OPTIMAL DESIGN AND SCHEDULING OF IRRIGATION PUMPS BY USING GENERAL ALGEBRAIC MODELLING SYSTEMS (GAMS) A CASE STUDY OF FENTALE-QAWA PUMP STATION

BY

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LIST OF SYMBOLS

Ns	=specific speed
Q	=discharge
H	=head in meter
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Q	=discharge
H	=head in meter
C_i	=initial cost of i^{th} pump
C'_I	=cost of i^{th} pump at the end of construction period, C_t
C_E	=unit energy cost
E_k	=total annual consumed energy
$Q_{i,j}$	=discharge from pump i at time j
$H_{i,j}$	=pump head from pump I at time j
Δt	=time step on demand duration curve
IQ_j	=total demand at time step j
$e_{i,j}(H_{i,j},Q_{i,j})$	=pump efficiency as a function of discharge and head
$H_{i,j}$	= pumping head by pump i in month j
$H_{max\ i}$	=maximum pumping head of pump i
$H_{min\ i}$	=minimum pumping head of pump i
$Q_{i,j}$	= discharge generated by pump i in month j
$Q_{max\ i}$	=maximum discharge of pump i
ATC	= Annual Total Cost
CRF	=capital recovery factor
D_i	=delivery pipe diameter of pump i
DP	=Dynamic Programming
DICOPT	= DIscrete and Continuous OPTimizer
E_k	=total annual consumed energy of k^{th} pump set
f	=friction factor
GA	=Genetic Algorism
HBMO	=Honey-bee Mating Optimization

H_d	=generated pump head
$hf_{i,j}$	=friction head loss of pump i during time step j
$HS_{i,j}$	=static head of pump i during time step j
IQ_j	=crop water requirement in month j
Li	=delivery pipe length of pump i
LP	=Linear Programming
N	=speed in rpm
NLP	=Non- Linear Programming
P	=power required
Q	=pump discharge
$Q_{i,j}$	=discharge of pump i during time step j
r	=interest rate
T	=project design life
TDH	=Total Dynamic Head
VSD	= Variable Speed Derive
η	=Pump efficiency

DECLARATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

Traditionally, design engineers tend to be conservative in calculating pump station decision variables by focusing on peak demands that occur about1% of the time. On the other hand, optimal design and operation of pumping stations are mathematically large-scale non-linear problems. Consequently, there is a possibility of using an optimum operation schedule on a set of non-optimum pump combinations that are selected narrowly based on peak discharge of system demand. Thus, optimization model is developed in this thesis work to tackle optimization problems in pump stations.

Optimal design and operation of irrigation pump station system is carried out with a help of a computer model developed in a General Algebraic Modeling Systems (GAMS). The model makes use of the latest advances in optimization techniques that utilize in-built solvers in GAMS to solve optimization problems with lots of decision variables and constraints. It is based upon one major objective function to find optimized solutions of equations. Automatically generated model outputs include selected pump type, capacity, number of pumps and optimum schedule of pump operation for problems involving design phase. For existing pump stations, it simply generates a preliminary optimum operation schedule.

The developed optimization model was tested on previously optimized problem by different researchers and then implemented on a case study, Fentale-Qawa Pump Station, to optimize the annualized investment cost of the pumping station and its annual operating cost. GAMS results were presented and compared with five other well-known optimization techniques. The results were unique and stood second to Lagrange multipliers (LM) method in minimizing Annual Total Cost (ATC) of the sample problem.

Implementation of the model would have saved 35% of Initial Investment Cost in pumps had it been used during design phase. The savings occurred in the annual operation cost is 11% compared to the optimized operation cost of the existing pump station. It is clear that the developed optimization model provides the designer and the operator with optimized combination of design variables and operation parameters.

(Key words: GAMS, Optimum design variables, Optimum operation schedule, Pump)

CHAPTER ONE

1.1. Introduction

The ever-increasing costs of establishing new pump station and energy have caused researchers to pay more attention to the optimal design and operation of pumping stations. About 65% of operation cost of pumped water systems is its energy cost. The amount of consumed energy depends on the system flow rate, operating pressure and time of operation. Savings can therefore be realized by optimizing these variables. Consequently, either the system characteristic curve or the pump characteristic curve should be changed to get a different operating point that minimizes total annual cost of the project as a result. Some of the techniques that can be used to reduce energy consumption are decreasing the volume of water to be pumped (e.g. soil moisture balance), lowering the pressure head (e.g. Selection of target area), reducing the consumption of energy (e.g. Selecting optimum pump type, capacity, number and operation schedule), increasing pump efficiency (e.g. ensuring pumps are operating near their best efficiency point).

No matter how well a design engineer knows the leading equations in pump system design, optimizing the decision variables has never been easy. The fact that optimal design and operation of pumping stations are mathematically large-scale non-linear problems, there is the possibility of using an optimum operation schedule on a set of non-optimum pump combinations (Rasoulzadeh-Gharibdousti, Bozorg Haddad and Marin'o, 2011). Therefore, the use of computer program for such complex problems is a wise approach.

Optimization Models written in GAMS can search the space of possible design variable values and identify an optimal design and/or operating policy for a given system design objective and set of constraints. The sensitivity of the optimal solution to changes in the model parameters can be readily determined and tradeoffs between several conflicting objectives can also be calculated with optimization models. These models include unknowns like design or operating variables (decision variables) of each alternative. They include relationships which describe the state variables and costs or benefits of each alternative as a function of the decision variables. Constraints are also included in the models to restrict the values of the design or state variables.

Optimization models are generally used for preliminary evaluation or screening of alternatives and to identify important data needs prior to extensive data collection and simulation modeling activities.

1.2. Problem Statement

Typically, pump stations are designed considering only the conditions at the maximum pump station flow rate (design point). Unfortunately, this approach focuses on conditions that are met only 1 percent of the time. The other 99 percent of the time, the system is operating under different conditions, so this design approach results in poor efficiencies during most operating conditions. It also lends itself to conservative pump sizing. It meets the delivery requirement of the maximum amount of water without any problem, but it adds to the inefficiency during normal operations. Thus, it is necessary to examine the operating conditions over the entire range of operation, with an emphasis on the average or normal operating conditions to increase the efficiency of the system. That necessitates a decision making model. Optimization model is developed in GAMS environment to help filter optimal pump configuration and set preliminary operation schedule thereby minimizing the annual total cost of a system.

1.3. Thesis Objectives

In this thesis work, minimization of Annual Total Cost (ATC) for Fentale-Qawa pump station is done by developing a model in GAMS platform. The purpose of constructing the model is to aid engineers, planners and decision makers in identifying and evaluating alternative designs and to determine which ones meet project objectives in an efficient manner. These mathematical models are able to predict a system’s response to different design alternatives and conditions.

General Objective

The objective is to develop optimization model that helps to minimize annualized capital and operation costs over a project design period subject to a set of constraints that include performance constraints, hydraulic behavior of the system, bounding constraints on the value of decision variables and constraints that may reflect either operator preferences or system limitations.

Specific Objective

The specific objective of the research is to select pump type, capacity, and number of units; schedule operation of irrigation pumps that run on least cost for a given set of demand curve.

1.4. Scope of the Research

The research involves developing optimization model that determines optimal number of selected pump types and their capacity for design stage pump projects and that can also set preliminary operation schedule for both new and existing pump stations. The effort of applying and testing the model practically on the Fentale-Qawa Pump Station was not successful because the scheme was being run under its capacity.

1.5. Thesis Layout

This thesis is divided into seven parts: chapter one offers an introduction to the thesis followed by literature review about optimization of pump stations in chapter two. Chapter three sees theoretical outline of the optimization model and the application of GAMS to solve the model problems. The solver in GAMS is also discussed is this section of the document. Validation and application of the developed model is covered in Chapter four while discussion of the results is done in the Chapter five. Finally, conclusion and recommendation part is presented in the last chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1. INTRODUCTION TO MODELING METHODS

Water resources systems are characterized by multiple interdependent components that together produce multiple economic, environmental, ecological and social impacts. Planners and managers working to improve the performance of these complex systems must identify and evaluate alternative designs and operating policies, comparing their predicted performance with the desired goals or objectives. These alternatives are defined by the values of numerous design, target and operating policy variables. Constrained optimization together with simulation modeling is the primary to estimate the values of the decision variables that will best achieve specified performance objectives. Finding the values by trial and error is often difficult. Some type of optimization procedure, or algorithm, is useful in such cases. Mathematical optimization methods are designed to make this search for the best solution (or better solutions) more efficient. Optimization methods are used to identify those values of the decision-variables that satisfy specified objectives and constraints without requiring complete enumeration. While optimization models might help identify the decision-variable values that will produce the best plan directly, they are based on all the assumptions incorporated in the model. Often these assumptions are limiting. In these cases the solutions resulting from optimization models should be analyzed in more detail, perhaps through simulation methods, to improve the values of the decision-variables and to provide more accurate estimates of the impacts associated with those decision-variable values. In these situations, optimization models are used for screening out the clearly inferior solutions, not for finding the very best one.

2.2. Overview of Simulation and Optimization Models

Optimization methods are used to identify those values of the decision-variables that satisfy specified objectives and constraints without requiring complete enumeration. While optimization models might help identify the decision-variable values that will produce the best plan directly, they are based on all the assumptions incorporated in the model. Once the preferred designs and operating policies have been identified, unless there is a reason to believe that a particular alternative is really the best and needs no further analysis, each of these preferred alternatives can be further evaluated with the aid of more detailed and robust simulation models. Simulation models address '*what if*' questions: What will likely happen over time and at one or more specific places if a particular design and/or operating policy is implemented?' Simulation models are not limited by many of the assumptions incorporated into optimization models.

Simulation methods rely on trial and error to identify near-optimal solutions. The value of each decision variables is set, and the resulting objective values are evaluated. The difficulty with the simulation approach is that there are often a frustratingly large number of feasible solutions or plans. Even when combined with efficient techniques for selecting the values of each decision variable, an enormous computational effort may lead to a solution that is still far from the best possible. To their credit, simulation methods are able to solve water resource systems planning model with highly nonlinear relationships and constraints.

Constrained optimization procedures are seldom able to deal with all the complexities and nonlinearities which are easily incorporated in a simulation model. Still, when an optimization procedure can be constructed to efficiently solve an adequate approximation to the real problem, they can greatly narrow down the search with simulation for a global optimum by identifying plans that may be close to the optimum. Constrained optimization algorithms include a diverse set of techniques that use calculus and matrix algebra. Optimization techniques include Lagrange multipliers, linear programming, dynamic programming and Genetic Algorisms. The applicability of each of these solution procedures highly depend on mathematical structure of the optimization model.

Typical optimization model generally include at least one objective function that is either to be maximized or minimized and which serves to rank the alternative solutions or plans. In addition to an objective, planning problems incorporates a number of requirements which are formulated as constraints. It is important to distinguish the different roles played by the objective function and the constraints.

The optimal solution of the planning problem is a plan that achieves the largest (or smallest) value of the objective while satisfying all the constraints.

2.3. Genetic Algorithms

Genetic algorithms are randomized general-purpose search techniques used for finding the best values of the parameters or decision-variables of existing models. It is not a model-building tool like genetic programming or artificial neural networks. Genetic algorithms and their variations are based on the mechanisms of natural selection. Numerically, the process uses reproduction, crossover and mutation to evolve encoded variables. The algorithm is designed to produce populations of solutions whose offspring display increasing levels of optimality. Unlike conventional optimization search approaches based on gradients, genetic algorithms work on a population of possible solutions, attempting to find a solution set that either maximizes or minimizes the value of a function of those solution values. This function is called the objective function. Some populations of solutions may improve the value of the objective function, others may not. The ones that improve its value play a greater role in the generation of new populations of solutions than those that do not (Goldberg, 1989).

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2.4. Linear Programming

Linear programming is arguably the most popular and commonly applied optimization algorithm it is used when the objective function and constraints of an optimization model are all linear. Many water resources problems contain many variables and constraints, too many to be easily solved using non-linear or dynamic programming methods. Linear programming procedures or algorithms for solving linear optimization models are often the most efficient ways to find solutions to such problems.

Many models of complex water resources systems are, or can be made, linear. Many are also very large. The number of variables and constraints simply defining mass balances and capacity limitations alone at many river basin sites and for numerous time periods can become so big as to preclude the practical use of most other optimization methods. Because of the power and availability of computer programs that can solve large linear programming problems, a variety of methods have been developed to approximate non-linear (especially separable) functions with linear ones just so linear programming can be used to solve various otherwise nonlinear problems.

In spite of its power and popularity, for most real world water resources planning and management problems, linear programming, like the other optimization methods, is best viewed as a preliminary screening tool. Its value is more for reducing the number of alternatives for further more detailed simulations than for finding the best decision. This is not just because approximation methods may have been used to convert non-linear functions to linear ones, but more likely because it is difficult to incorporate all the complexity of the system and all the objectives considered important to all stakeholders into the linear model. Nevertheless, linear programming, like other optimization methods, can provide initial designs and operating policy information that simulation models require before they can simulate those designs and operating policies [Daniel P. Loucks (1981)].

2.5. Dynamic Programming

Dynamic programming is ideally suited for sequential decision problems. Sequential decision problems are those in which decisions are made sequentially, one after another, based on the state of the system. Unlike linear programming problems, dynamic programming problems are not amendable to a single, standard algebraic formulation. Different types of sequential decision problems may need to be formulated differently considering specific features of the problem and therefore, dynamic programming problem is said to be as much an art as it is a mathematical technique. In many practical situations a net-benefit function may not be so continuous, or so conveniently concave for maximization or convex for minimization, making calculus-based methods for their solution difficult. A possible solution method for constrained optimization problems containing continuous and/or discontinuous functions of any shape is called discrete dynamic programming. Each decision-variable value can assume one of a set of discrete values. For continuous valued objective functions, the solution derived from discrete dynamic programming may therefore be only an approximation of the best one. For all practical purposes this is not a significant limitation, especially if the intervals between the discrete values of the decision-variables are not too large and if simulation modeling is used to refine the solutions identified using dynamic programming. Dynamic programming is an approach that divides the original optimization problem, with all of its variables, into a set of smaller optimization problems, each of which needs to be solved before the overall optimum solution to the original problem can be identified. The water supply allocation problem, for example, needs to be solved for a range of water supplies available to each firm. Once this is done the particular allocations that maximize the total net benefit can be determined. Dynamic programming models can be applied to design problems, such as the capacity expansion problem or a reservoir storage capacity–yield, or to operating problems, such as the water allocation and reservoir operation problems, but rarely to problems having both unknown design and operating policy decision-variables. While there are some tricks that may allow dynamic programming to be used to find the best solutions to both design and operating problems encountered in water resources planning and management studies, other optimization methods, perhaps combined with dynamic programming where appropriate, are often more useful[Daniel P. Loucks (1981)].

2.6. Lagrange Multipliers Method

Consider the general constrained optimization problem containing *n* decision-variables *xj* and *m* constraint equations *i*.

Maximize (or minimize) $F(\boldsymbol{X})$ subject to constraints

$g_i(X)=b_i \qquad i=1, 2, 3, \ldots m$

where $\boldsymbol{X}$ is the vector of all x_j.

The Lagrange function is formed by combining the equations, each equaling zero, with the objective function equation.

$$L(\boldsymbol{X}, \lambda)=F(X)+\sum_i \lambda_i (g_i(X)-b_i)$$

Solutions of the equations

$\frac{\partial L}{\partial x_j}$=0 for all decision variables j and

$\frac{\partial L}{\partial \lambda_i}$=0 for all constraints i are possible local optima.

Since there is no difference in the Lagrange multipliers procedure for finding a minimum or a maximum solution, one needs to check whether in fact a maximum or minimum is being obtained[Daniel P. Loucks (1981)].

2.7. Honey Bee Mating Optimization Algorithm (HBMO)

Honey-bee mating may also be considered as a typical swarm-based approach to optimization in which the search algorithm is inspired by the process of mating in real honeybees. The algorithm receives two sets of model input parameters: (a) model structure parameters that are mainly problem-dependent, such as number of decision variables, upper and lower bounds on decision variables, penalty coefficients, etc., and (b) algorithm parameters that may be used as tuning parameters, such as number of mating flights, size of hive, number of solutions in the simulated annealing process, queen’s initial speed and energy, as well as type and number of heuristic functions defined by different workers.

The algorithm begins with the random generation of a set of initial solutions. The generated solutions may or may not belong to the feasible region. In fact, most of the generated solutions may be non-feasible. Randomly generated solutions are then ranked using a penalized objective function. The fittest solution is named the queen, whereas the remaining solutions are categorized as drones (i.e. trial solutions). By defining the queen, drones, broods, and workers (predefined functions), the hive is completely formed and mating can be started then.

The proficiency of HBMO has been demonstrated by different researchers by applying it to well-known mathematical optimization problems and compared the final solutions with other method (Omid Bozorg Haddad and Miguel A. Marin˜o, 2007).

2.8. Pre-selection of Pumps for Modelling

Pumps are a means of adding energy to water. They convert fuel energy, such as petrol or diesel, into useful water energy using combustion engines or electric motors. Thus, energy is needed to pump water. The amount required depends on both the volume of water pumped and the height to which it is lifted. It can be calculated using the following formula:

$$\text{Water Energy (KWh)} = \text{Volume}(m^3)*H(m)/367$$

Pump selection, however, depends on several other factors and all comes down to the cost finally. A typical approach to the design of pumping systems includes the following factors:

- Minimum Pump Station Flow Rate
- Average Pump Station Flow Rate
- Maximum Pump Station Flow Rate
- Type of Fluid Pumped
- Total Dynamic Head (TDH)
- Available Pumps

The TDH is determined from a number of factors, which include:

- Friction Losses in the System
- Static Head Differences
- Water Temperature
- Age and Conditions of the Pipe (and future conditions)
- Flow Control

Typically, pump stations are designed considering only the conditions at the maximum pump station flow rate (design point). Unfortunately, this approach focuses on conditions that are met only 1 percent of the time. The other 99 percent of the time, the system is operating under different conditions, so this design approach results in poor efficiencies during most operating conditions. This approach to design and construction of pump stations also lends itself to conservative pump sizing. It will meet the delivery of the maximum amount of water without any problem, but it adds to the inefficiency during normal operations. Thus, it is necessary to examine the operating conditions over the entire range of operation, with an emphasis on the average or normal operating conditions to increase the efficiency of the system. Understanding the range of flows and heads in combination with each other is critical to an energy-efficient design; that is supplying to the system demand without significant loss.

For example, a system where the TDH changes drastically from summer to winter may require pumps with a wider range of higher efficiencies and the use of variable frequency drives. If the system head curve (change in discharge pressure with increased flow) is flat and not dependent upon the flow rate leaving the pump station, or the static elevation on the suction and the discharge do not change over time, then pumps with a higher best efficiency point (without a wide range of higher efficiency) and constant speed motors will be the best fit from an energy-efficiency perspective.

One of the tools that can be used to assist with pump station design and pump selection is specific speed.

Specific speed (Ns) $=NQ^{1/2}/H^{3/4}$

Where N=speed in rpm

Ns=specific speed (no unit)

Q=discharge (m^3/s)

H=head in meter (m)

It is used to:

- Select the shape of the pump curve
- Determine the efficiency of the pump
- Anticipate motor overload
- Predict NPSH requirements
- Select the lowest pump cost for the application

As the specific energy increases, the steepness of the pump curve increases. As the specific speed decreases, the flow range of higher efficiencies increases for the pump. Understanding of these characteristics helps the design engineer to tune the design to be energy efficient(Chris Reinbold and Vincent Hart, 2009).

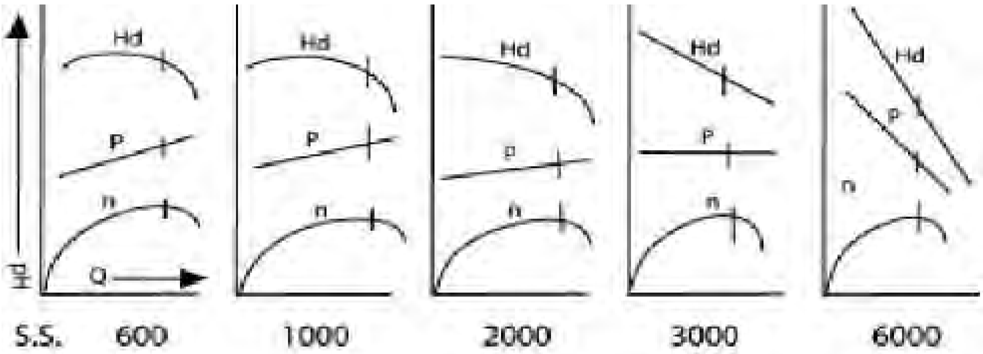


Figure.1.1 Impact of Changing Specific Speed on Pump Curve and Efficiency Characteristics (courtesy McNally Institute)

Where

H_d=generated pump head

P=power required

n=pump efficiency

Q=pump discharge

No matter how well a design engineer knows the leading equations in pump system design, optimizing the decision variables has never been easy. The fact that optimal design and operation of pumping stations are mathematically large-scale non-linear problems, there is the possibility of using an optimum operation schedule on a set of non-optimum pump combinations (Rasoulzadeh-Gharibdousti, Bozorg Haddad and Marin'o, 2011). Therefore, the use of computer program for such complex problems is a wise approach.

2.9. Interest Rates

Interest is a time value of money. Interest rate includes a number of considerations. One is the time value of money (a willingness to pay something to obtain money now rather than to obtain the same amount later). Another is the risk of losing capital (not getting the full amount of a loan or investment returned at some future time). A third is the risk of reduced purchasing capability (the expected inflation over time).

Assuming an amount V_0 is invested at the beginning of a time period, e.g., a year, in a project or a savings account earning interest at a rate r per period, then at the end of the period the value of that investment is $(1+r)V_0$. The investment at the end of t years, V_t, would be $V_0\ (1+r)^t$. Thus the present worth or present value, V_0, of an amount of money V_t at the end of period n is given as:

$$V_o = \frac{V_t}{(1+r)^t}$$

Capital Recovery Factor (CRF) is given as:

$$CRF_t = \frac{r(r+1)^t}{(1+r)^t - 1}$$

This factor is often used to compute the equivalent annual end-of-year cost of engineering structures that have a fixed initial construction cost C_0 and annual end-of-year operation, maintenance, and repair (OMR) costs. The equivalent uniform end-of-year total annual cost, ATC, equals the initial cost times the capital recovery factor plus the equivalent annual end-of-year uniform OMR costs and is expressed as:

$$ATC = CRF_t . C_o + OMR$$

These concepts of engineering economics are applicable to many of the problems faced in water resources planning and management [Daniel P. Loucks (1981)].

2.10. Revision on Pump Station Optimization

Over the last decade, several optimization techniques have been used as search and optimization tools in various problems. Energy costs constitute the largest expenditure for nearly all water utilities worldwide and can consume up to 65% of a water utility annual operating budget (F. Barutcu). Hence, attempts to improve the design and operation efficiency of existing or newly developed pumping stations are continuously increasing. These focus on three different aspects:

(1) Efficient pump combination;

(2) Efficient pump scheduling and operation; and

(3) Pump selection i.e. type, capacity, and number of units.

Results indicated that the models could effectively reduce the cost of energy consumed by pumping stations while maintaining hydraulic constraints.

Various algorithms have been oriented towards least-cost pump scheduling policies (typically proper on–off pump operation) based on optimization tools such as linear, non-linear and dynamic programming (LP, NLP and DP), enumeration techniques, general heuristics and genetic algorithms (GAs). The success of these procedures has been limited and few have been applied to real water resource systems. The limited acceptance of optimal control models in engineering practice may stem from several factors. These models:

1. are generally quite complex and involve a considerable amount of mathematical sophistication (e.g. requiring extensive expertise in systems analysis and careful selection and calibration of parameters)
2. are usually highly dependent on the number of pumps being considered and the duration of the operating period
3. are generally subject to oversimplification of model components and involve several simplifying assumptions to accommodate non-linear hydraulic constraints that require, for example, demands to be known with certainty
4. tend to be computationally demanding, leading to added costs and delays (M. A. Marin'o, O. Bozorg Haddad and S. Rasoulzadeh-Gharibdousti, 2010).

Mahdi Moradi-Jalal et.al developed a computer program which solves one major objective function optimizing scheduling of operation of irrigation pumps based on minimum yearly consumed energy, total cost for all sets of pumping stations and selection of the least-cost set among the feasible sets of pumping stations by using Genetic Algorism (GA). Application of the model showed considerable savings; about 25% in total annual cost of the pumping station. Bozorg Haddad and Marin'o (2007) optimized the design and operation of a pumping station using Honey-bee Mating Optimization (HBMO) with dynamic and static penalty functions. M .H .Afshar et.al used Particle Swarm Optimization Algorithm to optimize irrigation pump systems in similar way to Mahdi Moradi-Jalal.(2003). The energy savings were obtained from optimum combination of pump sets only that supply a given demand curve. On the other hand, F. Barutcu et.al matched pump and irrigation characteristic curves by introducing variable Speed Derive (VSD) that it resulted in the largest decrease in energy consumption in on-demand irrigation system. The case under consideration is about pumps with fixed speed. When pump speeds are considered fixed, the solutions for pump discharges are a discrete set of feasible operating points (Nitivattananon et al., 1996).

In designing pumping stations, LP and NLP solvers cannot be used for the reason of discrete selection of pump types. Thus, M. A. Marin'o et al. (2011) developed a hybrid model, NLP-GA, and compared its solution with results previously obtained for the same problem by the Lagrange multiplier (LM) method, a GA and the HBMO algorithm. The result showed relatively small difference in annualized cost between the optimal sets and the pre-sets of the existing design. The main savings occurred in the annual operation cost, with nearly 32% savings in energy cost. And, a decrease of about 20% is obtained in total annualized cost. This specific problem is considered in our case study to develop GAMS model so as to compare the results before we use it to solve our problem.

GAMS has a merit over the other optimization techniques in that it has inbuilt solvers that can handle several kinds of problems. The user is expected to write a code in a GAMS integrated development environment (IDE) in the right syntax unlike the other methods where the user is expected to solve a complex mathematical problem on its own. As a result, its application saves time and cost in solving a problem. Thus, it is selected as optimization tool in this thesis work.

CHAPTER THREE

3.1. Model Design

3.1.1. Mathematical Development of the Model

A pumping station typically includes a number of pumps meeting specified demand characteristics. An appropriate method is needed to minimize annualized cost, which includes both the annual cost of energy consumption for all pumping sets (based on a discharge distribution of demand curve) and the annualized cost of initial capital investments. Thus, the objective function may be expressed as (Marino et al., 2011):

$$Min(ATC) = \sum_{i=1}^{n} CRF.C_i' + C_E E_K \tag{1}$$

Where CRF-capital recovery factor

C_i-initial cost of ith pump

C'_i-cost of ith pump at the end of construction period, C_t

C_E-unit energy cost

E_k-total annual consumed energy

An appropriate method to minimize the consumed energy by each pumping set, based on increment time discharge duration curves, is given as:

$$E_K = \rho g \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{(Q_{i,j} H_{i,j} (IQ_j))}{e_{i,j}(H_{i,j}, Q_{i,j})} \Delta t \tag{2}$$

Where E_k –total annual consumed energy of kth pump set

$Q_{i,j}$-discharge from pump i at time j

$H_{i,j}$-pump head from pump I at time j

Δt-time step on demand duration curve

IQ_j-total demand at time step j

Δt-time step on demand duration curve

$e_{i,j}(H_{i,j},Q_{i,j})$-pump efficiency

The number of equations in the model is directly dependent on the type, size and number of pump units, as well as on the demand curves and their temporal discretization. Using a time step of one month simplifies both the solution and the discretization of the demand duration curves (Mahdi Moradi-Jalal et al, 2003)[3]. By introducing these assumptions into Equation 2, the formulation of consumed energy of pumping station E_k is reduced to:

$$P_{k,j} = \rho g H_j \sum_{n=1}^{n} \frac{Q_i}{e_i(Q_i)} \qquad (3)$$

Even though efficiency $e_{i,\,j}(H_{i,\,j},\ Q_{i,\,j})$ is a function of the net pumping head and discharge, it is assumed as a function of discharge only as it has no significant effect on the optimization result (Deppo and Datei ,1984). It is therefore given as:

$$e_i(Q_i)=a_iQ_i^2+b_iQ_i+c_i \qquad (4)$$

where the coefficients $a_{i,}$, b_i and c_i are found from performance curve for i^{th} pump.

The net pumping head $H_{i,j}(IQ_i)$ is related to gross pumping head, $H_{i,j}$ by

$$H_{i,j}=HS_{i,j} + (h_f)_{i,j} = HS_{i,j} + \frac{8f\,L_i Q_{i,j}^2}{2g\,\pi^2 D^5} \qquad (5)$$

where *Li*-delivery pipe length of pump *i*

f-friction factor

Di -delivery pipe diameter of pump *i*

$HS_{i,\,j}$-static head of pump *i* during time step *j*

$(h_f)_{i,\,j}$-friction head loss of pump *i* during time step *j*

$Q_{i,\,j}$-discharge of pump *i* during time step *j*

Minimum consumed energy in time Δt is thus given as

$$MinE_{k,j} = \sum_{j=1}^{m} P_{k,j} \Delta t_j \tag{6}$$

cost of i[th] pump at the end of construction period, C’, is given as

$$C'_i = \left(1 + \frac{r * c_t}{2}\right) * C_i \tag{7}$$

Capital Recovery Factor (CRF) is given as

$$CRF = \frac{r(r+1)^T}{(1+r)^T - 1} \tag{8}$$

Where,

r-interest rate

T-project design life

3.1.2. Model Constraints

This research work mainly focus on economic optimization of irrigation pump system subject to various technical and resource constraints. The constraints may include maximum and minimum available pump capacity in the market, source of water, and pumping head.

$$Q_{i,j} \le Q_{max\ i} \tag{9}$$

$$\sum_{i=1}^{n} Q_{i,j} = IQ_j \tag{10}$$

$$\sum_{i=1}^{n} Q_{i,j} \le Q_{min\ j} \tag{11}$$

$$H_{i,j} \le H_{max\ i} \tag{12}$$

$$H_{i,j} \ge H_{min\ i} \tag{13}$$

Where,

$Q_{i,j}$ = discharge generated by pump i in month j

$Q_{max\,i}$ =maximum discharge of pump i

IQ_j =crop water requirement in month j

$H_{i,j}$ = pumping head by pump i in month j

$H_{max\,i}$ =maximum pumping head of pump i

$H_{min\,i}$ =minimum pumping head of pump i

3.1.3. Model simplification

The case study under consideration is in a different condition in that there is only a single source of water and a single pump station from the source. Thus, there is a constant static head. If the system head curve (change in discharge pressure with increased flow) is flat and not dependent upon the flow rate leaving the pump station, or the static elevation on the suction and the discharge do not change over time, then pumps with a higher best efficiency point (without a wide range of higher efficiency) and constant speed motors will be the best fit from an energy-efficiency perspective (Chris Reinbold and Vincent Hart, 2009). Thus, best efficiency of respective pumps is assumed in the modeling. Total dynamic head (TDH) is also separately calculated and entered into model as a parameter. As a result, equation 3 is more simplified as:

$$P = \rho g H_{TDH} \sum_{n=1}^{n} \frac{Q_i}{\eta} \qquad (14)$$

Where P= annual consumed energy

ρ= density of water

g= gravity

H_{TDH}= Total dynamic head

Q_i= discharge of pump i

η = efficiency of pumps

3.1.4. Decision Variables

Key decision variables include:

- pump type and capacity
- number of pumps
- Preliminary schedule of pump operation

3.1.5. Input Data

Data required as input to the model are:

- source flow discharge (m^3/s)
- pumping head constraint (m)
- maximum pump discharge (m^3/s)
- Crop water requirement hydrograph (Q(m^3/s) vs month)
- Initial pump cost c_i (Birr)
- Interest rate r
- Project life T (year)
- Pump efficiency η
- Gravitational acceleration (m^2/s)
- Density of water (Kg/m^3)

3.2. Overview of General Algebraic Modeling Systems (GAMS)

3.2.1. Introduction

GAMS is a software package used to solve systems of equations. It contains different solvers for different purposes. Various kinds of economic models can be written down as a system of equations, including systems analysis, non-linear optimization and equilibrium modeling.

3.2.2. General Structure of GAMS

The first step in modeling in GAMS is to write an input file. After writing the input file, run the model in GAMS and look at the output file for the results. The general structure of a simple GAMS input file contains the following elements:

- Sets-Declaration and assignment of members
- Data-consists of Parameters, Tables and Scalars with declaration and assignment of values
- Variables-indicates the variables that will be determined (calculated) within the model. It involves declaration and declaration of its type. They have options of upper and lower bounds, and initial values.
- Equations-first, the equations have to be declared, and then they are defined.
- Model-the model is a given name to the model being developed
- Solve-the solution mode is specified, that is a declaration whether the optimand should be maximized or minimized.

Each of these elements can exist more than once in a single GAMS model. The restrictions and special meanings of these words are all together called the syntax of a model. GAMS is a computer package and will only understand what the user want if it is written in the correct syntax.

3.2.3 The Solver DICOPT

DICOPT (DIscrete and Continuous OPTimizer) is an inbuilt program in GAMS for solving mixed-integer nonlinear programming (MINLP) problems that involve linear binary or integer variables and linear and nonlinear continuous variables. While the modeling and solution of these MINLP optimization problems has not yet reached the stage of maturity and reliability as linear, integer or non-linear programming modeling, these problems have a rich area of applications and they often arise in engineering design. The program is based on the extensions of the outer-approximation algorithm for the equality relaxation strategy. The MINLP algorithm inside DICOPT solves a series of NLP and MIP sub-problems. These sub-problems can be solved using any NLP (Nonlinear Programming) or MIP (Mixed-Integer Programming) solver that runs under GAMS.

DICOPT system has been designed with two main goals in mind:

- to build on existing modeling concepts and to introduce a minimum of extensions to the existing modeling language and provide upward compatibility to ensure easy transition from existing modeling applications to nonlinear mixed-integer formulations.

- to use existing optimizers to solve the DICOPT sub-problems. This allows one to match the best algorithms to the problem at hand and guarantees that any new development and enhancements in the NLP and MIP solvers become automatically and immediate available to DICOPT.

It solves models of the form:

$$\begin{aligned}&\text{Min or Max } f(x,y)\\&\text{Subject to } g(x,y) \sim b\\&l_x \le x \le u_x\\&y \in [\, l_y, u_y]\end{aligned}$$

Where x are the continuous variables and y are the discrete variables. The symbol ~ is used to denote a vector of relational operators. The constraints can be either linear or non-linear. Bounds *l* and *u* on the variables are handled directly. The discrete variables can be either integer variables or binary variables.

3.2.4. Algorithm of DICOPT

The algorithm of DICOPT is based on three key ideas:

- Outer Approximation
- Equality Relaxation
- Augmented Penalty

Outer Approximation refers to the fact that the surface described by a convex function lies above the tangent hyper-plane at any interior point of the surface. (In 1-dimension, the analogous geometrical result is that the tangent to a convex function at an interior point lies below the curve). In the algorithm outer-approximations are attained by generating linearizations at each iterations and accumulating them in order to provide successively improved linear approximations of nonlinear convex functions that under estimate the objective function and overestimate the feasible region.

Equality Relaxation can be explained by using non-linear programming. Suppose the MINLP problem is formulated in the form:

$$\text{Min/Max } f(x) + C^T y$$

$$\text{Subjected to } G(x) + Hy \sim b$$

$$l \leq x \leq u$$

$$y \in \{0,1\}$$

If we reorder the equations into equality and inequality equations, and convert the problem into a minimization problem, it can be written as:

$$\text{Minimize } C^T y + f(x)$$

$$\text{Subject to } Ay + h(x) = 0$$

$$By + g(x) \leq 0$$

$$l \leq x \leq u$$

$$y \in \{0,1\}$$

Let $y^{(0)}$ be any fixed binary vector and let $x^{(0)}$ be the solution of the corresponding NLP sub-problem

$$\text{Minimize } C^T y^{(0)} + f(x)$$

$$\text{Subject to } Ay^{(0)} + h(x) = 0$$

$$By^{(0)} + g(x) \leq 0$$

$$l \leq x \leq u$$

Further let

$$T^{(0)} = \text{diag}(t_{i,i},)$$
$$t_{i,i} = \text{sign}(\lambda_i)$$

where λ_i is the Lagrange multiplier of the i-th equality constraint.

If *f* is pseudo-convex, *h* is quasi-convex, and *g* is quasi-convex, then x^0 is also the solution of the following NLP:

$$\text{Minimize } C^T y^{(0)} + f(x)$$

$$\text{Subject to } T^{(0)}(Ay^{(0)} + h(x)) \leq 0$$

$$By^{(0)} + g(x) \leq 0$$

$$l \leq x \leq u$$

That means, an equality constraint can be “relaxed” to be an inequality constraint under certain assumptions for the convexity of the nonlinear functions. This property is used in the MIP master problem to accumulate linear approximations.

Augmented Penalty refers to the introduction of (non-negative) slack variables on the right hand sides of the just described inequality constraints and the modification of the objective function when assumptions concerning convexity do not hold.

The algorithm underlying DICOPT starts by solving the NLP in which the 0-1 conditions on the binary variables are relaxed. If the solution to this problem yields an integer solution the search stops. Otherwise, it continues with an alternating sequence of non-linear programs (NLP) called sub-problems and mixed-integer linear programs (MIP) called master problems. The NLP sub-problems are solved for fixed 0-1 variables that are predicted by the MIP master problem at each (major) iteration. For the case of convex problems, the master problem also provides a lower bound on the objective function. This lower bound (in the case of minimization) increases monotonically as iterations proceed due to the accumulation of linear approximations. Note that in the case of maximization this bound is an upper bound. This bound can be used as a stopping criterion through a DICOPT options.

Another stopping criterion that tends to work very well in practice for non-convex problems (and even on convex problems) is based on the heuristic: stop as soon as the NLP sub-problems start worsening (i.e. the current NLP sub-problem has an optimal objective function that is worse than the previous NLP sub-problem). This stopping criterion relies on the use of the augmented penalty and is used in the description of the algorithm below. This is also the default stopping criterion in the implementation of DICOPT for the model developed in this thesis work as well. The algorithm can be stated briefly as follows:

1. Solve the NLP relaxation of the MINLP program. If $y^{(0)} = y$ is integer, stop(“integer optimum found”). Else continue with step 2.
2. Find an integer point $y^{(1)}$ with an MIP master problem that features an augmented penalty function to find the minimum over the convex hull determined by the half-spaces at the solution $(x^{(0)}, y^{(0)})$.

3. Fix the binary variables $y = y^{(1)}$ and solve the resulting NLP. Let $(x^{(1)}, y^{(1)})$ be the corresponding solution.
4. Find an integer solution $y^{(2)}$ with a MIP master problem that corresponds to the minimization over the intersection of the convex hulls described by the half-spaces of the KKT points at $y^{(0)}$ and $y^{(1)}$.
5. Repeat steps 3 and 4 until there is an increase in the value of the NLP objective function. (Repeating step 4 means augmenting the set over which the minimization is performed with additional linearizations - i.e. half-spaces - at the new KKT point).

CHAPTER FOUR

MODEL VALIDATION AND APPLICATION

4.1. Model Validation

Validation of the program was done by optimizing frequently researched problem, Farabi Agricultural and Industrial project, by several researchers. The project was last researched by M. A. Marin'o et al. in (2011). The results of their research were used for validation purpose in our model development. Annual Total Cost (ATC) of the project was optimized by using GAMS and the results were compared with the previous results obtained by different methods. The pump station supplies irrigation water to agricultural area of 20,000 ha. The demand curve in discrete monthly time steps that must be supplied by the pumping station is depicted in figure. 3.1.

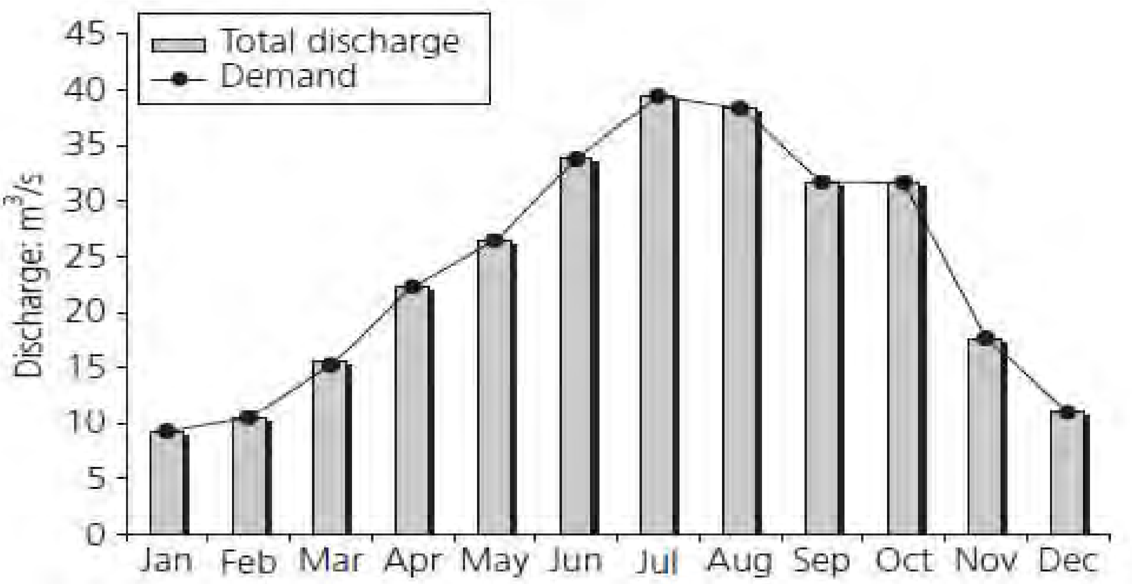


Figure 3.1 Discrete Monthly Demand Curve and Total Discharges of 10 Pumps

In the practical design of the project, only three initial sets of pumps were selected and cost analysis was limited to a comparison between the results of those three sets. Hence, the optimal set was selected as one of those three initial sets i.e. 16 pumps set of type 1 pump. The model result was summarized as in table 4.1 and table 4.2 for comparison with results of other models for the same case study.

Table 4.1 Number of pumps of each type

Optimized sets by different methods							Existing pump type
Pump type	NLP-GA	D-HMBO	S-HBMO	GA	GAMS	LM	Design
1	3	3	3	4	3	3	0
2	2	4	3	2	3	4	0
3	3	0	3	0	1	0	16
4	2	3	1	3	3	3	0
Total	10	10	10	9	10	10	16

Optimized numbers of pumps were obtained by consecutive methods. GAMS model proposed a unique arrangement under a constraint that total number of pumps is less than or equal to 10. The arrangement resulted in the least initial capital investment cost as compared to all other considered methods (table 4.2) and hence the annual depreciation cost. Similarly, the estimated cost of annual operation of the pump station with GAMS result of arrangement of pumps stands the least compared to the considered methods. Setting the assumed efficiency of pumps to 80% would add 6.4% to the annual operation cost.

Table 4.2 Cost of optimized sets

Optimized sets by different methods							
Description of Economic parameters	NLP-GA	D-HMBO	S-HBMO	GA	GAMS	LM	Design
Initial capital investment (10^6)	1219	1207	1248	1253	1200	1224	1327
Annual depreciation cost (10^6)	115.8	114.7	118.7	119.1	113.9	114.7	126.1
Annual operation cost (10^6)	72	72.4	71	71.5	66.65	67.7	102.2
Annual total cost (10^6)	187.8	187.1	189.7	190.6	180.55	182.4	228.3
Relative ATC in %	104	103.6	105	105.5	100	101	126.4

In table 4.2, the figures for the economic parameters under GAMS are automatic model results from GAMS model for the same problem that had been solved by other methods like NLP-GA. GAMS model minimized the ATC of the sample problem better than the listed methods. As a result the developed model can be used to solve Fentale-Qawa pump station optimization case study.

4.2. Model Application

4.2.1. Description of Fentale-Qawa Pump Station

Fentale-Qawa Pump Station is located in Arsi zone of Oromia National Regional State at 194Km from Addis Ababa. It supplies 847 ha of land with irrigation water by employing two pump stations; Pump Station-1 (PS1) with a station design capacity of 1.24m3/sec & Pump Statin-2 (PS2) with a station design capacity of 0.526 m^3 / sec. PS1 is supplied via a short channel which is connected to the main canal. PS1 discharges to night service reservoir-1(NSR-1) which stores water for irrigation and supply water to PS2. PS2 discharges to night service reservoir 2, NSR2.

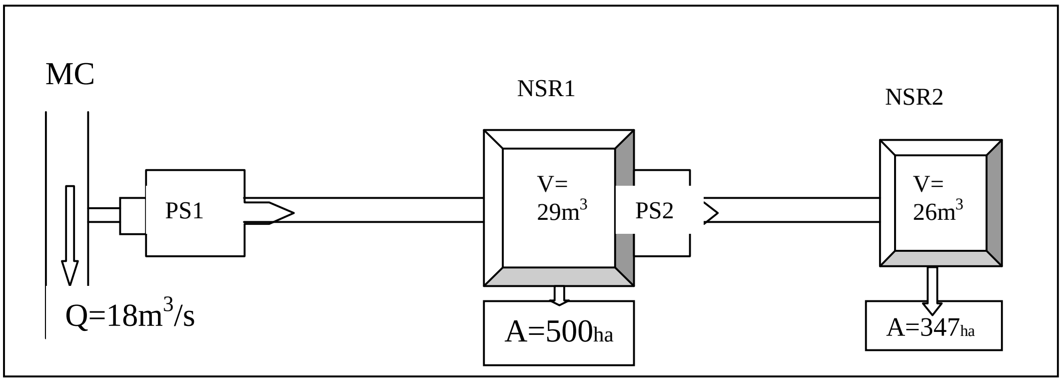


Figure 4.1 Schematic representation of Fentale-Qawa Pump Irrigation Scheme

Table 4.3: Efficiency-Discharge Relationship for the Installed Pump Type

Q (m3/hr)	H (m)	η (%)
141.78	58.23	20.48
354.46	58.04	44.91
708.92	54.66	70.49
1112.11	48.65	81.64
1196.30	46.49	82.77
1417.83	39.45	81.39

Figure 4.2 Installed pumps at Fentale-Qawa Pump Station

PS1 houses four pumps with one additional standby pump; a total of five pumps are installed. Each pump can operate at system duty point of 1112m^3/hr with efficiency of 81.6%. The unit cost of the pump is Birr 214,515.

Figure 4.3 Pump station intake site (left) and Night service storage reservoir (Right)

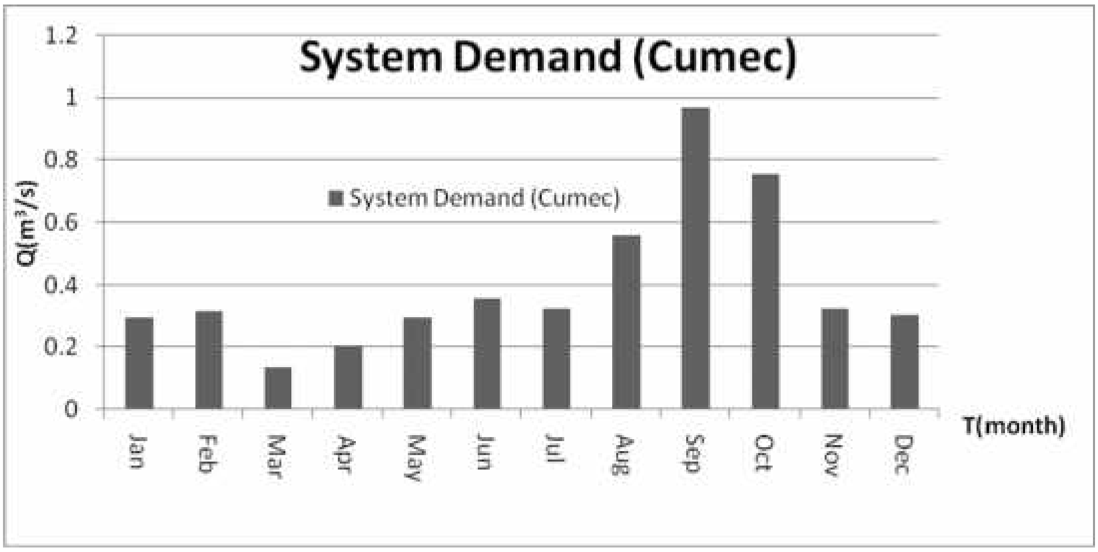
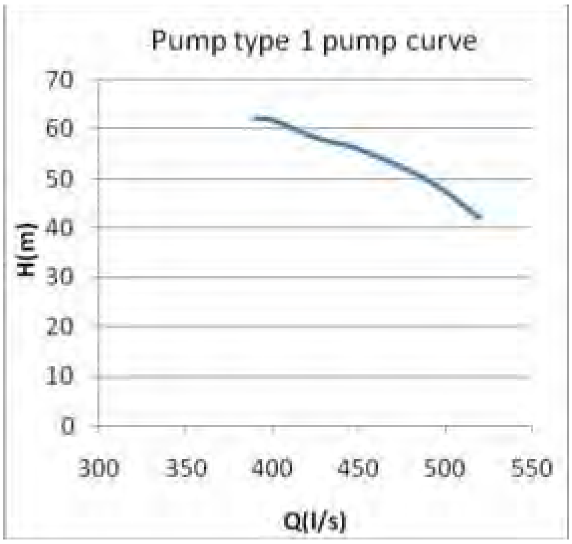


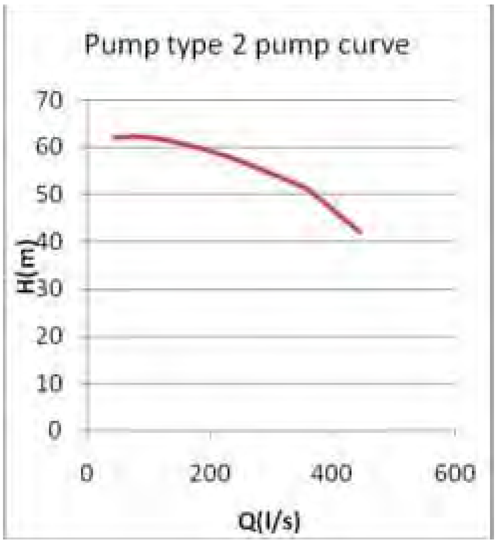
Figure 4.4 Discrete Monthly Demand Curve

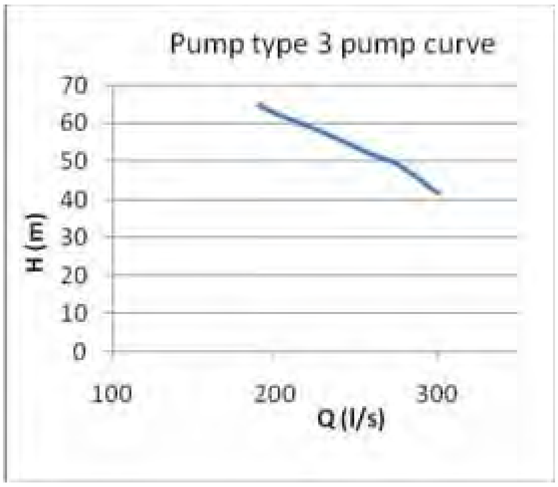
(Source: Final Design Report, Vol. 1, Qawa Pump Station)

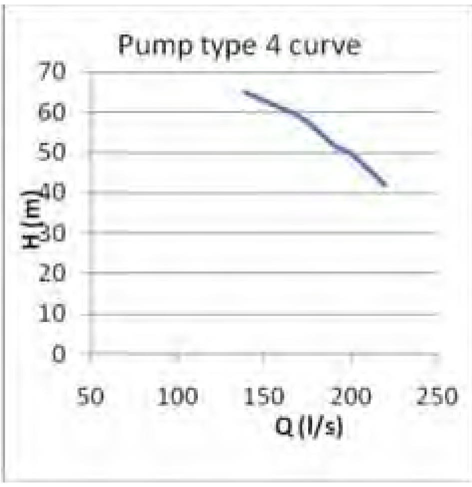
Table 4.4: Discharge-Head-Efficiency relationships for considered pumps

Pump Type 1			Pump Type 2			Pump Type 3			Pump Type 4		
Q(l/s)	H(m)	η(%)	Q(l/s)	H(m)	η(%)	Q(l/s)	H(m)	η(%)	Q(l/s)	H(m)	η(%)
409.6	58.04	86%	341.3	58.04	86%	227.6	58.04	86%	172.94	58.04	86%
369.0	54.66	81.7	307.5	54.66	81.7	205.0	54.66	81.7	155.80	54.66	81.7
450.0	48.65	83.2	375.0	48.65	83.2	250.0	48.65	83.2	190.00	48.65	83.2
328.5	46.49	75.2	273.8	46.49	75.2	182.5	46.49	75.2	138.70	46.49	75.2
492.8	39.45	79.1	410.6	39.45	79.1	273.8	39.45	79.1	208.05	39.45	79.1









CHAPTER FIVE

5. RESULTS AND DISCUSION

As stated earlier, the main purpose of the optimization model is to minimize the total annualized cost of feasible sets, which comprises both the annualized cost of the initial capital investment cost and the operation cost. The developed model was run for two different cases. The first was to optimize the operation schedule of existing pumps. This model simply gives the preliminary operation schedule of the installed pumps depending on the type, number and capacity of the pumps. The second model considers design phase scenario where four different pumps were set to the model so that the model selects the optimum combination of pumps.

5.1. Optimization of Operation Schedule for Existing Pump Station

The operation schedule of the existing pump station was optimized by the model and the result is presented in Figure 5.1. The designed four pumps operate simultaneously for only 16.6% of the time annually while two pumps can cover the system demand for about 50% of the time. The remaining percentage of time can be supplied by just a single pump.

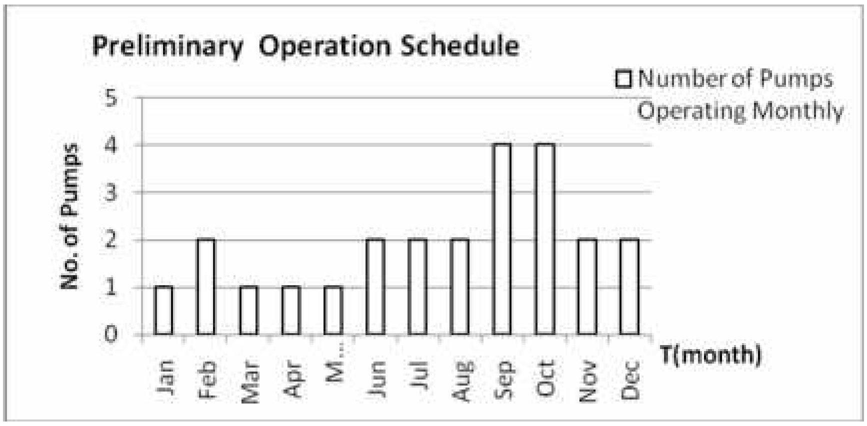


Figure 5.1: Number of pumps operating monthly

The existing system could supply the irrigation demand even if it is not optimized as shown in Figure 5.3 because the system was designed to supply the peak demand of the system. The result of optimization of operation schedule by GAMS shows adjustment of supply discharge to demand discharge as shown in Figure 5.2. That could avoid over operation and save its cost.

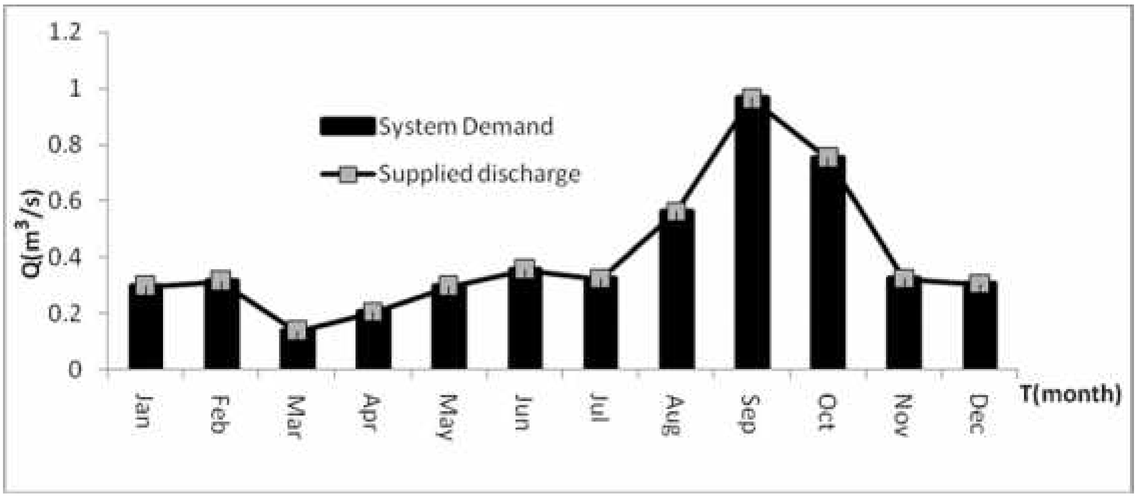


Figure 5.2: Monthly demand curve and total discharge (four pumps) of pumping station

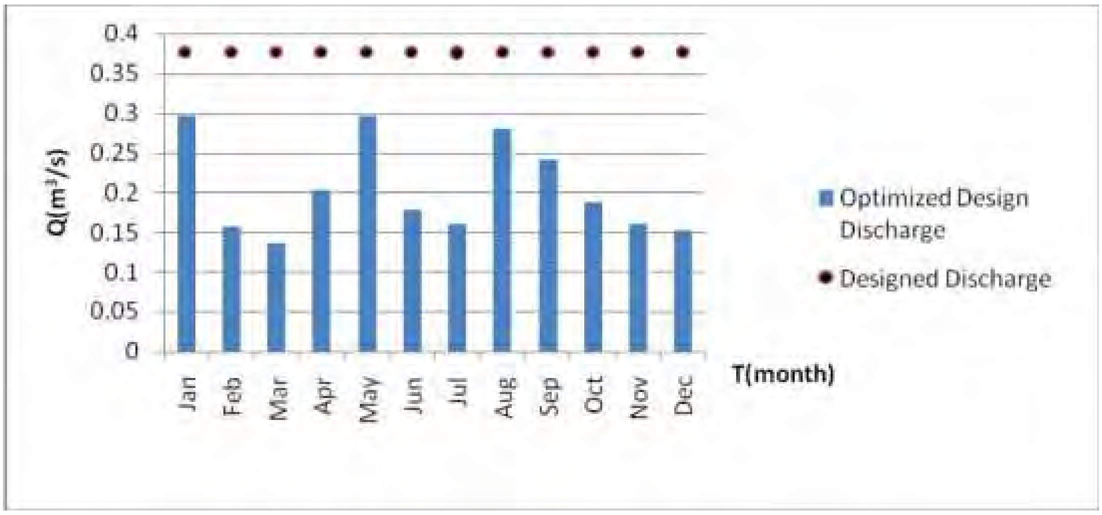


Figure 5.3: Monthly discharge of optimized discharges and design discharge.

5.2. Optimal Design and Scheduling of Fentale-Qawa Pump Station

The model was run by considering design phase scenario where four different pumps were set to the model that it selected the optimum combination of pumps. The results include:

i. number of pumps and pump types of the set
ii. a value for pumped discharge in every time step and for each pump
iii. initial capital investment and its annualized depreciation cost
iv. annual operation cost
v. annual total cost (ATC) of the optimal set, which is the main parameter of the optimization model.

GAMS results including the iteration number of the program, values of the objective function for all runs, Echo Print, Reference Maps, Equation Listings and Model Status Reports are presented in the end of optimization process. Model results include number and types of selected pumps, Preliminary Operation Schedule and discharges of each pump which are presented in Figure 5.1 and 5.5, and Table 5.3 respectively. Comparison between optimized and existing pumps ATC is presented in Table 5.4.

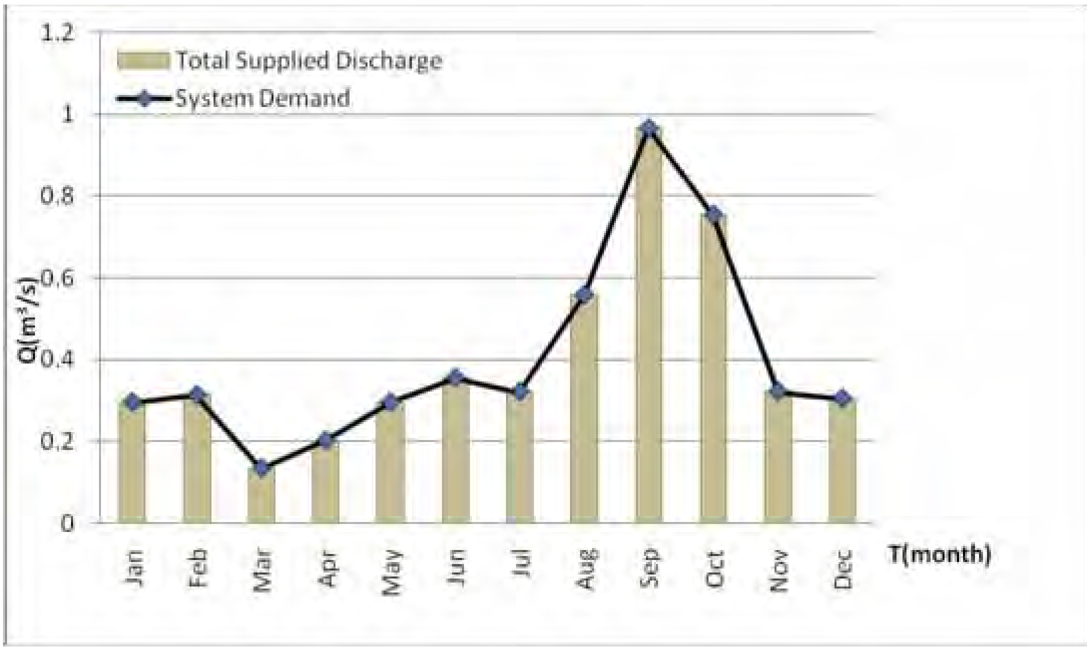


Figure 5.4 Supplied Discharges by Optimized Pumps

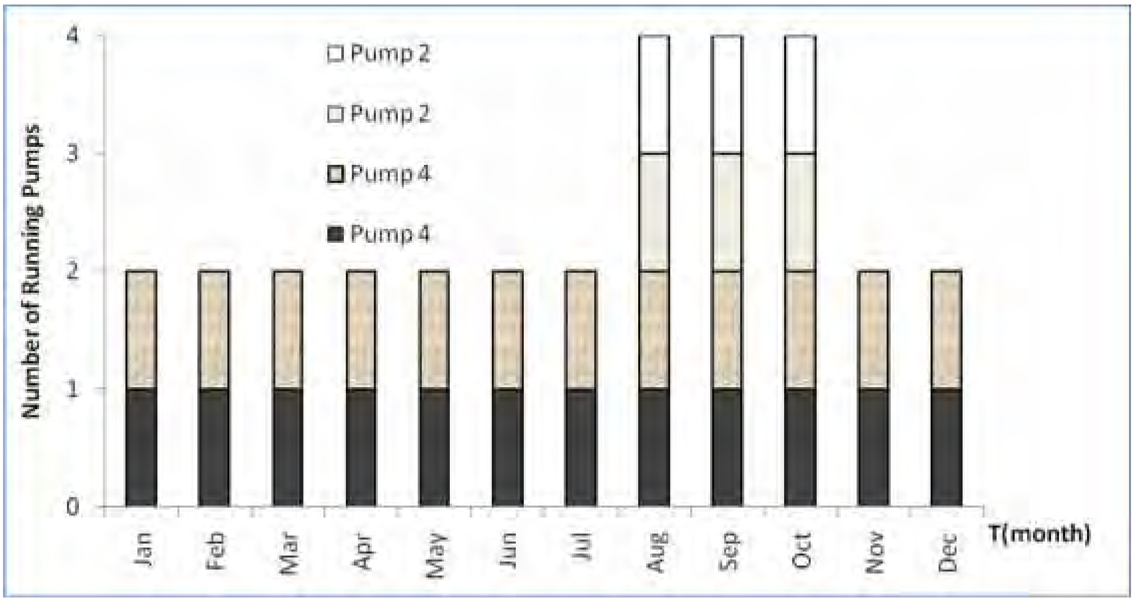


Figure 5.5: Preliminary Schedule of Pumps

Table 5.2: Number of pumps of each type

Optimized number of pumps		Existing pump type
Pump type	GAMS	Design
1	0	0
2	2	4
3	0	0
4	2	0
Total	4	4

Table 5.4 Comparison of GAMS result and Design Economic parameters

Description of Economic parameters	GAMS result	Design sets	Relative saving in %age
Initial capital investment (10^6)	0.685	0.858	25.2%
Annual depreciation cost (10^6)	0.06	0.081	35%
Annual operation cost (10^6)	2.586	2.871*	11%
Annual total cost (10^6)	2.646	2.953	11.6%
Relative ATC in %	100	111.6	

Annual operation cost for existing pump station is theoretical as it resulted from optimization of its operation schedule. On the other hand, pump cost for the existing pump station is real and calculated explicitly. The relative saving from pump cost is not reflected in ATC as much as it is in annual depreciation cost because pump cost is so small compared to the system's annual operation cost.

Table 5.3 Optimized Discharge and Number of Pumps

Month	Monthly Irrigation Demand (m^3/s)	No. of pump Type 2	No. of pump Type 4	Pump Type 2 discharge (m^3/s)	Pump Type 4 discharge (m^3/s)	Total Monthly supplied Discharge (m^3/s)
Jan	0.296	0	2		0.148	0.296
Feb	0.313	0	2		0.157	0.314
Mar	0.136	0	2		0.068	0.136
Apr	0.203	0	2		0.100	0.200
May	0.296	0	2		0.148	0.296
Jun	0.356	0	2		0.178	0.356
Jul	0.322	0	2		0.161	0.322
Aug	0.559	2	2	0.090	0.190	0.560
Sep	0.966	2	2	0.293	0.190	0.966
Oct	0.754	2	2	0.187	0.190	0.754
Nov	0.322	0	2		0.161	0.322
Dec	0.305	0	2		0.152	0.304

* Annual operation cost for existing pumps is optimized by GAMS

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATION

6.1. CONCLUSION

Minimization of Annual Total Cost (ATC) for Fentale-Qawa pump station is done by developing a model in GAMS platform. Model results include pump type, capacity, and number of units and preliminary operation schedule of irrigation pumps that run on least cost for a given set of demand curve. The total monthly supplied discharge by the sum of operating pumps equaled the discretised monthly irrigation demand. The model result showed that Operating pumps discharged at similar rate and head.

The developed model was used to optimize a design problem with one discretized annual demand curve, four different pump types and a maximum allowable number of four pumps. The model selected two different pumps, Pump Type 2 and Pump Type 4. The total number of pump is four, two from each. The difference in annualized cost of pumps between the optimal sets and the pre-sets of the existing design is relatively high. The saving gained from depreciation cost is 35% while the savings occurred in the annual operation cost is 11% compared to the optimized operation cost of the existing pump station. Higher cut in annualized cost of pumps is observed because the comparison is done between the non-optimized pre-selected pumps and the optimized ones by the model unlike the annual operation cost. It is clear that by using these optimization models, a saving of about 11.6% is obtained in annualized total cost.

Modeling in GAMS showed competent result when compared to other optimization methods which are used to solve non-linear optimization problems. While solving those problems by mathematical programming requires higher expertise in the field and longer time, it is relatively easy to employ GAMS programming platform because it has got inbuilt solvers that can solve the problem equations.

6.2. RECCOMENDATION

The cost required to run pumping stations in irrigation projects is much more significant than the one for gravity irrigation. Thus, serious consideration must be taken to improve the design and operation efficiency of existing or newly developed pumping stations. That necessitates optimization and simulation techniques which in turn require appropriate model development and/or application.

Thus, this thesis work can be used as a beginning step in utilizing GAMS to solve complex problems specially in pump stations system design.

Application of the model for optimal scheduling of the actual Fentale-Qawa pumping station was not possible because only two pumps out of the designed four pumps were running alternatively as a result of insufficient electricity and severe silting in wet well. There were no operation schedule in place and pump operators would start the pumps when the storage ponds water level deplete. Nevertheless, the scheme would have been used to test such an important model practically that it is essential to maintain the scheme not only for educational purpose but also for its fundamental purpose, food security.

The developed model would assist irrigation pumping station designers and the training of operators in selecting and scheduling efficient pump combinations that run on low cost while satisfying hydraulic constraints. This may be made easier by making the model user interactive as GAMS environment requires expertise in programming. Microsoft Excel Macro may be suitable for this purpose.

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ANNEX A: GAMS PROGRAM FOR THE EXISTING FENTALE-QAWA PUMP STATION

```
sets
i pumps  /Pump_1/
*only one pump is considered in the existing pump station.
t months(days) /Jan,Feb,Mar,Apr,May,Jun,Jul,Aug,Sep,Oct,Nov,Dec/;
parameter Demand(t)
*monthly irrigation water demand in m3 per second
        /Jan      0.29645
        Feb      0.31339
        Mar      0.13552
        Apr      0.20328
        May      0.29645
        Jun      0.35574
        Jul      0.32186
        Aug      0.55902
        Sep      0.96558
        Oct      0.75383
        Nov      0.32186
        Dec      0.30492/;

parameter QMax(i) Maximum pump discharge in m3 per s


           /pump_1  0.375/;

parameter C(i)
*pump cost in 10^6 BIRR
/pump_1  0.2145152/;



parameter H(i)
*maximum head in m
/pump_1  48.5/;

parameter d(i)  delivery pipe diameter of pump i
*        (m)
```

```
/pump_1  1.35
 /;

Display Demand;
Display QMax;
Display C;
Display H;

*Scalar paramenters
scalar
*the following data are obtained from model problem
r interest rate  /0.06/
CC construction period in years /1.09/
CP project period in years /20/
gama density multiplied by gravity in kiloNewton per metrecub /9.810/
EC energy cost per KWH  /1/
* note here that EC per KWH is set to unity, meaning we are dealing with
power for simplicity.
eff assume average efficiency of all pumps /0.8/
CRF cost recovery factor /0.0871/
;

display gama;
Display r;
Display CC;
Display CP;
Display EC;
Display eff;

variable
ATC
*E(t)
Q(i,t)
Qs(t)
```

```
n(i)
Em
Ea
Hf(i,t)

Qrel(i,t)
;
integer variable Nm(i,t);

Q.up(i,t)=0.8*QMax(i);
Q.l(i,t)=QMax(i);
Q.lo(i,t)=0;
*discharge boundary

Nm.up(i,t)=4;
Nm.l(i,t)=1;
Nm.lo(i,t)=1;
*boundary for total number of pumps. the same is true in model problem

*initialization of number of pumps
Hf.l(i,t)=  H(i);

*Define List of equatins
Equations

EnerAnnual annually consumed energy

EnerMonthly monthly consumed energy

Dis total monthly discharge constraint

*Ntot total number of pumps

Qsupply supplied discharge
```

```
Qpercet(i,t) Discharge in percent

;

*DEFINE THE EQUATIONS

EnerAnnual..Ea=e= sum(t,(0.001*gama*sum(i,Nm(i,t)*Q(i,t)*H(i)/eff)));

EnerMonthly(t)..Em(t)=e=0.001*gama*Qs(t)*48.5/eff;

*Ntot..Nt=e=sum(i,n(i));

Dis(t)..Qs(t)=g=Demand(t);

Qsupply(t)..Qs(t)=e=sum(i,Nm(i,t)*Q(i,t));

Qpercet(i,t)..Qrel(i,t)=e=(Q(i,t)*100/QMax(i));


Model PUMPOPTIMIZATION /All/;
option sysout = on;
SOLVE PUMPOPTIMIZATION using MINLP minimizing Ea;
n.l(i)=Smax(t,Nm.l(i,t));
*Smax is used to choose the highest of Nm, that is number of pumps
allocated monthly
ATC.l=sum(i,CRF*CC*n.l(i)*C(i))+EC*Ea.l;
*PC=annualized pump cost
parameter PC,IIC  ;
PC=sum(i,CRF*CC*n.l(i)*C(i));
IIC=sum(i,n.l(i)*C(i));
Display ATC.l;
Display IIC;
Display Ea.l;
```

```
Display PC;
Display n.l;
Display Nm.l;
Display Q.l;
Display Em.l;
Display Hf.l;
Display Qrel.l;
parameter Srel(t);
Srel(t)=Qs.l(t)/ Demand(t);
Display Srel;
display demand;
Display Qs.l;
```

ANNEX B: OUTPUTS OF GAMS PROGRAM FOR THE EXISTING PUMP STATION

**** SOLVER STATUS FILE LISTED ABOVE

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G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m

E x e c u t i o n

```
----    146 VARIABLE ATC.L              =       2.953

----    147 PARAMETER IIC               =       0.858

----    148 VARIABLE Ea.L               =       2.871

----    149 PARAMETER PC                =       0.081

----    150 VARIABLE n.L

Pump_1 4.000


----    151 VARIABLE Nm.L

            Jan        Feb        Mar        Apr        May        Jun

Pump_1      1.000      2.000      1.000      1.000      1.000      2.000

    +       Jul        Aug        Sep        Oct        Nov        Dec

Pump_1      2.000      2.000      4.000      4.000      2.000      2.000


----    152 VARIABLE Q.L

            Jan        Feb        Mar        Apr        May        Jun
```

Pump_1	0.296	0.157	0.136	0.203	0.296	0.178
+	Jul	Aug	Sep	Oct	Nov	Dec
Pump_1	0.161	0.280	0.241	0.188	0.161	0.152

---- 153 VARIABLE Em.L

Jan 0.176, Feb 0.186, Mar 0.081, Apr 0.121, May 0.176, Jun 0.212
Jul 0.191, Aug 0.332, Sep 0.574, Oct 0.448, Nov 0.191, Dec 0.181

---- 154 VARIABLE Hf.L

	Jan	Feb	Mar	Apr	May	Jun
Pump_1	48.500	48.500	48.500	48.500	48.500	48.500
+	Jul	Aug	Sep	Oct	Nov	Dec
Pump_1	48.500	48.500	48.500	48.500	48.500	48.500

---- 155 VARIABLE Qrel.L

	Jan	Feb	Mar	Apr	May	Jun
Pump_1	79.053	41.785	36.139	54.208	79.053	47.432
+	Jul	Aug	Sep	Oct	Nov	Dec
Pump_1	42.915	74.536	64.372	50.255	42.915	40.656

---- 159 PARAMETER Srel

Jan 1.000, Feb 1.000, Mar 1.000, Apr 1.000, May 1.000, Jun 1.000
Jul 1.000, Aug 1.000, Sep 1.000, Oct 1.000, Nov 1.000, Dec 1.000

---- 160 PARAMETER Demand

Jan 0.296, Feb 0.313, Mar 0.136, Apr 0.203, May 0.296, Jun 0.356
Jul 0.322, Aug 0.559, Sep 0.966, Oct 0.754, Nov 0.322, Dec 0.305

---- 161 VARIABLE Qs.L

Jan 0.296, Feb 0.313, Mar 0.136, Apr 0.203, May 0.296, Jun 0.356
Jul 0.322, Aug 0.559, Sep 0.966, Oct 0.754, Nov 0.322, Dec 0.305

ANNEX C: GAMS PROGRAM TO OPTIMIZE DESIGN VARIABLES AND OPERATION SCHEDULE OF FENTALE-QAWA PUMP STATION

```
*Pump Optimization Model For Fentale-Qawa Pump Station

sets
i pumps  /Pump_1,Pump_2,Pump_3,Pump_4/
*four different pumps are specified in the model so that the model can select
from them
t months(days) /Jan,Feb,Mar,Apr,May,Jun,Jul,Aug,Sep,Oct,Nov,Dec/;
parameter Demand(t)
*monthly irrigation water demand in m3 per second
        /Jan      0.29645
        Feb      0.31339
        Mar      0.13552
        Apr      0.20000
        May      0.29645
        Jun      0.35574
        Jul      0.32186
        Aug      0.55902
        Sep      0.96558
        Oct      0.75383
        Nov      0.32186
        Dec      0.30492/;

parameter QMax(i) Maximum pump discharge in m3 per s

        /pump_1  0.450
         pump_2  0.375
         pump_3  0.250
         pump_4  0.190/;

parameter eff(i) efficiency of each pump at design discharge

        /pump_1  0.8
         pump_2  0.85
```

```
        pump_3  0.8
        pump_4  0.9/;

parameter C(i)
*pump cost in 10^6 Birr
/pump_1  0.300
pump_2   0.214
pump_3   0.189
pump_4   0.100/;

parameter Hmax(i)
*maximum head in m
/pump_1  48.5
pump_2   48.5
pump_3   48.5
pump_4   48.5/;

Display Demand;
Display QMax;
Display C;
Display Hmax;

*Scalar paramenters
scalar
*the following data are obtained from model problem
r interest rate  /0.06/
CC construction period in years /1.09/
CP project period in years /20/
gama density multiplied by gravity in kiloNewton per metrecub /9.810/
EC energy cost per KWH  /1/
CRF cost recovery factor /0.0871/
;

display gama;
```

```
Display r;
Display CC;
Display CP;
Display EC;
Display eff;

variable
ATC
E(t)
Q(i,t)
Qs(t)
*n(i)
Nt
Ea;
integer variable n(i);

Q.up(i,t)=QMax(i);
Q.l(i,t)=QMax(i);
Q.lo(i,t)=0;
*discharge boundary

Nt.up=4;
Nt.lo=2;
*boundary for total number of pumps

n.l(i)=1;
n.lo(i)=0;
*initialization of number of pumps

*Define List of equatins
Equations

Cost Annual Total Cost
```

```
Energy(t) monthly unit energy consumption

EnerAnnual annually consumed energy

Dis total monthly discharge constraint

Ntot total number of pumps

Qsupply supplied discharge
;

*DEFINE THE EQUATIONS
Cost..ATC=e=sum(i,CRF*CC*n(i)*C(i))+EC*Ea;

Energy(t)..E(t)=e=0.001*gama*sum(i,n(i)*Q(i,t)*Hmax(i)/eff(i));

EnerAnnual..Ea=e=sum(t,E(t));

Ntot..Nt=e=sum(i,n(i));

Dis(t)..Qs(t)=g=Demand(t);

Qsupply(t)..Qs(t)=e=sum(i,n(i)*Q(i,t));

Model PUMPOPTIMIZATION /All/;
option sysout = on;
SOLVE PUMPOPTIMIZATION using MINLP minimizing ATC;
Display ATC.l;
Display Q.l;
Display Qs.l;
Display n.l;
Display Nt.l;
Display E.l;
```

```
Display Ea.l;
parameter PC, IIC;
*PC=annualized pump cost
*IIC=initial investment cost
PC=sum(i,CRF*CC*n.l(i)*C(i));
IIC=sum(i,CC*n.l(i)*C(i));
Display PC;
Display IIC;
```

ANNEX D: OUTPUTS OF GAMS PROGRAM TO OPTIMIZE DESIGN VARIABLES AND OPERATION SCHEDULES

```
**** SOLVER STATUS FILE LISTED ABOVE
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G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m
E x e c u t i o n


----    143 VARIABLE ATC.L              =        2.646

----    144 VARIABLE Q.L

               Jan         Feb         Mar         Apr         May         Jun

Pump_4       0.148       0.157       0.068       0.100       0.148       0.178

     +         Jul         Aug         Sep         Oct         Nov         Dec

Pump_2                   0.090       0.293       0.187
Pump_4       0.161       0.190       0.190       0.190       0.161       0.152


----    145 VARIABLE Qs.L

Jan 0.296,    Feb 0.313,    Mar 0.136,    Apr 0.200,    May 0.296,    Jun 0.356
Jul 0.322,    Aug 0.559,    Sep 0.966,    Oct 0.754,    Nov 0.322,    Dec 0.305


----    146 VARIABLE n.L

Pump_2 2.000,    Pump_4 2.000


----    147 VARIABLE Nt.L               =        4.000

----    148 VARIABLE E.L
```

Jan 0.157,	Feb 0.166,	Mar 0.072,	Apr 0.106,	May 0.157,	Jun 0.188
Jul 0.170,	Aug 0.301,	Sep 0.529,	Oct 0.410,	Nov 0.170,	Dec 0.161

---- 149 VARIABLE Ea.L = 2.586

---- 155 PARAMETER PC = 0.060

---- 156 PARAMETER IIC = 0.685