A MODEL PREDICTIVE CONTROL APPROACH TO GENERATOR MAINTENANCE SCHEDULING

by

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SUMMARY

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The maintenance schedule of generators in power plants needs to match the electricity demand and needs to ensure the reliability of the power plant at a minimum cost of operation. In this study, a comparison is made between the modified generator maintenance scheduling model and the classic generator maintenance scheduling model using the reliability objective functions. Both models are applied to a 21-unit test system, and the results show that the modified generator maintenance scheduling model gives better and more reliable solutions than the regular generator maintenance scheduling model. The better results of the modified generator maintenance scheduling model are due the modified and additional constraints in the modified generator maintenance scheduling model. Due to the reliable results of the modified generator maintenance scheduling model, a robust model is formulated using the economic cost objective function. The model includes modified crew and maintenance window constraints, with some additional constraints such as the relationship constraints among the variables. To illustrate the robustness of the formulated GMS 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.

OPSOMMING

MODEL VOORSPELLENDE KONTROLE TE KRAGOPWEKKER ONDERHOUDSKEDULE

deur

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Sleutelwoorde:	kragopwekker onderhoudskedule, kragopwekker, modellering, onderhoud, optimalisering, partikel swerm optimalisering, genetiese algoritme, model voorspellende kontrole, swerm intelligensie en kontrole

Die onderhoudskedule vir kragopwekkers (OSK) in kragstasies moet kan voorsien in die vraag na elektrisiteit en moet die betroubaarheid van die kragstasie teen 'n minimum operasiekoste verseker. In hierdie studie word die betroubaarheidsdoelwitfunksie gebruik om 'n gewysigde onderhoudskeduleringsmodel vir kragopwekkers te vergelyk met die konvensionele onderhoudskeduleringsmodel. Beide modelle word toegepas op 'n 21-eenheid-toetsstelsel, en die resultate toon dat die gewysigde model 'n beter en meer betroubare oplossing bied as die konvensionele model. Die beter resultate van die gewysigde model is die gevolg van die gewysigde en bykomende beperkings in die gewysigde model. As gevolg van die betroubare resultate van die gewysigde onderhoudskeduleringsmodel word die koste-ekonomie-doelwitfunksie gebruik om 'n robuuste model te formuleer. Die model sluit gewysigde bemanning- en onderhoudvensterbeperkings in, met 'n paar bykomende beperkings soos die verhoudingsbeperkings tussen die veranderlikes. Om die robuustheid van die geformuleerde OSK-model te illustreer word die instandhouding van die Arnot kragstasie in Suid-Afrika geskeduleer met oop- en geslotelus-beheerders. Beide beheerders voldoen aan al die beperkinge, maar die geslotelusresultate is beter as die ooplusresultate.

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CHAPTER 1

INTRODUCTION

This dissertation formulates a new optimisation model for generator maintenance scheduling with the necessary constraints required. The open loop problem is solved using particle swarm optimisation. This open loop problem is then transformed into a closed loop problem using the model predictive control (MPC).

1.1 BACKGROUND

Modern power systems are experiencing increased demand for electricity with related expansions in system size, which has resulted in lower reserve margins making the generator maintenance scheduling problem complicated. Concerns for high reliability, low production cost and energy management in electricity generation plants has stimulated interest in automated production, operation, transmission and schedule maintenance of various machines in a generation plant [1].

The reliability of system operation and production cost in power plants are affected by the maintenance outage of generators. Optimised maintenance schedules could potentially defer some capital expenditure for new plants in times of tightening reserve margins, and allow critical maintenance work to be done which might not otherwise be achieved. Therefore, maintenance scheduling is a significant part of the overall operations scheduling problem [2].

Maintenance of generators in electricity generation plants takes a large percentage in the operation cost of the plant because of this, scheduling of generators for maintenance has become an important aspect in energy management and reliability in the power system.

Generator maintenance scheduling (GMS) involves arranging generators in certain periods for preventive maintenance at a desired time and level so that the cost involved are minimised, the generator life time is extended, and the system and other constraints are satisfied [3].

There are generally two criteria that GMS problems are based on, economic cost and reliability of the power plant. The economic cost objective is to minimise the total operating cost. The reliability objective is to meet the required energy demand and maintain reserve level of the power plant [1].

1.2 RESEARCH APPROACH

The objective of this research is to formulate a GMS model and derive an optimal solution. The GMS model is to schedule generator maintenance that will reduce the operational cost of the generator which includes, the maintenance cost while satisfying all the necessary constraints involved.

The problem lies in finding a set of scheduling periods that minimise the total operational, production and maintenance cost, as well as meet the load demand and other constraints over a given period of time. A study of the existing GMS models is done and constraints missed in the historic GMS models are added to the new formulated GMS problem.

A comparison between the formulated GMS model and the classical reliability GMS model is done using a case study of 21-unit test system. This comparison is to highlight the effectiveness of the new GMS model when compared to other models.

An open loop optimisation model for the GMS problem is defined with all the necessary constraints such as the maintenance and system constraints. This open loop model is then transformed to the close loop GMS problem using model predictive control. The generic open loop and closed loop models are then applied to a case study. The Arnot power plant in Mpumalanga, South Africa is selected for this case study.

Particle swarm optimisation (PSO) technique is used to evaluate the open loop and closed loop problem. Simulations of the results of the open loop and closed loop evaluations are compared.

1.3 DISPOSITION

This Chapter introduces the background to the research problem and briefly describes the research approach. In Chapter 2 the literature survey which includes, the description of the research problem, studies of different solution techniques that have been applied to the GMS models, the research approach and the contributions of this research are covered. Chapter 3 compares the reliability objective function modified GMS (MGMS) model to the classical GMS model of [1], [4], [5] and the economic cost objective function GMS problem is formulated with some modified and additional constraints. In Chapter 4 the comparison of the MGMS and GMS models are applied to a 21-unit case study and the economic cost GMS model is applied to the Arnot power plant. Chapter 5 reports the simulated results of the two case studies. Chapter 6 concludes and makes recommendations for further research.

CHAPTER 2

LITERATURE STUDY AND MOTIVATION

This chapter covers the literature survey. It includes the study of existing work, the research approach and the contributions of this research.

2.1 TERMINOLOGIES OF GENERATOR MAINTENANCE SCHEDULING

Generator maintenance scheduling (GMS) involves arranging generators in certain periods for preventive maintenance at a desired security/reserve level so that the costs involved are minimised and all the necessary constraints are fulfilled [1]-[6].

2.1.1 Objective functions

Objective functions are the performance indicators against which an optimisation problem solved. For optimisation problems it can be a minimisation, maximisation or even a combination of both. There are generally two objective functions considered in GMS problems, the economic cost and the system reliability. The latter objective is often incorporated into the economic cost model [6]. There are constraints that the objective functions are subjected to in order for the GMS problem to reach its optimal solution. The constraints are similar for both objective functions.

2.1.1.1 Economic cost objective function

The economic cost function focuses on the minimisation of the operation cost for the power plant while still producing the required output and satisfying all the constraints. The operation cost can be divided into the production, maintenance and start up cost [7]-[10].

2.1.1.2 Reliability objective function

The reliability objective function aims to maintain the capacity level of the generator at a certain level with known parameters. It also tries to maximise the system reliability under certain conditions of uncertainty [6], [11]-[21].

2.1.2 Constraints

Constraints are conditions that must be satisfied for an optimal solution to be achieved. In optimisation problems these constraints can include equalities and inequalities.

2.1.2.1 Relationship constraints

The relationship constraints show that the variables in GMS problems are not necessarily independent, they sometimes depends on each other in order to obtain an optimal solution. An example is the relationship between the start up and maintenance variables in [10].

2.1.2.2 Maintenance constraints

Maintenance constraints ensure that once a generator is removed from the system for maintenance, it completes the maintenance without interruptions, within the planning horizon and utilises only the crew available for the period [13], [14]. As said earlier, the constraints for both economic cost and reliability are similar.

2.1.2.3 System constraints

System constraints are constraints of the power system that must be satisfied, such as the demand and supply constraint and the generator limit [15], [16], [17].

2.2 GMS MODELLING

In modern power systems, the demand for electricity has greatly increased with related expansions in power system size, which has resulted in higher numbers of generators and lower reserve margins, making the generator maintenance scheduling (GMS) problem a complex one. An optimal GMS reduces generation cost, increases system-operating reliability, and extends generator life span [1], [18], [19].

A typical GMS problem considers a generator i in a power system that contains I generators over a planning horizon of T periods. Each generator i must be maintained within a duration N_i periods in the horizon without interruptions until the maintenance is complete. The maintenance of generator i depends on the number of crew available for the period t. However, these generators must produce generated output g_{it} that must satisfy the demand D_t and maintain a reserve S_t for that time horizon while not exceeding their rating limit. The aim of any GMS is to satisfy all these basic constraints above and still schedule an optimal maintenance.

There are generally two categories of criteria for GMS problems, and they are: economic cost and reliability of the system. The economic cost objective is to minimise the total operating cost, which includes the cost of energy production and maintenance. The reliability objective function is used to maximise the system's reliability under some conditions of uncertainty. This is carried out by the levelling of the reserve generation over the entire operational planning period. It is very crucial to maintain proper level of reserve margin between the supply i.e. the capacity of the generator and the estimated load demand from the system's reliability point of view. As such the reliability GMS problem is solved by minimising the sum of squares of the reserve over the entire operational planning period [1], [6]. The problem has a number of maintenance and system constraints to be satisfied. The constraints include the maintenance window, crew, and demand, constraints.

The economic objective function is used in [7]-[10], [20] to minimise the production cost over the planning horizon. The planning horizon considered for maintenance scheduling is often 52 weeks. The models have the maintenance, crew and demand constraints but fail to include the generator maintenance limit which could prove problematic for the energy planner when considering unit commitment or economic dispatch. The existing models treat the variables as independent of each other.

The reliability objective function is used in to [1], [3], [11], [21], [4], [24] to minimise the sum of squares of the reserve over the entire operational planning period. The maintenance window and crew constraints are not formulated in the manner that describes the problem explicitly. For example, the mathematical representation of the crew constraint in [25] does not specify the stages of maintenance for each interval.

The generator maintenance limit is considered in [26] when considering the maintenance schedules of thermal power plants but failed to add the ramp rate constraint. The ramp rate has not been added to any of the above mentioned models. The association of the start up to maintenance variable is formulated in [10] but failed to consider the relation between the start up and generated output.

A summary of GMS models with the constraints used is listed in Table 2.1. This table shows that the GMS models of the literature and the constraints considered in these models. From the table it can be seen that these models have not considered all the constraints needed to make the problem robust. Hence, the formulation of a new GMS model that will contain all the necessary variable relationship, maintenance and system constraints. This GMS model should be able to handle the economic cost and reliability criteria.

Table 2.1: Summary of the GMS model references

References	objective		constraints		
	Economic	Reliability	Relationship	Maintenance	System
[1]		X		X	X
[3]		X		X	X
[7]	X			X	X
[8]	X			X	X
[9]	X	X		X	X
[11]		X		X	
[21]	X	X		X	X
[4]		X		X	X
[24]		X		X	X
[25]		X		X	X
[28]	X			X	X

2.3 TECHNIQUES USED TO EVALUATE GMS PROBLEMS

A variety of exact mathematical and heuristic techniques has been employed to solve the GMS. Mathematical techniques are mainly based on dynamic programming, branch and bound programming and implicit enumeration programming. The main problem with these techniques is that the numerical solutions require extensive computational efforts, which increases exponentially with the problem complexities. The size and non-linearity of GMS problems make the mathematical techniques computationally prohibitive [1], [3]. In order to obtain an approximate solution of a complex GMS, new concepts have emerged in recent years. They include the decomposition techniques, simulated annealing, tabu search, generic algorithm, and ant colony optimisation.

The comparison between differential evolution (DE) and particle swarm optimisation

(PSO) algorithm are presented in [1]. The application of genetic algorithm to GMS presented in [22] has been compared with, and confirmed to be superior to other conventional algorithms such as heuristic approaches and branch and bound (B&B) in the quality of solutions [11].

There are three broad categories for the evaluation of GMS optimisation problems. They are: classical mathematical optimisation, neighbourhood search and population search.

2.3.1 Classical mathematical optimisation techniques

2.3.1.1 Dynamic programming

Dynamic programming (DP) is used for sequencing problems. It is used in [4] to minimise the production cost and schedule the exact period in the horizon that the generators will start maintenance. The model used for this technique considers only the reserve level and demand of the power plant. DP is not suitable for non-linear objective, and constraints of generator maintenance schedule as well as its computational time grows prohibitively with problem size [7]. DP is not efficient in handling problems with discrete variables such as the GMS problems, and the convergence to an optimal solution depends on the chosen initial solution [9].

2.3.1.2 Branch and Bound

The branch and bound method carries out a systematic search in the space of all feasible solutions to find the maximum. It does this by partitioning the space of all feasible solutions into smaller subsets and calculates an upper bound on the value of the objective function associated with the solutions that lie within a given subset. After each partitioning, those subsets whose upper bound are less than the best known feasible solution are excluded from further partitioning and are discarded. The partitioning continues until the value of the objective function for the best feasible solution is not less than the upper bound of any subset. The best feasible solution is then the optimal solution. The technique is used in [11] to obtain a scheduling using the maximisation of reliability objective function.

The strength of this technique is the property of excluding infeasible and non-optimal subsets from further search without them being fully expanded [23].

2.3.1.3 Implicit enumeration algorithm

Implicit enumeration is similar to branch and bound method. However, branching in implicit enumeration is specific, since the branching variable has to be either 0 or 1. Based on this fact, the branch and bounding process and determination of the node infeasibility are highly simplified. Implicit enumeration has the same strengths and weaknesses as branch and bound above. It is used as the solution technique for the economic cost objective function in [28] where a penalty function is added to the model for maintenance started too early or late.

2.3.2 Neighbourhood search

Neighbourhood search refers to those search methodologies where a single solution is transformed over time by making use of predefined neighbourhood. There are two neighbourhood search techniques that have been used in GMS.

2.3.2.1 Simulated Annealing

Simulated annealing (SA) assumes an analogy between the annealing of a metal and a combinatorial optimisation problem. The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. The heat causes the atoms to become unstuck from their initial positions (a local minimum of the internal energy) and wonder randomly through states of higher energy, the slow cooling gives them more chances of finding configurations with lower internal energy than the initial one

[29], [30], [32].

The components of the simulated annealing are basically as follows:

1. The description of the state space.

2. The score function.

3. The rules for the move set.

4. The acceptance function.

5. The annealing schedule.

In the annealing schedule, "annealing" is a thermal process for obtaining low energy states of a solid in a heat bath. This process contains two steps:

1. Increasing the temperature of the heat bath to maximum value, at which the solid melts. The solutions in the combinatorial optimisation problems are equivalent to states of a physical system.

2. Carefully decreasing the temperature of the heat bath until the particles arrange themselves in a ground state of the solid. The cost of the solution is equivalent to the energy of the state.

A new solution is generated through a neighbourhood structure, a set of solution which is "close" to the present solution, and a generation mechanism, selecting a new solution from the neighbourhood of the present solution. SA is used in [8], [31] to minimise economic cost and schedule start of maintenance. Due to its more advanced method of optimisation than that of the classic mathematical method, reserve constraint is included in the GMS model that is evaluated. Although SA produces near optimal solutions, the computation time is very long compared to other optimisation techniques.

2.3.2.2 Tabu search

Tabu search is defined as an algorithm which deals with cycling by temporarily forbidding moves that would return a solution recently visited. This is accomplished by means of a tabu list which records the most recent solutions and prevents the search from continuing with these non-feasible moves. This list can act as either regency-based memory, where the list classifies solutions according to the length of time they have spent in the list, or frequency-based memory, where the number of times a solution occurs has an influence [32]. Tabu search starts at some initial solution then moves to a neighbourhood solution. A neighbourhood solution is generated by a set of admissible moves. At each iteration, the method moves to the best solution in the neighbourhood of the current solution. The distinguishing characteristic of this technique is the tabu list it keeps that prohibits the algorithm from moving to solutions that have certain attributes. The most basic form of the Tabu search algorithm consists of the following:

1. A method for generating an initial solution.
2. A mechanism for generating a neighbouring solution of the current solution.
3. A function that measures the attractiveness of each neighbouring solution.
4. A Tabu list in order to prevent cycling and lead the search to unexplored regions of the solution space.
5. An aspiration criterion.
6. Diversification scheme [32].

A more complex Tabu search algorithm is used in [21] to solve for the minimization of the economic cost objective function. Although the Tabu search algorithm produces better results than the implicit enumeration algorithm, the Tabu search algorithm still has weaknesses similar to the SA.

2.3.3 Population based search

Population based search is characterised by a population of candidate solution which are adaptive over time. It is further divided into two groups: evolutionary search and swarm intelligence.

2.3.3.1 Evolutionary search

Evolutionary search is based on natural genetic and evolution mechanism models of genetic change in a population of individuals. In evolutionary search the candidate solutions compete for survival. Some of the evolutionary search optimisation techniques used in GMS problems are explained below.

Genetic algorithm (GA)

The GA is a search algorithm that is based on the concept of natural selection and genetic inheritance. It searches for optimal solution of optimisation problems by manipulating a population of strings (chromosome) that represent different potential solutions, each corresponding to a sample point from the search space. A chromosome is a long, complicated thread of deoxyribonucleic acid (DNA). Hereditary factors that determine particular traits of an individual are strung along the length of these chromosomes, like beads on a necklace. Each trait is coded by some combination of DNA there are four bases, A (Adenine), C (Cytosine), T (Thymine) and G (Guanine). Like an alphabet in a language, meaningful combinations of the bases produce specific instructions to the cell.

GA's search by simulating evolution, starting from an initial set of solutions or hypotheses, and generating successive "generations" of solutions. This particular branch of artificial intelligence is inspired by the way living things evolved into more successful organisms in nature. The main idea is survival also known as natural selection and changes occur during reproduction. The chromosomes from the parents exchange randomly by a process called crossover. Therefore, the offspring exhibit some traits of the father and some traits of the mother. A rarer process called mutation also changes some traits. Sometimes an error may occur during copying of chromosomes (mitosis) [33].

At each iteration, all the populations are evaluated based on their fitness, an individual with a larger fitness has a higher chance of evolving into the next generation. The coding of parameters helps the genetic operator to evolve the current state into the next state with minimum computation. Although GA has been used to evaluate GMS problems such as in [9], there are a few set backs to GA when GMS problems are involved such as trapping into a local minimum [33]. Also implementation of GA are expensive. The working principle in a basic GA is as follows:

1. Formulate initial population.
2. Randomly initialise population.
3. Evaluate objective function.
4. Find the fitness function.
5. Apply genetic operators which are, reproduction, crossover, and mutation.
6. Continue from 3 until stopping criteria is reached.

Differential evolution (DE)

Differential evolution is a method that optimises a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimised, which means DE does not require for the optimisation problem to be differentiable as is required by classic optimisation methods such as gradient descent and quasi-newton methods.

DE optimises a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimisation problem at hand. In this way the optimisation problem is treated as a black box that merely provides a measure of quality given a candidate solution and the gradient is therefore not needed [35].

It is used in [7] to evaluate a complex power systems problem which aims to reduce production cost by combining GMS and economic dispatch in its model using an economic cost objective function. The set backs of DE are similar to those of GA.

2.3.3.2 Swarm intelligence

Swarm intelligence is inspired by the social behaviour of animals such as birds to solve optimization problems. There are two swarm intelligence techniques that have been used in GMS problems. They are ant colony and particle swarm optimisation.

Ant colony optimisation (ACO)

The ACO technique is inspired by the foraging of ant colonies. ACO is adapted by ants marking paths they have followed with pheromone, with these trails they are able to communicate indirectly and find the shortest distance between their nest and the food source when foraging for food [24], [36].

When adapting this search metaphor of ants to solve discrete combinatorial optimisation problems, artificial ants are considered to explore the search space of all possible solutions. The ACO begins with random solutions within the decision space of the problem. As the search progresses over discrete time intervals ants deposit pheromone on the components of promising solutions. In this way, the environment of a decision space is iteratively modified and the ACO search is gradually biased towards more desirable regions of the search space, where optimal or near optimal solutions can be found.

ACO is used in [24] to maintain the reliability of the power plants while scheduling maintenance. It uses the reliability objective function by maximising the reliability of the power plant within the planning horizon. This technique produces better solutions than some other techniques in terms of computational efficiency and quality when applied to optimisation problems. It cannot handle problems with continuous variables like the GMS problem in this research [36].

Particle swarm optimisation (PSO)

PSO is inspired by the ability of flocks of birds, schools of fish, and herds of animals to adapt to their environment, find rich sources of food, and avoid predators by implementing an "information sharing" approach, hence, developing an evolutionary advantage [37]. PSO is an algorithm inspired by the social behaviour of birds flocking or fish schooling, which is used for finding optimal regions of complex search spaces though interaction of individuals in a population of particles. In PSO, a set of randomly generated solutions (initial swarm) propagates in the design space towards the optimal solution over a number of iterations (moves) based on large amount of information about the design space that is assimilated and shared by all members of the swarm.

PSO is similar to GA, they are both algorithms which start with a group of a randomly generated population, and both have fitness values to evaluate the population. Both update the population and search for the optimal solutions with random techniques. However, PSO has memory and does not have genetic operators such as crossover and mutation. PSO also updates itself with internal velocity. Information sharing in PSO is significantly different to that of GA. In GA, chromosomes share information with each other, so the whole population moves like one group towards an optimal area. In PSO, only the best solution at that iteration gives out information to others [27]. The flow chart showing the procedure of the PSO is found in Figure 2.1.

PSO is used in [3], [38], and [39] to evaluate the reliability objective function for GMS problems. It is deduced from those studies that PSO has the ability to search simultaneously, converge fast and preserve former history related to the maintenance schedules. It can access on non linear problems such as GMS having many feasible

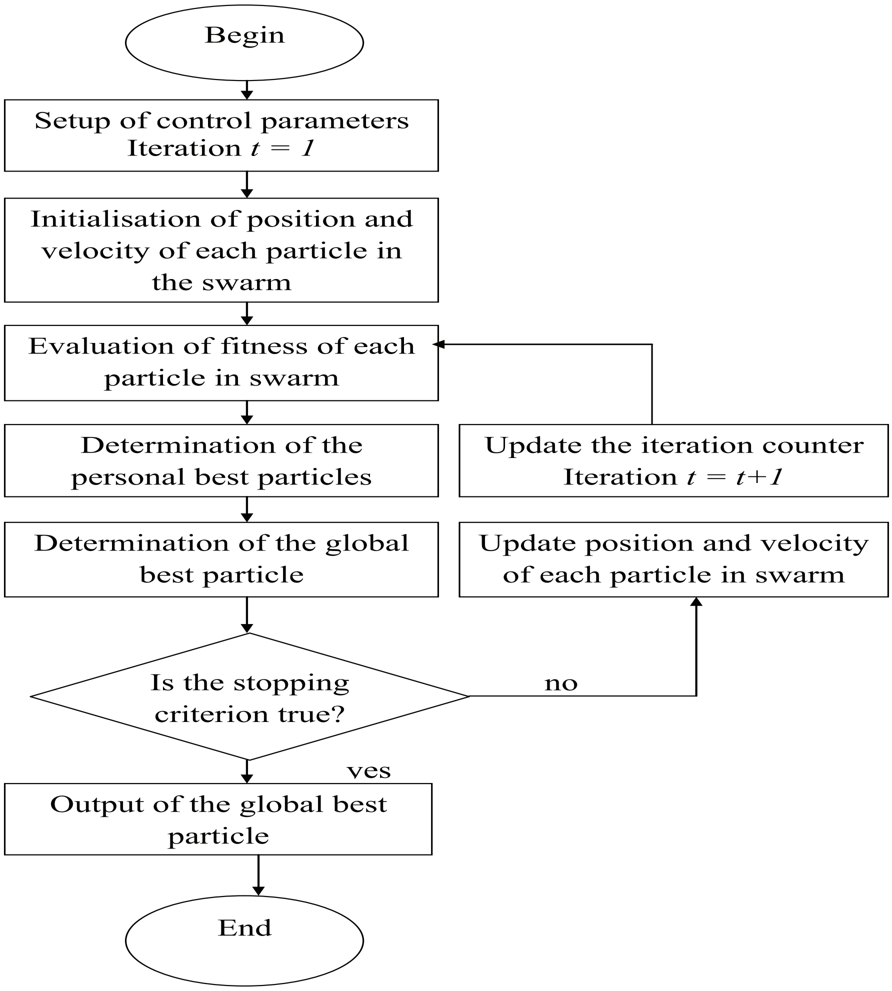


Figure 2.1: Procedure of a classic PSO approach [40]

points. The algorithm is simple. It also has the ability to control the search spaces global and local, to find the optimal solution The original PSO algorithm can evaluate problems with only continuous variables. Modifications have been made to the original algorithm so it can evaluate problems with mixed integer variables [3], [40].

There are variations of PSO used in optimisation problems. Some of those variants are binary PSO, discrete PSO, modified discrete PSO [41] and penalty function mixed integer PSO amongst others. In this research, modification to penalty function mixed integer PSO algorithm is made. The modification is to ensure that the algorithm evaluates the GMS problem with mixed integer variables. More on PSO is discussed in Chapter 4.

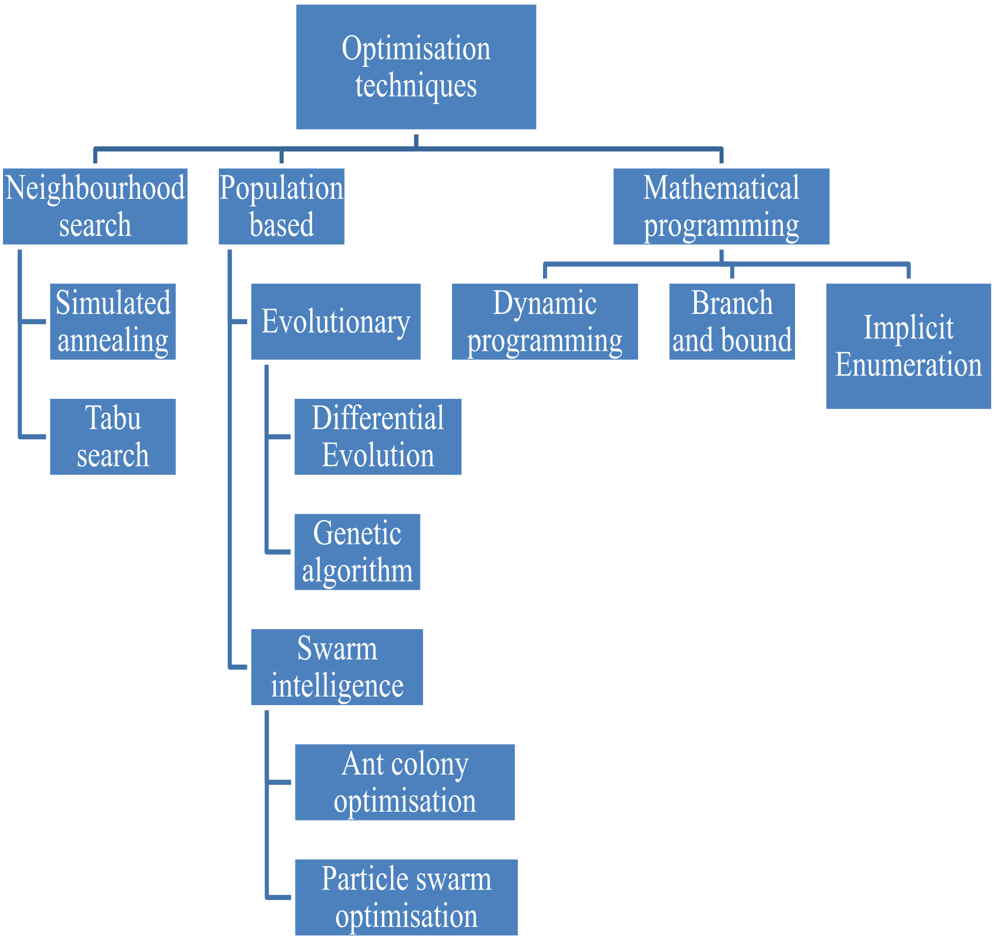


Figure 2.2: Summary of optimisation techniques

2.3.3.3 Hybrid optimisation techniques

Hybrid techniques combining genetic algorithm, simulated annealing and tabu search have been used in [4], [23], [28], and [42] with reliability objective function to schedule the start of maintenance and level reserve of the power system.

2.4 RATIONALE FOR THIS STUDY

All the techniques mentioned above only evaluate open loop optimisation problems, there has been no consideration for future changes in the system after a solution has been obtained. All the models in the researched literature treat each variable as independent but variables in GMS are dependent on each other. Some of the constraints were incorrectly expressed. These flaws in GMS problem modelling brought about the need to formulate a new GMS model.

There has been no study thus far on closed loop GMS problems. The open loop GMS model is transformed to a closed loop model which will consider all the changes that occur in the system and feed it back to the input. The solution obtained from the closed loop model is more reliable than the open loop.

2.5 APPROACH FOR THE STUDY

2.5.1 Hypothesis of study

The hypothesis is that a new GMS model is formulated which contains all the necessary constraints. This open loop GMS problem is solved using the particle swarm algorithm and the problem is transformed to a closed loop problem using the model predictive control.

2.5.2 Motivation for MPC approach

The motivation of this study is the need to schedule optimal maintenance for power plants that will reduce the operational cost of the power plant. This is achieved by formulating the GMS model. This GMS model contains all the necessary variables and constraints. The optimal closed loop GMS model is implemented using MPC.

The main idea of MPC is to measure the plant output $y(t)$, make some calculations (including a state estimate $\hat{x}(t)$) and deliver a new control action to the plant input $u(t)$, all the while trying to achieve some pre-specified objective. A basic MPC block model and timing of MPC can be seen in Figure 2.2 and 2.3 respectively which is found is [43].

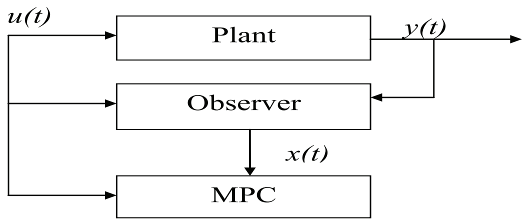


Figure 2.3: Block diagram of MPC

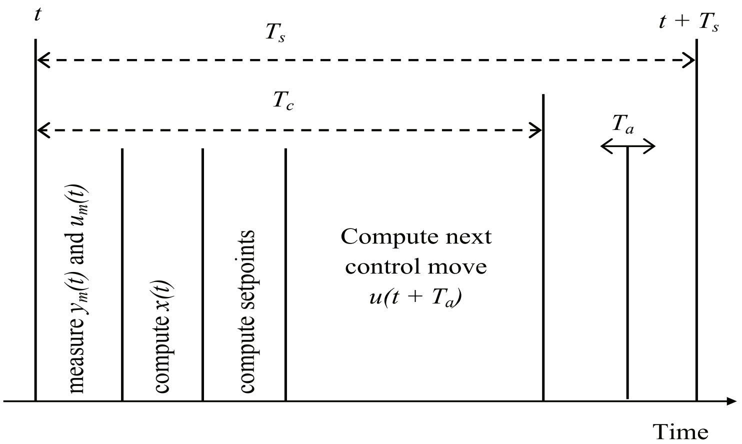


Figure 2.4: Timing diagram of MPC

MPC has characteristics that are useful for obtaining optimal solutions for GMS. Some of the characteristics are:

1. It is a closed loop technique that adapts to changes of the system.
2. Its convergence and easy implementation.
3. Its robustness and simplified model.
4. Stability against external disturbances.
5. It has reduced dimensions compared to the open loop techniques.

6. It can be started and restarted at any time while an open loop controller must be started at the correct simulated stated time.

7. It is a generic closed loop optimisation technique that is not applicable to a specific optimisation problem [44], [45].

Based on the characteristics of MPC mentioned above and all the studies carried out on past GMS approaches, using MPC in GMS problems will introduce a new era in power system problems. MPC has been used successfully in resource allocation [45], economic dispatch [46] and plant process allocations [47] problems. For this reason MPC is used to transform the open loop GMS problem to a closed loop GMS problem.

2.5.3 Research process and modelling

The research comprises of the following sequential steps:

1. The existing GMS models are studied to identify the different approaches that have been used to implement GMS, their achievements and shortcomings.

2. Modifications are made to the constraints of a classic reliability objective function GMS model and applied to a case study of 21 unit test system. A comparison is made between the modified GMS (MGMS) and the classic GMS models. Due to more reliable results obtained by MGMS after the comparison, a new model is formulated using the economic cost objective function.

3. An open loop GMS model using economic cost objective function is formulated. This model has three variables: maintenance, start-up and generator output. The necessary constraints are then added to the model. This GMS model is an open loop non linear mixed integer optimisation problem.

4. Modifications to PSO are made [48] in order for the algorithm to evaluate the

open loop GMS problem.

5. The open loop non-linear mixed integer optimisation problem is then evaluated using one of the existing solution techniques: particle swarm optimisation (PSO).

6. A study of MPC is done.

7. The open loop problem is applied to a case study and compared with an existing GMS model to test the feasibility of the formulated GMS model.

8. The open loop problem is transformed into a closed loop optimisation problem.

9. The open loop and closed loop problems are applied to a case study and solved using the PSO and MPC approaches respectively.

10. The results of the open loop and closed loop problem are compared.

2.5.4 How this approach addresses current issues

1. Relationship constraints are important in maintenance scheduling and are added to this study's GMS model.

2. Constraints that were formulated incorrectly in existing GMS models are modified.

3. The selected approach affirms that GMS problems can be expressed as closed loop optimisation problems.

4. The selected approach utilises a modified penalty function PSO algorithm for evaluating open loop GMS problems.

5. The selected approach optimises with the maintenance period, for example one

week interval.

6. The closed loop approach is a generic approach that is not specific to the optimisation problem. The only difference is the modelling of the optimisation problem.

7. The selected approach determines the optimal schedule for maintenance over a time period.

2.5.5 Limitations and challenges of selected approach

The limitations and challenges of this approach are:

1. The GMS model is simplified for simulation purposes and as a result, certain factors are excluded for example, the effect of the transmission network on the power plant during maintenance is not considered.

2. The design does not include the ageing of each generator with respect to time.

3. Modelling and optimisation of GMS models is challenging especially when taking into consideration the constraints of the GMS model. Thus, this GMS model and simulated results provide information as a guide for further applications.

4. The simulated results are limited to only the specified case studies. The aim is to confirm the hypothesis by adding to the existing body of knowledge.

2.6 CONTRIBUTION OF THE STUDY

1. The major contribution to this research is the addition of the relationship constraints to the GMS model. This study proves that variables in the GMS model

are not independent and as a result relationship constraints are added to the model.

2. The maintenance window and crew constraints used in the models of [1]-[26], [28], and [29] are also modified to ensure that the GMS model provides an accurate mathematical representation of the problem.

3. The ramp rate and generator limit constraints are added to the proposed GMS model.

4. The comparison of the proposed GMS model to the classical GMS model of [5] shows the advantage of the modification and addition constraints to the proposed GMS model which provides reliable solutions.

5. This study affirms that an MPC approach can be used to transform an open loop GMS model to a closed loop GMS model.

6. This study validates all the unique characteristics of MPC as listed above.

7. This study proves that closed loop GMS models provide better solutions than open loop GMS solutions.

CHAPTER 3

GENERATOR MAINTENANCE SCHEDULING MODEL

The purpose of this chapter is to compare the modified generator maintenance scheduling (MGMS) model with the classic generator maintenance scheduling (GMS) model in [1], [4] and [5]. Both the MGMS and GMS problems have the reliability objective functions. Then an economic cost objective function GMS problem is formulated incorporating the modified constraints of the MGMS and adding some new constraints.

3.1 COMPARISON OF THE MGMS AND GMS MODELS

There are two basic types of objective functions in GMS problems: the economic cost objective function and reliability objective function. The economic cost objective function focuses on minimising the cost of operation of the power plant, while the reliability objective function aims to maximise the systems reliability and maintain the reserve of the power system at a certain level [24].

The reliability GMS problem is solved by minimising the sum of squares of the reserve over the entire operational planning period [1], [4], [25]. The problem has a number of units and system constraints to be satisfied. The constraints include: the maintenance window, crew, demand, and reserve constraints.

The GMS model in [1], [4], [5] is given below.

$$Min\{\sum_{t=1}^{T}(\sum_{i=1}^{I} g_{i,t} - \sum_{i\in I_t}\sum_{k\in S_{i,t}} x_{i,k}g_{i,k} - D_t)^2\}, \tag{3.1}$$

subject to

$$\sum_{t\in T_i} x_{i,t} = 1 \text{ for all } i = 1,\ 2,\ \ldots,\ I, \tag{3.2}$$

$$\sum_{i\in I_t}\sum_{k\in S_{i,t}} x_{i,k}M_{i,k} \leq A_t,\ \text{for all } t = 1,\ 2,\ \ldots,\ T, \tag{3.3}$$

$$\sum_{i=1}^{I} g_{i,t} - \sum_{i\in I_t}\sum_{k\in S_{i,t}} x_{i,k}g_{i,k} \geq D_t,\ \text{for all } t = 1,\ 2,\ \ldots,\ T. \tag{3.4}$$

The notations of (3.1)-(3.4) are defined below.

The MGMS model using the reliability objective function is given below.

$$Min\{\sum_{t=1}^{T}(\sum_{i=1}^{I} g_{i,t} - \sum_{i\in I_t}\sum_{t=q}^{N_i} x_{i,t}g_{i,t} - D_t)^2\}, \tag{3.5}$$

subject to

$$\sum_{t=1}^{T} x_{i,t} = N_i,\ \text{for all } i = 1,\ 2,\ \ldots,\ I, \tag{3.6}$$

$$\sum_{t=1}^{T-N_i+1} x_{i,t}x_{i,t+1}\ldots x_{i,t+N_i-1} = 1,\ \text{for all } i = 1,\ 2,\ \ldots,\ I, \tag{3.7}$$

$$\begin{gathered}
\textstyle\sum_{i=1}^{I}(1 - x_{i,t-1})x_{i,t}M_i^1 \leq A_t,\\
\textstyle\sum_{i=1}^{I}(1 - x_{i,t-1})x_{i,t}x_{i,t+1}M_i^2 \leq A_{t+1},\\
\vdots \qquad\qquad \vdots \qquad\qquad \vdots\\
\textstyle\sum_{i=1}^{I}(1 - x_{i,t-1})x_{i,t}\ldots x_{i,t+N_i-1}M_i^q \leq A_{t+N_i-1},\\
\text{for all } t = 2,\ \ldots,\ T - N_i + 1.
\end{gathered} \tag{3.8}$$

$$\sum_{i=1}^{I} g_{i,t} - \sum_{i\in I_t}\sum_{t=q}^{N_i} x_{i,t}g_{i,t} \geq D_t,\ \text{for all } t = 1,\ 2,\ \ldots,\ T, \tag{3.9}$$

$$g_i^{min}(1 - x_{i,t}) \leq g_{i,t} \leq g_i^{max}(1 - x_{i,t}), \quad \text{for all } i = 1,\ 2,\ \ldots,\ I,\ \text{ and } t = 1,\ 2,\ \ldots,\ T, \tag{3.10}$$

$$LR \leq g_{i,t+1} - g_{i,t} \leq UR,\ \text{ for all } i = 1,\ 2,\ \ldots,\ I,\ \text{ and } t = 1,\ 2,\ \ldots,\ T-1, \tag{3.11}$$

where

t:	Index of time periods, $t = 1,\ 2,\ \ldots,\ T$.
T:	Total number of planned horizons.
i	Index of the number of generators $i = 1,\ 2,\ \ldots,\ I$.
I:	Total number of generators.
$g_{i,t}$:	Generating capacity for each generator [MW].
I_t:	The set of indices of generators in maintenance at time t.
k:	Index of start periods of maintenance for each generator $k = t, \ldots,\ S$.
$S_{i,t}$:	Set of start time periods k such that if the maintenance of generator i starts at period k that generator will be in maintenance at period t, $S_{i,t} = \{k \in T_i : t - N_i + 1 \leq k \leq t\}$.
T_i:	Set of periods when maintenance of generator i may start, $T_i = \{t \in T : e_i \leq t \leq l_i - N_i + 1\}$.
e_i:	Earliest period for generator i to start maintenance.
l_i:	Latest period for generator i to start maintenance.
$x_{i,k}$:	Variable for the start of maintenance for each generator i at time k. If generator i is on maintenance $x_{i,k} = 1$, otherwise $x_{i,k} = 0$.
D_t:	Demand per time period.
$M_{i,k}$:	Number of crew used for maintenance of generator i at time k.
A_t:	Available number of crew at every time t.
N_i:	Duration of maintenance on each generator i.
M_i^q:	Number of crew needed for the q-th stage of maintenance of each generator, $q = 1,\ 2,\ \ldots,\ N_i$.

g_i^{min}: Minimum output electric power for each generator [MW].

g_i^{max}: Maximum output electric power for each generator [MW].

LR: Maximum down ramp rate per time period.

UR: Maximum up ramp rate per time period.

The minimisation problems of (3.1) and (3.5) are the sum of squares of the demand and the power lost due to maintenance subtracted from the total generating capacity of all the generators at that time period. The problems are subject to a number of constraints.

The maintenance window of (3.6) ensures that each generator is maintained only once during the planning horizon while (3.2) only defines the start of maintenance for each generator. MGMS includes another constraint in the maintenance window which is (3.7), it defines the exact periods that maintenance for each generator is considered to start and finish without interruptions. The crew constraints are (3.3) and (3.8) for the GMS and MGMS models respectively. The inequality of (3.8) provides 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. The load constraint in (3.4) and (3.9) are the same for both models. MGMS adds two new constraints which are the generator limit (3.10) and ramp rate constraint (3.11). The addition of these constraints in the model provides an avenue for the energy planner to consider unit commitment for the power system while scheduling maintenance for the generators. The MGMS model incorporates the necessary constraints and components needed to make maintenance scheduling feasible.

The case study for this comparison is explain in Chapter 4 and the simulated results are explained in Chapter 5.

3.2 ECONOMIC COST OBJECTIVE FUNCTION GMS MODEL

As it will be seen from Chapter 5, the modified constraints in the MGMS model enhanced the ability of the MGMS model to produce more reliable solutions for the test system than the classical GMS model. Thus the formulation of 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 section.

A typical economic cost objective function GMS problem is heterogeneous with binary variables [10] for example maintenance, start up, and continuous variables [7], [24], [38]. The objective function J of this model contains three variables: the maintenance state, start up state and generation variable. This problem has a number of constraints to satisfy which are divided into the relationship, maintenance and system constraints.

The relationship among variables has not been mentioned in any o the existing literature and as such the need to explain and show that the variables are not independent of each other but rather all have a connection to one another in some way hence, the relationship constraints. The maintenance constraints consist of the maintenance window and the crew constraint. Both constraints have been modified from the classical formulations that have been used over the years. The system constraints ensure that during maintenance the demand and reserve constraints are not violated. The ramp rate constraint is added to the MGMS model to ensure that the ramp rate of each generator is not violated for every time period.

3.2.1 Objective function

The GMS problem is to schedule maintenance and minimise the operational cost of the power plant while producing enough electricity to meet the demand and other constraints. The operational cost consists of the maintenance, start up and production cost. The objective function J in (3.12) contains three variables, the maintenance state $x_{i,t}$, start up state $y_{i,t}$, and generated output $g_{i,t}$, for which $i = 1, 2, \ldots, I$, $t = 1, 2, \ldots, T$, c_i, f_i and k_i are the cost of maintenance, start up and generation respectively. $x_{i,t}$ is the maintenance variable of each generator. If generator i is on maintenance at time t then, $x_{i,t} = 1$, otherwise $x_{i,t} = 0$. $y_{i,t}$ is the start up variable of each generator. If 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 emulate real life cases where there is a substantial amount of money reserved specifically for the start up of any generator in the power plant. The open loop economic cost objective function GMS model is give below:

$$\text{Min } J = \sum_{i=1}^{I}\sum_{t=1}^{T} c_i x_{i,t} + \sum_{i=1}^{I}\sum_{t=1}^{T}(f_i y_{i,t} + k_i g_{i,t}), \tag{3.12}$$

The objective function is subject to the relationship, maintenance and system constraints as explained in the subsequent subsections below.

3.2.2 Relationship constraints

The relationship constraints show that the variables in GMS problems are not independent. Two of the relationship constraints are new constraints that have been added to the GMS model, they have not been addressed in any of the existing literature.

3.2.2.1 Maintenance - start up relationship

$$x_{i,t} + y_{i,t} \leq 1; \text{ for all } i = 1, 2, \ldots, I \text{ and } t = 1, 2, \ldots, T \tag{3.13}$$

The constraint (3.13), shows that during maintenance of generator i, the generator can not be started until maintenance is completed. A variation of this constraint is used in [10].

3.2.2.2 Maintenance - generation relationship

$$(1 - x_{i,t})g_{i,t} = 0; \text{ for all } i = 1, 2, \ldots, I \text{ and } t = 1, 2, \ldots, T. \tag{3.14}$$

The equality of (3.14), shows that generator i can not generate electricity while it undergoes maintenance.

3.2.2.3 Generation - start up relationship

$$y_{i,t}\text{sgn}(g_{i,t})[1-\text{sgn}(g_{i,t-1})]+[1-y_{i,t}][1-\text{sgn}(g_{i,t})][1-\text{sgn}(g_{i,t-1})]$$
$$+[1-y_{i,t}][1-\text{sgn}(g_{i,t})]\text{sgn}(g_{i,t-1})+[1-y_{i,t}]\text{sgn}(g_{i,t})\text{sgn}(g_{i,t-1})=1, \qquad (3.15)$$
$$\text{for all } t=2,\ \ldots,\ T,$$

where $\text{sgn}(g_{i,t})$ is the sign value of the generated output of generator i at time t. If $\text{sgn}(g_{i,t})=1$ then there is a generated output from generator i, otherwise $\text{sgn}(g_{i,t})=0$. The constraint in (3.15) gives the relationship between the start up of generator i and the output power generated from it at every period. Equation (3.15) shows that if the generator is producing electricity then it cannot be started at the same time. Equations (3.14)-(3.15) are new constraints that are added to the show the relationship among the variables of the GMS problem.

3.2.3 Maintenance Constraints

The maintenance constraints ensure that once a generator unit is removed from the system for maintenance, it completes the maintenance continuously without interruptions, within the planned horizon and utilises only the crew available for that time period.

3.2.3.1 Maintenance window

This constraint indicates the start of maintenance on the generator and the duration it will take for completion of the maintenance on that generator [6], [7], and [47].

$$\sum_{i=1}^{I} x_{i,t}=1;\ \text{for all } t=,\ 2,\ \ldots,\ T, \qquad (3.16)$$

$$\sum_{t=1}^{T} x_{i,t}=N_i;\ \text{for all } i=1,\ 2,\ \ldots,\ I, \qquad (3.17)$$

$$\sum_{t=1}^{T-N_i+1} x_{i,t}x_{i,t+1}\ldots x_{i,t+N_i-1} = 1,\ \text{for all } i = 1,\ 2,\ \ldots,\ I, \tag{3.18}$$

where N_i is the duration of maintenance on generator i.

The equality constraint in (3.16) means that once maintenance starts it will continue till completion without interruptions this constraint is used in [6]. In (3.17) for every generator i maintenance will take a duration of N_i periods this constraint is used in [7], [47]. Equation (3.18) gives the specify duration for each stage of maintenance, from start to finish, without interruptions for all the generators. This constraint is new and is added to the model to specify the duration of maintenance for every generator.

3.2.3.2 Crew availability

The crew availability means that the number of crew needed to maintain a generator at any period in time should be less than or equal to the available number of crew at that time [1], [9], [48], and [26]. A modification to the existing constraint is given below.

$$\begin{aligned}
&\textstyle\sum_{i=1}^{I}(1-x_{i,t-1})x_{i,t}M_i^1 \le A_t,\\
&\textstyle\sum_{i=1}^{I}(1-x_{i,t-1})x_{i,t}x_{i,t+1}M_i^2 \le A_{t+1},\\
&\quad\vdots \qquad\qquad \vdots \qquad\qquad \vdots,\\
&\textstyle\sum_{i=1}^{I}(1-x_{i,t-1})x_{i,t}\ldots x_{i,t+N_i-1}M_i^q \le A_{t+N_i-1},\\
&\text{for all } t = 2,\ \ldots,\ T,
\end{aligned} \tag{3.19}$$

where M_i^q is the number of crew needed for the q-th stage of maintenance of each generator, $q = 1,\ 2,\ \ldots,\ N_i$, A_t is the available number of crew at every time t.

3.2.4 System Constraints

In any power plant, there is a desire that the demand must be supplied under an adequate reliability level, without exceeding the power limit imposed on the generator.

The system constraints are conditions imposed on the system that must be satisfied in order to accomplish this desire.

3.2.4.1 Demand constraint

The amount of output power that a generator produces at any period of time should be equal to the demand required at that time [1]-[12], [26], [49]-[51].

$$\sum_{i=1}^{I} g_{i,t} = D_t; \text{ for all } t = 1,\ 2,\ \ldots,\ T, \tag{3.20}$$

where D_t is demand per time period.

3.2.4.2 Reserve constraint

A sufficient reserve is required from generator i at time t to maintain the system reliability [6], [7]. This constraint is needed for two reasons: in the case of an unexpected outage of a generator and in cases where the actual peak load is higher than the forecast [52].

$$\sum_{i=1}^{I} g_{i,t}^{max} \geq D_t + S_t, \text{ for all } t = 1,\ 2,\ \ldots,\ T, \tag{3.21}$$

where S_t is the reserve per time period.

3.2.4.3 Generated power limit

This constraint is a safety margin for the generator to preserve the generator life [26].

$$\begin{gathered} g_i^{min}(1 - x_{i,t}) \leq g_{i,t} \leq g_i^{max}(1 - x_{i,t}), \text{ for all } i = 1,\ 2,\ \ldots,\ I, \\ \text{and } t = 1,\ 2,\ \ldots,\ T. \end{gathered} \tag{3.22}$$

where g_i^{min} and g_i^{max} are the minimum and maximum output electric power for each generator respectively.

3.2.4.4 Ramp rate constraint

The ramp rate for generator i must be satisfied as generated output changes from time t to $t+1$. The ramp rate constraint is a new constraint added to the GMS model to ensure that the ramp rates of the generators are not violated when considering maintenance and general operations of the power plant.

$$-LR \leq g_{i,t+1} - g_{i,t} \leq UR, \text{ for all } t = 1,\ 2,\ \ldots,\ T-1, \tag{3.23}$$

where LR and UR are the maximum down and up ramp rate respectively.

3.2.5 Transforming the open loop MGMS to closed loop MGMS using MPC

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

The closed loop MGMS approach is defined with the same state model as the open loop model in (3.12). Thus, the open loop GMS problem is transformed to a closed loop problem as below. Given, $I,\ T,\ DR,\ UR,\ D_t,\ R_t$, let $x_{i,t} := x_{i,m+t},\ y_{i,t} := y_{i,m+t},\ g_{i,t} := g_{i,m+t},\ D_t = D_{m+t},\ 1 \leq t \leq T-1$,

$$\text{Min } J = \textstyle\sum_{i=1}^{I} \sum_{t=m+1}^{m+T} c_i x_{i,t} + \sum_{i=1}^{I} \sum_{t=m+1}^{m+T} (f_i y_{i,t} + k_i g_{i,t}), \tag{3.24}$$

The constraints for closed loop are the same as those of the open loop GMS model in (3.13)-(3.23), the only difference is that the constraints for the closed loop GMS problem 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 [45]. The advantages of MPC in GMS problems include:

Reduced dimension: Consider a power plant with 100 generators, maintenance period of 52 weeks, and sampling period of week with maintenance, start up and generated output variables for each generator. The open loop GMS algorithm must solve an optimisation problem of 100 x 52 x 3 = 15600 variables. However, each iteration step of MPC algorithm, starts with an initial input, that is the optimal solution of the previous iteration, and solves an optimisation problem of 100 x (52 - 1) x 3 = 15300 variables which reduces the dimension by 300 [46].

Robustness and simplified model: The MPC controller has traits that detect disturbances and make corrections automatically [45], [46].

Easy implementation: when the constraints are satisfied in the first sampling period, the optimal solution at each step will converge to the optimal solution of the GMS problem. This implies that, the GMS problem can be restarted at anywhere even after interruptions while the open loop algorithm can not [46].

The closed loop problem is solved using the steps below.

Step 1: Input all the initial parameters, input the maximum number of switching intervals M and let $m = 1$.

Step 2: Compute the open loop PSO optimal solution over $(m, m + T)$ to the GMS problem in (3.24).

Step 3: Apply the optimal solution to the plant in the sampling interval $(m, m + 1T)$ the remaining solutions are discarded.

Step 4: Let $m = m + 1$ and go to *Step 2*.

3.3 VALIDATION OF THE PROPOSED GMS MODEL

The open loop and closed loop model are solved with particle swarm optimisation (PSO) algorithm. This optimisation technique is explained in Chapter 4. The generic open loop and closed loop MGMS models are validated in Chapter 5 where these models are applied to the Arnot power plant, South Africa. Both the applied open loop and closed loop models are then simulated and compared with each other. The results show that the applied closed loop model reduces operational cost more than the open loop model within all the constraints of the model. The results also show that the MGMS model satisfies all the constraints even with external disturbances.

CHAPTER 4

APPLICATION OF THE GMS MODEL TO CASE STUDIES

This chapter describes the two selected case studies. The generic GMS model from Chapter 3 is applied to both studies.

4.1 21-UNIT TEST SYSTEM

The case study is a test system comprising of 21 generators over a planning period of 52 weeks, this case study is obtained from the example in [1], [4], [5], [25]. During this period, all 21 generators need to undergo maintenance. Data for the 21-unit test system is given in Table 4.1.

Each generator is allowed to start maintenance anywhere within a 26 week period. As shown in Table 4.1, generators are allowed to start maintenance either between weeks 1 and 26 or between weeks 27 and 52. The number of generators considered for maintenance I_t are generators 1 to 13 for weeks 1 to 26 and generators 14 to 21 for weeks 26 to 52. The earliest e_i and latest l_i periods for maintenance on generators 1 to 13 are weeks 1 and 26 respectively and the earliest e_i and latest l_i periods for maintenance on generators 14 to 21 are weeks 27 and 52 respectively. To ensure that similar schedules are compared, all generators are required to complete their maintenance by week 52. This requires that each generator being maintained in the second half of the year to start their maintenance before week $52 - N_i$, where N_i is the duration of the maintenance on generator i, $i = 1, 2, \ldots, I$. Thirteen generators begin their maintenance in the first half of the year; the remaining eight generators begin their maintenance in the second half of the year. The maximum generated output for all the generators $\sum_{i=1}^{I} g_{i,t}$ in each week is given to be 5688MW/week.

In real world terms, the objective value which is the minimum sum of squares of reserve (SSR) measures the reliability of the power system. The lower the values of the SSR, the more uniformly distributed, and the higher the reliability [1]. The maintenance outages for the generators in Table 4.1 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 [4], [5], [25].

2. Crew constraint: the available crew A_t is 20 for every week [1], [4], [5]. A solution with a high reliability that is a low SSR but requiring some extra crew is acceptable in a power plant. The flexibility for the crew constraints is given that 5% of total available man-weeks (TMW) which is 695 can be hired [5].

3. Load constraint: the system's peak load D_t is 4739MW/week is used as the flat load for the test problem [1], [4], [5].

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 peal load which is 4739MW and the capacity given in Table 4.1 respectively. These limits are fixed to illustrate the usefulness of the generator limit constraint. In practise the minimum and maximum generator limits are always percentages of the installed capacity of the generator.

In this case study the unit commitment of the generators is not considered hence, (3.11) is not used. It is assumed that no generator is shut down due to unit commitment or a forced outage.

In order to combat the violation of the crew constraint, the GMS model in [25] increased the number of available crew to 40 and added an extra 6.5% spinning reserve to the peak load. This adjustment to the case study ensured that the crew, load and maintenance window were not violated. And as such a lower SSR is achieved and the TMW is not considered.

The case study considered is to illustrate the robustness and feasibility of the GMS model in Chapter 3 when compared to the GMS model in [5]. The simulations and results are given and explained in Chapter 5.

4.2 ARNOT POWER PLANT OVERVIEW

Arnot power plant is located approximately 50km east of Middelburg in Mpumalanga, South Africa. The plant consists of 6-thermal power generating units. Maintenance is also done on three major sections of the plant. The seal oil section system, gas control plant and main generator assembly [53]. For this dissertation, the maintenance scheduling is focused on the main generator assembly. The constraints associated with this power plant are:

1. The number of maintenance crew M_i^q used for maintenance each week must be less than or equal to the crew available A_t that week.

2. Once maintenance starts on a generator it cannot be interrupted until the maintenance is complete.

3. The total maximum generated output must be greater than or equal to the summation of the total demand and spinning reserve for the power system.

Table 4.1: Data for the 21-unit test system

Unit	Capacity(MW) / g_i^{max}	g_i^{min}	Allowed period	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	5688	4739			

The operation cost of a power plant is broadly divided into three, the maintenance cost, start up cost, and production cost. The production cost can be derived from the sum of squares of the fuel cost with equation (4.1)

$$k_i g_{i,t} = 168(a_i + b_i g_{i,t} + c_i g_{i,t}^2) \tag{4.1}$$

The maintenance cost is fixed at R 100,000 for each generator and the start up cost is fixed at R 4,000,000 for the purpose of this study.

4.2.1 Assumptions for the MGMS Model

1. The system and transmission losses are neglected.
2. The system's spinning reserve is 6.5% of the peak generated power.
3. All the generators are on the same priority level.
4. The maintenance schedule is done for the duration of one year, i.e. $T = 52$ weeks
5. The duration of maintenance N_i for each generator is 6 weeks.
6. Preventive maintenance must be done on each system at least once every 52 weeks without interruptions.
7. The available maintenance crew members A_t for each week is 15.

Table 4.2: Capacity ratings for 6-generators of Arnot power plant

Gen	g^{min}	g^{max}	$a_i(R/h)$	$b_i(R/MWh)$	$c_i(R/MW^2h)$	LR	UR
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

4.2.2 The open loop MGMS Model with PSO

The generic open loop model in (3.2) applies to the Arnot power plant case study. The generators have identical capacity rates. The ratings are shown in Table 4.2 above. The constraints for the power plants are already included in the generic GMS model therefore, modifications to the constraints of the model are not necessary. The objective function in (3.12) consists of three variables, the maintenance on/off variable $x_{i,t}$, the start up on/off variable $y_{i,t}$ and the generated output variable $g_{i,t}$. $x_{i,t}$ and $y_{i,t}$ are binary variables while $g_{i,t}$ is a continuous variable. The constraints in (3.13)-(3.23) are inequality and equality constraints which have some non-linear properties. Thus the proposed GMS model is a mixed integer non linear optimisation problem. The problem is solved with a penalty function mixed integer PSO.

4.3 PARTICLE SWARM OPTIMISATION

The particle swarm optimisation (PSO) is a population based search algorithm based on the simulation of the social behaviour of birds within a flock. In PSO, individuals, referred to as particles, are 'flown' through multidimensional search space [36], [37]. The PSO basic principle is based on the idea that each solution can be represented as a particle in a swarm and each particle has a position of the particle and a velocity vector [38].

Changes to the position of the particle within the search space are based on the social - psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influence by experience or knowledge of its neighbours [36]. The best information *p-best* possessed by particles and the optimal value *g-best* of the group are used to find the global optimal or quasi-optimal solutions, to multi-modal functions with continuous variables, taking account of the previous iteration.

4.3.1 Updating position and velocity

The PSO algorithm defines d particles. Each particle corresponds to a possible position x. These d particles are evaluated with an initial value. At the first loop $k = 0$, each particle d with position x_d^k is moved with the velocity v_d^k to the next position x_d^{k+1}. The detailed formula to define x_d^k and the updating rule of the positions and velocities are given below:

$$x_d^{k+1} = x_d^k + v_d^{k+1}, \tag{4.2}$$

$$v_d^{k+1} = wv_d^k + c_1r_1(P_d(k) - x_d^k) + c_2r_2(P_g - x_d^k), \tag{4.3}$$

where c_1, c_2 are positive acceleration constants used to scale the contribution of the individual and social components respectively, r_1 and r_2 are random numbers on the interval [0,1], w is the inertia term, $P_d(k)$ is the best solution *p-best* achieved by the particle d till the k-th iteration, P_g represents the best position *g-best* among $P_d(k)$ until now. Because P_g is selected among $P_d(k)$, P_g is not updated until the better $P_d(k)$ appears. As a result, it is expected that the (local) search ability will be enhanced, and fast convergence will be expected.
The position acceleration constants c1 and c2 are recommended to keep the following relationship [37].

$$c_1 + c_2 \leq 4 \tag{4.4}$$

In this project $c_1 = c_2 = 2$ is used.

The inertia term, w often decreases linearly from 0.9 to 0.4 during each iteration [36]-[39], [48]. Its values are set according to the equation below.

$$w = w_{max} - \frac{k(w_{max} - w_{min})}{k_{max}}, \tag{4.5}$$

where w_{max} and w_{min} is the maximum and minimum values of inertia term respectively and k_{max} is the maximum number of iterations. From researched studies 0.9 and 0.4 are used as the w_{max} and w_{min} respectively.

The original PSO algorithm [37] is applicable to the problems that are continuous with no constraints. The GMS problem in Section 3 is a non linear mixed integer constrained problem. The original PSO algorithm is revised to consider the discrete variables and constraints for the GMS problem using the penalty function approach as explained in [48] with a few modifications.

4.3.1.1 The penalty function method

There are several methods of handling constraints in optimisation problems; one of the methods is the penalty function method. The penalty function method is motivated by the idea to use unconstrained optimisation techniques to solve constrained problem. The general penalty method for optimisation problem is obtained by adding a penalty for infeasibility and forcing the solution to feasibility.

In general, a mixed integer non linear problem is described as follows

$$\text{Min} f(x), \tag{4.6}$$

subject to

$$x_i^L \leq x_i^c \leq x_i^U;\ i = 1,\ 2,\ \ldots,\ m, \tag{4.7}$$

$$g_u(x) \leq 0;\ u = 1,\ 2,\ \ldots,\ ncon, \tag{4.8}$$

$$h_p(x) = 0;\ p = 1,\ 2,\ \ldots,\ con, \tag{4.9}$$

where, x is the design variable which consist of binary x_i^b and continuous x_i^c variables, f is the objective function of variable x, x_i^L is the lower bound of continuous variable, x_i^c is the continuous variable, x_i^U is upper bound of continuous variable, m is the number of continuous variables, g_u is the inequality behavioural constraints, u is the index of the number of inequality constraints, $ncon$ is the number of inequality constraints, h_p is the equality behavioural constraints, p is the index of the number of equality constraints, con is the number of equality constraints.

The penalty function is to enable the binary variables x_i transform to continuous variables. The penalty function in [48] has been simplified to the equation below for binary variables.

$$\Phi(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} \frac{1}{2}\{\sin 2\pi(x_i - 0.25) + 1\} \tag{4.10}$$

where, Φ is the binary penalty function, $x_1,\ x_2,\ \ldots,\ x_n$ are the binary variables and n is the number of binary variables.

The augmented objective function incorporates the penalty function in (4.10) and behaviour constraints. Due to this transformation all variables can be treated as continuous variables. The mixed integer constrained problem transforms to minimisation of the unconstrained augmented objective function.

$$F(x) = f(x) + s\Phi(x) + r\sum_{u=1}^{ncon} max\,[0, g_u(x)] + r\sum_{p=1}^{con} |h_p(x)|, \tag{4.11}$$

subject to

$$x_i^L \leq x_i^c \leq x_i^U;\ i = 1,\ 2,\ \ldots,\ m, \tag{4.12}$$

where, F is the augmented objective function of variable x, f is the objective function of variable x, s is the penalty parameter which is determined by (4.13), $\Phi(x)$ is the binary penalty function determined by (4.10), r is the penalty parameter for the behaviour constraints it is usually a very large number in this case study 100000 is used.

$$s(k+1) = \begin{cases} s(k)e^{[1+\phi(P_g(k))]} & \text{, if } C_c > \varepsilon, \\ s(1) & \text{, if } C_c \leq \varepsilon, \end{cases} \tag{4.13}$$

where, k is the iteration indicator, $P_g(k)$ is the best solution for the k-th iteration, $s(1)$ is the initial penalty parameter which is given by (4.15), C_c is the convergence equation which is computed by (4.16), ε is small positive number.

The initial position of particle d is chosen at random, the penalty parameter is calculated for every particle and the initial penalty parameter is determined from the equation below. The purpose of s is to add an additional cumulative penalties to the objective function, and thus enhance the ability of the algorithm to push the variable toward the nearest whole number value.

$$s_d = 1 + \Phi(x_d);\quad d = 1,\ 2,\ \ldots,\ D, \tag{4.14}$$

where s_d is the penalty parameter for the d-th particle. The initial penalty parameter $s(1)$ is set to the smallest value among the s_d.

$$s(1) = min\{s_1,\ s_2,\ \ldots,\ s_D\}. \tag{4.15}$$

This approach is intended to provide multimodality to the augmented objective function, and to generate extrema, optimal solutions, near the discrete values.

$$C_c = \frac{|F(P_g(k)) - f(P_g(k))|}{|F(P_g(k))|}. \tag{4.16}$$

The components of P_g^k can be expressed as follows:

$$P_g(k) = \begin{pmatrix} x^c \\ x^b \end{pmatrix} \tag{4.17}$$

where $x^c = (x_1, x_2, \ldots, x_m)^T$ and $x^b = (x_{m+1}, x_{m+2}, \ldots, x_{m+n})^T$. The components of the continuous variables x^c are neglected and only the components of the binary variables x^b are adopted when the convergence equation (4.16) is evaluated.

4.3.1.2 The PSO algorithm

The PSO algorithm for evaluating mixed integer optimisation problems is discussed below.

Step 1: Set the initial parameter,the number of particles d is set where $d = 1, 2, \ldots, D$, the maximum number of iterations k_{max}, the iteration counter $k = 1$. Also set the position x_d and velocity v_d at random for every particle, where the positions x_d are the variables $x_{i,t}$, $y_{i,t}$ and gi, t

Step 2: Calculate the penalty function in (4.10) for all binary variables and the initial penalty parameter s from (4.15) for every particle d.

Step 3: Evaluate the augmented objective function of the GMS problem from (4.11) for every particle.

Step 4: Determine P_d^k and P_g. Here P_d^k is the value of x of particle d that gives the minimum evaluated GMS result from initial iteration to the present iteration. P_g is the value of x that gives the minimum evaluated result in the whole swarm from initial iteration to the present iteration.

Step 5: Evaluate the convergence equation in (4.16). If (4.16) is less than or equal to ε, then a discrete valued is considered to exist near P_g and the penalty parameter is reset to the initial value $s(1)$, otherwise the penalty parameter is updated using (4.13).

Step 6: Update the position and velocity of every particle by (4.2) and (4.3) respectively. Calculate the inertia term in (4.3) by (4.5).

Step 7: Increase the iteration counter k to $k = k + 1$.

Step 8: Compare the iteration counter to the preset maximum number k_{max}. If $k \leq k_{max}$, then return the algorithm to *Step 6*. Otherwise output P_g as the optimal solution and terminate the search.

4.3.2 Advantage of proposed PSO method over the binary PSO

The binary PSO handles the discrete variables easily; however, the search process of binary PSO is stochastic [48]. The GMS problem is a mixed integer problem and as such the binary PSO can not handle the continuous variable in the GMS model. Therefore, the penalty function mixed integer PSO algorithm is the best fit for solving the GMS optimisation problem.

4.4 CLOSED LOOP MGMS WITH PENALTY FUNCTION PSO

The closed loop GMS model is defined with the same model as equation (3.24). The objective function is minimised subject to the constraints in equations (3.13)-(3.23) over the prediction horizon $[m, m + t]$, as described in section 3.2.5. This means that the closed loop model is not a simple optimisation problem, but a series of optimisation solutions with iterative implementations of obtained solutions.

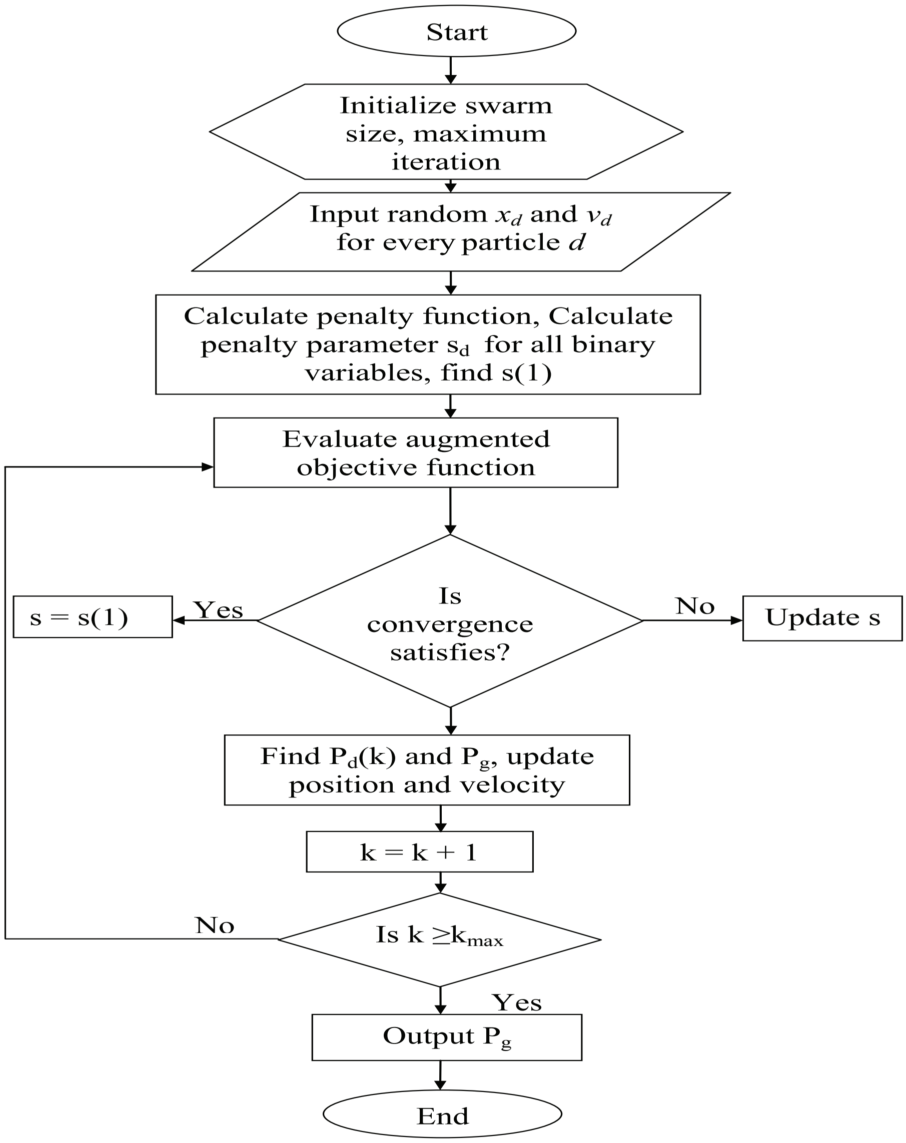


Figure 4.1: The flow chart of the penalty function PSO algorithm

4.5 CHOICE OF POPULATION SIZE AND NUMBER OF ITERATION

The particle size is chosen to be 30 and the maximum iteration 2500. These are chosen as a trade off between the computational time and cost saving. The effect of the particle size to the open loop GMS model is covered in Section 5.

4.6 CHOICE OF SWITCHING INTERVAL

The control interval is the smallest discrete time increment for the GMS problem. The control interval for the generated output $g_{i,t}$ is one hour, this is because the ramp rate for each generator is considered hourly. The switching interval for the maintenance variable $x_{i,t}$ is 1 week. The switching interval of 1 week is chosen instead of 1 hour because there is no preventive maintenance activity that can be carried out on a generator within 1 hour. This helps limit the number of variables and reduces the work load of the optimization algorithm, the switching also interval coincides with real life maintenance scheduling intervals.

4.7 CHOICE OF MAINTENANCE HORIZON

The maintenance control horizon is selected as 52 weeks for all of the simulations in Chapter 5. This time horizon is used for both the closed loop and open loop evaluations. There are no assumptions for the maintenance horizon since in real life cases all maintenance scheduling have 52 weeks maintenance scheduling planning horizon.

4.8 SOLVING THE PROBLEM WITH MATLAB

The open loop and closed loop GMS optimization problems are solved with the Matlab [54] environment. Matlab does not have any PSO programming function and as such, the mixed integer PSO program is written using the M-file. An M-file is created and edited in the Editor/Debugger Widow of the Matlab program.

PSO is a metaheuristic technique, it cannot necessarily guarantee that the solution is optimal but it gives a very good approximation of the true optimal solution. The algorithms written for the closed loop and open loop problems can be summarised from the flow charts in Figure 4.1.

The Matlab environment is summarised in Table 4.3.

Table 4.3: The Matlab simulation environment

Component	Description
Computer	Intel C2Q Top End System
Processor	Intel Core2, Quad CPU Q8200, 2.33Ghz
Random access memory	2GB
Operating system	Windows XP
Matlab version	Version 7.11.0.584 (R2010b)

CHAPTER 5

SIMULATION RESULTS OF THE APPLIED GMS MODEL

This chapter simulates and compares the GMS models that are defined in Chapter 3. The comparison includes the effect of the population sizes and maximum iteration is evaluated in Section 5.1 for the 21-unit test system. The proposed open loop MGMS model is compared with the classical GMS model in [5] in Section 5.2. The open loop and closed loop simulations of Arnot power plant MGMS is discussed in Section 5.3. The robustness of the GMS model is tested in Section 5.4. The practicality and disadvantages of the MGMS model is explained in Section 5.5.

5.1 EFFECT OF POPULATION SIZE AND NUMBER OF ITERATION

Choosing the population size determines the diversity and search space for each particle. More particles in the swarm provide a good uniform initialisation scheme but at the expense of the computational complexity, as a result the search degrades to a parallel random search. The number of iterations to reach a good solution is always problem dependent. In this section the MGMS problem in Chapter 3.1 applied to the test system in Chapter 4.1 is simulated with a different number of population sizes and iterations

Table 5.1: Effect of population size and number of iterations on the open loop GMS model

Iteration	Population size	Computational time (sec)	Objective function ($\times 10^5$MW)
1500	10	150	234
1500	20	312.9	223.9
1500	30	494	224.5
1500	40	351	212.2
2500	10	249	251
2500	20	528.4	123.4
2500	30	811	104.7
2500	40	1136.8	104.69
3500	10	347.4	151
3500	20	722.8	108.7
3500	30	1145.3	104.6
3500	40	1590	104.6

over the 52 weeks period. The effect of the different population sizes is shown in Table 5.1. Figures 5.1 and 5.1 show the graphical representation of the results in Table 5.1.

Table 5.1 shows that the model generates similar results for the population of 30 and 40 particles at the 2500 and 3500 iterations. The population size of 30 particles does not have an increased computational time as that of 40 particles population while it still generates the same results. Note the number of iteration is used as a stopping condition for the optimisation problems and as such the smaller the iteration value used to obtain the best results the better. As such the population size of 30 particles and 2500 iterations is chosen for both case studies. The chosen population size and iteration ensures that the search space is utilise to the fullest without putting a strain on the computation time and complexity. Figures 5.1 show the objective function values of four different population sizes for case study 1. The population sizes of 30 and 40 particles give the minimum values under each iteration. The computational time of all the population sizes considered is shown in Figures 5.1.

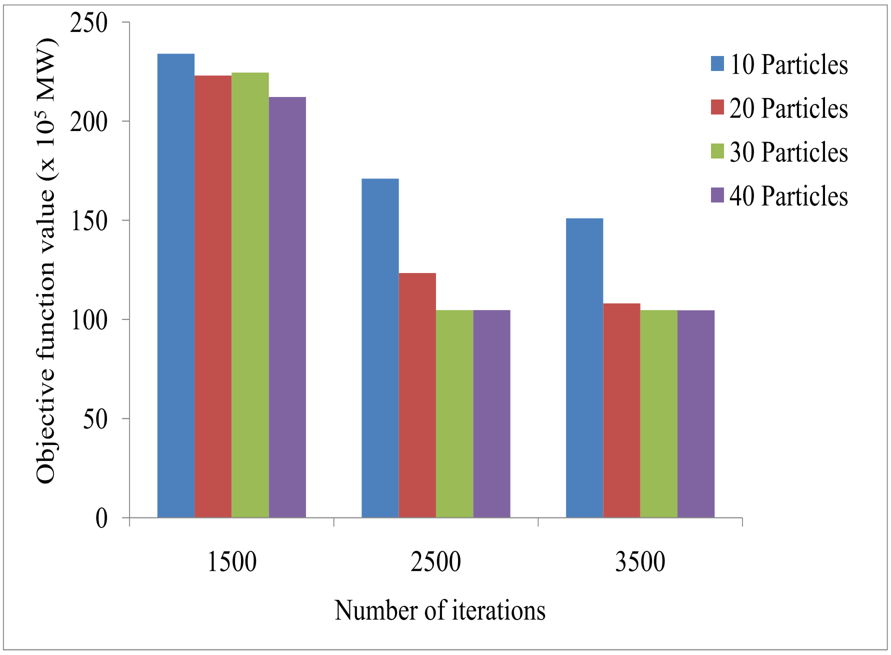


Figure 5.1: Case study 1 - Comparison of population sizes for objective function values

5.2 TEST SYSTEM - A COMPARISON OF TWO GMS MODELS

The maintenance scheduling for the test system in Chapter 3 is simulated over a 52 weeks period. The test system is simulated with the data defined in Table 4.1. The maintenance schedules for the modified GMS (MGMS) model, which is the formulated GMS model in Chapter 3 is compared with the classic GMS model in [5] is given in Table 5.2.

The MGMS problem is solved using the penalty function PSO algorithm explained in Chapter 4. A population size of 30 particles is chosen. The results obtained are compared to GMS results obtained in [5]. The MGMS model is simulated using the PSO algorithm with $c_1 = c_2 = 2$ and $w =$ decreasing linearly using the formulae in (4.5). The generator maintenance schedule obtained for the 21-unit case study is presented in Table 5.2. Table 5.2 shows that in week 1, generators 1 and 10 are on maintenance for the MGMS model and generators 3, 10, and 13 are on maintenance for the GMS model. A comparison is made between the MGMS and the GMS scheduling results and it can

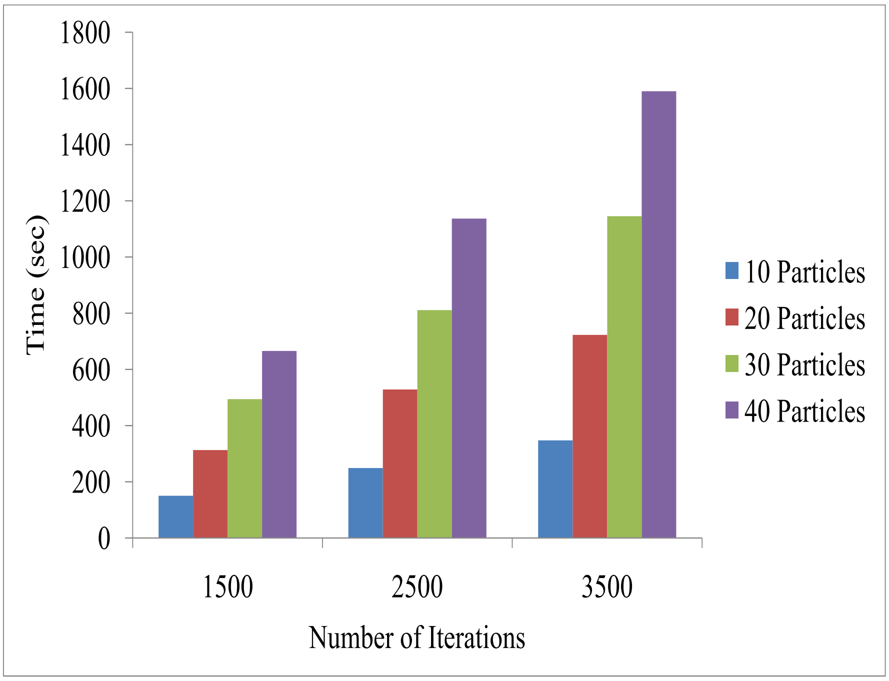


Figure 5.2: Case study 1 - Comparison of population sizes for computational time

be seen that the maintenance window constraints of (3.2) for the GMS model and (3.6) and (3.7) for the MGMS model are satisfied. All the generators are maintained just once during the planning horizon. Once maintenance on a generator begins it is not interrupted until the allocated duration N_i of maintenance for that generator.

Table 5.3 summarises the objective function that is the SSR and the violation of the TMW of the MGMS and GMS models. The maintenance schedules are given in Table 5.2. Figures 5.3(a) and 5.3(b) show the reserve margins for both models. The reserve margins are non negative because the load constraints of (3.4) and (3.9) are satisfied for both the GMS and the MGMS models respectively. The crew required for each week is given in Figures 5.4(a) and 5.4(b) for the MGMS and GMS respectively. The available generation for the MGMS is given in Figure 5.5.

As explained in Chapter 4, the power plant can hire 5% of TMW extra crew if the reliability is cost effective. The GMS has the 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

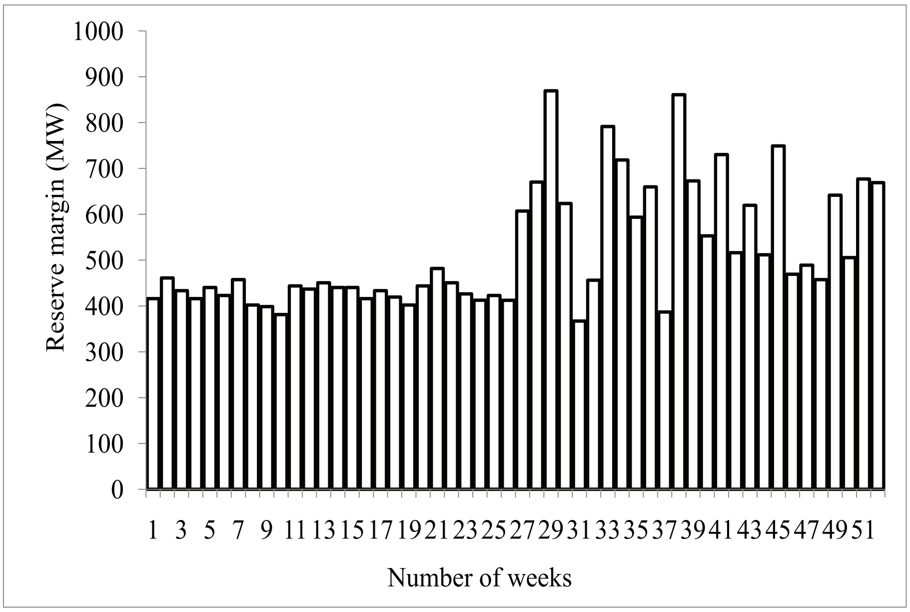
Table 5.2: Case study 1 - Maintenance schedules obtained by MGMS and GMS [5] for the case study

Week no.	Generator scheduled for maintenance		Week no.	Generator scheduled for maintenance	
	MGMS	GMS [5]		MGMS	GMS [5]
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

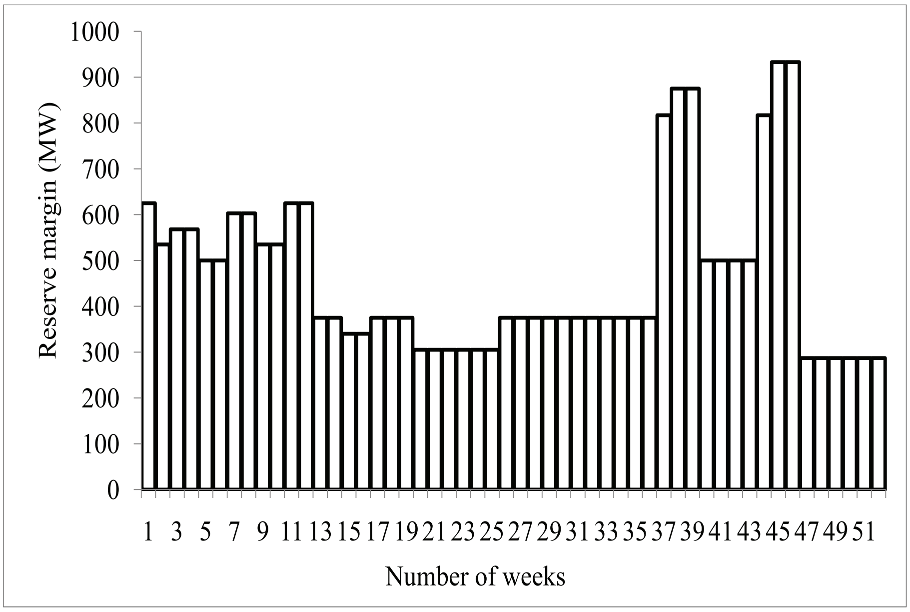
Table 5.3: Case study 1 - Solutions for the MGMS and GMS models

Evaluation solutions	MGMS	GMS
SSR ($\times 10^5$)	104.71	133.4
TMW	10	37

SSR of the GMS model as shown in Table 5.3. The trade off between the crew violation and higher reliability in the MGMS model is much better than that of the GMS



(a) MGMS reserve margin



(b) GMS reserve margin

Figure 5.3: Case study 1 - Reserve margin

model because the MGMS model requires a hired crew of 10 which is 27% less than the crew needed in the GMS model. Thus the MGMS model provides a better economic solution than the GMS model. The reason for the better solutions can be traced to the modification of the maintenance window (3.7) and the crew (3.8) constraints. The addition of the generator limits (3.9) ensures that the load constraint is never violated and thus reduces the SSR. Figure 5.5 is to illustrate the effectiveness of the generator limits constraint.

5.3 CASE STUDY 2 - ANORT POWER PLANT

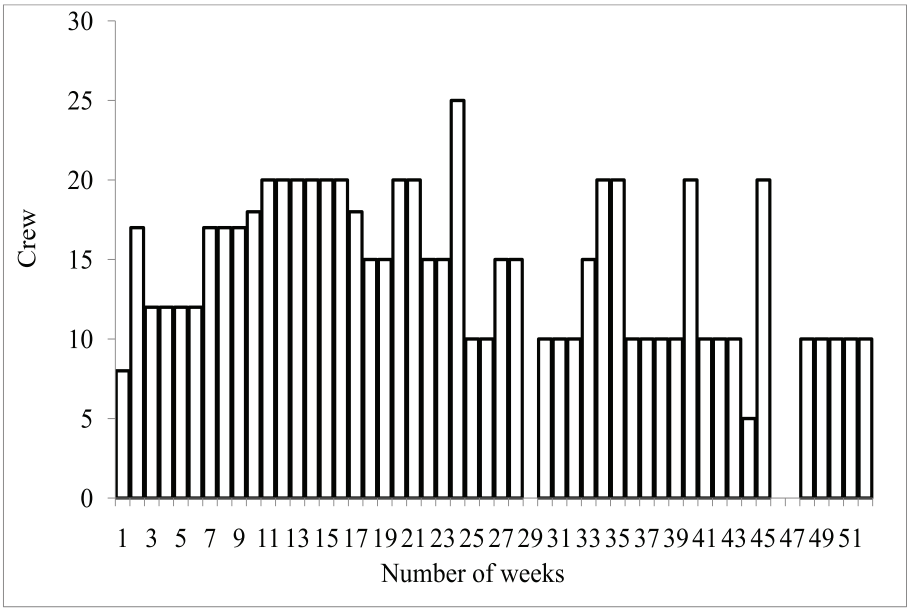
A population size of 30 particles and 2500 iterations are chosen to provide sufficient range for the population taking into account the dimensionality and complexity of the problem. The particle size ensures that the domain is examined but not at the expense of the execution time. The parameter settings are $c_1 = c_2 = 2$, w is obtained from (4.5). The open loop and closed loop results are compared to verify that the proposed closed loop approach to MGMS problems can be applied.

The closed loop model minimises the operation cost of the power system while satisfying all the constraints. In Table 5.4, it can be seen that the closed loop operation cost results are less than the open loop results while generating more electricity. Although both satisfy the demand constraint, the closed loop model satisfies the constraint at lesser cost. Table 5.4 gives the values of the objective function values of the closed loop and open loop MGMS models. Figure 5.6 shows the graphical representation of the objective function values of the closed loop and open loop GMS models.

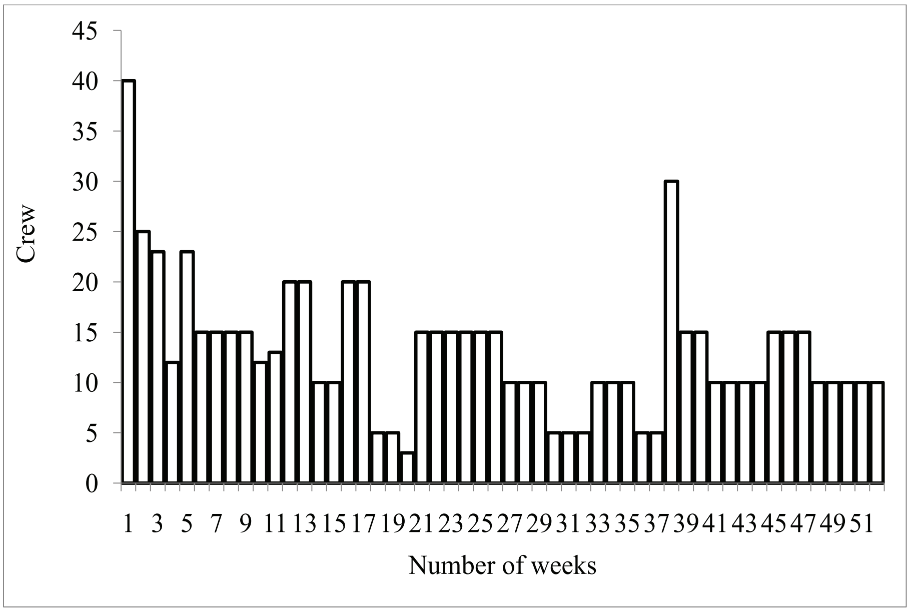
Table 5.4: Results for operation cost and electricity generation over 52 weeks

Attributes	Closed loop	Open loop
Operation cost (Rand)	7817300000	94981000000
Generated output (MW)	9965170	9426130
Reserve (MW)	3487809	3380154
Demand (MW)	4940000	4940000

Table 5.5 gives the maintenance schedule for the open loop and closed loop MGMS



(a) MGMS available crew



(b) GMS available crew

Figure 5.4: Case study 1 - Crew availability

problem for the Arnot power plant. The maintenance window constraints are satisfied for both problems and the optimal maintenance schedule is obtained for both problems. The model ensured that the condition that all the generators must be maintained at

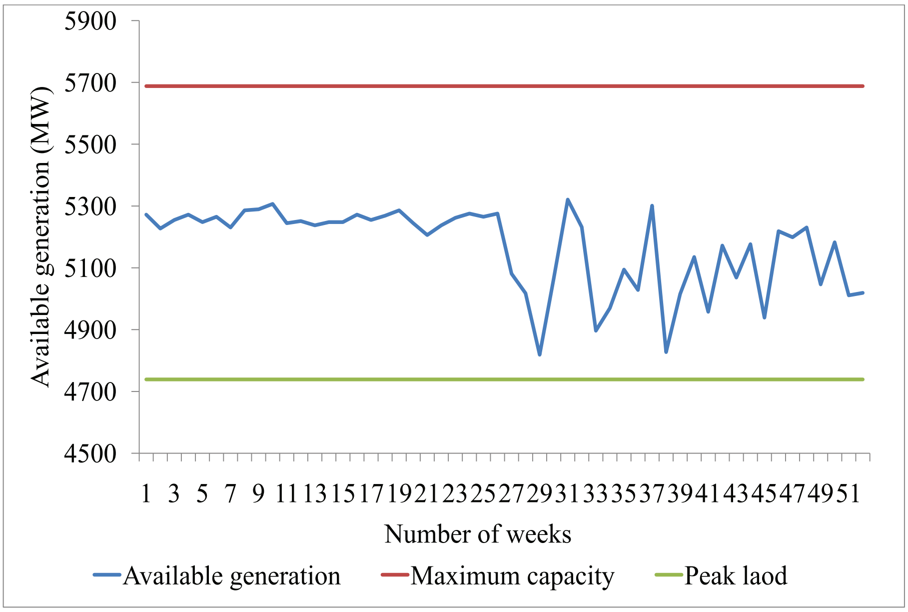


Figure 5.5: Case study 1 - MGMS available generation

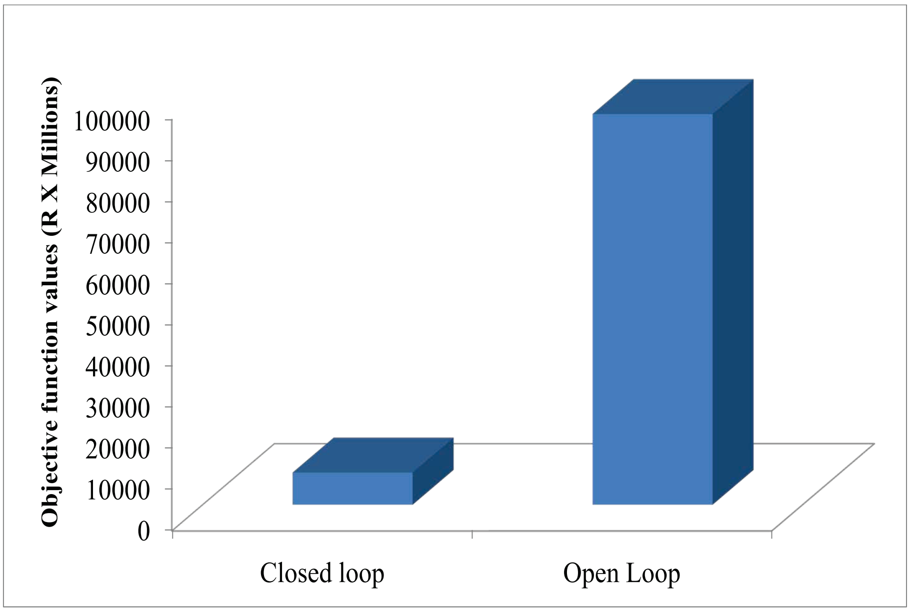


Figure 5.6: Case Study 2 - Objective function values of closed and open loop MGMS

least once within the planned horizon is also satisfied. Since there is no preference on any generator to be maintained at a particular time the model scheduled the generators that best satisfy all the constraints.

Table 5.5: Maintenance schedule obtained for the closed loop and open loop model

Week	Generator scheduled for maintenance		Week	Generator scheduled for maintenance	
	Closed loop	Open loop		Closed loop	Open loop
1	1	1	27	2	3
2	1	1	28	2	3
3	1	1	29	2	3
4	1	1	30	2	3
5	1	1	31	-	3
6	1	1	32	-	3
7	-	4	33	6	-
8	-	4	34	6	-
9	-	4	35	6	-
10	-	4	36	6	-
11	-	4	37	6	-
12	-	4	38	6	-
13	5	-	39	-	-
14	5	-	40	-	6
15	5	-	41	-	6
16	5	-	42	-	6
17	5	-	43	-	6
18	5	-	44	-	6
19	4	-	45	-	6
20	4	-	46	-	-
21	4	5	47	3	2
22	4	5	48	3	2
23	4	5	49	3	2
24	4	5	50	3	2
25	2	5	51	3	2
26	2	5	52	3	2

5.3.1 Open loop MGMS model

The open loop GMS model with penalty function PSO is simulated to get the benchmark for comparison with the closed loop GMS model that is proposed. The open loop MGMS model is simulated over a 52 weeks period. The total cost of operation is given in Table 4.1. The generated output for all the generators through out the 52 weeks period is given in Figure 5.7.

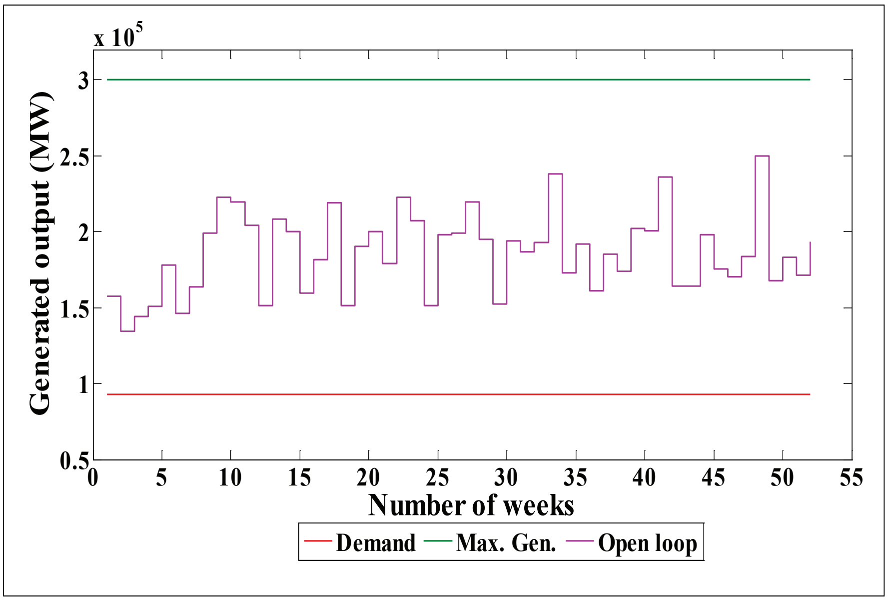


Figure 5.7: Case Study 2 - Open loop GMS model generated output

5.3.2 Closed loop MGMS model

The closed loop MGMS model with penalty function PSO is simulated over a 52 weeks period. Figure 5.8 gives a comparison of the closed loop model to the open loop model. The closed loop model is simulated for 7 iterations and the closed loop generated output is compared to the open loop generated output, the closed loop model converges with the open loop model at week 6. The advantage of the closed loop model is that it produces higher generated output than the open loop model and yet still schedules optimal maintenance through out the 52 weeks period.

Figure 5.9 gives a comparison of the reserves for both models. Table 5.4 and Figure 5.9 shows that the closed loop MGMS model has a higher reserve margin than the open loop MGMS model. The significance of this reserve margin is that the higher the reserve margin of a power plant the more reliable the plant is. Thus the proposed MGMS model considers both the economic and reliability effects when scheduling maintenance.

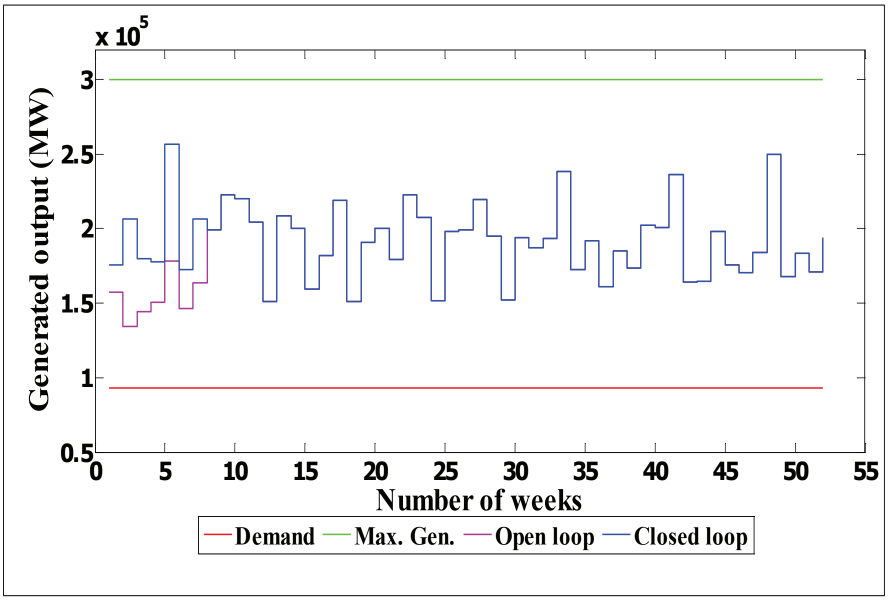


Figure 5.8: Case Study 2 - Closed loop MGMS model generated output

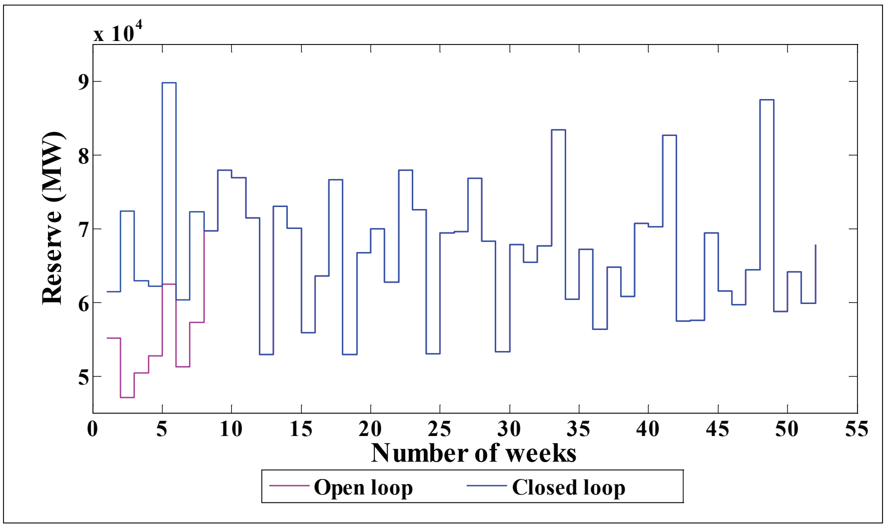


Figure 5.9: Case Study 2 - Reserves of open loop and closed loop GMS models

5.4 ROBUSTNESS OF THE MGMS MODEL

This section evaluates the robustness of the closed loop MGMS model against disturbances in the model. Figures 5.10(a) and 5.10(b) show the results of the open loop and closed loop MGMS models with a positive random disturbance on the generated output. That is,

$$D_t = 2r(n)D_t, \tag{5.1}$$

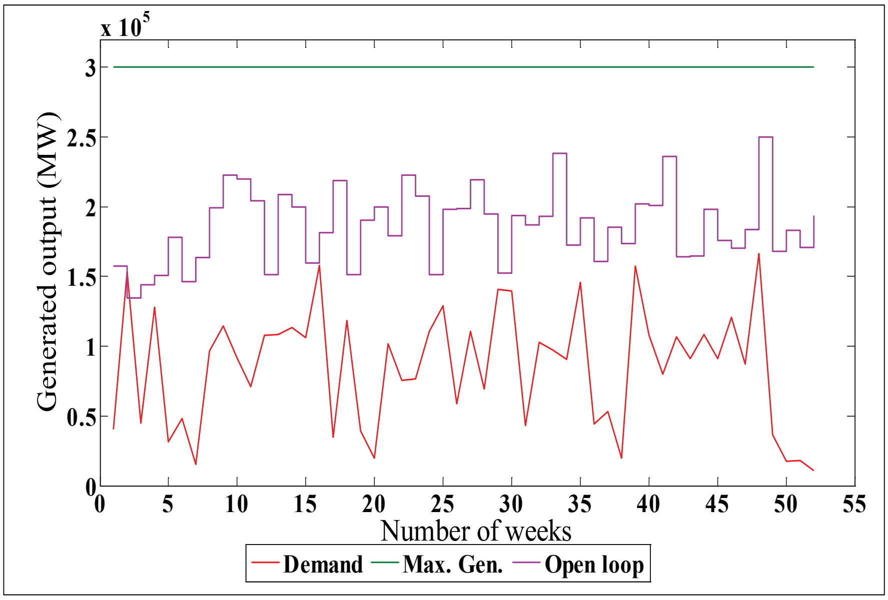
where $r(n)$ is a random number between 0 and 1. That means that the generated output is altered with random disturbances. This disturbance is applied to the entire 52 weeks planned horizon. Figure 5.10(a) and 5.10(b) show that the generated output $g_{i,t}$ does not exceed the generator limits and the peak demand is met for the open loop and closed loop MGMS model 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 model can still generate optimal schedules for the maintenance of the generators in the power system.

5.5 PRACTICALITY OF THE MGMS MODEL

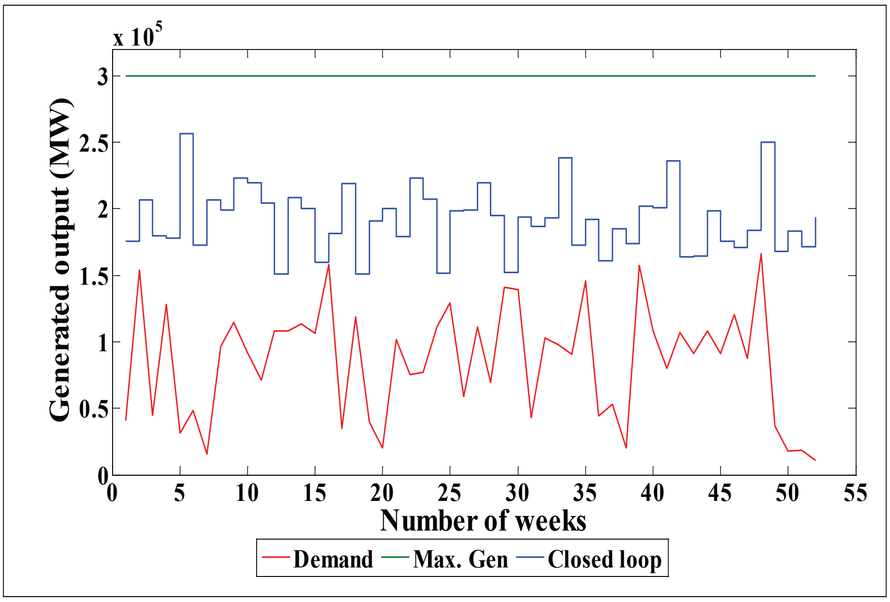
The main problem with the practicality of the MGMS model is the large objective function values obtained from the simulations. For the reliability criterion the values of the objective function are not as important as the generated output power. Thus, this is not a major problem when scheduling maintenance. For the economic cost criterion, the objective function which is to minimise the operational cost, the high objective values do not help achieve this goal.

The reason for the high objective function values for the economic cost criterion is because all the cost considered in the operation of the power plant. Models in [1]-[9], [11]-[4], do not consider the start up cost.

However, the MGMS model schedules optimal maintenance for power plants. As in the case of the test system, all the constraints are satisfied and the demand is met. In the case of the economic cost objective function for the Arnot power plant, there trade off between the high operational cost and high generated output which is not really significant.



(a) Open loop available generation with demand disturbance



(b) Close loop available generation with demand disturbance

Figure 5.10: Case study 2 - Available generation with demand disturbance

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

This dissertation investigates the missing constraints in generator maintenance scheduling (GMS) problems. A comparison is made between the modified GMS (MGMS) and the GMS model of [5]. The GMS model using the reliability objective function solved with the penalty function PSO is compared with the classical reliability objective function GMS model in [5]. The aim of this comparison is to test the effectiveness of the formulated GMS model with other classical GMS models that have been used in the existing literature.

Both models are applied to a case study of a 21-unit test system and the simulation results are compared. The results show that Both models obtain maintenance schedules for the case study which does not violate the maintenance window constraint. The MGMS model produces a more reliable solution than the GMS model, this better solution is due to the modification and addition of the maintenance window, crew and generator limit constraints to the model. The results of the MGMS model offer a feasible and practical solution that can be implemented in real time.

Due to the reliable results of the MGMS, a MGMS model is formulated using the economic cost objective function with some modified and additional constraints. The model incorporates constraints that have been used in some existing literature with new constraints that ensures that the MGMS model is robust. The new constraints added include, the relationship, the generator limit and the ramp rate constraints. The maintenance window and the crew constraints are modified to output better results.

The economic objective function MGMS model formulated in Chapter 3 is solved using the penalty function PSO algorithm. The formulated economic cost objective function MGMS model is used to schedule maintenance for the Arnot power plant, South Africa.

The simulations of the case study focuses on minimising the operation cost of the plant while scheduling maintenance for the maintenance horizon of 52 weeks. The closed loop and open loop of the formulated GMS problem are simulated and compared. The simulation results show that both the closed loop and open loop MGMS models satisfy the constraints imposed on the model. The closed loop model simulations produce better results than the open loop MGMS model.

The effect of disturbances on the economic cost objective function MGMS model is simulated for the open loop and closed loop PSO models. The results shows that the MGMS model compensates for the disturbances and is still able to produce optimal solutions. This shows that the MGMS model is robust and can adjust to disturbances and produce optimal solutions.

The contribution of this research in the context of existing work are also discussed. In summary the contributions are:

- the background that led to formulating a new MGMS model is explained,
- the comparison of two GMS models is carried out,
- the formulation of a new economic cost objective function MGMS model is done,

- the effectiveness of the penalty function mixed integer PSO algorithm is shown,
- the effect of number of particle size and iterations on simulated results is discussed,
- the application of closed loop to generator maintenance scheduling using an MPC approach is affirmed,
- the robustness of the MGMS model is demonstrated.

It is recommended that further research should be conducted on closed loop GMS problems. The closed loop approach to GMS problems should be applied in real plant scenario to identify the real-time challenges of implementation such as the physical limitations of the generators. The GMS problem should be expanded to include network and transmission maintenance using the MPC approach. It is also recommended that the generator limit and rate of ageing for each generator is investigated to consider the unit commitment of the power plant.

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