Multi-Objective Optimization for Time-based Preventive Maintenance within the Transport Network: A Review

Preprint · February 2018

DOI: 10.13140/RG.2.2.36132.01929

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Abstract

Preventive maintenance in transportation is essential not only to safeguard billions in business and infrastructure investment, but also to guarantee safety, reliability and efficacy within the network. Government, industry and society have been increasingly recognising the importance of keeping transport units condition well-preserved. The challenge, however, is to achieve optimal performance of the existing transport systems within acceptable costs, effective workforce use and minimum disruption. Those are generally conflicting objectives. Multi-objective optimisation approaches have served as powerful tools to assist stakeholders to properly deploy preventive maintenance in industry. In this study, we review the research conducted in the application of multi-objective optimisation for preventive maintenance in transport-related activities. We focus on time-based preventive maintenance for production, infrastructure, rail and energy providers. In our review, we are interested in aspects such as the types of problems addressed, the existing objectives, the approaches to solutions, and how the outcomes obtained support decision.

Keywords: Maintenance, Preventive Maintenance, Multi-objective Optimisation, Bio-inspired Computation, Transportation Maintenance

Technical Report *February 13, 2020*

1. INTRODUCTION

The importance of maintenance in transportation is increasingly recognised. For all transport modes and their infrastructures, most efforts are shifted to operation and maintenance after production is finished. From the point of view of executives, government, and the general public, maintenance is vital to not only to safeguard billions in business and transport pathway (highways, railways, etc.) investment but also to continuously provide safety, reliability and efficacy within the transport network [1]. The challenge for maintenance stakeholders is therefore to achieve optimal performance of the existing transport systems within acceptable costs, effective manpower use and minimum disruption.

According to the transportation research circular E-C092 produced by the United States Transport Research Board [1], several trends are identifiable as the main influencers on transport maintenance activities. The first pattern observable in most transport networks is a fast growth in development that reaches a steady-state when all the infrastructure is set up, followed by aging and deprecation. As a consequence, the second trend regards the challenges that aging network infrastructures present to maintenance managers, who need to deploy adequate methods and materials to improve maintenance effectiveness. The following trend regards technology, that dictates how and what information is gathered and processed, as well as how maintenance is performed. The public perception is also an important trend, as variables such as safety, reliability and expectations influence on maintenance decisions. Finally, government regulations and environment concerns have significant impact on maintenance, as institutional and cultural aspects of maintenance organizations are heavily influenced by regulations enforcement.

Several objectives and constraints are therefore present in preventive maintenance activities. To achieve optimal maintenance, the tool set of multi-objective optimisation methods have been largely exploited, for many components and aspects of the transport industry. To the best of our knowledge, there is however little literature regarding surveys of time-based multi-objective optimisation for preventive maintenance in transportation. The purpose of this paper is therefore to contribute to this area by making a state-of-the-art systematic review of the publications devoted to time-based multi-objective optimisation in preventive maintenance in transport for the last thirty years. From our survey we are able to identify four main areas related to transport preventive maintenance where multi-objective optimisation approaches are largely employed: maintenance in production, in infrastructures, in rail and in energy providers. For each of these areas we review the sets of objectives defined, existing constraints and the approaches commonly adopted.

The remainder of this paper is organised as follows. Section 2 introduces the main terms and concepts related to transport maintenance, including preventive maintenance, maintenance management and maintenance optimisation. Subsequently, Section 3 outlines the main objectives of preventive maintenance in transport. Sections 4, 6, 7 and 8 present the related work in production, infrastructure, rail and energy, respectively. Finally, in Section 9, a discussion and final conclusions regarding the survey conducted are presented.

2. Transport Maintenance

Maintenance regards the set of processes of preserving the condition or the state of a unit. In maintenance activities, there are models that assume that after maintenance, the unit is expected to perform to the same standards as a new unit. In practice, however, this assumption is not always accurate [2]. This is because maintenance outputs are subject to their available resources. There are therefore three states a system can assume after maintenance: (i) perfect, when the system functionality and purpose have been fully restored; (ii) imperfect, when the system assumes a condition between perfect and as bad as previously; and (minimal) where no change in the system's state occurs after maintenance [3].

2.1. Preventive Maintenance

Traditionally, preventive maintenance regards unit inspection or replacement before failure. It employs maintenance actions not to fix a unit; instead, the deployment of maintenance is performed to avoid failure occurrence.

Preventive Maintenance is triggered either by (i) historical failure data, which determines a lifespan of the unit; or by (ii) combined data-driven reliability models, with data collected from monitoring sensors. The first strategy is known as time-based maintenance (TBM); and the data-driven strategy is named condition-based maintenance (CBM) [4]. General TBM models, their types and approaches to solutions have been largely studied in the literature [5, 6, 7]. CBM, on the other hand, has recently gained attention due to advances in data collection and sensor systems. A review on the existing CBM models for stochastic deteriorating systems is found in Alaswad and Xiang [4].

From our search, we observed that there is little literature regarding surveys of time-based multi-objective optimisation for preventive maintenance in transportation. Therefore in this paper, we review the existing methods and their applications to transport in the literature. We do not include in our review, however, condition-based maintenance.

2.2. Maintenance Management

In industry, the term total productive maintenance (TPM) refers to the activities responsible for maintaining and improving production integrity and quality through a better employment of machines, equipment, processes, and workforce that add business value to an organization. The main remit of maintenance management within TPM practices is to produce effective system maintenance in order to guarantee safe, fully-functioning system with efficient logistics. For that to happen, maintenance management oversees and controls all maintenance resources. Successful management practices therefore occur when a company's profits are increased, and manpower as well as supplies for maintenance are deployed with minimal waste, risk and delays.

2.3. Maintenance Optimisation

The research in maintenance optimisation aims at providing assistance in maintenance management, including aspects ranging from design and conceptualisation to planning and execution, taking all problem characteristics and constraints into account. A maintenance optimization model is a mathematical model in which both costs and benefits of maintenance are quantified and in which an optimum balance between both is obtained [6]. General optimisation models encompass three major elements, the variables, constraints and objective functions. For maintenance, the problem modelling into those three elements requires knowing the description of the system with its functions and importance. Furthermore, it is important to understand how the system deteriorates in time and the impact of it as well as what is the available information and the actions open to management. In addition, maintenance management needs to agree on what needs to be optimised, subject to identified constraints.

Depending on their deterioration character, maintenance models can be classified into deterministic, stochastic, under risk or under uncertainty [6].

Models under risk differ from those of uncertainty as they assume a well-known probability distribution of the time of failure. Conversely, for uncertainty models, this distribution is unknown; therefore, they must include adaptive strategies.

Maintenance optimization models can be simple (one or two variables) or complex (multiple variables). Their results allow for decisions to be made in several aspects of the maintenance management process. For instance, policies can be evaluated and compared with respect to cost-effectiveness and reliability characteristics, which from our review below seems to be a practice very common in transport. In addition, optimal policies can be offered to decision makers. Models can also assist in determining how often to inspect or to maintain a certain equipment or infrastructure.

There are several approaches for modelling different aspects of maintenance. Scarf [8] discusses common areas of maintenance optimisation modelling and how the development of mathematical models have been proposed to solve inspection, maintenance, condition-based maintenance, and single or multi-component replacement/repair of industrial systems. The author also draws attention to the importance of joint, multi-disciplinary efforts to model real-world problems and their existing challenges.

3. Preventive Maintenance Objectives in Transportation

In transportation, time-based multi-objective preventive maintenance occurs generally in four major areas: manufacturing and production; infrastructure, rail and in the energy providers. These four sectors therefore are the focus of our review. In this section, we present their main maintenance objectives. For private vehicles, lorries and aircrafts, however, it appears that advances in condition-based maintenance [9, 10, 11, 12, 13], vehicle health [14, 15] and incident prevention [16, 17] conditioned to human behaviour [18, 19, 20, 21] are far more common, due to the widespread of sensors and wireless communication. Therefore, they are out of the scope of our research into the literature.

In equipment production, ensuring the overall system functionality is the prime maintenance objective. Maintenance has to provide therefore the right amount production reliability, availability, efficiency, capability and costs. And the right amount for each of those variables depend on the maintenance management particular needs [6].

When maintaining transport infrastructures, such as bridges, roads and other civil structures, the objectives of maintenance are to ensure system life, with maximum reliability and safety; and minimal disruption and costs. In this type of problems, often norms are set to define failure and due to the complexity of the systems and the dramatic consequences of faults, breakage or disruption, the cost-benefit of maintenance activities are more difficult to quantify.

For rail, efficiency, reliability and safety play major roles. Therefore, often the objectives aim at reducing disruption and keeping cars, equipment and rail tracks in their best acceptable condition. Similarly, those objectives are often present in maintenance optimisation for energy providers. For both rail and energy (especially those coming from nuclear sources) testing and inspection activities constitute an important part of the maintenance work. Maintenance costs have to be preferably minimised while risks must be kept within strict limits and meeting statutory requirements.

There are several approaches to solve multi-objective optimisation problems in transport. The optimisations are mostly conducted employing exact or bio-inspired methods, as described in the next sections. Alternative solutions (out of the scope of our review) employ systems simulation [22].

4. Transport Production Preventive Maintenance

In transport, production preventive maintenance occurs mostly before transportation activities start. It ensures that the equipment, systems, infrastructure and transport modes are adequately manufactured and delivered in a timely manner. For production, increasing outputs while ensuring appropriate maintenance activities are the main objectives; and these goals have conflicting interests. Depending on the complexity of the operations, satisfying the associated constraints and maintaining the continuance of the system, without detriment to business, poses several optimisation challenges. These challenges are part of a larger class of optimisation problems, namely job shop problems (JSPs) [23]. JSPs are a well-studied class of problems, which include the following variations and features: (i) there are different types of machinery interactions (they can be related, independent or equal); (ii) there can be gaps between jobs; (iii) tasks sequence dependency occur; and (iv) there is single or multi-objective (and multi-criteria) optimisation of processes with production and maintenance associated constraints.

For JSPs, there are several reviews in the literature, which consider the different types of problems [23, 24] and the different approaches to solutions. Further, Dave and Choudhary [25] discuss the development of traditional and non-traditional approaches to solve Job Shop Scheduling Problems (JSSP) [26] on the last decades. The authors outline the classical traditional and non-traditional methods that are largely employed to solve JSPS, as shown in Figure 1. In the figure, the methods are classified into *Traditional* and *Non-traditional Approximation* methods. Within the *Traditional* class the following are included: (i) Mathematical Programming, which comprises of methods such as Linear Programming, Integer Programming, Dynamic Programming, Network Techniques and Branch and Bound Techniques. The *Non-traditional Approximation* category of approaches includes **Constructive Methods**, such as Priority Dispatch Rules and Composite Dispatch Rules; **Evolutionary Methods**, such as Genetic Algorithms (GAs) [27], Particle Swarm Optimisation (PSO) [28], Differential Evolution (DE) [29]; and **Local Search Methods**, such as Ant Colony Optimisation [30], Simulated Annealing [31] and Tabu Search [32]. The authors also discuss several novel developments (such as the application of the Clonal Selection Algorithm [33] and Fuzzy Logic methods [34]) and variations of those classical methods applied to JSPS. As shown in the next sessions, these methods and their variations have also been largely employed to other multi-objective optimisation tasks in transport.

Additional developments in JSPs are reported by Genova *et. al* [24], in which a detailed survey on solving methods for multi-objective flexible JSSPs is conducted. Their work updates a previous review conducted by Wojakowski [35]. The Flexible Job Shop Scheduling Problems (FJSSPs) extend on the classical JSSPs by adding flexibility to the production system, where one operation can be executed on different machines or one machine can execute different operations [35]. Similarly to the review conducted by Dave and Choudhary [25] for JSPs, Genova *et. al* [24] divide their review in two main classes of solutions: mathematical programming models and solutions with heuristics and meta-heuristics. There is a significant overlap between the solutions employed in traditional JSSPs (Figure 1) and those used for flexible JSSPs. Several variations of some of the methods shown in Figure 1 are discussed in the authors' review. In addition, hybrid methods combining multiple meta-heuristics and memetic algorithms [36] are also included. The authors observed emerging trends on the methods reviewed, such as the hierarchical (decomposition) approach being often applied aim

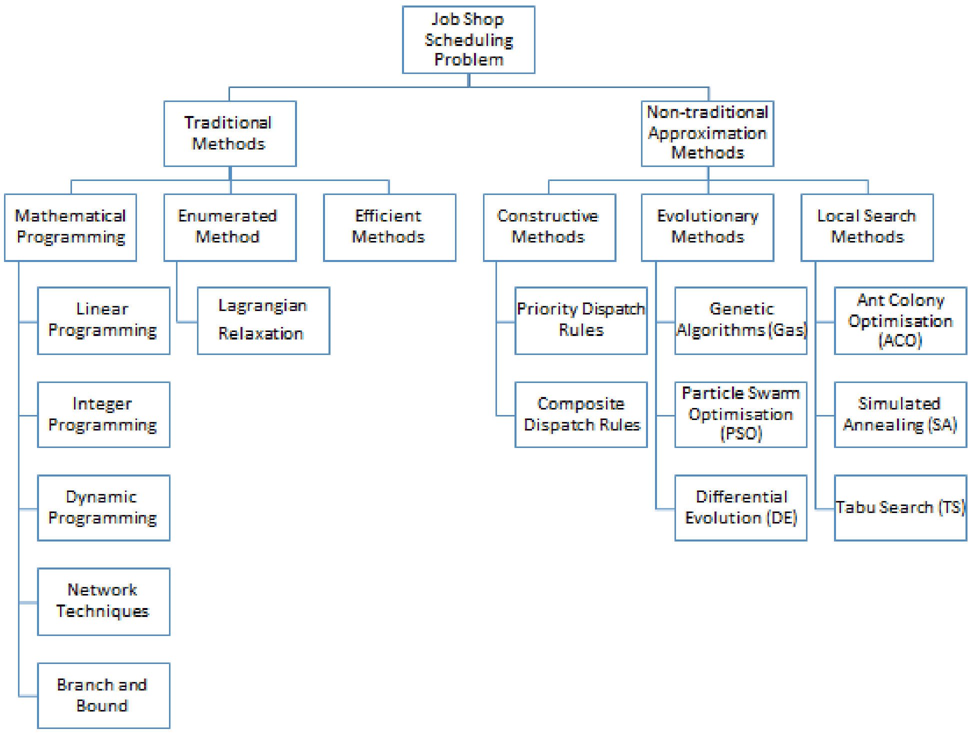

Figure 1: Common solutions for the Job Shop Scheduling Problem (adapted from Dave and Choudhary [25])

to decrease computational complexity. Additionally, the combination of different heuristics to achieve better initial solutions and avoid local optima seems to be increasing in trend. There is also the application of novel, non-traditional metaheuristics and simplifications of the existing algorithmic schemes to adapt to changes in assumptions and in problem constraints.

Next we further discuss the synergy between production activities and maintenance. We review the relevant literature particularly focusing on reducing production delays during maintenance scheduling.

5. Maintenance Scheduling *versus* Production

Maintenance scheduling approaches are classified as deterministic (or sequential) or stochastic (or integrated) [37]. For deterministic preventive maintenance, all the actions and time intervals required to complete maintenance are known *a priori*. In the stochastic approach, the preventive maintenance starting times are also considered decision variables. To better satisfy the constraints imposed by the synergy of production and maintenance, several multi-objective optimisation approaches have been proposed. Classical approaches employed are discussed in the previous section (Figure 1).

In this section we review different general preventive maintenance scheduling problems, novel methods and variations of the classical methods employed as solvers, as well as the quality of the results obtained by each approach. We divide this section into a collection of exact approaches and another review of bio-inspired methods.The objectives of the reviewed work mostly involve optimising both production and maintenance aspects. As the approaches reviewed output many feasible solutions within the Pareto front, part of the work conducted in preventive maintenance also attempts to assist decision makers in finding the solution that best matches their optimisation preferences and goals. In such cases, we also review their strategies for decision support.

5.1. Exact Approaches

Galante and Passannanti [38] propose a method to select the components undergoing maintenance during a system planned downtime. Their approach is based on Kettele's algorithm for redundancy optimisation of a series system. The algorithm has been adapted to maintenance and extended to handle series-parallel systems. Operators in the algorithm are defined to reduce processing time. A case study for naval unit maintenance has been investigated. As continuation of the exploration of the case study, Certa *et al.* [39] propose an exact approach for a constrained multi-objective maintenance problem of systems operating without interruption between two consecutive fixed stops. The authors claim their solution obtains a fast and complete description of the Pareto optimal frontier even for problems involving complex systems. They test their method to a problem of maintenance of a military naval unit that has to stop for maintenance periodically. Results show that the complete Pareto front set is obtained. The method performance, however is not compared to other existing approaches and it is limited to being tested to only one case study.

Moghaddam [40] introduces a multi-objective nonlinear mixed-integer optimization model to optimise fixed interval preventive maintenance and replacement schedules for a multi-workstation manufacturing system with increased failure. Operational costs, reliability and the system availability are the objective functions. The model is solved using a hybrid Monte Carlo simulation and a goal programming procedure. The author shows the effectiveness and feasibility of his methodology in a manufacturing setting.

Gustavson *et al.* [41] introduce the preventive maintenance scheduling problem with interval costs (PMSPIC). PMSPIC is employed to schedule preventive maintenance of the components of a system over a finite and discretized time horizon, given a common set-up cost and component costs dependent on the lengths of the maintenance intervals. The authors present a 0-1 integer linear programming (0-1 ILP) model [42] for the PMSPIC. The authors claim that PMSPIC is extensible to address side-constraints or multiple tiers. To support their claim, they employ three case studies in transport and energy maintenance: (i) rail grinding schedulling; (ii) two approaches for scheduling component replacements in aircraft; and (iii) components replacement in wind mills in a wind farm. They are chosen to span several levels of unmodeled randomness requiring fundamentally different maintenance policies, which are all handled by variations of their basic model. For each case study, the 0-1 ILP model is compared with age or constant-interval policies; the maintenance costs are reduced by up to 16% as compared with the respective best simple policy. The approach appears to perform better for the first two applications, as they present low levels of unmodeled randomness.

5.2. Bio-Inspired Approaches

Among the metaheuristics approaches to multi-objective optimisation in preventive maintenance, evolutionary methods, in particular multi-objective genetic algorithms (MOGAs) appear to be largely employed.

Yulan *et al.* [43], for instance, employs MOGA to solve the integrated problem of preventive maintenance and production schedule. Their objectives are to minimise maintenance cost, makespan, total weighted completion time of jobs, total weighted tardiness, and maximise machine availability. The total weighted percent deviation (representing the preferences within the objectives and the deviations of the solutions) is proposed to assist decision-makers select the best solution in the Pareto set obtained by the MOGA. A numerical example is provided to demonstrated the significance of integrating optimisation of preventive maintenance with production scheduling when multiple objectives are considered.

Quan *el al.* [44] introduces a GA coupled with a method based on incompletely specified multiple attribute utility theory (ISMAUT) to minimise both workforce and preventive maintenance task completion time. In addition, the objective with their methodology using ISMAUT, differently from the approach adopted by Yulan*et al.* [43] above, is to identify solutions in the Pareto set that best address manager's expectations. Their approach therefore targets a subset of Pareto optimal solutions based on user preferences and eliminates the need to specify weights in a weighted sum evaluation of potential solutions. They employ their technique to two test cases and demonstrate that their method provides outcomes closer to management expectations.

Berrichi *et al.* [37] employ two multi-objective evolutionary algorithms to solve their proposed bi-objective integrated model for parallel machines. Their model considers two optimisation objectives, the minimisation of makespan for production and the minimisation of the system unavailability caused by maintenance. A set of constraints to the problem is also considered. The two approaches employed are the Weighted-Sum Genetic Algorithm (WSGA) and the Non-dominated Sorting Genetic Algorithm (NSGA-II) [45]. As an attempt to improve the obtained results, Berrichi *et al.* in [46] propose a new method, the Pareto Ant Colony Optimisation (PACO), based on Multi-Objective Ant Colony Optimisation approaches. The method is compared to NSGA-II and SPEA-2 [47] for the same testing framework as that from [37]. A satisfactory performance is obtained and comparable results are achieved with the novel approach, considering several evaluation metrics.

Moradi*et al.* [48] integrates flexible JSPs and fixed time intervals preventive maintenance objectives in a bi-objective optimisation exercise. Similarly to Berrichi *et al.* [37], their goal is to simultaneously minimise the makespan and system unavailibility. The authors evaluate four MOGA approaches, NSGA-II, the Non-dominated Ranked GA (NRGA) [49] and two of their variations applying the composite dispatching rule (CDR) algorithm [50] and active scheduling to the GA, i.e., CDRNSGA-II and CDNNRGA. on a set of nine benchmark problems and a total of 4860 instances. For comparison of the methods, two metrics are employed: H and the C metrics. The authors conclude that the MOGA based on dominance concept performs better. In addition, the inclusion of the CDR method to NSGA-II and NRGA is also efficient for the metrics employed.

In a recent example of the use of evolutionary approaches, Gao *et al.* [51] propose a MOGA framework to control preventive maintenance with dynamic interval for a multi-component system. The authors employ their framework to a rotary table system of NC machine tool. Their results show that their approach achieves the optimal non-periodic maintenance schedule with higher system availability and lowest cost.

Similarly, Wang and Liu [52] address a multi-objective parallel machine scheduling problem with machines and moulds resources, within flexible preventive maintenance. They aim at minimising the makespan, unavailability of the machines and the unavailability of the mould system for the maintenance. An adptation of the NSGA-II is proposed to solve their problem. Their results reveal that their approach outperforms the method with periodic preventive maintenance for this problem, in terms of multi-objective metrics. In addition, the authors demonstrate the existing effects of different flexibilities of resources for job processing.

6. Maintenance in Transport Infrastructures

The maintenance in civil structures for transport aims at keeping the systems as such in proper conditions, as there are only indirect links to production of goods and services [6]. This section tackles preventive maintenance for structures such as bridges, highway crossheads, civil marine structures and road pavement maintenance. For multi-objective optimisation in this area, MOGAs appear to be the preferable tool.

Liu and Frangopol [53] study deteriorating reinforced concrete highway cross-heads using a MOGA-based method, employing niching strategies combined with a non-dominated sorting technique. Their goal is to obtain a set of solutions minimising bad road conditions, maximising safety and minimising cost. Uncertainty scenarios regarding deterioration of bridge components under no maintenance and different maintenance strategies were considered using Monte Carlo simulations. Time-based preventative silane and performance-based essential rebuild interventions were applied; in the first case, a large pool of solutions was obtained. Conversely, for the second case, solutions do not scatter widely for condition and safety. This is caused by the effect of rebuilding interventions. As a conclusion, the authors confirm the importance of including deterioration and maintenance intervention uncertainty when planning and optimising maintenance. As an extension Liu and Frangopol [54], under the same methodology, alternative performance-based maintenance strategies (rebuild, minor concrete repair, and cathodic protection) are also considered to obtain bridge maintenance solutions. In addition, they investigate the network-level bridge maintenance management, in which limited resources are prioritised to specific bridges of a highway, yet maintaining satisfactory longterm performance of the network. Similar conclusions to the previous work are reached, where the authors confirm the importance of considering uncertainty when modelling the problem.

Neves *et. al* [55] argue that the disadvantage of the methods proposed by Liu and Frangopol in [53] and [54] lies on the fact that the obtained outcomes are a set of deterministic optimum maintenance plans. Instead, a set of probabilistic maintenance solutions, from which managers could choose from, given the current state of the system is preferable. The authors therefore propose a probabilistic approach, where of instead of considering static performance indicators, it assumes they are continuously changing. To achieve that, the MOGA is coupled with the Latin hypercube sampling method. The authors conclude that their approach is effective for solving complex, discontinuous multi-objective lifetime-oriented optimisation related to cross-heads under uncertainty. Okasha and Frangopol [56] improve the work conducted by Neves *et. al* [55] by incorporating redundancy in lifetime maintenance optimisation. For the optimisation, NSGA-II is adopted coupled with a book-keeping database and algorithm to prevent re-evaluation of objective functions already analysed. A modification to the penalty constraint method is used in the handling of constraints in these problems. The advantage of the novel approach is the ability to avoid maintenance interventions to non-critical structural components.

More recently, Barone and Frangopol [57] assess and compare advantages and drawbacks of four different performance indicators (annual reliability index, annual risk, availability and hazard functions) related to multi-objective optimization of maintenance schedules of deteriorating civil and marine structures. These indicators are coupled with the total maintenance cost to evaluate the Pareto fronts associated with optimal maintenance schedules. For all four cases, the maintenance cost plan is to be minimised. In case 1 reliability index is maximised; annual risk is to be minimised in the second scenario; for the third study, the objectives are to maximise the availability; and the fourth case regards the minimisation of hazard. For the opmimisation, a variant of NSGA-II has been employed. The four approaches are applied to a case study relative to a bridge superstructure and the advantages and drawbacks of each method are discussed.

For pavement, Fwa *et al.* [58] state that an ideal management program for a road network should maintain a high level of structural conditions for safety and community activities, with reduced costs and low environment impact. While all these factors are important objectives for pavement maintenance optimisation, according to the authors, most work conducted in this area is single objective. This is due to the difficulty in tackling the multi-objective character of the problem. To overcome this issue, their research proposes the use of a MOGA for network-level pavement maintenance. In their MOGA they use rank-based fitness evaluation and two selection methods. The objectives considered were to maximise the work production, to minimise the cost and to maximise the overall pavement condition. The authors test their approach to a synthetic problem in which optimisation of a hypothetic network level pavement maintenance program is conducted. They consider two scenarios, with two and three objectives. Their proposed algorithm was able to produce a set of solutions well spread across the Pareto frontier.

7. Maintenance in Rail

Significant productivity gains are obtained considering both maintenance and upgrade to lower maintenance equipment in rail [59]. There are two major sectors in the rail industry: (a) building and maintenance of trains (mechanical and electrical parts) and (b) construction and maintenance of racks and related infrastructure (signaling, telecomunications, teminals, stations and related roads and buildings) [60]. Similarly to other maintenance activities in transport, the grand challenges are to obtain a balance between efficient use of facilities coupled with minimised delays, maximised safety and reasonable costs [60].

The literature regarding single-objective maintenance scheduling activities in railway is vast. Soh *et. al* [61] review the state-of-the-art rail maintenance schedulling methods employed mostly for single-objective optimisation. In their review they include work regarding strategic gang scheduling, local search heuristics and project swapping, GAs, GAs coupled with Robust Evaluation, and ontology-based remote condition monitoring. In order to complement their survey, in this section we further review the work focused on multi-objective optimisation.

Ferreira and Murray [59] review the main aspects for rail tracks maintenance planning. They focus on (i) the physical factors affecting track deterioration (such as dynamic effects, train speeds, axle loads, breaks, etc.); (ii) the review of scope and current capabilities of existing track degradation and maintenance planning models; and (iii) the optimisation parameters to be included when modelling maintenance. The authors also enumerate the important elements to be considered when developing optimised maintenance planning for rail tracks.

Pondofillini *et al.* [62] investigate tracks defects such as cracks and misalignments due to fatigue and other failure mechanisms. In order to monitor and measure rail breakage and internal cracks, the authors employ ultrasonic inspection cars and develop a framework for their optimal use. Similarly to other authors reviewed in this section, their aims are to reduce costs and increase performance and safety. The authors propose a non-homogeneous Markov model to determine the probability of failure of a rail section, considering different degradation, inspection and maintenance procedures. They employ real-world data from generic statistics, literature and expert input to determine the values of the model's parameters. A MOGA is employed to minimise the yearly rail operation costs and the rail probability of failure. The Pareto front obtained shows that, for their experiments, the inspection interval is the most influencing variable on the two objective functions.

Hani *et al.* [63] couples discrete-event simulation with GAs (a non-pareto approach and NSGA-II) to optimise the schedule of a real-world railway maintenance facility. Their simulation model incorporates the maintenance facility blueprint, the characteristics of the maintenance elements, the job sequence for each railway vehicle, the simulation timeline and the statistical rules for time between arrivals of vehicles. The model outputs are the number of railway elements maintained over the simulation timeline, the duration of the vehicles immobilisation (maintenace and waiting time), and the maintenance facilities occupation rates. For their optimisation model, four vehicle maintenance sequencing rules are assessed: first in, first out (FIFO); last in, first out (LIFO); shortest processing time (SPT) and highest processing time (HPT). For each of those policies, the objectives are (i) to maximise the number of vehicles maintained per year; (ii) to minimise the vehicle's waiting time; and (iii) to minimise the locations occupation rate. In their implementation, the simulation model serves as the fitness function calculation for each individual. Their results show that both GA approaches produce better results than the current real-world simulation. In addition, the NSGA-II version of their method produces overall better results.

Min *et al.* [64] propose an advanced evolutionary algorithm, namely Chaos Self-adaptive Evolutionary Algorithm (CSEA), to optimise the maintenance of catenary systems in traction power supply systems. The authors consider three types of maintenance, mechanical, repair and replacement. The objectives are to minimise the maintenance cost and to maximise the system reliability. Their multi-objective optimisation approach builds up on NSGA-II by including the use of a chaotic logistic model to generate the initial population, a grouping selection strategy and a self-adaptive genetic operator to allow dominated solutions to enter the mating pool more frequently and to preserve diversity. The data employed to test the methodology includes information based on 10 year records of Zhengzhou 100Km section of Beijing-Guanzhou highway. Their results show that CSEA outperforms NSGA-II in optimal solution diversity-preserving and convergence.

8. Maintenance in Transport Energy Providers

In this section we review the multi-objective optimisation strategies applied to power sources maintenance management, as vehicles, infrastructure and the transport network rely heavily on energy providers.

Kralj and Petrovic [65] introduce a multi-objective branch and bound algorithm with successive approximations to annual preventive maintenance scheduling of fossil fuel thermal units in electric power systems. The objectives investigated are the minimisation of fuel costs, the maximisation of reliability and minimisation of constraints violations. Although the selected objectives involved economical, reliability and technological concerns, the authors claim that other performance criteria could be included in the model. The authors test their method in a realistic example of annual maintenance scheduling of 21 thermal generating units. The authors conclude that the objective function values corresponding to the selected schedule are sufficiently close to the ideal values. In addition, in their experiments, the authors observed that the convergence toward the satisfactory solution is relatively fast.

Huang [66] proposes a genetic-evolved fuzzy system to schedule the maintenance of power generating units. The author aims at optimising the increased production cost and the reserve margin. GAs are employed to tune the fuzzy membership functions. Subsequently, a fuzzy dynamic programming is embedded with the fuzzified constraints to obtain optimal maintenance schedules. Huang tests his method on a real-world problem of maintenance scheduling of 31 generating units from a power company from Taiwan. In their tests only high capacity units, such as those from thermal and nuclear sources were considered. In their case-study, each maintenance period takes five days, and they were provided with the dataset on the year of 1992 maintenance periods' load demand. The authors compare their results with the actual scheduling strategy employed by the power company and with a conventional fuzzy system without the GA optimisation. The authors found that their method produced the least increased production cost and and the highest reserve margin.

Yang *et al.* [67] proposes a modular system to optimise electric power substation maintenance. The authors model the stochastic and maintenance-dependent deteriorations of individual components using discrete time Markov processes [68]. Minimum cut sets [69] is employed to assess the impacts of changes in substations configuration and maintenance on the system costs and reliability. In addition NSGA-II and NSGAII-DE, a modified version of NSGA-II introduced by the authors, are employed and compared to optimise the preventive maintenance activities. The authors employ four substation configurations to test their approach. Pareto front graphs are shown as the results of the method for each configuration. The authors discuss the trade offs between cost reduction and the expected unserved energy and conclude that overall the method is successful and is easily adaptable to more complex configurations. In addition, when comparing NSGA-II and NSGAII-DE, although NSGAII-DE requires less computational time, NSGA-II produces Pareto fronts more widely spread.

Fetanat [70] introduces a 0-1 integer programming method, based on a continuous formulation for the ACO method (ACO_R [71]) for optimal maintenance in power system units. Their objectives are to minimise costs and maximise reliability. The method is tested on a power system with six generating units, under a simulation environment. The authors compare their results to other optimisation methods, including an earlier fuzzy-version of their approach, and conclude that their method is superior for their case study.

Carlos *et al.* [72] propose a Particle Swarm as optimization technique and a tolerance interval approach based on Monte Carlo simulations to (a) optimise maintenance; and (b) to address the uncertainty related to variations of maintenance frequency observed in the real world. The authors point that their multi-objective problem can be formulated in terms of reliability, availability, maintainability, cost, which are the decision criteria. Surveillance test and maintenance strategies act as decision variables. In their work, the authors present two examples of maintenance optimisation. The first case involves the search for (a) the best maintenance plan to cover all the dominant failure causes of motor-driven pumps, which are part of nuclear plants safety system; and (b) to analyse the effects of uncertain task intervals on unavailability and cost. The second case studied is focused on the maintenance plan optimization of a High Pressure Injection System (HPIS) of a nuclear power plant. This system removes heat from the reactor under accidental conditions. The authors conclude from their results that their optimisation framework helps to find a maintenance strategy with high level of availability and minimum cost.

Ayoobian [73] researches the use of NSGA-II to optimise availability, cost and exposure time of maintenance programs in nuclear plants. After the Pareto is determined, differently from the other works in the area, a Sensitivity Index is introduced as a decision tool to extract the most suitable, optimised solution. Their sensitivity index is calculated as a rate around specific objective function values on the Pareto optimal curve. They demonstrate their methodology applied to a simplified HPIS maintenance, where the objectives optimised, i.e., unavailability, cost and exposure time were reduced by 86%, 58% and 30%, respectively.

Ren *et al.* [74] introduce a multi-objective linear programming (MOLP) methodology to determine the optimal operating strategy for a distributed energy resource system where various technologies are available to satisfy part of the energy needs. Their objective is to minimise energy costs and the enviroment impact, measured as CO_2 emissions. They employ their method to a case study in Kitakyushu Science and Research Park, Japan. The trade-off between economic and environmental performances is analysed. The authors also investigate the effects of introducing electricity buy-back and carbon tax, as well as fuel switch to the biomass energy.

9. CONCLUSIONS

The importance of preventive maintenance in transportation activities is widely acknowledged within industry, government and society. Keeping the transport modes and infrastructure within acceptable conditions is necessary to safeguard the investment in construction and vehicles, while assuring the safety of their users. The main objectives of maintenance therefore regard reliability, safety, efficiency and reduction in costs.

To assist maintenance managers with decisions, various multi-objective optimisation approaches have been largely employed. Literature regarding surveys of time-based multi-objective optimisation for preventive maintenance in transportation, however, is scarce. We have therefore contributed to this area by making a state-of-the-art systematic survey of the work on time-based multi-objective optimisation in preventive maintenance in transport. We identified four main areas: maintenance in production, in infrastructures, in rail and in energy providers. For each of these areas we review the sets of objectives defined, existing constraints and the approaches commonly adopted. We have surveyed around forty papers for the past 30 years of research conducted in the area. We observed a few tendencies in the research conducted:

- Overall the objectives within preventive maintenance in transport are similar for different problems and domains (safety, reliability, availability, costs). What changes is the importance and the weight of each objective and the influence of business requisites, policies and regulations on them.

- Many researchers are now acknowledging the importance of considering the system's uncertainty and its influence on decisions regarding maintenance. Approaches that incorporate or simulate uncertainty are therefore more frequently adopted.

- The use of bio-inspired methods to solve multi-objective preventive maintenance problems appears to be prevalent. In particular, MOGAs are very popular. Exact approaches are far less used.

- The adoption of hybrid approaches, considering (i) multiple bio-inspired methods, (ii) Monte Carlo approaches coupled with optimisation methods, and (iii) hybrid Fuzzy logic approaches are also employed.

- There appears to be also a concern regarding the final decision-support process, after the feasible solutions are identified. A number of approaches are therefore also aiming at determining the sub-set of optimal solutions within a Pareto front that better matches the preventive maintenance management particular preferences.

- Time-based multi-objective preventive maintenance literature for private vehicles, lorries and aircrafts is scarce. Instead, condition-based maintenance and data-driven approaches appear to be more popular, due to the dynamic, uncertain and individual nature of these systems.

As future opportunities, we intend to investigate and compare the current approaches with the performance of equivalent data-driven and condition-based maintenance methods. We want to understand the main advantages of each approach, the applications in which they are better suited as well as their advantages and disadvantages.

10. ACKNOWLEDGEMENTS

This report has received funding from the European Unions research and innovation programme under grant agreement number 680515.

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