FUMP SCHEDULING OPPINIZATION FOR LEGIRICAL FREESY CONSUMPTION AND RELIABILITY LEVEL OF WATER SUPPLY SYSTEM

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# PUMP SCHEDULING OPTIMIZATION FOR ELECTRICAL ENERGY CONSUMPTION AND RELIABILITY LEVEL OF WATER SUPPLY SYSTEM

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A project report submitted in partial fulfilment of the requirements for the award of the degree of

Master of Engineering (Electrical-Mechatronics & Automation Control)

Faculty of Electrical Engineering Universiti Teknologi Malaysia I declare that this project report entitled "Pump Scheduling Optimization for Electrical Energy Consumption and Reliability Level of Water Supply System" is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Specially dedicated to

my beloved parents and wife for their support and caring

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#### **ABSTRACT**

Pump scheduling and optimization are very essential and important to the operation management of the water supply system in order to reduce high operational cost. Scope of this study is limited to only the water supply part and distribution system. This study will consider fixed pumps and use approximated model in order to reduce its complexity. The inputs for the optimization process include the average of data demand profile, the pump technical characteristic, the electric tariff and reservoir parameters. Adaptive Weight Genetic Algorithm (AWGA) is used as an optimization search engine. The process started with initialization, fitness evaluation, selection, crossover and mutation. Elitism is also included during the process to ensure that some of the best individuals are retained in each generation. Six tests have been conducted and the optimal result that produces the least electric energy cost with percentage difference index (PDI) is 37.97%. The tolerance for six tests is about ± 3%.

#### **ABSTRAK**

Penjadualan pam adalah sangat penting dalam pengurusan sistem bekalan air bagi menggurangkan kos pengoperasian yang tinggi. Skop kajian hanya terhad kepada sistem penyaluran dan pengagihan air. Kajian ini hanya akan mempertimbangkan pam tetap dan model anggaran digunakan supaya kerumitan dapat dikurangkan. Input untuk proses pengoptimuman ini termasuk purata isipadu penggunaan air, spesifikasi teknikal pam, tarif elektrik dan juga parameter tangki air. Adaptasi Jumlah Wajaran Algoritma Genetik (AWGA) digunakan dalam enjin carian pengoptimuman. Proses ini bermula dengan pengawalan, kecergasan penilaian, pemilihan, persilangan dan mutasi. Elitisme juga dimasukkan dalam proses pengoptimuman untuk memastikan individu terbaik dapat dikekalkan dalam setiap generasi. Enam ujian telah dijalankan dan hasil yang optimum bagi penghasilan penggunaan tenaga elektrik yang paling kurang dengan indek perbezaan peratus (PDI) adalah 37.97%. Toleransi bagi enam ujian adalah ±3%.

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#### LIST OF ABBREVIATIONS

GA - Genetic Algorithm

EA - Evolutionary Algorithm

AWGA - Adaptive Weighted Genetic Algorithm

MOEA - Multi Objective Evolutionary Algorithm

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#### **CHAPTER 1**

#### INTRODUCTION

#### 1.1 Introduction

Water distribution systems play an important role in an urban infrastructure. As water demand increases, the system becomes more complex. Water distribution system is a network of pipelines between the treatment plant, storage tank and end users. The designs of this system not only to satisfy the consumer demand but also to operate at certain performance level to meets its operational objectives and to overcome various constraints.

The conventional water supply system is equipped with numerous energy consuming components and the set of hydraulic pumps. These pumps either have same sizes or otherwise depending on location or station to convey water from various resources to users within the station. While doing this, hydraulic and technical constraints such as maximum level in the reservoir and pump power must be fulfilled. The most energy consumed is due to pumping water process.

There is a need for the optimization of the pump scheduling operation in order to reduce the energy consumption associated with the system. Optimizing the pump scheduling has proven to be a practical and highly effective method to reduce operation costs without making changes to the actual infrastructure of the whole system. There are many types of optimal control model have been developed to optimize the water supply system operation such as to minimize the cost of electric

energy, maintenance cost, maximum peak, environment protection. Techniques such as linear, non-linear, integer, dynamic, mixed, and other kinds of programming have been applied to various model types of the water system (Benjamin Baran, *et al.* 2005).

The scheduling pumps operation operates by choosing the right combination of pumps that will be working at each time interval of a scheduling period. Then, a pump schedule is the set of all pump combinations chosen for every time interval of this scheduling horizon. An optimal pump schedule can optimize the objective functions, while fulfilling system constraints.

#### 1.2 Problem Statement

The pumps play important roles in order to satisfy water demand requirement and referring (Curic Vladimir, et al. 2010) its mention that the total budgets depend on pumping process. According previous research, pumps operate based on switched on and off at a difference instances. Operation of pumps resulting in varying amount of energy consumed. In most electricity supply system (Benjamin Baran, et al. 2010) electric energy tariff is not the same throughout the whole day but pumps in existing system operates based on water demand requirement and definitely not influenced by time and electrical tariff.

Thus, in order to make the system more economical, there are needs to minimize the electric energy cost and at the same time it should be able to satisfy water demand. To achieve this objective, the operation of the pumps needed to be scheduled to allow pumps to operate at the right time and able to meet the demands.

#### 1.3 Objectives

The objectives of this study are:-

- To simulate pump scheduling of water distribution system with several constraints parameters and objective functions
- To minimize electrical energy consumption of pump scheduling optimization problem using Genetic Algorithm.

# 1.4 Significance of study

Pump schedule optimization is very important to the operation and management of the water supply system. It helps to minimize electric energy cost 34.97% on a daily basis without changing the structure of the existing system and also be able to meet the demand requirement.

# 1.5 Scope and limitation

Pump schedule optimization is a complex system and involve many considerations and constraints. In order to obtain an optimal model these assumptions will be put into consideration.

- i. The scope of this study limited to only the water supply part.
- ii. This study will only consider fixed pumps with well defined parameters based on actual specification.
- The system is assumed to satisfy demanded requirements.
- iv. The system model is approximated to reduce its complexity.

v. The inputs for the optimization included demand profile, the pumps technical characteristic and the electric tariff plan and elevated reservoir parameters.

# 1.6 Report Outline

Chapter 1 presents the overview of the study, problem statement, objective significance of study and scope and limitation. The overview of study presents the importance of water distribution system in an urban infrastructure, the instruments involved in order to satisfy water demand requirement and also explanation section of the system where it contributes the highest cost of operation.

Chapter 2 describes the water supply system and distribution system in general terms. Pump scheduling problem and constraints are discussed. In addition, the recent literature on the approach is reviewed. The types of hydraulic pump model and also optimization method Genetic Algorithm (GA) are included.

Chapter 3 discusses the modeling of water supply system, objective function and constraint parameter for study area. A brief explanation implementation on Adaptive Weight Genetic Algorithm (AWGA) as an optimization method for pump schedule process is provided.

Chapter 4 discusses and analyses the results obtained in terms of parameter AWGA such as generation, population, mutation rate (Pr) and crossover rate (Pc) also the electric energy cost after optimization process.

Chapter 5 concludes and summarizes the result obtained. The suggestion for future work for this study has been proposed.

#### **CHAPTER 2**

# LITERATURE REVIEW

#### 2.1 Introduction

This chapter is divided into four sections. The first section presents the overview of the water supply system, its components and function. The second part discusses pump scheduling problem of the water supply system, suitable operation time and type of constraint was explained.

The third part is the review of previous approach in term of optimizations method, types of hydraulic network models, demand forecast model and types of optimization algorithm. The last section describes Genetic Algorithm basis, process of operation and application in details.

# 2.2 Description of the Water Supply System and Distribution System

This section describes the water supply system and also included the components and their basic function in the system. Typically water supply system is divided into two main subsystems namely the supply system and distribution system. Briefly explanation is included in the next section.

#### 2.2.1 The Water Supply System

Water supply systems come from a water treatment facility to residential consumer for use as drinking water, water for cooking, water for sanitary conditions and other water uses in a domestic environment. The two primary requirements needed in water supply system are:

- i. Its needs to deliver adequate amount of water to meet consumer consumption requirements plus needed fire flow requirements
- ii. The water supply system needs to be reliable meaning that the required amount of water needs to be available 24 hours a day.

Reservoirs supply water to a treatment plant that processes the water to remove impurities and adds chemicals to bring the water into compliance with the standard regulations on clean water for drinking and commercial cooking. The purified water, or finished water, then is pumped to several different storage tanks and storage basins around the supply area for release into the distribution system piping network on demand for consumer use or in the case of a working fire. Depending on the different elevations points throughout the supply area, additional pumping stations are provided to maintain adequate pressure in the water system during varying periods of consumer use or emergency water supply demand requirements. Water flows from the storage locations through the primary, secondary, and distributor mains to supply service lines to individual water consumers (Harry E. Hickey, 2008).

#### 2.2.2 The Water Distribution system

The distribution pumping station and the storage perform similar functions as those of the water supply system. The only difference is that they are located in the distribution part and they serve as supplementary facilities to the aid the supply subsystem in cases of inadequacies. According to (Harry E. Hickey, 2008) mention that

there are many ways to distribute water which depends on local conditions or on regulations and requirement that influence water supply design. The command methods of water distribution to the pipe network are reviewed under the following:

- i. Gravity distribution: This is possible when the treated water source is a retention pond, clear well, or storage tank at some needed elevation above the community. In this type of system, sufficient pressure is available due to gravity to maintain water pressure in the mains for domestic consumption and fire service demand. This is the most reliable method of distribution if the piping leading from the treated water source to the community is adequate in size and safeguarded against accidental breaks.
- ii. Pump and elevated storage: Through the use of pumps and elevated storage, the excess water pumped during periods of low consumption is stored in elevated tanks or reservoirs. During periods of high consumption, the stored water supplements the water that is being pumped. This method allows fairly uniform flow rates and pressures throughout the water system. Consequently, this method generally is economical because the pumps may be operated at their rated capacity.
- iii. Pumps without storage: When stationary pumps are used to distribute water, and no storage is provided on the distribution system, the pumps force water at the required volume and pressure directly into the mains. The outlet for the water is through domestic taps on the system or through fire hydrants. This is the least desirable type of distribution system because a power failure could interrupt the water supply. In addition, as consumption varies, the pressure in the water mains is most likely to fluctuate. To conform to varying rates, several pumps are made available to add water output when needed, a procedure requiring constant attention at the water plant. Another disadvantage is the fact that the peak power demand of the water plant is likely to occur during periods of high electric power consumption,

thus increasing power costs to operate the water system. However, one advantage of direct pumping is that a large stationary fire pump may be used on demand for structure fires. This pump increases the residual pressure to any desired amount permitted by the construction of the water mains.

#### 2.3 The Pump Scheduling Problem

When we turn on a tap at home we expect potable water to come out with adequate flow of water at sufficient pressure. In order to satisfy our expectations, sufficient volume of water must be transported from treatment plant to demand points (consumers) through a network of pipes. Although water can be transported by gravity, more often it must be pumped in order to reach higher elevations with sufficient pressure. However, pumps cannot be activated whenever we turn on a tap and people do not consume water uniformly throughout the day: within a single day there is periods of high and low consumption. Therefore, water must be stored in tanks at a higher elevation, so that it can be supplied whenever there is a higher demand (Manuel, 2009).

Reducing the energy consumption of water distribution networks has never had more significance in the present day. In order to minimize that energy used the scheduling of the operation of pumps are proposed. Moreover, the cost of operating pumps in a water distribution network represents a significant fraction of the total expenditure incurred in the operational management of water distribution networks worldwide. Pumps consume large amounts of electrical energy for pumping water from source to storage tanks and/or demand nodes. In addition, they eventually need to be repaired and replaced, resulting in maintenance costs. Therefore, the goal of the pump scheduling problem is to minimize the total operational cost, which includes pumping cost and pump maintenance cost, while guaranteeing a competent network service. In most cases, a competent network service is equivalent to supplying water to consumers at adequate pressures and achieving full recovery of tank levels by the end of operating period.

# 2.3.1 The Cost of Pumping Water

The main goal in the pump scheduling problem is to minimize the cost of supplying water, while keeping within physical and operational constraints by means of scheduling daily pump operations. There are two types of costs associated with the operation of pumps: energy costs and maintenance costs. The energy cost may be composed of an energy consumption charge (RM/kWh), i.e., the cost of electric energy consumed during a time interval, and a demand charge (RM/kW), i.e., the cost associated with the maximum amount of power consumed within a billing period. Maintenance costs are mainly associated with the wear and tear of pumps, which will result in future repair or even replacement of damaged pumps. For this study we are focusing on electric energy cost consumed (Manuel, 2009). The electric energy cost is charged by Tenaga Nasional Berhad (TNB) is not the same throughout the whole day. During peak hour in between 0800 and 2200, the charge is RM 0.312 and 20% discount is given to the consumer during off-peak hours in between 2200 and 0800.

#### 2.3.2 Constraint of the Pump Scheduling Problem

In order to be useful in practice, feasible schedules must satisfy certain constraints. These constraints include hydraulic constraints, also called implicit system constraints, which define the hydraulic equilibrium state of the system, e.g., Conservation of Mass at each node and Conservation of Energy around each loop in the network. On the other hand, implicit bound constraints represent system performance criteria. They include constraints on junction pressures, pipe flow rates or velocities, and tank water levels. Implicit bound constraints may also include constraints on pump operation switches.

Frequently switching a pump on and off results in maintenance costs due to increasing wear on the pump, thus constraining the number of pump switches limits future maintenance costs. Constraints on tanks water levels typically include

minimum and maximum limits on tank levels, and balance between supply and demand from tanks. Minimum and maximum tank limits may be explicit constraints of the problem or can be implicitly enforced by a hydraulic simulator. Balance between water supplied and consumed from tanks is achieved by ensuring that tanks recover their levels by the end of scheduling period.

### 2.4 Review of Previous Approach

The optimal control policy is defined as the schedule of pump operations that will result in the lowest total operating cost for a given set of hydraulic and implicit bound constraints. In very general terms, a system that automatically controls the operation of pumps in order to obtain an optimal control policy is made up of three main components: a hydraulic network model, a demand forecast model, and an optimal control model. A calibrated hydraulic network model is used to calculate the response of the water distribution system to different operational policies. A demand forecast model is used to predict water demand during scheduling period from historical data. These demands are incorporated into the hydraulic network model. The optimal control model, which we will refer as the optimization algorithm thereafter, generates optimal control policies by minimizing an objective, usually electricity cost, subject to a number of operational constraints.

Many researches have been done regarding pump scheduling optimization in water distribution system to minimize the cost of supplying water. Baran et al. 2004 introduced Multi Objective Evolutionary Algorithm (MOEA), Wang et al. 2009 with Genetic Algorithms (GA), Vladimir et al. 2010, Selek et al. 2012, D. Borkowski et al. 2012 with Branch & Bound, Novel Neutral Evolutionary Search and Global Optimization Toolbox respectively. Most of them were used Mass Balance Model and explicit representation in their researches. Mass balance model which is to simplify a single tank system based on some assumptions and explicit meaning that it specifies the status of each pumps in binary representation. The detail explanations are described in the next section. Following are summarizing in Table 2.1.

We can see that the various approaches also can be classified according to the type of system addressed by the model: the pumping locations, either individual pumps or pump stations. Additionally, we identify the three main components in an operation control system: the hydraulic network model, the demand forecast model, and the optimization algorithm. Finally, another relevant aspect is whether the approach uses explicit or implicit representation of pump schedules.

Hak Milik

Table 2.1: Summary of optimization approaches for pump scheduling

References	Tanks	Tanks Pumps	Hydraulic	Optimization algorithm	Representation	Comments
Baran et al. 2004	1	5	Mass Balance	MOEA's	Explicit	The system is decomposed in space and time.
Wang et al. 2009	1	4	Mass Balance	GA	Explicit	The system is decomposed in space and time.
Vladimir et al. 2010		32	Mass Balance	Branch & Bound	Explicit	Pumps are switched on and off based on water demand
Selek <i>et al</i> . 2012	00	11	Regression Model	Novel Neutral Evolutionary Search	Explicit	Decision variable is number of active pumps at each pump station.
D. Borkowski et al. 2012	_	4	Mass Balance	Global Optimization Toolbox	Explicit	Designing the control hardware for the deployment of the intake pump switching system. Pumps are switched on and off based on water level in the reservoir

#### 2.4.1 Hydraulic Network Model

Each type schedule of the pumps must be evaluated in order to calculate its associated costs and assess its feasibility with respect to the problem constraints. Since testing potential pump schedules on the real system would be impractical, some type of mathematical model of the water distribution system is required. There are many types of model such as mass-balance models, regression models, simplified hydraulics and full hydraulic simulation are potential techniques for modeling network hydraulics.

A mass-balance model simplifies a single tank system based on some assumptions. First, the volume of flow into the system must be equal to the daily demand plus the difference in water level in the tank. Mass-balance models assume, as well, that some combination of pumps exists that will be able to generate the desired variation of water level in the tank. Finally, some constraints, such as the pressure-head required to achieve flow into the tank and minimum pressure constraints at demand nodes, are either neglected or considered to be satisfied if water level in tanks is above certain elevation.

Regression models are defined by a set of nonlinear equations that is constructed from the response of a given network over a particular range of demands. This approach results is more accuracy than mass-balance models while still being very fast to evaluate. However, regression models are very sensitive to the data used to construct the model. Significant changes in either the network or the demand distribution may lead to erroneous results. In such case, the model must be built again from newly collected data.

In simplified hydraulics, network hydraulics is approximated using a highly skeletonised network model, where the effects of several components are related in a single equation. Extensive system analysis is necessary to accurately represent the real system.

Finally, a full hydraulic simulation solves hydraulic equations (conservation of mass and conservation of energy) to model the nonlinear dynamics of a water distribution system. Simulation models generally require more data to formulate, and require a significant amount of work to calibrate. On the other hand, simulation models are robust both in terms of system changes and demand variations. While mass-balance or regression models would require significant modifications to account for changes in the system response, a well-calibrated simulation model would be able to provide the hydraulic response of the modified system (Manuel, 2009).

#### 2.4.2 Demand Forecast Models

Water demand is very important in order in order to develop an optimal pump schedule. Nowadays, most distribution systems have the potential to gather data on system demands. This data is used to statistically estimate typical system demands in order to construct a forecast model. Forecast model may be used depending on the accuracy temporal data available and on the particular hydraulic model, either a lumped, proportional or distributed demand.

Mass-balance hydraulic models use a lumped model, which aggregates system demands into a single value. A regression-based hydraulic model is considering proportional demand models, which varies a single demand pattern proportionally to the total demand. Finally, in a full network simulation model, the total system demand is distributed both temporally and spatially among several network demand nodes. This distributed demand model is the most accurate.

Although a forecast model is an essential part of the system, the choice of a particular model does not depend directly on the optimization algorithm but on the data available and the hydraulic model.

# 2.4.3 Representation of Pump Schedule

Another relevant aspect is the representation of pump schedules within the optimization algorithm. This representation can be either explicit, directly specify the status of each pumps or implicit by defining the operations of pumps in terms of properties of other elements of the network.

The two most widely used representations are explicit binary representation and implicit representation based on tank-level triggers. The binary representation divides the scheduling period in smaller time intervals and encodes a pump schedule in a string of bits, each bit representing the status (on/off) of a pump during a time interval. On the other hand, tank-level triggers change the status of pumps when water on a tank reaches a certain elevation. They are typically used in pairs: the pump is turned off when water level goes above an upper trigger level and it is turned on when water level falls below a lower trigger level (Manuel, 2009).

# 2.4.4 Optimization Algorithm

There are many types of optimisation model such as linear, non-linear, integer, dynamic and mixed programming. These techniques are still used and their usefulness are limited when applied to complex water distribution networks. This limitation has led researchers to consider other optimisation techniques, such as Evolutionary Algorithm, (M"ackle, et al., 995; Simpson et al, 1999), Particle Swarm Optimization (Wegley, et. al., 2000) and etc.

M"ackle, et al., (1995) developed an evolutionary algorithm to optimize the daily scheduling of four pumps with a single tank. Schedules were represented by binary strings of 4 x 24 bits. The cost of each schedule was the sum of the electricity cost and penalties for constraint violations on minimum, maximum, and final tank levels. The fitness of each schedule was calculated as the inverse of the overall cost.

Simpson et al. (1999) developed an evolutionary algorithm where the two decision variables are the tank level triggers. Their goal was to minimize the total cost which is calculated from the unit cost per m³ of water pumped plus penalty costs for violations of constraints: the upper trigger level should be higher than the lower trigger level; tank levels should be within specified ranges; and there must not be more than an average of 6 pump starts per hour.

Wegley, et. al., (2000) studied Particle Swarm Optimization for optimizing the operation of pumps that can operate at various speeds (variable frequency drive, VFD). Their goal was to minimize the energy cost of pumping while keeping nodal pressure head, demand, and tank water levels within bounds. Violation of these constraints resulted in penalties that were added to the objective function. The decision variables were the VFD speeds at discrete periods. Hydraulic simulation was performed by EPANET.

# 2.5 Genetic Algorithms

The basic principles of GA's were first proposed by Holland in 1970's. During that years, the concept of this not clearly understood and the obvious obstacles that may drive engineer away from using GA is the difficulty of speeding up the computational process, as well as the intrinsic nature of randomness that leads to a problem of performance assurance. Nowadays, GA development has reached a stage of maturity and grows rapidly due to the easy availability of fast speed small computer with low cost.

GA is not considered a mathematically guided algorithm. The optima obtained are evolved from generation to generation without stringent mathematical formulation such as the traditional gradient-type of optimizing procedure. In fact, GA is much different in that context. It is merely a stochastic, discrete event and a nonlinear process. The obtained optima are an end product containing the best elements of previous generations where the attributes of a stronger individual tend to

be carried forward into the following generation. The rule of the game is "survival of the fittest will win" (Man, et, al, .1996).

#### 2.5.1 Chromosome Representation

Bit string encoding of the classical approach commonly used by GA researchers because of its simplicity and traceability. To apply GA to the real-world continuous-case problem, it is necessary to encode a pumping schedule as n x m intervals, where n is the number of pumps and m is the number of time intervals (Wang, et, al., 2009).

#### 2.5.2 Population

To get a good result, chromosome must be generated at the beginning of the process. As shown in Savic et al. (1997), if all initial solutions are determined randomly, the convergence speed and the solution quality may be uncertain. Hence, a greedy algorithm is used for choosing a good initial solution according to the water demand and Constraints (3.1).

For example, the most economic pump in the interval [0,1] needs to be determined first. Here, a pump is said to be economic if it pumps the same amount of water but spend less cost than other pumps do. The greedy algorithm keeps on choosing the most economic pump one by one from the remaining available pumps until Constraint (3.2) fails. So far, what pumps should be active in [0, 1] have been determined. That is, the first part of the schedule is determined. Later, the other parts of the schedule for [1, 2], [2, 3], ... [7, 8], [17, 18], [18, 19]. .. [23, 24], [8, 9], [9, 10], ..., and [16, 17] can be determined by the same way. Evidently, pumping water during off-peak load hours is the top priority of the greedy algorithm (Wang, et, al,. 2009).

#### 2.5.3 Objective and Fitness Value

The objective function of a problem is a main source providing the mechanism for evaluating the status of each chromosome. This is an important link between GA and the system. It takes the chromosome as input and produces a number or list of numbers (objective value, generally in least square form) as a measure to the chromosome's performance. However, its range of values varies from problem to problem. To maintain uniformity over various problem domains, objective value is rescaled to a fitness value (K.F.Man, et, al, 1996).

#### 2.5.4 Selection

There are two selection operator employed in the selection procedure which are one for single-objective optimization and one for bi-objective optimization. For this thesis, we use single-objective optimization the roulette wheel selection is considered (Wang, et, al., 2009).

(K.F.Man, et, al., 1996) mention from the previous research state that there are three method two measures performance of selection algorithms which are bias, spread, and eficiency. Bias defines the absolute difference between actual and expected selection probabilities of individuals. Spread is the range in the possible number of trials that an individual may achieved. Eficiency is related to the overall time complexity of the algorithms.

Roulette wheel selection tends to give zero bias but potentially inclines to spread unlimitedly. It can generally be implemented with time complexity of the order of  $N \log N$  where N is the population size (K.F.Man, et, al, 1996).

#### 2.5.5 Crossover

Crossover is a recombination operator that combines subparts of two parent chromosomes to produce offspring that contain some parts of both parents' genetic material. A probability term, crossover rate, pc, is set to determine the operation rate (Tang, et al., 1996). The crossover rate controls the frequency with which the crossover operator is applied. In each new population, C (Crossover Rate) \* N (Population Size) structures undergo crossover.

The higher the crossover rate, the more quickly new structures are introduced into the population. If the crossover rate is too high, high-performance structures are discarded faster than selection can produce improvements. If the crossover rate is too low, the search may stagnate due to the lower exploration rate (Grefenstett, 1986). The current experiments allowed two difference crossover rate between guideline had been introduced by (Jong, et, al., 1990) and (Grefenstett, 1986) and stochastically method based on the best result is obtain.

# 2.5.6 Mutation

Mutation is a secondary search operator which increases the variability of the population. After selection, each bit position of each structure in the new population undergoes a random change with a probability equal to the mutation rate M. Consequently, approximately M \* N \* L mutations occur per generation. A low level of mutation serves to prevent any given bit position from remaining forever converged to a single value in- the entire population. A high level of mutation yields an essentially random search (Grefenstett, 1986).

#### 2.5.7 Elitism

The selection operation does not guarantee the selection of any particular individual including the fittest individual in population, unless it is much filter than any other else it dies out if not selected. The movement of the GA's to get the optimal solution cannot satisfy. Hence the elitism was introduced by Kenneth De Jong in 1975 to ensure that the some numbers of the best individual (elites) are retained in each generation. Elitism is usually achieved by maintaining the elite solution in the population or by the storing the elite in an external population and restoring them into the population later. The use of elitism ensures that minimum fitness of the population can never be reduced from one generation to next ensuring the rapid convergence of the population, thereby improving the chances of locating the optimal individuals (Sumathi and Surekha, 2010; Weise, 2009).

# 2.6 Summary

In this chapter, the detail review of the subject matter has been presented. A brief description water supply system is described. There are various optimization method has been used by researcher for pump schedule in order to optimize operational cost. There are many type of hydraulic model. In this study, we use mass balanced model, explicit representation and GA's as an optimization method has also been described.

#### **CHAPTER 3**

#### RESEARCH METHODOLOGY

#### 3.1 Introduction

This chapter is divided into 2 main sections. The first section discusses modelling of the water supply system and also objective function to the problem wants to be optimized. The second part focuses on the discussion of development of the proposed Adaptive Weighted Sum GA's and its application to the problems in details.

## 3.2 Modelling of the water supply system

Water supply system is a very complex system. In order to solve the problem, the complexity needed to be reduced. A simplified hydraulic model based on the mass balance model discussed earlier in section 2.4.1 is adopted for this system. Figure 3.1 the simplified hydraulic model consisting of the following:

- i. Water source
- A pumping station consisting of a defined number of fixed speed centrifugal pump s used to deliver water from the source to elevated reservoir.
- iii. An elevated water storage reservoir, which supplies water to the consumers.

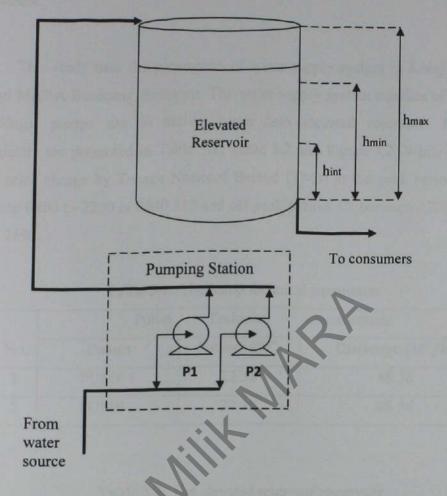


Figure 3.1. The simplified Hydraulic Model

These pumps work in parallel to deliver the amount of water into elevated reservoir and then ready to supply the water to consumer by gravity. The level of water in reservoir should not exceed the maximum level h<sub>max</sub> else results in waste of resource and also the level should not goes to minimum level h<sub>min</sub> else results in a shortage of supply. The goal is to maintain the level between the minimum and maximum level putting the initial level h<sub>int</sub> into consideration. The initial level h<sub>int</sub> corresponds to the start level and has to be recovered at the end of the optimization period.

The water demand profile, the pumps characteristic parameters such as the capacities and power rating which are assumed fixed throughout the time interval of one day (divided into 24 interval), reservoir capacity and electric tariff ( high tariff

period and low tariff period) as a parameter model are needed in order to optimize the system.

This study uses the parameters of water supply system in Kolej Kemahiran Tinggi MARA Beranang, Selangor. The water supply system consists of two sets of centrifugal pumps use to deliver water into elevated reservoir. The system parameters are presented in Table 3.1, Table 3.2 and Figure 3.2. While the electric tariff price charge by Tenaga Nasional Berhad (TNB) at the peak period tariff, Ch between 0800 to 2200 is RM0.312 and off peak period, Cl between 2200 to 0800 is RM0.2496.

Table 3.1: The pump technical parameters

	Pump	Technical	characteristic	
No.	Pumps	Power (kW)	Discharge (m³/h)	
1	PUMP 1	22.38	88.36	
2	PUMP 2	22.38	88.36	

Table 3.2: The elevated reservoir parameter

	Elevated Reservoir				
No.	Parameter Description	Values			
1	Area of elevated reservoir	128.48 m <sup>2</sup>			
2	Maximum height, hmax	4 m			
3	Minimum height, hmin	2 m			
4	Initial height, hint	3 m			

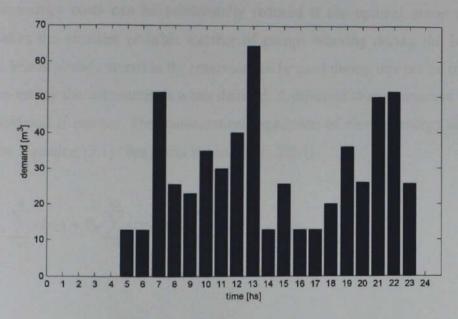


Figure 3.2: The water demand profile

## 3.3 Objective Function

This section defines the objective function and constraints of the scheduling problem. The objective functions are the electric energy consumption cost. In order to optimize the system, it is required to define the function equation representing this cost functions.

## 3.3.1 Electric Energy Cost

Electric energy cost is the cost of all electric energy consumed by all pumps of the pumping station, during the optimization period. In most electricity supply systems, electric energy cost charge by the electrical company is not the same throughout the whole day. This work considers the following charge structure:

- Low cost: (CL): from 0:00 to 08:00 hour and from 22:00 to 24:00 hour
   (20% Discount).
- High cost: (CH): from 08:00 to 22:00 hour (Normal Rate).

Electric energy costs can be substantially reduced if the optimal pump schedule establishes the smallest possible number of pumps working during the high cost period. Water already stored in the reservoir can be used during this period of time in order to satisfy the community's water demand. A different charge structure can also be considered if needed. The mathematical expression of electric energy cost  $E_c$  is given by Equation (3.1) (Benjamin Baran, et al., 2004).

$$E_C = C_L \sum_{i=1}^{8} c(p_i) + C_H \sum_{i=9}^{22} c(p_i) + C_L \sum_{i=23}^{24} c(p_i)$$
(3.1)

Where

i: Time interval

 $P_i$ : Pump combination at interval i

n: Number of pump in the station

 $c(p_i)$ : Electrical energy consumed

## 3.3.2 Constraint Parameter

There are three levels to be considered in the elevated reservoir:

- a minimum level that guaranties enough pressure in the pipeline. This
  level must also be kept for security reasons, since unexpected events,
  as a fire, may demand a large amount of water in little time;
- a maximum level, which must not be exceeded in order to avoid pipeline losses. This level must also be compatible with the reservoir's capacity; and
- an initial level that has to be recovered by the end of the optimization period.

Maximum and minimum levels are considered as constraints. Hence, at the end of each time interval, water level must end up in some position between the maximum

level  $h_{max}$  and the minimum level  $h_{min}$ ; as shown in Equation (3.3). However, level variation between the beginning and the end of the optimization period  $\Delta h$ ; is stated as another objective to be minimized, since small variations do not necessarily make a solution not acceptable, as shown in Equation (3.2) (Benjamin Baran, et al., 2004).

$$\Delta h = \sum_{i=1}^{24} [D(p_i) - d_i]/s \tag{3.2}$$

With

$$h_i = h_{i-1}[[D(p_i) - d_i]/s$$
 (3.3)

Subject to:

 $h_i \le h_{max}$  $h_i \ge h_{min}$ 

Where

S Reservoir surface, assumed constant

 $D(p_i)$  Discharge pumped at time interval t using pump combination  $p_i$ 

d<sub>i</sub> Water demand at time interval i

Other constraints are considered as follows:

- amount of water supplied by water source: it is supposed that the water source supplies enough water at any time and without additional costs;
- pipeline pressure constraints: maximum and minimum pressure constraints in the pipeline are always fulfilled, no matter what level is kept in the reservoir;
- valves in the system are not considered;

## 3.4 The Adaptive Weighted-sum Genetic Algorithm

Genetic Algorithms are population based on evolutionary approach that searches for possible solution to a problem within the defined criterion space. Basically the weighted sum approach is an extension of the methods used in multi-objective optimization to Genetic Algorithm in other to optimize the defined objectives. In this approach weights are assigned to a single objective function.

#### 3.4.1 Initialization

Optimal pump schedule processes start with an initialization stage. At this stage all the parameter of the water supply system such as the water demand profile, the pump characteristics of the system, the electric tariff plan as well as the constraint to be satisfied are defined. Also specified at the initialization stage are the parameters of the Genetic Algorithm itself which includes the number of generations, the number of chromosomes in the initial population, the rates of mutation, crossover and selection.

#### 3.4.2 Initial population and constraint evaluation

After initialization stage was done, the next stage is to find the best chromosome of the initial population in order to ensure that they satisfy the constraint of the system.

To generate the chromosomes, it is required that the decision variables are encoded in any of the available techniques to represent the chromosomes of the Algorithm. The binary coding technique was adopted to encode the decision variable (the pump), with each pump represented by bit of '1' pump is on or '0' pump is off in a string of bits at each time interval. The number of bits required to represent a

chromosome is determined by multiplying the number of decision variables by the total number of intervals in the optimization period. An optimization period of a day is chosen, with an interval of 1 hour resulting in a total interval of 24, hence the number of bits *nbits* required to represent the chromosomes equals to

$$nbits = nvar \ x \ n \ interval \tag{3.4}$$

Where nvar is the number of decision variables (the pumps in the system), n is the number of interval in the optimization period.

This system have 2 pumps hence a string of 2x24 = 48bits are used to encode a possible solution (a complete pump schedule). Table 3.3 shows the encoding of the pumps for the entire 24 interval of the optimization period. While Table 3.4 shows the possible combination of the pumps that can be operate at each interval alongside with amount of energy consumed and water delivered.

Table 3.3: Encoding of the decision variables

Time Interval	MI		2		 24	
Pumps	Pi	P2	P1	P2	 P1	P2
Status	ON	OFF	OFF	ON	 ON	ON
Bits	1	0	0	1	 1	1

Table 3.4: The possible combination of the pumps and codes

Pump Combination	Code		Discharge (m³/h)	Power (kW)	
0	0	0	0	0	
P1	1	0	83.36 m <sup>3</sup>	22.38	
P2	0	1	83.36 m <sup>3</sup>	22.38	
P1,P2	1	1	166.72m³	44.76	

In this proposed algorithm, the chromosomes are individually created and checked if it satisfies the constraint of the system, it is passed to the initial population else it is rejected. This process is repeated until the required number chromosomes specified in the initialization stage are met.

## 3.4.3 Adaptive Weight Formation

The adaptive weights are formed in order to evaluate the fitness values from the individual objective function. The Adaptive weight relies heavily on the fitness values of the chromosomes in the current generation for its determination and readjustment on every generation or iteration of the process. This methodology also ensures that no one fitness function completely dominates or takes control of the other in their combination to form the total weighted sum objective function.

## 3.4.4 The Genetic Operations

The genetic operator refers to the selection, crossover and mutation. The first operator to be initialized is the selection operation. This is aimed at selecting the best and most suitable chromosomes based on their fitness values to be seeded to the next iteration of the Genetic process and also to go into the crossover and mutation process.

The roulette wheel selection approach otherwise known as the fitnessproportional method is implemented to select suitable chromosomes based on the selection probability equation given by Equation (3.5).

$$p_i = \frac{f_{max}(x) - f(x)}{\sum_{i=1}^{c} (f_{max}(x) - f(x))}$$
(3.5)

Where  $p_i$  the probability of is selecting individual i, f(x) is the weighted sum fitness value of C in the current population, C is the number of chromosome in the current population,  $f_{max}(x)$  is the maximum fitness value of f(x) in the current population.

From the selected chromosomes a certain percentage based on the crossover probability defined are allowed to undergo the mating process otherwise known as the crossover in order to form new offspring. The single point crossover is adopted wherein the parents forming the new offspring splits at a particular randomly selected fixed point. The mutation operation comes in so to ensure that the newly produced offspring have some trait completely different from their individual parents. This is achieved by changing the status of some of the genes in the chromosomes based on the mutation rate probability using the flip bit technique.

## 3.4.5 The Repair Strategy and Elitism

After the mutation process, there is a high probability that some of the offspring produced violates the constraint. A repair strategy was introduced as a means of handling the constraint violation. The steps to implement the repair strategy are as follows.

Step 1.Initialize the repair counter

Step 2.Discard offspring

Step 3. Repeat the crossover process with the same parents and then the mutation.

Step 4. Check the newly created offspring for the constraint violation

Step 5.If the constraint is satisfied move the offspring to next generation population Step 9.

Step 6.If the constraint is violated, Increment the repair counter and go to step 3

Step 7.If the repair counter >= stop condition, initiate the repair strategy

Step 8. Repair strategy

Search for the interval with the violation

If overflow switch OFF one or more pumps until constraint is satisfied

If underflow switch ON one or more pumps until constraint is satisfied

Move offspring to next Generation population

Step 9.Next Generation population

The Elitism is another mechanism is used to ensure the safety of best and most feasible solutions of a generation and they are seeded to the next generation. Two most suitable chromosomes are selected and stored separately, upon the completion of the genetic operations of a generation they are then returned into the population to be seeded for the next generation. This ensures that the best chromosome of each generation makes it through to the next iteration of the genetic process.

With the completion of the repair operation on all offspring that violates the constraint and the elites installed back into the next generation population. This new population is then seeded to the next iteration and the process start all over again from the evaluation of fitness values, through the determination of the Adaptive weights to the genetic operation and down the formation of new population. This operation continues for the specified number of iteration specified at the initialization stage until optimum solutions is obtained.

#### 3.5 Summary

The modelling of the water supply system has been presented with defining the input parameters required as well as the formulation of the objective functions of the problem and the constraint of the system. The Adaptive Weighted-sum Genetic Algorithm (AWGA) is applied to optimize the defined objective.

The optimal pump schedule process starts with an initialization stage with is to specify the parameter of water supply system and Genetic Algorithm (GA). The next stage continues to find the best chromosome to satisfy the constraint of the system. In order to determination and readjustment on every generation, the adaptive weights are formed to evaluated fitness values from the individual objective function. The process continues with selection, crossover and mutation. There is a constraint violation is produced during this process and repair strategy was introduced to handle this problem. After completion of the repair and elitism process, the operation continues until optimal solution is obtained.

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## **CHAPTER 4**

#### RESULTS AND DISCUSSION

#### 4.1 Introduction

This chapter is divided into two main sections. The first section describes the process of obtaining the desired parameter of the AWGA in order to optimize the performance of AWGA. The best parameters obtained are applied for the rest of the simulation and the results are presented and analysed in the second section.

## 4.2 AWGA Parameter Determination

In order to obtain the best performance, it is required that parameters of GA are carefully selected as described in Chapter 3. From the Figure 4.1 it can be seen that when the population size (C=50) the algorithm took longer time to converge. The convergence time of the algorithm improve when population size (C) is been increased from 100, 200 and 250. It can be seen that the convergence of C= 200 is faster than the other, although it; computational time higher than C=50 and C=100, as shown in Figure 4.2. Hence, C=200 is selected in this study.

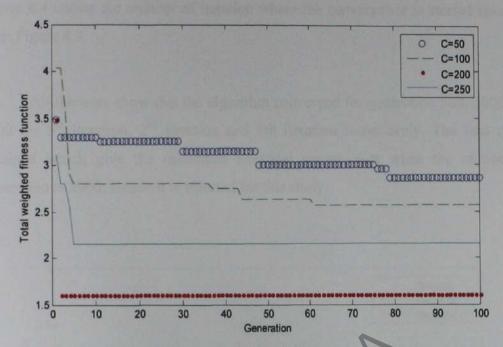


Figure 4.1: Convergence with difference population size

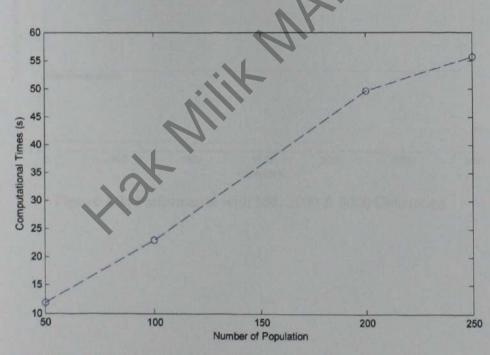


Figure 4.2: The effect of population size on computational time

The next step is to select the number of generation to ensure that the algorithm is not terminated before an optimal solution is obtained. A few tests have been done with various numbers of generations such as 500, 2000 and 3000. Figure 4.3 shows the performance of the AWGA with the variation number of generations.

Figure 4.4 shows the number of iteration where the convergence is started enlarged from Figure 4.3.

All the tests show that the algorithm converged for generation 500, 2000 and 3000 are 5<sup>th</sup> iteration, 2<sup>nd</sup> iteration and 6th iteration respectively. The best result obtained which give the minimum electrical energy cost when the number of generation is 2000. Hence it is selected for this study.

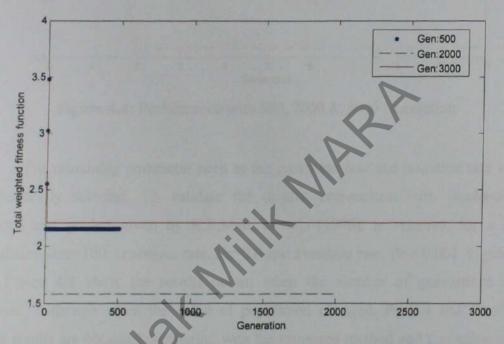


Figure 4.3: Performance with 500, 2000 & 3000 Generation

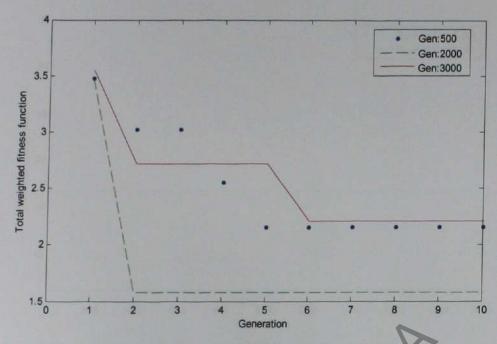


Figure 4.4: Performance with 500, 2000 & 3000 Generation

The remaining parameter such as the crossover rate and mutation rate where stochastically selected. To validate the results, comparison with stochastically selected and guided given by K.F.Man, et al.. (1996), is selected, for a large population size=100, crossover rate, Pc=0.6 and mutation rate, Pm=0.001. Figure 4.5 and Figure 4.6 show the results obtain when the number of generations were retained. Although when the value of population changed, Pc=0.4 and Pm=0.05, better results are obtained comparing with the proposed method and that value is use in this study.

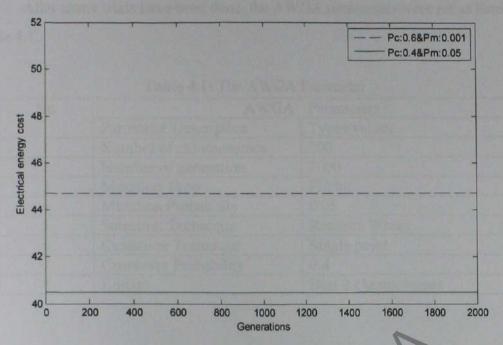


Figure 4.5: The electrical energy cost comparison for C=100

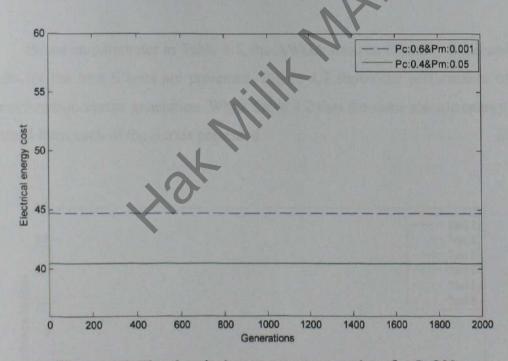


Figure 4.6: The electrical energy cost comparison for C=200

After many trials have been done, the AWGA parameters were set as listed in Table 4.1

Table 4.1: The AWGA Parameter

No	AWGA	Parameters	
	Parameter Description	Types/values	
1	Number of chromosomes	200	
2	Number of generation	2000	
3	Mutation Type	Flit bit	
4	Mutation Probability	0.05	
5	Selection Technique	Roulette Wheel	
6	Crossover Technique	Single point	
7	Crossover Probability	0.4	
8	Elitism	Best 2 chromosomes	

## 4.3 Pump Scheduling Optimization Result

Based on parameter in Table 4.1, the AWGA was run for many times and the results for the best 6 tests are presented. Figure 4.7 shows the performance of the fitness function versus generation. While Table 4.2 lists the value electric energy cost obtained from each of the 6 tests presented.

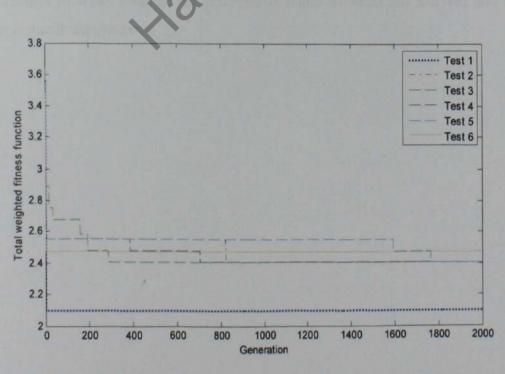


Figure 4.7: Total weighted fitness function versus generation

Refer to Table 4.2, Test 1 produces the least electric energy cost with percentage difference index is about 34.97%. Test 2 till Test 5 give the same result with PDI is at 32.47%. These results show the consistencies of the AWGA in obtaining optimum result as within 3%. The goal of the optimization is to obtain an optimal pump schedule with reduced cost as given by Test 1.

Table 4.2: Results of Tests

Test	Electric Energy Cost (RM) (Current)	Electric Energy Cost (RM) (Proposed Optimization)	Percentage Difference Index (PDI) %	
1	55.84	36.31	34.97	
2	55.84	37.71	32.47	
3	55.84	37.71	32.47	
4	55.84	37.71	32.47	
5	55.84	37.71	32.47	
6	55.84	39.1	29.98	

The optimal pump schedule and level variation in the reservoir for Test 1 are presented in Figure 4.8 and Figure 4.9 respectively. Refer to Figure 4.8, it can be seen that the schedule delivers more water into the reservoir during high water demand. Pumps are fully utilized during off peak period at 24hrs. Figure 4.9 shows the changes in water level in the reservoir remains between 3m and 4m and meet water demand requirement.

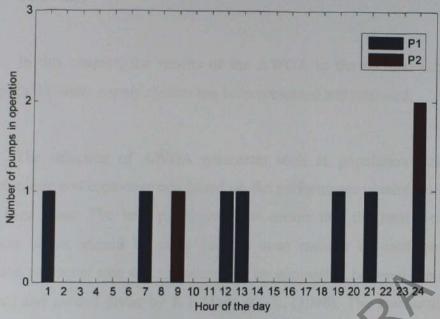


Figure 4.8: The Optimal Pump Schedule

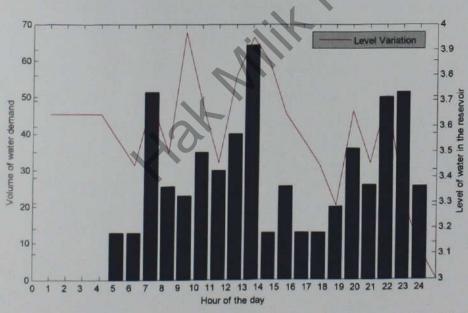


Figure 4.9: The level variation in reservoir versus demand profile

## 4.4 Summary

In this chapter, the results of the AWGA to the optimal schedule for the pumps in the water supply system has been presented and analysed.

The selection of AWGA parameter such as population size, generation, mutation rate and crossover rate based on the performance obtained after many trial have been done. The best population size means that the total weighted fitness function values should be same for the most number of each generation. The selection crossover rate and mutation rate by comparing between the stochastically selected and guided given by K.F.Man, et. al,. (1996). The stochastically selected method is produced a good result. The AWGA for optimal pump scheduling is reduced 34.97% electric energy cost. As a result the objective of this study is achieved.

#### **CHAPTER 5**

## CONCLUSION AND FUTURE WORK

#### 5.1 Conclusion

Review on water supply system has been made to get an idea about their operation, components and function. Many researches have been done to minimize the operation cost of water supply system. Researchers observed that it is impossible to change the overall structure of the system in order to minimize the operation cost and the highly cost is spend for pumping process in order to satisfy the water demand equipment. As a result they came out pump scheduling with various method of optimization process. The objective is to minimize the electric cost, maintenance cost, minimize maximum power peak and etc. The result they were obtained is very effective and a lot of cost can be reduced.

For this study, the AWGA is used as an optimization method. The electric energy cost for pumps operation for one day is RM55.84. After an optimization proposed, the cost is reduced to RM19.53. The objective of the project to minimize the energy cost has been reduced to 34.97%.

Although the performance of the AWGA is good, there is some aspect of the AWGA that needs to be improved in order to make it more reliable and adaptive for more case study implementation. Presented in the following section are some areas open for improvement of the AWGA.

#### 5.2 Future work

The following are some areas open for improvement of the AWGA for the optimization problem.

- The consideration of more objective functions related to the system other than the electric cost.
- ii. The Consideration of Water supply system with variable speed pumps as well as other encoding techniques rather than the binary approach.
- iii. The Application of the AWGA for the scheduling of operations of large water supply system such as that controls area by SYABAS in order to see an accurate of the result.

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#### APPENDIX A

## Source code for AWGA

```
*Parameters of the GA to be implemented
 kw pump=[22.38 22.38];
Q pump=[83.36 83.36];
price=[0.2496 0.2496 0.2496 0.2496 0.2496
                                               0.2496 0.2496
0.2496...
          0.2496
                    0.312
                           0.312
                                   0.312
                                                  0.312
0.312...
          0.312
                    0.312
                            0.312
                                   0.312
                                                  0.312
0.2496];
water_demand=[0 0 0 0 12.85 12.85 51.4 25.7 23 35 30 40 64.25
12.85....
    25.7 12.85 12.85 20 36 26 50 51 4 25.7 0 ];
surface area=128.48;
hmin=3;
hlow=2;
hmax=4;
main program code for the Adaptive Weighted-sum Genetic Algorithm for Pump Scheduling optimization.
%Initialize the parameters of the Genetic Algorithm and water Plant
clear
clc
tic
    %to initiate the time clock to calculate the execution time
 %input the parameters
                         %initializes the plant parameters
   start parameters;
                         %The Selection probability
   Pc=0.4;
   mutation_rate = 0.05; %The Mutation rate
   popusize=100;
                         The Population size
                         %The number of bits in a chromosomes
   bit=24;
   nvar=2; %The Number of decision variables(number of fixed pumps)
   chrom=nvar*bit; %The formation of chromosomes
                       %The number of iteration
   Gen=2000;
```

```
*create initial population
 initial pop=rand(popusize, chrom) > 0.5;
%Evaluate the initial population for the constraint variation
%using the greedy approach:
%checks each chromosome to ensure it satisfies the constraint and if
not it is replaced.
for m=1:popusize
   schedule=initial pop(m,:);
      for i=1:24
         interval pump=schedule((i-1)*nvar+1:i*nvar);
         layout interval(:,i)=interval_pump;
      end
      for j=1:24
      water_supplied(j)=Q_pump*layout_interval(:,j);
      surplus(j)=water supplied(j)-water_demand(j);
      level=surplus./surface area;
      for k=1:24
          if k==1
              level(k)=level(k)+hmin;
              level(k)=level(k)+level(k
              if k = 24
                  level(k)=hmin;
             end
         end
      end
      for i=1:24
         if (level(i) < h low | | level(i) > h max)
             sch1=rand(nvar,1)>0.5;
             water_supplied=Q_pump*schl;
             surplus=water_supplied-water_demand(i);
             level(i)=surplus/surface area;
             if i==1
                 level(i)=level(i)+hmin;
             else
                 level(i) = level(i-1) + level(i);
                 if i==24
                    level(i)=hmin;
                end
             end
             layout interval(:,i)=schl;
             while (level(i)<hmin || level(i)> hmax)
                    sch2=rand(nvar,1)>0.5;
                    water_supplied=Q_pump*sch2;
                    surplus1=water_supplied-water_demand(i);
                    level(i)=surplus1/surface_area;
                    if i==1
                       level(i)=level(i)+hmin;
```

```
else
                           level(i) = level(i-1) + level(i);
                           if i==24
                               level(i)=hmin;
                            end
                       end
                        layout_interval(:,i)=sch2;
                end
           end
       end
         sch4=layout_interval;
         schedule=[sch4(:,1)' sch4(:,2)' sch4(:,3)' sch4(:,4)'...
sch4(:,5)' sch4(:,6)' sch4(:,7)' sch4(:,8)'
sch4(:,9)' ...
                     sch4(:,10)' sch4(:,11)' sch4(:,12)' sch4(:,13)'
sch4(:,14)'...
                     sch4(:,15)' sch4(:,16)' sch4(:,17)' sch4(:,18)'
sch4(:,19)'...
                     sch4(:,20)' sch4(:,21)' sch4(:,22)' sch4(:,23)'
sch4(:,24)'];
        initial pop(m,:)=schedule;
% feeds in the initial population into the GA process// Start of the
                                      ++++++++++++++++++++++++++++++
initial_pop; % Returns the value of the initial population to meets the constraint of level in the reservoir.
                              calculate the size of the population
 pop_n=size(initial_pop,1);
                   % iteration counter
 for C=1:Gen
                   % Returns the value of population that meets
                     the constraint of level in the reservoir.
 initial pop;
 %Evaluate the initial pop for the objective // Electric cost
     fitness_11=fitness_1(initial_pop,Q_pump,kw_pump,price,nvar);
 fitness1=fitness 11;
  %formation of the Adaptive weights
  t searching for the maximum and minimum point to form the Adaptive %
           Weights
  [zl_max locl]=max(fitnessl); %%Selection of maximum value in
  obj/electric cost
```

```
[z1_min loc2]=min(fitness1); %Selection of minimum value in
obj/electric cost
*Calculating the coefficients of the weights wl=wieght for
%function/electric cost,
   d w1=z1 max-z1 min;
   wl = 1/d w1;
                             %weight w1
%formation of the weighted sum fitness function by xply by
%wl*fitnessl
    for i=1:pop n
        fitness1_w(i)=w1.*fitness1(i);
        fitness_w(i)=fitness1 w(i));
   end
%Elite selection (the best 2 solution each iteration of the AWGA)
    [val m location] = sort(fitness_w);
   elite=initial_pop([location(1) location(2)].
   all fit1(:,C)=fitness1_w;
   all fit2(:,C)=fitness2_w;
%To ensure the current solution is better than the previous.
%solution replaces it.
      if C==1
            fitness_all=fitness_wx
            [best index b] = min(fitness_all);
            opt_val(C,:)=min(fitness_all);
            opt_fit1(C,:) fitness1_w(index_b);
opt_fit2(C,:) fitness2_w(index_b);
            optimal schedule(C,:)=initial_pop(index_b,:);
            real_fitness1(C,:)=fitness1(index b);
            real fitness2(C,:)=fitness2(index b);
    end
    If C>1
        fitness all=fitness W;
        [best index_b] = min(fitness_all);
        if opt val(C-1,:) < best
        opt_val(C,:)=opt_val(C-1,:); %stores the optimal weighted-
                   fitness
        optimal_schedule(C,:)=optimal_schedule(C-1,:); %stores the
        optimal schedule for each iteration
        initial_pop(index_b,:)=optimal_schedule(C-1,:); %returns the
        best solution into population
            opt_fit1(C,:)=opt_fit1(C-1,:); %stores w1*f1
            opt_fit2(C,:)=opt_fit2(C-1,:);
            w2*f2
            fitness_all(index_b)=opt_val(C-1,:);
```

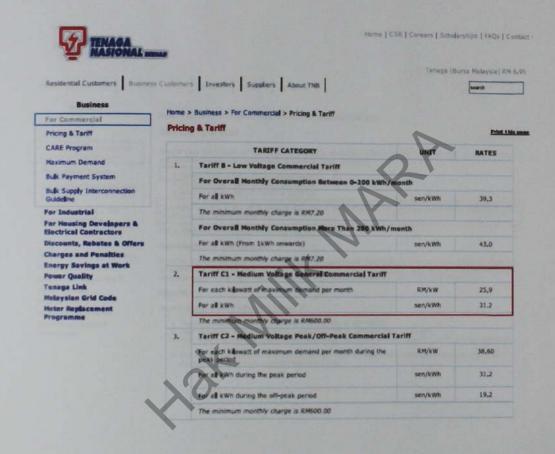
```
real_fitness1(C,:)=real_fitness1(C-1,:);%stores the real
            values of the Electric produce
            %by each chromosomes
            real_fitness2(C,:)=real_fitness2(C-1,:);
            the real values of the mtce cost produce
            %by each chromosomes
        else
           opt_val(C,:)=min(fitness_all);
           opt_fit1(C,:)=fitness1_w(index_b);
           opt_fit2(C,:)=fitness2_w(index_b);
           optimal_schedule(C,:)=initial_pop(index_b,:);
           real_fitness1(C,:)=fitness1(index_b);
           real_fitness2(C,:)=fitness2(index_b);
       end
   end
    %Selection operator//Roulette wheel
    *Determination of the probality of selection
    pop_s=size(initial_pop,1);
    length_2=size(initial_pop,2);
    fitness w3=fitness w;
    fitness num=max(fitness_w)-fitness_w3;
    fitness_den=sum(fitness_num);
    fitness prob=fitness num/fitness den;
    fitness cum=cumsum(fitness prob);
   rw spin=rand(pop s,1);
    rw_spin=sort(rw spin);
The roulette wheel
    for iirw=1:pop s
      for irw=1:pop s
          if rw spin(iirw) <fitness cum(irw), break, end
      end
         new_pop_r(iirw,:)=initial_pop(irw,:);
    end
    new_pop=new_pop_r; % Selected population to be seeded for
    repod and
  *next iteration
  keep=floor(Pc*pop_s);
                           The number of chromosomes to undergo
                           mating
  M=ceil(keep/2);
                           %remaining parents=ceil(pop size-keep)
  counter=0;
  pass=0;
  for u=2:M+1 %2:floor(pop_s/2)
       rw=rand (1,8)> 0.5;
      bit4=rw(1 ,:) ;
      integer= polyval(bit4, 2);
       r_xop2=integer*(1/(2^length(bit4)-1));
```

```
crosspoint1=ceil(r xop2*(length_2-1));
        parent1 = new_pop_r(u*2-1, :);
        parent2 = new_pop_r(u*2, :);
        *Crossover Operation // Single Point method
        new pop xox(u*2-1,:)=[parent1(1:crosspoint1)...
        parent2(crosspoint1+1:length_2)];
        new_pop_xox(u*2,:)=[parent2(1:crosspoint1)...
        parent1(crosspoint1+1:length_2)] ;
%Mutation // Flip-bit method
mask=rand(1,length 2) < mutation rate;
        new_pop_m=new_pop xox(u*2-1,:);
        new_pop_m=xor(new_pop_m, mask);
        mask=rand(1,length 2) < mutation rate
        new pop n=new pop xox(u*2,:);
        new_pop_n=xor(new_pop_n, mask);
%check if the offspring new_pop_n and new_pop_m satisfies the
%constraint
                                start_compute_level ; %1 ok compute the level again
        state1=find(level1<hlow|level1>hmax);
        state2=find(level2<hlow|level2>hmax);
        if (isempty(state1) == 1 && isempty(state2) == 1)
           new_pop(u*2-1,:)=new_pop_m;
           new_pop(u*2,:)=new pop n;
        else
          start repeat crossover; %repeat the crossover process
          with same parent
          %initiate the repair strategy if the offsprings violates
          level
          %constriants
          %// REPAIR STRATEGY
          if stop==1200 % any number can be used depending on
          chioce
              start repair n; %Repair offspringl
```

```
start_repair_m; %Repair offspring2
                  new_pop(u*2-1,:)=new_pop_m; %Return offspring into
                  new_pop(u*2,:)=new_pop_n;
                                              %Return offspring into
                  new_pop
              else
                  new_pop(u*2-1,:)=new_pop_m;
                 new_pop(u*2,:)=new_pop_n;
             end
          start_compute_level %1 ok checking level again
     %new_pop_1= installelite_outer(new_pop,initial_pop,nvar,...
     %kw_pump,price,index_1,index_2,fitness1);
    %new_pop=new_pop_1;
    new_pop([1 2],:)=elite([1 2],:);%Return elite into new_pop
    initial_pop=new_pop; %Return the new_opo into the next pop for
    next iteration
end
figure;
x=1:Gen;
plot(x, opt_val);
xlabel('Generation'); ylabel('Total weighted function');
figure ;
x=1:Gen;
plot(x,real_fitness1);
xlabel('Generations'); ylabel('Electric Cost');
toc
```

## APPENDIX B

# Electric Energy Cost Charge by TNB during Normal Hours



#### APPENDIX C

## Electric Energy Discount given by TNB during Off-Peak Hours

