A Tri-Objective Model for Generator Maintenance Scheduling

LEARNMORE MOYO[1], NNAMDI I. NWULU[1], (Senior Member, IEEE),
UDUAKOBONG E. EKPENYONG[1,2], AND RAMESH C. BANSAL[3,4] (Senior Member, IEEE)

[1]Centre for Cyber-Physical Food, Energy and Water Systems, University of Johannesburg, Johannesburg 2006, South Africa
[2]Aurecon Group PTY Ltd., Melbourne, VIC 3008, Australia
[3]Department of Electrical Engineering, University of Sharjah, Sharjah, United Arab Emirates
[4]Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria 2000, South Africa

Corresponding author: Nnamdi I. Nwulu (nwulu@uj.ac.za)

ABSTRACT The complexity of power systems is increasing as new generating units are added to power systems in order to supply power to the growing economies. This has resulted in further research into the generator maintenance scheduling (GMS) problem which seeks to ensure optimal preventive maintenance scheduling that is effective and reliable. This research is focused on developing a generator maintenance schedule using a tri-objective model. The GMS tri-objective model is solved using two solution methodologies. The first is an exact solution method using mathematical modelling software, Advanced Interactive Multidimensional Modelling System (AIMMS). The second solution method is a recently developed metaheuristic algorithm called Exchange Market Algorithm (EMA). Results show that the tri-objective model finds a trade-off solution of the individual solution methods. The metaheuristic algorithm gives a better solution for larger optimization problems.

INDEX TERMS AIMMS, exchange market algorithm, generator maintenance scheduling, tri-objective.

NOMENCLARURE

i	index of generators, $i = 1, \ldots, I$
t	index of time periods, $t = 1, \ldots, T$
$Gmax_i$	maximum capacity of generator i
$Gmin_i$	minimum capacity of generator i
d_i	duration of maintenance of generator i
D_t	demand at time period t
S_t	safety margin at time period t
$x_{i,t}$	binary variable that is 1 when generator is on maintenance
$y_{i,t}$	binary variable that is 1 if maintenance of generator i starts at time t
cm_i	maintenance cost of generator i
f_i	fuel cost function
a_i, b_i, c_i	fuel cost coefficients for generator i
λ_i	failure rate of generator i
s_i	cost of starting up generator i
Q_t	maximum crew available at time period t

RoF_i	probability that generator i will fail before maintenance
RoF_{max}	maximum allowed probability that a generating unit will fail before maintenance
$iter_{max}$	number of iterations
k	iteration number
n_{pop}	population size
t_{pop}	number of the t-th member of the population
$g1_{min}, g1_{max}$	minimum and maximum risk co-efficients in non-oscillating mode
$g2_{min}, g2_{max}$	minimum and maximum risk co-efficients in oscillating mode
$r_1, r_2, rand$	random numbers between 0 and 1
s_k	share variation of group 3 members in non-oscillating mode
Δn_{t1}	share increase of group 2 members in oscillating mode
Δn_{t2}	share decrease of group 2 members in oscillating mode
η_1	risk level associated with each member of the group 2 in oscillating mode

η_2 risk level associated with each member of the group 3 in oscillating mode

Δn_{t3} share variation of group 3 members in oscillating mode

I. INTRODUCTION
A. MAINTENANCE SCHEDULING

Due to the growth of economies, the demand for electricity has subsequently increased. If the increase in demand is not met with a corresponding increase in generation capacity, power systems end up with lower reserve margins. When reserve margins are low, power utilities tend to be reluctant to put generators offline for maintenance as the generation capacity will be close to the demand. This leads to an increase in the failure of generating units due to lack of maintenance [1].

In recent years South Africa has experienced shortage of generating capacity leading to load shedding. One of the major reasons that caused the load shedding is poor maintenance leading to boiler tube failures and breakdowns [2]. The power utility, Eskom, had to implement stage 4 load shedding because of the severe shortage of capacity. This meant that up to 4000MW of national load could be shed at a time [3].

The generator maintenance scheduling is a preventive maintenance plan in which a well-planned schedule is prepared for taking units out of service for maintenance in order to avert a crisis such as faced by generation companies. Various constraints are considered and should be satisfied by the schedule. An appropriate maintenance schedule should minimize the operating and maintenance cost of the power generating system or improve the reliability of the system [4]. The maintenance scheduling problem is very important as it affects other decisions regarding the operation of generating plants such as unit commitment and unit dispatch.

Historically, maintenance scheduling has been conducted based on the expertise of maintenance personnel as well as instructions from generator manufacturers. However, this kind of approach is not satisfactory as it does not effectively take into consideration the system constraints and becomes difficult to apply to a multi-unit system. A well planned, optimal GMS is crucial for the smooth and efficient operation of a power plant [5]. Many other short term and long-term planning activities in a power plant that include unit commitment, generation dispatch, import and export of power and generation expansion of a power utility are directly affected by the maintenance schedule [6]. A schedule which warrants timely maintenance of generating units thereby increasing lifespan has the effect of postponing the huge capital investment into new generation facilities [7].

B. EXISTING SOLUTION METHODS

The research into the GMS problem has gained traction over the years. Several criteria are used when modelling the GMS problem. The two most common criteria used are the reliability criteria and economic cost criteria [6], [8]. In some cases, the optimization of the generator maintenance schedule is done based on just one criterion, which is single objective optimization, [7], [9], [10]. In other cases, multi-objective optimization is performed to find a solution that takes into consideration both reliability and economic cost criteria [8]. A bi-objective maintenance schedule model is implemented in [11], [12] for substations in electrical railway systems and energy hub while in [13], a bi-objective scheduling of a micro-grid consisting of tidal resources and storage devices is studied. Often when multi-objective optimization is employed, the solution will be a trade-off of the objectives under consideration [8], [14].

The GMS model is formulated mathematically as a highly constrained combinatorial optimization problem. It is therefore obligatory to implement a suitable optimization tool to determine the best feasible maintenance schedule. Various solution methodologies are used for optimization. These include mathematical methods which are mainly based on Integer Programming, Dynamic Programming, Benders Decomposition and Branch and Bound techniques [15]. Some modern exact software suites capable of solving mathematical programs generally use the branch and bound method [7]. Because of the large combinatorial nature of the GMS problem, exact solution approaches fall short in terms of reasonable computational time [9], [16]. Thus, there is growing attention in the development of approximate solution methodologies such as heuristic and meta-heuristic techniques [17]. Unlike mathematical methods, metaheuristics can obtain an optimal solution to a complex problem fast and are not subjected to limitations such as linearity, continuity, differentiability and convexity that are faced by mathematical programs [18].

The application of new metaheuristic techniques to solve the GMS problem is still being investigated. As the number of generating units increases in power system networks, the complexity of the GMS problem grows. It becomes imperative to find solution methods that can solve and give a feasible maintenance schedule. Traditional methods of maintenance scheduling often recommend frequent unnecessary maintenance routines which are costly otherwise there will be increased risk of failures [19]. In [20], a discrete integer cuckoo search optimization algorithm is proposed to solve the GMS problem. Existing metaheuristic algorithms are also being modified to improve their solving capabilities. A Modified Genetic Algorithm is utilized in [21] to solve a bi-objective optimization problem.

The objective of this research is to develop a robust GMS model that is formulated using three objectives, namely, reliability, economic cost and risk of expectation (of a generating unit breaking down before it is put on maintenance). The research aims to model the GMS problem in a comprehensive manner where several objectives are optimized concurrently. Minimizing the three objectives at the same time makes the solution reliable and robust in that the reliability criteria ensures that the system as a whole is able to meet load

requirements by leveling the reserve over the maintenance horizon, the economic criteria ensures minimum cost in conducting maintenance and power system operation and the risk of failure objective seeks to ensure that each unit does not breakdown before its scheduled maintenance slot. It reduces the risk of having to change the schedule in the case where a generator fails before it reaches its maintenance time.

The research also explores the use of the mathematical modeling package, AIMMS (Advanced Interactive Multidimensional Modeling System), in solving the GMS problem and validates the results with those of a relatively new meta-heuristic search algorithm, EMA. To the authors' knowledge, there is no literature where the tri-objective GMS problem is solved. In [6] and [22], single objective optimization based on the economic cost and reliability criterion respectively is used to solve for an optimal GMS. Bi-objective GMS is implemented in [8] to find a trade-off solution between energy production cost and levelling the reserve margin (reliability). The author is also not aware of any record of the GMS problem being solved using the solution methods employed in this paper. Reference [4] uses a modified ABC algorithm to solve the GMS problem while in [6] modified Particle Swarm Optimization is used. In [23], a proposal is put forward to compute the bi-objective GMS using simulated annealing (SA). In this study, the tri-objective GMS problem is solved. This research will contribute to the field of generator maintenance scheduling modelling and solution techniques in the following ways:

1. Modelling and solving a tri-objective GMS problem resulting in an optimal solution that minimizes disruptions to the maintenance schedule due to breakdowns.
2. Showing the effectiveness of EMA and AIMMS in solving GMS problems of different complexity.
3. Evaluation of the maintenance schedule obtained by each optimization criterion independently and the effect of each individual objective criterion on the value of the others and on the overall tri-objective function value.

The outline of the rest of this paper is as follows. Section 2 gives the formulation of the GMS model and describes the objective functions and constraints. In section 3, the solution techniques used to solve the GMS problem are detailed. Section 4 discusses the simulation results of EMA and AIMMS on a common test case found in literature and the results of the tri-objective model of a real-life case study. Section 5 is the conclusion.

II. FORMULATION OF THE GMS MODEL

GMS problems typically consider a generator, i, in a power system with a total of I generating units. The maintenance must be done within a planning horizon of T periods. The planning horizon can vary in length. Each period, t, can be an hour, a day or a week. Maintenance on each generator must be done for a duration of N_i time periods (maintenance duration of each generator) without interruption. For each period, t, each generator that is not on maintenance must generate

an output power of $g_{i,t}$, and the total generation for that period must meet the demand, D_t and a safety margin S_t. The generators cannot, however, exceed their generation capacity, $Gmax_i$.

A. OBJECTIVE FUNCTIONS

Objective functions are the performance indicators against which an optimization problem is solved [6]. Depending on the objective function, the goal can be either to minimize or maximize it. The most common objective functions considered in literature are the reliability and economic cost [4]. The desired outcome is a high system reliability and low operation and maintenance cost.

1) RELIABILITY

The reliability criterion aims to ensure that the power system is always able to meet demand regardless of load variations. In order to achieve this, the utility generally provides a spinning reserve by generating more power than demanded which improves system reliability at the expense of operation cost [24]. The reliability criterion has been defined in a number of different ways which include loss of load probability (LOLP) expected energy not supplied (EENS) and sum of squared reserves (SSR) [9].

The most common reliability criterion used is the sum of squared reserves [25]. The objective is to level the reserve over the planning period. The leveling of the reserve power enhances the reliable operation of the power system over the planning horizon enabling it to meet unexpected variations in load [20]. This is achieved by minimizing the sum of squared reserves. This approach is used in [9], [10], [20]. The objective function is formulated as follows:

$$\min_{x_{i,t}} \left\{ \sum_{t=1}^{T} \left(\sum_{i=1}^{I} Gmax_{i,t} - \sum_{i=1}^{I} \sum_{t=1}^{T} Gmax_{i,t} \times x_{i,t} - D_t \right)^2 \right\} \quad (1)$$

2) ECONOMIC COST

Economic cost objective is concerned with minimizing the costs involved in the operation of a power plant. In the model developed in [6], these costs comprise of cost of maintenance, start-up and power generation. The cost of generation is sometimes taken as the fuel cost since fuel is the most significant cost associated with power generation [8]. As modern power systems are becoming decentralized, some recent literature has seen the economic criteria shifting from minimizing of operational costs to maximization of profits [26], [27]. In [28], various cost components that affect maintenance activities in deregulated power markets are modelled. These include costs due to failures, interruptions of maintenance, contractual compensation (having to buy power from other supplies in order to meet contractual obligations), rescheduling of maintenance and market opportunity [28]. The objective function for minimizing the operational cost, consisting of maintenance cost, start-up cost and cost of generation, over

the planning horizon is given by:

$$\min_{x_{i,t} y_{i,t}} \left\{ \sum_{i=1}^{I} \sum_{t=1}^{T} cm_i \times x_{i,t} \right.$$
$$\left. + \sum_{i=1}^{I} \sum_{t=1}^{T} \left(s \times y_{i,t} + f_i \left(G_{i,t} \right) \right) \right\} \quad (2)$$

In some literature, the cost is taken as only the fuel cost, $f_i(G_{i,t})$, which is given in (3) [29]. This is because the fuel cost is the most dominant cost in the operation of a generator.

$$\min_{G_{i,t}} \left\{ f_i \left(G_{i,t} \right) \right\}$$
$$= \min_{G_{i,t}} \left\{ \sum_{i=1}^{I} \sum_{t=1}^{T} a_i + b_i \times G_{i,t} + c_i \times G_{i,t}^2 \right\} \quad (3)$$

3) RISK OF FAILURE

As generators are in operation, there is a gradual wear and tear that occurs. The degree of wear and tear depends on the age of the generating unit and on the time that has elapsed since its last refurbishment or repair. The risk of failure criterion aims to minimize the probability that a generating unit fails before its scheduled maintenance period. Failure of generating units can be estimated using methods from the reliability theory [25]. The objective will be to maximize the probability that a failure occurs at least t time units from the present time i.e. maximize the reliability given by:

$$R(t) = e^{-\lambda t'} \quad (4)$$

To turn it into a minimization problem, the objective function is changed to:

$$\min_{t} \left\{ 1 - R(t) = 1 - e^{-\lambda t'} \right\} \quad (5)$$

This is to minimize the probability that a unit will fail before t time units.

4) TRI-OBJECTIVE FUNCTION

The combined objective function is formulated as a sum of the reliability, cost and risk of failure functions, (1), (2) and (5). The desired result is a set of solutions close to the true pareto-optimal front. A challenge is introduced by the fact that the target space has more than one dimension. This is addressed by using the weighted sum method which scalarizes a set of objectives by pre-multiplying each objective with a user supplied weight [30]. Since different objective functions can have different magnitudes, normalization of the objective functions is required to get a pareto optimal solution consistent with the assigned weights [31]. This leads to a multi-objective constrained optimization problem of the form:

$$\text{Minimise} \sum_{i} u_i \times \theta_i \times f_i(x)$$
$$\text{s.t } x \in \Omega \quad (6)$$

where u_i is the weight of the i-th objective, θ_i is the normalization factor, f_i is the i-th objective and Ω is the set of constraints. The sum of the weighting factors should be 1.

For this study, all the objectives are equally weighted by a weighting factor of 0.33. Different weighting factors can be assigned to objective functions in proportion to their relative importance. The objective function with the highest weighting factor will be minimized more at the expense of the other objective functions. A normalization factor is applied that puts all objective functions in the same order of magnitude to give the following tri-objective function. The objective function (Equation (7)) is a Mixed Integer Non-Linear Programming (MINLP) problem minimized over the planning period of one year which is discretized into 365 days.

$$\min_{x_{i,t}, y_{i,t}, G_{i,t}} \left\{ \frac{1}{3} \times \theta_1 \times \left[\sum_{t=1}^{T} \left(\sum_{i=1}^{I} G\,max_{i,t} \right. \right. \right.$$
$$\left. \left. \left. - \sum_{i=1}^{I} \sum_{t=1}^{T} G\,max_{i,t} \times x_{i,t} - D_t \right)^2 \right] \right\} + \frac{1}{3} \times \theta_2$$
$$\times \left[\sum_{i=1}^{I} \sum_{t=1}^{T} cm_i \times x_{i,t} + \sum_{i=1}^{I} \sum_{t=1}^{T} \left(s \times y_{i,t} \right. \right.$$
$$\left. \left. + f_i \left(G_{i,t} \right) \right) \right] + \frac{1}{3} \times \theta_3 \times \left[\left(1 - e^{-\lambda t'} \right) \right] \quad (7)$$

5) CONSTRAINTS

A GMS that is developed must be able to satisfy specified constraints. These constraints ensure that the operational requirements of the power system are met and that it is feasible to conduct the maintenance of generating units at the allocated time periods. Several constraints are defined.

Maintenance Window Constraint:

$$\sum_{w \in W_i} y_{i,w} = 1: \quad i \in I, \ \{ w \in W_i : e_i \leq w \leq l_i \} \quad (8)$$

Maintenance duration constraint:

$$\sum_{t \in T} x_{i,t} = d_i \quad (9)$$

and for uninterrupted maintenance:

$$x_{i,t} - x_{i,t-1} \leq y_{i,t} \quad (10)$$

Load and minimum reserve constraint:

$$\sum_{i \in I} G\,max_{i,t} - \sum_{i \in I} \sum_{t \in T} G\,max_{i,t} \times x_{i,t} \geq D_t + R_t \quad (11)$$

Risk of failure constraint:

$$RoF_i < RoF_{max} \quad (12)$$

Generator output constraint:

$$Gmin_i \leq G_{i,t} \leq Gmax_i \quad (13)$$

Crew constraint:

$$\sum_{i \in I} q_{i,t} \times x_{i,t} \leq Q_t \quad (14)$$

The maintenance window constraint specifies the time interval during which the maintenance of a generating unit should take place. It is defined using the earliest and latest generator maintenance start times. The maintenance duration constraint sets the specific amount of time that a generating unit should be undergoing maintenance. Each maintenance instance must be carried over a continuous period without interruption. At any particular time, the available generation capacity should ensure a secure reserve capacity. This is enforced by the load and minimum reserve constraint. If there is a conflict between unit maintenance and minimum reserve, the system cannot operate in a secure and reliable way

therefore the schedule will need to be rearranged. The generator output constraint limits the maximum output of a generator to its capacity. The crew constraint limits the number of units that can be put on maintenance at the same time based on the maintenance crew requirement of each generating unit. The maximum probability that a generating unit will fail before maintenance is defined by the risk of failure constraint. Any probability above the maximum will not be allowed.

III. SOLUTION METHODOLOGY
The GMS problem is solved using the exact solution method, AIMMS, and the metaheuristic algorithm, EMA.

A. AIMMS IMPLEMENTATION
AIMMS provides modelling and optimization capabilities across a wide variety of industries. It incorporates top class solvers for linear, mixed integer and non-linear programming such as Gurobi, Conopt, Baron, CPLEX, etc. The formulation of optimization problems is done through declaration of language elements such sets and indices, scalar and multidimensional parameters, variables and constraints which allow for a concise description of most mathematical optimization problems [32]. Two major sets are defined in this model, the set of generators and the set of time periods. There are also subsets of the generator set which contain generators that cannot go on maintenance at the same time (exclusion sets). The generator and demand data are modelled as parameters and the constraints are defined explicitly in AIMMS. The objective function is defined as a variable and set as the Mathematical Program to be optimized. The model is then executed and gives the results.

B. EMA IMPLEMENTATION
EMA is one of the most recent optimization algorithms [33]. In the same fashion as other metaheuristic algorithms like PSO [34], ACO [35], FA [36] etc., it is population based. It is suitable for solving continuous non-linear optimization problems which are so common. The algorithm is inspired by the trading of shares on the stock market. In a stock market, each broker buys and sells shares, taking a certain level of risk, in order to increase their share portfolio.

In EMA, each individual in the exchange market is a solution to the problem represented by the variable *pop*. The individuals compete to have the best share value and be ranked at the top. There are two different modes of the EMA which emulate how certain conditions in real world affect the stock market. The first mode is the balanced or non-oscillating mode. In the balanced mode, individuals in the lower ranks try to use the experience of the high ranked shareholders in order to improve their share value and be recruited into the elite class. The second mode is the oscillating mode in which the market is unstable and individuals tend to take calculated risks by identifying other shares that can improve their overall ranking. The algorithm goes through the two modes during each iteration. Due to the fact that EMA uses two efficient search and absorbing operators, it can overcome

the limitations that are faced by other algorithms [37]. The solution in EMA is a vector of maintenance start time periods for all the generators in the power system. After each iteration, the members are sorted according to fitness. Members with the best solution are put in first group which consists of 10%-30% of the population, medium fitness members go into second group and are 20%-50% of the population and the third group which is also 20%-50% of the population is made up of weak fitness members. For each iteration, members of the first group do not change their shares.

1) NON-OSCILLATING MODE
In the non-oscillating mode, individuals in the second and third group use the experiences of the individuals in the first group to enhance their rank standing. This mode seeks to find better solutions by searching within the proximity of the existing optimal solutions. The equations that define share trading of the second and third group members in the non-oscillating mode are as follows [37]:

Individuals with intermediate fitness:
$$pop_i^{group(2)} = r \times pop_{1,i}^{group(1)} + (1-r) \times pop_{2,i}^{group(1)} \quad (15)$$

where $pop_j^{group(2)}$ is the new value of the jth member of the second group, which in this instance is an array of maintenance start times, r is a random number between 0 and 1, $pop_{1,i}^{group(1)}$ and $pop_{2,i}^{group(1)}$ are members of the first group.

Individuals with weak fitness:
$$pop_k^{group(3),new} = pop_k^{group(3)} + 0.8 \times s_k \quad (16)$$

where $pop_k^{group(3),new}$ is the new value of the kth member of the third group, s_k is the share variation given by:
$$
\begin{aligned}
s_k = {} & 2 \times r_1 \times \left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) + 2 \times r_2 \\
& \times \left(pop_{i,2}^{group(1)} - pop_k^{group(3)}\right) s_k = 2 \times r_1 \\
& \times \left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) + 2 \times r_2 \\
& \times \left(pop_{i,2}^{group(1)} - pop_k^{group(3)}\right)
\end{aligned}
\quad (17)
$$

where r_1 and r_2 are random numbers between 0 and 1.

2) OSCILLATING MODE
After the non-oscillating mode, the individuals are ranked according to fitness and the market changes to oscillating mode during each iteration of the algorithm. In oscillating mode, the individuals of the second and third group perform risks based on their rank position in order to improve their fitness. In this mode, the algorithm searches for optimal solutions in a wider search space. In this way, unknown points are evaluated thereby minimizing getting stuck in a local optimum. The individuals in the second and third group change their shares according to the following equations:

Individuals with intermediate fitness: Initially, shares of the individuals increase according to the equation:
$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \quad (18)$$
$$\mu = \frac{t_{pop}}{n_{pop}} \quad (19)$$

Parameter	Value
Population size	50
Number of variables (dimension)	157
Maximum number of iterations	10 000
[g1$_{\min}$ g1$_{\max}$]	[0.01 0.005]
[g2$_{\min}$ g2$_{\max}$]	[0.05 0.01]

$$n_{t1} = \sum_{y=1}^{n} |S_{ty}| \qquad (20)$$

$$\eta_1 = n_{t1} \times g_1 \qquad (21)$$

$$g_1^k = g_{1,\max} \times \frac{g_{1,\max} - g_{1,\min}}{iter_{\max}} \times k \qquad (22)$$

where Δn_{t1} is the number of shares to be added, n_{t1} is total shares of the tth member before change, S_{ty} is the shares of the tth member, δ is the market information, r is a random number between 0 and 1, η_1 is risk level associated with each member of the group 2, t_{pop} is the number of the tth member, n_{pop} is the number of members in the exchange market which is the population size, μ is a constant co-efficient for each member, g_1 is a common market risk, $iter_{\max}$ is the total number of iterations, k is iteration number, $g_{1,\max}$ and $g_{1,\min}$ are the maximum and minimum values of the risk in the market respectively. Each individual will also have to reduce their shares by the following value, Δn_{t2}, so that the sum of shares remains constant:

$$\Delta n_{t2} = n_{t2} - \delta \qquad (23)$$

where n_{t2} is the share amount of the tth member after share changes. Individuals with weak fitness: Individuals change share values by adding the following amount:

$$\Delta n_{t3} = 4 \times r_s \times \mu \times n_2 \qquad (24)$$

$$r_s = 0.5 - rand \qquad (25)$$

$$\eta_2 = n_{t1} \times g_2 \qquad (26)$$

$$g_2^k = g_{2,\max} \times \frac{g_{2,\max} - g_{2,\min}}{iter_{\max}} \times k \qquad (27)$$

where Δn_{t3} is the change in shares to be applied to the shares of each member in the third group, r_s is a random number between -0.5 and 0.5, μ is a constant co-efficient for each member, η_2 is the risk associated with each member of the group and g_2 is the variable risk co-efficient.

All these variables are used in randomly and intelligently changing the values of the maintenance start times in order to end up with the best maintenance schedule. The parameters for this EMA implementation are given in Table 1. Figure 1 shows the flow chart for EMA.

3) CONSTRAINT HANDLING
Unlike in AIMMS where the constraints of the optimization problem are explicitly defined in the modelling language, metaheuristic methods are generally suited for unconstrained problems. The most common method of handling constraints in metaheuristic algorithms is the penalty function [38]. The
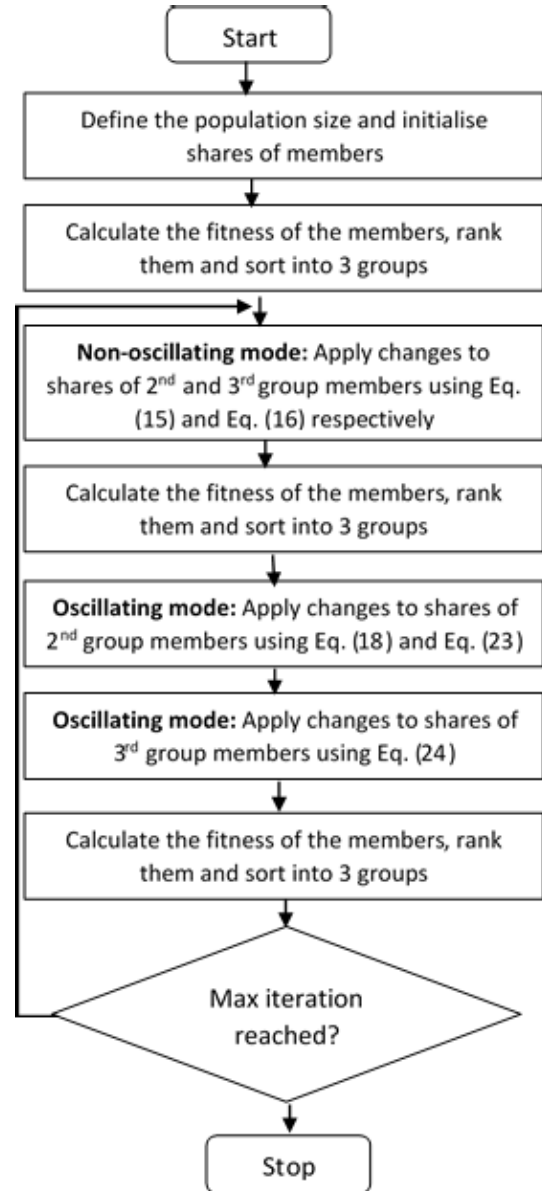

FIGURE 1. EMA flow chart.

penalty function is used for handling constraints and only solutions with no penalty violation are accepted. With the penalty function added, Equation 6 becomes:

$$Minimise \sum_i u_i \times \theta_i \times f_i(x) + Constraint\ Violation \qquad (28)$$

In EMA. each constraint equation is evaluated to determine if there is a violation at each iteration. If there is a violation, the equation gives a non-zero value and that value is amplified by a large number carefully chosen such that when the solutions are ranked according to best fit, the solutions with constraint violation are not selected among the best.

IV. TEST CASE STUDIES AND RESULTS
A. GENERATOR SYSTEM CASE STUDY
The two solution methods are first applied on a common GMS problem that is used in [22], [39]. This case study consists

Generator Unit	(MDPSO)[39]	(ALO)[22]	EMA	AIMMS
1	17	19	9	14
2	2	17	1	12
3	1	4	26	13
4	24	14	3	21
5	14	1	6	24
6	4	4	16	1
7	8	8	23	8
8	13	7	20	1
9	5	5	21	2
10	9	2	16	4
11	12	17	17	4
12	1	12	1	11
13	5	7	20	1
14	38	40	48	27
15	44	35	36	40
16	28	45	27	45
17	21	27	45	33
18	52	43	34	51
19	34	44	34	51
20	27	29	33	32
21	49	31	41	36
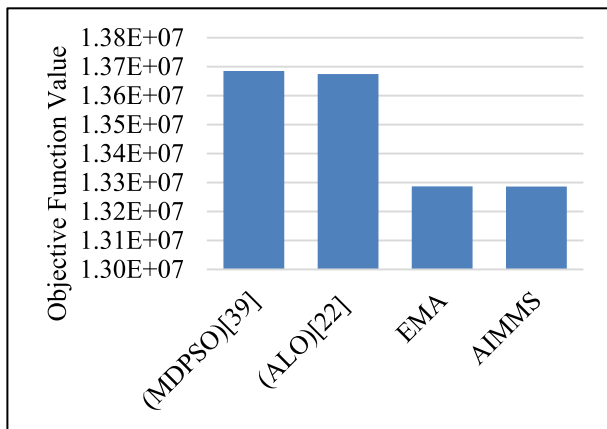
FIGURE 2. Comparison of objective function values.

of 21 Generator systems. The aim in this case study is to maximize the system reliability by minimizing the sum of squared reserves as depicted in (1). Table 2 shows the start times obtained using AIMMS, EMA and results obtained in [22] using Ant Lion Optimizer (ALO) and [39] using Modified Discrete Particle Optimization (MDPSO).

The corresponding objective function values which represent the SSR are given in Figure 2.

Figure 2 shows that EMA and AIMMS give a lower objective function value than the solutions presented in the referenced literature. Of the two, AIMMS gives a minimum SSR of 13 286 403 while EMA gives 13 287 043. AIMMS therefore gives the better maintenance schedule in
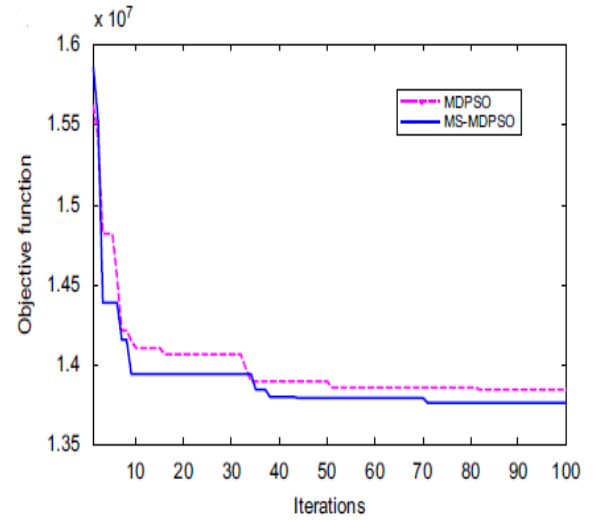

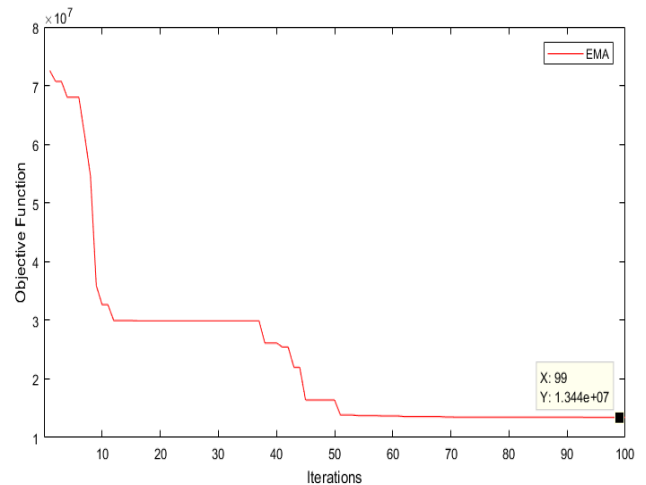**FIGURE 3.** Convergence curves for MDPSO and MS-MDPSO [39].

FIGURE 4. Convergence curve for EMA.

the least amount of time, <65 seconds, compared to EMA's 82 seconds. The typical convergence curves of MDPSO and MS-MDPSO (a variant of MDPSO) are shown in Figure 3 and the typical convergence curve of EMA is shown in Figure 4. These convergence curves are for the same GMS problem and the number of iterations is 100. The results show that the objective function converged to 13 863 021 and 13 749 264 for MDPSO and MS-MDPSO respectively and 13 442 439 for EMA. This indicates that EMA converges to a better solution faster than MDPSO and MS-MDPSO.

There are no constraint violations for the obtained solutions as depicted in the Figures 5 and 6 which show the available generation capacity and the crew required over the maintenance window.

B. GENERATOR UNIT ESKOM CASE STUDY

The solution methods, AIMMS and EMA, are then applied to the Eskom case study given in [40] to solve a tri-objective GMS model. Eskom is the sole electricity utility in South
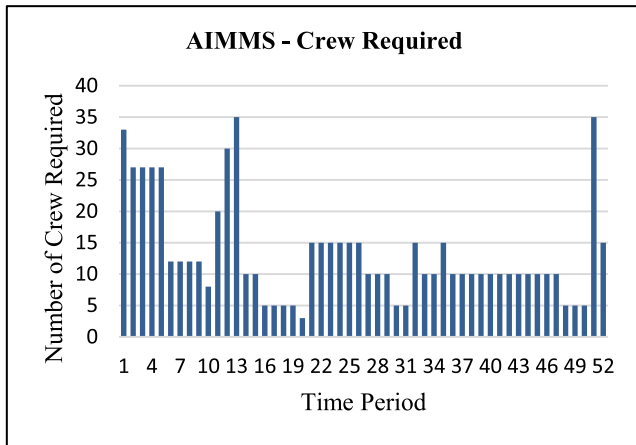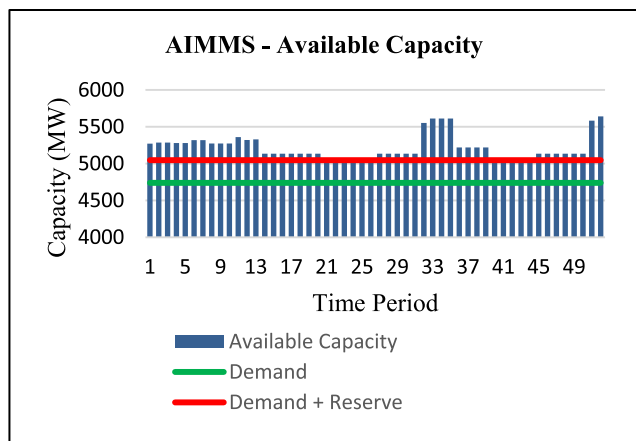
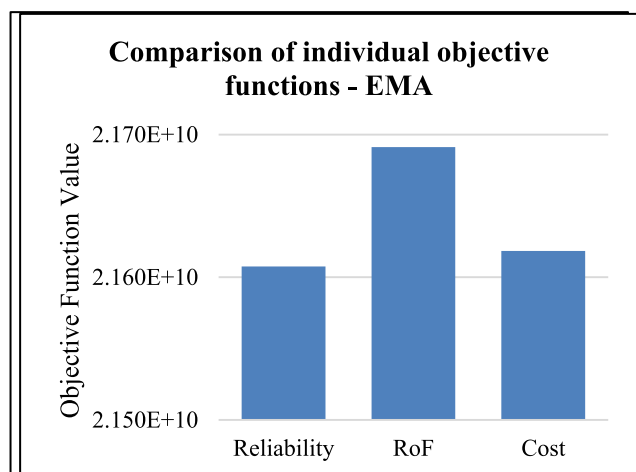**FIGURE 5.** Crew required.

FIGURE 6. Available capacity.

FIGURE 7. Comparison of individual criterion objective functions – EMA.

FIGURE 8. Comparison of individual criterion objective functions – AIMMS.

TABLE 3. Comparison of EMA result with literature result.

	EMA	**Literature** [40]
SSR	1.349E+10	1.355E+10

The individual criteria are solved independently at first. Figures 7 and 8 show the objective function values obtained when each criterion is optimized on its own. The objective function is the sum of the weighted objectives, SSR, the total cost and the probability that a unit will not reach its maintenance period before failure.

As can be seen from the Figures 7 and 8, the reliability criterion gave the lowest overall objective function, followed by the cost and lastly the risk of failure. The reliability criterion therefore gives the best maintenance schedule in terms of minimizing the objective function. The schedule obtained by the risk of failure objective function puts generating units off for maintenance at the earliest time possible, regardless of cost or reliability implications. This result was observed when solving with both EMA and AIMMS which shows solution consistency. Individual simulations showed that each variable (SSR, Cost, Risk of Failure) attained its minimum value when it is being optimized independently. This is because the solution aims to minimize only the single objective without considering the impact on the values of the other objectives. All solutions met the stipulated constraints of the problem.

For the Eskom case study, the running time to reach a solution was longer for AIMMS than EMA. The Eskom case study has more generators than the 21-generator unit case study and the planning horizon is discretized into days rather than weeks which makes it more complex. Because of the increase in number of variables, AIMMS takes much longer to solve the problem, which is a setback of exact solution methods, compared to EMA. AIMMS took 8028 seconds to reach best solution while EMA took 1647 seconds at most.

The reliability criterion was solved independently in [40]. The solution obtained using EMA and the solutions in literature are compared in the Table 3.

Africa. The system consists of 105 generating units, however, because some units require more than one maintenance instances, dummy units are added for the additional maintenance instances. This is because the solution methods require one maintenance period per generator for easy implementation. Due to confidentiality concerns, the data used is not the exact parameters in the field [40].
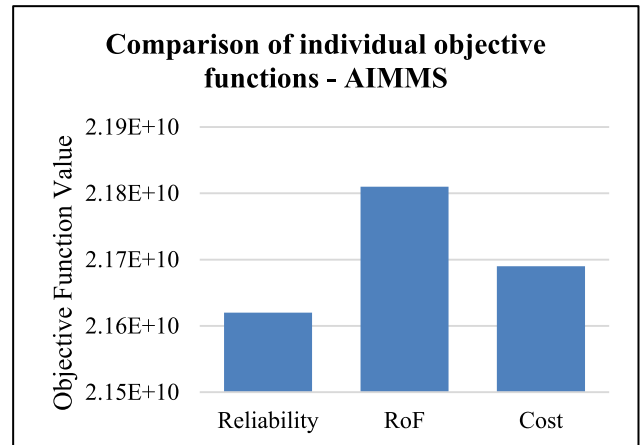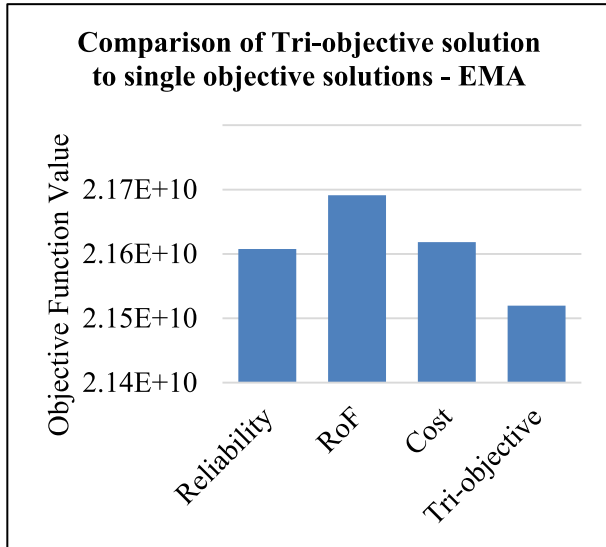
FIGURE 9. EMA comparison.

TABLE 4. Comparison of objective functions using AIMMS and EMA.

	Reliability	RoF	Cost	Tri-objective
AIMMS	2,162E+10	2,169E+10	2,181E+10	2,159E+10
EMA	2,161E+10	2,169E+10	2,162E+10	2,152E+10

The SSR obtained using EMA is lower than the one in literature which shows the superior solution search qualities of EMA. There is a 0.4% decrease in the SSR with EMA.

1) TRI-OBJECTIVE GMS IMPLEMENTATION

In the tri-objective model, the three objective functions are added together to form a combined objective function. Equal weighting factors of 0.33 are applied to the individual objective functions. The weighting factors are chosen in proportion to the relative importance of the objective function. In this study, the objective functions are considered equally important. A constraint violation is added to the equation so that solutions that do not fall within the system constraints are discarded. The constraint violation variable has a value of 0 for feasible solutions. The objective function is constructed in the following way:

$$Min \left\{ \frac{1}{3} \times Eq\,(1) + \frac{1}{3} \times Eq\,(3) + \frac{1}{3} \times Eq\,(5) \right.$$
$$\left. + \; Constraint\; Violations \right\} \quad (29)$$

The constraint violations are only included in the EMA solution method. Figures 9 and 10 show how the objective function values, obtained using both AIMMS and EMA, of the single objective function optimization and tri-objective optimization compare.

From Figures 9 and 10 and Table 4, the results show that EMA obtains a lower objective function that AIMMS for the 157-generator unit system.
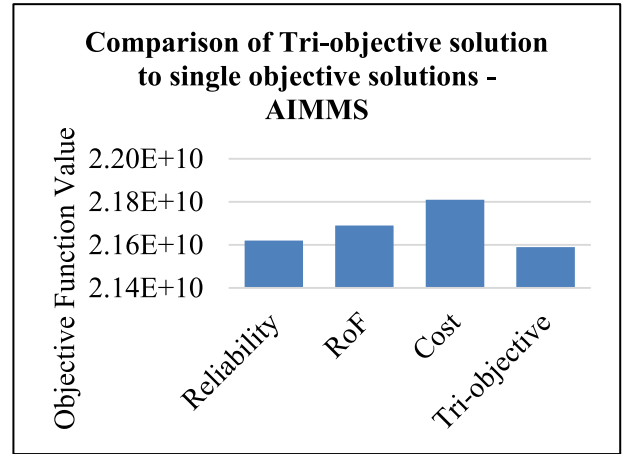

FIGURE 10. AIMMS comparison.

TABLE 5. Tri-objective solution comparison.

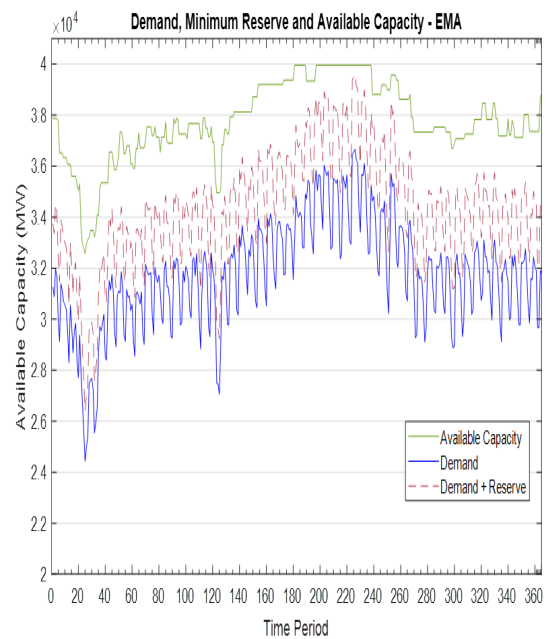|	AIMMS	EMA
Objective Function value	2.159+10	2.152+10
Execution time (s)	8028	1996

FIGURE 11. Demand, minimum reserve and available capacity – EMA.

The solution obtained using tri-objective optimization is a trade-off of the single objective optimization solutions. The tri-objective optimization solution minimizes all three objectives concurrently and therefore finds the lowest objective function value. In the EMA and AIMMS solution, the objective function value is the lowest. Although the values are different for the two solution methods, the tri-objective solution remains the best. This solution ensures system reliability in a cost-effective manner while also minimizing the probability of pre-mature failure of units. Table 5 shows the tri-objective solution obtained using EMA and AIMMS.

From Table 5, it can be seen that EMA provides a better solution and in less execution time than AIMMS showing the superior solving capabilities of EMA for large optimization problems.

Both solutions satisfied the system constraints. The available capacity, the demand and minimum reserve during each period based on the EMA solution are shown in Figure 11.

V. CONCLUSION

This research investigated the development of a tri-objective GMS model, with the aim of minimizing the Sum of Squared Reserves, cost and risk of failure concurrently. The GMS problem has load, maintenance window, maintenance duration, crew and non-interruption of maintenance constraints. It also explored the application of two solution methods, AIMMS and EMA to solve the GMS problem. A comparison of the performance of the two solution methods, AIMMS, an exact solution method, and EMA, a metaheuristic solution algorithm, on two case studies is also done.

The EMA and AIMMS 21-unit test system models are compared with the solutions obtained in literature for minimizing the sum of squared reserves. The objective function values obtained by EMA and AIMMS are 13 287 043 and 13 286 403 respectively compared to literature values of 13 685 127 and 13 675 000. AIMMS, however, gives a better maintenance schedule than EMA for the 21-unit test system. The tri-objective GMS problem of the Eskom case study consisting of 105 generating units is also solved using AIMMS and EMA. The tri-objective solution is a trade-off of the single objective optimization solutions and ensures high system reliability at minimized cost and low probability of generator units failing. The tri-objective solution gives the lowest objective function value as it minimizes the individual objective functions simultaneously. The Eskom case study is more complex than the 21-unit test system and EMA gave a better result than AIMMS.EMA obtained an objective function value of 2.152×10^{10} while AIMMS obtained an objective function value of 2.159×10^{10}.

This study can be extended in future to include renewable energy sources which are fast growing on the national grid. Further work can involve integrating the Generator Maintenance Scheduling Model with transmission network maintenance in order to have a holistic model of the entire power supply system.

REFERENCES

[1] G. Klempner and I. Kerszenbaum, *Handbook of Large Turbo-Generator Operation and Maintenance*, 2nd ed. Hoboken, NJ, USA: Wiley, 2008.
[2] J. Caboz. (Mar. 18, 2019). *Business Insider South Africa*. Accessed: Jun. 29, 2019. [Online]. Available: https://www.businessinsider.co.za/6-quick-fixes-that-can-save-south-africa-from-more-load-shedding-2019-3
[3] Eskom. (May 18, 2019). *Interpreting Scedules*. Eskom. Accessed: Jun. 29, 2019. [Online]. Available: http://loadshedding.eskom.co.za/LoadShedding/ScheduleInterpretation
[4] R. Anandhakumar, S. Subramanian, and S. Ganesan, "Modified ABC algorithm for generator maintenance scheduling," *Int. J. Comput. Electr. Eng.*, vol. 3, no. 6, pp. 812–819, 2011.
[5] H.-C. Jo, R. Ko, and S.-K. Joo, "Generator maintenance scheduling method using transformation of mixed integer polynomial programming in a power system incorporating demand response," *Energies*, vol. 12, no. 9, pp. 1–14, 2019.
[6] U. E. Ekpenyong, J. Zhang, and X. Xia, "An improved robust model for generator maintenance scheduling," *Electr. Power Syst. Res.*, vol. 92, pp. 29–36, Nov. 2012.
[7] E. Reihani, A. Sarikhani, M. Davodi, and M. Davodi, "Reliability based generator maintenance scheduling using hybrid evolutionary approach," *Int. J. Electr. Power Energy Syst.*, vol. 42, no. 1, pp. 434–439, Nov. 2012.
[8] B. G. Lindner, R. Brits, J. H. van Vuuren, and J. Bekker, "Tradeoffs between levelling the reserve margin and minimising production cost in generator maintenance scheduling for regulated power systems," *Int. J. Electr. Power Energy Syst.*, vol. 101, pp. 458–471, Oct. 2018.
[9] K. P. Dahal and N. Chakpitak, "Generator maintenance scheduling in power systems using Metaheuristic-based hybrid approaches," *Electr. Power Syst. Res.*, vol. 77, no. 7, pp. 771–779, May 2007.
[10] E. Umamaheswari, S. Ganesan, M. Abirami, and S. Subramanian, "Deterministic reliability model based preventive generator maintenance scheduling using Ant Lion Optimizer," in *Proc. ICCPCT*, Nagercoil, India, Mar. 2016, pp. 1–8.
[11] S.-K. Chen, T.-K. Ho, B.-H. Mao, and Y. Bai, "A bi-objective maintenance scheduling for power feeding substations in electrified railways," *Transp. Res. C, Emerg. Technol.*, vol. 44, pp. 350–362, Jul. 2014.
[12] S. Amiri, M. Honarvar, and A. Sadegheih, "Providing an integrated model for planning and scheduling energy hubs and preventive maintenance," *Energy*, vol. 163, pp. 1093–1114, Nov. 2018.
[13] M. Javidsharifi, T. Niknam, J. Aghaei, and G. Mokryani, "Multi-objective short-term scheduling of a renewable-based microgrid in the presence of tidal resources and storage devices," *Appl. Energy*, vol. 216, pp. 367–381, Apr. 2018.
[14] J. Soares, M. A. F. Ghazvini, Z. Vale, and P. B. de Moura Oliveira, "A multi-objective model for the day-ahead energy resource scheduling of a smart grid with high penetration of sensitive loads," *Appl. Energy*, vol. 162, pp. 1074–1088, Jan. 2016.
[15] N. I. Nwulu and X. Xia, "Multi-objective dynamic economic emission dispatch of electric power generation integrated with game theory based demand response programs," *Energy Convers. Manage.*, vol. 89, pp. 963–974, Jan. 2015.
[16] J. Silvente and L. G. Papageorgiou, "An MILP formulation for the optimal management of microgrids with task interruptions," *Appl. Energy*, vol. 206, pp. 1131–1146, Nov. 2017.
[17] N. Hajibandeh, M. Shafie-khah, G. J. Osório, J. Aghaei, and J. P. S. Catalão, "A heuristic multi-objective multi-criteria demand response planning in a system with high penetration of wind power generators," *Appl. Energy*, vol. 212, pp. 721–732, Feb. 2018.
[18] S. Ikeda and R. Ooka, "Metaheuristic optimization methods for a comprehensive operating schedule of battery, thermal energy storage, and heat source in a building energy system," *Appl. Energy*, vol. 151, pp. 192–205, Aug. 2015.
[19] M. Yildirim, X. A. Sun, and N. Z. Gebraeel, "Sensor-driven condition-based generator maintenance scheduling—Part I: Maintenance problem," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4253–4262, Nov. 2016.
[20] S. Lakshminarayanan and D. Kaur, "Optimal maintenance scheduling of generator units using discrete integer cuckoo search optimization algorithm," *Swarm Evol. Comput.*, vol. 42, pp. 89–98, Oct. 2018.
[21] B. Hadjaissa, K. Ameur, S. M. A. Cheikh, and N. Essounbouli, "Bi-objective optimization of maintenance scheduling for power systems," *Int. J. Adv. Manuf. Technol.*, vol. 85, nos. 5–8, pp. 1361–1372, Jul. 2016.
[22] E. Umamaheswari, S. Ganesan, and S. Subramanian, "Stochastic model based reliability centered preventive generator maintenance planning using ant lion optimiser," in *Proc. Int. Conf. Circuit, Power Comput. Technol. (ICCPCT)*, Kollam, India, Apr. 2017, pp. 1–8.
[23] G. B. Lindner, J. Eygelaar, D. P. Lotter, and J. H. Van Vuuren, "Tri-objective generator maintenance scheduling for a national power utility," in *Proc. ORSSA Annu. Conf.*, Johannesburg, South Africa, 2015, pp. 1–93.
[24] D. Srinivasan, K. C. Aik, and I. M. Malik, "Generator maintenance scheduling with hybrid evolutionary algorithm," in *Proc. IEEE 11th Int. Conf. Probabilistic Methods Appl. Power Syst.*, Jun. 2010, pp. 632–637.
[25] J. Eygelaar, D. P. Lötter, and J. H. van Vuuren, "Generator maintenance scheduling based on the risk of power generating unit failure," *Int. J. Electr. Power Energy Syst.*, vol. 95, pp. 83–95, Feb. 2018.
[26] G. G. Samuel and C. C. A. Rajan, "Hybrid: Particle swarm optimization–Genetic algorithm and particle swarm optimization–Shuffled frog leaping algorithm for long-term generator maintenance scheduling," *Int. J. Electr. Power Energy Syst.*, vol. 65, pp. 432–442, Feb. 2015.

[27] G. Balaji, R. Balamurugan, and L. Lakshminarasimman, "Mathematical approach assisted differential evolution for generator maintenance scheduling," *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 508–518, Nov. 2016.

[28] K. Dahal, K. Al-Arfaj, and K. Paudyal, "Modelling generator maintenance scheduling costs in deregulated power markets," *Eur. J. Oper. Res.*, vol. 240, no. 2, pp. 551–561, Jan. 2015.

[29] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *Int. J. Elect. Power Energy Syst.*, vol. 75, pp. 19–27, Feb. 2016.

[30] K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*. Chichester, U.K.: Wiley, 2001.

[31] O. Grodzevich and O. Romanko, "Normalization and other topics in multiobjective optimization," in *Proc. Fields-MITACS Ind. Problems Workshop*, Toronto, ON, Canada, 2006, pp. 99–114.

[32] (Sep. 2018). *AIMMS: Mathematical Modelling Language*. AIMMS B.V. Accessed: Sep. 2018. [Online]. Available: https://aimms.com/english/developers/product-info/aimms-developer/mathematical-modeling-language/

[33] N. Ghorbani, E. Babaei, and F. Sadikoglu, "BEMA: Binary exchange market algorithm," *Proc. Comput. Sci.*, vol. 120, pp. 656–663, Jan. 2017.

[34] C. M. N. A. Pereira, C. M. F. Lapa, A. C. A. Mol, and A. F. da Luz, "A PSO approach for preventive maimtenance scheduling optimisation," in *Proc. Int. Nuclear Atlantic Conf.*, Rio de Janeiro, Brazil, 2009, pp. 1–7.

[35] W. K. Foong, H. R. Maier, and A. R. Simpson, "Power plant maintenance scheduling using ant colony optimization: An improved formulation," *Eng. Optim.*, vol. 40, no. 4, pp. 309–329, Apr. 2008.

[36] X.-S. Yang and X. He, "Firefly algorithm: Recent advances and applications," *Int. J. Swarm Intell.*, vol. 1, no. 1, pp. 36–50, 2013.

[37] N. Ghorbani and E. Babaei, "Exchange market algorithm," *Appl. Soft Comput.*, vol. 19, pp. 177–187, Jun. 2014.

[38] Ö. Yeniay, "Penalty function methods for constrained optimization with genetic algorithms," *Math. Comput. Appl.*, vol. 10, no. 1, pp. 45–56, Apr. 2005.

[39] Y. Yare and G. K. Venayagamoorthy, "Optimal maintenance scheduling of generators using multiple swarms-MDPSO framework," *Eng. Appl. Artif. Intell.*, vol. 23, no. 6, pp. 895–910, Sep. 2010.

[40] E. B. Schlunz, *Decision Support for Generator Maintenance Scheduling in the Energy Sector*. Stellenbosch, South Africa: Univ. Stellenbosch, 2011.

UDUAKOBONG E. EKPENYONG received the bachelor's degree in electrical and electronics from Igbinedion University Okada, Nigeria, and the Master of Science degree in applied sciences (electrotechnics) and the Doctor of Philosophy degree in electrical engineering from the University of Pretoria, South Africa.

She is a Certified Asset Management Assessor. She is a member of the Institute of Asset Management, Australia, and Southern African Asset Management Association (SAAMA), a Registered Candidate Engineer at the Engineering Council of South Africa, and a member of Engineering New Zealand. She also serves as a Senior Research Associate for the University of Johannesburg. She is an Electrical Engineer working in asset management space, where she interacts with clients to unlock the potential of the assets to enhance their business. She is a key part of Aurecon's Asset Management Team, which provides solutions in the planning, construction, preservation, and use of assets to extract value and manage costs through offerings, such as strategic asset management planning to establish a baseline assessment of assets; data analysis and systems set up to create a foundation for clients' asset management structure; portfolio optimization to maximize ROI and minimize risk; and operational readiness to get assets up and running, among other unique offerings. Besides being an Engineer, she is also a Researcher. She is involved in several research initiatives for educational and personal purposes with topics ranging from the adoption of energy efficiency programs in rural communities and renewable energy in residential sectors to researching different power systems. Her research interests include electricity distribution and transmission, demand side management, and energy efficiency.
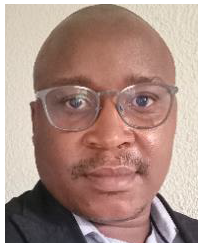
LEARNMORE MOYO received the B.Sc. degree in electrical engineering from the University of KwaZulu-Natal, in 2014, and the M.Eng. degree in electrical and electronic engineering from the University of Johannesburg, in 2020. Since his first graduation, he has been working in the railway, renewable energy, and mining industries. His research interests include mathematical optimization techniques, renewable energy, and power systems.

NNAMDI I. NWULU (Senior Member, IEEE) is currently a Full Professor with the Department of Electrical and Electronic Engineering Science, University of Johannesburg, and the Director of the Centre for Cyber Physical Food, Energy and Water Systems (CCP-FEWS). His research interests include the application of digital technologies, mathematical optimization techniques, and machine learning algorithms in food, energy, and water systems. He is a Professional Engineer registered with the Engineering Council of South Africa (ECSA), a Senior Member of the South African Institute of Electrical Engineers (SMSAIEE), and a Y-Rated Researcher by the National Research Foundation of South Africa. He is the Editor-in-Chief of the *Journal of Digital Food Energy and Water Systems* (JDFEWS) and an Associate Editor of *IET Renewable Power Generation* (IET-RPG) and *African Journal of Science, Technology, Innovation and Development* (AJSTID).

RAMESH C. BANSAL (Senior Member, IEEE) is currently a Professor with the Department of Electrical Engineering, University of Sharjah, and an Extraordinary Professor at the University of Pretoria (UP), South Africa. Previously, he was a Professor and the Group Head (Power) with the ECE Department, UP. Prior to his appointment at UP, he was employed by the University of Queensland, Australia; The University of the South Pacific, Fiji; BITS Pilani, India; and Civil Construction Wing, All India Radio. He has more than 25 years of diversified experience of research, scholarship of teaching and learning, accreditation, industrial, and academic leadership in several countries. He has significant experience of collaborating with industry and government organizations. These utilities include NTPC (a 60 GW Indian power generation company), Powerlink, and ESKOM. He has made significant contribution to the development and delivery of B.S. and M.E. program for utilities. He has extensive experience in the design and delivery of CPD program for professional engineers. He has carried out research and consultancy and attracted significant funding from industry and government organizations. He has published over 350 journal articles, presented papers at conferences, books, and chapters in books. He has Google citations of over 12000 and H-index of 50. He has supervised 25 Ph.D. and four postdoctoral students. His diversified research interests include renewable energy (wind, PV, DG, and micro grid) and smart grid.

Prof. Bansal is a fellow and a Chartered Engineer of IET, U.K., and a fellow of the Institution of Engineers, India. He is an Editor of several highly regarded journals, such as *IET-RPG* and IEEE Systems Journals.

• • •