=1}^{N} X_{i,t}) \right] + \sum_{i=1}^{N} M_i \times \sum_{t=0}^{T} X_{i,t} \times (1 - CP_{i,t}) \tag{7}$$

Where FM is the fixed maintenance cost and M_i is the maintenance cost of component i. Minimization of Eq. (7) will subject to the best maintenance time for the system components. This minimized value of MR and the found failure risk of FR will be apply to Eq. (1) to find the total risk R.

B. Gray Wolf Optimization

Gray Wolf Optimization technique depends on the social behavior of gray wolf pack during hunting. The algorithm depends on the pack hierarchy of member dominance and power in which the solution is formed by incorporating three solution members namely alpha (best solution), beta (second best) and delta (third best). These solutions contribute into the final solution [14].

For mathematically modelling the GWO, the fittest solution is called the alpha (α), the second and third best solutions are called beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). The hunting is guided by α, β, δ, and ω follows these three candidates.

The encircling behavior during hunting can be modelled as a directional vector of the pray position $X_P(t)$ and gray wolf position X(t+1) as,

$$\vec{X}(t+1) = \vec{X}_p(t) + \vec{A}.\vec{D} \tag{8}$$

Wher A is coefficient vector and D is found from,

$$\vec{D} = \left| \vec{C}.\vec{X}_p(t) - \vec{X}(t) \right| \tag{9}$$

The A and C coefficient can be calculated from,

$$A = 2a.\vec{r} - a \tag{10}$$

$$C = 2\vec{r}_2 \tag{11}$$

Where a is decreased from 2 to 0 over the course of iteration and r_1 and r_2 are randomly generated values in the range of [0, 1].

In order to mathematically simulate the hunting behavior of grey wolves, the alpha (best candidate solution) beta (the second best candidate solution), and delta (the third best candidate solution) are assumed to have better knowledge about the potential location of prey. The first three best candidate solutions obtained during each iteration and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. So, the updating for the wolves positions is as

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{12}$$

Where the vectors X_1, X_2 and X_3 is calculated using Eq. (8) above as,

$$\vec{X}_1 = \left| \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha \right|$$

$$\vec{X}_2 = \left| \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta \right| \tag{13}$$

$$\vec{X}_3 = \left|\vec{X}_\delta - \vec{A}_3.\vec{D}_\delta\right|$$

Where X_α , X_β and X_δ are the first three best solutions in the pack at iteration t. A_1, A_2 and A_3 is calculated using Eq. 19 and D_α , D_β and D_δ is calculated using Eq. (9).

Equations (12) and (13) are basically used for continuous optimization problems, however, the problem maintenance scheduling involve a very limited scale (binary for non-replacement policy and (0,1,2) for replacement policy) model. Therefore, binary Gray Wolf optimization algorithm based on [15] is used to replace Eq. (12) above by the equation,

$$X_d^{t+1} = \begin{cases} 1 & if(sigmoid(\frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}) \geq rand \\ 0 & otherwise \end{cases} \qquad (14)$$

With,

$$sigmoid(a) = \frac{1}{1+e^{-10(x-0.5)}} \qquad (15)$$

X_d^{t+1} is the bit at position d in the solution which is find by the corresponding bit in X_1, X_2 and X_3.

IV. Result and Discussion

In order to test the proposed system, two case studies are used, such that, the first case study is used to test the approach against other meta-heuristic algorithms, while the second case study is about a simplified Erbil city electrical grid maintenance scheduling.

A.First Case Study

The first case study consists of four components and was used for GA and PSO maintenance optimization tests in [17]. The full set of parameters and values are shown in Table 1. The provided data consist of components costs for maintenance and failure, in addition to, fixed maintenance and failure cost of the system. Moreover, the component failure probability rate parameters are provided, which are scale, shape, and increment factors.

Table1: Case Study Parameters for Maintenance without Replacement

	Comp1	Comp2	Comp3	Comp4
Shape Parameter (β)	2	2	2.15	2
Scale Parameter (λ)	2	1	0.5	1.5
Increment	0.12	0.2	0.15	0.09
Failure Cost	$2,500	$5,300	$7,500	$4,800
Maintenance Cost	$180	$300	$250	$400
Fixed Failure Cost	$12,500			
Fixed Maintenance Cost	$500			

The result of BGW is shown in Fig. 3 and Table 2. The figure shows failure probability for each component, while Table 2 shows the best maintenance periods for each component over an interval of 50 months.

From Fig. 1 and Table 2, it is obvious that component C3 requires more maintenance periods during its operation because of the higher probability of failure corresponding to its shape parameter (largest) and smaller scaling parameter. Therefore, as the shape parameter grows bigger and scale parameter becomes smaller, the component will have a higher probability of failure, which leads to more maintenance actions required to keep the component in operation.

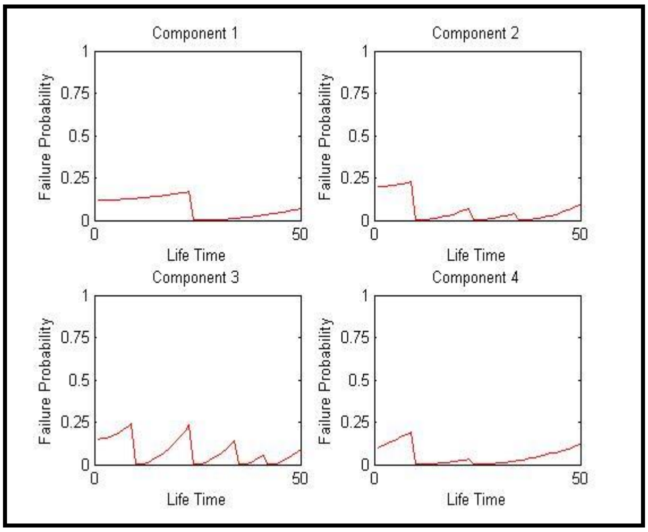


Figure 3: Failure probability of each component.

Table2: Maintenance Times for the four Components over 50 months period

Component	Maintenance Time				
C1		23			
C2	15	23		36	
C3	15	23	29	36	42
C4	15	23			

Table 3 shows the comparison for the BGW algorithm compared to Genetic Algorithm (GA) and three types of Particle swarm algorithms (com-pso, im-pso and no-pso) presented by [17] for different population size. It can be seen that BGW shows a better results for higher population size better than low population size (population size >150) because the algorithm depends on best first three solutions to form a new solution. In this case, higher pack (population) provide a better diversity to the selection pool and therefore there will be a bigger chance a different (new) solution is found at each iteration. Meanwhile, lower population size may force the algorithm to select from less diverse pool and that will limit the chance to find new solutions.

Table3: Maintenance cost ($) comparison for the four Components over 50 months period using different techniques

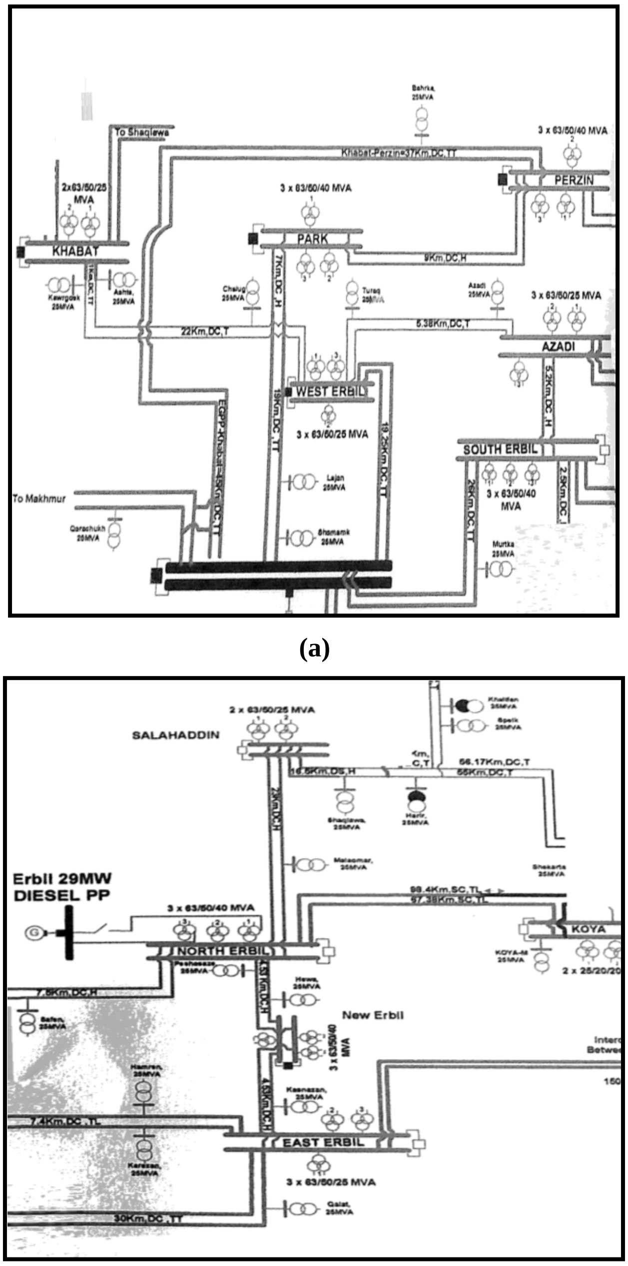
Population Size	15	75	150	300	600	1500
GA	24,187	21,410	21,183	21,056	20,984	20,961
com-pso	**21,063**	**20,905**	20,883	20,874	20,836	20,793
im-bpso	21,218	20,975	20,890	20,819	20,873	20,798
no-bpso	22,991	21,907	21,383	21,439	21,169	20,975
BGW	21,859	21,892	21,350	**20,851**	**20,849**	**20,471**

B.Second Case Study

The second data set represents a simplified Erbil power grid. It consists of twenty components with their parameters as shown in Table 4. These values represent the shape and scale parameters for generators and substations. This model is simplified in order to scale the problem and ignored other components in the grid such as transmission lines and transformers. The estimated costs for maintenance and failures were set based on similar problems with similar setups [18][19][20]. In overall, the system consist of 9 generators (one diesel unit with 29MW and 8 gas units with 125MW rating) plus 13 substations with 4 stations having 2x63/50/40 MVA and 9 stations with 3x63/50/40MVA rating. Figure 4 shows the map for Erbil power grid connection.

Table 4: Case Study Parameters for Erbil Power Grid

Component	Shape Parameter (β)	Scale Parameter (λ)	Increment	Failure Cost ($)	Maintenance Cost ($)
G1	2.05	1.5	0.16	7000	300
G2	2.05	1.5	0.16	7000	300
G3	2.05	1.5	0.16	7000	300
G4	2.05	1.5	0.16	7000	300
G5	2.05	1.5	0.16	7000	300
G6	2.05	1.5	0.16	7000	300
G7	2.05	1.5	0.16	7000	300
G8	2.05	1.5	0.16	7000	300
G9	2.85	1.08	0.14	5000	250
Substation1	2.8	0.95	0.12	4000	200
Substation2	2.8	0.95	0.12	4000	200
Substation3	2.8	0.95	0.12	4000	200
Substation4	2.8	0.95	0.12	4000	200
Substation5	2.8	0.95	0.12	4000	200
Substation6	2.8	0.95	0.12	4000	200
Substation7	2.8	0.95	0.12	4000	200
Substation8	2.8	0.95	0.12	4000	200
Substation9	2.8	0.95	0.12	4000	200
Substation10	1.83	1.39	0.1	3000	1500
Substation11	1.83	1.39	0.1	3000	1500
Substation12	1.83	1.39	0.1	3000	1500
Substation13	1.83	1.39	0.1	3000	1500
Fixed Failure cost	15000$				
Maintenance Fixed Cost	1000$				



(a)

(b)

Figure 4: Erbil power grid setup, (a) West District and (b) East District.

The result of maintenance scheduling of these components over a period of 50 months is shown in Table 5. Total maintenance cost for the shown task is 105190USD compared to 115750 USD when Genetic Algorithm was applied. The 8 generators have less maintenance times since the failure distribution parameters (shape and scale) has a slow failure rate. As a result, there will be less maintenance actions required compared to the others. Most maintenance actions are performed to G9 and substations 1 to 9. These have high shape parameter and lower scale parameter which will cause a faster failure rate effect on failure distribution function in Eq. (5).

Table 5: Maintenance times for Erbil grid components

Component	Maintenance Time (month)
G1	5-11-15-20-23-30-37-43
G2	5-11-15-20-23-30-37-43
G3	5-11-15-20-23-30-37-43
G4	5-11-15-20-23-30-37-43
G5	5-11-15-20-23-30-37-43
G6	5-11-15-20-23-30-37-43
G7	5-11-15-20-23-30-37-43
G8	5-11-15-20-23-30-37-43
G9	3-6-11-14-19-23-27-32-36-40-43-47
Substation1	3-7-10-15-20-24-27-31-35-40-45-49
Substation2	3-7-10-15-20-24-27-31-35-40-45-49
Substation3	3-7-10-15-20-24-27-31-35-40-45-49
Substation4	3-7-10-15-20-24-27-31-35-40-45-49
Substation5	3-7-10-15-20-24-27-31-35-40-45-49
Substation6	3-7-10-15-20-24-27-31-35-40-45-49
Substation7	3-7-10-15-20-24-27-31-35-40-45-49
Substation8	3-7-10-15-20-24-27-31-35-40-45-49
Substation9	3-7-10-15-20-24-27-31-35-40-45-49
Substation10	4-8-11-14-20-24-28-33-38-43
Substation11	4-8-11-14-20-24-28-33-38-43
Substation12	4-8-11-14-20-24-28-33-38-43
Substation13	4-8-11-14-20-24-28-33-38-43

V. CONCLUSION

In this paper a binary Gray wolf optimizer is used to find the best maintenance schedule of Erbil Grid. The optimizer is used to find the minimum cost for the applied maintenance actions during grid operation. The proposed system depends on wiebull distribution analysis for unit failure during operation to form maintenance model. This maintenance model takes under consideration the cost of failure and maintenance for each component, as well as, fixed cost for system maintenance and the losses (fixed failure) cost.

The binary Gray Wolf optimization scored a maintenance cost of 105190USD compared to 115750 USD when genetic algorithm is used. This enhancement is obtained from the mechanism of having three existing solutions (best three) used to form new solution compared to genetic which used only two. This mechanism will guarantee the diversity of solutions in the search space. The final result give a promising prospect for using this algorithm in similar case studies and applications.

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