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Multi-objective Optimization for Groundwater Resources Development Using Genetic Algorithms: Case Study of Akaki Catchment Well Fields, Addis Ababa, Ethiopia

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Multi-objective Optimisation for Groundwater Resources Development Using Genetic Algorithms: Case Study of the Akaki Well Field, Ethiopia"

Master of Science Thesis
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Dedicated to my mother

Abstract

In regions where groundwater resource availability is very limited resource management is very important, especially when potable water supply is highly dependent on this fresh water source. Regular planning and management of groundwater should include techniques and tools, such as groundwater simulation and optimization models, that can be implemented in reliable decision support tools. These tools are needed to analyse and propose sustainable groundwater development and management strategies, by simultaneously considering different objectives such as total abstraction rates for meeting the demands, development and maintenance costs or limitations of groundwater drawdown. Such strategies are nowadays commonly developed by making use of simulation and optimization models.

In this study multi-objective optimization algorithm is used for a groundwater management problem by using Genetic Algorithm (GA). This Multi Objective Genetic Algorithm (MOGA) is simulation-optimization model developed by coupling of a GA algorithm with commonly used groundwater flow simulation code MODFLOW. The MOGA approach is developed and tested for a case study of the Akaki catchment in Ethiopia, where a number of well fields are considered for future groundwater development. Two objectives are considered concurrently: maximization of the total abstraction rate and minimization of costs (installation and operational). Well configurations consisting of number, location and pumping rates of potential wells are used as decision variables. For purposes of controlling the overexploitation of the aquifer and the associated pumping costs drawdown constraints are introduced at 23 locations within the well fields. MOGA is implemented using the NSGA-II optimization algorithm coupled with a steady state MODFLOW model of the Akaki catchment. Optimal solutions (well configurations) were sought for drawdown constraints of 15m, 20m, 25m and 30m. Several different methods for handling the drawdown constraints were tested such as: 'static' penalty function (constant penalty on costs for constraint violations), 'dynamic' penalty function (varying penalty dependent on magnitude and number of constraint violations) and implicit constraint handling by introducing a third objective function that minimizes the number of constraint violations. Different initialization alternatives were also tested for these methods. The results of these methods were compared to an existing result for the same case (using LINGO - in a previous study) obtained by single objective linear optimization of costs, with same drawdown constraints and minimum total abstraction rate as a constraint.

MOGA provided optimal solutions of the abstraction rate from the well fields in the range of 20394m3/day to 26197m^3/day with average cost of 15 million ETB to 23million ETB for different drawdown conditions (15m,20m,25m,30m). None of the solutions obtained was better than the LINGO solution, however, the obtained Pareto solutions can provide information about trade-offs between abstraction rates and costs. The analysis of the constraint handling methods showed that the introduction of an additional objective function (minimization of constraint violations) is a promising approach for obtaining better solutions which gives results close to LINGO solution with only few constraint violations.

Keywords: multi-objective optimization, groundwater, drawdown constraints, penalty function, Akaki, well configuration

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Contents

List of Tables

List of Figures

List of Symbols

MOGA	Multi-Objective Genetic Algorithm
MODFLOW	Modular Three Dimensional Groundwater Flow Model
GA	Genetic Algorithm
EA	Evolutionary Algorithm
NSGA II	Non-dominated Sorting Genetic algorithm
AAWSA	Addis Ababa Water Supply and Sewerage Authority
LP	Linear Programming
LINGO	Linear Interactive Discrete Optimizer
SA	Simulated Annealing
ANN	Artificial Neural Network
ϵ-NSGA-II	ϵ- Non-dominated Sorting Genetic algorithm (Improved NSGA II)
SPEA 2	Strength Pareto Evolutionary Algorithm
3-D	Three Dimensional

1. Introduction

1.1 BACKGROUND

The capital of Ethiopia, Addis Ababa is a highly populated city, which uses surface and ground water for city water supply. Due to alarming growth rate of the population the city is facing potable water scarcity. Because of the higher construction and treatment costs of surface water, well fields for groundwater exploitation have been designed and implemented by Addis Ababa Water Supply Authority (AAWSA) as an alternative source for the city water supply.

Studies indicate that an increase in pumping rate from the well fields to satisfy the ever-growing water demand of the city of Addis Ababa results in substantial regional groundwater level decline, which is leading to the drying of springs and shallow hand dug wells and frequent pump failure. Therefore the groundwater resource development and system management is crucial for solving these problems.

1.2 PROBLEM STATEMANT

In many parts of Ethiopia fresh water shortage is increasing due to rapid population growth. Movement of people to the capital city, urbanization, growing number of investments and construction works, increase in demand of water in domestic and industrial production cause an increased dependence on groundwater. This continuously increasing withdrawal from groundwater reservoirs leads to systematic or continuous lowering of water table, with high installation and operational cost.

AAWSA has a plan to increase the water supply as fast as the population growth rate in order to solve the water supply shortage problem. The well fields in the suburb of Addis Ababa are one of the solutions for obtaining fresh water in addition to the surface water supply in order to meet the increasing demand of the city (AAWSA 1994; WWDE, 1996, 2008). According to this plan they designed many projects that are still in realisation for expanding the well fields to the previously recommended areas (Fanta, Dalota, Dukem up and Dukem down).

Most of these new well fields are also designed to draw water from the deep aquifer with high abstraction rates of the wells. This will possibly result in groundwater resource depletion which increases the operational costs and affects the whole ecosystem of the area.

The main problem is therefore the determination of appropriate strategy for groundwater resources development in the area, formulated as optimal well configurations (number, locations and pumping rates). The optimal well configurations should produce maximum abstraction with minimal costs and satisfy target drawdown limits (constraints) in the area. Previous studies have approached this problem as a single-objective optimisation (Wagena, 2011). This current study analyses possible solutions of the problem when formulated as a multi-objective optimisation problem, in which the maximization of abstraction rates and minimisation of costs are simultaneously realised, while satisfying the drawdown constraints. This is achieved by coupling of a MODFLOW simulation model with a multi-objective optimisation using a Genetic Algorithm.

1.3 GENERAL OBJECTIVE

The general objective of this study is to combine a multi-objective GA with a MODFLOW groundwater flow simulation model and develop solutions (well configurations) for optimal development of groundwater resources. These solutions should also be compared to those obtained by single-objective optimisation using linear programming carried out by (Wagena, 2011). Optimal well configurations achieve a system-wide maximum head distribution (minimal drawdown) with maximum abstractions for meeting water production targets, and minimal costs. In relation to this general objective, one of the key scientific problems addressed in this study is formulation and handling of drawdown constraints when using the above described model-based optimisation approach

1.4 SPECIFIC OBJECTIVES

The following specific objectives are identified for this study:

1. To obtain optimal well configurations for this specific case by simultaneously maximizing abstraction rates and minimizing costs (two optimization objectives) while satisfying drawdown constraints, using multi-objective model-based optimization that combines GA and MODFLOW simulation model.

2. To evaluate optimization approaches for this specific case i.e., to compare the solutions from single-objective linear programming (from (Wagena, 2011)) and multi-objective GA.

3. To verify the efficiency of multi-objective GA for optimization combined with the MODFLOW simulation model.

4. To apply and compare different methods for handling drawdown constraints in the GA approach with possible recommendations for preferred methods for this specific case.

1.5 RESEARCH QUESTIONS

This study is going to answer the following questions based on the mentioned specific objectives:

1. What are the optimal well configurations obtained by the multi-objective GA for this specific case and what are the resulting total abstraction rates and costs?

2. Which of the two methods of optimization (single-objective linear programming and the multi-objective GA) provides better solutions for optimal development of groundwater resources in the area?

3. What is the efficiency of the multi-objective GA approach in terms of needed computational resources, especially computational time?

4. Which of the proposed methods for handling drawdown constraints is recommended for use in this specific problem?

1.6 OVER VIEW OF THE STUDY AREA

1.6.1 Location

The study area is sited at the western edge of the Main Ethiopian Rift, in the central Ethiopian highlands. The total surface area of the catchment is 1462 km2. Large central volcanoes characterize the watershed boundary such as the Entoto mountain range (3200 masl) forming the main recharge area. The major recharge to the aquifer comes from precipitation and river channel losses. The groundwater from the well fields is exploited by different industries and institutions, in addition to wells that are operated by AAWSA and used for public services.

The catchment is situated within the north western Awash River basin between 8° 46′ – 9° 14′ N and 38° 34′ – 39° 04′ E, bounded from the north by the Entoto Mountain Range system, in the west by Mount Menagesha and the Wechecha volcanic range, in the south west by Mount Furi, in the south by mountains of Bilbilo and Guji and in the southeast by the Gara-Bushu hills and in the east by the Yerer Mountain. The city of Addis Ababa located in the centre (Figure1. 1) (Demlie, 2007). The focus of this study is the area to the south of Addis Ababa – the Akaki Well Field. (Tesfaye, 2009)

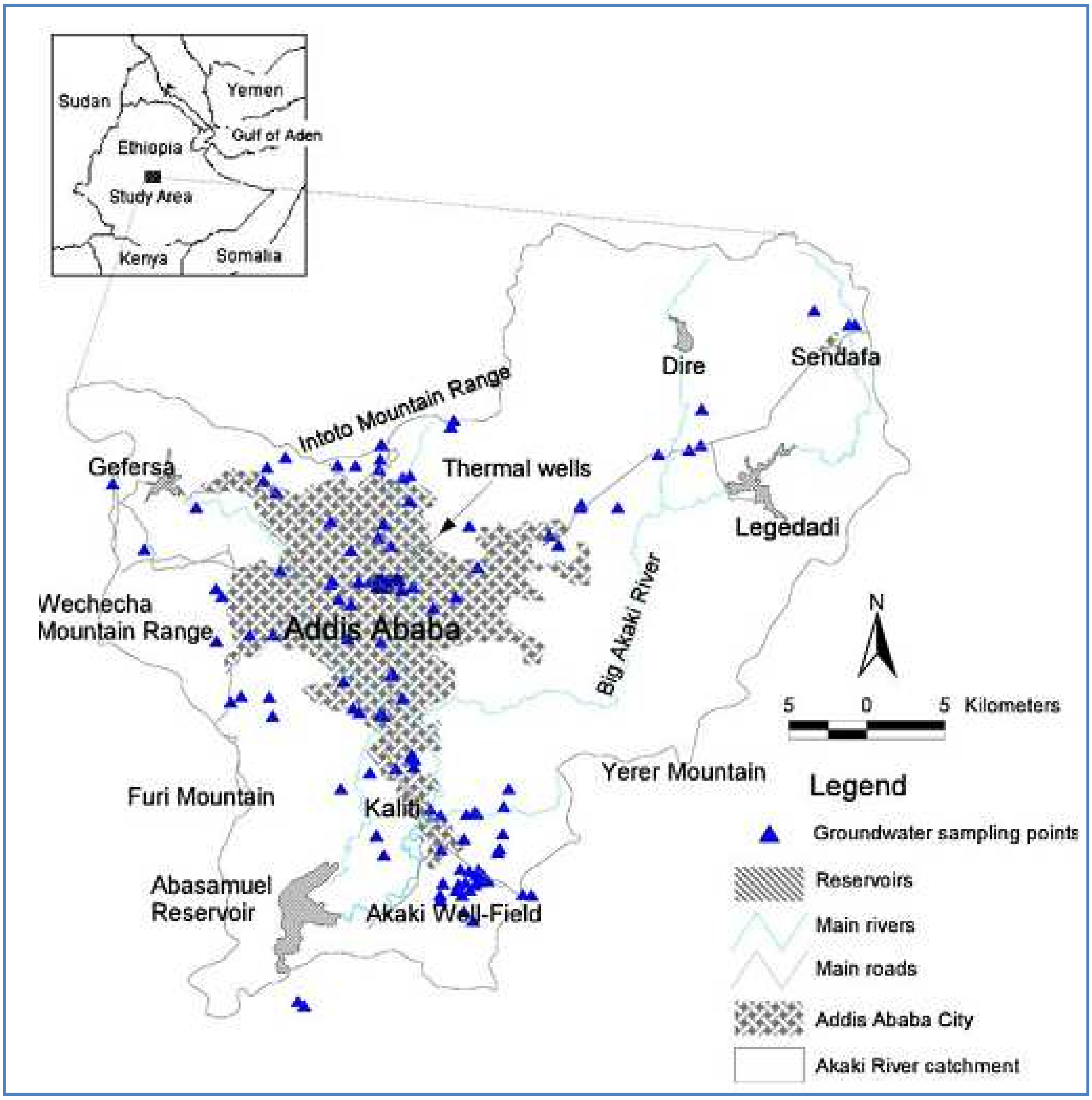

Figure1. 1 Location Map of the Study Area (Demlie, 2007)

1.6.2 Administration and Population

The Capital Addis Ababa is located in the centre of the catchment and inhabits more than 550 square kilometres of the total area. The population of Addis Ababa is almost 4 Million which are dependent on these well fields for potable water. In addition there are highly populated small towns as Akaki, Burayu, Dukem situated in the catchment.

1.6.3 Land Use

The general land use or cover pattern of the Akaki has a very diverse groups of forest, urban area, agricultural or open areas and water bodies. According to BCEOM-Seurca (2000), in the northern part of the area on Entoto Mountain the land is covered by forest of eucalyptus trees dominantly and the top of the mountain range has gentle slope that helps the infiltration of precipitation into the ground. While the slope gets steeper down to the Addis Ababa city the land is characterized by paved and lined surfaces and built up areas that affect the infiltration rate and most of the rainfall is converted into surface runoff that drains into the networks of rivers. The agricultural area is situated in the central, southern and south western of the catchment.

1.6.4 Geology and Hydrogeology of Akaki Catchment

Since Akaki catchment is located at the western margin of the Main Ethiopian Rift; the geological formation is part of the creation and development of the Ethiopian plateau and the Rift system. The catchment is characterized by volcanic rocks superimposed by alluvial deposits with estimated thickness 0-66m, black cotton soil is the major component of the Alluvium. The dominant volcanic rocks are basalts, rhyolites, trachytes, scoria, trachybasalts, ignimbrites and tuff of different ages (Figure1. 2). At some part of the area the upper Basalt is semi confined due to the black cotton soil.

The Upper basalt aquifer is weathered and fractured linked to Rift system, the transmissivity and specific discharge of the aquifer is extremely inconsistent, fluctuate from 3 m2/day to 105,000 m2/day (BCEOM, (2000 and 2002)), based on the tectonic effect and weathering degree, the occurrence and thickness of the scoria penetrated has a great role in determining the transmissivity . The thickness of this aquifer can measure 250 to 350m. Due to the tectonic activity of the area the static water level linked with the lower aquifer, which is highly variable from one area to the other measures 5m to more than 90m.

The Lower Basalt aquifer is consists of tertiary Tarmaber basalt it is highly productive with dominantly composed of scoraceous basalt. It is highly confined, which leads the static water level possibly artesian state. It is Regional aquifer with very high transmissivity of 715 -14,000 m2/day (WWDSE, 2010). The Hydrogeology of the Akaki Catchment is complex due to multi layer rock composition, active tectonic structure and varying weathering degrees.

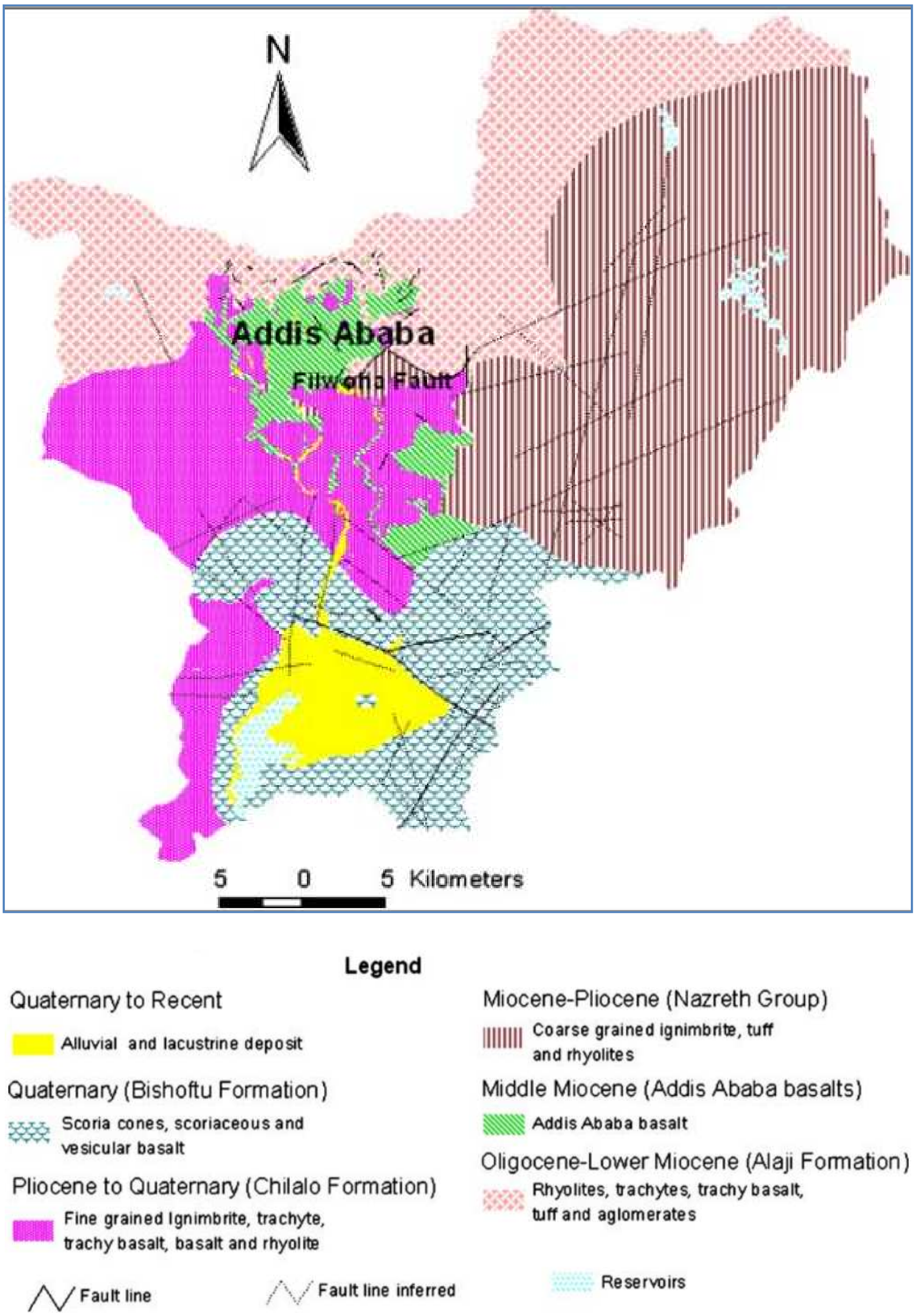

Figure1. 2 Geological Map of Akaki Catchment (Demlie, 2007)

1.6.5 Hydrology

Akaki catchment drainage system covers a total of 1500 km2. Akaki River is tributary of Awash River; originates from Entoto mountain range has length of 95km. Akaki watershed comprises two main river system; the Big Akaki River from the eastern part and small Akaki River from the western, the two rivers meet at Abba Samuel Reservoir which is non functional due to silt; drain to Awash River after 18km to the west of Abba Samuel Reservoir. The well fields are part of this River system.

According to (BCEOM, (2000 and 2002)) the northern part of the catchment has low contribution to the recharge of the system due to wide urban area cover however, the southern part has higher recharge rate comparatively. The northern urbanized area contributes 33mm/year and the southern part has recharge of 74mm/year.

1.6.6 Soil Type and Permeability

Alluvial deposits are the major soil type of the area found in middle reach of Akaki River. The dominant composition of this soil type is black cotton soil characterized by very low permeability. The other type of soil in this area is a Residual soil which lies in the Northern and North Eastern part of the catchment. There are also Lacustrine sediments along the Akaki Rivers and lake areas at southern and south-eastern part.

All soil types of the catchment has compacted clayey nature, it has very low permeability with very low percolation rate (BCEOM, (2000 and 2002)).

2. LITURATURE REVIEW

This chapter reviews related scientific literature. In Section 2.1 different types of groundwater management problems are reviewed and section 2.2 reviews different GA and EA methods used to solve the groundwater management problems.

2.1 Groundwater management problems

Extensive research has been carried out in groundwater system to solve problems in: sustainable management of groundwater resource development for water supply and designing aquifer remediation for contaminated aquifers. Several solutions to these problems include solving of non-linear mathematical programming along with multiple objective function and constraint sets.

Groundwater management should be carried out with management models such as optimization to obtain optimal solutions. Optimization methods are nowadays, combined with simulation models for obtaining best possible solutions for groundwater resource management. Different optimization methods are developed and applied such as linear, mixed integer, genetic, and dynamic algorithms, depending on the status and type of the management problem, the groundwater table conditions and nature of the aquifer.

A traditional optimization method such as linear programming (LP) with its extended branch of mixed Integer programming has been used to determine optimal abstraction rate and well locations for the Akaki well fields (Wagena, 2011) using objective function of maximization of abstraction rate and minimizing cost. Same approaches have been used in many other problems, such as solving aquifer contamination problem by locating new monitoring wells for remediation action (Meyer, 1988), where the objective function is to minimize the contaminated area while maximizing consistency of the monitoring network.

On the other hand nonlinear programming methods also applied for solving similar groundwater problems by several researchers in the past decades. In this method optimal solutions in terms of decision variables are found by gradient-based algorithms to optimize the objective functions. (Gorelick, 1983)

In recent times complex groundwater optimization problems are solved by combinatorial optimization methods. For instance in (Zheng, 1998) EA and SA were combined with MODFLOW for optimal solution as well to compare the efficiency of the two global search methods in solving water supply problems. (McKinney, 1994) Used GA to solve groundwater management problems: and (Masky et.al, 2002) applied coupling of global optimization algorithms with MODFLOW to compute optimum pumping rate in plume removal strategy.

Optimization problem solving was also applied in coastal aquifer management, to treat fresh water aquifer from saltwater intrusion (Mantoglou, 2008.), used combinatorial multi-objective optimization for costal aquifer treatment with the objective of maximizing abstraction rate with minimum possible drawdown. The typical objectives are to abstract a maximum amount of water with a minimum of drawdown and at minimum saltwater intrusion risk (Katsifarakis, 2006.); (Mantoglou, 2008.)

In addition multi-objective optimization can be used in management of boundary crossing shared aquifer to solve water supply problem of certain neighbour communities or countries.

In many places groundwater is limited source of freshwater supply, consequently excessive abstraction for irrigation and potable water supply can lead to groundwater depletion. Advanced management of the groundwater system would lead to resource sustainability.

2.2 GA and EA optimization methods applied in groundwater management

Groundwater problem is difficult to solve as it is highly non-linear and because of the complex nature of the subsurface system.

Groundwater optimization by Evolutionary Algorithms (EA) has confirmed to be a valuable tool by different researchers. Since the beginning of the nineties EA applications have progressively increased. The search method in these algorithms does not depend on derivatives; however it is a heuristic method that requires objective function evaluation. This makes it more efficient in solving discrete and highly non-linear problems. The main framework of EA designed at the first use has not changed. However some improvement of few parts has done time to time. As a result it becomes more successful problem solving tool with better search actions and speed.

EA depends on individual populations that evolve in each generation. This makes it different from the other optimization algorithms.

Simulated annealing and EA shares some similar principles, as both are heuristic methods (Dougherty, 1991). Among the problem solving tools, simulated annealing can be mentioned as method that has been used at earliest in groundwater problems.

In most water resources planning and management studies GA have been the most frequently applied EA. GA can be illustrated by some basics: 1- an initial population generated as potential solutions, each categorized as a chromosome; 2- objective function evaluation and fitness function computation at each solution followed by ranking of chromosomes based on this fitness; 3- phase of chromosome ranking and selection of individual solutions for the mating operator, to produce offspring solutions after combining information from two or more parent solutions and 4- mutation of each individual offspring helps in continuation of diversity by avoiding premature convergence to local optima.

Most recent EA codes apply a form of tournament and/or truncation selection. In addition the combination of the two schemes is implicitly elitist contain best population members with high certainty of survival into the next generation. It is also significant quality to improve EA effectiveness in water resources applications management application. (Bayer, 2004.)

The most common and popular Elitist selection operators in recent works are the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et.al, 2002), the enhanced version ϵ-Non-dominated Sorting Genetic Algorithm II (ϵ-NSGA-II) and the Strength Pareto Evolutionary Algorithm 2 (SPEA 2) are used.

Both NSGA-II and ϵ-NSGA-II use binary tournament selection between individuals. This selection is applied depending on the fitness value of the selected individuals. The density of the Pareto front described as parameter, ϵ, in ϵ-NSGA-II. A small ϵ value causes a dense Pareto front, whereas light density in the case of large ϵ value. In ϵ-NSGA-II selection Pareto front commences a dynamic pool size, that altered based on the number of individuals it dominates. (John Nicklow, et al., 2010)

SPEA2 assigning fitness depends on the dominancy of the individual and on the crowding distance. In each generation all the non-dominated individuals selected to the pool which size is fixed. This fixed size attempt two cases in selected individuals; when the selection has got only few number of non-dominate individuals the pool size is larger to hold best solution but the algorithm incise and remove the individuals with the smallest crowding distance when the number of non-dominated individuals is larger than the pool size.

2.3 Simulation-Optimization Model

The operation of Multi-objective Genetic Algorithm (MOGA) starts with construction of the initial generation and organizing of the initial Pareto optimal followed by ranking and fitness checking depending on the objective function formulation and constraints, then reproduction of these initial sets made by applying the selection, crossover, and mutation operators finally the pareto optimal set re-evaluate again. In MOGA each generation confirmed for the fitness function in each population entity, which helps the algorithm to produce strings of two fitting parents that can be reproduce by crossing over and mutating; this will continue until the last population of the system. After all operation the strings of the new generation decoded and evaluated again (Saafan, 2011).

In this case the link between the simulation model MODFLOW and optimization model NSGA II has done by Matlab code as shown in flowchart (Figure 3. 1). According to (Saafan, 2011) the link could be also with other computer program other proposed theorem on pareto optimal set, that is set of Pareto optimal solutions for the aimed objectives are considered as equally satisfied in a Pareto optimal sets. The assessment is made by considering all the decision criteria defined at the starting stage.

In multi objective optimization, the formulation set up allows multiple objectives to be optimized at the same time, as compared with single objective optimization problems. This approach might not found an optimal single solution which satisfies all objectives of the multi objective optimization problem set up. However, a set of solutions will be created which contains superior solutions to all other existing solutions in the search space with regard to all objectives. In this set each solution has equal value and no solution in this set is better than the other. This set of solutions is called the Pareto optimal set (Saafan, 2011).

2.3.1 Simulation Model

Detailed groundwater heads and flow distributions of complex aquifer systems in the study area is obtained from groundwater simulation models which will be combined with different optimization algorithm in order to get the optimal solutions for decision making, in this case the well configurations (number, location and abstraction rates of wells).

The frequently used groundwater simulation model which describes the three dimensional movement of groundwater with constant density in the course of porous media, is MODFLOW, based on numerical solution of groundwater flow partial differential equation. It is 3-D finite difference method for modelling groundwater flow. The three dimensional differential equation of groundwater flow is; (McDonald MG, 1988)

$$\frac{\partial}{\partial x}\left(K_{xx'}\frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(K_{yy'}\frac{\partial h}{\partial y}\right)+\frac{\partial}{\partial z}\left(K_{zz'}\frac{\partial h}{\partial z}\right)-W=S_{s'}*\frac{\partial h}{\partial t} \tag{2. 1}$$

Where $K_{xx'}$, $K_{yy'}$, $K_{zz'}$ = x, y, z coordinate hydraulic conductivity value parallel to the major axes of hydraulic conductivity [LT^{-1}]

h =groundwater head [L]

W= volumetric flux per unit volume may be terms of sources or sinks of water

$S_{s'}$ =specific storage [L^{-1}]

t = time

2.3.2 Optimization Model

The Optimization problem can be single objective or multi objective created by putting together definite linear and non linear objective functions (minimization or maximization of abstraction rates, cost minimization, head minimization at certain locations, etc.). Aquifer nature could be confined or unconfined and formulation of the management problem can be linear or non linear, combination of simulation and optimization model is done by management model.

Multi-objective optimization problem formulation is generally not the same to single objective optimization problem formulation. In the single objective case, the formulation is designed to get the optimal solution, which is extremely best to all existing options. whereas in the case of multiple objectives, it might not be essential to get a best solution with respect to all objectives since there is a big difference between multiple objectives, that means the best solution of one objective might not fit to other objectives.

Non-dominated Sorting Genetic algorithm (NSGA II) is a Multi objective evolutionary algorithm which has been first proposed by (Deb et.al, 2002). It has computational complexity of O (MN^2). The initial population created randomly, this random population is sorted by considering non-domination.

2.4 Previous Work of Akaki Catchment

There are different Hydro chemical, Numerical groundwater modelling of Akaki Well field that have been developed by different researchers to investigate groundwater recharge, flow and the hydro chemical evolution within the Akaki volcanic aquifer system. The first groundwater model of the well field has been developed in year 2000 (BCEOM & Seureca Space JV in association with Tropics Consulting Engineers, September 2000) and revised in 2004 by increasing the model span. Using this model sustainable pumping rate from the well field was proposed and continuous monitoring of the pumping rate and drawdown proposed, (Ayenew T, 2008). In addition the sub surface hydrodynamics of the well field was analyzed after calculating the groundwater fluxes under steady state MODFLOW model set up. According to the model result it is possible to pump 30,000m^3/day to 35,000m^3/day by this proposed pumping rate and the drawdown will reach 20 to 23m for 20 years of pumping. (BCEOM, (2000 and 2002)).

2.5 Regional Ground Water Model of Akaki Catchment

Prior to the development of regional groundwater model of Akaki catchment there are some conditions that have been taken into account for the development. These conditions are, Akaki River aquifer is considered as one hydrologic unit, the recharge of the whole catchment (Groundwater, springs and rivers) is from precipitation, the groundwater head map track the topographic gradient of the area (continuous from north (Entoto area) to south towards well fields), the prospective well field is directly influenced by the recharge of model area because the groundwater origin and occurrence of this area is highly dependent on hydrologic and hydro geological conditions within Akaki catchment and well field area.

Furthermore, the groundwater flow direction is towards the south-southeast (Dukem plain) by crossing Akaki river catchment. Multiple layers modelling of the well field is difficult because of the unknown complexity of the geological formation of the aquifer; the aquifer must be modelled by considering the whole Akaki catchment area due to complexity of the hydrological and hydro geological condition of the area.

2.4.1 Model Set up

The regional groundwater model set up of Akaki catchment was developed by using Processing MODFLOW (Version 5.0.54) software. The regional groundwater flow system of whole Akaki catchment has been included in as the model area that is from North (Entoto Mountain the river source) and to south, extended to Awash River and Debreziet town (Figure 2. 1**Error! Reference source not found.**). According to groundwater head obtained from the borehole data the constant head boundary is considered to be in between Dukem Awash and Debreziet. However, the northern, western and eastern parts of the catchment boundaries are assigned as no flow boundary conditions.

The model grid set up consists of 106 columns and 136 rows which cover the total area of 2254km2 of the catchment. Akaki well field is located at the central part of the model area where the grid spacing is 250 m but the grid spacing varies in X and Y directions increasing to 500m and 1000m. The thickness of the aquifer is taken to be constant, 100 m and the model layer condition is arranged as single layer with variable transmissivity.

Generally infiltration from precipitation is the source of recharge to the aquifer system of the study area. The recharge of model area is 51mm per year determined in previous study (Reference to BCEOM report) from semi distributed water balance model with monthly time step. But due to hydro geological complexity and in order to keep the spatial distribution of recharge in the model area, two recharge zones have taken in to account. First the northern mountainous area has high runoff with recharge of 33 mm/year; secondly for the other part of the model area has a recharge value of 74 mm/year. The recharge other than the precipitation infiltration is from the leakage of three man made reservoirs, which is implemented by MODFLOW well package. The regional groundwater model area has also groundwater output, such as instance springs (Fanta, Akaki gorge) which are simulated using the drain package of MODFLOW. Existing pumping wells are specified in the well package and the main rivers have been modelled with the MODFLOW river package.

2.4.2 Model Calibration

The model calibration has been done under steady state condition. Initial model transmissivity values were calculated from borehole pumping test results. After that, the transmissivity values have been varied in the model until the model output was similar to the related to the observed groundwater head and observed discharge of Akaki River, Fanta and Aba Samuel gorge springs (BCEOM, (2000 and 2002))

The transient model calibration has been done by considering time variation and storage coefficient of aquifer in the model. The transient model calibration also includes the Time series of groundwater head of some wells and flows of springs, with storage coefficients of pumping wells. The storage coefficient has been calibrated according to the observed groundwater head (BCEOM, (2000 and 2002)). The transient model was not used in this study.

The transmissivity of the aquifer is highly variable all through the model area. It ranges from very small value of 6.94e-5 m2/s to maximum of 1.22 m2/s (Tesfaye, 2009). The well fields were developed at high transmissivity value of 0.25m2/s. (Figure 2. 1.) The hydraulic head distribution of the regional model and the groundwater flow is from North to south of the catchment area (Figure 2. 2).

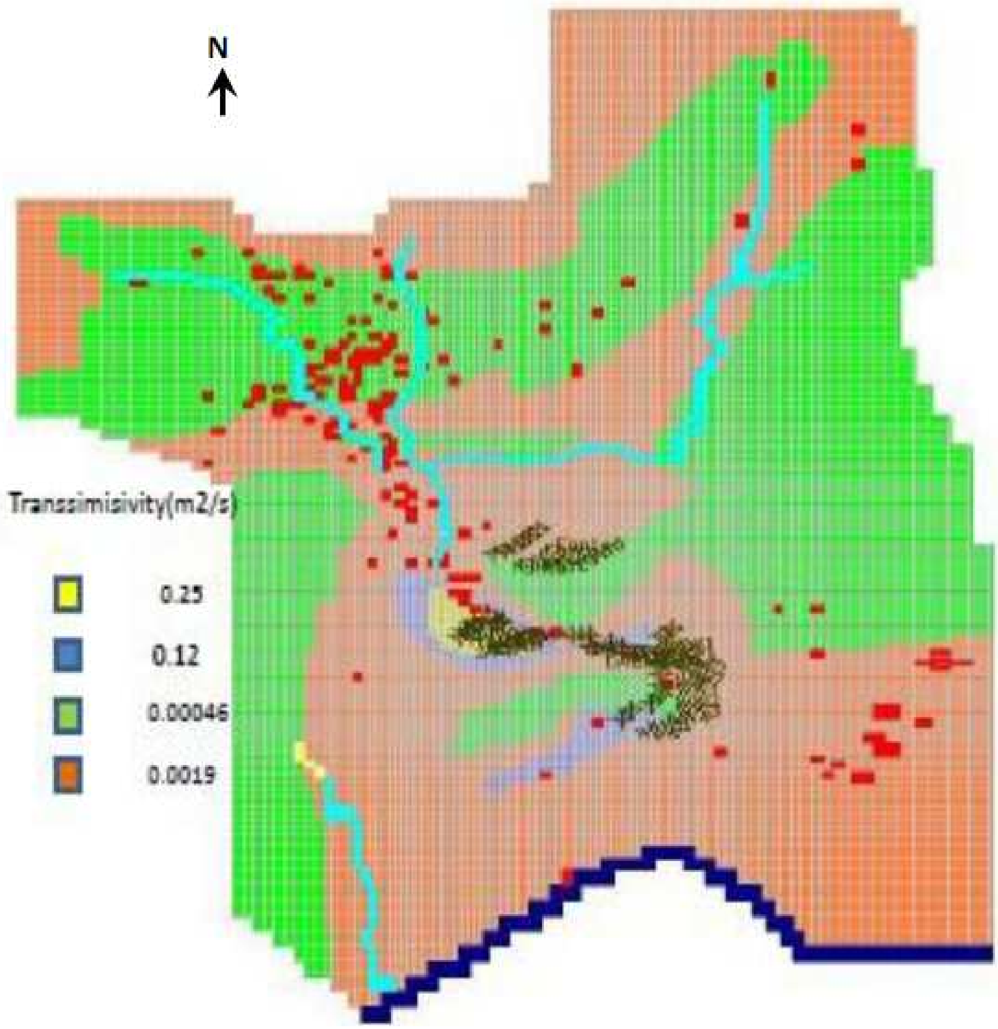

Figure 2. 1 Grid Structure and Transmissivity of the Regional Model (Wagena, 2011)

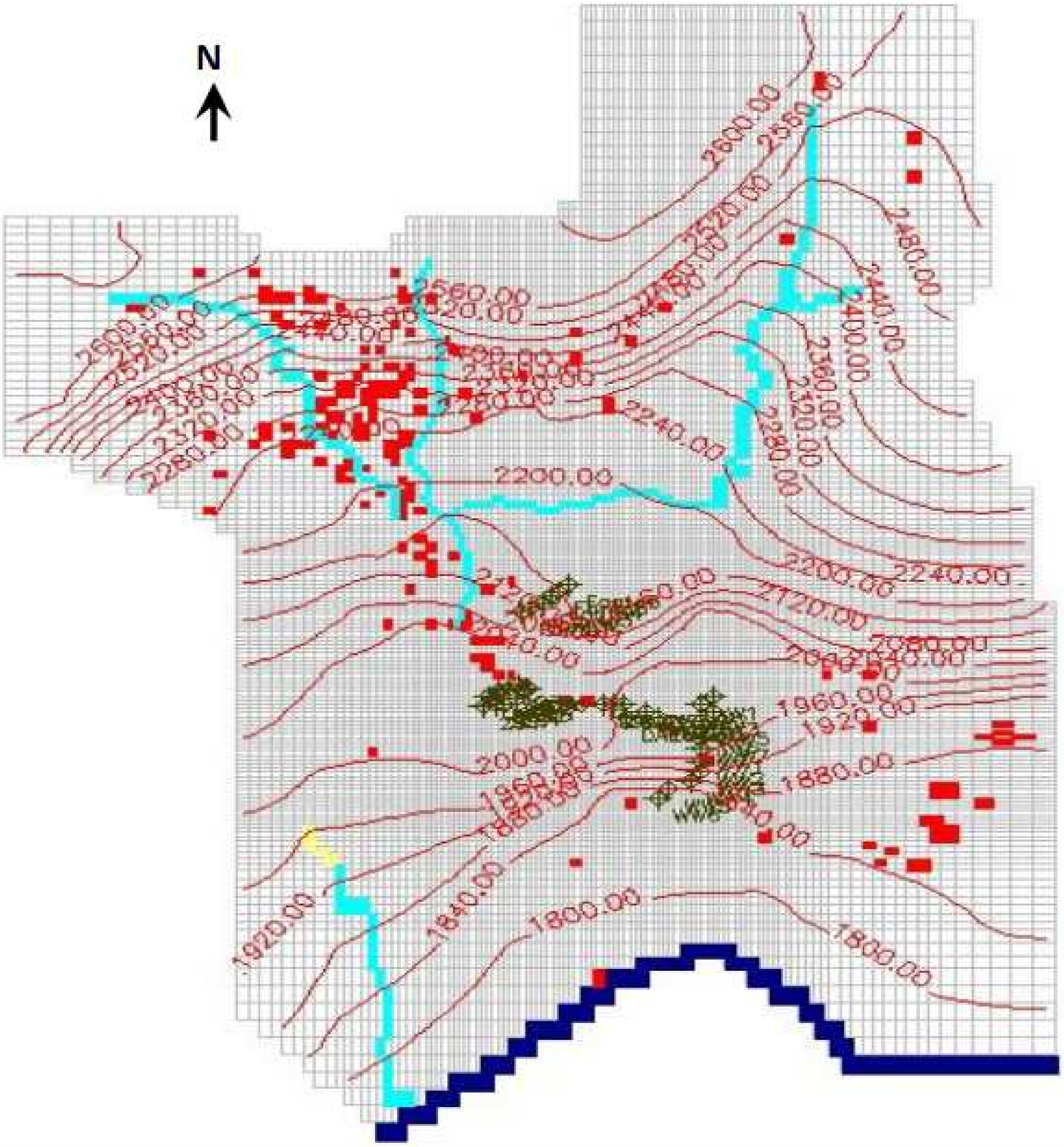

Figure 2. 2 Hydraulic Head Distribution of Regional Model (Wagena, 2011)

The water balance result from the steady state calibration of regional groundwater model demonstrates that almost all inflow to the model is from natural recharge (Table 2-1). Consequently, 66.5% of the recharge is flow out by constant head boundary, 23% by river, 8.7% by wells, and 1.9% by drains (springs).

Table 2. 1: Groundwater Balance of the Model in m3/day

Inflow to Catchment			Out Flow from the catchment				
Natural Recharge	River Recharge	Total	Constant Head Boundary	Well	Drain	River Flow	Total
281,059.20	518.4	281,577.60	187,228.80	24,451.20		64627.2	281,577.60
99.80%	0.20%	100%	66.5%	8.70%	1.90%	23%	100%

(Wagena, 2011)

3. RESEARCH METHODOLOGY

3.1 Data Collection

The metrological (rainfall, temperature, sunshine) and river flow (discharge of Akaki river) data are collected from the metrological agency and Ministry of Water and Energy Resources. The location of reservoir sites which collects pumped water from the wells, cost for drilling of wells and operational costs are gathered from AAWSSA. The existing water abstraction rate from the wells and future plan of abstraction rate is also collected. In addition to this the regional groundwater model of Akaki catchment (presented at the end of previous section) is obtained from Addis Ababa water supply and sewerage Authority. Site inspection was also carried out to investigate status of the existing wells within the well fields.

3.2 Optimization Model and Problem Description

3.2.1 Introduction

Genetic algorithms are global search procedures derived from the method of natural selection of natural genetics that induce an artificial survival of the fittest with genetic operators (Zheng, June 1998). Initial population assigned randomly then the decision variables encoded in binary digits to form substrings. The consecutive substring series linked to form chromosomes. The selection of fittest individual depending on evaluation of Objective function and constraint, the selected individual reproduce and create next generation. After the crossover and mutation process the objective function is evaluated all over again for the newly designed solution in addition the selection procedure repetitively made until stop if condition satisfied however, it continuous in until it attain maximum search. (John Nicklow, et al., 2010) Figure 3. 1.

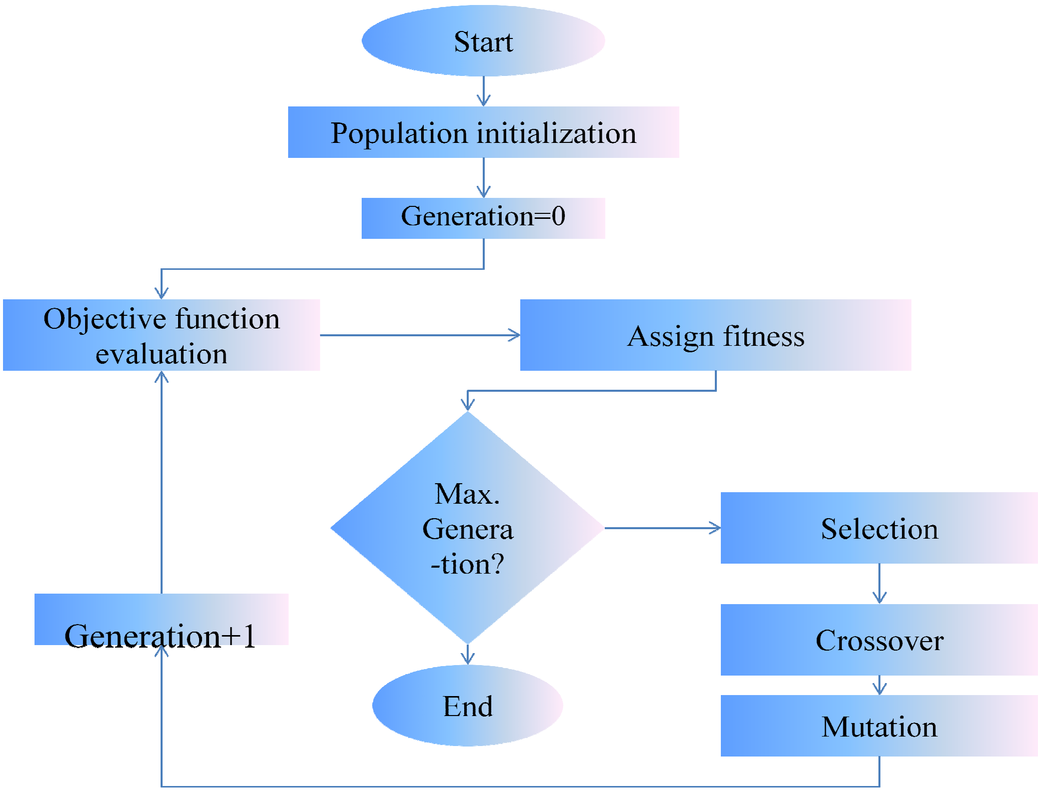

Figure 3. 1 Basic framework of GA

3.2.2 Formulation of the optimization problem (Objective functions Constraints, decision variables)

The two objective functions that are considered to be optimized are to maximize total pumping rate and to minimize of cost, described as follows:

- Maximization of total pumping rates (f_1): This objective needs to be maximized, the discharge which can be extracted from the groundwater aquifer with sustainable groundwater level. The objective function can be written as:

$$f_1 = \sum_{j=1}^{n} Q_j \qquad \textbf{3. 1}$$

Where n = number of potential pumping wells (36 in this case)
Q_j= pumping rate in cell j (j=1 ... n)

From (Equation 3. 1) f_1 is maximization function but the algorithm used to solve these optimization problems is designed to minimize all objective functions, therefore to change f_1 to minimization function we subtract f_1 from a maximum constant, representing pumping from all potential wells at maximum rate. (). So that f_1 should be minimized to get maximum of the difference.

$$minf_1 = \sum_{1}^{n} Q_n - f_1 \qquad 3. 2$$

Where Q_n = pumping rate of n pumping wells. That maximum constant used is in fact 1850 l/s. This value for the constant is obtained as 37 wells x 50 l/s, which is the maximum pumping rate per well. Using one additional well pumping rate in this calculation ensures that the difference expressed by equation 3.2 will always be positive. As the maximum constant is 1850 the equation of the reverse maximization is:

$$min f_1 = 1850 - f_1 \qquad \textbf{3. 3}$$

- Minimization of operation cost (f_2): to minimize the total cost. This essentially requires the identification for locations of wells and their spacing, also their pumping rates, determines the installation and operational cost.

$$min f_2 = \sum_{j=1}^{n} C_j Q_j + d_j I_j \qquad \textbf{3. 4}$$

Where n = number of potential pumping wells,

Q_j= pumping rate in cell j (j=1,.... n)
C_j= cost per unit pumping rate at location j,
d_j = Installation and maintenance cost
Q_j= is pumping rate at well j
I_j= is 1 if well is active, or else zero

To calculate cost per unit pumping rate C_j , the average pumping rate of each well is assumed to be 30 l/s; at pumping head of 60m; with 30year life time of wells and 8hour working time at each well. As a result, the cost of unit pumping rate is 262,800ETB.

The installation and maintenance cost d_j is obtained from drilling and construction cost of wells, including pipe lines to a reservoir. In order to determine the installation cost for pipes that connect wells to main reservoir; shortest straight line is considered between a well and location of main reservoir.

$$\boldsymbol{d_j = \sum_{j=1}^{n}(w_c + p_c)} \qquad \textbf{3. 5}$$

Where d_j= total drilling and pipe installation cost in ETB
w_c =drilling cost of each well
p_c = is pipe cost in ETB

$$\boldsymbol{p_c = \sum_{j=1}^{n} pl * cost\ per\ meter} \qquad \textbf{3. 6}$$

Where p_l = pipe length from well location to reservoir
Cost per unit meter of length is 266.4 ETB

The constraints of the above objective functions are subjected to drawdown with respect to pumping rate and cost. The Pumping rate (Qj) depends on the water demand, which leads the pumping rates to be minimum (Q_j^{min}) or maximum (Q_j^{max}) at potential pumping wells. The allowable pumping rates are formed as follows:

$$Q_j^{min} \leq Q_j \leq Q_j^{max}, \;\; 0 \leq Q_j \leq 50\ l/s \qquad 3.\ 7$$

Where, j=1,......N_w , N_w = number of wells

In Drawdown constraint (D_i): to protect the ground water from depletion due to excessive exploration to meet the demand.

$$\boldsymbol{D_i \leq D_{max}} \qquad \mathbf{3.\ 7}$$

Where D_i is the drawdown at control point *i* . There are 23 such control points. D_{max} is the maximum possible drawdown at control point *i*.

The 23 drawdown control points in this model consist of 22 drawdown constraint locations (with drawdown limits of 15, 20, 25 and 30m) and one location representing a spring (which is always with a limit of 6m - to protect the spring from drying out). The 22 control points are assigned depending on the value of transmissivity at a particular well field zone. As a result, for zones with higher trasnsmissivity the control point is at the centre of the zone and for zones with lower transmissivity the control point is at each control well.

Objective function evaluation depends on the decision variable vector. In this particular case the decision variables are in represented as an array of pumping rates for the 36 potential well locations.

In the previous study of (Wagena, 2011), the same problem was solved by single objective linear optimization, using minimisation of costs as the objective function (here introduced as the second objective). The total abstraction rate (here introduced as first objective) was introduced as constraint that had to be satisfied and the drawdown constraints were introduced in exactly the same manner as introduced here. This solution, obtained using LINGO optimization package for linear optimization serves as a reference solution for comparison of the solutions generated in this study using MOGA.

3.3 MODFLOW and NSGA II coupling

Matlab is used as coupling tool between MODFLOW and NSGA II. The code of the algorithm NSGA-II was originally developed by researchers in Kanpur Genetic Algorithm Laboratory but modified according to this specific problem to link with MODFLOW.

In general the formulation of the multi-objective optimization formulation in NSGA II was with population size of 100 and the same number of generations. The decision variables are the pumping rates of the 36 potential well locations ranging between values of 0and 50 l/s. The initialization of the first population is done randomly, however nearly always relatively closely to the known LINGO solution, as will be shown later. The two objective functions are formulated and implemented as described in the previous section. The drawdown control locations are 23 in total and the maximum drawdown imposed in different cases are 15m, 20m, 25m and 30m (for 22 control locations) and 6m for the spring control location.

For obtaining the values of the objective functions MODFLOW runs are not needed. For the value of first objective function a simple summation of the non-zero pumping rates out of the 36 potential wells is sufficient. The value of the second objective function (the costs) is also calculated from this well configuration. MODFLOW run with that well configuration is only needed for handling the drawdown constraints. After each MODFLOW run the drawdown at the control locations are extracted from the result files and checked. If obtained drawdown are higher than the maximum drawdown limit a penalty value is introduced which is added to the cost function (the second objective) . The different ways in which such penalty is introduced is described in the following section.

After these steps for obtaining the values of the objective functions the NSGA-II algorithm proceeds. From the current generation members with good fitness magnitude are selected non-dominantly. Reproduction between parents with good fitness value produces better offspring that could survive to the next generation. NSGA II selects the parents by using binary tournament selection with the probability of 0.4. The individual with a better fitness among two individuals is selected and assigned to be a parent. Moreover in advanced way if individual of the current generation has low magnitude of fitness it is replaced by fitting individual of previous generation (i.e. elitism) (Davis, 1991). The tournament selects the fittest pair of strings that is followed by application of crossover and mutation operations in the probability of 0.9 and 0.27. Fitness evaluation, the application of reproduction, crossover and mutation operations continues until the maximum generation is attained. The flow chart below illustrates (Figure 3. 2) these general steps of NSGA II.

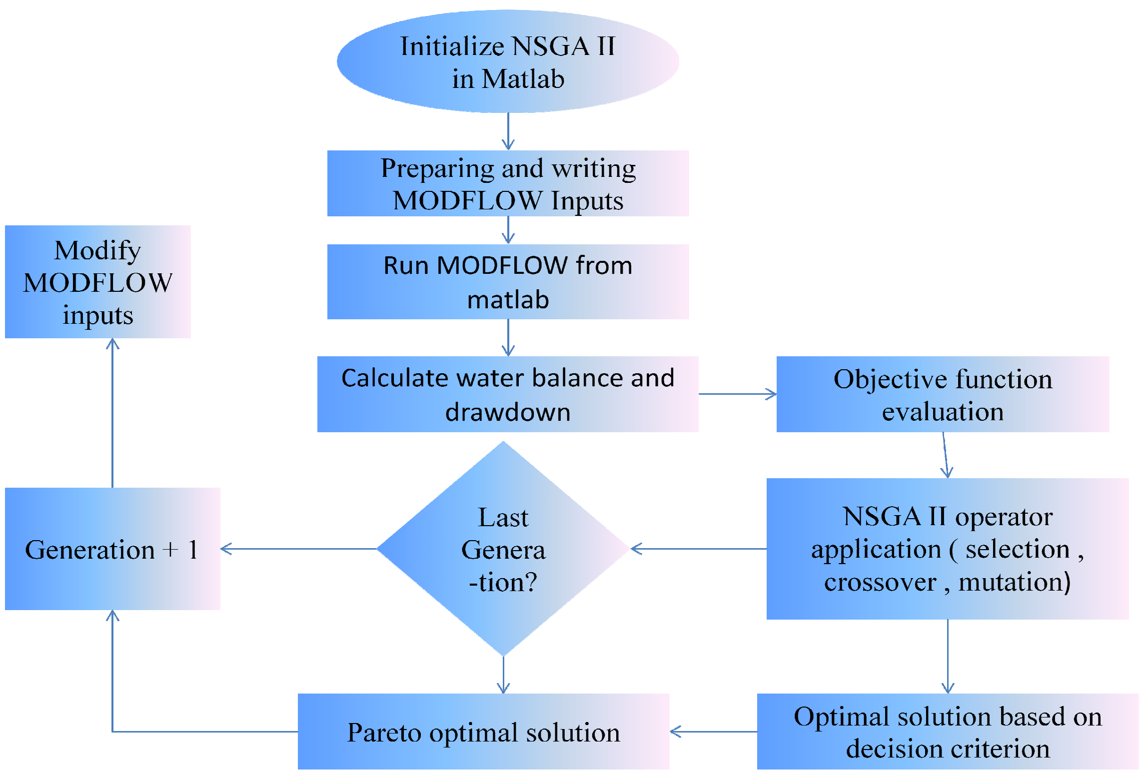

Figure 3. 2 NSGA II and MODFLOW link flow chart.

3.4 Alternatives for constraints handling tested in NSGA II

There are different techniques proposed in NSGA II to handle constraints in optimization problems. According to (Deb, 1998) Constraint handling methods in optimization algorithms can be classified in two groups:

(i) Generic methods - these methods do not consider the structure of the constraint, and can be applies for both linear and non linear constraint configuration. Some generic methods, as the penalty function method, the Lagrange multiplier method, and the complex search method are the commonly used methods because they are easy to apply to any problems without significant change of the algorithm.

(ii) Specific methods - this is used to handle unique type of constraints, such as problems having convex feasible regions, problems having a few variables, and constraints having large number of variables due to their high computational load with large number of variables.

In most cases, GAs for constrained optimization problems has used the penalty function method of handling constraints because of the generic character GA search methods.

The penalty function used in this particular case is adopted from a normally distributed Gaussian function. The graph of a Gaussian function is characterized by symmetric "bell curve" shape that continuous to plus/minus infinity. In this case the penalty function has truncated tail at the right hand side of the curve. It is in fact a half bell-shaped curve. (Equation 3. 8)

$$f(x) = ae^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad \textbf{3. 8}$$

$where\ x =$ Actual drawdown value at control location

$\mu =$ Mean of the Gaussian-like curve - maximum allowed drawdown

σ = 0.4 (Standard deviation of the curve)

$a =$ 50 (maximum constant, chosen in accordance to the real cost values))

In equation 3. 8 is the critical point corresponding to the maximum allowed drawdown (the constraint value). With the chosen values of standard deviational and the constant a penalty starts to have significant values at $(\mu - 1)$, and sharply increases towards the maximum value of a when the actual drawdown is equal to the mean (x=μ). The value of a is assigned to be about twice as large as the maximum expected real costs. For actual drawdown that are larger than the mean the function is not used any longer, but a maximum penalty is assigned in different ways for different methods presented in the following sections. After calculating the penalties for all control locations the maximum penalty p is selected and added to the second objective function:

$$p = Max_{i=1}^{n} f_{(x)} \qquad \textbf{3. 9}$$

Where n= the number of decision variables

The region beyond the given maximum constraint is infeasible, for instance if the maximum drawdown constraint has to be 15m, the solution above 15 will violate the constraint (Figure 3. 3).

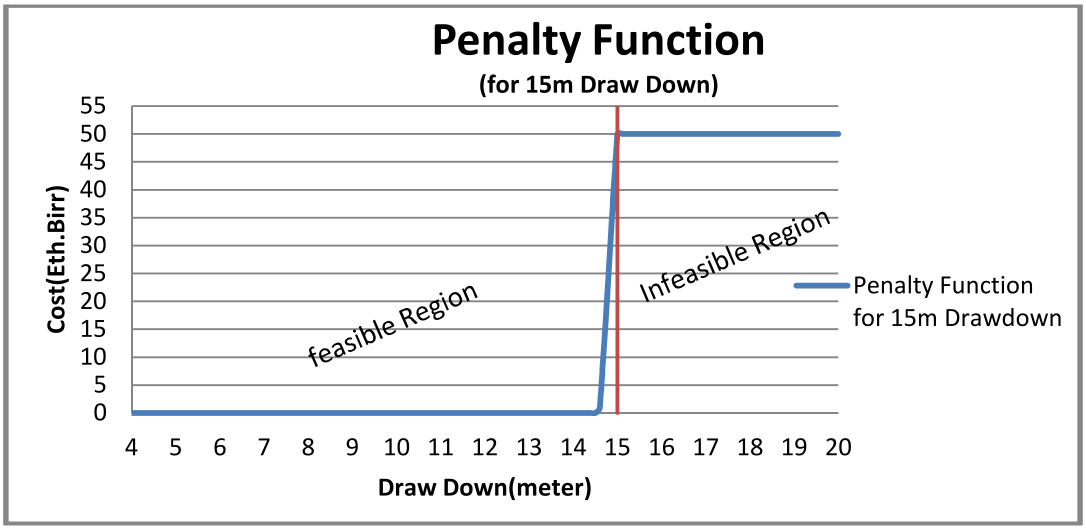

Figure 3. 3 Penalty functions for 15m DD.

In each case where penalties are introduced the penalty calculation starts only at x=μ-1, till x=μ, and after this point a maximum penalty is calculated. The methods described in the following sections are essentially different in the way of calculating this maximum penalty. These methods, tested in this study are presented as follows:

3.4.1 'Static' Penalty Function; Random initialization (Case 1)

Random population initialization within the range of 0- 50 l/s and the decision variable vector contains 36 active wells. The maximum penalty function is constant which does not depend on the magnitude and number of violations. It basically introduces high cost upon constraint violation. The penalty starts at $(\mu - 1)$ (Equation $\boldsymbol{start\ penalty = \mu - 1}$ 3. 10), therefore,

$$\boldsymbol{start\ penalty = \mu - 1} \qquad \textbf{3. 10}$$

where, μ = mean of the Gaussian-like function, it is the maximum drawdown of the given case (checked for 15m, 20m, 25m, 30m at well sites but 6m at spring sites)

If $x < \mu - 1$ then, all x values fall under feasible region with zero penalties. As a result none of the constraints will be violated.

If $(\mu - 1) \leq x \leq \mu$ the penalty function is described as

$$\boldsymbol{f_x = ae^{-\frac{(x-\mu)^2}{2\sigma^2}}} \qquad \textbf{3. 11}$$

If $x > \mu$,

$$f_x = a * 1.1 \qquad 3.\ 12$$

$where\ a = 50$ Therefore for every constraint violation the penalty function $f_x = a * 1.1$ 3. 12) mentioned above appear as 'static' with maximum constant of 55 at all constraint violation without consideration of number and magnitude of violations.

3.4.2 'Static' Penalty Function; Initialization near to LINGO Solution;

The penalty function formulation is the same to the above mentioned case but the population initialization is using the near to LINGO optimal solutions. This kind of initialization helps the algorithm to search for better solution, but close to the region of known optimal solution.

A. Initialization slightly lower Than Lingo solution (Case 2)

In this option the initialization is made by the known near optimal LINGO solution by slight lowering of the pumping rate, that is 20% lower than the LINGO. But the range of decision variables is the same as in the previous case (0 - 50 l/s). The LINGO solutions are the optimal and near optimal points that lie inside the feasible region are used for initialization.

B. Initialization slightly lower Than Lingo solution using only active wells from Lingo solution (Case 3)

In this set up the decision variable vector contains only non-zero active wells with 20% less than LINGO solution. In other words, the number and locations of wells were much smaller, for which the pumping rates are varied. But the range (0-50 l/s) and the penalty function remain the same with the previous cases.

With static penalty formulation initialization was also tried using slightly higher values than LINGO solution that means with the same range of the decision variable, but initialized by slightly 20% higher value of pumping rate than the optimal solution of LINGO. With this option the results are far from feasible region that all solution falls outside the optimal solution set. Thus these results are not enclosed in this report.

3.4.3 'Dynamic' Penalty Function Depending on Magnitude of Constraint Violation (Case 4)

The penalty function starts with the Gaussian Normal distribution function as the previous cases but the function depends on the magnitude of the constraint violation. Therefore it is different at each control location. Regardless of the penalty function variation all initializations remain the same to the previous case of static penalty function which has 36 decision variables and near to LINGO optimal solutions.

The introduction of penalty is assigned as described as follows;

$$start\ penalty = \mu - 1 \tag{3. 13}$$

If $x < (\mu - 1)$, penalty is zero all the solution set lies under feasible region.

If $(\mu - 1) \leq x < \mu$, the penalty functions is;

$$f_x = ae^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{3. 14}$$

But if $x \geq \mu$,

$$\boldsymbol{f_x = (x - \mu) * a} \tag{3. 15}$$

Therefore the penalty depends on the magnitude of x and it is different for different x values. The fitness evaluation of individuals depends on the magnitude of constraint violation. Then the penalty is;

$$p = Max_{i=1}^{n}(f_x)_i \tag{3. 16}$$

Beside to this penalty function formulation Initialization of the decision variable is done by slightly lower and slightly higher than Lingo optimal solution.

3.4.4 Dynamic Penalty Function Depending on Magnitude and Number of Constraint Violation (Case 5)

The Initialization of decision variables and range is remains the same to the case 3.4.3 but the penalty depends not only on the magnitude but also it depends on the number of violation and the penalty also starts at $\mu - 1$,therefor penalty is zero for $x < (\mu - 1)$,

If $\mu > x \geq (\mu - 1)$, the penalty function will be:

$$f_x = ae^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{3. 17}$$

Then if $x > \mu$, the penalty function is calculated by considering the number and the magnitude of constraint violation as shown in Equation below

$$f(x) = (x - \mu) * a * n_v \tag{3. 18}$$

Where n_v = number of constraint violations, then the penalty is;

$$p = Max_{i=1}^{n}(f_x)_i \tag{3. 19}$$

Additionally initialization by slightly lower and slightly higher value than LINGO solution was used.

3.4.5 Implicit Introduction of Penalty Function using a third Objective Function

In this particular optimization problem formulation the aim is to optimize two objective functions that is maximizing the pumping rate and to minimize cost under some penalized constraints. But in this section the penalty function is introduced implicitly using a third objective function.

A. Third objective as minimization of number of constraint violations (Case 6)

The objective function design of the whole problem that has presented in above section is two; maximization of abstraction rate and minimization of cost. However in this case a third objective function was introduced aiming at minimization of number of constraint violations. By aiming to minimize the number of constraint violations the drawdown constraint condition in the well field are satisfied. The new objective function f_3 can be written as;

$$minf_3 \sum_{i=1}^{n} cv_i \qquad 3.\ 20$$

Where = cv_i= number of constraint violation, n= control locations

B. Third objective as minimization of the product of number of constraint violations and maximum violation (Case 7)

In this case the third introduced objective function is minimizing the product of constraint violation and maximum violation magnitude. In addition the constraints are different draw down condition. The function can be written as;

$$\boldsymbol{minf_3 = c_v * Max_{i=1}^{n}(g_x)_i}, \qquad \mathbf{3.\ 21}$$

Where $Max_{i=1}^{n}(g_x)_i$= maximum magnitude of constraint violation, c_v= number of constraint violations.

In all cases attempted above the initialization of the decision variables using slightly higher than LINGO solution has been checked additionally, but came up with highly violated solutions which are very far from the optimal region. It takes very long time to reach the feasible region and the obtained results are always far from the feasible region. Thus these results are not enclosed in this report.

4. RESULTS AND DISCUSSIONS

The Algorithm has been checked for maximum number of 100 Population and generation size. Binary tournament selection, cross over and mutation system used by the algorithm for the selection and combination of the individuals. The crossover probability was 0.9 and with mutation probability of 0.02 (for 36 decision variables). The tournament size was two and the mating pool size is half of the population size.

4.1 Case 1; Results from Random initialization; 'Static' Penalty Function;

The penalty function is static which is not dependent on the constraint violation and magnitude. The population initialized at random with the decision variable range of 0 to 50 l/s. Whereas in MOGA selection of first pareto optimal set of two individuals are selected at random from specified decision space. The selection is non-dominated at the first tournament. The individual with better rank is selected as parent; the two competent individuals could be far from feasible zone due to random initialization however by considering the rank and the crowding distance, the nearest possible individual is assigned to be a parent for the next procedure.

Therefore the result of this case is entirely out of the feasibility zone and provided extremely bad results due to random initialization. The first parents selected by non-dominated search nature of MOGA contain outliers which makes the pareto optimal sets out of the real feasibility zone. As a reason the results are not included in this discussion.

4.2 Case 2; Result of Initialization near to LINGO Solution; with 'Static' Penalty Function;

The penalty function considered in this case is static with the aim of introducing high cost in constraint violation. The pareto optimal set obtained from this setup is presented in (Figure 4. 1). The algorithm used for four different drawdown values. As the pumping rate is maximized the cost becomes higher. The obtained solutions are also compared with the LINGO solution points by taking the point from the pareto set closest to the LINGO solution (this is done for all analysed cases).

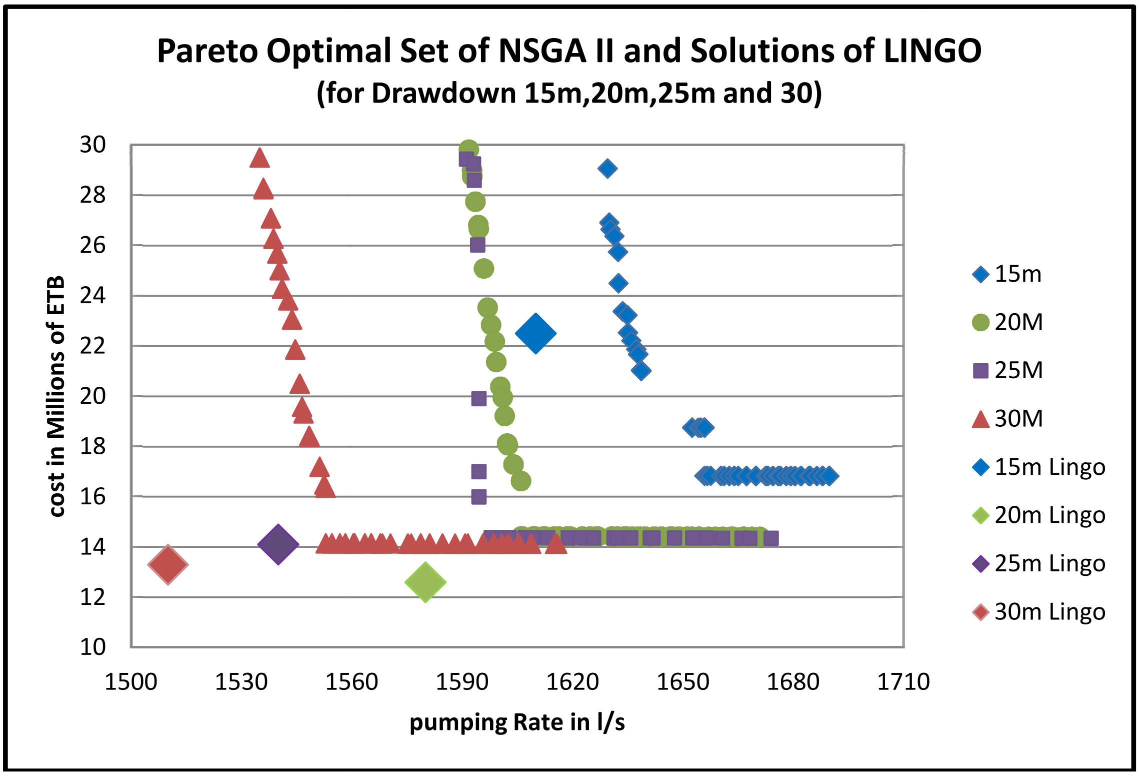

Figure 4. 1 Pareto optimal set of MOGA and LINGO for four drawdown values

The well configuration according to MOGA has lower abstraction rate in compared to LINGO solution with a higher cost. In the configuration presented at (Table 4. 1) the GA solutions come up with new well configuration as can be seen in the case of 25m and 30m drawdown constraint. Despite of the new configuration the GA results are not better than LINGO.

Table 4. 1 MOGA and LINGO well configuration and assigned pumping rate at four different drawdown cases

			Pumping rate in m3/day at different Draw down							
			15m drawdown		20m drawdon		25m drawdown		30m drawdown	
Well Id	**Row**	**Column**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**
287	**101**	**52**	1548.5	1613.1	4229.8	4320.0	3160.2	3169.2	0.0	3121.6
291	**101**	**50**	4292.9	4320.0	3504.6	4320.0	4208.0	4320.0	2683.3	0.0
Dal_1	**101**	**72**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3608.1
fanta_6	**72**	**66**	3344.3	3849.1	1625.7	2374.3	1824.0	0.0	0.0	0.0
Dal_3	**101**	**76**	0.0	0.0	0.0	0.0	0.0	0.0	3634.7	0.0
Dal_4	**104**	**76**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4320.0
Dup_1	**98**	**92**	605.9	870.9	1430.3	1986.3	2233.6	2115.1	2988.8	0.0
Dup_2	**100**	**90**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_5	**104**	**94**	480.8	930.5	0.0	0.0	0.0	2044.2	2501.5	3452.5
Dup_6	**106**	**92**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_7	**108**	**94**	489.7	1004.0	0.0	0.0	0.0	0.0	2919.0	3524.3
Dup_8	**108**	**90**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_1	**111**	**90**	2376.7	2073.6	4243.6	4320.0	4278.8	4320.0	3820.6	4320.0
Ddwn_3	**116**	**90**	252.7	180.6	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_4	**118**	**88**	62.6	348.2	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_5	**120**	**84**	2262.5	1094.7	1761.2	1687.4	1578.5	2174.7	2858.4	2737.2
Ddwn_6	**122**	**82**	4173.0	4320.0	4284.9	4320.0	3947.7	4320.0	4263.5	4292.4
Total pumping (m3/day)			**19889.6**	**20604.7**	**21080.2**	**23328.0**	**21230.7**	**22463.1**	**25670.0**	**29376.0**
Total cost (ETB)			**23.2**	**22.5**	14.4	**12.6**	**14.4**	**14.1**	**14.1**	**13.3**

4.3 Case 3; Initialization slightly lower Than LINGO solution using only active wells from LINGO solution

In this case the population initialization is restricted to only few active none zero well sites as calculated by LINGO. The pareto optimal sets presented in (Figure 4. 2); the result obtained from this setup is not better than case 2.

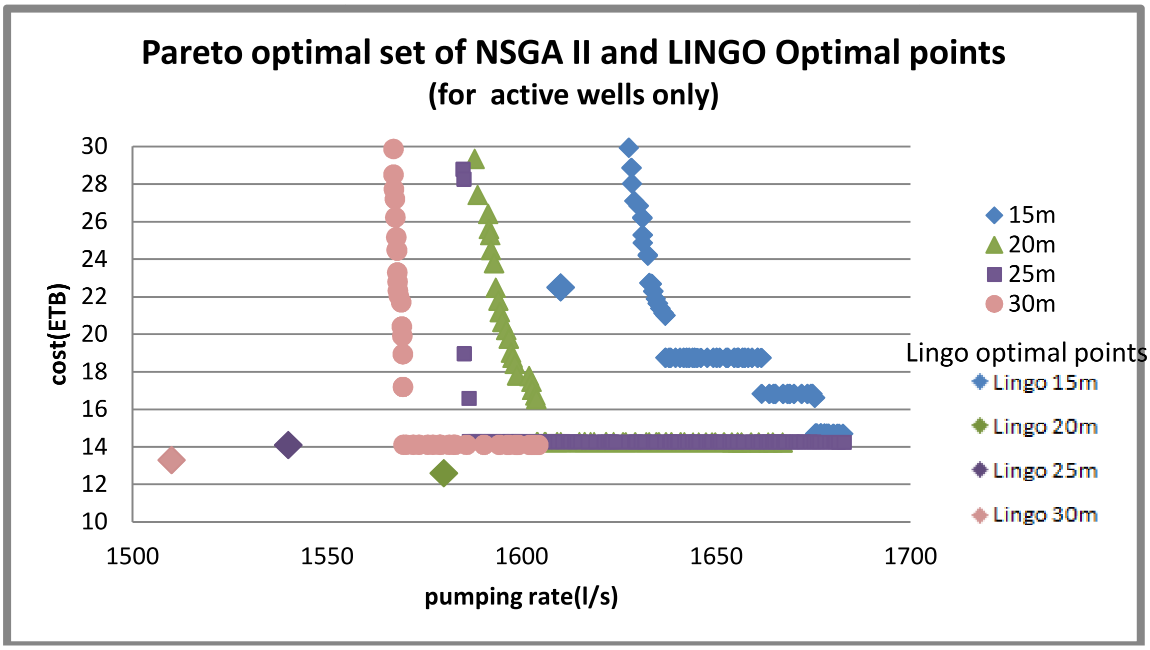

Figure 4. 2 Pareto optimal sets of MOGA and Lingo at different drawdown values

In this case the usage of only smaller number of wells (decision variables) resulted in more rapid selection of near optimal solutions compared to previous cases. Nevertheless the achieved solution is not better than that of case two.

In the table below (Table 4. 2) under the condition of static penalty and restriction of number of decision variables, the MOGA new well configuration made by reducing the number of active well sites in order to get optimal abstraction rate and minimum cost. For instance in 15m drawdown case the wells Ddwn_3 and Ddwn_4 were active in the case of Lingo however, in MOGA these sites are omitted and different abstraction rates are assigned to the rest of the sites. Nevertheless the Lingo solution is preferable for better abstraction rate at fair cost.

Table 4. 2 Well configuration along with Abstraction rate and cost proposed by MOGA and Lingo for different drawdown constraint

		Pumping rate in m3/day at different Draw down								
			15m drawdown		20m drawdon		25m drawdown		30m drawdown	
Well Id	**Row**	**Column**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**
287	**101**	**52**	1363.5	1613.1	3889.8	4320.0	3551.0	3169.2	2497.3	3121.6
291	**101**	**50**	3881.7	4320.0	3952.0	4320.0	4302.7	4320.0	3155.2	0.0
Dal_1	**101**	**72**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3608.1
fanta_6	**72**	**66**	3113.0	3980.4	1429.5	2374.3	0.0	0.0	0.0	0.0
Dal_3	**101**	**76**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dal_4	**104**	**76**	0.0	0.0	0.0	0.0	0.0	0.0	2674.8	4320.0
Dup_1	**98**	**92**	743.9	870.9	1925.7	1986.3	0.0	2115.1	0.0	0.0
Dup_2	**100**	**90**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_5	**104**	**94**	1403.1	930.5	0.0	0.0	1719.4	2044.2	2838.1	3452.5
Dup_6	**106**	**92**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_7	**108**	**94**	761.4	1004.0	0.0	0.0	0.0	0.0	3090.3	3524.3
Dup_8	**108**	**90**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_1	**111**	**90**	1958.7	2073.6	4243.8	4320.0	2013.1	4320.0	3757.7	4320.0
Ddwn_3	**116**	**90**	0.0	180.6	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_4	**118**	**88**	0.0	348.2	0.0	0.0	4285.4	0.0	0.0	0.0
Ddwn_5	**120**	**84**	1184.3	1094.7	1752.9	1687.4	2324.2	2174.7	2172.2	2737.2
Ddwn_6	**122**	**82**	4170.0	4320	4071.4	4320	4302.7	4320.0	3982.4	4292.4
Total pumping (m3/day)			**18579.5**	**20736**	**21265**	**23328**	**22498.6**	**22463.2**	**24168.0**	**29376.1**
Total cost (ETB)			**22.3**	**22.5**	**14.3**	**12.6**	**14.3**	**13.3**	**16.1**	**13.3**

4.4 Case 4; 'Dynamic' Penalty Function Depending on Magnitude of Constraint Violation

The penalty formulation is dependent on the magnitude of constraint violation, the Pareto optimal sets presented on (Figure 4. 3). The algorithm selected points depending on the magnitude of constraint violation which allow the constraint with smaller magnitude of constraint violation in the optimal sets of points. The result presented in case 3 is better than this case since in case 3 a smaller number of wells were considered.

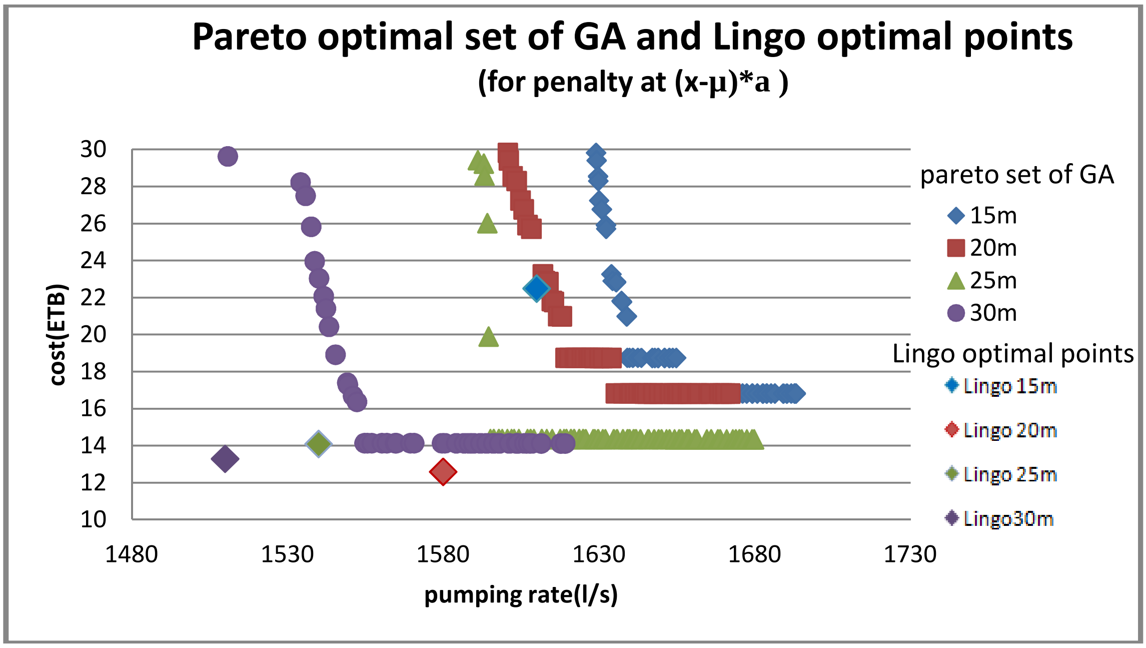

Figure 4. 3 Pareto optimal sets of MOGA and Lingo at four drawdown conditions

The results obtained incase 3 do not show new well configuration except that they present better abstraction rate with better costs when compared to this case. In (Table 4. 3) it can be seen that in this case new well configuration was introduced in the case of 15m and 30m drawdown. However for all tested drawdown Lingo solution is better than the MOGA optimal sets.

Table 4. 3 Well configuration along with Abstraction rate and cost proposed by MOGA and Lingo for different drawdown constraints at dynamic penalty formulation

		Pumping rate in m3/day at different Draw down								
			15m drawdown		20m drawdon		25m drawdown		30m drawdown	
Well Id	**Row**	**Column**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**
287	**101**	52	1602.9	1613.1	4183.7	4320.0	3141.4	3169.2	2541.8	3121.6
291	**101**	50	3501.8	4320.0	4026.9	4320.0	4311.8	4320.0	0.0	0.0
Dal_1	**101**	72	0.0	0.0	0.0	0.0	0.0	0.0	2739.8	3608.1
fanta_6	**72**	66	3323.5	3980.4	1250.6	2374.3	0.0	0.0	0.0	0.0
Dal_3	**101**	76	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dal_4	**104**	76	0.0	0.0	0.0	0.0	0.0	0.0	3589.8	4320.0
Dup_1	**98**	92	375.5	870.9	1472.4	1986.3	1816.8	2115.1	0.0	0.0
Dup_2	**100**	90	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_5	**104**	94	596.5	930.5	0.0	0.0	2686.1	2044.2	3015.3	3452.5
Dup_6	**106**	92	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_7	**108**	94	1071.8	1004.0	0.0	0.0	0.0	0.0	2885.5	3524.3
Dup_8	**108**	90	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_1	**111**	90	2066.3	2073.6	4196.9	4320.0	4309.2	4320.0	3809.1	4320.0
Ddwn_3	**116**	90	0.0	180.6	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_4	**118**	88	0.0	348.2	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_5	**120**	84	993.3	1094.7	1732.8	1687.4	1574.4	2174.7	2768.0	2737.2
Ddwn_6	**122**	82	4302.4	4320.0	4320.0	4320.0	3943.5	4320.0	4160.6	4292.4
Total pumping (m3/day)			**17833.9**	**20736.0**	**21183.3**	**23328.0**	**21783.3**	**22463.2**	**25510.0**	**29376.1**
Total cost (ETB)			**18.8**	**22.5**	**14.4**	**12.6**	**14.4**	**13.3**	**16.1**	**13.3**

4.5 Case 5; Dynamic Penalty Function Depending on Magnitude and Number of Constraint Violation

The penalty in this case considers the magnitude and number of violations. As the pareto optimal set presented on the (Figure 4. 3) show - the set of the solutions are better here than case 4 formulation. The cost is moderately less and the abstraction rate is comparatively high besides the solution set are closer to Lingo optimal solution than case 4 .

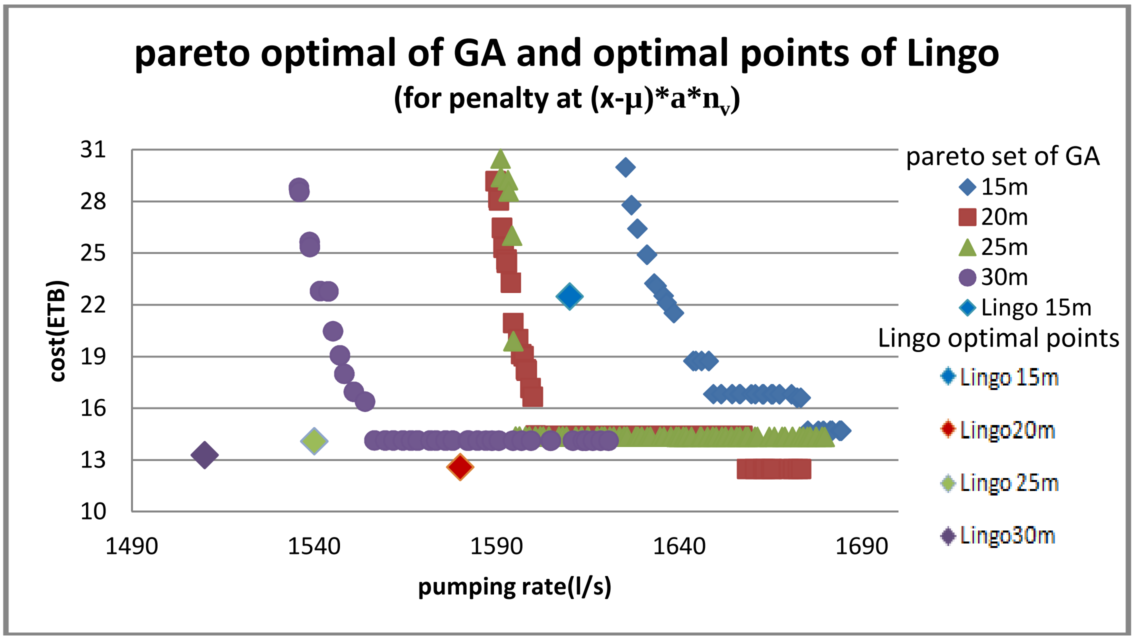

Figure 4. 4 Pareto optimal sets of MOGA and Lingo optimal points at four drawdown conditions

In this setup the MOGA results provided new well configuration with is relatively high abstraction rate along with fair cost. However, the new well configurations found for 15m and 30m drawdown are not better solution when compared to the Lingo solution.

Table 4. 4 Some points from MOGA and LINGO

		Pumping rate in m3/day at different Draw down								
			15m drawdown		20m drawdon		25m drawdown		30m drawdown	
Well Id	**Row**	**Column**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**
287	**101**	52	1595.9	1613.1	4216.9	4320.0	3145.3	3169.2	2541.8	3121.6
291	**101**	50	3789.8	4320.0	4071.4	4320.0	4314.6	4320.0	0.0	0.0
Dal_1	**101**	72	0.0	0.0		0.0	0.0	0.0	2739.8	3608.1
fanta_6	**72**	66	3207.5	3980.4	1286.4	2374.3	0.0	0.0	0.0	0.0
Dal_3	**101**	76	0.0	0.0	0.0	0.0	0.0	0.0	3589.8	0.0
Dal_4	**104**	76	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4320.0
Dup_1	**98**	92	921.9	870.9	1833.5	1986.3	1868.5	2115.1	0.0	0.0
Dup_2	**100**	90	0.0	0.0	0.0	0.0	0.0	0.0	3015.3	0.0
Dup_5	**104**	94	1093.7	930.5	0.0	0.0	2569.0	2044.2	0.0	3452.5
Dup_6	**106**	92	0.0	0.0	0.0	0.0	0.0	0.0	2885.5	0.0
Dup_7	**108**	94	658.3	1004.0	0.0	0.0	0.0	0.0	0.0	3524.3
Dup_8	**108**	90	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_1	**111**	90	2006.6	2073.6	4026.6	4320.0	4296.3	4320.0	3809.1	4320.0
Ddwn_3	**116**	90	0.0	180.6	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_4	**118**	88	0.0	348.2	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_5	**120**	84	1096.6	1094.7	1724.8	1687.4	1568.5	2174.7	0.0	2737.2
Ddwn_6	**122**	82	4312.7	4320.0	4199.3	4320.0	3929.9	4320.0	2768.0	4292.4
Total pumping (m3/day)			**18683.1**	**20736.0**	**21358.9**	**23328.0**	**21692.1**	**22463.2**	**21349.4**	**29376.1**
Total cost (ETB)			**23.1**	**22.5**	**14.4**	**12.6**	**14.1**	**13.3**	**14.1**	**13.3**

4.6 Implicit Introduction of Penalty Function using a third Objective Function

A. (Case 6)Third objective as minimization of number of constraint violations

The introduction of the third objective function is aimed to minimize number of constraint violation. The result of this objective function design is much better than the above mentioned methods. The pareto optimal solution presented in (Figure 4. 5) shows better solution nearer to LINGO solutions.

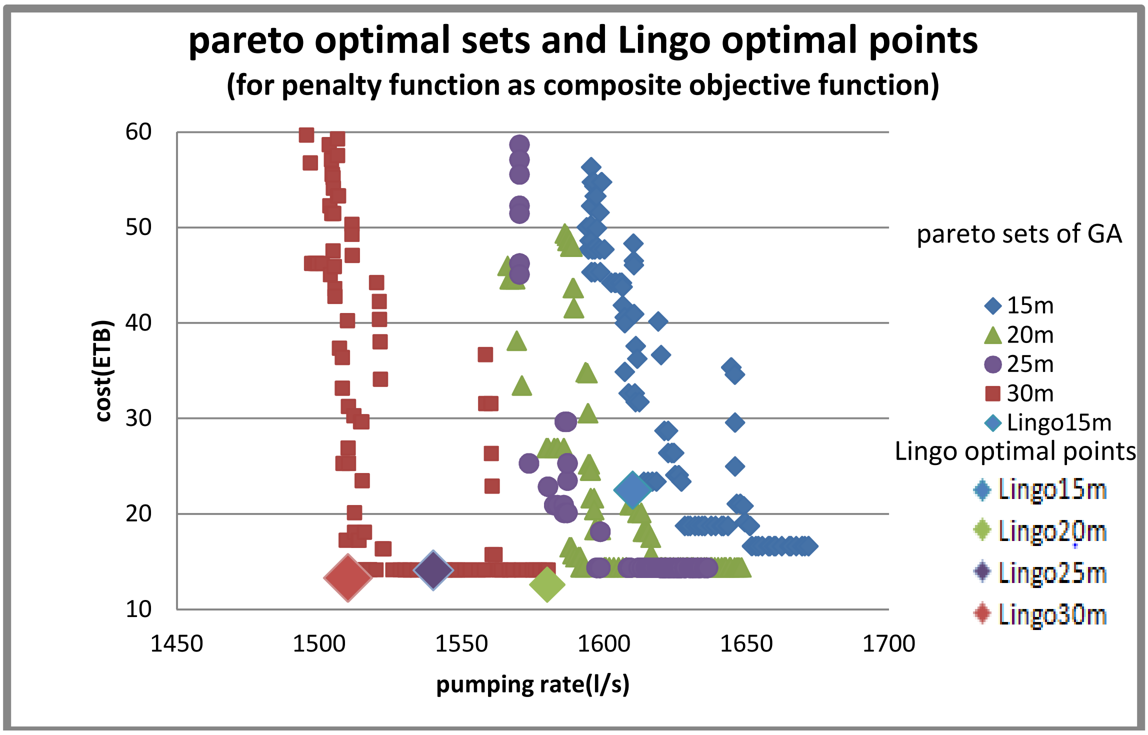

Figure 4. 5 Pareto solution points of MOGA and Lingo points

As shown in (Table 4. 5) the algorithm proposed some optimal solution of improved pumping rates compared to the previous cases however it violates the constraint in small degree (as checked subsequently in MODFLOW). At some drawdown control locations the drawdown constraints are still violated.

Table 4. 5 Some pareto optimal points from MOGA and Lingo

		Pumping rate in m3/day at different Draw down									
			15m drawdown		20m drawdon		25m drawdown		30m drawdown		
Well Id	**Row**	**Column**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	
287	**101**	52	1548.5	1613.1	4040.3	4320.0	2793.5	3169.2	3438.2	3121.6	
291	**101**	50	4292.9	4320.0	4305.2	4320.0	3947.4	4320.0	0.0	0.0	
Dal_1	**101**	72	3849.1	0.0	0.0	0.0	0.0	0.0	3689.8	3608.1	
fanta_6	**72**	66	3849.1	3980.4	2004.8	2374.3	0.0	0.0	0.0	0.0	
Dal_3	**101**	76	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
Dal_4	**104**	76	0.0	0.0	0.0	0.0	0.0	0.0	3807.4	4320.0	
Dup_1	**98**	92	605.9	870.9	1549.1	1986.3	2012.7	2115.1	0.0	0.0	
Dup_2	**100**	90	0.0	0.0	0.0	0.0	0.0	0.0	3396.2	0.0	
Dup_5	**104**	94	480.8	930.5	0.0	0.0	1331.9	2044.2	0.0	3452.5	
Dup_6	**106**	92	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
Dup_7	**108**	94	489.7	1004.0	0.0	0.0	0.0	0.0	3626.0	3524.3	
Dup_8	**108**	90	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
Ddwn_1	**111**	90	2376.7	2073.6	3900.9	4320.0	4179.8	4320.0	4314.6	4320.0	
Ddwn_3	**116**	90	252.7	180.6	0.0	0.0	0.0	0.0	0.0	0.0	
Ddwn_4	**118**	88	62.6	348.2	0.0	0.0	0.0	0.0	0.0	0.0	
Ddwn_5	**120**	84	2262.5	1094.7	2084.3	1687.4	1796.2	2174.7	2800.0	2737.2	
Ddwn_6	**122**	82	4173.0	4320.0	4316.3	4320.0	4270.9	4320.0	4287.3	4292.4	
Total pumping (m3/day)			**24243.5**	**20736.0**	**22201.0**	**23328.0**	**20332.5**	**22463.2**	**29359.6**	**29376.1**	
Total cost (ETB)			**23.2**	**22.5**	**14.4**	**12.6**	**14.1**	**13.3**	**14.2**	**13.3**	

B. (Case 7) Third objective as minimization of the product of number of constraint violations and maximum violation

Various formulation and initializations as well as different penalty formulation were attempted. Among all cases this case gives best result. In the third objective design, the algorithm attempts to minimize the product of maximum violation and number of violations. The result is best of all above mentioned cases regarding maximized abstraction rate at minimum cost. The pumping rate proposed by MOGA model is introduced in MODFLOW model for final checking and it is confirmed that it gives good results with no constraint violation.

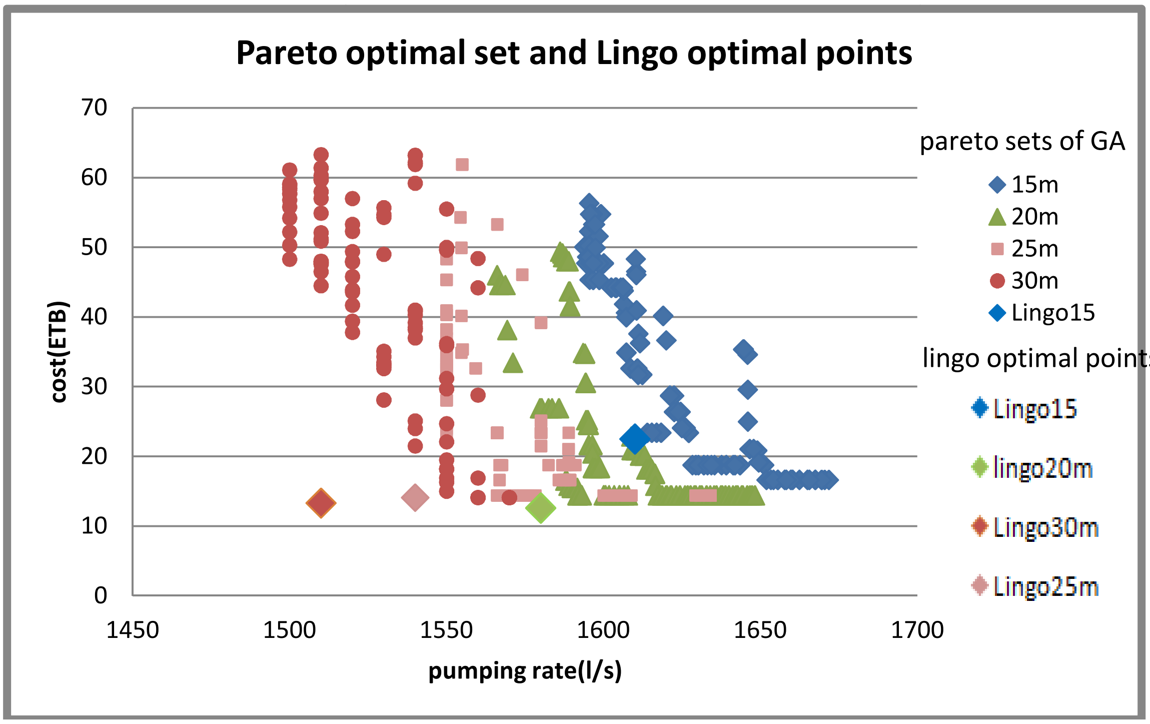

Figure 4. 6 Pareto solution points of MOGA and Lingo points

The abstraction rates shown in (Table 4. 6) are much better to that of former cases. The new well configuration and optimal solution of pumping rate proposed by the algorithm performs best to handle constraints with less violation comparable at some points of LINGO solution. However the abstraction rate in LINGO solution is higher with less cost.

Table 4. 6 Some pareto optimal points from MOGA and Lingo

			15m drawdown		20m drawdon		25m drawdown		30m drawdown	
Well Id	**Row**	**Column**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**	**GA**	**LINGO**
287	**101**	52	1548.5	1613.1	4072.1	4320.0	4034.9	3169.2	2998.1	3121.6
291	**101**	50	4292.9	4320.0	4291.6	4320.0	4294.1	4320.0	0.0	0.0
fanta_6	**72**	66	3849.1	3980.4	1975.3	2374.3	1995.8	0.0	0.0	0.0
Dal_1	**101**	72	0.0	0.0	0.0	0.0	0.0	0.0	3257.3	3608.1
Dal_2	**101**	74	0.0	0.0	0.0	0.0	0.0	0.0	1.2E-04	0.0
Dal_3	**101**	76	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dal_4	**104**	76	0.0	0.0	0.0	0.0	0.0	0.0	4294.1	4320.0
Dup_1	**98**	92	605.9	870.9	1573.9	1986.3	1546.6	2115.1	0.0	0.0
Dup_2	**100**	90	0.0	0.0	0.0	0.0	0.0	0.0	2972.2	0.0
Dup_5	**104**	94	480.8	930.5	0.0	0.0	0.0	2044.2	0.0	3452.5
Dup_6	**106**	92	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dup_7	**108**	94	489.7	1004.0	0.0	0.0	0.0	0.0	3248.6	3524.3
Dup_8	**108**	90	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_1	**111**	90	2376.7	2073.6	3883.7	4320.0	3896.6	4320.0	3628.8	4320.0
Ddwn_3	**116**	90	252.7	180.6	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_4	**118**	88	62.6	348.2	0.0	0.0	0.0	0.0	0.0	0.0
Ddwn_5	**120**	84	2262.5	1094.7	2227.2	1687.4	2203.2	2174.7	2324.2	2737.2
Ddwn_6	**122**	82	4173.0	4320.0	4304.2	4320.0	4320.0	4320.0	3473.3	4292.4
Total pumping (m3/day)			**20394.4**	**20736.0**	**22328.0**	**23328.0**	**22291.2**	**22463.2**	**26196.5**	**29376.1**
Total cost (ETB)			**22.9**	**22.5**	**15.5**	**12.6**	**14.1**	**13.3**	**15.0**	**13.3**

The pumping rate proposed by the algorithm was used as an input to the MODFLOW to confirm constraint violation and to check the resulting water balance..

The drawdown contour shown in (Figure 4. 7) is the result of MODFLOW run by input of MOGA optimal result for 15m drawdown. However the result shows the drawdown exceeds 15m with the obtained pumping, which means that there are some violations of the constraints. In addition the well configuration of the MOGA is the same to that of Lingo.

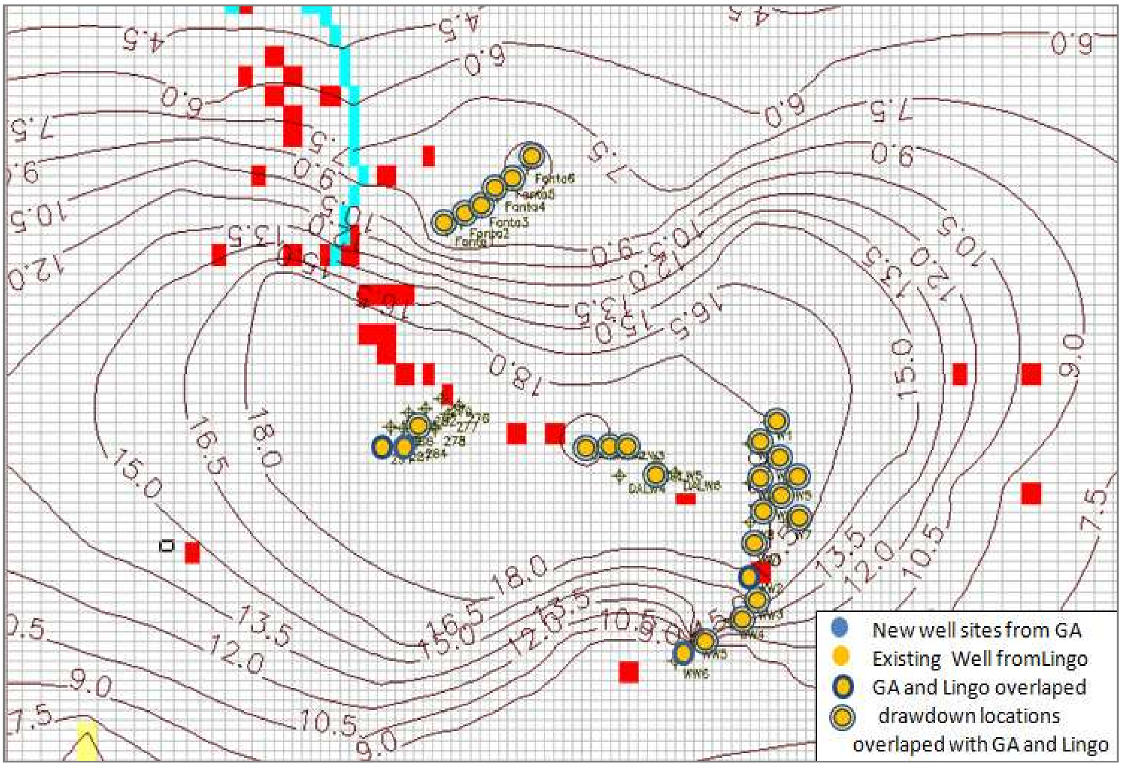

Figure 4. 7 Drawdown control sites and 15m drawdown of case 7.

The water balance (Table 4. 7) displays; high outflow is by constant head boundary that is 62.3% and the outflow by well and river is 15.9% and 20.6 respectively, the drain contribution is less which is 1.1%. Whereas comparing with water balance of original steady state model, the abstraction rate increased by 20,301.4 m^3/day, which influences the river outflow to decrease by 6595 m^3/day followed by lowering of constant head boundary by11, 513.5 m^3/day and the drain decreased by 2,113.1 m^3/day.

Table 4. 7 Water Balance of 15m drawdown

	Inflow to Catchment			Out Flow from the catchment				
	Natural Recharge	River Recharge	Total	Constant Head Boundary	Wells	Drains	River Flow	Total
Steady state	281,059.20	518.4	281,577.6	187,228.8	24,451.2	5270.4	64627.2	**281,577.6**
Water balance	99.80%	0.20%	100%	66.5%	8.70%	1.90%	23%	**100%**
Water balance	281,059.20	572.5	281642.45	175715.3	44752.6	3157.3	58032.2	**281657.4**
of15m DD	99.80%	0.20%	100%	62.30%	15.90%	1.10%	20.60%	**100%**
Difference(m3/day)	0	**54.1**	**64.9**	**-11,513.5**	**20,301.4**	**-2,113.1**	**-6,595.0**	**198.7**

For 20m drawdown imposed on control locations, MODFLOW was run with the input from the MOGA obtained pumping rates. In fact this solution does not give any new pumping well site, instead it rearranges only the pumping rates.

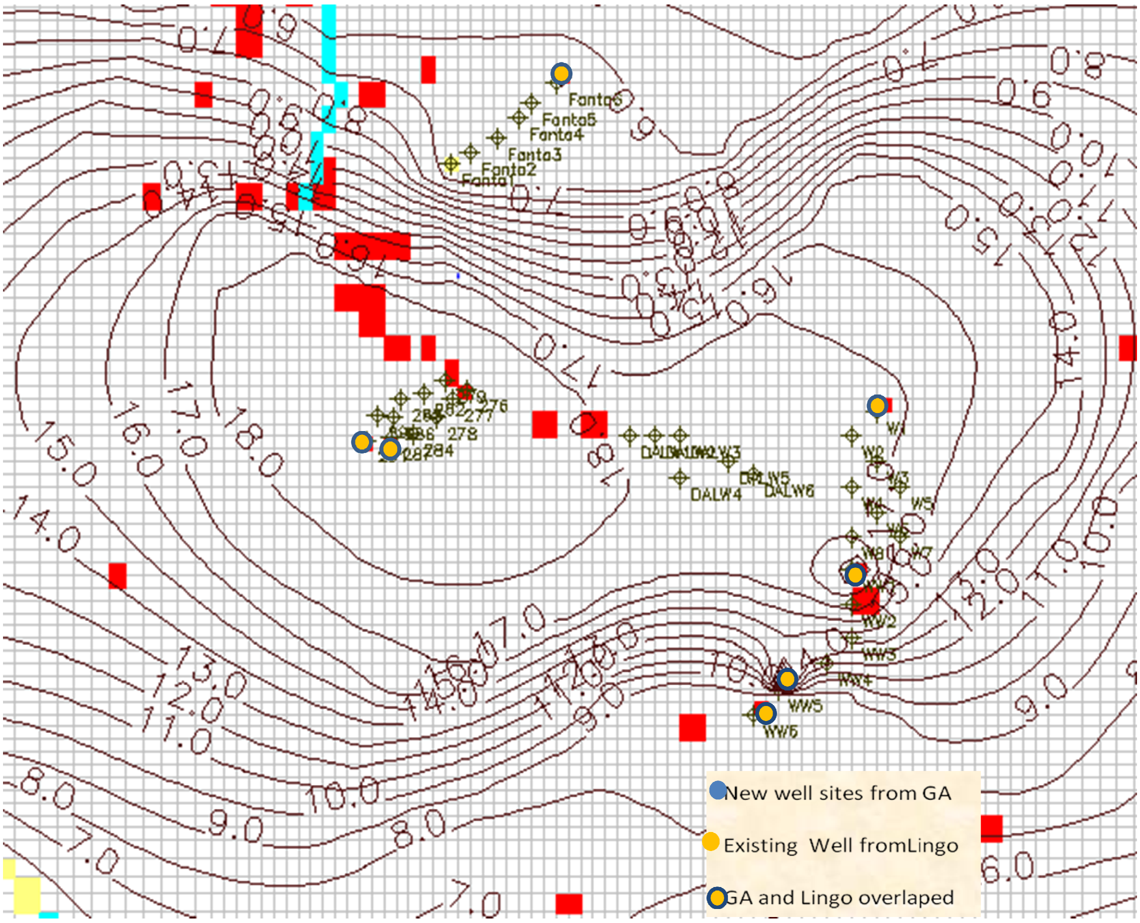

Figure 4. 8 Drawdown contours and New well sites of 20m DD of Case 7

The water balance from this run is presented in (Table 4. 8); 66.5% is outflow to constant head boundary that covers large part of outflow and the outflow by well and River is 16.6% and 20.6% respectively, the drain contribution is less which is 1.08%. When compared to the water balance of original steady state model, the abstraction rate increased by 22,212.8 m^3/day that causes the lowering of constant head boundary by 13,379.5 m^3/day river out flow affected to decrease by 6553.1 m^3/day and the drain decreased by 2,205.1 m^3/day.

Table 4. 8 Water balance of 20m DD of case 7

	Inflow to Catchment			Out Flow from the catchment				
	Natural Recharge	River Recharge	Total	Constant Head Boundary	Wells	Drains	River Flow	Total
Steady state	281,059.2	518.4	281,577.6	187,228.8	24,451.2	5270.4	64627.2	281,577.6
Water balance	99.8%	0.20%	100%	66.5%	8.70%	1.90%	23%	100%
Water balance	281,059.2	567.8	281,637.8	173,849.3	46,664.0	3,065.3	58,074.1	281,652.7
of15m DD	99.8%	20.2%	100%	61.7%	16.6%	10.8%	20.6%	100%
Difference(m3/day)	0	**49.4**	**64.9**	**-13,379.5**	**22,212.8**	**-2,205.1**	**-6,553.1**	**189.4**

Although the setup of the problem formulation of this case the well sites and the pumping rate initialization has been made by values that are slightly lower than the Lingo optimal solution. After the problem is solved by MOGA new well configuration was obtained with no constraint violation however the abstraction rate maximization and cost is not still better than LINGO.

In the figure below (Figure 4. 9) MOGA proposed new site at Fanta springs with injection rate of 0.023m^3/s at maximum draw down of 6m for springs while 25m drawdown imposed at well sites. The contour of drawdown reads drawdown location at all area is less than the assigned value; without constraint violation.

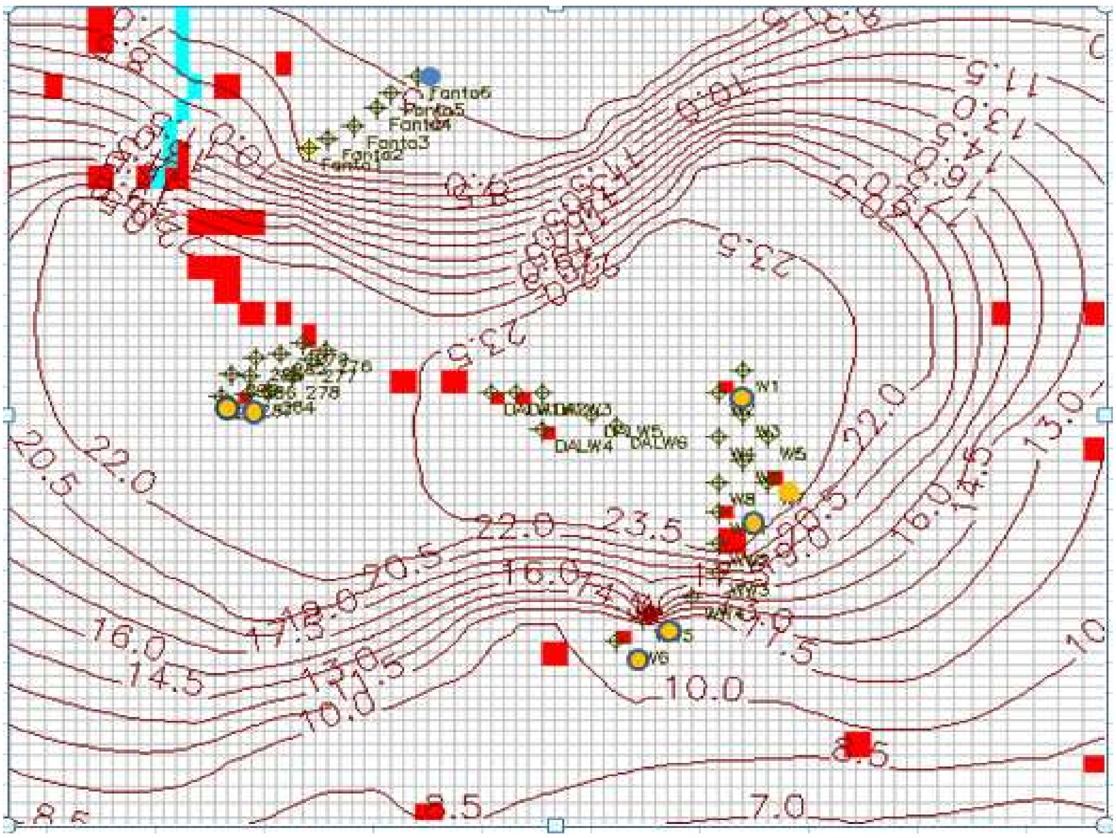

Figure 4. 9 Drawdown contours and New well sites of 25m DD of Case 7

The water balance from this run presented in (Table 4. 9); 61.7% is out flow to constant head boundary that covers large part of outflow and the outflow by well and River is 16.75% and 20.6% respectively, the drain contribution is less which is 1.08%. Where compared to the water balance of original steady state model, the abstraction rate increased by 22,038.8 m3/day that causes the lowering of constant head boundary by 13,244.6m3/day river out flow affected to decrease by 6528 m3/day and the drain decreased by 2190.3 m3/day.

Table 4. 9 Water balance of 25m DD of case 7

	Inflow to Catchment			Out Flow from the catchment				
	Natural Recharge	River Recharge	Total	Constant Head Boundary	Wells	Drains	River Flow	Total
Steady state	281,059.2	518.4	281,577.6	187,228.8	24,451.2	5270.4	64627.2	281,577.6
Water balance	99.8%	0.2%	100%	66.5%	8.7%	1.1%	23%	100%
Water balance	281,059.2	567.8	281,637.8	173,984.2	46,489.2	3,080.1	58,099.2	281,652.7
of 25m DD	99.8%	20.2%	100%	61.70%	16.60%	10.9%	20.6%	100%
Difference(m3/day)	0	49.4	60.2	-13,244.6	22,038.0	-2,190.3	-6,528.0	184.7

The results for 30m drawdown are presented in figure below (Figure 4. 9). The new well configuration obtained by MOGA is at Dup _ 2 with pumping rate of 2972160m3/day. The additions of new well site with additional abstraction rate do not violate the constraints.

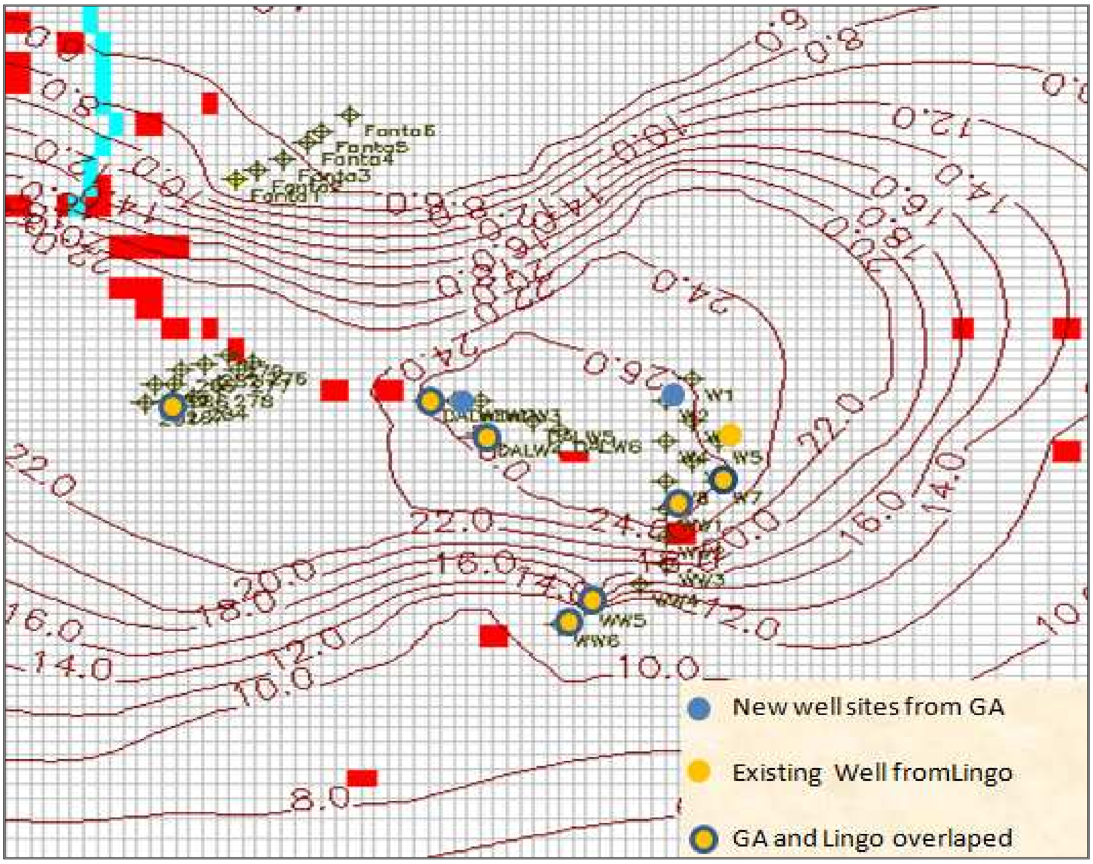

Figure 4. 10 Drawdown contours and New well sites of 30m DD of Case 7

The water balance is presented in (Table 4. 10); 60.5% is outflow to constant head boundary that covers large part of outflow and the outflow by well and River is 18% and 20.6% respectively, the drain contribution is less which is 1.07%. Where compared to the water balance of original steady state model, the abstraction rate increased by 26,202.5m^3/day that causes the lowering of constant head boundary by 16712.2m^3/day river out flow affected to decrease by 6987 m^3/day and the drain decreased by 2425.9m^3/day.

Table 4. 10 Water balance of 30m DD of case 7

	Inflow to Catchment			Out Flow from the catchment				
	Natural Recharge	River Recharge	Total	Constant Head Boundary	Wells	Drains	River Flow	Total
Steady state	281,059.2	518.4	281,577.6	187,228.8	24,451.2	5270.4	64627.2	281,577.6
Water balance	99.8%	0.2%	100%	60.5%	8.70%	1.0%	23%	100%
Water balance	281,059.2	570.0	281,640.0	170,516.6	50,653.7	2,844.5	57,640.0	281,654.8
of 30m DD	99.8%	20.20%	100%	61.70%	16.57%	1.0%	20.6%	100%
Difference(m3/day)	0	51.6	62.4	-16,712.2	26,202.5	-2,425.9	-6,987.2	191.1

All attempts using initialization with values slightly higher than LINGO solution resulted in highly violated solutions which are very far from the optimal region. Some changes to the design has been attempted to modify this result, namely by increasing the generation size to 200. This takes double computing time compared to the 100 generation but the results are without significant improvements.

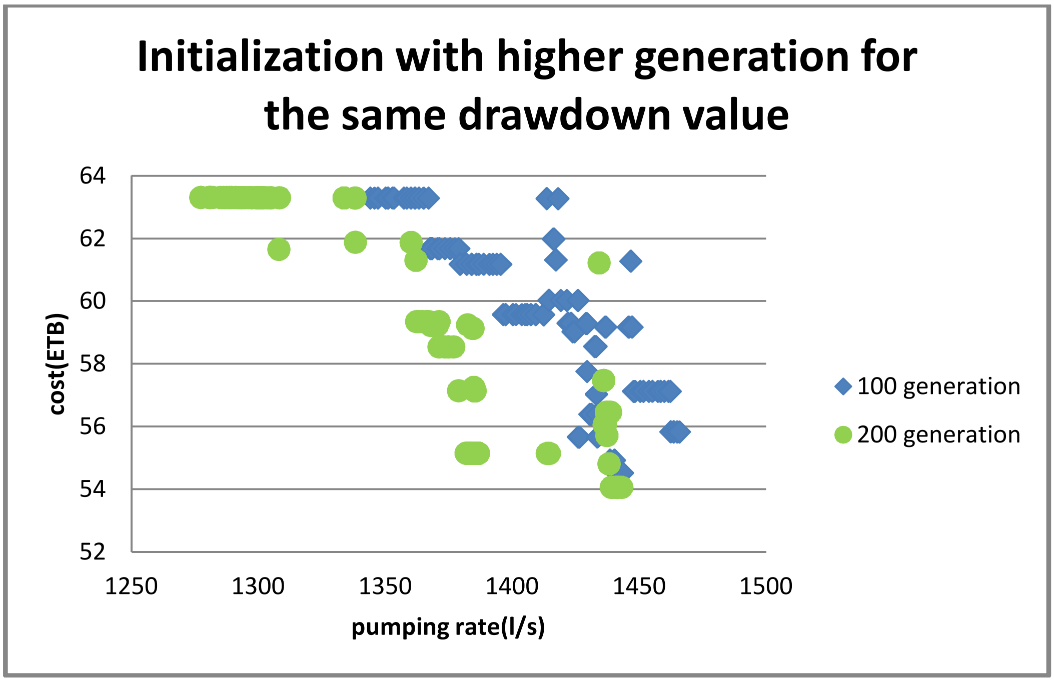

Figure 4. 11 Initialization with higher generation at 15m drawdown

The above figure (Figure 4. 11) presents comparison of the results with 100 and 200 generations. For large number of generation the algorithm tries to find the points near to the feasible region with very slow rate.

5. Conclusion and Recommendation

5.1 Conclusion

The general objective of this study of setting up a multi-objective optimization using NDSGA-II and MODFLOW model for the Akaki well fields was achieved. This allowed for analysis of the optimal results and comparison with existing solutions from linear optimization obtained from previous study. It also allowed testing of different options for handling constraints in this set-up.

With respect to the specific objectives and the corresponding research questions the following conclusions can be drawn:

1. According to MOGA optimal result the abstraction rate from the well field is varying between 20394m^3/day and 26197m^3/day with average costs of 15 million ETB to 23million ETB based on constraints for different drawdown conditions (15m, 20m, 25m, 30m). The well configurations and the corresponding abstraction rates and costs are different for different drawdown constraint conditions. In all analyzed cases the drawdown constraints were satisfied, except some violations in Cases 6 and 7.

2. All analyzed cases with MOGA (with different methods for handling the drawdown constraints) show worse results compared to the LINGO optimal solution obtained from linear optimization in previous study of Wagena (2011). The MOGA approach however has the advantage of providing the pareto set of solutions, from which the trade-off between the two objectives can be assessed.

3. The MOGA approach is less efficient compared to the linear optimization, because it requires more computational resources, especially computational time. For 100 generations the investigated set-up required 6 hours, whereas for 200 generations the time was doubled.

4. Several methods for handling drawdown constraints, some using penalty functions and others using a third objective function were tested. Out of all tested methods for handling drawdown constraints, case 7 , which introduced implicit penalty by using a third objective function, formulated as a product of the number of constraint violations and the maximum magnitude of violation, provided most promising results. Even though for some drawdown conditions there were some violations, overall this method gave results closest to the LINGO solutions, sometimes with new well configurations.

The reasons for this particular case that MOGA did not achieve better solutions than LINGO may be as follows:

- The study area is located at the western margin of main Ethiopian rift so that the whole area undergoes progression and expansion of the Rift system all the time. This moving of the rift system causes some structures to happen to the rock layers such as faults, joints that affect the transmisivity of the rock layer. On the other hand the MODFLOW model adopted and coupled to the MOGA does not include the many details of this condition.

- The volcanic rock cover of the area has complex spacio-temporal distribution that differs within few meters. They are highly non-linear which is yet again difficult to include in MODFLOW model. Therefore the nature of the model is nearly linear which gives better solution in linear programming rather than EA.

  The coupling of NSGA II and MODFLOW solution becomes better as the number of generation increased. However the computational time required increases with increasing number of generation and objective function. When the complexity of the problem formulation increases the algorithm requires more time to obtain optimal solutions. As a result MOGA implementation becomes expensive.

5.2 Recommendation

Regarding the simulation model the following recommendations can be given:

- The simulation model of MODFLOW that has been adopted from existing Regional Groundwater Model has to be refined and developed again by considering the natural condition of the study area. The secondary structures due to Rift system and the complex hdrogeological condition require to be revised in detail.
- The simulation model MODFLOW used in the simulation-optimization model is only the steady state. However transient state is more descriptive for the study area, especially because the study is about long term groundwater resources development when available groundwater from storage may become important. Therefore the simulation-optimization model should also set up for transient state of flow.

Regarding the optimization model the following recommendations are proposed:

- The NSGA II algorithm desires need to be tested with larger number of generations. Most tests in this study were with 100 generations.

- The usage of NSGA II may benefit from implementation on multiple parallel computers. This may allow running the algorithm with shorter computational time.

- Constraint handling techniques by penalty function has generic nature as it gives satisfactory results for some problems but sometimes not. It needs to be further investigated with different penalty formulation. Constraint handling via introduction of a third objective should be further investigated as it provided more promising results in this study. Additional constraint handling methods may also be included in future.

- Finally, regarding the groundwater development in the well fields of Akaki catchment the following recommendation can be given: Integrated well field monitoring network needs to be installed in the area for sustainable groundwater level management along with current considerations of extraction of maximum discharge at fair cost.

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Appendices

Appendix 1 Potential Well Location

	Wells	Row	Column	X	y
1	Akaki_276	97	58	479696	976936
2	Akaki_277	98	57	479405	976735
3	Akaki_278	99	56	479061	976370
4	Akaki_279	96	56	479246	977104
5	Akaki_282	97	55	478808	976867
6	Akaki_284	100	54	478580	976051
7	Akaki_285	97	53	478347	976752
8	Akaki_286	99	52	478199	976361
9	Akaki_287	101	52	478154	975966
10	Akaki_290	99	51	477856	976402
11	Akaki_291	101	50	477651	975923
13	fanta_2	78	59	479770	981620
14	fanta_3	77	61	480290	981890
15	fanta_4	75	62	480732	982295
16	fanta_5	74	64	481000	982596
17	fanta_6	72	66	481520	983000
18	Dal_1	101	72	483000	976000
19	Dal_2	101	74	483500	976000
20	Dal_3	101	76	484000	976000
21	Dal_4	104	76	484025	975180
22	Dal_5	103	80	485000	975500
23	Dal_6	104	82	485500	975250
24	Dup_1	98	92	488000	976500
25	Dup_2	100	90	487500	976000
26	Dup_3	102	92	488000	975500
27	Dup_4	104	90	487500	975000
28	Dup_5	104	94	488500	975000
29	Dup_6	106	92	488000	974500
30	Dup_7	108	94	488500	974000
31	Dup_8	108	90	487500	974000
32	Ddwn_1	111	90	487500	973350
33	Ddwn_2	114	89	487500	972650
34	Ddwn_3	116	90	487500	972000
35	Ddwn_4	118	88	487000	971500
36	Ddwn_5	120	84	486000	971000
37	Ddwn_6	122	82	485500	970500

Appendix 2 Calculated cost of Drilling and pipe Installation

	Well	Distance feom Reservior(m)	Pipe cost/unit meter (ETB)	Pipe Installation Cost(ETB)	WellDrilling cost(ETB)	Total cost(ETB)
1	Akaki 276	2980	266	793918	496591	1290509
2	Akaki 277	3269	266	870876	496591	1367467
3	Akaki 278	3638	266	969275	496591	1465866
4	Akaki 279	3440	266	916496	496591	1413087
5	Akaki 282	3866	266	1029848	496591	1526439
6	Akaki 284	4162	266	1108811	496591	1605402
7	Akaki 285	4327	266	1152613	496591	1649204
8	Akaki 286	4496	266	1197813	496591	1694404
9	Akaki 287	4597	266	1224523	496591	1721114
10	Akaki 290	4834	266	1287816	496591	1784407
11	Akaki 291	5099	266	1358425	496591	1855016
12	Fanta_2	5622	266	1497809	496591	1994400
13	Fanta_3	5616	266	1496004	496591	1992595
14	Fanta_4	5823	266	1551229	496591	2047820
15	Fanta_5	6028	266	1605782	496591	2102373
16	Fanta_6	6301	266	1678651	496591	2175242
17	Dal_1	869	266	231489	496591	728080
18	Dal_2	1154	266	307433	496591	804024
19	Dal_3	1552	266	413434	496591	910025
20	Dal_4	2114	266	563130	496591	1059721
21	Dal_5	2668	266	710698	496591	1207289
22	Dal_6	3226	266	859481	496591	1356072
23	Dup_1	5335	266	1421360	496591	1917951
24	Dup_2	4893	266	1303602	496591	1800193
25	Dup_3	5484	266	1461011	496591	1957602
26	Dup_4	5153	266	1372820	496591	1869411
27	Dup_5	6100	266	1625022	496591	2121613
28	Dup_6	5804	266	1546215	496591	2042806
29	Dup_7	6467	266	1722757	496591	2219348
30	Dup_8	5583	266	1487223	496591	1983814
31	Ddwn_1	5936	266	1581336	496591	2077927
32	Ddwn_2	6369	266	1696671	496591	2193262
33	Ddwn_3	6811	266	1814397	496591	2310988
34	Ddwn_4	6846	266	1823731	496591	2320322
35	Ddwn_5	6691	266	1782439	496591	2279030
36	Ddwn_6	6910	266	1840779	496591	2337370
Total Cost in ETB				46,814,631	183,73,868	65,188,499