Chapter 24
Preventive Maintenance Scheduling Optimization: A Review of Applications for Power Plants

Neha Prajapat, Ashutosh Tiwari, Xiao-Peng Gan, Nadir Z. Ince and Windo Hutabarat

Abstract This review paper considers literature in the field of preventive maintenance scheduling optimization, particularly for applications to power plants, with the view to assess the methods used and identify research trends and gaps. Aspects of each of the papers such as application domain, problem formulation, model formulation and optimization techniques have been analyzed and assessed. Research trends such as the increasing use of stochastic parameters, multiple objectives and hybrid optimization methods have been identified. A research gap has been identified: the application of discrete-event simulation methods with multi-objective hybrid optimization for power plant preventive maintenance scheduling. These areas provide exciting research opportunities with significant potential benefits for power generation companies including increased profit and reliability.

24.1 Introduction

Various different types of maintenance scheduling can be defined: Corrective Maintenance (CM), Preventive Maintenance (PM), and Condition Based Maintenance (CBM). CM is performed upon component failure and generally leads to high failure cost and large downtimes [1]. Monitoring technologies are often used to perform on-line assessment of the condition of equipment and then condition based maintenance activities can be applied to prevent high failure costs. Prognostics can be used as an extension of condition based maintenance strategies. Prognostics use condition based maintenance technologies to diagnose failures of components and to potentially forecast future failures [2]. Preventive maintenance

A. Tiwari (✉) · W. Hutabarat
EPSRC Centre for Innovative Manufacturing in Through-Life Engineering Services, Cranfield University, Cranfield, UK
e-mail: a.tiwari@cranfield.ac.uk

N. Prajapat · X.-P. Gan · N.Z. Ince
GE Power, Newbold Road, Rugby, UK

L. Redding et al. (eds.), *Advances in Through-life Engineering Services*, Decision Engineering, DOI 10.1007/978-3-319-49938-3_24

can be used in conjunction with, or as an alternative to, monitoring based maintenance strategies. Preventive maintenance constitutes a predefined schedule or routine of check-ups and repair tasks [3]. The focus of this review is on optimizing preventive maintenance schedules.

Preventive maintenance scheduling has been widely used within industry and these activities are often performed at a higher frequency than is required to prevent unnecessary failures [4]. The manufacturer or equipment supplier will usually predefine a set of constraints and maintenance intervals for the schedule to abide [5]; these are often based on the experience of engineers. A number of industry sectors have identified the benefits which can be achieved through optimization of preventive maintenance schedules, for instance: increased reliability and profit and lower risk and costs. Applications for preventive maintenance scheduling optimization have appeared in a range of industry sectors including transport [6, 7], manufacturing [8] and power industries [5, 9, 10]. This work is concerned with the application of preventive maintenance scheduling optimization for power plants.

Optimization of maintenance schedules within the power generation industry is vital as generation equipment must be reliable, to enable generation companies to provide a reliable service to customers. This optimization could also produce large cost savings through increased sales and decreased downtime, also increasing the overall utilization of the plant. These savings made in operational costs can also assist generation companies by enabling them to provide competitive energy prices [11]. For larger power plants the main equipment can have different manufacturer's guidelines and maintenance intervals; in such a scenario it could be beneficial to perform simultaneous maintenance on major equipment as the opportunity arises.

A number of review papers considering maintenance scheduling optimization exist: in [12] a detailed literature review is performed of scheduling research covering job shop scheduling, work in [13] focusses on multi-objective production scheduling research. These reviews cover the generic machine scheduling problem and do not consider preventive maintenance scheduling within the power industry. In [1] authors provide a brief overview of different levels of maintenance scheduling within power systems and outline the maintenance scheduling problem in power systems for various time scales. Studies [3, 14] examine literature for the Generator Maintenance Scheduling problem (GMS). In [14] authors provide details on problem features, goals for optimization and optimization techniques. Authors in [3] provide a comprehensive description of problem features, objective functions and interfaces with other scheduling problems. This paper presents an up to date review of papers within all areas of power plant preventive maintenance scheduling optimization with detailed information about objective functions, constraints and optimization methods. In particular this paper examines various optimization methods for the preventive maintenance scheduling problem including: dimensionality reduction [4], expert systems [15], Genetic Algorithms (GA) [9, 16–18], hybrid methods [19–21], Particle Swarm Optimization (PSO) [22–24], Simulated Annealing (SA) [25] and Tabu Search (TS) [26]. Notably the application of hybrid optimization methods is a new research area which has not been covered by previous reviews.

24.2 Methodology

Scopus, being the largest abstract and citation database for peer-reviewed literature, was chosen as the main database to access papers. Initially scheduling optimization review papers were studied to provide a good overview of scheduling optimization within industry. Subsequently a number of review papers for maintenance scheduling were found and used to identify journals and conferences which contain the most relevant papers. Papers were chosen based on relevance to preventive maintenance scheduling with application to the power industry and optimization.

A primary search in Scopus using the keywords: 'maintenance scheduling power' resulted in over 1000 results. Hence, a more focused search was made using the keywords: 'preventive maintenance scheduling optimization power plant.' This search returned around 25 papers among which 11 papers were chosen. The number of papers which focus on power plant equipment maintenance is limited; hence papers which explore the GMS problem were found through a further search using 'generator maintenance scheduling', as generator has been used as a synonym for power plant by many authors. There is a large amount of literature on the GMS problem, hence a subset of GMS papers were chosen. Papers were chosen which specifically applied optimization methods and also had more citations. This paper focusses on the optimization methods applied by papers in the area of preventive maintenance scheduling for power plants.

Information about 45 chosen papers was collated in an Excel spreadsheet. Columns within the spreadsheet include: year of paper, journal or conference, country, name of paper, authors, objective functions, constraints, application area, optimization method and any further comments. From the spreadsheet, trends were easily identified using graphs. For instance, the column titled 'year' was analysed and a trend indicating an increasing amount of research within recent years was identified; Fig. 24.1 illustrates this trend.

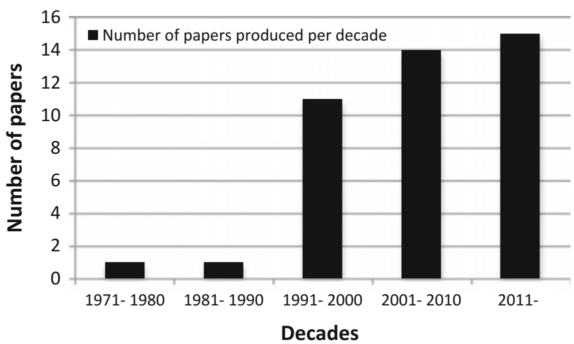

Fig. 24.1 A graph to show the number of papers produced per year group

24.3 Application Domains

The optimization of preventive maintenance schedules has been applied on various different levels within the power sector. Preventive maintenance scheduling has been applied to a range of types of plant: nuclear [27], gas [5], hydro-electric [28] and wind [29] among others. In addition to generation, distribution services have had their maintenance schedules optimized. For example, transmission maintenance has been optimized [30, 31]. The majority of papers consider the Generator Maintenance Scheduling problem, which typically involves maintenance on a number of equipment types across a number of power plants. Only seven of the papers studied addressed preventive maintenance scheduling for single power plants.

24.3.1 Multiple Generator Maintenance Scheduling

The optimal maintenance scheduling of multiple generators is imperative as generators govern the routines of other equipment and particularly because a number of planning activities are based around this schedule [9]. The maintenance scheduling of systems of power plants has been described as a 'challenging optimization problem,' [14]; this is mainly due to the increasing complexity of models within recent years and the enormous scale of the problem. In particular, the reliability of the power supply for customers is crucial and hence this problem has received a lot of academic interest since the first paper was produced.

Many very large scale power maintenance scheduling problems have been proposed. In [28, 32, 33] the authors consider large scale systems with around 80 units including thermal, hydroelectric and nuclear plants. The author extends previous work in [29] to include maintenance scheduling of wind and hydroelectric units, which are becoming increasingly important within the power generation industry. Another large system is provided in [15]. This study looks at the scheduling of 33 generation units and 179 transmission lines.

The IEEE Reliability Test System (RTS) has been widely used [10, 34, 35]. Work in [16] modifies and extends the IEEE RTS to include more units and 38 transmission maintenance lines.

The vast majority of papers consider the maintenance of between 20 and 35 units [18, 30, 36, 37]. Wind and nuclear units are also considered in paper [18]. A comparison of results for various test cases is made by some papers [34, 38]. A much smaller system has been considered by [27], the system has only 4 units.

Studies have also considered the optimization of maintenance schedules for various plant components. In [26] authors assume that the generating unit schedule is fixed and they align the outages for 61 other maintenance tasks. In [11] authors optimize a smaller scale problem for 42 pieces of equipment in total within 2 co-generation plants.

24.3.2 Single Power Plant Maintenance Scheduling

The problem of optimizing the maintenance schedules of components within a single power plant has also been studied within literature. The study in [5] considers the gas turbine preventive maintenance scheduling problem; the gas turbine is considered to be a deteriorating system. Authors in [23] consider the maintenance schedules of the components of a nuclear power plant separately. These components must be maintained and all possible scheduling combinations must be considered. The study in [39] looks at single nuclear plant subsystem availability and similarly [40] optimizes the maintenance scheduling of nuclear power plant sub systems. Work in [41] looks at tasks based in maintenance classes for subsystems of a coal fired plant. Authors in [4] collect data from 18 turbines to determine ideal maintenance intervals.

24.4 Problem Formulations

24.4.1 Objective Functions

Within the field of preventive maintenance scheduling, the vast majority of papers acknowledge the importance of cost and reliability for the MS optimization problem. These criteria are conflicting and this is particularly significant when the system is maintained by an operator who is independent from the generation company. Amongst the papers which were analyzed for this review, all of the papers used cost or reliability or some combination as the basis of their objective functions for optimization. Figure 24.2 indicates the proportion of

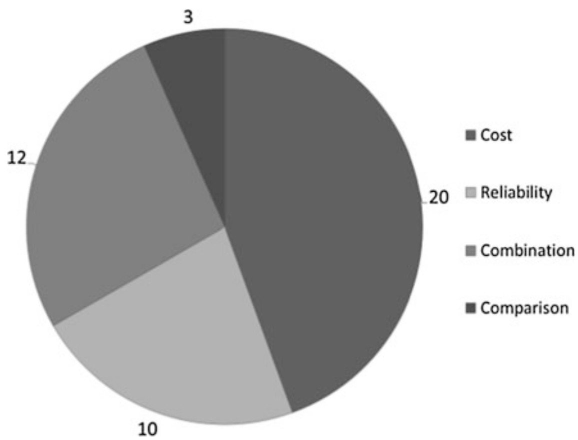

Fig. 24.2 A pie chart to show the objective functions of papers studied

papers which use cost, reliability, both objectives and which compare each criterion separately through test cases. From this pie chart it can be seen that cost is used as a primary objective function by almost half of the papers, which is the largest proportion.

24.4.1.1 Cost Minimization

Numerous studies consider cost minimization as the main objective for optimization [27, 30, 31, 33, 38, 41–46]. Cost based objective functions fall under either profit based or cost based objective functions. The cost based objective functions often account for the cost of maintenance and the cost of production or operations [47], whereas profit based objective functions take into consideration factors such as fuel cost and electricity price.

A cost approach with the aim to minimize the total maintenance and production costs has been considered within studies [4, 30, 31, 44, 48]. In addition to these costs, [33] also considers the start-up costs within the objective function. In [45] authors append transmission maintenance costs to generator maintenance costs and operational costs. In [17] minimization of expected energy production cost is used and maintenance costs are disregarded. On the other hand, [15, 41] consider the minimization of maintenance costs to be their primary objective. In [49] a detailed profit based approach is applied. A stochastic optimization method is applied to deal with the uncertainties of electricity and fuel prices. Work in [24] uses the minimization of Maintenance Investment Loss (MIL) as a profit criterion. Authors in [43] set the sale of electricity according to market clearing price forecast, this is used as an objective for maximization.

A combination of both profit and costs are considered in a number of studies. For instance [27] consider the ‘spread,’ (the difference between energy price and the cost of generation) for UK plants. Profit and cost based objective functions are modelled individually and then compared in [5] for the sequential problem formulation. The study concludes that the profit based formulation could potentially improve profitability for the plant.

Other cost based objectives are proposed in a number of studies. For instance utilization maximization in [11] could be considered as a cost based optimization criteria as it effectively increases profitability. Study [41] also increases availability of plant and reduces cost through optimization. Another cost based method proposed by [38] is the ‘minimum possible disruption of an existing schedule’. In this particular example an optimal schedule is devised and changes must be incorporated in the schedule in a way that minimizes the overall cost.

24.4.1.2 Reliability Maximization

Reliability maximization is considered to be a highly significant objective function for a number of different studies, particularly for the GMS problem. This objective is considered by many papers [9, 18, 25, 34, 36, 37].

The GMS problem is to serve to a number of generators whilst ensuring that the customer demand for electricity is met. The main objective function used for the GMS problem is to level the reserve rate; the difference between the total capacity of the available units and the demand [9]. If the demand is not met at any point in time, this could result in power outages for customers and a poor reputation for the provider. Thus the reliability of the supply is critical. Papers considering the GMS problem account for levelling the reserve rate in some form and many consider it to be a primary objective function [9, 17, 18, 21, 25, 36, 42].

Another form of reliability criteria for the GMS problem is the Loss of Load Probability (LOLP); this has been applied by a number of papers [14, 20, 34, 42, 47]. This is defined as the likelihood that the system demand for electricity will surpass the available capacity; this can be used to evaluate the risk for each individual time period [34].

24.4.1.3 Combination Approaches

Approaches which combine a number of objective functions have been proposed within literature such as weighting methods and vectors of objective functions. A weighted sum method is used in two studies to combine objective functions and coefficients [19, 47]. For example, [19] use the weighted method to minimize the fuel and maintenance costs and to level the reserve rate. More than two objective functions have also been proposed by a number of studies. In [50] authors simultaneously consider three objective functions: reliability maximization, fuel cost minimization and constraint violation minimization. Similarly [16] use a triple objective function consisting of reliability, risk and economic objectives. A non-dominated solution set is created, hence it is concluded that the method is preferable to a weighting method. In [24] the competing objectives for the servicing and the generation company are both modelled as objectives.

24.4.1.4 Comparison Approaches

A number of studies using comparisons of cost and reliability criteria have also been proposed. For instance cost and reliability have been considered separately as objective functions and the results have been compared by [17, 47]. In [47] production costs and reliability are compared and it is concluded that reliability is a better objective function, as maximizing reliability simultaneously minimizes the production costs. In [17] authors find that their proposed method performs well for integer GAs irrespective of which objective function is applied.

24.4.2 Constraints

It is suggested in [14] that constraints can be categorized into three main types: power generation constraints, resource constraints and technological constraints. Power generation constraints ensure that customer demand is met, resource constraints include manpower and inventory limitations and technological constraints are applied by manufacturers on maintenance intervals. Figure 24.3 shows the number of papers which apply each of the constraints. The constraints are split into the sections by type.

Studies considering a number of constraints have shown that the application of constraints often reduces the objective function values. Authors in [49] demonstrate that the risk constraint reduces the profit function. In [42] integer programming is applied to a test case with exclusion, sequence and reserve constraints for two objective functions; the impact of constraints on the objectives is demonstrated. Authors in [30] consider two different case studies using reliability and transmission security as different constraints, they show that there are significant impacts on the costs when transmission limits are applied to the problem.

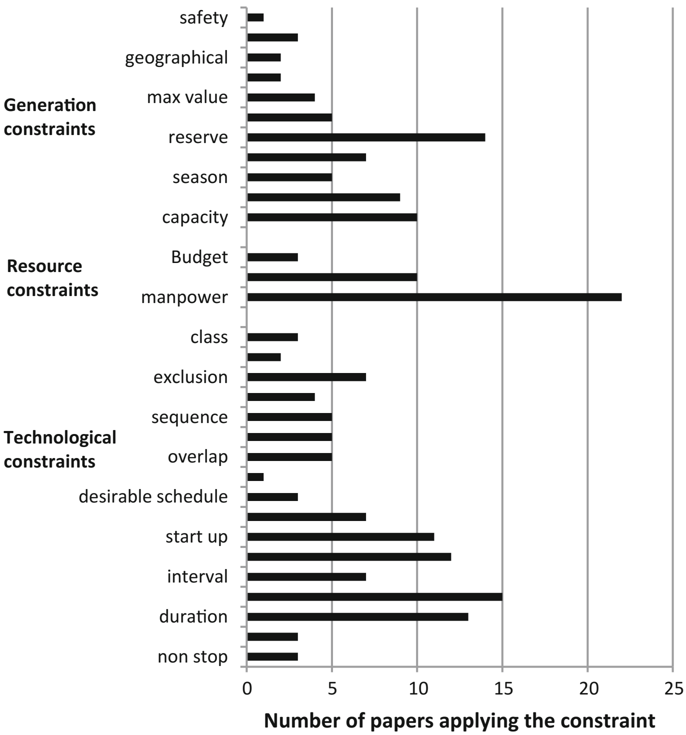

Fig. 24.3 A bar chart to show the number of papers applying each constraint

Studies have fuzzifed the constraints so that the constraints are soft in order to evaluate the trade-off between the constraints and the objective functions. For example, authors in [21] fuzzify the manpower, maintenance window and geographical constraints. Similarly authors in [9] use a fuzzy evaluation function to consider the flexibility of the manpower constraint and compare to alternative methods. The fuzzy evaluation function is able to effectively deal with the trade-off between reliability and manpower within the allowed flexibility.

A number of papers compare two objectives separately, setting one as a constraint and the other as an objective function [21, 40, 42, 47]. Some studies use cost as the objective function and then formulate the reliability as a constraint, these are under power generation constraints. The manpower constraint is the most common constraint among all papers studied. Authors in [9] claim that requiring up to 5% extra manpower might be allowable for a generation company as extra manpower can be hired if this produces better solutions with respect to the objective functions. Extra manpower can be costly for companies; hence the manpower constraint is a cost based constraint. It is clear from the objective functions pie chart that cost is a very significant factor for the optimization and this explains the large number of papers considering manpower as a constraint.

Maintenance duration is defined as a technological constraint [14] and hence this is a highly important constraint which cannot be overlooked by studies, hence it is also considered by a large number of papers. Demand and supply is a power generation constraint used to ensure that the power production is at least equal to the electricity demand [33]; hence this is a reliability based constraint and is applied by a number of papers.

24.5 Model Formulations

Almost all papers studied in this review formulate the maintenance scheduling problem as a mathematical programming problem and then proceed to solve this problem. The most common formulation is integer programming formulation which has been widely used [9, 11, 19, 26, 30, 31, 33, 34, 38, 42, 49–51]. Other formulations include dynamic programming [21] and discrete programming [18, 27] among others. The first part of this section addresses how the problem has been formulated mathematically and the second part addresses stochastic formulation of evaluation functions which is an area of growing interest.

24.5.1 Schedule Formulations

Mathematical programming formulations such as integer programming, mixed integer programming and dynamic programming and decomposition methods have been mainly used to formulate models.

24.5.1.1 Integer Programming Models

Integer programming and mixed integer programming formulations have been proposed by a significant number of studies with several advantages. In [50] integer programming is suggested to be a convenient approach to the resource allocation problem; the main shortcoming is suggested to be the limited accuracy of power system simulation as uncertainties cannot be modelled [47], in addition the method exceeds computational limits. Conversely authors in [42] suggest that integer programming approach is the only true optimization approach which is practical for the problem.

Dopazo in [38] presented the first 0/1 integer programming representation for the GMS problem. For each period and maintenance unit a binary integer is assigned. One of the weaknesses of the approach is identified to be that only one constraint can be applied at a time [30]; this approach has been applied by a number of studies [11, 19, 31, 35, 42].

An alternative to the 0/1 integer programming representation is presented by [9]; in this approach integer variables can be used to represent the period in which maintenance of each unit starts. Authors in [17] also apply this approach to find the starting periods for each maintenance activity.

24.5.1.2 Dynamic Programming Models

In [47] authors claims that dynamic programming is best suited to the optimal preventive maintenance scheduling problem; suggested due to the sequential nature of the problem. In [14] it is agreed that dynamic programming can only be applied to a problem which has previously been formulated as a sequential decision process. In [21] authors formulate the problem as a dynamic programming problem with fuzzy objective functions.

24.5.1.3 Decomposition Approaches

Bender's decomposition method has been applied to maintenance scheduling problems by splitting the original problem into a master and a sub problem [33]. This method can be used after a problem is formulated as an integer programming problem. Authors in [17] claim that a disadvantage of the decomposition approach is that it cannot accurately simulate power system operation due to the curse of dimensionality. In [31] Bender's decomposition is applied to the preventive maintenance scheduling problem. This approach is extended by authors in [33] to also include the transmission and network constraints.

24.5.2 Stochastic Formulations

The application of stochastic methods to evaluate solutions, as an alternative to deterministic methods, within maintenance scheduling optimization has grown within recent years. Studies have used these methods to deal with the uncertainty involved in reliability and costs for preventive maintenance scheduling. These uncertainties of the preventive maintenance scheduling problem for power plants render the optimization problem more complex.

In [35] the Weibull distribution is used to model the failure rate due to component deterioration and the exponential distribution is used to model the random failure rate. Similarly authors in [20] introduce a stochastic objective function to consider daily load variation and random outages. In [24] unavailability of the system is modelled using the Weibull distribution. Within [21] the membership functions of both objectives are fuzzified to deal with the uncertainty in the maintenance scheduling problem. Monte Carlo Simulation has been considered by [49]; it used to model the uncertainty for the price of fuel energy. The results show that for particular units, the use of stochastic prices considerably reduces the maintenance hours.

The use of methods such as discrete event simulation to deal with dynamic uncertainties has arisen in other fields for preventive maintenance scheduling. This could also be applied to the preventive maintenance scheduling problem for power plants to explicitly deal with the uncertainties in prices, reliability, load variation and random outages. These stochastic methods will become increasingly important with the uncertainty related to renewable energy sources.

24.6 Optimization Techniques

A range of optimization methods have been explored within studies to optimize the maintenance schedules within the power industry. The pie chart in Fig. 24.4 shows the different optimization methods used to solve the maintenance scheduling

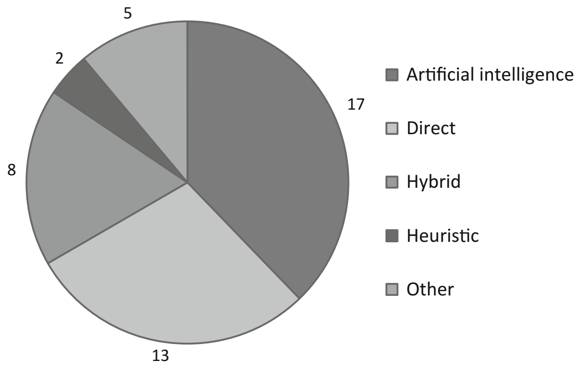

Fig. 24.4 A pie chart to show optimization techniques used

problem. Artificial intelligence methods are the most common method; Genetic Algorithms were used in 7 studies. Direct methods have also been applied to solve mathematical programming formulations. Hybrid methods have been used by 7 of the studies, to combine artificial intelligence, heuristic and direct methods; this is an area of growing research. Other methods include dimensionality reduction and Tabu Search among others.

24.6.1 Direct Methods

Various algorithms have been applied in literature to solve mathematical programming formulations directly for Integer Programming (IP) and Dynamic Programming (DP) formulations. In [34] authors claim that mathematical programming optimization methods such as IP and DP suffer from the curse of dimensionality and they cannot deal with nonlinearity and non-differentiability of objective functions. Authors using DP focus on reducing the computation time required. Authors using IP use various branch and bound type methods to solve their formulations.

24.6.1.1 Integer Programming

IP formulations are generally solved using enumeration techniques such as branch and bound algorithms. In [11] LINGO is used to model and solve the mixed integer programming problem. Authors in [29, 30, 33], also solve directly using GAMS software and [42] solves directly using PP/MS program. The author in [32] uses the simplex method to solve the 0/1 IP problem.

In [38] the authors used an extension of an implicit enumeration technique using a decision tree for the whole system where each branch is a solution; this method is combined with a heuristic method. In [35] a decision tree based approach is also used. A branch and bound algorithm is also applied in [51].

24.6.1.2 Dynamic Programming

A number of papers acknowledge that the computational time required for DP optimization is a disadvantage for this approach. In [47] the author agrees that the limitation for DP is the computational time.

Approaches have been proposed to deal with the problem of large computation times for this approach. In [47] a dimensionality reduction method, DPSA (Dynamic Programming by Successive Approximations), is applied to deal with the large computation time. The algorithm then iteratively keeps a set of solutions constant and then optimizes the remaining variables.

In [21] the author notes that the calculations do not need to occur in real time. The fuzzy dynamic programming approach is applied with objective functions and constraints replaced by membership values.

24.6.1.3 Heuristic Methods

Heuristic methods have been applied in a number of studies, as they use a rule of thumb type approach to search for a solution [42]. In [17] the author suggests that heuristic methods can solve some of the limitations of mathematical programming methods by splitting the problem into units and then scheduling activities sequentially. In [9] authors note that heuristics require significant operator input and may not even find solutions which are feasible. Although [14] states that literature indicates that heuristics are still widely in use.

In [38] a heuristic method called fathoming is used to search through the branches until each branch can no longer contain optimal solutions. In [41] a heuristic maintenance class based approach is applied to perform corrective and preventive maintenance to achieve cost effective maintenance intervals.

24.6.2 Artificial Intelligence Methods

A variety of Artificial Intelligence (AI) approaches have been applied in literature as alternatives to heuristic methods. For example Genetic Algorithms (GAs) are applied by 7 studies.

GAs are a well-established population based evolutionary search method. Various studies attempt to reduce the computation time associated with GAs. Authors in [17] propose modifications to the GA such as string reversal and reciprocal exchange mutation. The modifications proposed are shown to improve the computational performance of the algorithm and perform better than DP. In [18] the authors attempts to reduce the computation time by proposing a code specific constraint transparent process to deal with the heavy computation time. The results show improved computation time compared to binary GA approaches. In [16] the author uses the NSGAII algorithm to perform multi-objective optimization. This approach ensures reliability and power economy are both maximized simultaneously. In [39] the author proposes an Advanced Progressive Real Coded Genetic Algorithm (APRCGA), where the chromosomes consist of real numbers which are later converted into integers to represent solutions. In [37] authors apply a GA approach to move outages from periods of low reliability to high reliability.

Other evolutionary computation methods have been applied such as Simulated Annealing (SA) and Particle Swarm Optimization (PSO); the results have been compared to empirical and exact results to assess performance. In [25] a multi stage SA optimization process is applied; the approach was compared to an enumeration method with a near global optimal solution being found. Authors in [36] also apply

SA to compare different cooling schedules, neighbourhood move operators and hybrid approaches in an attempt to improve the traditional SA. Authors in [23] propose a non-periodic PSO based approach and use continuous values within the search space. In [52] a modified PSO (MPSO) algorithm is used to reduce the number of control parameters for the algorithm. Authors in [53] apply a revised PSO with capability to deal with inequality and equality constraints using a penalty function. An Improved Binary Particle Swarm Optimization (IBPSO) method is applied in [24] to avoid premature convergence and to improve the search quality of the traditional PSO.

Other methods include Ant Colony Optimization (ACO) algorithm [48], a clonal selection algorithm based on the Artificial Immune System [46] and a Teaching Learning Based Optimization algorithm [45].

24.6.3 Hybrid Methods

Hybrid methods have been increasingly applied in recent years; these methods combine the advantages of different approaches such as AI and heuristic methods. The proposed hybrid methods are generally found to outperform existing methods.

Hybrid methods involving SA are particularly popular. Authors in [20] compare GA and GA/SA hybrid approaches; the hybrid method produces the fastest convergence speed and both methods are shown to lead to the same results. In [19] authors also use a GA/SA hybrid approach using an encoding and decoding method. This method is shown to create remarkably shorter computation times than the SA approach and produce better convergence and results than the GA approach. In [54] it is found that by applying the GA/SA hybrid approach each individual solution can be improved by SA, and similarly to [19] the convergence of the GA/SA algorithm is superior to the convergence of the GA method alone. Investigation of hybrid local search and SA method in [36] finds that the solution quality can be improved through application of this hybrid method.

In [34] the authors apply a Hill Climbing Technique (HCT) and a hybrid Extremal Optimization and GA method (EO/GA) and compare the results. The EO/GA technique is shown to be superior in both cases with respect to the average objective function values. In [43] results are compared from a hybrid PSO/GA method and a PSO/Shuffled Leap Frog algorithm with other methods; the conclusion is that the Shuffled Leap frog hybrid is an efficient and robust optimization strategy.

A different combination of DP formulation and GAs is applied in [21]. This combination of dynamic programming, GAs and fuzzification is shown to produce optimal maintenance schedules for a given test case. In [15] an evolutionary programming method is applied to find a near optimal solution and subsequently a Hill-Climbing method is used to ensure the feasibility of solutions is maintained.

24.6.4 Other Methods

Several other optimization techniques have been identified and used within studies to solve scheduling optimization problems.

Deterministic solvers have been considered in the place of stochastic AI methods such as GAs. In [26] the authors use a Tabu Search algorithm for scheduling of outage tasks. This approach has a fast search speed and produces diversified solutions avoiding local optima.

Approaches which consider the problem to be continuous instead of discrete have also been considered. In [55] a sequential continuous approach to the gas turbine maintenance problem is proposed. The results indicate decreasing maintenance intervals as the turbine ages to ensure reliability.

Other approaches have also been considered within studies. Lagrangian Relaxation is applied in [49] to decompose the problem into tractable scenarios. In [4] a dimensionality reduction method is used to compare maintenance intervals and replacement rates.

24.7 Discussion

Through analysis of the chosen papers, a number of key deductions and trends can be identified; these are detailed as follows in section order.

The first trend identified was a significant increase in interest over the recent years. Figure 24.3 shows an increase in the number of papers produced per decade, indicating a strong increase in research in optimization of power plant preventive maintenance scheduling over recent years. This review focusses on papers where different optimization methods are applied; hence it can be seen that there is more research in application of different optimization methods in recent years.

Analyzing problem formulations has led to some key observations. The most common objective function considered is the cost objective function; this includes optimization of profit and maintenance and operational costs. Studies also combine and compare these objectives [5, 27]. Reliability is considered to be a vital objective function and the levelling of the reserve rate is used by a number of papers to ensure that demand is met at all times [9, 33, 34]. The conflict between reliability and cost has been acknowledged; it is more significant when the maintenance and operation are carried out by different companies [52]. The conflict between these objectives has been explicitly dealt with in a number of papers, which combine and compare results for these objective functions.

The most common constraint used within literature is the manpower constraint as this involves costs; it is often formulated as a soft constraint enabling solution flexibility. On the other hand technological constraints such as durations are hard constraints as these are formulated based on manufacturer requirements. Constraints are also used by some papers to compare 2 main objective functions, where one is set as an objective and the other as a constraint and vice versa. The application of constraints to the optimization problem is shown to reduce the objective function values in a number of papers [30, 42, 49].

The vast majority of papers formulate the model as mathematical programming models. IP and DP in particular are the main formulations for the MS problem.

An increase in the use of stochastic methods to evaluate solutions, as opposed to deterministic methods, has also been observed. In particular, in [50] a growing importance given to the explicit treatment of the non-deterministic parameters is noted. In [20] deterministic and stochastic methods are compared and it is concluded that stochastic methods can evaluate the risk involved with deteriorating equipment. A few other studies have begun to use stochastic parameters in some form [4, 5, 35].

The increasing use of multi-objective optimization and hybrid optimization methods has been observed. In [13] it is identified that the literature of multi-objective scheduling is much sparser than that of single objective scheduling and that since 1995 there has been an increasing interest in the area. For instance, in [50] a multi-objective optimization approach with the branch and bound method is applied, in [17] authors use a GA with two objectives. Hybrid methods have also been increasingly applied in recent years [19, 20, 54]. These areas of multi objective and hybrid optimization are an interesting area for future research.

A research gap has been identified in the use of stochastic methods to model the MS problem. Discrete Event Simulation has not been used for modelling the MS within the power industry although it has been applied within other industries. The explicit treatment of uncertain parameters using Discrete Event Simulation could be an interesting application. The application of Discrete Event Simulation with multi objective hybrid optimization is a novel and exciting area for research. These prospective areas for research could provide results with a number of benefits for power generation companies.

24.8 Conclusions

This study has reviewed papers in preventive maintenance scheduling of equipment for power plants. This paper presents up to date detailed review of papers within power plant preventive maintenance scheduling with details of objective functions, constraints, model formulation and optimization methods. Significant conclusions, trends and a research gap have been identified from the literature. Trends such as the increasing use of stochastic parameters and a growing use of hybrid methods and multi objective optimization have been noted. Research has not been carried out to apply Discrete Event Simulation with optimization to power plant preventive maintenance scheduling. Combining these various research gaps could generate interesting results and revelations. These are excellent opportunities to be exploited in future research.

References

1. Xu B, Han XS, Li M, Xiao DL (2012) System maintenance scheduling: review and prospect. 2012 IEEE innovative smart grid technologies—Asia, ISGT Asia 2012
2. Camci F (2009) Comparison of genetic and binary particle swarm optimization algorithms on system maintenance scheduling using prognostics information. Eng Optim 41(2):119–136
3. Yamayee ZA (1982) Maintenance scheduling-description, literature survey, and interface with overall operations scheduling. IEEE Trans Power Appar Syst V PAS-101(N 8):2770–2779
4. Katafuchi T, Nakamura M, Suzuki Y, Hatazaki H (2003) Proper decision for maintenance intervals of equipment in thermal power station based on operational rate and maintenance replacement rate. Electr Eng Jpn (English translation of Denki Gakkai Ronbunshi) 145(1):10–19
5. Zhao Y, Volovoi V, Waters M, Mavris D (2006) A sequential approach for gas turbine power plant preventative maintenance scheduling. J Eng Gas Turbines Power 128(4):796–805
6. Greasley A (2000) Using simulation to assess the service reliability of a train maintenance depot. Qual Reliab Eng Int 16(3):221–228
7. Oyarbide-Zubillaga A, Goti A, Sanchez A (2008) Preventive maintenance optimisation of multi-equipment manufacturing systems by combining discrete event simulation and multi-objective evolutionary algorithms. Prod Plan Control 19(4):342–355
8. Anne-Sylvie C, Floru I, Azzaro-Pantel C, Pibouleau L, Domenech S (2003) Optimization of preventive maintenance strategies in a multipurpose batch plant: application to semiconductor manufacturing. Comput Chem Eng 27(4):449–467
9. Dahal KP, Aldridge CJ, McDonald JR (1999) Generator maintenance scheduling using a genetic algorithm with a fuzzy evaluation function. Fuzzy Sets Syst 102(1):21–29
10. Liu Y, Meng X, Sheng W (2011) Research and application of maintenance schedule optimization based on intelligent algorithm. APAP 2011—proceedings: 2011 international conference on advanced power system automation and protection, vol 2, p 957
11. Alardhi M, Hannam RG, Labib AW (2007) Preventive maintenance scheduling for multi-cogeneration plants with production constraints. J Qual Maint Eng 13(3):276–292
12. Maccarthy BL, Liu J (1993) Addressing the gap in scheduling research: a review of optimization and heuristic methods in production scheduling. Int J Prod Res 31(1):59–79
13. Lei D (2009) Multi-objective production scheduling: a survey. Int J Adv Manuf Technol 43 (9–10):925–938
14. Kralj BL, Petrovic R (1988) Optimal preventive maintenance scheduling of thermal generating units in power systems: a survey of problem formulations and solution methods. Eur J Oper Res 35(1):1–15
15. El-Sharkh MY, El-Keib AA (2003) Maintenance scheduling of generation and transmission systems using fuzzy evolutionary programming. IEEE Trans Power Syst 18(2):862–866
16. Zhang D, Li W, Xiong X (2012) Bidding based generator maintenance scheduling with triple-objective optimization. Electr Power Syst Res 93:127–134
17. Baskar S, Subbaraj P, Rao MVC, Tamilselvi S (2003) Genetic algorithms solution to generator maintenance scheduling with modified genetic operators. IEE Proc: Gener Trans Distrib 150(1):56–60
18. Wang Y, Handschin E (2000) New genetic algorithm for preventive unit maintenance scheduling of power systems. Int J Electr Power Energy Syst 22(5):343–348
19. Kim H, Nara K, Gen M (1994) A method for maintenance scheduling using GA combined with SA. Comput Ind Eng 27(1–4):477–480
20. Mohanta DK, Sadhu PK, Chakrabarti R (2007) Deterministic and stochastic approach for safety and reliability optimization of captive power plant maintenance scheduling using GA/SA-based hybrid techniques: a comparison of results. Reliab Eng Syst Saf 92(2):187–199
21. Huang S (1998) A genetic-evolved fuzzy system for maintenance scheduling of generating units. Int J Electr Power Energy Syst 20(3):191–195

22. Suresh K, Kumarappan N (2013) Coordination mechanism of maintenance scheduling using modified PSO in a restructured power market. In: Proceedings of the 2013 IEEE symposium on computational intelligence in scheduling, CISched 2013—2013 IEEE symposium series on computational intelligence, SSCI 2013, p 36
23. Pereira CMNA, Lapa CMF, Mol ACA, Da Luz AF (2010) A particle swarm optimization (PSO) approach for non-periodic preventive maintenance scheduling programming. Prog Nucl Energy 52(8):710–714
24. Suresh K, Kumarappan N (2013) Generation maintenance scheduling using improved binary particle swarm optimisation considering aging failures. IET Gener Transm Distrib 7 (10):1072–1086
25. Yokoyama R, Niimura T (1996) Thermal generating unit maintenance scheduling by multi-stage application of simulated annealing. Proc IEEE Int Conf Syst Man Cybern 2:1531
26. Sawa T, Furukawa T, Nomoto M, Nagasawa T, Sasaki T, Deno K, Maekawa T (1999) Automatic scheduling method using tabu search for maintenance outage tasks of transmission and substation system with network constraints. IEEE engineering society, winter meeting, vol 2, p 895
27. Cao J, Bell KRW, Kockar I, San Martin LAS (2010) Generation maintenance scheduling in a liberalised electricity market. Proceedings of the universities power engineering conference
28. Perez-Canto S (2011) A decomposition approach to the preventive maintenance scheduling problem: an empirical example for the Spanish power plant system. Int J Manuf Technol Manage 22(1):58–77
29. Perez-Canto S, Rubio-Romero JC (2013) A model for the preventive maintenance scheduling of power plants including wind farms. Reliab Eng Syst Saf 119:67–75
30. Badri A, Niazi AN, Hoseini SM (2012) Long term preventive generation maintenance scheduling with network constraints. Energy Procedia 14:1889
31. Marwali MKC, Shahidehpour SM (1998) A deterministic approach to generation and transmission maintenance scheduling with network constraints. Electr Power Syst Res 47 (2):101–113
32. Perez-Canto S (2011) Using 0/1 mixed integer linear programming to solve a reliability-centered problem of power plant preventive maintenance scheduling. Optim Eng 12(3):333–347
33. Perez-Canto S (2008) Application of Benders' decomposition to power plant preventive maintenance scheduling. Eur J Oper Res 184(2):759–777
34. Reihani E, Najjar M, Davodi M, Norouzizadeh R (2010) Reliability based generator maintenance scheduling using hybrid evolutionary approach. 2010 IEEE international energy conference and exhibition, EnergyCon 2010, p 847
35. Abiri-Jahromi A, Fotuhi-Firuzabad M, Parvania M (2012) Optimized midterm preventive maintenance outage scheduling of thermal generating units. IEEE Trans Power Syst 27 (3):1354–1365
36. Schlünz EB, Van Vuuren JH (2013) An investigation into the effectiveness of simulated annealing as a solution approach for the generator maintenance scheduling problem. Int J Electr Power Energy Syst 53(1):166–174
37. Eshraghnia R, Mashhadi HR, Shanechi MHM, Karsaz A (2005) A novel approach for maintenance scheduling of generating units in a competitive environment. 2006 IEEE power India conference, vol 2005, p 821
38. Dopazo JF, Merrill HM (1975) Optimal generator maintenance scheduling using integer programming. IEEE Trans Power Appar Syst PAS-94(5):1537–1545
39. Aghaie M, Norouzi A, Zolfaghari A, Minuchehr A, Mohamadi Fard Z, Tumari R (2013) Advanced progressive real coded genetic algorithm for nuclear system availability optimization through preventive maintenance scheduling. Ann Nucl Energy 60:64–72
40. Mohammad Hadi Hadavi S (2009) A heuristic model for risk and cost impacts of plant outage maintenance schedule. Ann Nucl Energy 36(7):974–987
41. Adhikary DD, Bose GK, Bose D, Mitra S (2013) Maintenance class-based cost-effective preventive maintenance scheduling of coal-fired power plants. Int J Reliab Saf 7(4):358–371

42. Mukerji R, Merrill HM, Erickson BW, Parker JH, Friedman RE (1991) Power plant maintenance scheduling: optimizing economics and reliability. IEEE Trans Power Syst 6 (2):476–483
43. Giftson Samuel G, Christober Asir Rajan C (2015) Hybrid: particle swarm optimization-genetic algorithm and particle swarm optimization-shuffled frog leaping algorithm for long-term generator maintenance scheduling. Int J Electr Power Energy Syst 65:432–442
44. Fattahi M, Mahootchi M, Mosadegh H, Fallahi F (2014) A new approach for maintenance scheduling of generating units in electrical power systems based on their operational hours. Comput Oper Res 50:61–79
45. Abirami M, Ganesan S, Subramanian S, Anandhakumar R (2014) Source and transmission line maintenance outage scheduling in a power system using teaching learning based optimization algorithm. Appl Soft Comput J 21:72–83
46. El-Sharkh MY (2014) Clonal selection algorithm for power generators maintenance scheduling. Int J Electr Power Energy Syst 57:73–78
47. Yamayee ZA, Sidenblad K (1983) Computationally efficient optimal maintenance scheduling method. IEEE Trans Power Appar Syst PAS-102(2):330–338
48. Vlachos A (2013) Ant colony system algorithm solving a thermal generator maintenance scheduling problem. J Intell Fuzzy Syst 24(4):713–723
49. Wu L, Shahidehpour M, Li T (2008) GENCO's risk-based maintenance outage scheduling. IEEE Trans Power Syst 23(1):127–136
50. Kralj B, Rajaković N (1994) Multiobjective programming in power system optimization: new approach to generator maintenance scheduling. Int J Electr Power Energy Syst 16(4):211–220
51. Kralj B, Petrovic R (1995) A multiobjective optimization approach to thermal generating units maintenance scheduling. Eur J Oper Res 84(2):481–493
52. Kumarappan N, Suresh K (2005) Coordinated maintenance scheduling in power system using combined genetic algorithm and simulated annealing. 2006 IEEE power India conference, vol 2005, p 416
53. Ekpenyong UE, Zhang J, Xia X (2012) An improved robust model for generator maintenance scheduling. Electr Power Syst Res 92:29–36
54. Leou R (2006) A new method for unit maintenance scheduling considering reliability and operation expense. Int J Electr Power Energy Syst 28(7):471–481
55. Zhao Y, Volovoi V, Waters M, Mavris D (2005) A sequential approach for gas turbine power plant preventive maintenance scheduling. Proceedings of the ASME power conference, 2005, vol PART A, p 353