

Development of Optimized Maintenance Scheduling Model for Coal-Fired Power Plant Boiler

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(Received April 30, 2024; Revised March 03, 2025; Accepted April 21, 2025)

Abstract: Efficient maintenance scheduling for coal-fired power plant boilers requires systematic approaches due to frequent upkeep needs. Computing intelligence, a subset of AI, aids in gaining insights. Optimization methods like MILP and PSO rely on constraints and variables to minimize or maximize objectives. This study applied MILP and PSO to address maintenance optimization. Mathematical formulations were devised specifically for these methods to tackle boiler maintenance scheduling effectively.

Keywords: coal-fired power plant boiler; maintenance scheduling model; mixed integer linear programming (MILP); particle swarm optimization (PSO)

1. Introduction

Many coal plants still provide electricity for many parts of the world ¹⁾. Renewable energy sources are gaining ground, but coal-fired power plants still contribute more than a third of global power generation, and are the largest contributor to providing energy to the iron and steel industries. It offers reliability and flexibility of the power system ²⁾. A suitable example of this is the case where coal-fired power plants are rebuilt as dispatchable or flexible system service providers so that they can supply less energy. It can be relied upon at a certain time while also ensuring a stable power system ³⁾. Moreover, coal plants, which may have CCUS (Carbon Capture, Utilization and Storage) technology, are now considered as another alternative to clean energy solutions. They will give additional space for surplus capacity reducing operating costs ^{4) 5)}.

Creating and ensuring energy security and favorable economic performance are basic conditions for enabling developing countries to use renewable energy sources. A suitable example of this is Asia where the maximum lifespan of coal-fired power plants is 13 years and no decommissioning infrastructure plans have been made. With this, plants can be retrofitted with carbon capture and storage technology ⁶⁾. This will facilitate the transition

from fossil fuel-based energy to 100% renewable energy ⁷⁾. But on the other hand, such ongoing operations in coal-fired power plants naturally incur costs, and one cannot curb carbon emissions that encourage global warming ⁸⁾. The key goals of removing exhaust pollutants from coal-powered power plants and converting their operations to clean power plants could be considered top air priorities among the net zero goals. These steps could lead to a significant reduction in fossil energy's negative impacts ⁹⁾. Machines and equipment are kept safe by maintenance, which is a crucial support for the power generation industry. Power plant operators are therefore more profitable and competitive when maintenance activities are efficient ¹⁰⁾. Corrective and Preventive maintenance are required to ensure power plant's machines and equipment can generate power smoothly without any problems ¹¹⁾. Corrective maintenance is a maintenance performed after a breakdown or outage that led to severe performance costs. While preventive maintenance is a predetermined or scheduled maintenance to reduce the probability of failure and replaces parts before the end of their useful life ¹²⁾. Maintenance cost could constitute one-third of power plant operating expenditure and it may worsen through bad planning, overtime costs and bad use of preventive maintenance ¹³⁾. Standard maintenance scheduling problem are based on several constraints such as

maintenance window, manpower, reserve margin and transmission constraint. A good maintenance scheduling can reduce the production cost, increase system reliability and extend machinery lifetime ¹⁴⁾.

Electricity demand subsequently increased due to economic growth, and if it isn't met by an increase in generation capacity, the reserve margin is lowered. Consequently, reluctance to perform maintenance will increase generating unit failures due to a lack of willingness to take generators off line for maintenance ¹⁵⁾. Over the last decade, studies of maintenance scheduling problems with different methods such as multi-criteria decision making, swarm intelligence, linear programming as well as mathematical modeling are conducted by focusing on design and development of an optimized maintenance schedule especially for steam boilers ¹⁶⁾.

Maintenance scheduling and optimization system is a combination of ranking and prioritization with maintenance optimization ¹⁷⁾. To design and model the maintenance schedule, maintenance window with the preceding sequence and the performance of the maintenance scheduling with respect to maintenance costs should be taken into account. By analyzing the historical operational data, the maintenance optimization systems will automatically reschedule the maintenance activities based on the priority, importance and preceding order. The advantages of the system are facilitating scheduled maintenance, allowing the user an ability to identify the critical activities and costs. The system also would be able to predict the performance of the maintenance and automated report with graphic data ¹⁸⁾.

The process of optimizing the maintenance schedule of coal-fired power plants involves many complex problems to be solved. This process requires combining operational research methods and reliability engineering principles with specialized knowledge about power plant systems ¹⁹⁾. Many previous studies have investigated optimization approaches that include mathematical modeling along with simulation-based optimization based on artificial intelligence techniques because each method has its own strengths and weaknesses ^{20) 21)}. In this study, the effectiveness comparison between MILP and PSO methods as used in boiler maintenance schedule optimization algorithms is investigated. The reliability and economic feasibility of adhering to the maintenance schedule in coal-fired power plants depend on effective maintenance scheduling. Equipment failures that interrupt operations cause significant financial damage to operations and power outages that cause significant material losses. Optimized maintenance schedules implemented by power plant operators reduce downtime while extending equipment life and making operations more efficient. The research project focuses on power plant boilers to create a maintenance schedule design that reduces operating expenses and shortens maintenance duration, leading to

improved power generation efficiency.

The objective of maintenance activities in a power plant is to ensure that appropriate work is carried out at the ideal time ²²⁾. The accountability of the system should be used to develop an efficient prioritization method. Work should be planned in accordance with criticality, resource availability and time allocated using a priority approach ²³⁾. Research priorities were analyzed based on previous studies. An optimal maintenance solution can be described as a preference approach compatible with the objective when certain considerations apply. An objective function can be minimized or maximized by identifying values of modeled parameters ²⁴⁾. Numerous researchers have recently considered optimization systems as optimization tools, according to the literature. The application of optimization algorithms in power engineering has become very widely spread and has become one of the most powerful optimization tools. Various problems including neural network training, function optimization, fuzzy system control and pattern classification had been successfully solved using these stochastic population-based optimization algorithms ²⁵⁾.

Hence, the motivation for this study was to consider a number of questions: How will the algorithms of the maintenance scheduling optimization system be affected by the parameters? Secondly, what is the reliability of a maintenance improvement system? Thirdly, is the new maintenance schedule more efficient than the old one? Fourth: How have maintenance improvement systems affected steam boiler performance?

The results of this study were analyzed to answer these questions. A maintenance scheduling optimization system was developed by taking into account some parameters. Among the parameters are the maintenance window, the availability of manpower, the previous maintenance sequence, and the cost of maintenance. The model is developed using actual coal-fired power plant data. A comparison will be made between the simulation results and the actual results, and the system will then be validated by the maintenance team to guarantee that the optimization system is effective and reliable. In order to find optimal solutions, each parameter solution will be analyzed to determine how it affects other objective functions. On the basis of maintenance reliability, performance is then analyzed. As a result, future maintenance is minimal, and system availability is enhanced. In terms of maintenance scheduling, the model presented an interesting approach. This study seeks to verify and analyze historical steam boiler generating station maintenance scheduling data. Also, creating maintenance scheduling optimization models by formulating constraints in power plants for steam boilers with the lowest maintenance costs and durations. Validate applicable models with plant maintenance guides/experts. Finally, evaluate the system results in terms of power plant operational performance.

This study presents its original aspects in three parts.

1. The boiler maintenance scheduling problem uses MILP and PSO optimization techniques in an innovative and comparative fashion because of their established presence in literature yet rare application in this specific power plant example. There is a lack of direct comparison studies between these two methods which addresses boiler maintenance for this particular application according to existing literature. The study provides a detailed explanation of the relevant parameters which include maintenance periods along with available workforce and previous maintenance order and associated expenses.
2. A specific study investigates boiler maintenance scheduling within coal-fired power plant systems while numerous researches address maintenance of entire power systems as well as other equipment types. The study selects the boiler as its subject because it positions itself towards the solution of a crucial complex issue in coal-fired power facilities.
3. The model accounts for multiple operational requirements which align with actual power plant operational barriers such as scheduling windows besides workforce scheduling and task priority levels and maintenance budget limitations. The research value increases when the work adopts real-world practical elements. Operating records from the past are additionally incorporated.

2. Methodology

This study can be divided into three phases as presented in Figure 1. In this research, one of coal-fired power plant in Malaysia has been adopted as a real data source for the proposed maintenance scheduling and optimization systems.

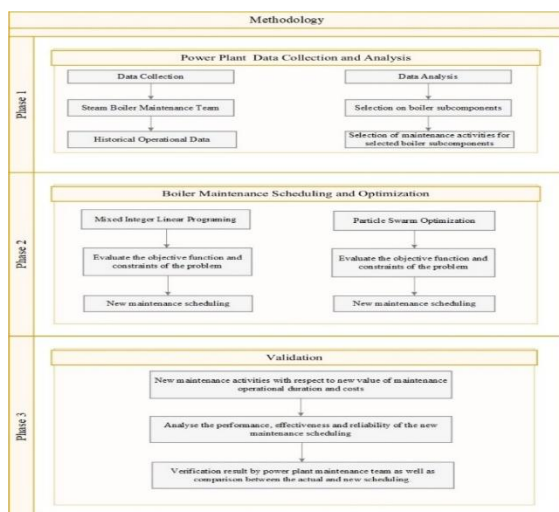


Fig. 1: Methodology

2.1. Phase 1: Power Plant Data Preparation

Data preparation is about constructing a completed dataset from one or more sources to be implemented for research and modeling. Good data preparation is necessary to establish a model. In this study, one of coal-fired power plant in Malaysia which generated 700MW was selected as a real data source for the proposed boiler maintenance scheduling and optimization model.

2.1.1. Coal-Fired Power Plant Boiler

The boiler is a piece of complex equipment in the power generation industry involving two main energy conversion processes. The boiler releases the chemical energy stored in the coal and converts it to heat energy. The heat energy is then transmitted as the steam generated when the heat absorbed the water. Subsequently, this heat energy then is converted into electrical energy in the turbine. The output of the coal-fired power plant increases as the vapor pressure and temperature rise. It has contributed to a greater boiler system with better efficiency under challenging circumstances ²⁶⁾.

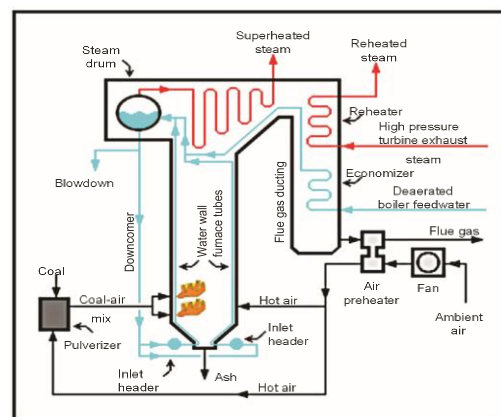


Fig. 2: Cross section of a steam boiler in coal fired power plant ²⁶⁾

2.1.2. Historical Operational Data

Neither exotic technologies nor expensive systems are necessary to perform effective maintenance. The key to reliable plant systems lies in performing simple, basic tasks. Completed maintenance scheduled was received from the plant maintenance engineer. In this study, the completed maintenance schedule delivered by the plant maintenance engineer was adopted. This procedure is adopted because it ensures that data integrity verification steps are followed and that there is consistency in handling of missing/abnormal data by the plant maintenance team. Based on the maintenance scheduled received, a full-scope investigation with the respected engineers was carried out to fully understand the maintenance schedule. Out of fifteen components involved in the boiler major overhaul from the last major overhaul in 2017, the pendant and fluid cooled spacer will be adopted into the boiler maintenance

scheduling and optimization model due to its critical maintenance and duration.

Major overhaul of this coal-fired power plant boiler was carried out from October to December 2017. During the major overhaul, some boiler tubes defects were identified outside of planned works, such as thinning defects and cracks, those identified were observed and rectified ²⁷⁾. Table 1 and Table 2 show the maintenance activities executed to resolve the major issues on the boiler tubes which affect the operation duration and are illustrated in Figure 2 ²⁸⁾.

Table 1: List of maintenance activities

ID	Task Name	Duration	Formally
6	Pendant & Fluid Cooled Spacer Tubes Works	47.99 days	
7	Pendant Tubes Repair (IHI)	29 days	
8	HTS1 Tube	23 days	
9	Cutting=216/216 jts	23 days	
10	F/Up=216/216 jts	23 days	9SS
11	Welding=216/216 jts	23 days	10SS
12	PAUT=216/216 jts	23 days	11SS
13	PWHT=216/216 jts	23 days	12SS
14	HTS2 Tube	23 days	
15	Cutting=531/531 jts	23 days	
16	F/Up=531/531 jts	23 days	15SS
ID	Task Name	Duration	Predecessor
17	Welding=531/531 jts	23 days	16SS
18	PAUT=531/531 jts	23 days	17SS,23SS,27SS
19	PWHT=448/448 jts	23 days	18SS
20	HTS1 Attachment	23 days	
21	F/Up=105/105 jts	23 days	
22	Welding= 106/105 jts	23 days	
23	PWHT= 85/85 jts	23 days	
24	HTS1/HTS2(T22) Cleaning & Repair Works	6 days	13,19,23,27
25	Fluid Cooled Spacer Tubes Upgrades (IHI)	24 days	
26	Preparation & PFW (Including scaffolding)	8 days	
27	Cutting & remove existing FCS Tube	2 days	32
28	Tube Fabrication-contractor's workshop (Include surface preparation & bevelling)	7 days	33

29	NDT (PT) for attachment & supports	5 days	34SS+2 days
30	Surface preparation & bevelling	3 days	33
31	Lifting, fit-up and welding work	7 days	36FS+2 days
32	NDT (PAUT) for tube joint	5 days	37SS+3 days
33	NDT (DPT) for attachments	2 days	38SS+3 days
34	Final Inspection	1 day	39

Table 2: Maintenance cost involved for this case study

Work Scopes	Major Overhaul
Pendant tubes repair, services (RM)	3,450,000.00
Pendant tubes repair, spare parts and consumable (RM)	936,000.00
Fluid cooled spacer tubes, service & boiler tube supply (RM)	600,000.00
Total (RM)	5,000,000.00
Completion Time (days)	48
Maintenance manpower allowed per day (pax)	30

First of all, all the following parameters are studies and identified:

- Critical maintenance activities in coal-fired power plant boilers.
- The longest operation duration with highest maintenance cost.
- The preceding constraint to implement ranking and prioritization method.
- The maintenance costs that will be affecting the optimization method.

The main objective of this study is to model a new maintenance scheduling with minimal maintenance operation duration and cost. Also, developing new mathematical equations corresponding to the constraints of the optimization methods. The listed parameters above help to smooth the research procedure and achieve the objectives successfully.

2.2. Phase 2: Boiler Maintenance Scheduling and Optimization Systems

Boiler maintenance scheduling and optimization systems were identified in previous studies as a multi-criterion with restricted combination optimization problem with the nonlinear objective and constraint functions. The objective of the optimization problem is to determine a set of global ideal solutions. In relation to the systems, the objective was defined as the assessment of the scheduling and sequencing of the maintenance activities of each generating unit in the power generation industry, considering that the maintenance duration is constant. As a result, the set of variables in solving the problem are

implicitly defined by the start time of maintenance for all generating units. The objectives and constraints adopted into the scheduled maintenance in the previous studies are varied based on the requirements of the independent power providers. Therefore, in this section, methods and limitations for maintenance scheduling and optimization in previous studies are reviewed and determined.

2.2.1. Methodology of AHP

In the AHP, evaluation criteria are examined along with alternative options, and a decision is made based on the most appropriate criteria. As decision makers compare pairs of evaluation criteria, AHP generates a weight for each criterion. It is possible to use a generic list of maintenance optimization criteria as a guide for setting maintenance optimization objectives. Among those criteria, a prioritization should be made based on expertise within a company. As a next step, compute the weighted vector for each criterion. Equation 1 illustrates how the AHP calculates a pairwise comparison matrix S . S is a m by n real matrix, where m indicates the number of criteria to consider.

$$S = \begin{bmatrix} 1 & \cdots & s_{1n} \\ \vdots & \ddots & \vdots \\ \frac{1}{s_{1n}} & \cdots & 1 \end{bmatrix} \quad (1)$$

After that, computing matrix option score. The matrix of option scores is a $n \times m$ real matrix S . The score matrix S is obtained using Equation 2.

$$S = [s^{(1)} \dots s^{(m)}] \quad (2)$$

or AHP, to know the reliability of the matrix form, the consistency must be check. However, for TOPSIS, the procedure is ended here and proceed with the ranking options. To check the consistency, there are three steps that need to be follows.

The λ_{\max} in Equation 3, is the highest eigenvalue of the matrix has to be calculated.

$$\lambda_{\max} = \sum_{j=1}^m \frac{(S.v)_j}{m.v_j} \quad (3)$$

Then the consistency index (CI) can be calculated as in Equation 4.

$$CI = \frac{\lambda_{\max} - m}{m - 1} \quad (4)$$

In a perfect consistency matrix, CI equals 0. With an increase in pairwise comparisons, there is also an increase in consistency errors. Accordingly, Saaty²⁹⁾ suggested an alternative method for calculating consistency ratios (CR) as shown in Equation 5, also RI is defined as the random consistency as tabulated in Table 3.

$$CR = \frac{CI}{RI} \quad (5)$$

Table 3: Average random consistency

m	RI
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.51

Lastly, to choose the best option, Equation 6 enables AHP to obtain a vector v of the global scores after calculating the weight vector w and the score matrix S .

$$v = S.w \quad (6)$$

According to the AHP, the i th option has gotten a global score of i . To rank options, the global scores are arranged in order of increasing importance^{30) 31) 32) 33) 34) 35)}.

2.2.2. Methodology of MILP

To formulate and develop MILP model, the two major issues on how to present the process or sequence of maintenance scheduling and time allocation had arises. A set of binary variables formulated in Equation 7 is considered to determine the preceding tasks and allocation constraints.

$$\sum_{i \in I_j} W_{ijt} \leq 1, \forall j \in J, t \in T \quad (7)$$

Where I_j is the set of maintenance tasks that can be performed in unit j . If a maintenance task starts in a time interval, no other maintenance can start in the same unit until the task is completed. The requirement shall be applied as shown in Equation 8.

$$\sum_{i' \in I_j} \sum_{t' \in T}^{t + \alpha_{ij} - 1} W_{i'jt'} - 1 \leq M(1 - W_{ijt}), \forall j \in J, i \in I_j, t \in T \quad (8)$$

Where, α_{ij} is the fixed processing time of the task i in unit j and M must be positive numbers. In addition to the binary variables, there are more parameters need to be considered such as the amount of the time interval, the capacity constraints, the mass balance and also the resource. However, these parameters are based on the modelling problems. Previous section had presented the overview of the past studies on the development of the mixed integer linear programming approaches for the scheduling problems. It is apparently the most significant approaches to be implemented^{36) 37) 38) 39)}. Figure 3 shown the simplified methodology of the mixed integer linear programming.

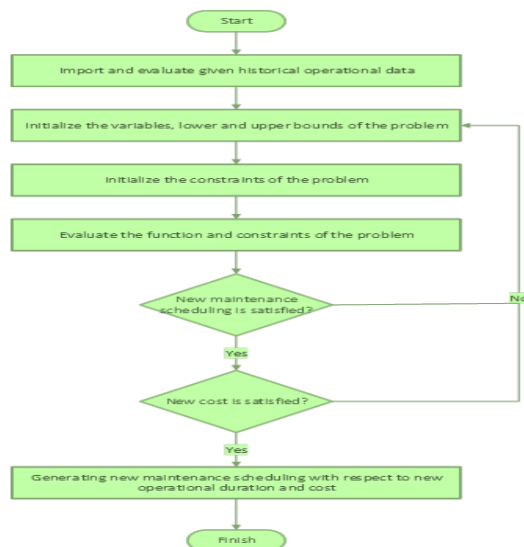


Fig. 3: Simplified MILP Flowchart

2.2.3. PSO Approach

In PSO, several candidate solutions are simultaneously maintained in the search space. Repeated iterations of the PSO algorithm will continue until a stopping condition is met. Particles determine the best local and global positions, adjust the velocity, and evaluate the function in each iteration. The objective function being optimized determines the fitness of each candidate solution during each iteration of the algorithm. The solution "flying" through the n-dimensional search space of the optimization problem identifies the maximum or minimum objective function of each candidate solution. Upon obtaining the maximum number of iterations or achieving no significant improvement over previous iterations, the algorithm is terminated.

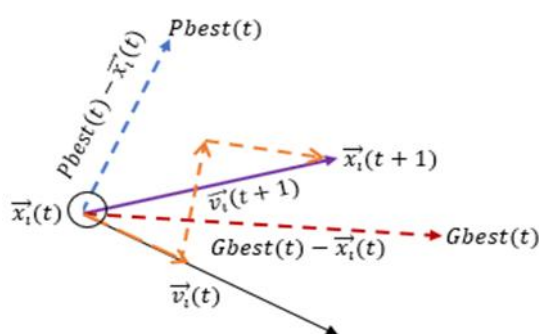


Fig. 4: PSO Concept of Searching Point

In the beginning, the PSO algorithm randomly selected a candidate solution within the search space. In Figure 4, the PSO algorithm is shown seeking the global maximum in an n-dimensional search space. All possible solutions along the best position are included in the search space. There is no way for the PSO algorithm to determine whether any candidate solution is close to or far from a local or global maximum because it does not know what

the objective function is. PSO algorithms evaluate candidate solutions based on fitness function values. A particle's velocity and position are updated in an n-dimensional search space based on two components of cognitive information from the particle's own experience and social information from the particle's neighbours, as presented in Equation 9 and Equation 10.

$$v_{i,n}(t+1) = w, v_{i,n}(t) + c_1 r_1 (pBest_{i,n}(t) - x_{i,n}(t)) +$$

$$c_2 r_2 (Gbest_{i,n}(t) - x_{i,n}(t)) \quad (9)$$

$$x_{i,n}(t+1) = x_{i,n}(t) + v_{i,n}(t+1) \quad (10)$$

Particles maintain their positions based on their candidate solutions, fitness and velocity. Also, it remembers the particle that achieved the individual best fitness value thus far during the operation of the algorithm, as well as the particle that achieved this position. According to Equation 11, the particle that achieved this position represents the individual best fitness so far.

$$\overrightarrow{pBest}_i(t) = \{pBest_{i,1}(t), \dots, pBest_{i,n}(t)\} \quad (11)$$

As shown in Equation 12, the algorithm also maintains the particle with the global best position and the particle with the best fitness value among all particles in the swarm.

$$\overrightarrow{gBest}_i(t) = \{gBest_{i,1}(t), \dots, gBest_{i,n}(t)\} \quad (12)$$

Here, r_1 and r_2 are two elements of the arithmetic progression, with each unique number evenly spaced between zero and one. The constants c_1 and c_2 are specified as constant acceleration, and most of them are the same except for a few values of $pBest$ and $Gbest$. Higher values of W promote global searching and searching, known as w_{max} , while lower values of w_{min} promote local searching. One of the quickest ways to find and maintain a balance between global and regional searches is to make the search time limit shorter. The bubble is formed via random generation and the ideal position of each section is updated in each iteration. Once the stopping criteria are no longer reached, the particles gradually accelerate and become more stable. Figure 5 is an easy way to use the correct parts ^{40) 41)}.

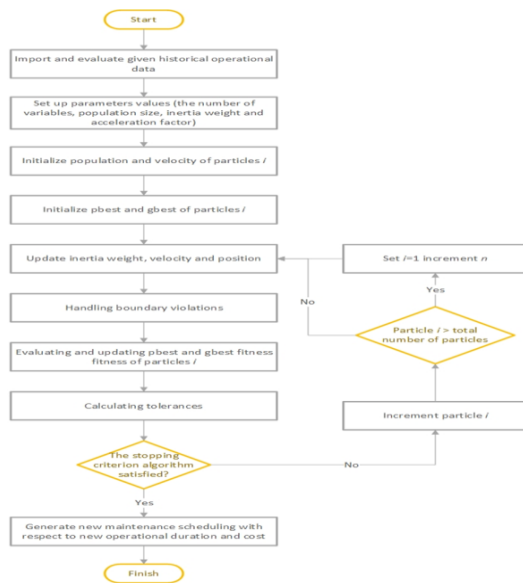


Fig. 5: Simplified PSO Flowchart

2.2.4. Comparing MILP with PSO

MILP and PSO are compared here in terms of cost and manpower requirements in large projects through various evaluation factors, including:

Cost Comparison

MILP requires higher startup costs because the accurate optimization solution requires detailed planning. Through its problem-solving process, MILP generates optimized solutions that include both higher startup costs and better long-term operating efficiency ⁴²⁾. MILP offers efficient computational processing that helps reduce the overall operating costs of computer resources ⁴²⁾.

The use of PSO often increases variable expenses during operations that rely heavily on gas or alternative fuel resources ³⁶⁾. Procedures Solution Optimization (PSO) demonstrates the ability to handle non-linear challenges although it typically involves longer computational periods that result in additional expenditure of computational resources ^{42) 43)}.

2.2.5. Manpower Requirements

Since MILP uses fixed mathematical formulas, the implementation and maintenance process require less staff involvement. Efficient MILP models require minimal human supervision after their setup especially when users deploy commercial solutions such as CPLEX ⁴²⁾.

PSO requires additional human resources because it acts as a heuristic algorithm along with parameter optimization requirements especially for inertia and acceleration coefficient settings. The performance of PSO requires fine tuning under human expertise because these parameters affect its results in a very sensitive way ^{42) 43)}. Since PSO lacks an objective stopping parameter, it requires longer computational times and human supervision to determine when the algorithm should stop running ⁴²⁾.

Runtime

MILP achieves optimized long-term efficiency through its results although this optimization might produce solutions with longer runtime durations for single tasks. The solutions that MILP produces prove to be more stable and dependable ⁴²⁾.

PSO produces faster execution periods under specific situations through its optimization feature which handles non-linear or dynamic system constraints and conditions. The PSO performance depends on parameter tuning selection as well as the nature of the addressed problem ^{44) 45)}.

MILP delivers high initial expense coverage yet uses computational resources efficiently while generating results with lowered workforce requirements and PSO shows adaptability for nonlinear problems yet requires additional computational time and parameter adjustment support from personnel. Which optimization method gets selected depends on individual project specifications along with their operational restrictions.

2.3. Phase 3: Established Maintenance Scheduling Validation

In order to prove the developed models are workable and applicable, a validation process is required. The validation process is segregated into two process which are comparison with the actual scheduling and verification with power plant maintenance team. This phase is very crucial in order to achieve the objective of the study. Two different models are developed and generated a new set of different maintenance scheduling with respect to new value of the maintenance cost and operational duration.

The new generated maintenance schedules will be analyzed in terms of the performance, effectiveness and reliability. The analysis will be segregated into two types validation which are comparison with the actual scheduling and based on the expert's evaluations and opinions. The experts that will be involved in this verification is a team from the coal-fired power plant maintenance planning team. Thus, the objectives of the study will be able to achieve ⁴⁶⁾.

2.4. Analysis of operational constraints, model constraints, and parameter justifications

The evaluation includes operational limits and model limits with an explanation of parameter validation.

Operational Constraints

The main operational constraints evaluated in the maintenance scheduling model include:

The maintenance window functions as a time constraint for when maintenance can be performed but operational requirements create potential scheduling conflicts.

Maintenance capacity is dependent on the number of personnel available to perform maintenance activities.

Maintenance tasks must be synchronized in a specific order that requires task A to be completed before task B

can be started. Maintenance activities are interdependent, so this constraint applies to the scheduling model.

Budget constraints control the expenditures allocated to maintenance operations.

The specific constraints present in maintenance schedules correctly account for both operational requirements and organizational resource availability. The model determines the best maintenance schedule that minimizes time and expense and meets all the described boundary conditions. The research model targets significant improvements in steam boilers in Malaysian coal-fired power plants using the operational history of a 700 MW facility. The model shows limited use of alternative types of power plants and equipment. The model includes only two important boiler components consisting of the evaporator and the liquid cooled separator. The model also relies on historical operational information including maintenance records and expenses as well as performance times. The measurement accuracy and complete data quality affect the operational performance of the modeling system.

The model defines the maintenance duration as a constant value but this assumption does not reflect real conditions. The reality shows that maintenance periods change due to unforeseen problems and limited resource availability.

The finite objective function has the function of minimizing both maintenance expenses as well as operating periods. The system does not explicitly take into account other essential elements such as system reliability and environmental impact.

Optimization algorithm limitations: The model uses MILP and PSO, both of which have inherent limitations. MILP can be computationally expensive for large-scale problems, while PSO may not always converge to the global optimal solution.

AHP limitations: The AHP method relies on pairwise comparisons and expert judgment. This introduces subjectivity into the model, which can affect the accuracy and consistency of the results.

Lack of Validation: Validation is described as involving the maintenance team ensuring the effectiveness and reliability of the optimization system. This subjective assessment may not be as robust as quantitative testing against a discrete dataset or real-world implementation.

Parameter Rationale

Here are some justifications for the parameters used in the model:

Critical Maintenance Activities: The selection of critical maintenance activities is based on the longest operating duration and highest maintenance cost. This focuses the model on the most impactful maintenance tasks.

Historical Data: The use of historical data from a coal-fired power plant provides a realistic basis for the model.

Maintenance Costs: Maintenance costs are included as a parameter to reflect budget constraints and optimize the maintenance schedule for cost-effectiveness.

Previous Constraints: The previous constraint is incorporated to maintain the integrity of the maintenance process and ensure that tasks are performed in the correct order.

Maintenance Duration: The main objective of this study is to model a new maintenance schedule with the minimum operating duration and maintenance cost.

Mathematical Equations: Develop new mathematical equations that are consistent with the constraints of the optimization methods.

In short, operational constraints are based on real-world constraints, while model constraints arise from simplifications and assumptions made to make the problem solvable. The justifications for the parameters are based on the importance of maintenance activities and the need for optimization in terms of cost and duration.

2.5. Evaluation of the effectiveness of MILP and PSO models

In this evaluation many parameters must be revised and determined as in the followings:

2.5.1. Sensitivity to variations in input data

MILP models show high sensitivity to variations in input data that particularly affect both constraints and cost-related elements. Small variations that affect maintenance costs along with resource duration and availability levels lead to large variations in optimal scheduling decisions. Incorrect data about parameters lead to poor and unworkable scheduling results due to inaccurate or incomplete input information. MILP provides a deterministic solution generation process that produces the same optimal results from a given input set.

The heuristic features of PSO result in low sensitivity to variations in input data parameters. PSO-based exploration of the solution space leads to the discovery of suitable solutions even when the input parameters have uncertainty or noisy data. Large variations in the input data have large effects on the performance quality of the solutions produced by PSO. PSO generates different solutions in each execution run because its random search behavior produces varying results.

2.5.2. Dealing with constraints

MILP models impose strong constraints on their solutions. The model design includes a mechanism that ensures that all the mentioned constraints such as maintenance windows, workforce availability, and priority relationships remain satisfied in the resulting schedule. The MILP solution fails to identify any solution when the constraints it faces prove to be too narrow and unfeasible. Clients operating under the PSO model have more flexibility in managing the constraints. The search mechanism uses artificial penalties to guide itself towards feasible regions by accepting solutions with small violations of the

constraints. The approach proves useful in dealing with constraints that can be violated to a certain degree. PSO generates solution results that may not satisfy all feasibility requirements.

2.5.3. Scalability

MILP models present difficulties when dealing with problems that scale past a certain point. MILP problem requires exponential increases in computational resources when maintenance tasks along with their constraints and resources become larger in number. Big problems tend to take an excessive amount of time for the resolution process because both computing time and resources become critical factors for large-scale optimization tasks.

The PSO algorithm demonstrates superior scalability features than MILP when solving large-scale problems. The heuristic method of PSO helps it search large solution spaces quickly regardless of the number of problem variables and constraints. PSO yields solutions whose quality becomes increasingly compromised when dealing with larger problems since it loses the ability to discover the optimal solution of the problem.

2.5.4. Overall Robustness

Using MILP creates optimal solutions when both input data and problem constraints are accurate but becomes weak to data uncertainties and scalability limits.

PSO delivers better flexibility with scalability advantages while giving up performance guarantees and needing specific parameter adjustments.

The researchers did not perform robustness tests on the models because the provided maintenance team description focused only on system efficacy and dependability.

3. Assessment of result

3.1. Assessment of MILP Approach

A set of MILP model is developed and established by the parameters and constraints given. To illustrate the model, a thorough investigation and analyzation of the completed dataset is implemented and tested as explained in previous section.

In order to obtain the best scheduled, some trial had been carried out and found that the Figure 6 is the best result as it is complying all the parameters and constraints. Based on the observation, the operation duration reduced from 48 to 44 days and the maintenance costs are reduced from RM 4,978,065.07 to RM 4,351,065.07 which is around RM 627,000 reduction. Both reductions are equivalent to 8% and 28% respectively. Even though the duration is 8% reduction, it meant a lot to the power generation industry as 4 days reduction will be beneficial to them.

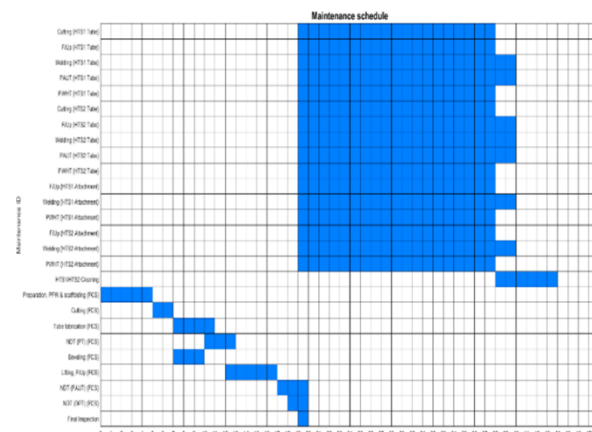


Fig. 6: Maintenance scheduled obtain from MILP

The approach can be a guidance for them to plan their preventive maintenance in terms of annual maintenance cost allocation. However, the parameters used in the optimization are subjected to the constraints or limitations based on the existing situations. In this MILP model, these limitations are beneficial for the approach to achieve the optimality and gap tolerance. Further investigation using PSO is necessary to ensure the reliability and to select the best approach is discussed in next section.

3.2. Assessment of PSO Approach

The PSO process is iterative and this iteration process will continue until the constraints are satisfied. The field selects the best single position, candidate position, rate of change of velocity, and number of steps examined in a single investigation. Evaluation tests, suitability, or performance measures evaluate the quality of the installation. The term "block parameters" refers to filtering search results. The iteration process of the algorithm will stop when the upper limit of iterations or fitness function is reached. If this maximum number of iterations is too small, the process can stop before the best solution is reached^{47) 48) 49)}.

The developed PSO was tested with initialized population of 2000 and iterations between 2000 to 3000. The patterns of the fitness function recorded are decreasing and optimal until iteration 2500 where it achieved optimal until iteration 3000. Based on these results, the study is required to increase and analyse a similar set of iterations with different populations.

Figure 7 is the maintenance schedule produced by the PSO runs. Each run producing exact schedule as shown in Figure 8 summarizes the iteration result produced by PSO, which represents all runs are satisfying the constraints and parameters settings in PSO. The new scheduling is highly constrained as it requires high amount of manpower for the first fifteen days. On the other hand, the duration optimization is satisfied as it is reduced from 48 to 22 days. However, the opinions and judgement from the expert in maintenance is necessary for the final decision making. The result obtained was observed and evaluated that there was a lack of failure in terms of the performance if this

schedule is selected. Hence, PSO algorithm is not effective to be applied for limited constraints due to its random behaviours.

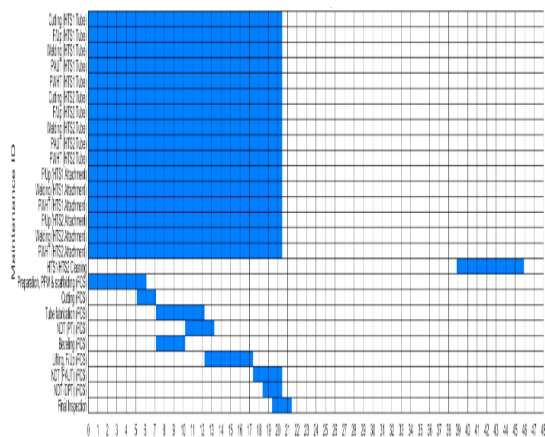


Fig. 7: Maintenance scheduling produced by PSO

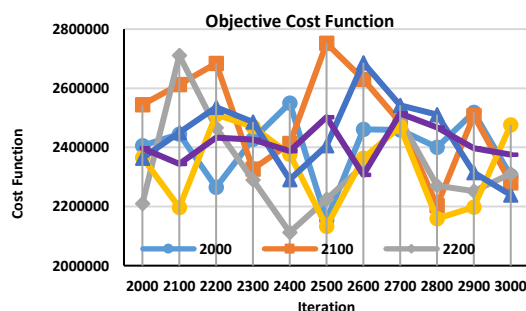


Fig. 8: Summary iteration result produced by PSO

Several parameters and limitations should be taken into account for future references. To recap, PSO approach is based on the mathematical simulation of random probability and considered a superior to other optimization due to adjustment of lesser number of parameters. As for this study, it may not produce a better result compared to the MILP approach due to the number of limitations. Therefore, the ability of PSO to determine effective scheduling is practical for a large amount of data with minimal limitations.

3.3. Overall Performance of Developed Models

By developing maintenance scheduling and optimization algorithms, the new best optimal values for MILP and PSO were founds and validated with the actual case study. Comparison results obtained by both algorithms are discussed in previous sections.

As mentioned previously, the number of evaluations (trial solutions) allowed in the PSO model are general and random. By using trial and error methods, a set of trial was selected as it produced the best objective function. In particular, the best results from both approaches were compared after few runs with similar given parameters. It can be seen that PSO algorithms have outperformed the MILP algorithm by producing a better maintenance cost

and operation duration. In addition, it can be seen that the difference cost reduction by MILP is much smaller than PSO, which indicates a consistent performance of the MILP formulation.

Among those approaches, the PSO, where initial population is generated using a heuristic that ranks the generating units in order of preceding sequences, was found to perform best result obtained. This indicates the potential of the benefit of a heuristic in solving optimization problems. However, with the assist and judgements from the experts in the power plant, the performance of the developed models was evaluated in terms of workability, applicability and reliability. Despite the identical schedule generated by MILP, it shows that the mathematical equations are reliable to be adopted into the real problem in power generation industry.

Other than that, power generation industries are known to have their own reserve margin. As discussed in previous section, PSO generating an optimized maintenance schedule with high number of cost saving compared to MILP because PSO is completing the tasks in short period. This will be affecting the reserved margin organized by the Grid System Operator (GSO) where the adopted power plant tends to operate earlier than scheduled. It is beneficial because they are able to generate profit early, but it also will cost the power plant in terms of the machinery performance after operating.

Therefore, it is shown that MILP is the most preferable and applicable model as only 30 manpower is accessible into a boiler per day for maintenance. Changes in maintenance scheduling in the deregulated industry has a significant impact on the applicability of maintenance experts experience / engineering judgement. To support this claimed, MILP is also been chosen by the expertise in the boiler maintenance planning team according to its similarity with the actual compared to PSO, even though PSO is having higher cost saving compared to MILP.

4. Data validation

To ensure data integrity and consistency, multiple validation steps were implemented throughout the study. The raw data used for maintenance scheduling optimization underwent pre-processing and cleansing to detect and manage potential missing values and outliers. Statistical techniques (interquartile range) analysis and Z-score methods were applied to identify and handle anomalous data points. Missing values were addressed using data imputation techniques, including mean, median replacement, and interpolation. Additionally, a cross-validation approach was adopted to verify the robustness of the optimization models (MILP and PSO), ensuring consistent and reliable outputs.

The study also adheres to ethical research standards by ensuring transparency, accuracy, and responsible data

management. The data set used in this research was collected with proper authorization from relevant stakeholders. In compliance with data privacy and confidentiality protocols, all sensitive information was anonymized and de-identified before processing. To uphold data security, multiple protective measures were enforced:

All research data was stored on secure, access-controlled servers with periodic backups to prevent data loss.

Encryption techniques (AES-256) were used to safeguard digital records. Access to the dataset was restricted to authorized researchers only.

Two different algorithms for maintenance scheduling and optimization were proposed in this research, motivated by the need to optimize the annual allocated maintenance costs. Both algorithms had fulfilled the research objectives by producing the best results. However, to ensure the results are reliable and verified, both algorithms will be assessed and validated. This section will elaborate on the validation process involving the performance of the component after implementing the developed models. To support the comparative assessment with the actual maintenance scheduling, opinions or judgements from the experts are necessary.

Table 4: Validation Number of Manpower

Manpower	Methods	Cost saved (RM)	Reduction (%)	Total cost after reduction (RM)
100	MILP	1,432,600.00	28.78	3,545,465.07
	PSO	235,248.37	4.73	4,742,816.70
70	MILP	1,463,300.00	29.39	3,515,062.07
	PSO	830,729.37	16.69	4,147,335.89
50	MILP	1,045,000.00	20.99	3,933,065.07
	PSO	1,771,190.13	35.58	3,206,874.94
30	MILP	627,000.00	12.59	4,351,065.07
	PSO	1,883,685.25	37.84	3,094,379.82

Initially, the developed models were tested with four different numbers of manpower required which are 30, 50, 70 and 100. Table 4 is presenting the results for each maintenance cost reduction according to the amount of manpower. It was then evaluated by the experts from the maintenance teams which advised and validated the values of 30 manpower required per day. Therefore, further investigations by enhancing the models with 30 manpower were executed. Details of the trial simulations run were discussed in the previous section. In other words, a

complete trial solution had satisfied the constraints and was verified by the experts before the detailed evaluation process is carried out. As for the PSO approach, the result obtained for 30 manpower are at population 600 with iteration 1500. This set of population and iteration are the benchmarking for the entire PSO runs as shown in Figure 9 where the fitness function value is not at an optimal value. The equations were reliable as the result obtained from MILP is similar to the actual. Therefore, the same equations were implemented in PSO algorithms. The objective functions and satisfaction of constraints associated with the PSO were discussed in previous sections. In addition, the costs associated with the schedules can be seen as the saving cost that could be achieved by both algorithms. The results obtained by both algorithms indicate their potential for being a practical maintenance scheduling tool.

The developed MILP model is the most capable of finding a reliable solution for the optimization problem and complied all the given parameters and constraints. Due to a small scale of data, the MILP model is more reliable and dependable compared to PSO as PSO working behaviour is a random optimization modelling and more effective to be implemented in a large scale of data.

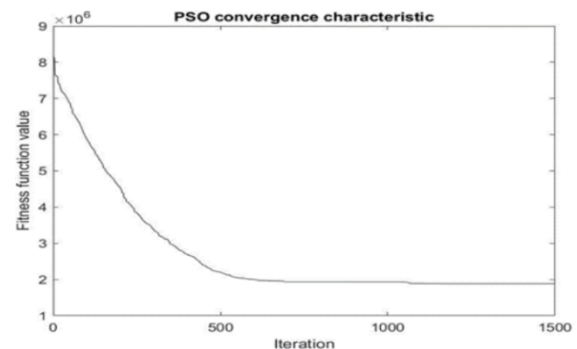


Fig. 9: PSO Convergence Graph for 30 Manpower

Table 5: Comparison between MILP and PSO

Material	MILP	PSO
Constraints	Complied all constraints	Complied all constraints
Amount of task	No removal of tasks	No removal of tasks
Operation duration	Reduced from 48 to 44 days	Reduced from 48 to 22 days
Cost saved (RM)	627,000.00 (12.59 %)	2,112,701.20 (42.44 %)
Manpower	Below 30 per day	More than 30 per day
Expert judgement	Most preferable as the schedule is applicable and similar to the actual	Unlikely preferable due to unapplicable schedule

Detailed investigations in this study were discussed and explained in the previous section. Table 5 is the overall comparisons between MILP and PSO based on specified problems. The optimization takes place by taking into consideration the minimum working hours and the amount of manpower required per activity. As a result, PSO required more than 30 manpower to complete the maintenance tasks which is violating the amount verified by the maintenance team. Based on the comparison results, if MILP is chosen, it will cost the power plant RM 4,352,056.07 for annual maintenance cost while PSO is costing RM 2,865,363.87. Even though the MILP is costing higher than PSO, the expert is choosing MILP as their assisting tool for optimization. The decisions were discussed by the maintenance team based upon the workability, reliability and applicability of the new maintenance schedule into real-world optimization problems. The results obtained show the robustness of the developed maintenance optimization formulation in handling real-world situations.

5. Conclusion

A set of mathematical equations were formulated for boiler maintenance scheduling problem has been developed, tested and applied to real systems which are MILP and PSO models. Based on the results obtained, it can be concluded that the developed models are working as a tool in assisting the maintenance schedulers, specifically when involving complicated objective function are involved in the scheduling process.

By developing maintenance scheduling optimization models that can be used to effectively monitor and reschedule maintenance activities based on current problems, the present work is expected to have contributed significantly to the operation of boiler coal-fired power plants. In addition to being used as maintenance guidelines, the developed models can also be used to reduce the number of failures or redundant activities when new scheduling is being planned. Changing parameters, if necessary, can assist the power plant maintenance team in planning maintenance scheduling which has the shortest operating duration and lowest cost.

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