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An improved robust model for generator maintenance scheduling☆

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ABSTRACT

The maintenance schedule of generators in power plants needs to match the electricity demand and ensure the reliability of the power plants at a minimum cost of operation. In this article, a reliability criterion modified generator maintenance scheduling (MGMS) model is formulated with additions and modifications made to the classic generator maintenance scheduling (GMS) model. The MGMS model includes modified maintenance window constraints with some newly added constraints. A comparison is then made between the MGMS model and the classic GMS model when both models are applied to a 21-unit test system. The results show that the MGMS model gives more reliable solutions than the GMS model. Due to the reliable results of the reliability criterion MGMS model, a robust model using economic cost objective function is formulated. To illustrate the robustness of the formulated MGMS model, the maintenance of the Arnot Power Plant in South Africa is scheduled with open loop and closed loop controllers. Both controllers satisfy all the constraints but the closed loop results are better than the open loop results.

1. Introduction

The problem that the generator maintenance scheduling (GMS) model faces is generating a time line for a preventive maintenance schedule for a given set of units over a certain period such that all the operating constraints are satisfied and the objective criterion is met [1–6]. GMS problems are based on either economic cost criterion [5,7,8] or reliability criterion [5,9].

The reliability GMS problem is solved by minimising the sum of squares of the reserve (SSR) over the entire operational planning period [3–6,10–12]. The maintenance window and crew constraints in [9] are not formulated in the manner that describes the problem explicitly.

The economic objective function is used in [7,13,14] to minimise the production cost over the planning horizon. The models fail to include the generator maintenance limit which could prove problematic for the energy planner when considering unit commitment or economic dispatch. The generator maintenance limit is considered in [15] but the ramp rate constraint is not added. The ramp rate constraint is used in economic dispatch problems to ensure the generator ramps up and down in at a desired rate [16,17]. The association of the start up to maintenance variable is formulated in [7] but the relation between the start up and generated output is not considered.

A variety of mathematical and heuristic techniques have been employed to solve the GMS problem. The techniques include dynamic programming [6], the branch and bound technique [18], and implicit enumeration [19]. The other techniques include benders' decomposition [7,15], fuzzy logic [20], tabu search [5], simulated annealing [14], genetic algorithm [21], differential evolutionary technique [13], ant colony [12], particle swarm optimisation (PSO) [8].

The GMS models discussed in existing literature above treat the variables as independent to each other, but variables in GMS problems are sometimes dependent. Certain constraints need to be modified or added to the GMS problem and as such the need for a new GMS model. All the techniques mentioned above only have open loop GMS solutions, there has been no mention of closed loop solutions.

Model predictive control (MPC) is a closed loop control technique that uses the explicit model of the plant to predict the future responses of the plant over a finite horizon [22]. This technique has been used successfully in resource allocation [22] and economic dispatch [23]. The advantages of MPC include its convergence and easy interpretation; robustness and simplified model; and attenuability against external disturbance.

There have been research on improving the solution methodology of GMS problems such as using the genetic algorithm [21], the ant colony algorithm [12] and the multiple-swarms modified discrete PSO [24] which provide efficient computational algorithms for given GMS models. The purpose of this paper is two folded. On the one hand existing GMS models are improved by adding new constraints, on the other hand a model predictive control (MPC) approach to solve the GMS problem is introduced. New constraints,

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such as the crew availability description and the dependent relations between maintenance, generation and start up, are added. These constraints, if ignored, would possibly result in inaccurate scheduling results. The proposed MPC approach for the GMS problem is an iterative approach which brings real time system changes into consideration at each iteration. Therefore, the solutions from the MPC approach are robust in the sense that disturbances, e.g. system changes, can be fed back as initial conditions of the GMS problem in each iteration loop and a more feasible optimal solution will be obtained. Since this MPC approach solves the GMS problem, an optimization problem, at each loop, PSO is chosen for these GMS optimization problems. In fact, any other optimization algorithm, which is applicable to nonlinear mixed integer programming, can be applied here.

The outline of this paper is as follows. In Section 2 a modified GMS model is formulated for the reliability and the economic cost criteria and a comparison of the MGMS model is made to the classic GMS model. The solution technique based on the penalty function mixed integer PSO algorithm is found in Section 3. Section 4 discusses the simulation results of two case studies. The first case study is used to compare the MGMS and GMS models, the second case study is used to compare the open and closed loop solutions of the economic cost criterion MGMS model of Section 2. Section 5 is the conclusion. For the reader's convenience, the following frequently used acronyms are listed:

GMS:	Generator maintenance scheduling
MGMS:	Modified generator maintenance scheduling
SSR:	Sum of squares of reserve
TWM:	Total available manpower-weeks
PSO:	Particle swarm optimisation

2. Mathematical formulation of the modified GMS problem

2.1. Reliability criterion modified GMS model

Consider the classic GMS model using the reliability objective function. The aim of the reliability objective function is to minimise the sum of squares of reserve (SSR) in the power plant. As explained in [10], the lower the value of the SSR, the more uniformly distributed the reserve margin is and the higher the reliability of the power plant. The GMS models in [6,10,11] are used with additions and modifications made to some of the constraints. The additions are made to enhance the accuracy of the model, provide more accurate mathematical description and further depict real life scenarios of generator maintenance problems in power plants.

The following notations are used to formulate the optimisation model:

t:	Index of time periods, $t = 1, \ldots, T$;
T:	Total number of planned horizons;
i	Index of the number of generators $i = 1, \ldots, I$;
I:	Total number of generators;
g_i^{max}:	Maximum output power for each generator [MW], these values are assumed constant;
$g_{i,t}$:	Generated output power for each generator [MW];
I_t:	The set of indices of generators in maintenance at time t;
N_i:	Duration of maintenance on each generator i;
$x_{i,t}$:	Variable for the start of maintenance for each generator i at time t, if generator i is on maintenance $x_{i,t} = 1$, otherwise $x_{i,t} = 0$;
D_t:	Demand per time period;
M_i^q:	Number of crew needed for the qth stage of maintenance of each generator, $q = 1, \ldots, N_i$;
A_t:	Available number of crew at every time t.
g_i^{min}:	Minimum output power for each generator [MW], these values are assumed constant;
LR:	Maximum down ramp rate per time period [MW/h];
UR:	Maximum up ramp rate per time period [MW/h].

The classic GMS model in [6,10,11] is transformed into the modified GMS (MGMS) model below.

$$Min\{\sum_{t=1}^{T}(\sum_{i=1}^{I} g_{i,t}^{max} - \sum_{i\in I_t}\sum_{t=q}^{N_i} x_{i,t} g_{i,t} - D_t)^2\}, \tag{1}$$

subject to maintenance window:

$$\sum_{t=1}^{T} x_{i,t} = N_i, \quad 1 \le i \le I, \tag{2}$$

$$\sum_{t=1}^{T-N_i+1} x_{i,t} x_{i,t+1} \ldots x_{i,t+N_i-1} = 1, \quad 1 \le i \le I, \tag{3}$$

crew constraint:

$$\sum_{i=1}^{I}(1 - x_{i,t-1}) x_{i,t} \ldots x_{i,t+q-1} M_i^q \le A_{t+q-1}, \quad 1 \le q \le N_i, \ \ 2 \le t \le T - N_i + 1, \tag{4}$$

load constraint:

$$\sum_{i=1}^{I} g_{i,t} - \sum_{i\in I_t}\sum_{t=q}^{N_i} x_{i,t} g_{i,t} \ge D_t, \quad 1 \le t \le T, \tag{5}$$

generator limit:

$$g_i^{min}(1 - x_{i,t}) \le g_{i,t} \le g_i^{max}(1 - x_{i,t}), \quad 1 \le t \le T, \ \ 1 \le i \le I, \tag{6}$$

ramp rate:

$$-LR \le g_{i,t+1} - g_{i,t} \le UR, \quad 1 \le t \le T, \quad 1 \le i \le I. \tag{7}$$

The objective function is to minimise the sum of squares of reserve (SSR) for a given set of generators at a given time horizon.

The maintenance window of Eq. (2) shows that for every generator i, maintenance will take a duration of N_i periods, this constraint is obtained from [13]. Eq. (3) gives the duration, from start to finish, of maintenance without interruptions for all the generators. The second maintenance window constraint as described by Eq. (3) ensures that the maintenance window operates at an optimised level, doing without it means that the maintenance window is an approximation. Given the importance of generator maintenance, having an approximation instead of an exact duration renders the maintenance window less effective than could be, hence the introduction of Eq. (3) into the MGMS model.

A modification to the existing crew constraint in [13,21,25] is given in (4). In the existing literature a precise description and formulation of the crew constraint is not given, this affects the accuracy of the results obtained for the GMS problem. Since the crew constraint is one of the important constraints needed in the GMS problem it is necessary to formulate a crew constraint that will provide a step by step description of the crew needed at every stage of maintenance for each generator, thereby always checking that the crew needed does not exceed the available crew at every interval. This is done in (4).

The generator limit constraint of (6) is a safety margin for the generator to preserve the generator life and is usually used in economic dispatch problems. This constraint is added to this model to further depict real life cases of maintenance problem.

The inequalities of (7) gives the ramp rate for generator i as the generated output changes from time t to $t+1$. The ramp rate constraint is not a new constraint in power systems it is used in unit commitment and economic dispatch [16,17]. The constraint is added to aid the energy planner when considering unit commitment.

2.2. Economic cost criterion modified GMS model

As will be seen in Section 4.1.1, the modified constraints in the MGMS model of Section 2.1 enhanced the ability of MGMS model to produce more reliable solutions for the test system than the classic GMS model. Thus formulating an economic cost objective function MGMS problem, incorporating the modified constraints and adding some new constraints to show the robustness of the MGMS model is carried out in this subsection. The economic cost objective function is chosen for the formulation of the MGMS model because of its ability to incorporate the system's reliability into the model [4]. The relationship among variables has not been mentioned in many papers and as such the need to show that the variables are not independent of each other but rather all have a connection to one another in some way is important, hence the relationship constraints.

The objective function J in (8) contains three variables, the maintenance state $x_{i,t}$, startup state $y_{i,t}$, and generated output $g_{i,t}$, for which $i = 1, \ldots, I$, $t = 1, \ldots, T$, c_i, f_i and k_i are the cost of maintenance, start up and generation respectively. When generator i is started at time t then, $y_{i,t} = 1$, otherwise $y_{i,t} = 0$. The addition of the start up variable to the objective function is to emulate real life cases where there is an amount of money reserved for the start up of any generator in the power plant.

$$\mathrm{Min}\, J = \sum_{i=1}^{I}\sum_{t=1}^{T} c_i x_{i,t} + \sum_{i=1}^{I}\sum_{t=1}^{T} (f_i y_{i,t} + k_i g_{i,t}), \tag{8}$$

subject to, the maintenance-start up relationship (9), maintenance-generation relationship (10), start up-generation relationship (11), maintenance window ((2), (3) and (12)), crew (4), demand (13), reserve (14), generator limit (6), and ramp rate (7) constraints.

$$x_{i,t} + y_{i,t} \le 1, \quad 1 \le t \le T, \tag{9}$$

$$(1 - x_{i,t}) g_{i,t} = 0, \quad 1 \le i \le I, \ \ 1 \le t \le T, \tag{10}$$

$$\begin{aligned} & y_{i,t}\mathrm{sgn}(g_{i,t})[1 - \mathrm{sgn}(g_{i,t-1})] + [1 - y_{i,t}][1 - \mathrm{sgn}(g_{i,t})][1 - \mathrm{sgn}(g_{i,t-1})] \\ & + [1 - y_{i,t}][1 - \mathrm{sgn}(g_{i,t})]\mathrm{sgn}(g_{i,t-1}) + [1 - y_{i,t}]\mathrm{sgn}(g_{i,t})\mathrm{sgn}(g_{i,t-1}) = 1, \\ & 2 \le t \le T, \end{aligned} \tag{11}$$

where $\mathrm{sgn}(g_{i,t})$ is the sign value of the generated output of generator i at time t. If $\mathrm{sgn}(g_{i,t})$ = 1 then there is a generated output from generator i, otherwise $\mathrm{sgn}(g_{i,t})$ = 0.

$$\sum_{i=1}^{I} x_{i,t} \le 1, \quad 1 \le t \le T. \tag{12}$$

$$\sum_{i=1}^{I} g_{i,t} = D_t, \quad \mathrm{forall}\ 1 \le t \le T, \tag{13}$$

$$\sum_{i=1}^{I} g_{i,t}^{max} \ge D_t + S_t, \quad \mathrm{forall}\ 1 \le t \le T, \tag{14}$$

where S_t is the reserve per time period.

The constraint (9) shows that during maintenance of generator i, the generator cannot be started until maintenance is completed. The equality of (10) shows that generator i cannot generate electricity while it undergoes maintenance. The equality (11) shows that if the generator is producing electricity then it cannot be started at the same time. Eqs. (10) and (11) are new constraints that are added to the show the relationship among the variables of the GMS problem. The inequality constraint of (12) used in [4] means that at most only one generator can be maintained for a given time period. Eq. (13) gives the demand constraint. This constraint is used in [3,20]. The inequalities of (14) give the reserve constraint, this constraint is explained in [25].

2.3. Model predictive control

The model predictive control (MPC) is a closed loop technique that adapts to changes, detect disturbances and make corrections automatically and is easily implemented [22,23]. The main reason for using the MPC approach is to obtain a closed loop solution for the MGMS model that is stable against any external disturbance and as such improving the robustness of the MGMS model. The MPC approach is used to solve the economic cost criterion MGMS problem to obtain closed loop solutions.

The open loop MGMS problem is defined over the time period T with the optimisation variables $x_{i,1}$, $y_{i,1}$, $g_{i,1}$, ..., $x_{i,T}$, $y_{i,T}$, $g_{i,T}$, $i = 1, 2, \ldots, I$. When the same MGMS problem is considered over a time interval $(m+1, m+T)$ then the optimisation variables are changed into $x_{i,m+1}$, $y_{i,m+1}$, $g_{i,m+1}$, ..., $x_{i,m+T}$, $y_{i,m+T}$, $g_{i,m+T}$. In an MPC approach, a finite horizon control problem is repeatedly solved and applied to the system based on the obtained optimal open loop solution.

The MPC approach is defined with the same state model as the open loop model in (8). Thus, the open loop MGMS problem is transformed to the model as below. Given I, T, DR, UR, D_t, R_t, let $x_{i,t} := x_{i,m+t}$, $y_{i,t} := y_{i,m+t}$, $g_{i,t} := g_{i,m+t}$, $D_t = D_{m+t}$, $t \ge 1$,

$$\mathrm{Min}\, J = \sum_{i=1}^{I}\sum_{t=m+1}^{m+T} c_i x_{i,t} + \sum_{i=1}^{I}\sum_{t=m+1}^{m+T} (f_i y_{i,t} + k_i g_{i,t}), \tag{15}$$

where $m = 1, 2, \ldots, M$ is the switching interval for the MPC controller. The constraints for closed loop are the same as those of the open loop MGMS solution, the only difference is that the constraints of the closed loop MGMS solution are updated after each iteration is implemented. The optimal solution is applied only in the first sampling period $(m, m+1)$ and this solution is executed as the input over the time period $(m+1, m+2)$, thus a closed loop feedback is obtained. The demonstration of how MPC controllers are implemented is explicitly explained in [22]. The simulation results of the economic cost objective function open loop and closed loop MGMS solutions are compared Section 4.2.

3. Solution methodology

The particle swarm optimisation (PSO) is a population based search algorithm which simulates the social behaviour of birds within a flock. Optimisation problems with mixed integer variables in Section 2 can be simplified as $\min f(x)$ subject to $g_u(x) \le 0$, $h_p(x) = 0$, where $f(x)$ is the objective function, x the mixed integer variables that contain the binary x_i^b and continuous x_i^c variables, $g_u(x)$ and $h_p(x)$ are the inequality and equality behavioural constraints.

The original PSO algorithm which solves continuous variable non constraint problems [26] is revised in [27] to consider discrete variables and constraints using the penalty function approach. The full version the mixed integer penalty function PSO algorithm is found in [27], this section is included to make this article concise. The binary variables are transformed to continuous variables using the penalty function Φ given as: $\Phi(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n}(1/2)\{\sin 2\pi(x_i - 0.25) + 1\}$, where x_1, x_2, ..., x_n are the binary variables and n is the number of binary variables. The mixed integer constrained problem $f(x)$ is transformed into the minimization of augmented problem which is: $F(x) = f(x) + s\Phi(x) + r\sum_{u=1}^{ncon} max\,[0, g_u(x)] + r\sum_{p=1}^{con}|h_p(x)|$, subject to, $LB \le x_i^c \le UB$, $1 \le i \le m$, where F is the augmented objective

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Table 1
Data for the 21-unit test system.

Unit	Capacity (MW)/g_i^{max}	g_i^{min}	Allowed period I_t	Maintenance duration N_i (weeks)	Manpower (M_i^q or $M_{i,k}$) required for each week
1	555	462	1–26	7	10 + 10 + 5 +5 + 5 +5 + 3
2	180	150	1–26	2	15 + 15
3	180	150	1–26	1	20
4	640	533	1–26	3	15 + 15 + 15
5	640	533	1–26	3	15 + 15 + 15
6	276	230	1–26	10	3 + 2 +2 + 2 +2 + 2 +2 + 2 +2 + 3
7	140	117	1–26	4	10 + 10 + 5 +5
8	90	75	1–26	1	20
9	76	63	1–26	2	15 + 15
10	94	78	1–26	4	10 + 10 + 10 + 10
11	39	32	1–26	2	15 + 15
12	188	152	1–26	2	15 + 15
13	52	43	1–26	3	10 + 10 + 10
14	555	462	27–52	5	10 + 10 + 10 + 5 +5
15	640	533	27–52	5	10 + 10 + 10 + 10 + 10
16	555	462	27–52	6	10 + 10 + 10 + 5 +5 + 5
17	76	63	27–52	3	10 + 15 + 15
18	58	48	27–52	1	20
19	48	40	27–52	2	15 + 15
20	137	114	27–52	1	15
21	469	392	27–52	4	10 + 10 + 10 + 10
Total capacity/week	5688	4739			

function of variable x, s is the penalty parameter, r is the penalty parameter for the behaviour constraints, u is index of the number of inequality constraints, *ncon* is the total number of inequality constraints, p is index of the number of equality constraints, *con* is the number of equality constraints, *LB* and *UB* are the lower and upper limit on the continuous variables x_i^c respectively. The penalty parameter $s(k)$ is determined as:

$$s(k+1)=\begin{cases} s(k)e^{[1+\phi(P_g(k))]} & , \text{if } C_c > \varepsilon, \\ s(1) & , \text{if } C_c \le \varepsilon, \end{cases}$$

where k is the iteration indicator, $P_g(k)$ is the best solution for the kth iteration, $s(1)$ is the initial penalty parameter, C_c is the convergence equation, $C_c = (|F(P_g(k)) - f(P_g(k))|)/|F(P_g(k))|$, ε is small positive number. The initial position of particle d is chosen randomly, the penalty parameter is calculated for every particle and the initial penalty parameter is determined as: $s(1) := \min\{s_1, s_2, \ldots, s_D\}$. $s_d = 1 + \Phi(x_d)$, $1 \le d \le D$, where s_d is penalty parameter for the dth particle, $s(1)$ is the initial penalty parameter, $F(P_g(k))$ is the best solution for the augmented objective function, $f(P_g(k))$ is the best solution for the objective function, $P_d(k)$ is the best solution *p-best* achieved by the particle d till the kth iteration, and $P_g(k)$ is the best position *g-best* among $P_d(k)$.

After all the above revision of the PSO algorithm, the formulae to define the particle x_d^k and the updating rule of the positions and velocities are given as $x_d^{k+1} = x_d^k + v_d^{k+1}$ and $v_d^{k+1} = wv_d^k + c_1 r_1 (P_d(k) - x_d^k) + c_2 r_2 (P_g(k) - x_d^k)$ respectively for the PSO algorithm, where c_1, c_2 are positive acceleration constants, r_1 and r_2 are random numbers on the interval [0,1], w is the inertia term.

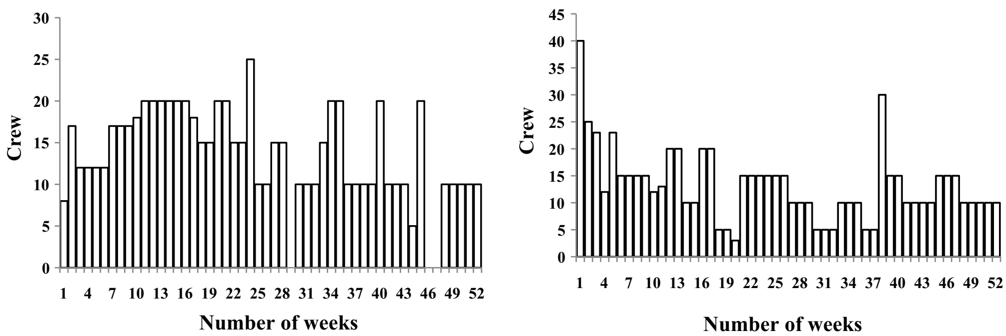
The penalty function PSO algorithm is chosen as a solution technique because it can handle both the continuous and binary variables of the MGMS model. The algorithm also has provision to handle the inequality and equality constraints.

4. Case studies, simulations and results

In this section two case studies are considered, the first is the comparison between the reliability objective function MGMS model to the classic GMS model and the second is the application of the economic cost objective function of the MGMS model to the Arnot Power Plant in South Africa. All the computations are carried out by the Matlab program.

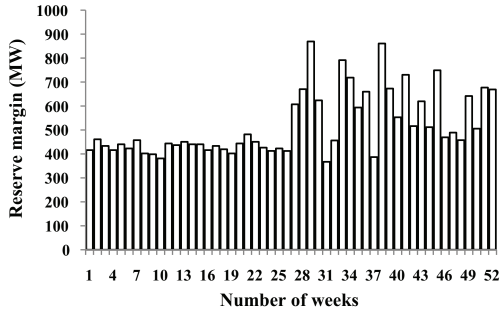
4.1. Case study for the reliability MGMS model

The case study is a test system with a total number of generators $I = 21$ over a planning period T of 52 weeks, this case study is obtained from the data in [6,9] and [11]. During this period, all 21 generators need to undergo maintenance, see Table 1 for the corresponding data.

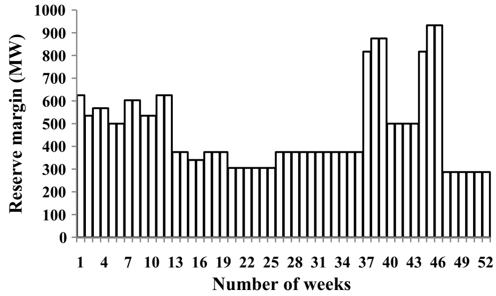


(a)MGMSavailablecrew (b)GMSavailablecrew

Fig. 1. Crew availability: (a) MGMS available crew and (b) GMS available crew.



(a) MGMS reserve margin



(b) GMS reserve margin

Fig. 2. Reserve margin: (a) MGMS reserve margin and (b) GMS reserve margin.

Table 2
Maintenance schedules obtained by MGMS and GMS [11] for the case study.

Week no.	Generator scheduled for maintenance		Week no.	Generator scheduled for maintenance	
	MGMS	GMS [11]		MGMS	GMS [11]
1	1, 10	3, 10, 13	27	18	16
2	1, 10	6, 10, 13	28	14	16
3	1, 10	6, 10, 13	29	14	16
4	1, 6, 10	6, 10	30	14	16
5	1, 6	6, 8	31	14	16
6	1, 6	6, 12	32	14	16
7	1, 6	6, 12	33	16	14
8	2, 6, 9	6, 9	34	16	14
9	2, 6, 9	6, 9	35	16	14
10	6, 12, 13	6, 7	36	16, 17	14
11	6, 12	6, 7	37	16, 17	15
12	6, 13	2, 7	38	16, 17	17, 18
13	6, 13	2, 7	39	19	17
14	13	1	40	19	17, 21
15	7	1	41	21	21
16	7	1, 11	42	21	21
17	7, 11	1, 11	43	21	21
18	7, 11	1	44	21	20
19	4	1	45	–	–
20	4	1	46	–	19
21	4	5	47	20	19
22	5	5	48	15	15
23	5	5	49	15	15
24	5	4	50	15	15
25	8	4	51	15	15
26	3	4	52	15	15

Each generator is allowed to start maintenance anywhere within a 26 week period. As shown in Table 1, the number of generators considered for maintenance I_t are generators 1–13 for weeks 1–26 and generators 14–21 for weeks 26–52. All generators are required to complete their maintenance by week 52. The total generated output for all the generators $\sum_{i=1}^{I} g_{i,t}^{max}$ in each week is given to be 5688MW/week. The maintenance outages for the generators in Table 1 are scheduled to minimise the SSR and satisfy the following constraints:

1 Maintenance window: each generator must be maintained exactly once every 52 weeks without interruptions [11].
2 Crew: the available members of crew A_t is 20 for every week [6,10,11]. A solution with a high reliability but requiring some extra crew is acceptable in a power plant. The flexibility for the crew constraint is given that 5% of total available man-weeks (TMW) which is 695 can be hired for maintenance [11].
3 Load constraint: the system's peak load D_t which is 4739 MW/week is used as the flat load for the test problem [11].
4 The generator limit: The total minimum g_i^{min} and maximum g_i^{max} capacity for all the generators per week are fixed to be the peak load and the capacity given in Table 1 respectively.

In this case study the unit commitment of the generators is not considered, hence (7) is not used. It is assumed that no generator is shut down due to unit commitment or a forced outage.

The MGMS problem is solved using the penalty function PSO algorithm explained in Section 3. A population size of 30 particles is chosen. The results obtained are compared to GMS results obtained in [11]. The MGMS model is simulated using the PSO algorithm with $c_1 = c_2 = 2$ and w is obtained using the formula $w = w_{max} - (k(w_{max} - w_{min}))/k_{max}$, w_{max} and w_{min} are the maximum and minimum values of inertia term respectively and k_{max} is the maximum number of iterations. From studies in [26,27] w_{max} and w_{min} are chosen as 0.9 and 0.4 respectively.

4.1.1. Results of the comparison between the MGMS model and the GMS model

The optimal objective function value or SSR value of MGMS and GMS problems are 104.71×10^5 and 133.4×10^5 respectively. The

Table 3
Data for Arnot power plant [28].

Gen	g_i^{min}	g_i^{max}	a_i(R/h)	b_i(R/MWh)	c_i(R/MW^{2}h)	*LR* (MW/h)	*UR* (MW/h)
1	150	355	4655.7658	82.9456	0.034265	53	132
2	150	355	4655.7658	82.9456	0.034265	53	132
3	150	355	4655.7658	82.9456	0.034265	53	132
4	150	355	4655.7658	82.9456	0.034265	53	132
5	150	355	4655.7658	82.9456	0.034265	53	132
6	150	355	4655.7658	82.9456	0.034265	53	132

GMS has a crew violation of 37 which is approximately 5% of the TMW. The MGMS has a crew violation of 10 which is approximately 1.4% of the TMW. The SSR of the MGMS is 104.71×10^5 which is 21.5% less than the SSR of the GMS model. The trade off between the crew violation and higher reliability in the MGMS model is much better than that of the GMS model because the MGMS model requires a hired crew that is 27% less than the crew needed in the GMS model. The results are illustrated in Fig. 1(a) and (b) of Fig. 1 which are the crew of the maintenance for the MGMS and GMS models respectively. Thus the MGMS model provides a better economic solution than the GMS model. Fig. 2(a) and (b) of Fig. 2 give the graphs of the reserve margins of the MGMS and GMS model respectively. The graphs show that the MGMS model have a more uniform reserve margin than the GMS model which from [10] means the MGMS is more reliable. The reason for the better solutions is due to the modification of the maintenance window (3) and the crew (4) constraints. The addition of the generator limits (5) ensures that the load constraint is never violated and thus reduces the SSR. Fig. 3 illustrates the use of the generator limits constraint. The generator maintenance schedule obtained for the 21-unit case study is presented in Table 2.

4.2. *Comparison between the closed loop and open loop economic cost objective function MGMS solutions*

For the simulation of the economic cost objective function MGMS problem in Section 2, maintenance scheduling is done on the Anort power plant, South Africa [28]. The power plant station is a thermal power plant with 6 generators of identical capacity ratings. Table 3 gives a list of all the generator ratings, fuel cost and ramp rates of the generators in the Arnot Power Plant. Since the production cost of the generators is expressed on an hourly basis, it is given as a quadratic function $k_i g_{i,t} = 168(a_i + b_i g_{i,t} + c_i g_{i,t}^2)$.

Total planning period T is 52 weeks. Total number of generators I is 6. Preventive maintenance must be done on each generator at least once every 52 weeks without interruptions. The duration N_i of any maintenance is 6 weeks. Available crew per week A_t is 15. The system's spinning reserve S_t is 6.5% of the peak generated power per week. A flat demand D_t 95,000 MW/week is considered for each week t. For the purpose of this study the maintenance and start up cost are assumed to be R 100,000 and R 4,000,000 respectively, where R is the symbol for the South African Rand. One US Dollar (USD) is approximately seven South African Rands (USD 1 = R 7.3, as at March 2012). The open loop and closed loop results are compared to verify that the proposed closed loop approach can be applied.

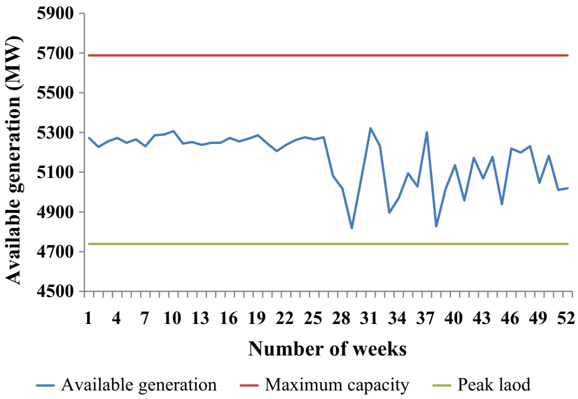


Fig. 3. MGMS available generation.

Table 4
Results for operation cost and electricity generation over 52 weeks.

	Closed loop	Open loop
Operation cost ($\times 10^6$ Rand)	7817.30	94,981.00
Operation cost ($\times 10^6$ USD)	1070.88	13,011.09
Generated output (MW)	9,965,170	9,426,130
Reserve (MW)	3,487,809	3,380,154
Demand (MW)	4,940,000	4,940,000

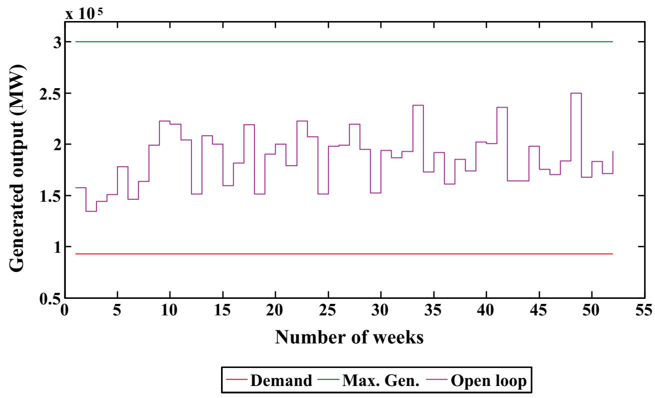


Fig. 4. Open loop available generation.

4.2.1. *Results*

In Table 4, it can be seen that the closed loop operation cost results are less than the open loop results while generating more electricity. Although the demand constraints are satisfied in both approaches, the closed loop solution satisfies the constraint at less

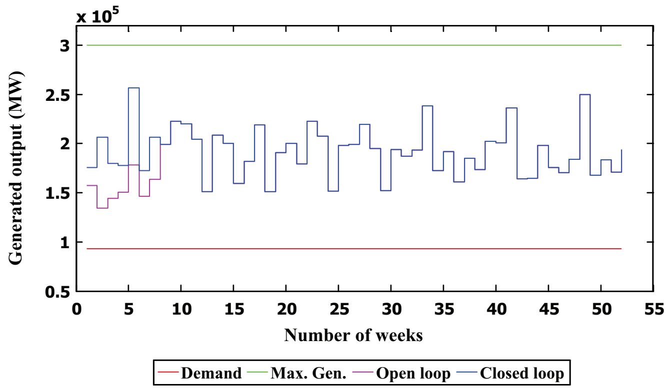
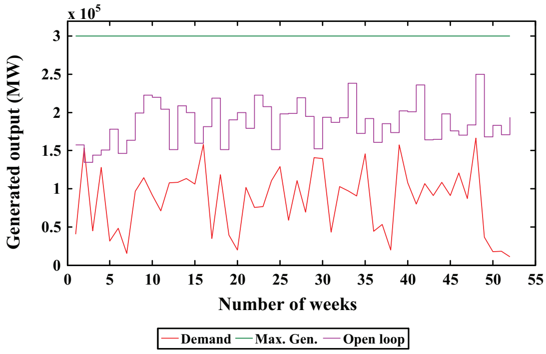
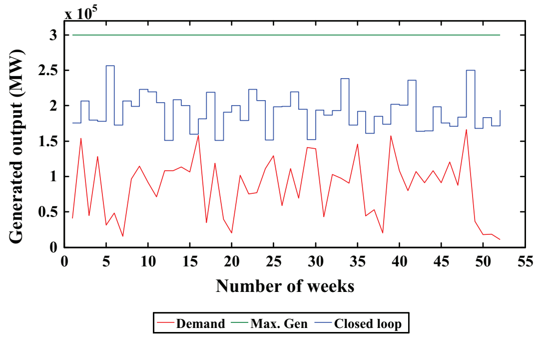


Fig. 5. Combined open loop and closed loop available generation.



(a) Open loop available generation with demand disturbance



(b) Closed loop available generation with demand disturbance

Fig. 6. Available generation with demand disturbance: (a) open loop available generation with demand disturbance and (b) closed loop available generation with demand disturbance.

Table 5
Maintenance schedule obtained for the closed loop and open loop solutions.

Generators	Closed loop schedule	Open loop schedule
1	Week 1 to week 6	Week 1 to week 6
2	Week 25 to week 30	Week 47 to week 52
3	Week 47 to week 52	Week 27 to week 32
4	Week 19 to week 24	Week 7 to week 12
5	Week 13 to week 18	Week 21 to week 26
6	Week 33 to week 38	Week 40 to week 45

cost. The MPC technique minimises the operation cost of the power system while satisfying all the constraints. The MGMS model is simulated with penalty function PSO to obtain the benchmark for comparison with the closed loop MGMS solution. The open loop results of generated output for all the generators through out the 52 week period is given in Fig. 4. Fig. 5 gives a comparison of the available generation for the closed and the open loop solutions and it shows that the closed loop solution convergences to the open loop model after week 6. The advantage of the closed loop solution is that it produces higher generated output than the open loop model and yet still schedules optimal maintenance throughout the 52 weeks period.

Fig. 6(a) and (b) show the results of the open loop and closed loop MGMS solutions with a positive random disturbance on the generated output. That is, $D_t = 2r(n)D_t$ where $r(n)$ is a random number between 0 and 1. This means that the generated output is altered with random disturbances. This disturbance is applied to the entire 52 weeks planned horizon. Fig. 6(a) and (b) show that the generated output $g_{i,t}$ does not exceed the generator limits and the peak demand is met for the open loop and closed loop solutions respectively. This is important because in practical application the electricity demand can change at any time. The MGMS model is robust in the sense that when a disturbance is introduced into the system, the closed loop solution can still generate optimal schedules for the maintenance of the generators in the power system. Table 5 gives the maintenance schedule for the open loop and closed loop MGMS solutions for the Arnot Power Plant.

5. Conclusion

This paper investigates the missing constraints in GMS problems and a comparison is made between the MGMS and the GMS model of [11]. New constraints such as the crew availability constraint in inequality (4) and the maintenance-generation, start up-generation relationship constraints in equations (10) and (11), are added to the GMS model. These constraints are either not explicitly formulated or ignored in existing literature which would possibly result in non-optimal, inaccurate, or even unfeasible scheduling results. The ramp rate and generator limit constraints, which are normally used in unit commitment problems, are also added to ensure that the generator's life span is considered in the maintenance scheduling. The MGMS model is compared with the classical GMS model using the 21-unit test system and the results show that the MGMS produces better and more reliable results than the GMS model. The formulated economic cost objective function MGMS model is used to schedule maintenance for the Arnot Power Plant, South Africa. The closed loop and open loop solutions of the MGMS model are compared through simulations and the simulations show that the closed loop results are better than the open loop results.

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