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Tradeoffs between levelling the reserve margin and minimising production cost in generator maintenance scheduling for regulated power systems

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ABSTRACT

One of the key focus areas for a power utility is the planned preventative maintenance of the power generating units in its power system. The well-known *generator maintenance scheduling* (GMS) problem involves finding a schedule for the planned maintenance outages of generating units in a power system. A novel bi-objective model is proposed for the GMS problem in which demand reliability is maximised, by minimising the *sum of squared reserves* (SSR), and electricity production cost (predominantly fuel cost) is minimised. A novel production planning module is proposed to estimate the production cost associated with an energy generation plan, using a *linear programming* (LP) model to solve the *economic dispatch* (ED) problem, which precedes application of a simple *unit commitment* (UC) algorithm. A dominance-based multi-objective simulated annealing approach is then adopted to determine trade-off solutions to the model. Parallel computing is also utilised to increase the efficiency of approximating the Pareto front. The modelling approach is demonstrated in the context of a case study involving the 32-unit IEEE Reliability Test System. The results are compared to the best known single-objective solution in the literature, which only minimises the SSR, and the conflicting relationship between the two model objectives is investigated. It is found that more non-dominated trade-off solutions result if the load demand increases (*i.e.* the gap between installed capacity and load demand decreases). Therefore, if the installed capacity is sufficiently high, the reliability objective of minimising the SSR produces sufficiently small production cost solutions. Fuel cost savings of 0.41% are achieved in respect of a most "reliable" solution in the literature, but considerable cost savings are possible (up to 7.11%) if the maintenance duration and crew constraints are relaxed.

1. Introduction

One of the key management focus areas for a power utility is the planned preventative maintenance of the power generating units in its power system [1–4] so as to satisfy demand as efficiently and effectively as possible. A schedule for the planned maintenance outages of generating units in a power system is sought in the celebrated *generator maintenance scheduling* (GMS) problem [5]. Since the solution of the GMS problem resides within the realm of combinatorial optimisation, finding a good maintenance schedule becomes considerably more difficult as the number of units in a power system increases, and as the complexity and number of constraints and objectives increases.

In this paper, a novel bi-objective approach to solving the GMS problem is proposed, based on the notion of trade-off solutions in the Pareto sense, and including manpower, maintenance exclusion, maintenance duration, and time window constraints. The two model objectives proposed are the most popular reliability and economic GMS criteria in the literature, namely levelling the net reserve margin and minimising the fuel cost. Although these objectives have separately been considered extensively in the GMS literature, they have not been considered together in true trade-off fashion. In addition, we propose a novel production planning module which consists of a *linear programming* (LP) model for solving the *economic dispatch* (ED)[1] problem in conjunction with a simple *unit commitment* (UC)[2] algorithm. This module may be used to estimate production costs for power utilities with a generation unit mix that includes coal-fired, hydroelectric (conventional and pumped storage), nuclear and gas-turbine units. A *dominance-based multi objective simulated annealing* (DMOSA) algorithm is finally employed to approximate Pareto optimal solutions which are compared with the best-known *single-objective* (SO) solution available in

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[1] The problem of determining the optimal output from available generating units, so as to meet the expected demand at the lowest possible cost, subject to various constraints.

[2] The problem of determining which available generating units (*i.e.* those not scheduled for maintenance) should be connected to the power generation system, so as to contribute actively to power generation.

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the literature in respect of levelling the reserve margins. We also illustrate the conflicting relationship between this objective and the minimisation of fuel costs.

2. Literature review

The GMS problem is typically formulated as a scheduling problem with binary decision variables representing whether or not maintenance of power generating units occur during each of a set of time periods over a fixed planning horizon. The number of units considered in the literature range from 5 [6], to 21 [2] to as many as 157 [7]. Maintenance plans usually span an annual planning horizon [8,9], but this varies, and planning horizons in the literature range from eight weeks [10] to five years [4]. Common time periods into which the GMS planning horizon is discretised are periods of one week [9], but this also varies, with values ranging in the literature from single-day and five-day to monthly periods [11].

Three dominant classes of scheduling criteria are usually incorporated in formulations of the GMS problem, namely economic criteria, reliability criteria, and convenience criteria [3,12], of which the first two are the most common [1,13,14].

Economic scheduling criteria usually involve minimisation of production, maintenance, and other operational costs for regulated power systems[3] [1,8,16]. The deregulation of the electric power market in many countries has, however, shifted the focus away from minimising operating cost or maximising reliability more towards maximising profitability [11,15,17]. GMS model formulations incorporating revenue predictions have been proposed in [18,19].

Maintenance costs are usually partitioned into fixed and dependent maintenance costs [17, p. 248], the latter typically involving the cost of subjecting a power generating unit to maintenance too early or too late [13,20].

Production costs usually include fuel, start-up, and shutdown costs. The production cost is sometimes merely taken as the fuel cost, since fuel is the most significant cost associated with power generation [8,17]. Production cost is included in many economic cost GMS objectives since it is often difficult to quantify maintenance cost accurately [17, p. 249]. Canto [8] noted, however, that maintenance costs are often insignificant compared to start-up and production costs. Maintenance costs are, in fact, often of the order of one thousand times smaller than generating unit start-up costs and of the order of one million times smaller than production costs [8]. There are also other operational costs, such as capital cost and the cost of residual staff for security and monitoring, but such costs are typically not significant [8].

Depending on a unit's Input-Ouptut (I/O) heat rate curve, its fuel cost may be modelled either as approximately linear [8,9,14,21] or approximately quadratic [10,22] with varying degrees of accuracy [23].

A number of authors [1,17,24,25] have claimed that operational costs (specifically based on fuel cost) are not very sensitive to variation of maintenance plans, with cost values ranging in the literature from 0.1 to 0.3% [13,26]. As noted in [24], however, the UC problem influences the production cost more significantly, with Johnson *et al.* [27] reporting a fuel cost saving of around 1% as a result of effective UC. It is therefore important to incorporate a sound UC logic within the larger GMS problem. In [19], operational costs, consisting of fuel cost with more elaborate formulations of start-up and maintenance costs, were found to vary as much as 6%.

Reliability scheduling criteria involve satisfying demand as reliably as possible. These criteria may be either stochastic or deterministic in nature [4,17]. The most common deterministic reliability criterion results in formulations aimed at levelling the reserve margin over the planning period in some way. This is usually accomplished by minimising the *sum of squares of the reserves* (SSR) [1,4,6,7,22,28,29], although the minimum reserve margin is also sometimes maximised [13].

In contrast, stochastic models are able to accommodate reliability more accurately by taking into account expected *forced outage rates* (FORs) and variations in expected demand. Stochastic reliability criteria in the GMS literature include minimising the total system *loss of load probability/expectation* (LOLP/LOLE) [26,30], or minimising the *expected unserved energy or expected energy not served* (EUE/EENS) [9]. Other stochastic formulations are based on levelling the risk, typically by minimising the sum of squared effective reserve margins over the planning period [4,29]. This is usually achieved by determining the effective reserve margin which results from calculating an *effective load carrying capacity* (ELCC) for each unit and an *equivalent load* (EL) for each time period in the planning horizon.

The constraints included in formulations of the GMS problem vary significantly, depending on the nature and underlying assumptions of the power utility's operations [28]. Typical constraints employed in the literature include maintenance window, load, reliability, service contiguity, resource, exclusion, and transmission constraints [3,13,31]. Maintenance window constraints ensure that each unit is serviced between a pre-specified earliest and latest time period. These time windows are typically dictated by annual generating unit service frequencies, as imposed either by power utility policy or by operational service levels. Load constraints ensure that the load demand is met during each time period over the planning horizon. This demand must, of course, be met by generating units that are not scheduled for maintenance during the relevant time periods. Reliability constraints may be incorporated by specifying a reserve or safety margin over and above the load constraints. Service contiguity constraints are imposed to ensure that the time periods during which a particular generating unit is serviced run consecutively (without interruption). Resource constraints specify a limit on the number of resources available for the purposes of maintenance. These resources may involve service budgets, the availability of adequately qualified service personnel and the availability of spare parts. Exclusion constraints are employed when certain generating units are not allowed to be taken out of service simultaneously (*e.g.* two units in the same power station or too many units in the same geographical region). Transmission/network constraints have recently been incorporated into GMS models and seek to ensure the transmission capabilities of the electrical network (*e.g.* maintaining voltage levels) or ensure that a power station meets the demands of the geographic regions within its service area *via* the existing transmission network infrastructure.

Solution techniques typically [15,28,31] employed for solving GMS models include metaheuristics, mathematical programming techniques, dynamic programming[4] [24,26,32], heuristic search algorithms, methods from fuzzy set theory [1,32], knowledge-based/expert systems [33], constraint programming [34], and game theory [35]. The most popular solution techniques, however, are metaheuristics, mathematical programming techniques, and dynamic programming [15]. Mathematical programming techniques are typically applied to solve single-objective instances of the GMS problem, and mostly include variations on the celebrated *branch-and-bound* (B&B) method [13,36]. Bender's decomposition has also been incorporated due to the often large dimensions of GMS problem instances [8]. Solving the GMS problem by traditional mathematical programming and dynamic programming techniques limits the size of instances that can be considered, due to the exponential increase of the memory requirements associated with solving large instances [37] and the extensive computing time [26] associated with these techniques. Metaheuristics, on the other hand, rather often obtain very good (although not necessarily optimal)

[3] A government usually regulates the system directly or indirectly in regulated systems. In this case the utility should not take advantage of the end consumer [15].

[4] Some authors classify dynamic programming as a mathematical programming technique [15].