OPTIMIZATION OF IRRIGATION WATER IN SOUTH AFRICA FOR SUSTAINABLE AND BENEFICIAL USE

Submitted in fulfilment of the requirements of the degree of

Doctor of Engineering

in the Department of Civil Engineering & Surveying,

Faculty of Engineering and the Built Environment at

Durban University of Technology

Akinola Mayowa IKUDAYISI

Approved for final submission:

Supervisor: ______________________ Date: _________________

Professor Josiah Adeyemo

JANUARY 2016

ABSTRACT

Water is an essential natural resource for human existence and survival on the earth. South Africa, a water stressed country, allocates a high percentage of its available consumptive water use to irrigation. Therefore, it is necessary that we optimize water use in order to enhance food security.

This study presents the development of mathematical models for irrigation scheduling of crops, optimal irrigation water release and crop yields in Vaal Harts irrigation scheme (VIS) of South Africa. For efficient irrigation water management, an accurate estimation of reference evapotranspiration (ET_o) should be carried out. However, due to non-availability of enough historical data for the study area, mathematical models were developed to estimate ET_o. A 20-year monthly meteorological data was collected and analysed using two data–driven modeling techniques namely principal component analysis (PCA) and adaptive neuro-fuzzy inference systems (ANFIS). Furthermore, an artificial neural network (ANN) model was developed for real time prediction of future ET_o for the study area.

The real time irrigation scheduling of potatoes was developed using a crop growth simulation model called CROPWAT. It was used to determine the crop water productivity (CWP), which is a determinant of the relationship between water applied and crop yield. Finally, a new and novel evolutionary multi-objective optimization algorithm called combined Pareto multi-objective differential evolution (CPMDE) was applied to optimize irrigation water use and crop yield on the VIS farmland. The net irrigation benefit, land area and irrigation water use of maize, potatoes and groundnut were optimized.

Results obtained show that ET_o increases with temperature and windspeed. Other variables such as rainfall and relative humidity have less significance on the value of ET_o. Also, ANN models with one hidden layer showed better predictive performance compared with other considered configurations. A 5-day time step irrigation schedule data and graphs showing the crop water requirements and irrigation water requirements was generated. This would enable farmers know when, where, and how much water to apply to a given farmland. Finally, the employed CPMDE

optimization algorithm produced a set of non-dominated Pareto optimal solutions. The best solution suggests that maize, groundnut and potatoes should be planted on 403543.44 m^2, 181542.00 m^2 and 352876.05 m^2areas of land respectively. This solution generates a total net benefit of ZAR 767,961.49, total planting area of 937961.49 m^2 and irrigation water volume of 391,061.52 m^3. Among the three crops optimized, maize has the greatest land area, followed by potatoes and groundnut. This shows that maize is more profitable than potatoes and groundnut with respect to crop yield and water use in the study area.

DECLARATION

I hereby declare that the work reported in this thesis "**Optimization of irrigation water in South Africa for sustainable and beneficial use**" is my original research work. All sources cited herein are indicated and acknowledged by means of a comprehensive list of references. I hereby certify that the work contained in this thesis has not previously been submitted either in its entirety or in parts for a degree in this or any other university. Its only prior publications are in forms of journal articles and conference papers published during the period of the research. This thesis presents a compilation of manuscripts that were prepared, compiled or published during the course of the research work.

Akinola Mayowa IKUDAYISI

DEDICATION

This doctoral thesis is dedicated to God Almighty, the source of all wisdom and knowledge, the true source of divine inspiration, the custodian of the spirit of power, love and sound mind. He brought me to South Africa by his mighty hand, gave me a supervisor and granted me every resource used in the course of this degree. He gave me the mind of Christ. To him alone be all the glory.

ACKNOWLEDGEMENTS

Foremost, my profound gratitude goes to the trinity, which comprise of GOD the Father, GOD the SON and GOD the Holy Spirit. My gratitude goes to the innumerable company of angels, for guiding me through every step of the way towards the successful completion of my doctoral degree in Civil Engineering.

I would like to express my unreserved appreciation to the following personalities and institutions that played significant roles in driving this research work to a successful completion.

Professor Josiah Adeyemo, my research supervisor; for his love, care, acceptance, help, advice, constructive criticism, guidance, patience, unflinching support, encouragements and painstakingly guiding and directing me towards the successful completion of my doctorate. You are indeed a great mentor and leader to me. You are a true source of inspiration, a symbol of excellence. As a young man who attained professorship at age 39, you wrote your name in the Guinness book of records among your peers. You showed yourself as the best supervisor any student could ever crave for. I specially thank you for providing useful guidance in the application for bursaries, conference attendance and other financial support necessary for the completion of this work. I bless the day our path crossed and I hereby promise my unalloyed loyalty to you in the course of our career and research life. I pray for more greatness for you in all your endeavours.

My wonderful parents, Dr (Pastor) Timothy Olasebikan Ikudayisi and Mrs Janet Foluso Ikudayisi, for the outstanding upbringing and solid academic foundation you bestowed upon me. You gave me the only family car as a means of transport to the university during my undergraduate days in Ado-Ekiti. I will never forget the day your colleagues at work insulted you all because you were giving me adequate comfort in the pursuit of my university education. I am forever grateful to you. I love both of you very much. I also appreciate my siblings, Yemi, Bukola, Ebenezer and Olorunyomi, for their unflinching support. You all mean so much to me.

Late Chief and Mrs Samson Oladejo Makinde, for the help they rendered to me during the course of visa application for this study. The letter of authority and bank statement issued to me went a big way in granting me study visa to South Africa. May God bless your family in Jesus name.

Professor Akinwale Coker, for the very solid academic foundation you gave me during my Masters degree study. I found it very useful in completing this task. I especially appreciate you for writing recommendation letters for me anytime a request is made for such. You advised me to go for the acquisition of international doctoral degree when there was a delay in securing admission within the coast of Nigeria. You are a father indeed.

Dr Wole Aremu, for the door God opened through you. You linked me with Professor Josiah Adeyemo and here I am today. I bless God for your life, and also for being a vessel of divine help in my doctoral degree. My God will bless you and your family.

My pastors, Pastor Paul Olubo, Pastor Chris Adetayo, Pastor Adebayo Adeoti, Pastor Stanley Nkwoji and their families for your prayers, spiritual guidance, godly counsels and moral support you gave during the course of the work. I treasure you all. God will enlarge your ministries in Jesus name.

I also appreciate my fellow pastors and minister friends in Winners Chapel Durban, who have been there for me during the course of this doctoral degree programme. They are Pastor Kayode Akindeji, Pastor Onor Kester, Pastor Osadanye Odaro, Deaconess Christiana Obagbuwa, Bro George Kedinga, Bro Promise Nonso. Thanks for being there for me all these periods.

I specially use this medium to appreciate the wife of my doctoral supervisor, Mrs Folasade Adeyemo. She donated money for the binding of this thesis. I pray that you shall not lack any good thing in Jesus name.

To all my brothers at 51 Myro Drive, Glenmore, for the hospitality, affection, support, concerns and acceptance, I love you all. Bukunmi Fatoyinbo, Akeem

Bakare, Amoo Oseni, Sijuwade Ogunsola, Jeremiah Adeyemo, Niyi Fashina and Adegoke Deji. To my one and only daughter, Nqobile Nkwakhwa, I say a big thank you for your moral support and encouragements during the course of this study.

I appreciate the entire staff of the Civil Engineering and Surveying department, Durban University of Technology (DUT) for hosting me during the course of the study. Also my unalloyed gratitude goes to the Faculty of Engineering and the Built Environment, the Dean and members of the faculty, for their support during the programme. May God move the faculty forward.

My unreserved appreciation goes to the entire staff of the College of Education, Ikere-Ekiti. I thank the Provost, Registrar, Bursar, Head of Department, Technical Education department, for granting me study leave in the pursuit of my doctoral degree. I also appreciate Mr Akinrotohun, Mr Fagbemi, Mr Rufus Bello, Dr Osuntuyi, Abiodun Olasehinde and Oluwaseun Omoniyi, for their support throughout the program and for being a reliable family.

My sincere thanks to South African Weather Service and Agricultural Research Council, South Africa, for their assistance in obtaining data and other information necessary for the completion of this research work.

To my cute sons, David and Victor Ikudayisi, I wonder how you sweet kids understood that daddy needed to study hard to be able to afford a better life for you. Indeed, I appreciate your endurance all through the period when I was away on international study. I thank God for giving you to us as gifts. I am so proud of you and I pray that you shall rule your world in Jesus name.

"… A virtuous woman, who can find? … For her price is far above rubies". My loving wife, the Proverbs 31 woman; Ruth Olayinka Ikudayisi, thank you for being a friend and life companion. You are the best thing that has ever happened to me in a long time. I appreciate your moral support, endurance and unfailing commitment to my academic and business success. I wonder how God made it such that so much strength could be drawn from a weaker vessel. I am truly favoured in this life. I am proud I am your husband. I will forever love you.

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LIST OF ABBREVIATIONS

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARC	Agricultural Research Council
CPMDE	Combined Pareto Multi-Objective Differential Evolution
CROPWAT	Crop Water Decision Support System
CWR	Crop Water Requirement
CWP	Crop Water Productivity
DAFF	Department of Agriculture, Forestry and Fisheries
DE	Differential Evolution
DP	Dynamic Programming
DUT	Durban University of Technology
DWA	Department of Water Affairs
EA	Evolutionary Algorithm
EMOA	Evolutionary Multi-Objective Algorithms
ES	Evolution Strategy
ET	Evapotranspiration
ET_o	Reference Evapotranspiration
ET_C	Crop Evapotranspiration
FAO	Food and Agricultural Organization
FIS	Fuzzy Inference Systems

GA	Genetic Algorithm
GAO	Genetic Algorithm Optimization
GDE3	Generalized Differential Evolution 3
GDP	Gross Domestic Product
GP	Genetic Programming
LP	Linear Programming
MATLAB	Matrix Laboratory
MDEA	Multi-Objective Differential Evolution Algorithm
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOOP	Multi-Objective Optimization Problem
MOPSO	Multi-Objective Particle Swarm Optimization
MOSOA	Multi-objective Self-organizing Algorithm
NF	Neuro Fuzzy
NLP	Non-linear Programming
NSGA-II	Elitist Non-dominates Sorting Genetic Algorithm
PBM	Process Based Models
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
R	Pearson Correlation Coefficient

RMSE	Root Mean Square Error
SAWS	South African Weather Service
TNB	Total Net Benefit
VBA	Visual Basic for Applications
VIS	Vaalharts Irrigation Scheme
WHO	World Health Organization
WRC	South African Water Research Commission
WU	Water Use
ZAR	South African Rand

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

1.1.1 Introduction

Among natural resources, water is the most important and its sustainable management is a necessity, particularly in the arid and semi-arid regions. These regions currently occupy more than 30% of the globe and characterized with low average annual rainfall (Belaqziz *et al.* 2014). Due to rising world population, climate change and contamination of water supply sources, scarcity of fresh water has been experienced in many parts of the world today. This is evident in the fact that there is an increase in water demands for irrigation, industrial, domestic and energy uses (Mishra and Singh 2011). This scarcity of water resources is further complicated by high temperature and drought which dries up both surface and groundwater resources (Mishra and Dehuri 2011).

Adequate supply of water is very vital for the development of healthy and viable economies around the world. The ability of a country to adapt to a situation of limited water resources is very essential because the country's prospect with regards to social, economic and political welfare is adequately maximized (Karlberg *et al.* 2007). The available consumptive water are contested for in areas of need such as domestic, industrial, hydropower, irrigation and flood control (Bieupoude, Azoumah and Neveu 2012).

Wardlaw and Bhaktikul (2004a) states that irrigation uses about 60% of available consumptive water in the world. This is because it is the main driving force affecting the water cycle (Giupponi *et al.* 2004). It is therefore imperative to manage the existing water resources more effectively and efficiently in areas of low average annual rainfall and this should be considered a process for continuous improvement and sustainable development (Singh 2014). As a result, optimization methods or techniques must be employed to effectively regulate and optimize the use of available water for irrigation purposes in order to achieve food security for the ever-increasing population.

The scheduling and management of irrigation is essential. Several delivery methods are used in irrigated agriculture throughout the world. Some of the approaches allocate water to different crops at farm level. Other studies developed mathematical models and algorithms to optimize irrigation water management for different irrigation systems (Belaqziz *et al.* 2014). Irrigators like to optimally allocate the available water for irrigation in order to amplify the annual net profits and increase farm efficiency by preventing excess water that may cause surface runoff, groundwater drainage and leaching of the fertilizers applied (Saleem *et al.* 2013). In allocating optimal irrigation water among crops, relevant simulation and optimization modeling techniques are required (Vasan and Raju 2009).

Optimization techniques are generally classified into two categories; (1) classical methods and (2) evolutionary or soft computing methods (Peralta, Forghani and Fayad 2014). Some examples of classical methods as outlined by Whitley (2001) include dynamic programming (DP), linear programming (LP) and non-linear programming (NLP). Classical methods sometimes have difficulties with extremely non-linear systems and do not directly yield alternative optimal solutions. On the other hand, evolutionary methods such as genetic algorithms (GAs), differential evolution (DE) algorithm, genetic programming (GP), evolution strategies (ES) and particle swarm optimization (PSO) can solve optimization problems having non-linear, non-differentiable, or even discontinuous functions (Whitley 2001).

The major difference between the classical optimization techniques and soft computing according to Azamathulla *et al.* (2008), is that in classical methods, the optimal solution is derived whereas in the soft computing techniques; it is searched from a randomly generated population of possible solutions. Among the optimization techniques employed for solving irrigation problems around the world are evolutionary algorithms. Evolutionary algorithms (EAs) go for discovery of the optimal from a population of solutions rather than from a single point. These gimmicks make them suitable for solving complex design issues (Reddy and Kumar 2007).

Simulation modeling techniques help in the design, creation, and evaluation of complex systems. It helps to understand and evaluate ‘what if’ case scenarios within a system (Singh and Panda 2013). It can model a real or proposed system using computer software and is useful when changes to the actual system are difficult to implement, involve high costs, or impossible. Categories of simulation models as spelt out by Nasr *et al.* (2014) include; (1) Discrete models (2) Continuous models and (3) Mixed models.

However, Ngo, Madsen and Rosbjerg (2007); Rani and Moreira (2010); Singh (2014) observed that it is usually not possible to get an appropriate management alternatives with either simulation or optimization techniques alone, and hence the combined use of simulation and optimization models is essential. Therefore, researchers have been adopting a combination of simulation–optimization models to solve real–world problems.

This study therefore, applied a simulation model called CROPWAT for real-time irrigation scheduling, as well as a novel evolutionary multi-objective optimization algorithm called combined Pareto multi-objective differential evolution (CPMDE), to solve real-world problems involving the minimization of irrigation water use and maximization of crop yield at the farm level. This is aimed at achieving more crop production with less irrigation water use on the farmland at Vaalharts irrigation scheme, South Africa. This will increase water use efficiency and also promote food security in the country.

1.1.2 Current state of the agricultural sector in South Africa

The agricultural sector in South Africa is the biggest user of water in the country. The country receives an average annual rainfall of about 500mm, which is regarded as low compared with the global accepted average of 860mm/year (Annandale *et al.* 2011). Drought is a common phenomenon because the available summer rain is poorly distributed. This led to the country being classified as an arid and semi-arid region (Oyebode and Adeyemo 2014a).

According to FAO (2005), the country's land suitable for rain-fed farming is about 13% of the total land mass, while the remaining lands are too dry for farming; hence the need for irrigation activities in the country. According to a report by the department of water affairs and forestry (DWAF),in year 2000, irrigated agriculture was practised on almost 1.3million hectares of South African lands, and these consumed about 61%

of the total runoff water explored by all sectors within that year (DWAF 2004). Figure 1 shows the map of irrigated agriculture in South Africa. Major food crops grown within the country include maize, wheat, pats, sugarcane, potatoes and sunflowers. Citrus and deciduous fruits produced are exported in large quantities abroad (Ramaila, Mahlangu and du Toit 2011). A large percentage of these food crops are produced under irrigation, and this makes farming of great importance to the economy and development of South Africa.

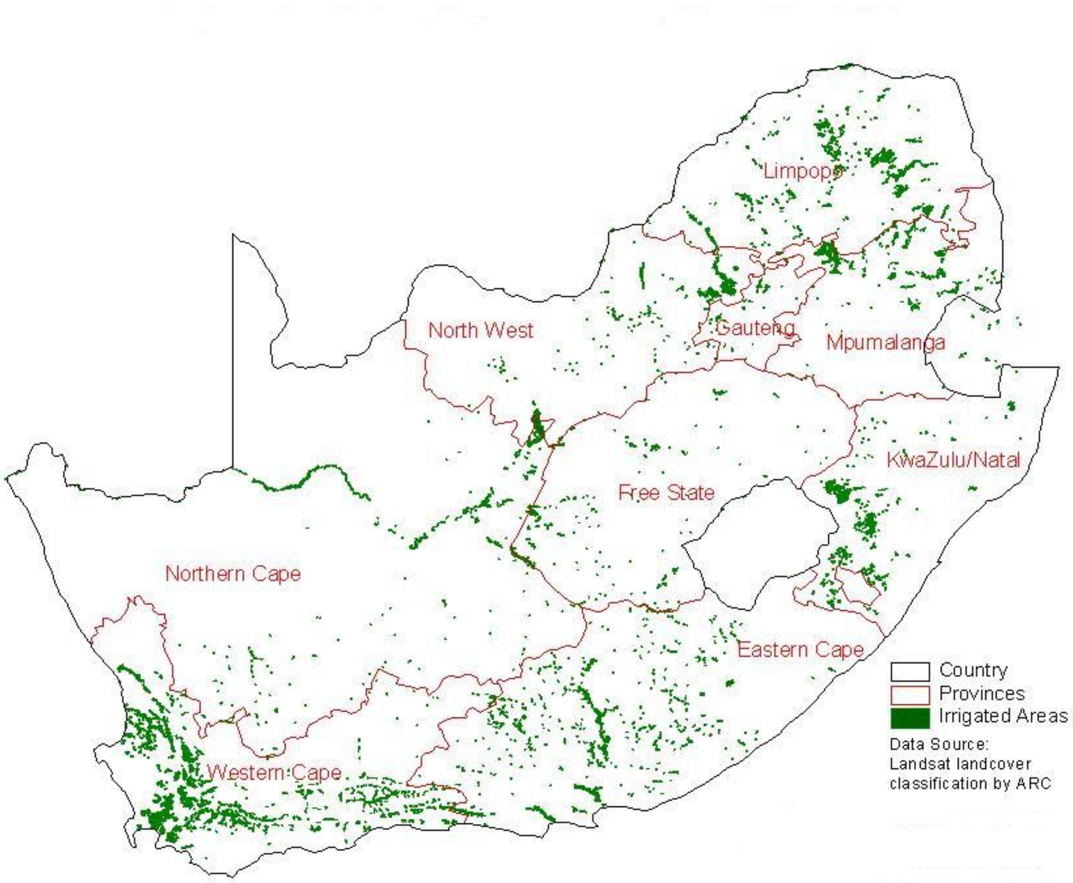

Figure 1: Irrigated agriculture in South Africa (USDA 2013)

Agriculture within South Africa is expected to guarantee food security in the nation while simultaneously creating employment opportunities for the teeming population (SANTO 2013).

A recent study indicated that in South Africa, the agricultural sector is relatively an inefficient user of water (Olofintoye 2015). For instance, in a report released by DWAF (2004), it was observed that when water is allocated for domestic use in Gauteng province of South Africa, it brings a higher economic returns compared to allocating water for irrigation purposes. Also, it was observed that in 1960, agriculture contributed 9.1% of the total economy of South Africa, but in year 2013, it has drastically reduced to 2.1% (DWA 2013b). Substantial differences in the order of 80 to 1 were also found with respect to employment opportunities. This implied a clear economic preference for using water in the Gauteng (industrialised) economy rather than for irrigated agriculture. The government had since been initiating programmes that promotes small scale farming in order to boost job creation for young South Africans (Ramaila, Mahlangu and du Toit 2011).

Ashton and Seetal (2002) observed that South African irrigation farmers need to increase water productivity in the face of current decreased water availability and increased prices. Studies that would accurately estimate irrigation water needs and crop yield in real-time will be greatly helpful for farmers in order to develop a budget so as to get the best returns on water use as they maximize water efficiency.

It has been reported that the objectives of maximizing irrigation from reservoirs are often in conflict with the objectives of hydropower (Chang *et al.* 2013). While hydropower generation requires that the reservoir is full so as to maintain high power generating heads at all times, irrigation depletes the reservoir especially during periods of extended low flows which often correspond to the dry seasons when irrigation is most essential (Reddy and Kumar 2006). Therefore, optimization strategies aimed at maximizing irrigation within the constraints of power generation and municipal water demands are crucial in promoting water management and economic growth in South Africa.

1.1.3 The use of evolutionary algorithms in water resources management

Evolutionary algorithms (EAs) are population-based meta-heuristic optimization algorithms that use biology-inspired mechanisms like mutation, crossover, natural selection and survival of the fittest in order to refine a set of candidate solutions iteratively (Weise 2009). EAs often perform well approximating solutions to all types of problems because they ideally do not make any assumption about the underlying fitness landscape. Apart from their use as mathematical optimisers, EAs have also been utilised in experimental frameworks to validate theories about biological evolution and natural selection, particularly through experiments in the field of artificial life. In general, they represent system-theoretic procedures for solving real world optimization problems (Price, Storn and Lampinen 2005).

In recent times, methods of EAs have found widespread use in solving both single and multi-objective water resources problems. This is due to their robustness in the resolution of such problems (Cai, McKinney and Lasdon 2001; Yuan *et al.* 2008; Selle and Muttil 2010). The application of EAs for solving water resources optimization problems in the agricultural sector have also been widely reported in the literature (Reddy and Kumar 2006; Reddy and Kumar 2007, 2008; Adeyemo and Otieno 2010a; Chang *et al.* 2013) and they have indeed been found excellent in solving water management problems in this sector. A comprehensive review of the state-of-the-art applications of EAs in solving water resources optimization problems is provided by Olofintoye, Adeyemo and Otieno (2013).

In this study, the application of EAs in resolving multi-objective water resources allocation problems in the agricultural sector in South Africa was demonstrated. Results obtained further demonstrated that the use of EAs in solving multi-objective water resources problems is beneficial to the economic growth and development of the nation.

1.2 STATEMENT OF THE PROBLEM

Irrigated agriculture in South Africa has not been profitable over the years. Despite the fact that it is the highest user of total consumptive water (Nkondo *et al.* 2012), its economic returns have not been impressive. The sustainable management of irrigation water resource is therefore a necessity. Crop development and food security are basically dependent on irrigation due to low annual average rainfall experienced in the country. Several simulation and optimization techniques have been developed and applied to manage irrigation water allocation both at the farm level and at the reservoir level around the world, yet there still exist some uncertainties about finding a generally trustworthy method that can consistently find real-time solutions which are really close to the global optimum of the problems in all circumstances. Therefore, further research aimed at developing simulation-optimization models that will maximize crop yield with limited water use in real time is still needed in the fields of water resources planning and management within South Africa.

1.3 STUDY OBJECTIVES

The main aim of this study was to mathematically model irrigation of crops and also optimize irrigation water release in Vaalharts irrigation scheme (VIS) in South Africa for optimum benefit. Specific objectives of the study are:

1. To mathematically model and quantify the impact of reference evapotranspiration variables at Vaalharts irrigation scheme in South Africa**.**
2. To develop mathematical models that could be used for effective real time prediction of reference evapotranspiration in Vaalharts irrigation scheme using artificial neural networks (ANN).
3. To develop irrigation schedules and soil – moisture conditions for real-time water application for crops
4. To conceptualize and apply a novel multi-objective evolutionary algorithm for solving multi-objective optimisation problems to optimize irrigation water use and crop yield in the Vaalharts irrigation scheme of South Africa.

1.4 SIGNIFICANCE OF THE STUDY

This study is highly significant because its results will guide local farmers on how to effectively plan, schedule and manage the total available water for irrigation during each cropping season in order to avoid water wastage. This is in line with the South African government’s commitment towards job creation, poverty eradication and ensuring food security.

1.5 LIMITATIONS OF THE STUDY

This study is limited to Vaalharts irrigation scheme (VIS) in Northern Cape Province of South Africa. This is the largest irrigation scheme in the whole world and also located in the driest province in South Africa. These two factors prompted the choice of the study area for this work. Also, the accuracy of the results of this study is dependent on the accuracy of data collected from relevant research and water institutions in South

Africa. The data was extracted from record books, hence, the possibility of human errors.

1.6 SCOPE OF THE STUDY

The main focus of this study includes the development of mathematical models for irrigation scheduling of crops, optimal irrigation water release and optimization of crop yields in Vaalharts irrigation scheme, South Africa. The developed models were majorly designed to solve irrigation water allocation and scheduling problems in the agricultural sector of South Africa. Three major crops which are important to the food security of South Africa were modelled. These are maize, groundnut and potatoes.

This study is limited to the application of Simulation-Optimization techniques such as; principal component analysis (PCA), adaptive neuro-fuzzy inference system (ANFIS), artificial neural networks (ANN) and CROPWAT in solving real-time water allocation and scheduling problems in the study area. An optimization modelling problem which maximizes crop yield and minimizes water use was solved using combined Pareto multi-objective differential evolution (CPMDE), which is a family of evolutionary algorithms (Olofintoye, Adeyemo and Otieno 2014).

1.7 STUDY AREA

Vaalharts irrigation scheme (VIS) was selected as study area for this research. VIS is located at Northern Cape Province, which is identified as the driest province in South Africa. This study area is strategic to agricultural production in South Africa because a lot of irrigation activities which create job opportunities for farmers are carried out there. Also, VIS is the largest irrigation scheme in South Africa and the entire world (Ellington 2003). This serves as one of the justifications of the choice of VIS as illustrative study area of this research. The scheme is located on a vast land area of about 370km^2 and majorly used for irrigation. The scheme is supplied with water abstracted from the Vaal River at the Vaal Harts weir about 8 km upstream of Warrenton (Ojo 2013). The water that serves the scheduled irrigation land flows via a network of canals with length 1176km. The total farmland area under irrigation is about 39,820ha, and this scheme currently supplies irrigation water to 1200 irrigation farmers. A breakdown of these farmers includes 564 commercial farmers, 636 upcoming small farmers (Olofintoye 2015). Figure 2 shows the geographical location of the VIS.

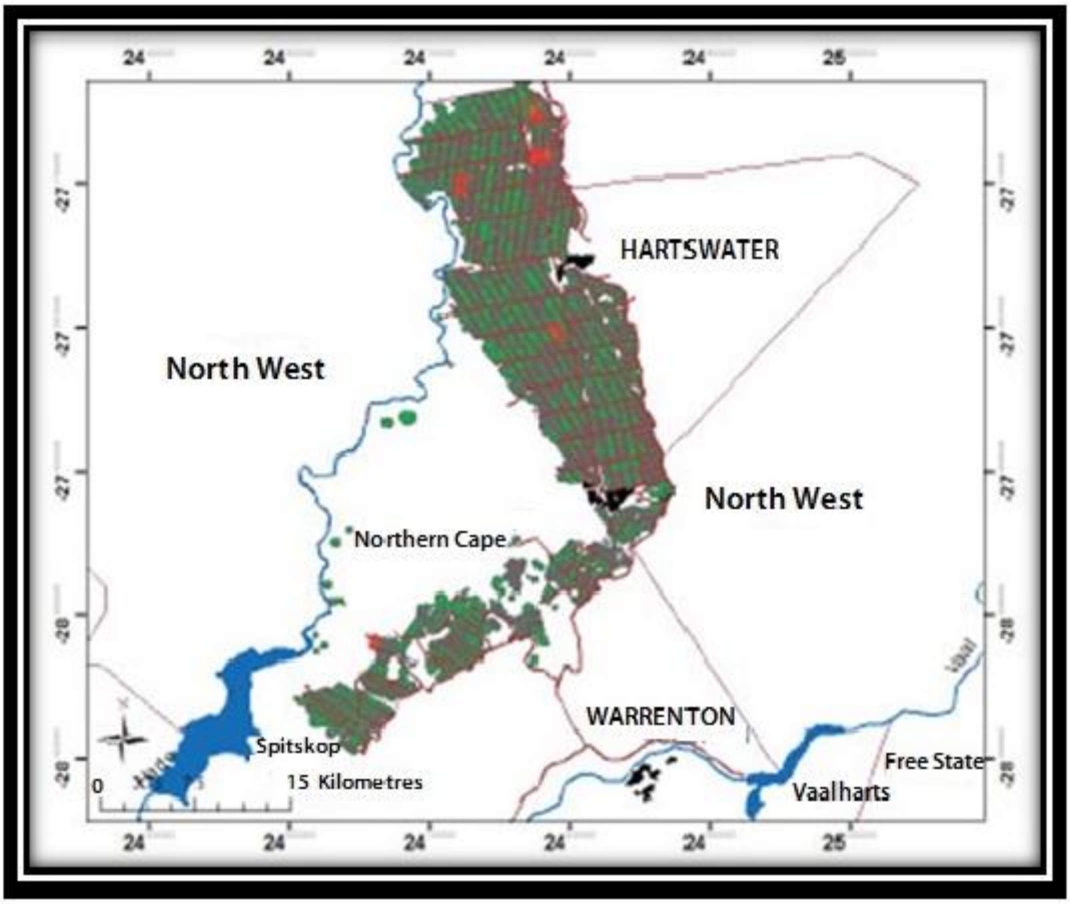

Figure 2: Vaalharts irrigation scheme (Olofintoye 2015)

The VIS area is characterised by low, seasonal and irregular rainfall of about 442mm per year (VIS 2013). During summer (October to February), the average rainfall is between 9.1mm and 9.6mm per day. In the month of July, VIS experiences only 3.6mm of rainfall per day; and during winter season, (April to October), almost no rainfall events occur (Annandale *et al.* 2011). Simulated mean rainfall runoff in the area is between 20 and 41mm, and the lowest 10-year measurement is between 4.8 and 9.3mm (Ellington 2003). The Department of Water Affairs (DWA) allocates water annually at the rate of 9,140m^3/ha to the scheme and it is charged at R8.77 cents per cubic metre of water use (Grove 2011). For the purpose of sustainable management and coordination, the scheme is divided into nine (9) water management zones namely; Hartswater, Jan Kemp, Magagong, Spitskopdam, Springboknek, Taung, Taung dam, Tadcaster and West Canal (Ellington 2003). The VIS provides employment opportunities for hundreds of people and also provides a means of farming livelihood, which results in an increase in the food security of South Africa.

1.8 OUTLINE OF THE THESIS

This thesis is organized into seven chapters. Chapters three to six contains independent studies which follows the sequence of the study objectives. It was compiled in manuscript paper format which is one of the accepted formats for doctoral thesis writing especially at Durban University of Technology. The general outline of each chapter is described as follows;

Chapter 1 contains the general introduction to the study. It describes water scarcity as the main issue affecting the water sector of South Africa. The current state of the agricultural sector of South Africa is discussed. The use of evolutionary optimization algorithm in water resources management is discussed, and also proposed as a good technique for resolving multi-objective water allocation problems in the agricultural sector in South Africa. The statement of the problem, study objectives, significance and limitations of the study are also presented. Finally, outline of the thesis is presented.

Chapter 2 contains the literature review. It gives a comprehensive review of the state-of-the-art applications of some existing evolutionary optimization algorithms in water resources management. Areas of application reviewed include irrigation water allocation, crop planning and reservoir operations. The advantages and areas of concern of adopting these techniques are listed as well as the impact of climate change on irrigation water management. It discusses the global impacts of climate change trends, future projections for Sub-Saharan Africa, climate scenarios and models and the impacts of climate change on irrigation and crop production. Irrigation scheduling and modeling was also discussed.

Chapter 3 presents a comparative study on modeling and quantifying the impacts of reference evapotranspiration variables at Vaalharts irrigation scheme in South Africa. Two data driven modelling techniques namely principal component analysis (PCA) and adaptive neuro-fuzzy inference systems (ANFIS) were adopted. This chapter achieves the first objective of the study.

In chapter 4, eight artificial neural network models that could be used for effective real time prediction of reference evapotranspiration in Vaalharts irrigation scheme were developed. Each model has five inputs and one output. The potentials of the developed models were evaluated using two standard statistical measures namely, Pearson correlation coefficient (R) and root mean square (RMSE). This chapter satisfies objectives two and three.

Chapter 5 consists of real-time irrigation scheduling of potatoes at VIS using a crop growth simulation model named CROPWAT.The predicted monthly values of reference evapotranspiration in chapter 4 was inserted into CROPWAT crop growth simulation model in conjunction with other required information such as rainfall data, cropping pattern, soil type and scheduling criteria to produce a 5-day time step irrigation schedule. This chapter achieves the third objective.

In chapter 6, a novel evolutionary multi-objective optimization algorithm called combined Pareto multi-objective differential evolution (CPMDE) was adopted to solve constrained and real world irrigation water use and crop yield problem on the VIS farmland. Findings of the study suggest that CPMDE is a good alternative suitable for resolving irrigation water allocation and crop yield problems in both single and multi-crop environments with limited freshwater for irrigation in a water-stressed country like South Africa. This satisfies the fourth objective of this thesis.

Chapter 7 presents a general summary and conclusion based on the results of the previous chapters. It also gives suggestions and recommendations for future research.

1.9 PUBLICATIONS

A total of 6 research articles were prepared during the course of this work. In all, five journal articles and one conference paper were written. Two of the journal papers have been published while three are under review in reputable academic journals at the time of compiling this thesis.

(a) Journal Articles

[1] **Ikudayisi, A.** and Adeyemo, J. 2015. Irrigation water optimization using evolutionary algorithms. *Environmental Economics*, 6 (1): 200-205.

[2] **Ikudayisi, A.** and Adeyemo, J. 2016. Effects of Different Meteorological Variables on Reference Evapotranspiration Modeling: Application of Principal Component Analysis. *International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering*, 10 (6): 623-627.

[3**] Ikudayisi, A.** and Adeyemo, J. Optimal irrigation water management using Evolutionary Algorithms technique: A critical review. *Artificial Intelligence Review*, *Under review.*

[4] **Ikudayisi, A.** and Adeyemo, J. The impact of climate change on irrigation water management in Sub-Saharan Africa: A review. *Journal of Water and Climate Change*, *Under review.*

[5] Adeyemo, J. and **Ikudayisi, A.** Artificial neural networks for predicting reference evapotranspiration in Vaalharts irrigation scheme, South Africa. *Agricultural Water Management - Elsevier*, *Under review.*

(b) Conference Papers

[6] **Ikudayisi, A.** and Adeyemo, J. 2015. Irrigation scheduling in South Africa using simulation-optimization models. Paper presented at the *4th YWP ZA Biennial and 1st African YWP Conference*. Pretoria, South Africa, 16 - 18 November, 2015. International Water Association,

CHAPTER 2

LITERATURE REVIEW

2.1 MULTI-OBJECTIVE OPTIMIZATION

Optimisation is an attempt to maximize a system's desirable properties while simultaneously minimizing its undesirable characteristics (Storn and Price 1995). Optimisation also refers to the process of finding one or more feasible solutions corresponding to extreme values of one or more objectives while satisfying specified constraints. A significant portion of research and applications in the field of optimisation has focused on single objective optimisation, whereas most of the natural world problems involve multiple objectives which are conflicting in nature (Olofintoye, Adeyemo and Otieno 2013). The task of finding one or more optimum solutions in an optimisation problem involving more than one objective is known as multi-objective optimisation (MOOP) (Deb, Mohan and Mishra 2003).

Most real world problems involve multiple objectives and it is basically difficult to find a solution that is best in respect to all the objectives rather there are equally good solutions which are referred to as Pareto optimal solutions (Adekanmbi and Olugbara 2015). A MOOP problem consists of more than one objective functions which are to be either maximized or minimized. It usually has some constraints which the feasible solutions must satisfy (Deb, Mohan and Mishra 2003). The goals of a MOOP is to find a set of solutions as close as possible to the Pareto-optimal front and to also find a set of solutions as diverse as possible. MOOP deals with two spaces namely decision variable space and objective space. Various studies have adopted multi-objective optimization techniques in solving real – world problems (Adeyemo and Otieno 2010a).

2.2 OPTIMAL WATER MANAGEMENT USING EVOLUTIONARY ALGORITHMS

Water is a scarce natural resource on the earth, yet it is highly essential for human existence (Ramaila, Mahlangu and du Toit 2011). It is equally the livewire of agricultural development because the availability of water is an important factor for crop production (Huang *et al.* 2012). Less than one percent of the water of the earth is available as freshwater while the rest is in the oceans, seas or in form of frozen ice on mountain tops and glaciers (Olofintoye, Adeyemo and Otieno 2013).

However, in South Africa, water is a limited resource and irrigated agriculture is the greatest user of the available consumptive water. It accounts for about 60% of the total water in the country (Nkondo *et al.* 2012). The sustainable management of water resource is a necessity, particularly in the arid and semi-arid regions where crop development and food security are basically dependent on irrigation due to low annual average rainfall experienced in such regions (Belaqziz *et al.* 2014). The demands for food, fibre and all other needs tend to shrink the available natural resources due to the expected global population growth. As the world population increases, food security must be in place and this can only be achieved essentially through the provision of irrigation (Singh 2012). According to research, the world population by year 2050 is projected to hit 9.5 billion, hence the need for adequate provision of irrigation (Singh 2014).

Due to this rising world population, changes in climate, contamination of water supply sources, scarcity of water has been the experience in many parts of the world today. This is evident in the fact that there is an increase in water demands for irrigation, industrial, domestic and energy uses (Mishra and Singh 2011). This scarcity of water resources is further complicated due to high temperature and drought which dries up both surface and groundwater resources (Mishra and Dehuri 2011). Countries and regions with little annual rainfall should be able to utilize its water resources in a more beneficial and sustainable way so as to avoid water stress in the future. To address this challenge, optimization techniques are adopted.

The objective of global optimization in irrigation planning and crop production is to achieve maximum crop yield under limited water supply within an irrigated area (Schütze *et al.* 2006). This involves the use of computer modeling techniques to find a near-optimal solution of the global optimization problem. Optimisation methods or techniques are employed to effectively regulate and optimize the use of water for irrigation. Efficient planning and management strategies are essential for optimum utilization of resources and it is considered a process for continuous improvement and sustainable development. Subsequently, it is fundamental to optimise accessible land and water assets to accomplish most extreme returns.

It is the duty of water resources managers to adequately allocate water for basic human consumption, sanitation and food production but in some cases, there had existed stipulated water right policies in which water was allocated to users according to their rights without considering the economic efficiency in water use (Reca *et al.* 2001). The available consumptive water are contested for in other areas of need such as domestic, industrial, hydropower, irrigation and flood control (Bieupoude, Azoumah and Neveu 2012). Also, it was stated by Wardlaw and Bhaktikul (2004b) that irrigation uses more than 60% of available consumptive water use in the world.

The scheduling and management of irrigation is essential. Several optimisation techniques that attempt to propound ways of mitigating or resolving water resources allocation problems have been reported in several studies. Among the optimisation techniques employed for solving irrigation problems around the world are evolutionary algorithms. Evolutionary algorithms (EAs) go for discovery of the optima from a population of points in parallel rather than from a single point. These gimmicks make them alluring for tending to complex design issues (Reddy and Kumar 2007).

They combine elements of directed and stochastic search and therefore, are more robust than existing directed search methods, providing the global optimum without being trapped in local optima. Additionally, they may be easily tailored to a specific application of interest, taking into account the special characteristics of the problem under consideration. They can also be easily parallelized (Karterakis *et al.* 2007).

In the past decades, several evolutionary algorithms that mimic biological entities' behaviours and evolution have emerged. Available EAs include but are not limited to genetic algorithm (GA), differential evolution (DE), evolution strategy (ES) and genetic programming (GP). A novel and recently developed EA called combined pareto multi-objective differential evolution (CPMDE) is adopted in this research work. The superiority of EAs in solving both single and multi-objective optimisation problems over other optimisation techniques has been demonstrated by several researchers in recent years (Nasseri, Asghari and Abedini 2008; Yousefi, Handroos and Soleymani 2008; Qin *et al.* 2010).

2.3 EVOLUTIONARY ALGORITHMS (EAs)

Evolutionary Algorithms (EAs) are well renowned meta-heuristic optimization tools which are suitable and useful for searching and solving diverse challenges that relates with planning, design and management of natural resources (Whitley 2001). EAs, though a global optimization technique uses the theory of Charles Darwin's natural selection to search for optima solutions in a given problem and they have been adopted over the years to solve diverse application problems (Adeyemo, Bux and Otieno 2010). Another interesting feature of evolutionary algorithms is their ability to solve multi-objective optimization problems (MOOP) without any hitch and this has actually popularised it in the last few decades (Adeyemo, Bux and Otieno 2010).

EAs have also been employed in experimental frameworks to validate theories about biological evolution and natural selection, particularly through works in the field of artificial intelligence. EAs belong to a class of search methods with remarkable balance between exploitation of the best solutions found and exploration of the search space.

According to Eiben and Smith (2003), the general procedures of EAs includes initialization, mutation, crossover and selection. A great population of individuals which are potential solutions are first randomly generated and after that, each solution is assessed by using fitness function (Deb 2001). A fresh population which will be more durable than the former population is derived via a selection process which is applied in every iteration; the solutions will thereafter undergo mutation and crossover to mimic the natural evolution technique and the iteration continues until convergence is reached (Eiben and Smith 2003).

Examples of evolutionary algorithms employed in water resources management include; genetic programming (GP), genetic algorithms (GA), differential evolution (DE), evolutionary strategy (ES), particle swarm (PS), ant colony, particle swarm optimization (PSO), evolutionary programming (EP) and the newly developed EA calledcombined pareto multi-objective differential evolution (CPMDE).

Azamathulla *et al.* (2008) considered Genetic Algorithms (GA) as the most popular EA. GA technique is robust in its capacity to search for optimal solutions and widely used in the optimization of water resources benefits. It was developed in the 1970s and had since been accepted as a powerful optimization method (Reddy and Kumar 2007). GA is a robust search mechanism based on a combination of survival of the fittest theory and extracted genetic operators (Goldberg 1989). Major characteristics of adopting GA in water resources optimization are the 'population-by-population approach when compared to the 'point-by-point used by classical optimization techniques (Chang and Chang 2009), the use of probabilistic transition rule instead of deterministic rules; the use of binary coding instead of the real values of the parameters involved (Raju and Kumar 2004); and the use of objective function information instead of the derivatives. Three major operators involved in GA techniques are reproduction, crossover and mutation (Deb 2001). Two types of GA identified by Chang *et al.* (2013) are real-coded GA and binary-coded GA. In a comparative study between these two types, it was discovered that real-coded GA is more robust, precise and efficient than the binary-coded GA.

Differential Evolution (DE) developed by Price and Storn in 1995 (Price, Storn and Lampinen 2005), is a simple yet powerful heuristic method for solving nonlinear, non-differentiable and multi-modal optimization problems. The algorithm combines simple arithmetic operators with the classical events of crossover, mutation and selection to evolve from a randomly generated initial trial population until a fittest solution is found. The key idea behind DE is the scheme it uses for generating trial parameter vectors. Mutation and crossover are used to generate new trial vectors while a selection scheme determines which of the vectors survives to the next generation (Reddy and Kumar 2007). In recent years, DE has gradually become more popular and has been used in many practical cases, mainly because it has demonstrated a robust convergence properties and is principally easy to understand.

Over the years in the field of operations research, EAs have found maximum usage in solving both single and multi-objective optimization problems (Sarker and Ray 2009). In solving single objective optimization problems, EAs always goes out to obtain the best global minimum or maximum as the case may be which is determined by the nature of the problem being addressed (Cheung *et al.* 2003). On the contrary, in multi-objective optimization problems, EA searches for a set of solutions that are better and fulfil the boundary conditions to the remainder solutions in the search space.

The advantages of adopting EAs in solving optimization problems are so numerous which includes (1) EAs are solid contender for issues with non-raised, irregular and multimodal functions. (2) EAs do not need to consider whether a function is convex, concave or continuous. It solves all functions without any hitch (Sarker and Ray 2009). (3) EAs are very ideal for solving multi-objective optimization problems because it can handle the many conflicting objective functions and also bring about lots of optimal solutions in a single simulation run (Sarker, Kamruzzaman and Newton 2003). (4) They do not make assumptions about the underlying fitness landscape (5) They are system theoretic (6) They are global optimizers (7) They are simple to apply (8) Their codes are available in free open sources online(Olofintoye, Adeyemo and Otieno 2013).

In recent years, a large number of research works had been done using evolutionary algorithms to solve irrigation management problems. Among such works are Adeyemo and Otieno (2010b); Adeyemo and Otieno (2010a); Adeyemo, Bux and Otieno (2010); Afshar (2012); Arunkumar and Jothiprakash (2013); Belaqziz *et al.* (2013a); Carrillo Cobo *et al.* (2014); Chang *et al.* (2010); Olofintoye, Adeyemo and Otieno (2014).

2.3.1 Applications of EAs in Irrigation Water Allocation and Scheduling

Over the years, comprehensive studies have been conducted on the application of EAs for optimizing irrigation water allocation and scheduling and EAs have proved to be a very useful technique for deriving irrigation water schedules (Wardlaw and Bhaktikul 2004b, 2004a; Adeyemo, Otieno and Ndiritu 2008; Azamathulla *et al.* 2008; Mathur, Sharma and Pawde 2009; Casadesús *et al.* 2012; Belaqziz *et al.* 2013b; Kamble *et al.* 2013; Parsinejad *et al.* 2013; Haq and Anwar 2014).

A Genetic algorithm (GA) was developed by Wardlaw and Bhaktikul (2004a) to solve an irrigation scheduling problem. The objective of the study is to optimize the water use in an irrigation system fed on a rotational basis and this was applied to the Pugal branch canal in the Indira Ghandi Nahal Pariyonaja (IGNP) irrigation system located in North West India. The authors discovered a research gap in the previous works done on irrigation scheduling. These research works only considered either scheduling based on a fixed amount of water demands within the constraints of canal system capacity alone, or by using soil moisture accounting models in determining water demands based on irrigation and hydro-meteorological conditions.

The novelty in their work is developing a scheduling approach which combines both canal delivery scheduling with in-field soil moisture requirements. GA was combined with a deterministic soil moisture water balance model so as to make sure there is equal delivery of water throughout the various seasons within the irrigation canal systems. Under the canal scheduling modelling, the soil moisture was maintained between field capacity and wilting point while minimizing losses via drainage. Two approaches were considered in the GA formulations viz; 0-1 approach and the rotational approach, which is known as w*arabandi* in the indian subcontinent.

In the soil moisture modelling, a dual crop coefficient approach was adopted to account for water stress periods and resulting reductions in evapotranspiration. Water schedules were modelled under the soil water stress condition and non-stress condition, an appreciable comparison was made. The conclusion of their study is that GA produces feasible schedules under both the 0-1, and also *warabandi* approaches but a binary representation of canal water diversion periods is the most appropriate decision variable for the problem. The 0-1 approach provides a more efficient and equitable water use than the *warabandi* approach. GA proved to be capable of solving water scheduling problems including those which involves extreme conditions of water stress.

Azamathulla *et al.* (2008) also conducted a study which involves the development and comparison of two models; a Genetic Algorithm (GA) and Linear Programming (LP) which was applied to real-time reservoir operation in an existing Chiller reservoir system in Madhya Pradesh, India. The model involves some on-site decisions, and also specifies when to release water and what amount of water is to be released from the reservoir. From the analysis, it was concluded that the models worked efficiently. Considering various time periods, the right amount of water needed was released from the reservoir. Also, there was a consideration for multi-crops on the farmland. Optimum allocation of water to these varieties of crops was achieved via the model developed. The model considered the different stages in crop growth as a determinant of the crop water requirements, this is essential to prevent the crops from experiencing water deficit at any point in their growth stages. Sufficient water was supplied to the crops as at when needed.

Secondly, an optimum crop pattern model was also developed in the study. This aids the reduction in the amount of wasted water due to over-irrigation and surface runoff. This allows for productive irrigation on the farmland. Subjecting these models to a comparative analysis by adopting both GA and LP techniques to solve them, the GA model gives better yields than the LP model. However, GA has proved to be capable of handling diverse irrigation scheduling and water allocation problems effectively. It produced a suitable outcome by generating a population of optimal solutions along the Pareto front.

Adeyemo, Otieno and Ndiritu (2008) applied DE to irrigation water use in the VIS, South Africa. DE is an EA which is an improved version of genetic algorithms. DE was used to maximize the net benefit derived from planting different crops on corresponding areas of land in order to maximize the usage of irrigation water. The objective is to maximize the total net benefit in monetary value (ZAR) derived from planting the 16 crops on 2,500 ha of land and irrigating with 900 Mm^3 of water. The 10 strategies of DE were tested on the program so as to determine the best one for the problem.

All the 10 strategies give the maximum total net benefit (TNB) of ZAR 45, 971,603.61. Strategy 8, DE/best/2/exp gives the lowest number of function evaluations of 62,000 and lowest number of iterations of 400, making it the best strategy for the problem. Also penalty function was introduced to convert the constrained problem into an unconstrained one. Therefore, the application of DE to maximize irrigation water application was successful. The convergence speed of DE was efficient and successful with no constraint violation as well.

Irrigation scheduling is necessary to ensure the fair water distribution between end-users and to organize gate keeper’s work. This is evident in the study done by Mathur, Sharma and Pawde (2009). A model for canal scheduling was developed because it is very important for crop production. GA was adopted to model the delivery of water within a distribution canal on the farm land. The performance of GA was then compared with integer programming (IP) in solving the same problem. The developed model was applied to Famen secondary canal in China. The farm has a large canal with a maximum discharge capacity of 2.8 m^3/s and a total command area of 3930 ha. There are 26 outlets in the Famen reach and each outlet has a discharge capacity of 0.2m^3/s. In solving the model using GA, the main decision variable is the starting time of the outlets. From the study, GA model was found efficient and robust in handling water scheduling for irrigation canal system at the time water is needed by the users on demand. It performed better than IP in solving this problem.

Paly and Zell (2009) conducted a study on the comparison of five Evolutionary Algorithms namely; Real Valued Genetic Algorithm, Particle Swamp Optimization (PSO), DE and two Evolution Strategy-based Algorithms. These techniques were adopted to solve a problem of optimal irrigation with limited amount of available water. Some constraints were introduced into the objective function. The outcome of the optimization showed that both DE and PSO, which are families of EAs proved to be effective in handling irrigation scheduling problems and achieved results that are very close to the global optimum.

Belaqziz *et al.* (2013a) proposed a new methodology for irrigation scheduling optimization based on the stochastic search algorithm called Covariance Matrix Adaptation Evolution Strategy (CMA-ES) and applied it on the irrigation scheduling optimization of an irrigated sector located in the eastern part of the semi-arid Tensift plain in Morocco. The developed algorithm is an EA. The main objective of the study is to offer the irrigation managers a complete scheduling tool for irrigation rounds, including dates and times of opening and closing the canals to irrigate plots and the amount of water needed. Therefore, an aggregation function *f*, which optimizes the irrigation priority index (IPI) of each plot, was proposed. As the best IPI is close to zero, the objective is to minimize IPI indexes for the whole area. Five constraints were adopted in the study which includes (1) the capacity constraint which ensures that supplies can never exceed the total capacity of the canal. (2) The interval constraint ensures that all the irrigation tasks can be scheduled during the irrigation round. (3) The overlap constraint ensures that all the practical actions can be applied consistently, taking into account (4) the geographical distance between the locations where the actions must be applied and the irrigation time span required for all the plots of a same canal. (5) The daily working time. The proposed algorithm proved very promising for managing and optimizing irrigation schedules in the gravity irrigation systems.

Haq and Anwar (2014) applied GA to sequential irrigation scheduling problems. The study explores the potential of GA to solve large practical application problems. The rate, frequency and duration of water delivery are all fixed under the rotation irrigation schedule. Each farmer is supplied water at a specific period of time. In their study, it was proved that the delivery of irrigation water could be flexible and not fixed distribution system. In the flexible system, the irrigator matches the scheduled start times to the target start times requested by the farmers and the suitability of such system is judged by determining how close the scheduled start time is to the target start times. Therefore, in their study, idle time was inserted in sequential irrigation system since there will be times within the irrigation intervals when water will not be used by any farmer. This however includes an excessive number of gate opening and closing operations. Two models were formulated and tested.

The first model considered the insertion of idle time between the jobs. The second model considered contiguous GA models where the insertion of idle time is considered at the end of the last job, before the start of the first job and before the end of the last job. Penalty strategy was adopted in the models to control infeasibility as the earliness and tardiness (in minutes) of the process was calculated. The models were tested on the irrigation district at Bula in Philipines and the outcome shows the sensitivity of the models to the insertion of idle time. The GA models performed well in sequential irrigation, it proved to be an efficient optimization tool especially for the contiguous irrigation scheduling problems. Insertion of idle time at the beginning and end of irrigation has been found useful. The models have the capacity to prioritize the irrigation turns, based on crop value and sensitivity to water stress.

2.3.2 Applications of EAs in Crop Planning

EAs have been applied to solve problems related to crop planning operations. Numerous studies have been carried out using different EAs in solving this problem. In the study carried out by Raju and Kumar (2004), GA, a family of EAs was adopted to prepare an efficient cropping pattern in order to maximize benefits on the farmland. The optimization of water allocation was done over time, among crops and also among competing crops at Sri Ram Sugar Project farm land in Pradesh, India. GA was adopted to maximize net benefits under different crops planted in the study area. Since the problem is a maximization problem, the fitness function is equal to the objective function. The results got from the GA model was contrasted with Linear Programming model and they inferred that genetic algorithms is a powerful optimization technique for irrigation crop planning and can be utilized for more intricate frameworks including non-direct optimization.

A crop planning problem was formulated as a multiobjective optimization model by Sarker and Ray (2009) and solved using three distinctive optimization approaches. The methodologies considered were; ε - constrained method, a well-known multi-objective evolutionary algorithm, NSGAII and their proposed multi-objective constrained algorithm (MCA). The performance of the proposed MCA with the other two methodologies were critically analysed in order to bring out a comparative analysis in the study. The purpose of the study was to choose the optimal combination of crops (cropping pattern) that will bring the highest yield with limited cultivation cost on the farmland. The two objectives considered were to maximize the gross margin and minimize variable cultivation cost. In all, the study had 39 variables and 15 constraints. NSGAII failed to discover plausible solutions in 69% of the cases experimented, whereas, the proposed MCA technique did more excellently by locating viable solutions in a single run than NSGAII in the crop planning model. The conventional ε - constrained method produced a worse performance compared to the two EA techniques adopted.

In the study carried out by Adeyemo and Otieno (2010b), an EA called multi-objective differential evolutionary algorithm (MDEA) was developed for solving multi-objective optimization problems and discovering optimal solutions. Four strategies of the developed algorithm namely MDEA1, MDEA2, MDEA3 and MDEA4 were adapted to solve a multi-objective crop planning problem. The objectives of the problem include minimization of total irrigation water, maximization of both the total net income from farming and the total agricultural output. The study area is VIS in South Africa and from the study, it was discovered that both MDEA1 and MDEA2 which uses binomial crossover method performed better than the remaining two strategies. From the study, it was concluded that MDEA is a good algorithm for solving crop planning problems also its an effective and concise model for solving multi-objective problems in water resources systems.

A new and innovative evolutionary algorithm developed specifically for solving spatial optimization problems was developed by Fotakis and Sidiropoulos (2012) and it is used for solving both land use planning and resource allocation problems. The optimization methodology is multi-objective, based on non-domination criteria and it is called multi-objective self-organizing algorithm (MOSOA). It was applied to solve a complex, non-linear, combined land use and water allocation problem. The objectives of the problem to be solves includes (a) The minimization of soil and groundwater pollution and (b) the maximization of economic profit. The studied area was divided into land blocks and it included a number of wells in fixed positions. The results obtained by MOSOA was compared to a standard multi-objective genetic algorithm called non-dominated sorting algorithm (NSGA - II) and the former yielded better and satisfactory outcomes as it generates a set of optimal solutions along the Pareto front and it also satisfy the compaction criteria.

In a study conducted by Adekanmbi and Olugbara (2015), a multi-objective optimization of mixed cropping planning was solved. The adopted technique in this study is an EA called generalized differential evolution 3 (GDE3). GDE3 is a technique which modifies the selection rule of the basic DE algorithm. The objectives of the study are to maximize net profit, maximize crop production and minimize planting area. The constraints of the optimization problem include economic demand of crops, land resource, labour cost and investment in crop production. Data retrieved from South African grain information service and the South African abstract of agricultural statistics were used in the optimization problem. The performance of GDE3 was evaluated by adopting NSGA-II to solve the same problem. About 207 crops are grown in South Africa but the authors grouped these crops into 8 categories. The land for farming is grouped into single, double and triple-cropped lands with values as 8, 14 and 3 respectively. The result of the optimization shows that both GDE3 and NSGA-II performed very well, but GDE3 produced a better performance than NSGA-II.

2.3.3 Applications of EAs In Reservoir Operations

At the planning stage of dam construction, optimization modeling is very important in deciding the ideal size of the reservoir and this system is known as the operation investigation of a dam (Abdulkadir, Sule and Salami 2012). In water resources, the study of reservoir operation is of importance. Reservoirs are constructed to suit unregulated abundance irregular streams. This abundant water is kept in the reservoir in the times of high inflows for utilization in low-stream period and water demands on reservoirs may be used for domestic, industrial, irrigation or hydropower generation purposes (Campos 2010).

Real-time operation of a reservoir obliges taking steps on moderately brisk choices with respect to discharges focused around transient data while choices are subject to the storage in the supply and data accessible as conjecture hydrologic and meteorological parameters (Chang and Chang 2009). This is especially important because the reservoir needs to respond quickly and adapt to any changes that may occur during floods and power generation (Mohan, Raman and Premganesh 1991). Diverse applications of EAs in reservoir operations are discussed below.

Reddy and Kumar (2006) developed a Multi-objective Evolutionary Algorithm (MOEA) and applied it to a problem involving a multipurpose reservoir system. A population based search EA named Multi-objective Genetic Algorithm (MOGA) was adopted to overcome the challenge faced by the classical methods for Multi-objective Optimization Problems (MOOP). The MOGA methodology was applied to a reasonable reservoir system, namely Bhadra Reservoir system, in India and the results obtained using the proposed evolutionary algorithm showed that it found a well distributed set of Pareto optimal solutions along the Pareto front and hence it shows the suitability of MOGA for solving multi-objective optimization issues.

In another study carried out by Chang and Chang (2009), a multi-objective EA named, non-dominated sorting genetic algorithm (NSGA-II) was applied to examine the operations of both Feitsui and Shihmen reservoir systems in Taiwan. The NSGA-II was used to minimize the shortage indices (SI) of the two reservoirs over a long term simulation period of 49 years. Their result demonstrated that NSGA-II is a compelling and vigorous multi - objective system to recognize joint operation methodologies that will address discriminating future maintainability needs later on.

Elferchichi *et al.* (2009) developed an optimization model based on real-coded GA for optimising the operation of reservoirs in an on-demand irrigation system. The model was applied and tested on the Sinistra Ofanto irrigation scheme in Italy. The model analysed the adequacy of the difference between supply and demand taking into account the storage capacity of the reservoirs. It was concluded that GA is an efficient model for solving problems relating to multi-reservoirs.

Regulwar, Choudhari and Raj (2010) applied DE to the operation of multipurpose reservoir in India and the main purpose is to maximize the use of water for hydropower purposes. The result of their study shows that DE is also a robust global optimization technique and can be adopted in solving complex non-linear optimization problems.

Arunkumar and Jothiprakash (2013) optimized the operations of Koyna Hydro Electric Project reservoirs by adopting chaotic EAs in order to maximize the hydropower production. GA and DE algorithms were both adopted in conjunction with chaos technique to enhance the search process by generating a better and healthier initial population. The chaos technique along with evolutionary algorithms has enhanced the global pursuit of the optimization method by having better beginning populace furthermore unites rapidly.

Peralta, Forghani and Fayad (2014) applied Multiobjective Genetic Algorithm (MGA) to a hydraulically and economically nonlinear system in which all significant flows, including stream-aquifer-reservoir-diversion-return flow interactions, are simulated and optimized simultaneously for multiple periods. The conflicting objectives in the study are maximizing water provided from surface and groundwater resources, maximizing hydropower production and minimizing operation costs of moving water from resources to destinations. The MGA optimizer satisfactorily generated diverse and well distributed solutions to show decision makers a true picture of trade-offs between conflicting objectives.

2.3.4 Advantages of adopting EAs in Irrigation Water Management

There are diverse advantages of adopting EAs to irrigation water managements. EAs go for discovery of the optima from a population of solutions rather than from a single point. These gimmicks make them suitable for solving complex design issues (Reddy and Kumar 2007). The major difference between the classical optimization techniques and soft computing according to Azamathulla *et al.* (2008) is that in classical methods, the optimal solution is derived whereas in the soft computing techniques; it is searched from a randomly generated population of possible solutions. EA searches for a set of solutions that are better and fulfil the boundary conditions to the remainder solutions in the search space (Chen and Chang 2009). EAs are solid contender for issues with non-raised, irregular and multimodal functions. EAs do not need to consider whether a function is convex, concave or continuous but it solves all functions without any hitch (Sarker and Ray 2009). EAs are very ideal for solving multi-objective optimization problems because it can handle the many conflicting objective functions and also bring about lots of optimal solutions in a single simulation run (Sarker, Kamruzzaman and Newton 2003). GA uses objective functions directly, and doesn't need any of its derivatives. They use randomized and stochastic algorithm in their operation hence, they overcome the problems of local optima by locating the search in any place within the search space (Raju and Kumar 2004).

2.3.5 Areas of concern

Whitley (2001) describes EAs as weak methods in Artificial Intelligence, and as such, weak methods do not possess domain specific knowledge. He describes EA as a blind search method, in which methods that are domain specific will always outperform a blind search method. He advised that before one will adopt an EA, he should first conduct a local search and any point where all of the neighbours are inferior is the local minimum.

Major disadvantages recorded by some researchers in their use of EAs are that sometimes, it may lead to slower convergence since it doesn't explicitly use derivative information (Raju and Kumar 2004). Also, Sarker and Ray (2009) discovered that after optimization, to choose the best solution from the population of solutions requires a preliminary treatment of the solution, which in some cases may be computationally cumbersome.

2.4 THE IMPACT OF CLIMATE CHANGE ON IRRIGATION WATER MANAGEMENT IN SUB-SAHARAN AFRICA

The desire to provide global food security to the ever increasing world population is one of the challenges of the 21st century, and to achieve this, adequate water resources must be in place. One major challenge of human beings is inadequate food production (Biazin *et al.* 2012). De Silva *et al.* (2007) observed that in developing countries around the world, almost 800 million people feed on poor nutritional diets due to a decline in crop production. In order to achieve increased crop production, water is of necessity and one major way to access adequate water for food and crop production is via irrigation. Irrigation water has helped farmers all over the world to increase crop yields, increase average crop production and also decrease variability since it reduces their sole dependence on rainfall for agricultural sustenance (Fischer *et al.* 2007).

Climate change is a global phenomenon that is expected to affect agricultural productivity with resultant effects such as reduced crop production, increased food prices and food insecurity (Calzadilla *et al.* 2014). A pertinent fact about the African continent as stated by Biazin *et al.* (2012), is that water resources in Africa is reducing and almost becoming variable because of the huge population explosion experienced in the continent. Also, climate change will lead to increased climatic variations and decreased fresh water resources (Cooper *et al.* 2008). It will pose a serious threat on the agricultural systems and crop productivity but the local communities will be at a higher risk (Biazin *et al.* 2012). Climate change has been discovered as a major factor affecting annual crop productions since crop yield is more sensitive to precipitation than temperature (Kang, Khan and Ma 2009). About 41% of Africa receives low or virtually no rainfall while about 25% experience intermediate rainfall (Burney and Naylor 2012). This led to the predictions of De Silva *et al.* (2007), that climate change will affect the intermediate rainfall areas more than other areas. It was also predicted by Fischer *et al.* (2007) that the crop yield will decline and the crop water demand will increase in Africa, most especially in the dry farm lands.

The Sub-Saharan African region has been identified as vulnerable to climate change as a result of its low capacity for adaptation (Calzadilla *et al.* 2014). The impact of this will be more pronounced in the nearest future than it was previously forecasted. An estimated 41% of the population in Sub-Saharan Africa lives in drought-prone dry lands while Sub-Saharan Africa have less than 2% of the world's total irrigated land (Biazin *et al.* 2012). Kusangaya *et al.* (2014) iterated that the residual effects of climate change on water resources will have both direct and indirect effects on both the socio-economic and biophysical environments; and will also affect both short and long term availability of water resources in Sub-Saharan Africa.

Several research works conducted on the impact of climate change on the availability of water resources have used the results of climate change models directly or by applying them to local climate datasets (De Silva *et al.* 2007). Climate change obviously has effects on water supply and quality in all sectors of the economy, such as health, industry, agriculture, energy supply, forestry, fisheries and recreation. These effects do occur via changes in the regularity and severity of events in water supply distribution (Olmstead 2013). Also, Connor *et al.* (2012) argued that due to the uncertainty associated with climate change, it can manifest itself in three scenarios namely mild, moderate and severe.

The main aim of this section is to review literatures on the full impact of climate change on irrigation water management in Sub-Saharan Africa, in which South Africa belong, as well as highlighting the research gaps and necessary needs that should be provided. It also provides background information for farmers, water decision makers and stakeholders on the impact of climate change on irrigated agriculture.

2.5 GLOBAL IMPACTS OF CLIMATE CHANGE TRENDS

In a report by IPCC (2007), it was inferred that an increase of atmospheric gases will cause a change in climate while the residual effect will result to the rise in sea level, heavy rainfall events and drought. Climate change includes changes of air temperature as well as an increase in the CO_2 content in the atmosphere which might have an adverse effect on crop yield (Schaldach *et al.* 2012). The resultant effect of climate change is evident in averaged global annual air temperature and variability in the regional rainfall around the world and these conditions are expected to continue into the future (Shiferaw *et al.* 2014). Studies revealed that agricultural yield will be drastically affected over the next hundreds of years due to the unpredictable changes and variability in climate systems and that two third of the world population will face water shortage conditions (Bär *et al.* 2010; Calzadilla *et al.* 2014; Chattaraj *et al.* 2014).

According to Calzadilla *et al.* (2014), there are five main factors that influence climate change on agriculture and they are precipitation, temperature, carbon dioxide (CO_2) fertilization, climate variability and surface water runoff. During climate change, a change in temperature is the most predictable effect and it will increase the rate of water losses from reservoirs, lakes and will also increase the demand for water via evapotranspiration. As a result, the overall effect is therefore an increase in crop water demand, irrigation demand while soil moisture will deplete at a faster rate (Turral, Svendsen and Faures 2010). Changes in the frequency and pattern of rainfall will cause the sea level to rise thereby causing more flooding and there will be severe drought also. It will adversely affect the watershed hydrology, runoff and river hydrology. All these effects will be felt directly in the case of irrigated agriculture.

Also, there will be an increase in both precipitation and runoff variabilities because an increase in temperature will melt glaciers / snowfields in regions with high mountains. This will cause more precipitations to fall as rain, which will eventually increase surface runoff (IPCC 2007).The levels of CO_2 in the atmosphere will also increases and cause both the rate of biomass formation and the mitigating water demands to increase. These occurrences will lead to shorter growing seasons and faster crop development (Fischer *et al.* 2007).

In a report by IPCC (2007), the amount of energy that reaches the earth from the atmosphere every second on a surface area of one square meter facing the sun during the day is estimated to about 1370 Watts and the amount of energy per square meter per second averaged over the entire planet is a quarter of this value. In the last 100 years, it was also noted that the global mean temperature has increased from -0.25°C to 0.74°C over the years (Figure 3). All these are global impacts of climate change trends on the atmosphere.

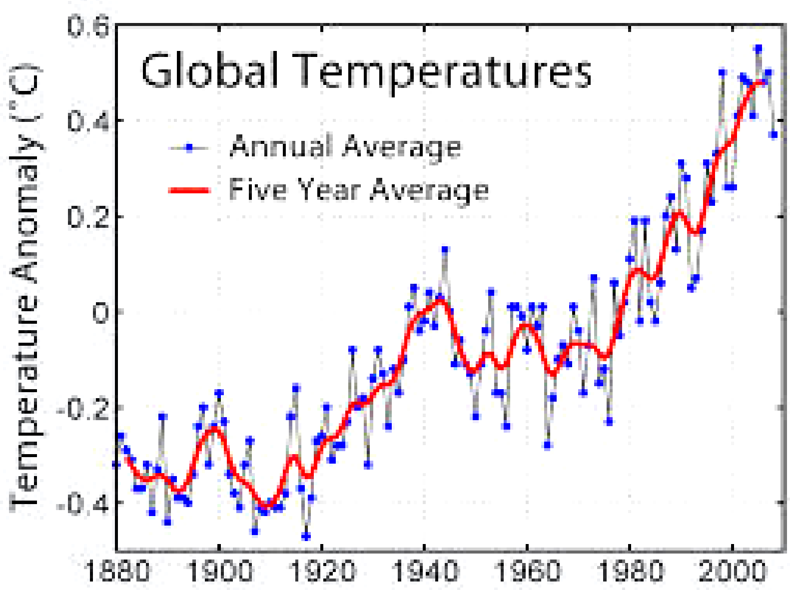

Figure 3: Global mean temperature during the last 100 years (IPCC 2007)

2.6 PREDICTED CLIMATE PROJECTIONS FOR SUB-SAHARAN AFRICA

This section discusses relevant studies where climate change projections for Sub-Saharan African were made. A good knowledge of these projections will help stakeholders and researchers choose the best adaptation strategy in order to increase agricultural productivity and food security. Misra (2011) predicted that by year 2050, rainfall in Sub-Saharan Africa is likely to reduce by 10%, which implies a drastic water shortage in the long run. This decrease in rainfall would further reduce surface drainage by 17%. At the moment, this change in climate has caused so much depletion in the water resources in Sub-Saharan Africa regions to the point that food production has reduced drastically therefore causing many people to die of starvation due to an acute shortage of food (Faramarzi *et al.* 2013). Numerous climate models around the world suggested a mean temperature increases between 3°C and 4°C in Africa by the end of the 21st century which is about 1.5 times the global average response and this will result in significant yield loss of staple crops like maize, millet, cassava, sorghum, of between 8 and 22 percent by year 2050 (Bryan *et al.* 2013). In Sub-Saharan Africa, the historic distribution of average maximum temperature ranges from 18 to 37°C and the changes in maximum temperature experienced in most water basins as a result of climate change is between 1 and 3°C (Faramarzi *et al.* 2013).

Countries in Sub-Saharan Africa are seriously vulnerable to adverse effects of climate change because of their inability to adapt as a result of poverty and malnutrition, while many depends on agricultural products for their livelihood (Bryan *et al.* 2013). Hence, adaptation is very important if people must survive climate change in Sub-Saharan Africa. Adaptation strategies against climate change takes place majorly at the farm and basin level, and such strategies include changes in crop management practices (changing crop types, change in cropping patterns, using different harvest and planting dates), livestock management, land and water use management such as irrigation, water harvesting, better use of fertilizers, soil and water conservation measures (World Bank 2007). Adaptation will help farmers in the rural communities to adjust to climate change and variability of rainfall.

Warming rates greater than the global ratings were predicted by IPCC (2007) for Africa. Table 1 shows the summary of predicted climate projections for Africa by the end of the 21st century. In the predictions, Africa is grouped into four regions namely; Sahel, West Africa, East Africa and Southern Africa, and assessment was based on a 3-monthly quantum assessment. From the table however, it is clear that the degree of warming in these regions differ one to another. The highest mean annual temperature change was predicted for the Sahel region while the highest mean annual rainfall change will occur in East Africa. In Southern Africa, the predicted mean annual temperature change is 3.4°C and mean rainfall change of -4%.

Table 1: Predicted climate projections for Africa by the end of the 21st century(IPCC 2007)

Region	Season	Temperature change (°C)			Rainfall change (%)		
		Min	**Max**	**Mean**	**Min**	**Max**	**Mean**
Sahel	DJF	2.4	5	3.2	-47	31	-18
	MAM	2.3	5.2	3.6	-42	13	-18
	JJA	2.6	5.8	4.1	-53	74	-4
	SON	2.8	5.4	3.7	-52	64	6
	Annual	2.6	5.4	3.6	-44	57	-6
West Africa	DJF	2.3	5.1	3		-16	23
	MAM	1.7	3.6	3.5	-11	11	-3
	JJA	1.5	3.7	3.3	-18	13	2
	SON	1.9	3.7	3.3	-12	15	1
	Annual	1.8	3.6	3.3	-9	13	2
East Africa	DJF	2	3.55	3.1		-3	33
	MAM	1.7	3.5	3.2	-9	20	6
	JJA	1.6	3.6	3.4	-18	16	4
	SON	1.9	3.6	3.1	-10	38	7
	Annual	1.8	3.4	3.2	-3	25	7
Southern Africa	DJF	1.8	4.4	3.1	-2.8	-6	10
	MAM	1.7	3.8	3.1	-25	12	0
	JJA	1.9	3.6	3.4	-43	-3	-23
	SON	2.1	4	3.7	-43	3	-13
	Annual	1.9	3.7	3.4	-12	6	-4

KEY:

DJF*-December, January, February* ***MAM****- March, April, May*

JJA*- June, July, August* ***SON****-September, October, November*

Furthermore, it was observed by Zinyengere, Crespo and Hachigonta (2013) that in Southern Africa, projected climates have negative implications on crop production because major crop production systems which support the livelihood are grown in the dry sub-humid and semi-arid zones of the region. These regions have extremely high temperature with an annual rainfall below 500mm (Oyebode, Adeyemo and Otieno 2014). The predictions of high temperature and low rainfall will definitely lead to crop failure, however, other climate projections also suggest that an increase in late summer rainfall should be expected in Southern Africa (Ngcobo *et al.* 2013; Zinyengere, Crespo and Hachigonta 2013). Calzadilla *et al.* (2014) however stated that a change in climate may not only be damaging to crop production but it may also present opportunities that can be exploited through adaptation. Most of the reviewed studies concluded that Southern Africa will become hotter and drier and this warming will be greatest over the interior margins of Sahel and Southern Africa (IPCC 2007).

Changes in temperature and rainfall has a direct effect on the quality of evapotranspiration and on both the quality and quantity of runoff and the water balance can be affected or altered by any change in temperature (Kusangaya *et al.* 2014). Therefore, warming increases the intensity of the storms in the Indian ocean causing the sea levels to rise and thereby causing flooding in the coastal areas (Ngcobo *et al.* 2013). Different scholars used different global climate models in their projections but they have all shown that the arid and semi-arid regions are likely to get drier due to the effect of climate change more than humid regions in countries like Tanzania and Zambia (Lankford and Beale 2007).

Cassman and Grassini (2013) however argued that Sub-Saharan Africa has a large storage of untapped groundwater resources compared to other continents of the world. The study referred to large groundwater resources which are above 10,000km^3 in Nigeria, Ethiopia, Angola, Botswana, South Africa and Kenya which can be very useful for irrigation purposes.

A study of the climatic change impact on agriculture was carried out by Calzadilla *et al.* (2014). The study was primarily conducted in South Africa based on four scenarios from two GCMs namely CSIRO and MIROC, and two IPCC SRES emission scenarios namely A1B and B1. Their analysis uses an updated GTAP-W model which distinguishes between rain-fed and irrigated agriculture. It was pointed out that CSIRO scenario runs show almost no increase in average annual precipitation at the smallest temperature increase of any of the general circulation model / greenhouse gas scenario combinations while MIROC runs shows the second largest increase in precipitation and its one of the largest increase in average temperature.

The study further found that an increase in agricultural productivity achieves better outcomes than when the irrigated areas are expanded. In 2050, irrigation is expected to cover only 5% of the total crop area in Sub-Saharan Africa (Zinyengere, Crespo and Hachigonta 2013). As a way of adaptation, they chose to evaluate two scenarios namely irrigation development and improvements in agricultural yields. It was estimated that only 1.4% of the current water supply is available to meet future water demands and hence, it is important to adopt water saving strategies for such purpose such as agriculture.

A study conducted on the economy-wide impacts of climate change on agriculture in Sub-Saharan African was presented by Calzadilla *et al.* (2013). An analysis of the impact of climate change under two adaptation scenarios was presented. The first doubles the irrigated area in Sub-Saharan Africa by 2050 but keeps the total crop area constant while the second scenario increases both the rain-fed and irrigated crop yields by 25% for all Sub-Saharan countries. These scenarios were analysed using IMPACT, a partial equilibrium agricultural sector model combined with a water simulation module and GTAP-W, a general equilibrium model including water resources. These two models were combined because IMPACT allows for combined analysis of water, food supply and demand hence, climate change on food and water can be analysed very well. GTAP-W model allows for a rich set of economic feedbacks and for a complete assessment of the welfare implications of alternative development pathways. The new GTAP-W distinguishes between rain-fed and irrigated agriculture hence, its use in the study.

The study uses the intermediate growth B2 scenario from Special Report on Emission Scenario (SRES) for the baseline projections up to 2050. In order to analyze the impacts of global change in climate and also formulate adequate adaptation measures, climate change components such as the yield effects of CO_2 fertilization, temperature change, altered hydrological cycles and changes in irrigation water demand was incorporated into the IMPACT model. The results obtained recommends that due to the limited initial irrigated area in the region, an increase in agricultural productivity achieves better outcomes than an expansion of irrigated area and that both scenarios help lower world food prices, stimulating national and international food markets.

Another study was carried out by Faramarzi *et al.* (2013) to analyze the impact of climate change on the availability of freshwater in Africa at the subbasin level for a period of twenty years (2020-2040). Climatic data from five global climate models (GCMs) namely HadCM3, PCM, CGCM2, CSIRO2 and ECHAM4, and four IPCC emission scenarios: A1F1, A2, B1, and B2 were used. The future climate was then fed to the SWAT model to simulate the changes in different water resources components involved. It was discovered that a change in the maximum temperature in most sub basins in Africa between 1°C in most West and Central Africa and 3°C in South and North Africa. Five basins were selected across the African continent for this study in different climatic regions and properly analysed to see what the effect of climate change could bring about. The outcome of the study reveals that in African nations, drought events will increase in future and this will pose a threat to agriculture and food production. Irrigation development is hereby recommended in the African continent to stabilize and increase food production.

In a study by Walker and Schulze (2008), the analysis on the impact of climate change on the agro-ecosystem sustainability of three climate regions in Highveld region of South Africa was done. The study used nine climate scenarios and modelled them using CERES-maize over a 44-year period. And from their study, it was deduced that climate change could have major negative effects on the already drier western part of South African Highveld region.

2.7 CLIMATE SCENARIOS AND MODELS

In a bid to deduce the effects of climate change and socio-economic factors on irrigation water requirements over a large geographical areas, explicit simulation models have been a valuable tool (Schaldach *et al.* 2012). These simulation models have been adopted in studies to project what the responses of crops will be to future climates (Zinyengere, Crespo and Hachigonta 2013). Researchers around the globe have made use of available data, methods, tools and techniques in a concise way to make good and logical projections of the climate change impacts on crop production. Several researchers have been adopting various climate models and scenarios in their quest to predict climate change parameters and climate vulnerability around the world. Studies about Sub-Saharan African climate change include Lankford and Beale (2007); Cassman and Grassini (2013); Calzadilla *et al.* (2013); Bryan *et al.* (2013) Zinyengere, Crespo and Hachigonta (2013); Waha *et al.* (2013); Kusangaya *et al.* (2014); Shiferaw *et al.* (2014); Calzadilla *et al.* (2014).

In order to predict the effect of climate change parameters such as rainfall and temperature, climate models and other scenarios must be put in place (Kang, Khan and Ma 2009). A climate scenario base its description on a range of mathematical representations which involves interactions between the atmosphere, land, oceans and sea ice which resulted from climate (Kirby *et al.* 2014). Climate scenarios can be discovered by global climate models (GCMs) and regional climate models (RCMs)(Kang, Khan and Ma 2009). GCMs are useful tools for simulating and describing both current and future climates of a region. Table 2 presents a detailed outline and summary of GCMs employed for projecting climate scenarios on a global scale.

The GCM model scenarios in Table 2 are capable of enabling scientists acquire a better understanding of the impacts of climate change on crop production as well as perform successful regional climate projections via simulations (Suppiah, Hennessy and Whetton 2007). GCMs have been very useful in predicting future climates around the world. The limitations of GCM models include; low resolution of several degrees, lack of spatial and temporal precision necessary for detailed regional analysis and uncertainties in predicting the future climate over a large scale (Kang, Khan and Ma 2009).

Table 2: GCM models used for climate scenarios(Suppiah, Hennessy and Whetton 2007)

S/No	Model	Vintage	Country	Simulated data used in slope analysis
1.	BCCR-BCM2.0	2005	Norway	1850-2099
2.	CCSM3	2005	USA	1870-2099
3.	CNRM-CM3	2004	France	1860-2090
4.	CSIRO-Mk3.0	2001	Australia	1871-2100
5.	ECHAM5/MPI-OM	2005	Germany	1860-2100
6.	ECHO-G	1999	Germany / Korea	1860-2100
7.	FGOALS-G1.0	2004	China	1850-2099
8.	GFDL-CM2.0	2005	USA	1861-2100
9.	GFDL-CM2.1	2005	USA	1861-2100
10.	INM-CM3.0	2004	Russia	1871-2100
11.	MIROC3.2 (hires)	2004	Japan	1900-2100
12.	MIROC3.2 (medres)	2004	Japan	1850-2100
13.	MRI-CGCM2.3.2	2003	Japan	1851-2100
14.	UKMO-HadCM3	1997	UK	1860-2099
15.	UKMO-HadGEM1	2004	UK	1860-2098

2.7.1 Modeling of climate change impacts on crop responses

In order to predict the potential impact of climate change on crop yield, crop models that describe how crops respond to weather is needed (Kloss *et al.* 2012). There are two major crop modelling techniques which are commonly used to perform an impact assessment of climate change on crop production around the world. These techniques are **process based crop modeling** and **empirical crop modeling** (Zinyengere, Crespo and Hachigonta 2013). A review of studies that applied some of these models is hereby presented in this section.

2.7.1.1 Process based crop modeling

Process based models (PBM) were developed to simulate crop responses to environmental conditions both at the plot and field levels. They are also designed to predict yields from the simulation of plant functioning according to endogenous plant properties and environmental conditions (Lobella and Burke 2010). This is achieved by computing crop dynamics based on the causes and effect equations and simulation of some processes which could span from minutes to days (Zinyengere, Crespo and Hachigonta 2013). Many research studies in Africa have employed the process based models to project the impact of climate change on crops on a large scale but it was discovered that they do not provide information on climate impacts at larger scale. Therefore, in order to use process-based model, climate data needs to be downscaled to the measure of a crop model or a crop model matched to the scale of the climate model output (Fischer *et al.* 2007). Also, process-based models are limited by the bio-physical processes they are based on such as radiation use efficiency (RUE), water-use efficiency and nitrogen use efficiency, which are determined by the aim of developing such models (Cassman and Grassini 2013). In reviewed studies, the most widely used process-based model is the Decision Support System for Agro-technology Transfer (DSSAT). It was applied by Walker and Schulze (2008); Calzadilla *et al.* (2013); Calzadilla *et al.* (2014) and Qureshi, Whitten and Franklin (2013). It integrates a single crop into a modular framework on a farmland. Another process-based model is CERES-maize which was used by Walker and Schulze (2008) to project over a 44 year period growth period. Generally, all process-based models are inadequate in complexities of the real world crop production systems but despite this, they allow us to carry out near-life experiments in order to figure out crop response to climate predictions and changes so that we can plan ahead (Zinyengere, Crespo and Hachigonta 2013). This is why this method is very popular and mostly used among climate impact analysts around the world.

2.7.1.2 Empirical based crop models

Empirical based crop models are divided into two types namely; statistical and ricardian methods. A description and application of these model types are discussed explicitly in the sub-sections below.

2.7.1.2.1 Statistical method

Statistical crop models were designed to operate at the multi-seasonal, regional scale and as a result, it is the best for analyzing inter-annual variability of regional production and this makes them an attractive alternative to process-based methods (Zinyengere, Crespo and Hachigonta 2013). Three types of statistical models include time series, panel, and cross-sectional models (Lobella and Burke 2010). An advantage of statistical methods is their limited reliance on field calibration data, their transparent assessment of models uncertainties as well as not based on cause and effects but solely relying on past relationships (Gaiser *et al.* 2011). Statistical crop models make use of historical data of crop yields and climate to develop its own statistical relationships (López-Moreno *et al.* 2014). Major disadvantages of this method includes absence of adaptation responses, non-validation of the past relationships established, changes in crop varieties grown and non-consideration of planting and harvest dates(Kirby *et al.* 2014). In order to overcome all these limitations, economic models are always introduced to account for adaptation in the context of farm level revenues (Kresovic *et al.* 2014).

2.7.1.2.2 Ricardian method

Ricardian approach was developed by Mendelson in 1994 and is concerned with the economic impact of climate change on agricultural practices by farmers. This method selects the best and most profitable farming activity for farmers on any given piece of land so that farmers can be economically prudent (Zinyengere, Crespo and Hachigonta 2013). Ricardian models are used to assess the impact of climate on net crop revenue per acre. This method uses climate variations with fluctuations in land value while in some regions like Southern Africa, net revenues are used instead of land value because of the poorly developed land markets (Calzadilla *et al.* 2014). This method not only includes the direct effect of climate on productivity but also considers the adaptation of farmers to the local change in climate of their area (Kusangaya *et al.* 2014). It offers the simplicity of empirical methods and also gave an opportunity to analyze the effect of adaptation options. Ricardian approach is based on Ricardo's observation that land rents reflect the net productivity of farmland and examines the impact of climate and other variables on land values and farm revenues (Mushtaq, Maraseni and Reardon-Smith 2013). The approach has been found to be attractive because it corrects the bias in the production function approach by using economic data on the value of land. It directly measures the farm prices or revenues and also accounts for introduction of different activities and other potential adaptations to different climates (Webber, Gaiser and Ewert 2014).

2.8 IRRIGATION AND IRRIGATION SCHEDULING

Irrigation is the largest consumer of water resources in both arid and semi-arid regions around the world and thus a good distribution and management of water for irrigation is highly essential (Belaqziz *et al.* 2013b). Irrigation eliminates water deficits, enhances crop yields in regions where rainfall cannot fully meet crop water requirements (Cassman and Grassini 2013). Irrigation water has enabled farmers to increase crop yields by reducing their dependence on rainfall patterns, thereby boosting the average crop production (Fischer *et al.* 2007). The development of irrigation is also part of the ways of mitigating the effects of climate change on food security and agricultural productivity (Faramarzi *et al.* 2013).

Irrigation scheduling is a process that solves the problem of when, where, and how much water to apply to a given farmland (Pereira 1999). It involves the application of optimization techniques in the management of water resources on a field. It ensures that crop water requirements are met at all times so that the crop will not suffer stress in its root zone due to lack of available water (Anwar and Clarke 2001). Irrigation scheduling is ideal when profit, crop yield and water efficiency are maximized under limited water supply (Elferchichi *et al.* 2009).

Kallestad *et al.* (2008) describes irrigation scheduling as a process by which the right amount of water at the right time meets the evapotranspiration (ET) demands of the crop(s) under consideration. This is to prevent the crop from wilting and also to maximize crop yields (Jumman and Lecler 2009). Also, Haq and Anwar (2014) describes irrigation scheduling as a means of conserving water which helps in making decisions on allocation of quantity and timing of water supply commensurate with crop needs. It is one of the key activities that improves the stability, equity and productivity of water use for agricultural purposes.

There are three main types of irrigation schedules namely demand, arranged and rotational schedules (Haq and Anwar 2014). Also, there are flexible and rigid methods of water delivery in irrigation systems (Mathur, Sharma and Pawde 2009). In flexible methods, the supply of water is done on demand by the user and may be a continuous release during the entire base period of crops. On the contrary, rigid method entails a constant frequency of water release. Improper water delivery schedules cause shortage or surplus of water to users, which adversely affects the performance of such individual irrigation system (Haq and Anwar 2014).

Irrigation scheduling may be very difficult because applying the right amount of water at the right time with a lower cost and minimum water losses, considering constraints such as human and technical factors, is a very complex task (Mathur, Sharma and Pawde 2009). However, simulation-optimization techniques and models have made it possible to solve irrigation scheduling problems effectively. The optimization of irrigation water allocation from a reservoir requires that irrigation water demand, cropping pattern, designated land area and reservoir operation be clearly understood via the use of mathematical models (Huang *et al.* 2012). Nagesh, Raju and Ashok (2006) states that the main inputs for such models are reservoir inflow and crop water requirements based on defined cropping pattern.

Several studies developed mathematical models and algorithms to optimize irrigation water management for different irrigation systems. Irrigators like to optimally allocate the available water for irrigation in order to amplify the annual net profits and increase farm efficiency by preventing excess water that may cause surface runoff, groundwater drainage and leaching of the fertilizers applied (Kamble *et al.* 2013).

In order to develop an irrigation schedule, it is necessary to measure crop water demand (CWD). This can be obtained from direct measurements on the plant, such methods include: stem or leaf water potential; or leaf vigor. Most recently, CWD is obtained from indirect measurements (Saleem *et al.* 2013). According to farmers interviewed, real-time measurement of soil moisture with devices such as granular matrix sensors, data loggers and tensiometers is labour and time-intensive (Salvador *et al.* 2011). Some of the excuses given by these farmers include: excessive learning time; tedious equipment operations; excessive time required to collect and manage data; challenges of data interpretations; and technical problems associated with the equipment use (Wang and Cai 2009). Hence, the need for improved methods of gathering information for appropriate irrigation scheduling operations. It is either we simulate, optimize or adopt both techniques to irrigation water allocation problems.

2.9 CONCLUSION

Having reviewed all the above literature, it is important to know that irrigation water plays a vital role in crop development and food security around the world. Since the average annual rainfall in the arid and semi-arid regions are low, adequate management of available water for irrigation purposes is also important. Different methods of designing irrigation schedules were also discussed. World Bank Report 2008 (World Bank 2007) suggests that the development of irrigation in agriculture-based economies such as Sub Saharan Africa will help agriculture play its role as a tool for growth and poverty reduction. The three ways by which irrigation alleviates poverty are: it enables smallholders to achieve higher yields and revenue from crop production; new employment opportunities on irrigated farms; more profits in agricultural productivity through irrigation can stimulate national and international markets by improving economic growth.

The usefulness and tenacious ability of EAs in solving real world problems effectively have been demonstrated. From this chapter, it can be concluded that many researchers around the globe have developed, initiated and applied various EAs to solve irrigation water problems with great results recorded. Also, the ability of EAs to evaluate multi-objective optimization problems and find optimal solutions was shown in this chapter.

EAs have been found to provide a better spread of solution and also converge better than the non-dominated set for test problems.

However, Whitley (2001) identified a flaw in the use of EAs and thereby advised that a local search should first be conducted before adopting an EA. EA was described as a blind search method. The above discussion is only advantageous in providing a focus for possible applications of EAs in water resources practice around the world. Another research gap observed from these review is that there are no enough studies that provides detailed information about the outcome of a comparative analysis of the performance of different EAs in solving water resources problems effectively. The few comparative studies that had been published remain mostly qualitative and are often restricted to a few algorithms.

Also, climate change impacts on both crops production and irrigation water resources on a global scale and also in the Sub-Saharan Africa region was reviewed. Most of the countries in the arid and semi-arid regions depend mainly on precipitation and river water to sustain their crop production. As the overall water stress keeps increasing globally due to warming, it is imperative to put in place relevant adaptive measures. It was also predicted by Faramarzi *et al.* (2013) that most of these countries will experience reduction in both the frequency and the intensity of rainfall in the nearest future and the resultant effect will be droughts and floods. It was discovered that in the continent of Africa, changes in climate will lead to variability and decrease in both blue and green water resources. This will therefore have a negative impact on the agricultural and water resources sectors since over 70% of the agriculture is via irrigation (Mishra *et al.* 2013). It is expected to pose a great impact on crop production as well and this will put the local communities at a high risk because of their poverty level. Crop production can be increased by expanding the cultivated area or by intensifying irrigation measures (Schaldach *et al.* 2012).

Results from various studies examined have shown that the expansion of irrigated area strongly depends on the combination of socio-economic drivers and climate change. This is because the effect of land-use change on net irrigation water requirements is larger than that of climate change. The combined analysis of socio-economic and climate drivers shows that when irrigation areas are expanded, it has no correlation with changes in irrigation water requirements rather an adaptation to sowing dates in consonance with climatic conditions will help reduce seasonal water stress. Irrigation should be enhanced in Sub-Saharan Africa so as to sustain adequate food production for the bourgeoning population.

CHAPTER 3

MODELLING OF REFERENCE EVAPOTRANSPIRATION VARIABLES USING PRINCIPAL COMPONENT ANALYSIS AND FUZZY LOGIC TECHNIQUES

3.1 OVERVIEW

Adequate data pre-processing procedures are required for long-term historical meteorological parameters before using adopting them in the estimation of reference evapotranspiration (ET_o). In irrigation management, the correct estimation of ET_o is required. However, theoretically, there are some variables that must be considered while estimating and modeling ET_o. The objective of this chapter is to model and quantify the impact of ET_o variables at Vaalharts irrigation scheme (VIS) in South Africa using Principal Component Analysis (PCA) and adaptive neuro-fuzzy inference systems (ANFIS) techniques. This procedures seeks to reduce the information in the measured variables into a smaller set of components without losing important information. Weather and meteorological data between 1994 and 2014 were obtained both from South African Weather Service (SAWS) and Agricultural Research Council (ARC) in South Africa for this study. Average monthly data of minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), and wind speed (m/s) were the inputs to both PCA and ANFIS models, while ET_o is the output. PCA technique was adopted to extract the most important information from the dataset and also to analyze the linear relationship between the five variables and ET_o. This is to determine the most significant variables affecting ET_o estimation at VIS; which are further modeled using ANFIS.

3.2 INTRODUCTION

Evapotranspiration (ET) has been described as the second most important component in the hydrologic cycle. It replaces the vapor lost to the atmosphere through condensation, thereby aiding the continuity of rainfall within the cycle (Ramoelo *et al.* 2014). ET is a very important component of hydrology, agriculture, meteorology and climatology because it is required for minerals and nutrient transport for plant growth (Traore, Kerh and Gibson 2008). The estimation of ET in the arid and semi-arid regions are very difficult because there are limited datasets of the variables that make up ET. In many developing countries around the world, data is limited and scarce. Most times, it may be necessary to model the available measured variables to produce the desired parameters. Therefore, in this chapter, it became necessary to find the correlation between the variables in order to determine the most significant variables affecting the estimation and modeling of ET.

The ET rate from a reference surface is called the reference ET and denoted by ET_o. (Allen *et al.* 1989; Allen *et al.* 1998). Estimation of ET_o is vital to the sustainability of water resources management practices around the world. The FAO-56 method requires climatic variables such as sunshine hour, wind-speed, relative humidity, solar radiation, average temperature as inputs. A major limitation to the successful use of this FAO-56 equation in developing countries like South Africa is non-availability or limited data sets of these required variables. It is therefore important to develop simulation models as an alternative way of estimating ET_o. In the process of developing models for estimating ET_o, it is imperative to determine *a-priori* the correllation and relationship between the variables that makes up ET_o, hence, principal component analysis (PCA) is adopted in this study.

Principal component analysis (PCA) is a powerful tool that has been widely used for the multivariate analysis of correlated variables (Lee and Vanrolleghem 2004). PCA aims at extracting the most important information from the data set. Additionally, it is used to compress the size of the data set by keeping only the important information (Costa, Alves and Ferreira 2009). PCA rotates the original data space such that the axes of the new coordinate system point into the directions of highest variance of the data. The axes or new variables are termed principal components (PCs) and are ordered by variance. The first principal component (PC1) represents the direction of the highest variance of the data. The second principal component (PC2) accounts for most of the remaining variance under the constraint to be orthogonal to the preceding component, PC1(Lennox and Rosen 2002).

PCA has been widely used in soil and water research to classify soils and water characteristics and variables (Visconti, de Paz and Rubio 2009). PCA has been adopted by researchers to analyze correlated variables in irrigation schemes around the world. For example, PCA analysis was conducted by Visconti, de Paz and Rubio (2009) on thirteen chemical properties of soil saturation extracts in an irrigated Mediterranean area. A total of 139 soil samples extracted from 39 sites at Segura River lowland in Spain were analyzed. Three principal components with a variance of 76% were retained after the eigenvector extraction. PCA was adopted by Köksal (2011) to analyze the relationship between crop growth level and water use status in an irrigated experimental field located in Turkey. The PCA analysis of smoothed spectral reflectance and first-order derivative spectra was conducted. Two principal components with a variance of about 99.9% were retained.

Biglari and Sutherland (2015) presented a study on the use of PCA as a combustion model applied to a non-premixed temporally evolving jet flame with extinction and re-ignition. Jeong *et al.* (2015) applied PCA in a study to determine the characteristics of polyphenolic contents of lettuce leaves grown under different night-time temperatures and cultivation durations up to 20 days using high performance liquid chromatography-tandem mass spectrometry.

An adaptive neuro-fuzzy inference system (ANFIS) is based on the terms fuzzy set and fuzzy relation introduced by Lotfi Zadeh in 1965 (Zadeh 1965). FIS is the overall name for a system that uses fuzzy reasoning to map an input space to an output space. It is an effective mathematical tool used for dealing with uncertainty and handling imprecision of real world problems (Nasr *et al.* 2014). Moreover, it is an effective technique for data modeling and analysis without using complex analytical equations. The fuzzy theory provides a mechanism for representing linguistic constructs such as "many", "low", "medium", "often", and "few". FIS has found applications in several areas of technology such as, non-linear control, automatic control, signal processing, system identification, pattern recognition, time series prediction, data mining, financial applications (Fiter *et al.* 2005).

The use of ANFIS in water resources and evapotranspiration modeling has recorded a huge success. Katambara and Ndiritu (2009) adopted FIS to streamflow modeling of Lebaka River in South Africa. The technique gave a good result in the study Also, Shiri *et al.* (2013) adopted ANFIS to estimate reference evapotranspiration based on two weather data from Spain and Iran. The obtained results showed the capabilities of generalized ANFIS model in estimating ET_o in different climatic zones. Petković *et al.* (2015) conducted a study to know the most influential weather parameter on ET_o. Adaptive Fuzzy Interference System technique was applied to the full weather datasets for seven meteorological parameters obtained from twelve weather stations in Serbia between 1980 and 2010. Vijayalaksmi and Babu (2015) adopted FIS to forecast water supply system demand for Hogenakkal Water Supply in India. The technique gave a very good result.

Generally, FIS consists of four major parts: fuzzification interface, fuzzy rule base, fuzzy inference engine and defuzzification interface. ANFIS is composed of inputs, outputs and a set of inference rules. Each input and output can have multiple numbers of membership functions (MFs) (Lu, Huang and He 2011). AMF is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The purpose of fuzzification is to convert classical data or crisp data into fuzzy data using a set of input MFs. The IF-THEN rule statements are used to formulate the conditional statements that comprise fuzzy logic. Fuzzy rules are a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controlling an output(Nasr *et al.* 2015). Defuzzification is the last step in the fuzzy inference process, which is the process of transforming a fuzzy output into a crisp (Sanchez *et al.* 2001). These steps can be achieved using the GUI tool "Fuzzy Inference System (FIS) Editor" in MATLAB fuzzy logic toolbox (MATLAB 2002).

The main objectives of this chapter are therefore: (1) to determine how the five measured parameters affect the estimation of ET_o at VIS, and (2) to identify the most significant variables for the estimation of ET_o at VIS.

3.3 MATERIAL AND METHOD

3.3.1 Principal Component Analysis (PCA)

PCA shows the correlation structure of a data matrix X, approximating it by a matrix product of lower dimension (T × P'), called the principal components (PC), plus a matrix of residuals (E). This can be formulated in equation (3.1) below. The term $\left(1 \times \overline{x'}\right)$

represents the variable averages; the second term, the matrix product $\left(T \times P'\right)$, models the structure; and the third term, E, contains the deviations between the original values and the projections.

$$X = \left(1 \times \overline{x'}\right) + \left(T \times P'\right) + E \tag{3.1}$$

Where, T is a matrix of scores that summarizes the X-variables (scores), and P is a matrix of loadings showing the influence of the variables on each score. The correlation matrix is calculated from equation (3.2). After that, the eigenvectors and eigenvalues are estimated, and then the eigenvalues are sorted in descending order. The eigenvector with the highest eigenvalue (PC1) is the most dominant principle component of the data set. The second component (PC2) is computed under the constraint of being orthogonal to PC1 and to have the second largest variance. The functions pca and pcacov in MATLAB R2009b were used to perform the PCA and to estimate the variable loadings.

$$r_{x,y} = \frac{\sum_{i=1}^{n} (x_i - \mu_x)(y_i - \mu_y)}{(n-1)\sigma_x \sigma_y} \tag{3.2}$$

Where: where μ_x and μ_y are the sample means of X and Y; σ_x and σ_y are the sample standard deviations of X and Y.

3.3.2 Adaptive Neuro-Fuzzy Interference System (ANFIS)

The Fuzzy Logic Toolbox™ product in MATLAB R2009b was used for designing the system based on fuzzy logic. Initially, the relationship between the input and output variables were modeled by clustering the data. After that, fuzzy logic was employed to capture the broad categories identified during clustering into a FIS. The following steps were followed in designing the ANFIS system.

3.3.2.1 Clustering the Data

Clustering is normally used to identify natural groupings of data from a large data set so that the system's performance can be concisely represented. The function *subclust* in

MATLAB R2009b was chosen to implement a clustering technique called subtractive clustering. Subtractive clustering is a fast and one-pass algorithm used for estimating the number of clusters and the cluster centers in a dataset. Results from clustering are further used to build a fuzzy inference system.

3.3.2.2 Generating the Fuzzy Interactive System

The function genfis2 was applied for creating the FIS using subtractive clustering (*subclust)*. The function *genfis2* employs *subclust* behind the scenes to cluster the data and uses the cluster centers and their range of influences to build a FIS. The fuzzy inference was modeled by Sugeno integral as an aggregation operator. The AND method was prod (product), which scales the output fuzzy set. The function genfis2 constructs the FIS in an attempt to capture the position and influence of each cluster in the input space. The simulation procedure was established by creating m-file/ MATLAB software.

3.3.2.3 Defuzzification

In defuzzification, the fuzzy output set is converted to a crisp number. For Sugeno-style inference, the commonly used techniques for defuzzification are *wtaver* (weighted average) or *wtsum* (weighted sum). In the current study, the *wtaver* method was chosen. Suppose there are M rules and the fuzzified output is represented by w1, w2, ... ,wM and crisp output is represented by z1, z2, ...,zM, then final crisp output *wtaver*is given by the expression in equation (3.3):

$$z = \frac{\sum_{i=1}^{M} w_i z_i}{\sum_{i=1}^{M} w_i} \tag{3.3}$$

3.4 RESULTS AND DISCUSSION

3.4.1 Principal component analysis

In this chapter, PCA was first adopted on a correlation matrix of 5 variables in the system; these are: rainfall, minimum temperature, maximum temperature, relative humidity and wind speed. It was adopted as a pre-screening technique to find the multivariate analysis of the ET_o variables. Since the studied variables have different variances and units of measurements, the data set was standardized. This step was done by subtracting off the mean and dividing by the standard deviation. At the end of standardization process, each variable in the dataset is converted into a new variable with zero mean and unit standard deviation. The original and standardized variables are displayed in Figures 4 and 5 respectively.

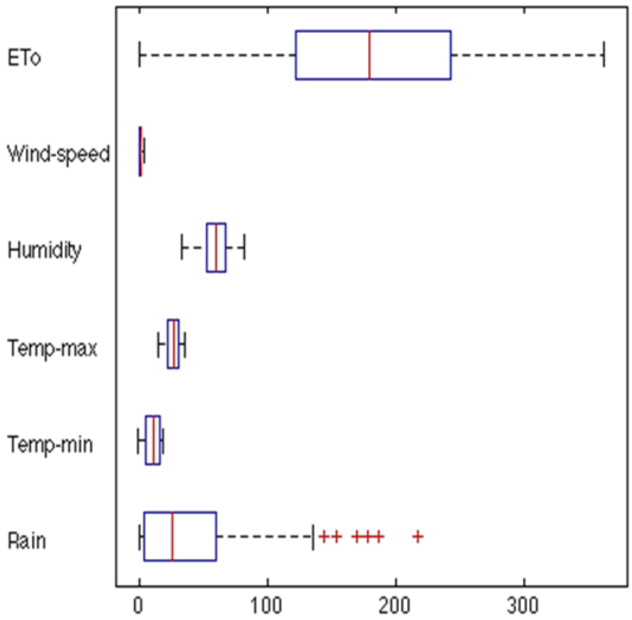

Figure 4: Original data distribution of the variables

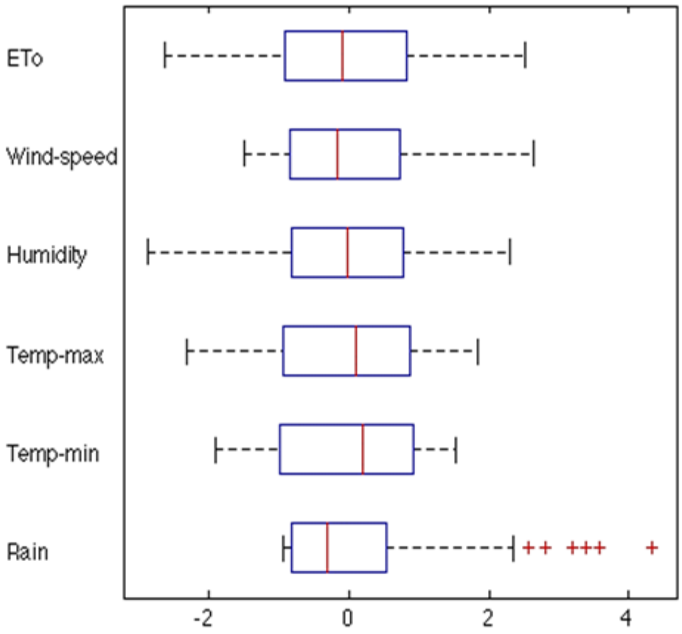

Figure 5: Data standardization (normalization)

The correlation between a variable and a PC is known as "loading". Loadings close to ± 1 indicate that the factor strongly affects the measured variable. Components represented by the high loadings can be taken into consideration in evaluating the system. In this study, loadings having an absolute value > 0.40 were considered for grouping.

As listed in Table 3, 82.67% of the information (variances) contained in the dataset were retained by the first two principal components (i.e. PC1 and PC2). However, each of the other remaining PCs has an eigen value lower than 1; thus only the first two PCs will be used in this study for interpretation.

Since PC1 has the highest total variance of 63.53% (Table 3), its parameters are the most important in estimating ET_o. The variables "minimum temperature", "maximum temperature", and "wind speed" have high loadings on PC1 with values of 0.47, 0.48, and 0.43, respectively. Those high loading variables are more important than other parameters. This indicates that PC1 increases with an increase in minimum temperature, maximum temperature, wind speed and ET_o. Those parameters are on the right side of PC1 (Figure 6). On the other side, rainfall and relative humidity have no role in explaining the variation in that PC since its absolute loading is lower than 0.4. Using the eigenvectors, the scores on PC1 can be computed as in equation (3.4).

$$PC1 = 0.25 \times \text{Rainfall} + 0.47 \times \text{Temp}_{min} + 0.48 \times \text{Temp}_{max} - 0.29 \times \text{Humidity}_{relative} + 0.43 \times \text{wind speed} \quad (3.4)$$

As listed in Table 3, PC2 explains about 19.14% of the total variance, accounting for the next highest variance. It is strongly correlated with rainfall and relative humidity with heavy loadings of 0.70 and 0.61, respectively (Figure 6). The scores on PC2 were estimated using the eigenvectors as in equation (3.5).

$$PC2 = 0.70 \times \text{Rainfall} + 0.28 \times \text{Temp}_{min} + 0.05 \times \text{Temp}_{max} + 0.61 \times \text{Humidity}_{relative} - 0.14 \times \text{wind speed} \quad (3.5)$$

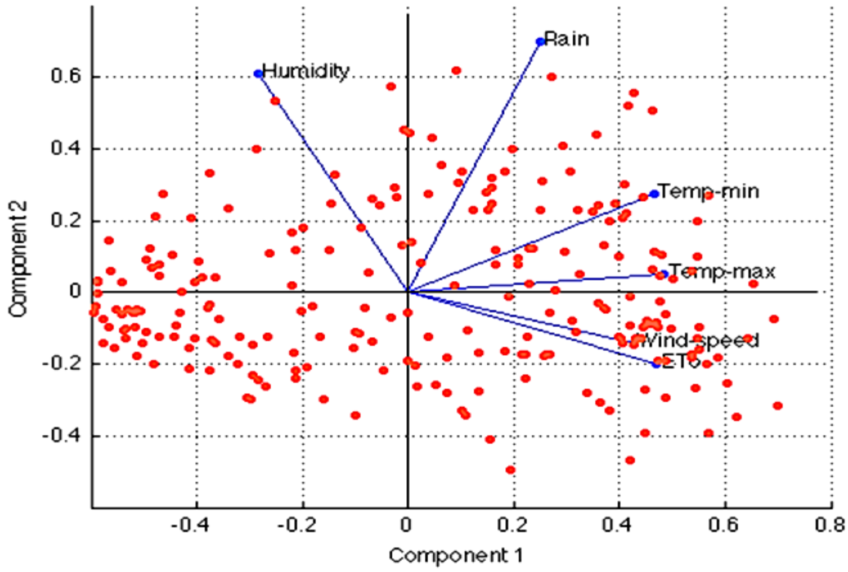

Figure 6: PCA loading plot of the dataset

Based on pre-screening using PCA, PC1 classified the measured data according to parameters that mostly affects ET_o.

Table 3: Loadings for the studied variables

VARIABLES	**LOADINGS**	
	PC1	**PC2**
Rainfall	0.25	0.70
Minimum temperature	0.47	0.28
Maximum temperature	0.48	0.05
Relative humidity	-0.29	0.61
Wind speed	0.43	-0.14
Eigenvalues	3.81	1.15
% variance	63.53	19.14
% Cumulative	63.53	82.67

3.4.2 Adaptive neuro-fuzzy inference system

ANFIS technique was also adopted as a post-screening technique to model the ET_o variables. ANFIS is a soft computing method, in which a given input–output data set is modeled. ANFIS uses a hybrid learning algorithm to tune the parameters of a Sugeno-type fuzzy inference system (FIS). The algorithm uses a combination of the least-squares and back-propagation gradient descent methods to model a data set. This was adopted as a comparative technique with PCA, to discover the most important variables in the estimation of ET_o at VIS. The five input variables were rainfall, minimum temperature, maximum temperature, relative humidity and wind speed, whereas the output variable to be predicted was ET_o.

The function *exhsrch* in MATLAB R2009b performs an exhaustive search within the available data to determine the one most influential input attribute in predicting the output. Essentially, the function *exhsrch* builds an ANFIS model for each combination, trains it for one epoch and reports the performance achieved. The exhaustive search operates by searching for the minimum training error for different permutations of inputs to the ANFIS. ANFIS uses a hybrid-learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the backpropagation gradient descent method for training ANFIS membership function parameters to emulate a given training data set. For building the ANFIS model, 70% of data is used for training process and 30% for checking set. The training argument stops if the designated epoch number is reached or the error goal is achieved, whichever comes first. The checking data are used for testing the generalization capability of the FIS, and monitor how well the model predicts the corresponding data set output values.

The current ANFIS model selected one input from five candidates, so that the total number of ANFIS models is C(5, 1) = 5. As presented in Figure 8, the left-most input variable had the least training and checking errors i.e. the most relevance with respect to the output (ET_o). Maximum temperature, wind speed, minimum temperature, relative humidity and rainfall have training root mean square errors (RMSE) of 26.9, 36.6, 43.8, 59.0 and 67.3, as well as checking errors of 24.6, 36.7, 47.4, 62.8 and 77.5, respectively (Figure 7). These results indicate that the three most important inputs affecting the ET_o

are in the order of maximum temperature > wind speed > minimum temperature. Those results were in accordance with pre-screening via PCA. Results from pre-screening indicated that inputs: minimum temperature, maximum temperature and wind speed have the most effect on ET_o. In a further analysis using surface fuzzy interference system, rainfall and humidity parameters will not be considered.

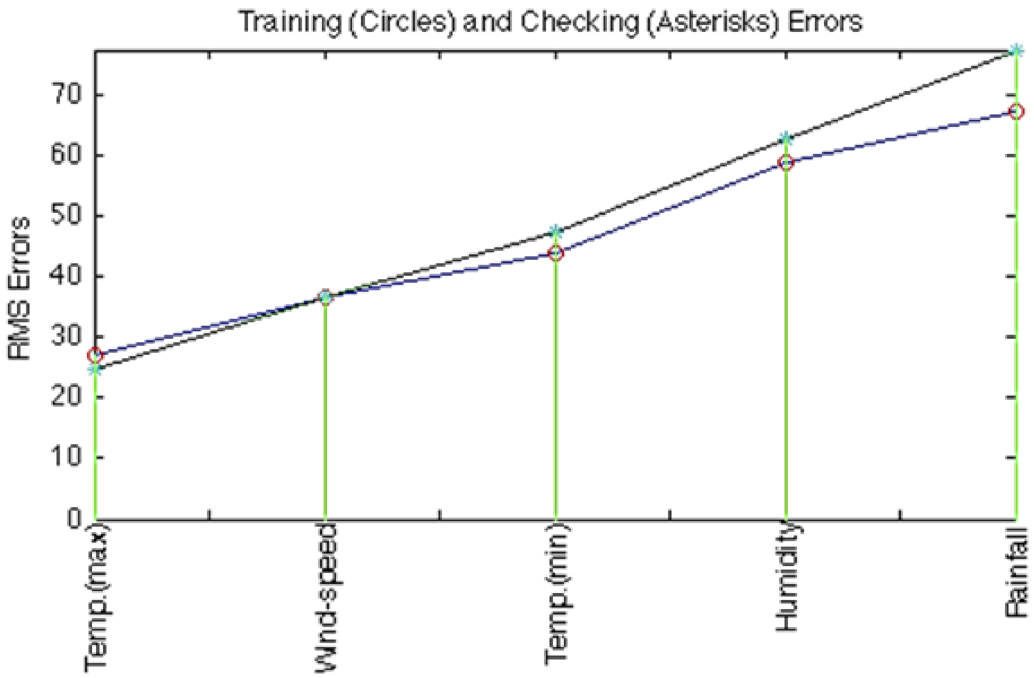

Figure 7: Influence of individual variables on ET_o.

3.4.2.1 Modeling using surface fuzzy inference system

In this step, parameters of minimum temperature, maximum temperature, wind speed and ET_o were modeled. The number of observations (samples) is 228. First, the model will initiate by clustering the data. The cluster centers will then be used as a basis to define a FIS. The variable C (containing the cluster values), which holds all the centers of the clusters that have been identified by *subclust.* Each row of C contains the position of a cluster. In this case, C has five rows accounting for five clusters. Additionally, the *subclust* has identified four columns that represent the positions of the clusters in each dimension.

Table 4: Clustering matrix results for variable C

3.8	21.0	0.6	109.7
15.8	31.1	2.0	238.2
13.3	26.8	1.2	156.8
7.5	25.5	2.2	213.8
14.9	32.3	3.4	298.0

The variable S (containing the sigma values), has four columns representing the influence of the cluster centers on each of the four dimensions. All cluster centers share the same set of sigma values.

Table 5: Sigma values of variable S

3.5	3.6	0.7	64.0

The function genfis2 constructs the FIS in an attempt to capture the position and influence of each cluster in the input space. Since the dataset has three input variables and one output variable, genfis2 constructs a FIS with three inputs and one output. The function subclust identified five clusters in the current dataset. Therefore each input and output will be characterized by five MFs. Also, the number of rules is equivalent to the number of clusters and hence five rules were created.

As listed in Table 6, the first MF of the first input (in1cluster1) is "gaussmf" (gaussian type membership function) and has the parameters [3.465 3.8], where 3.465 represents the spread coefficient of the gaussian curve and 3.8 represents the center of the gaussian curve. in1cluster1 captures the position and influence of the first cluster for the input variable population. (C(1,1) = 3.8, S(1) = 3.465).

Similarly, the position and influence of the other four clusters for the input variable "minimum temperature" are captured by the other four MFs in1cluster2, in1cluster3, in1cluster4 and in1cluster5. The other two input variables (maximum temperature and wind speed) follow the exact pattern mimicking the position and influence of the five clusters along their respective dimensions in the dataset.

The output of the FIS (i.e. ET_o) has five linear MFs representing the five clusters. The coefficients of the linear MFs are estimated from the dataset using least squares estimation technique. Those coefficients are listed in Table 2. All the five MFs are in the form a × Temp. (min) + b × Temp. (max) + c × wind speed + d

Table 6: Fuzzy linguistic set of input variables

Fuzzy linguistic sets of input variable "Minimum temperature" with universes of discourse [-0.2 19.4]					
MF name	in1cluster1	in1cluster2	in1cluster3	in1cluster4	in1cluster5
MF type	gaussmf	gaussmf	gaussmf	gaussmf	gaussmf
MF parameters	[3.465 3.8]	[3.465 15.8]	[3.465 13.3]	[3.465 7.5]	[3.465 14.9]
Fuzzy linguistic sets of input variable "Maximum temperature" with universes of discourse [15.5 35.7]					
MF name	in2cluster1	in2cluster2	in2cluster3	in2cluster4	in2cluster5
MF type	gaussmf	gaussmf	gaussmf	gaussmf	gaussmf
MF parameters	[3.571 21]	[3.571 31.1]	[3.571 26.8]	[3.571 25.5]	[3.571 32.3]
Fuzzy linguistic sets of input variable "Wind speed" with universes of discourse [0.2 3.9]					
MF name	in3cluster1	in3cluster2	in3cluster3	in3cluster4	in3cluster5
MF type	gaussmf	gaussmf	gaussmf	gaussmf	Gaussmf
MF parameters	[0.6541 0.6]	[0.6541 2]	[0.6541 1.2]	[0.6541 2.2]	[0.6541 3.4]
Fuzzy linguistic sets of input variable "ETo" with universes of discourse [0 361.9]					

MF name	out1cluster1	out1cluster2	out1cluster3	out1cluster4	out1cluster5
MF type	Linear	Linear	Linear	Linear	Linear
MF parameters	[-1.076 10.46 23.57 -112.8]	[-17.28 29.8 9.014 -429.7]	[1.363 13.72 40.71 -291.5]	[-5.127 21.82 -0.381 -318.2]	[-3.218 13.23 11.21 -131.4]

The response of the FIS is plotted against the inputs as a surface (Figure 8 to 10). This visualization is very helpful to understand how the system is going to behave for the entire range of values in the input space.

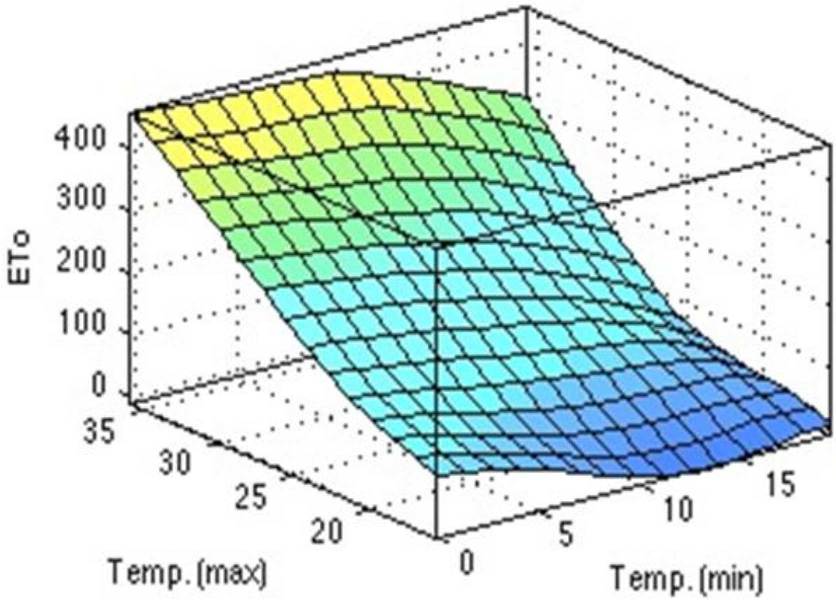

Figure 8: Surface view of maximum and minimum temperature against ET_o

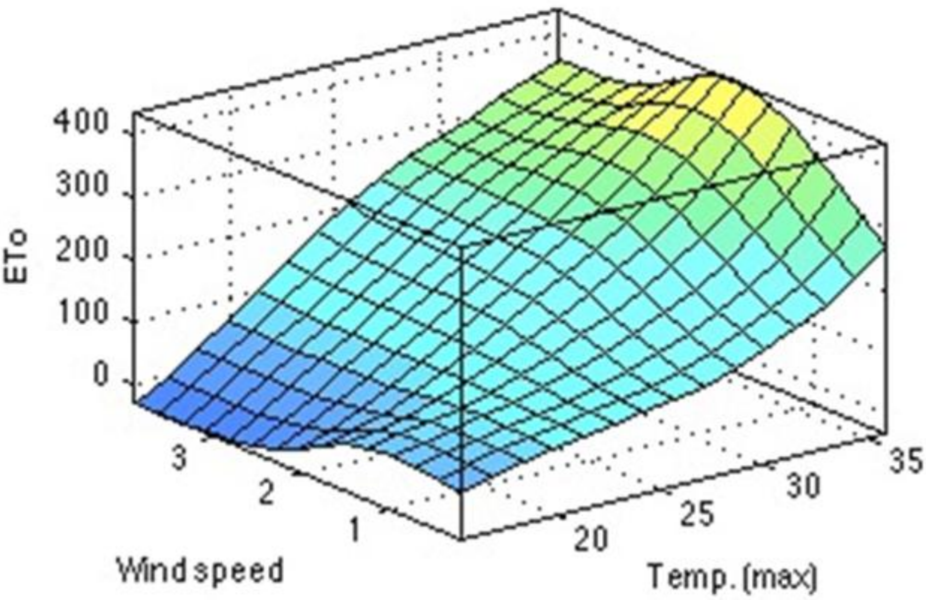

Figure 9: Surface view of windspeed and maximum temperature against ET_o

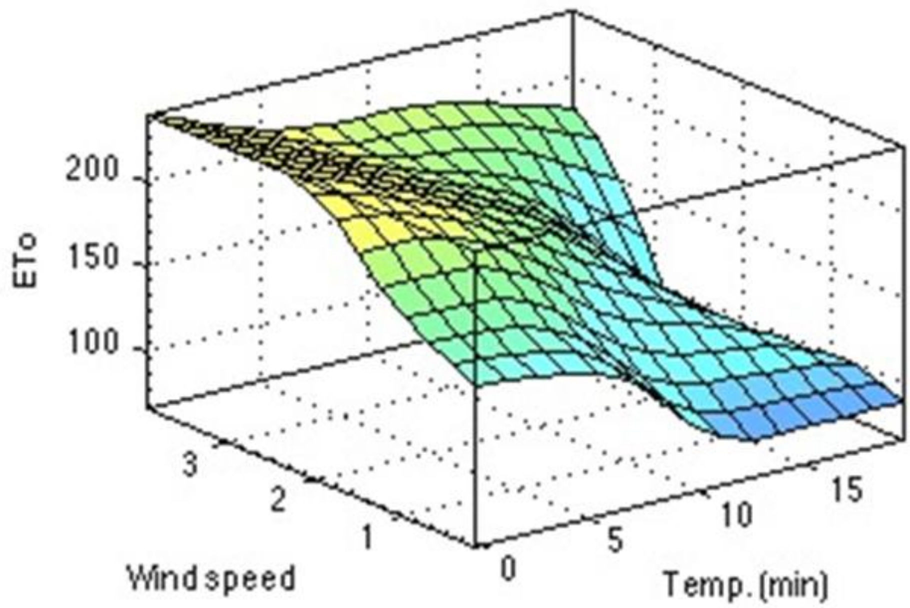

Figure 10: Surface view of windspeed and minimum temperature against ET_o

3.5 CONCLUSION

This chapter determines the multivariate analysis of correlated variables involved in the estimation of ET_o at VIS, South Africa using Principal Component Analysis (PCA) and ANFIS techniques. Six measured variables which are involved in the estimation of ET_o

were modeled and analyzed. From the PCA analysis (pre-screening), it was found that temperature (minimum and maximum) and wind speed are the most important variable in the estimation of ET_o. Other variables such as rainfall and relative humidity have less significance on the value of ET_o. Also in comparison with the ANFIS technique (post-screening), temperature (minimum and maximum) and wind speed are the most important variable in the estimation of ET_o.

Therefore, it can be concluded that out of all the variables considered, temperature (minimum and maximum) and wind speed are the most important variable in the estimation of ET_o at VIS. Their effect on ET_o is more pronounced than other variables. This simply infer that ET_o increases with temperature and windspeed.

CHAPTER 4

ARTIFICIAL NEURAL NETWORKS FOR PREDICTING REFERENCE EVAPOTRANSPIRATION IN VAALHARTS IRRIGATION SCHEME IN SOUTH AFRICA

4.1 OVERVIEW

Reference evapotranspiration (ET_o) is an important factor in irrigation planning and scheduling within an irrigated field. Variations in ET_o remains a major consequence of the complex, nonlinear and dynamic nature of weather and meteorological variables within and around an irrigation scheme (Gibson *et al.* 2013). The FAO-56 equation recommended and approved by the Food and Agriculture Organisation of the United Nations for estimating ET_o requires many climatic and meteorological variables, which are not fully available in developing countries like South Africa due to non-availability or limited data sets of the required measured variables. Thus, it becomes imperative to find alternative ways of estimating ET_o both on short term and long term basis. This chapter therefore develops and evaluates artificial neural network (ANN) models for predicting ET_o at Vaalharts irrigation scheme (VIS) in South Africa. Eight different ANN models, which were designed using feed-forward back propagation, were developed. Number of neurons and hidden layers of each model were varied for determining the optimum network structure that best soothes the prediction. Each model has five inputs and one output. The optimal model was discovered and then used to predict ET_o in the VIS.

4.2 INTRODUCTION

Evapotranspiration (ET) describes two processes of water loss from both land surface and leaves of plants into the atmosphere. These two processes are referred to as evaporation and transpiration respectively. Evaporation is the process where liquid water is converted to water vapor (vaporization) and removed from sources such as the soil surface, wet vegetation, pavement and water bodies (Ramoelo *et al.* 2014). Transpiration consists of the vaporization of liquid water within a plant and subsequent loss of water as vapor through leaf stomata (Wang, Traore and Kerh 2009).

ET has been described as the second most important component in the hydrological cycle, because it replaces the vapour lost to the atmosphere via condensation, thereby aiding the continuity of rainfall within the cycle (Ramoelo *et al.* 2014). ET is essential to hydrology, agriculture, meteorology and climatology because it is required for minerals and nutrient transport for plant growth (Traore, Kerh and Gibson 2008). ET is very difficult to estimate most especially in the arid and semi-arid regions, where plants are exposed to long term dry conditions and water stress because of challenges of limited or non-data availability. Factors that determine the estimation of ET include; climate, landscape heterogeneity, topography, climate, vegetation type, soil properties, management and environmental constraints (Rao *et al.* 2011; Ramoelo *et al.* 2014).

The evapotranspiration rate from a reference surface is called the reference ET and denoted as ET_o. "The reference surface is hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 sec m-1 and an albedo (reflectance of the crop-soil surface i.e. fraction of ground covered by vegetation) of 0.23, closely resembling the evapotranspiration from an extensive surface of green grass of uniform height, actively growing, well-watered, and completely shading the ground" (Allen *et al.* 1989; Allen *et al.* 1998). The grass is specifically defined as the reference crop. The crop coefficients (ET_C) of specific crops are multiplied with the values of ET_o to compute the actual ET at different growth stages of the crop.

Estimation of ET_o is vital to irrigation scheduling, terrestrial ecosystems, mass balance and water balance analysis (Tanasijevic *et al.* 2014) because irrigation engineers want to know how much of the supplied irrigation water is consumed by the crops; only then can they estimate, or calculate, the remaining components of the water balance. Also, the specific water requirements of a crop must be known in order to calculate the crop yield under prevailing irrigation conditions (Kisi 2011). According to Xiong et al. (2008), there are three groups of methods for estimating ET_o namely; water balance method, micrometeorological method and plant physiology method. Among these methods, micrometeorological method has gained a wide and popular application via the recommended and approved Penman-Monteith (PM) equation. The two other methods are regarded as traditional methods of estimating ET_o. However, the Food and Agriculture Organisation (FAO) of the United Nations, American Society of Engineers (ASCE) both approved the PM equation as one of the most accurate methods for estimating ET_o (Allen *et al.* 1989). It is popularly called FAO-56 equation and this method has the capacity to calculate ET_o at different time steps as decided by the user.

The FAO-56 equation requires climatic data such as sunshine hour, wind-speed, relative humidity, solar radiation, average temperature, soil heat flux density, saturation vapour pressure, actual vapour pressure, slope of the vapour pressure curve and psychrometric constant as inputs. A major limitation to the successful use of this FAO-56 equation in developing countries like South Africa is non-availability or limited data sets of the required parameters. Most of these input parameters are not readily available.

In order to solve the challenge of non-availability and limited data sets for calculating ET_o through FAO-56 equations, several data-driven models have been developed such as artificial neural networks (ANN). The use of ANN in modeling ET_o has been the interest of several researchers in recent years (Jain, Nayak and Sudheer 2008; Kim and Kim 2008; Kisi 2008; Kumar, Raghuwanshi and Singh 2009; Traore, Wang and Kerh 2009; Rao *et al.* 2011; Petković *et al.* 2015). Traore, Kerh and Gibson (2008) developed ANN models for the estimation of ET_o in Burkina Faso. In their study, Generalized Regression neural network (GRNN) was adopted because of its ability to model ET_o successfully. Minimum and maximum temperatures from 1996 to 2006 were the only available input variables to estimate ET_o via the developed model. Furthermore, a comparison was made concerning the performance of four different methods used for calculating ET_o, which are GRNN, RMBF, Hargreaves (HRG) and Blaney-Criddle (BCR) using the same datasets. The result of the study shows that using GRNN with minimum climatic data variables as input performs better than the other three methods in the estimation of ET_o.

Also, Masoud *et al.* (2013) used ANN to predict ET_o in the irrigation district of Hasanloo dam in Iran. The predicted output was used to calculate the irrigation water requirements for the scheme. Dataset for 21 years (1985-2005) were collected and used in the study. The input variables include: wind-speed, dry and wet temperature, air humidity, percent saturation humidity, air pressure, maximum and minimum daily temperature, and period of sunshine. Two types of ANN models were constructed, feed-forward back propagation and focused time-delay. Mean square error (MSE) statistical analysis was used to evaluate model performance in order to choose the best network among the two. It was concluded that feed-forward back propagation model was better for the prediction of ET_0.

Arif *et al.* (2012) also estimated ET_o using ANN for a paddy field in Indonesia. The model was calibrated using minimum, average and maximum temperature as input variables because other needed parameters were not available. From the result of the prediction model, soil moisture was further estimated through another ANN model. This shows the suitability of ANNs to predict ET_o in situations of unavailability of adequate meteorological data.

In a study conducted by Kisi (2011), ET_o was predicted via evolutionary artificial neural network (EANN). The ANN model was trained using DE, which is an EA. In the study, daily climatic weather data obtained from three weather stations in the United States were used to calibrate the model. After the model simulation, it was proved that neural networks have the capacity to model ET_o effectively.

The objective of this study is therefore to estimate ET_o from limited climatic data obtained from weather stations in VIS, South Africa using ANN models. A comparison is made among eight ANN models with different configurations. Model architecture is made up of different number of layers as well as neurons. Statistical methods are adopted to evaluate model performances by comparing the measured and predicted values of ET_o for each of the models. The optimal model will be selected and used to predict the monthly time step values of ET_o for year 2016.

4.3 MATERIAL AND METHOD

4.3.1 Artificial Neural Networks

In the last few decades, an alternative method for estimating ET_o is the use of artificial neural networks (ANNs). ANNs are non-linear data-driven networks which are opposed to the traditional model based methods. ANNs are computational intelligence method which was designed and inspired by the theory of neuroscience (Morimoto *et al.* 2007), hence, the name ‘neural’. ANNs are mathematical models based on the capabilities of the human brain to predict and classify problem domains. They have been widely adopted for predicting and forecasting in diverse fields of research such as finance, medicine, engineering and sciences and also to solve extraordinary range of problems (Maier and Dandy 2000). ANNs are specifically useful when the relationships between both input and output variables are discrete (Jha 2007).

ANNs became popular since 1986 when the back propagation training algorithm for feed forward networks was introduced (Maier *et al.* 2010). They possess a great feature that makes them alluring for solving nonlinear and complex problems. This is the adaptive nature, where the theory of ‘learning by example’ is adopted in solving problems. With this feature, ANNs can solve problems even when the user has little or no understanding of the problem to be solved. All it requires is a training data supplied to the network. After an ANN has been trained, it has the potential to predict the output of a new input data (Kisi 2006). This makes them so suitable and acceptable for modelling real-time water resources problems, which are mostly complex and non-linear (Abrahart *et al.* 2012). The structure of an artificial neural network is shown in Figure 11.

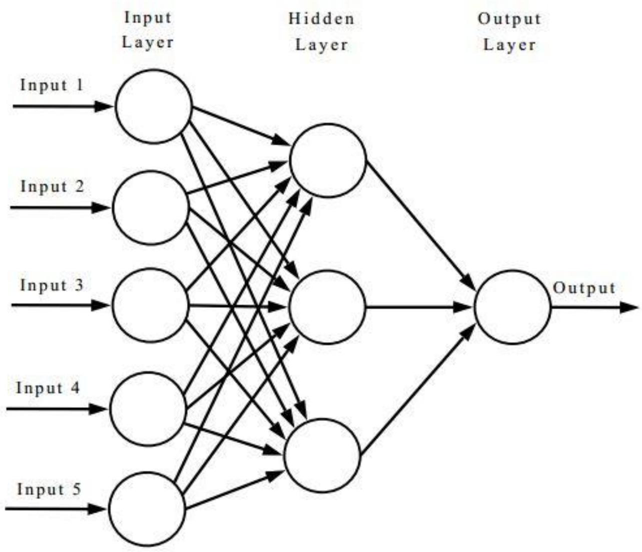

Figure 11: A typical neural network structure for 5 inputs, one hidden layer and one output.

ANNs perform well as a statistical and data analysis method because it was discovered that it improves model performance when adopted (Maier and Dandy 2000). They are also capable of predicting outcomes of an input set under time-series applications (Maier *et al.* 2010). ANNs are made up of a set of connected cells termed ‘neurons’.

The main function of these neurons is to receive impulse from other neurons or input cells and transform the impulse. The output is then transmitted to other neurons or to output cells (Oyebode and Adeyemo 2014). According to Jha (2007), the neuron is a real function of the input vector; while the output is obtained as a sigmoid (logistic or transient hyperbolic) function. The most important class of neural networks for solving real world problems are (i) Multilayer perception and (ii) Kohonen self-organizing features map (Jha 2007; Abrahart *et al.* 2012), while the two most widely used neural network architecture types include: feed-forward networks and recurrent or feedback networks (Maier and Dandy 2000).

In the feed-forward networks, the network connections do not form loops, while in feedback configuration; one or multiple loops can be formed. Abrahart *et al.* (2012) noted that layered network is the most common feed-forward network type, which involves the use of neurons are organized into layers with each layer connected to one another. In applying neural networks to predict or forecast water resources variables, the following steps must be followed in developing the model: (i) Variable selection (ii) Formation of training, testing and validation sets (iii) Neural network architecture (iv) Evaluation criteria (v) Neural network training (Maier and Dandy 2000; Jha 2007; Kisi 2008; Maier *et al.* 2010).

Several learning algorithms have been adopted in training ANNs. The popular ones include methods based on gradient descent such as back propagation (BP) algorithm, quick propagation (QP) algorithm and Levenberg Marquardt (LM) algorithm, and evolutionary-heuristic methods such as genetic algorithm (GA) and differential evolution (DE) algorithm (Traore, Kerh and Gibson 2008; Abdulkadir, Sule and Salami 2012; Dumedah, Walker and Chik 2014; Khanna, Piyush and Bhalla 2014).

The advantages of adopting neural networks models as outlined by Jha (2007) are numerous. These include (i) they exhibit mapping capabilities (ii) they learn by example. The NN architecture can be trained (iii) they have the capacity to generalize. They can predict new outcomes from an old trend (iv) They are robust systems and are fault tolerant. (v) They can possess information in parallel, at high speed and in a distributed manner. However, one major limitation to the use of ANN is in their inability to produce transparent models, because their internal operations are obscure and not interpretable. Other limitations are that the optimal network configuration for each modelling circumstance can differ (Abrahart *et al.* 2012), also, there are no standard or fixed rules for governing appropriate model design and development, thus making it impossible to establish a suitable model a priori; finally and most importantly, ANNs are highly susceptible to over-parameterization and over-fitting problems, especially when not properly put to use.

4.4 DESIGN AND PROGRAMMING OF ANN MODELS

In the design of ANN models, there are five basic steps to be followed as specified by Al Shamisi, Assi and Hejase (2011). These are: (1) collecting data, (2) pre-processing of data, (3) building the network, (4) training the network, and (5) test performance (evaluation) of model. Each of these steps will be described below as regards this study. Figure 12 presents a flow chart that describes the design process of an ANN model.

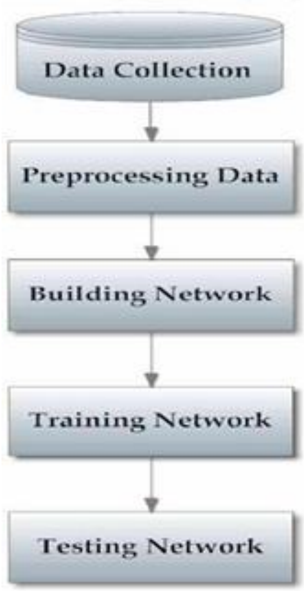

Figure12: Flow chart describing the design steps involved in ANN models (Al Shamisi, Assi and Hejase 2011)

4.4.1 Data Collection

In the design of ANN models, it is important to collect data for the model since ANNs are data-driven model techniques. In this study, measured average monthly data for six parameters were provided by the South African Weather Service (SAWS) and Agricultural Research Council (ARC). These data, which covers a period of 19 years (1994-2013) include: minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), windspeed (m/s) and ET_o (mm). Complete daily data of these measured variables were not available therefore, average monthly data was used for this study.

4.4.2 Pre-processing of data

After data collection, four data pre-processing procedures were conducted before training the model. The multivariate analysis was done on the dataset using PCA and ANFIS as reported in chapter 4 of this thesis. Furthermore, the dataset was also normalized and randomized. It is important to normalize the data before presenting them as input elements to the network. This is because if we mix variables with both small and large magnitude together, they may eventually confuse the learning algorithm and the aftermath may be a rejection of variables with small magnitudes within the network (Al Shamisi, Assi and Hejase 2011).

4.4.3 Building the Network

Different structures, with different number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function were selected. In this work, eight different models with different configurations of neurons and layers were designed (Table 7) to predict ET_o. This is to investigate the effects of different numbers of neurons and layers on the performance of the various models, and also to determine the optimal network architecture suitable for the prediction of ET_o. The actual numbers of hidden neurons were estimated based on trial and error. The feed-forward back propagation neural network type was adopted for all the models. From Table 7, it should be noted that models 1 to 5 were designed to show the effect of number of neurons on the network, while models 6 to 8 were designed to show the effect of number of hidden layers on ANN model performances.

Table 7: Configurations of the designed ANN models

Model No	Notation	No of input elements	No of hidden neurons	No of hidden layers
1	5-5-1	5	5	1
2	5-10-1	5	10	1
3	5-15-1	5	15	1
4	5-20-1	5	20	1
5	5-25-1	5	25	1
6	(5-15-1) * 2	5	15	2
7	(5-15-1) * 3	5	15	3
8	(5-15-1) * 4	5	15	4

For the model notations in Table 7, the first number indicates the number of input elements, middle number indicates the number of neurons and the last number represents the number of output elements. For example, model 1 with notation (5-5-1) comprises of 5 inputs, 5 neurons and 1 output. Model 6 with notation (5-15-1) * 2 comprises of 5 inputs, 15 neurons, 1 output and 2 layers.

4.4.4 Training the Network

This study adopted MATLAB tools in writing scripts that helps to develop the ANN models for the prediction of ET_o in VIS, South Africa. The input matrix consists of 228-column vectors of 5-variables, and the target matrix (output) consists of the corresponding 228- relative valuations. The Levenberg-Marquardt method (trainlm), which applies to small and medium-size networks, was used to train all the models. Thirteen years of data (1994-2006) which is 68% of the sample size was used for training the network. Logistic Sigmoid (tansig) transfer function was used for the network input and linear (purelin) for the output.

4.4.5 Testing and selection of optimum network architecture

In order to test the trained network, data for six years (2007-2012) was corresponds to 32% of the sample size was used for testing the network. Data for year 2014 was used to validate the network after it has been tested. The performances of the developed ANN models were evaluated by statistical model error parameters. The two statistical error parameters used in this study are Pearson coefficient of correlation (R) and the root mean square error (RMSE). RMSE provides the difference between predicted and observed values. The lower the RMSE, the more accurate is the estimation capacity of the developed model. Pearson correlation coefficient (R) indicates the strength and direction of a linear relationship between two variables (model output and observed values). It is obtained by dividing the covariance of the two variables by the product of their standard deviations. If we have a series *i* observations and *n* model values, then the Pearson correlation coefficient can be used to estimate the correlation between model and observations. The mathematical expression is given in equation (5.1).

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5.1}$$

The Root Mean Square Error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled.

The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error. Equation (5.2) shows the mathematical expression for RMSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})^2}{n}} \tag{5.2}$$

where X_{obs} is observed values and X_{model} is modeled values at time/place i. It should also be noted that the linear regression of target and predicted values produced by each of the eight models were also done.

4.5 RESULTS AND DISCUSSION

This chapter successfully demonstrated the development of models for predicting ET_o using ANN technique. Eight different models were developed to determine the effects of different configurations of neurons and layers on the prediction performance, as well as to determine the optimum network architecture. Table 8 lists the computed values of Pearson correlation coefficient (R) and root mean square (RMSE) for the eight developed ANN models considering different network structures.

From Table 8, it can be noted that the second model (2) with notation (5-10-1) is the best among all the investigated ANN models for predicting ET_o because it produced the lowest values of RMSE of 0.6mm/day with an acceptable R - value of 0.9692 respectively. This is true according to the assertions of Nasr *et al.* (2015) that ANN models with one hidden layer perform very well than multiple layers within its networks.

Table 8: Performance Statistics of the models in the validation period

Model No	Notation	No of hidden neurons	No of hidden layers	R	RMSE (mm/day)
1	5-5-1	5	1	0.9581	0.74
2	5-10-1	10	1	0.9692	0.62
3	5-15-1	15	1	0.9714	0.70
4	5-20-1	20	1	0.9517	0.76
5	5-25-1	25	1	0.9428	0.82
6	(5-15-1)*2	5	2	0.9396	0.91
7	(5-15-1) *3	5	3	0.9518	0.73
8	(5-15-1) *4	5	4	0.8678	1.19

Also, a consideration of the third model (3) with notation (5-15-1) shows a close range of good results as well. This model has five input elements, 15 neurons, one hidden layer and one output elements. It yields the highest values of R, which is 0.9714, and also a good value of RMSE, which is 0.7mm/day. In order to choose the optimal among these two top models (2 and 3), the recommendation of Kim and Kim (2008) was adopted. It states that the model with the lowest RMSE gives the best model performance. Hence, the second model (2) has been selected as the optimal model for predicting ET_o in this study.

The plot in Figure 13 shows the training process of the optimal model (2) for this study. It shows the magnitude of the gradient performance, number of validation checks and the best validation performance values. There are three criteria for training termination in ANN networks. Firstly, when the magnitude of the gradient is less than 1e-^{5}, secondly, when the number of validation checks reaches 6, and lastly, when validation increases and overfitting begins (Nasr and Zahran 2014).

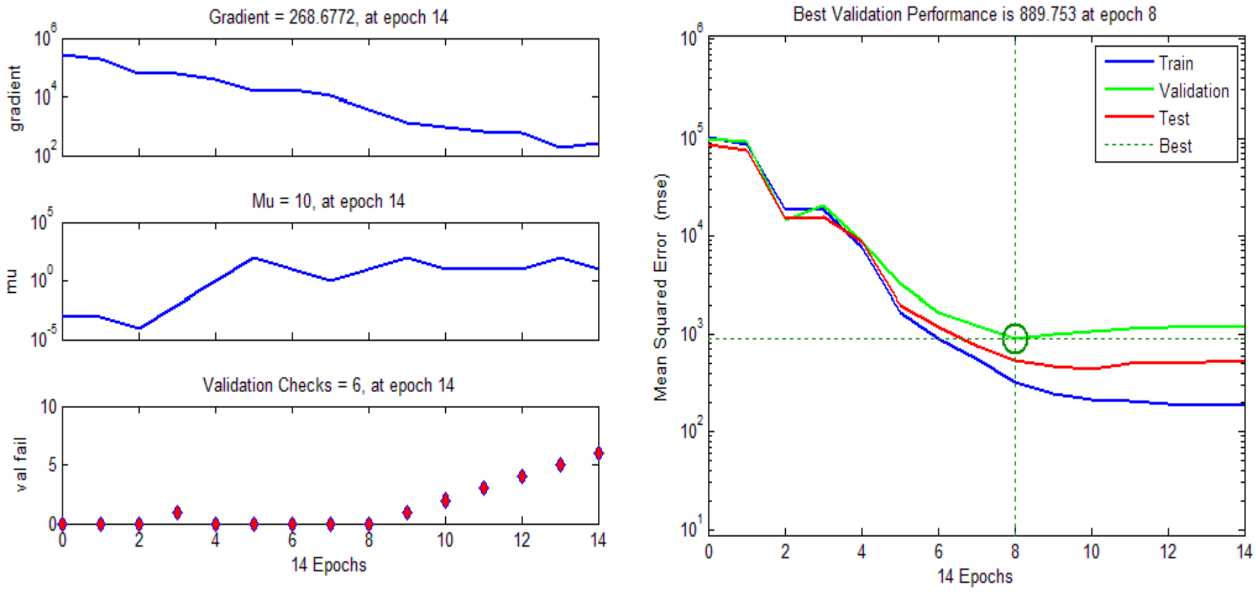

Figure 13: Training output values for the optimal model using MATLAB R2015a

The magnitude of the gradient of performance for the optimal model is 268.68 and the validation check is 6 (Figure 13). This shows that the training process was halted because the validation checks reached the optimal value of 6. Also, the plot of mean square error (MSE) versus the iteration number (epochs) are presented. The best validation performance was 889.75 at epoch 8 (Figure 13). After epoch 8, it was observed that the error on the validation set begins to rise typically, this shows that at this point, overfitting of the data has begun. Both the training and validation error decreased in the same trend until the epoch 8, where overfitting started, hence the training was stopped.

The regression plot for the optimal model is presented in Figure 14. It shows the correlation between the outputs and target values of the network under training. The dashed lines represent the best fit for the result, that is, output is equal to the target. The solid lines represent the best fit linear regression. It can be observed that the training, test and validation plots all have R values greater than 0.9. This indicates a good fit for all these datasets and it is similar to the result of Jain, Nayak and Sudheer (2008). The training plot gives R value of 0.9796, testing gives 0.9581, while validation plot gives R value of 0.905. It shows that all the data points in the optimal model have good fits.

Weights and bias of the optimal model (2) are shown below in matrix form. Weights from input 1 to layer 1 are as shown below:

$$\begin{bmatrix} 1.27286 & -1.45412 & 0.6225 & 0.8790 & -0.30278 \\ 0.5220 & 0.7142 & -1.112 & -1.0656 & -0.3575 \\ -0.9767 & 1.1754 & 0.7689 & -1.1273 & 0.7560 \\ 0.3138 & -0.2768 & 1.5582 & -0.5495 & 0.2538 \\ 1.1742 & 1.3288 & 0.4443 & -1.7891 & -0.8364 \\ -0.7182 & -1.2419 & 0.7638 & 0.8752 & -0.0954 \\ -0.9179 & -1.2272 & 0.6855 & 0.9334 & -0.5310 \\ 0.6672 & 1.6218 & -0.4421 & -0.6733 & 1.2506 \\ 1.7497 & 1.0566 & 0.5586 & 1.0358 & 1.0029 \\ 0.1877 & 0.6034 & -0.8169 & -0.2193 & 0.2725 \end{bmatrix}$$

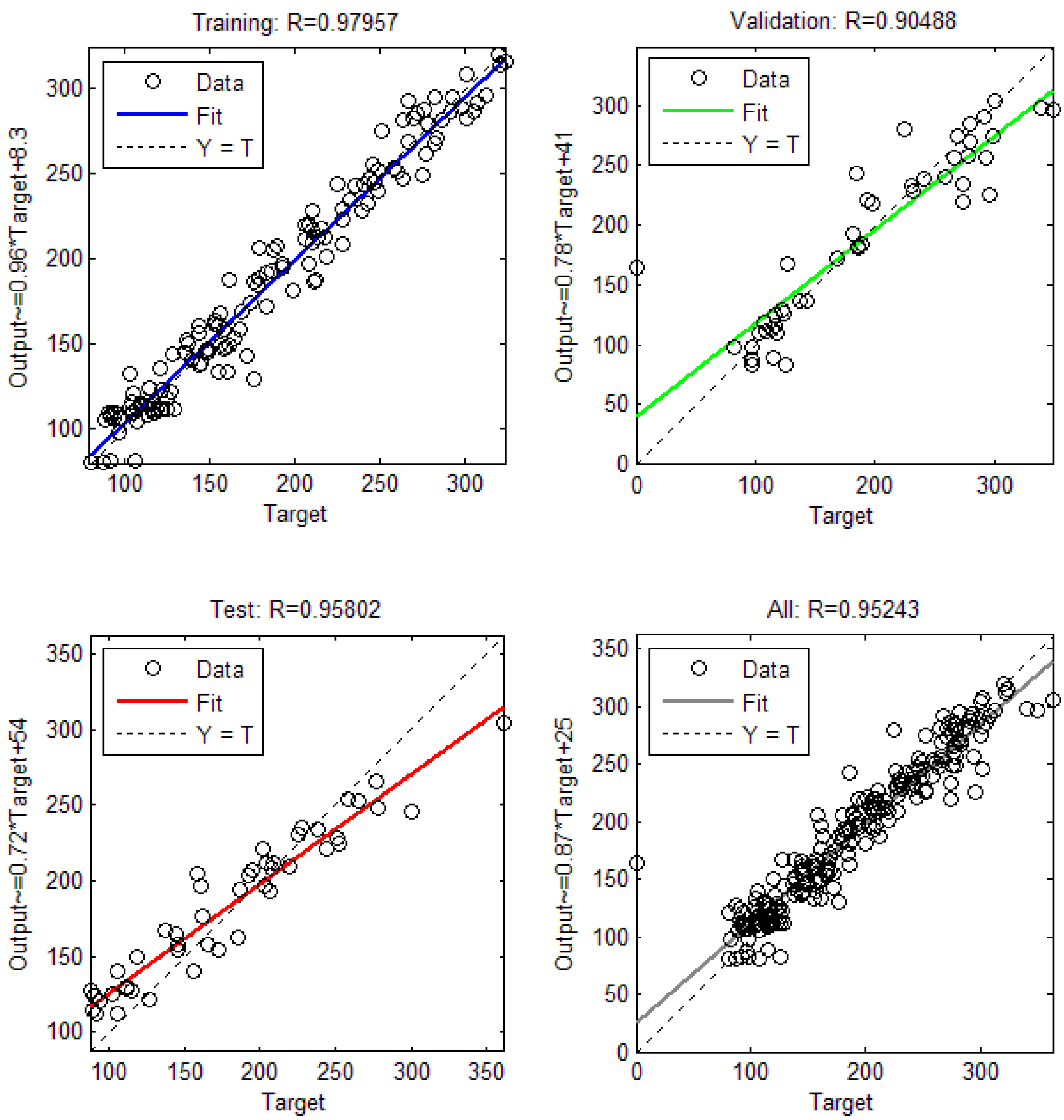

Figure 14: Regression plots for training, testing and validation datasets of the optimal model

ANN weights to output layer are as follows:

$$[0.4872 \quad 0.5204 \quad 0.2355 \quad 0.7182 \quad 0.0794 \quad 0.5798 \quad 0.1302 \quad 0.3209 \quad 0.0298 \quad 2.0698]$$

Bias to layer 1 is as follows:

$$\begin{bmatrix} -2.1527 \\ -2.3141 \\ 1.2664 \\ -0.6824 \\ -0.3995 \\ -0.0954 \\ -0.6371 \\ 0.6697 \\ 1.2575 \\ 2.9634 \end{bmatrix}$$

Bias to output is as follows:$[-0.9569]$.

A scatter plot of the measured and predicted values of ET_o for the optimal model (2) in the validation period (year 2014) is presented in Figure 15. The linear relationship with values of R^2 and the fit line equation of the model is presented. Since the R^2 value is 0.943, then the optimal model performed better in predicting ET_o in VIS, South Africa.

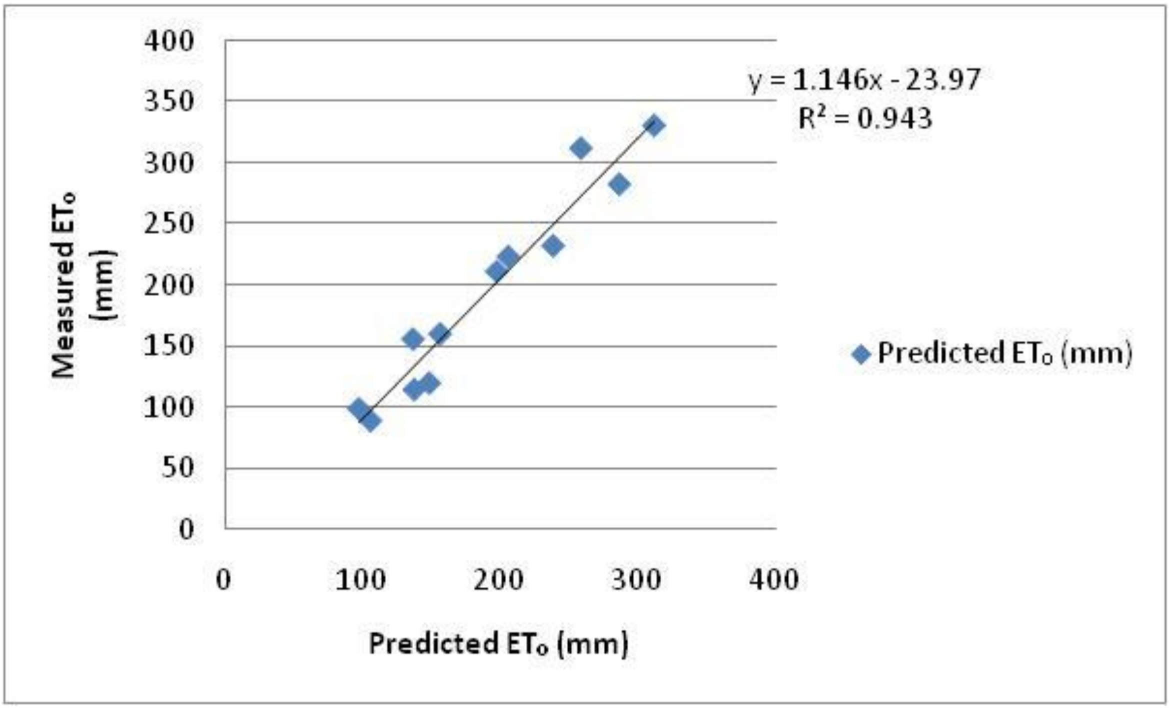

Figure 15: Measured and predicted monthly ET_o values in the validation period

Finally, the optimal model was used in predicting the monthly ET_o values for the year 2016, which is the end point of this chapter. The total monthly ET_o for year 2016 are presented in Table 9.

Table 9: Total Estimated Evapotranspiration for year 2016

Months	**Total ET_o (mm/month)**
January	304.10
February	216.8416
March	217.5064
April	174.0252
May	166.12
June	127.572
July	122.6774
August	134.274
September	129.4897
October	235.274
November	289.551
December	270.9449

4.6 CONCLUSION

This chapter explains the development of ANN models for prediction of ET_0 at Vaalharts irrigation scheme in South Africa. Eight different ANN models, which were designed using feed-forward back propagation, were developed. Number of neurons and hidden layers of each model were varied for determination of the optimum network structure. Each model has five inputs and one output.

The models are calibrated using weather and meteorological data between 1994 and 2013, which comprise of average monthly data of minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), wind speed (m/s) and ET_o (mm). 68% of the data sample was used for training the neural network models, while 32% of the sample was used for testing the network. Validation of the ANN models was done using the monthly data for year 2014. A major limitation in this study is the non-availability of daily values for these measured variables, therefore monthly average data was used for this study.

Two statistical procedures, Pearson correlation coefficient (R) and root mean square error (RMSE) were used in selecting the optimal model. The second model (2), with notation (5-10-1), which is made up of five inputs, 10 neurons and one hidden layer was selected as the optimal model that is best suitable for predicting ET_0 in this study. It is concluded that ANN models with a single hidden layer performs better than models with multiple layers in prediction problems. This is in consonance with the assertions of Abdulkadir, Sule and Salami (2012); Arif *et al.* (2012); Dumedah, Walker and Chik (2014); Nasr *et al.* (2015). In the next chapter, the predicted values of ET_o for year 2016 will be used as an input to a crop growth simulation model in order to determine daily crop water requirements and real-time soil moisture fluxes in this study area.

CHAPTER 5

REAL-TIME IRRIGATION SCHEDULING OF POTATOES IN VAALHARTS IRRIGATION SCHEME

5.0 OVERVIEW

Irrigation scheduling is a process of optimizing the use of water resources for irrigation purposes especially in the arid and semi-arid regions of the world. It is important to prevent wastage of water due to over-irrigation. South Africa, a country with low average annual rainfall, needs to minimize wasteful losses of water through evaporation, runoff and transpiration on the farm land, hence the need for irrigation scheduling. Scheduling involves the application of water to crops in the proper amount and at the appropriate time which will result in maximum crop yield and water use efficiency at the farm level. Irrigation uses about 60% of the fresh water in South Africa therefore, it is very necessary to determine the crop water requirement (CWR) of crops on the farmland before the commencement of irrigation water application. This chapter presents the outcome of a study involving the development of real-time irrigation scheduling of potatoes in Vaalharts irrigation scheme (VIS) in South Africa using a crop growth simulation model. The study involved the simulation of potatoes planted on a 100ha area of farmland at VIS using a novel 5-day irrigation schedule. The predicted monthly ET_o values for year 2016 (chapter 4) were inputs into a crop growth simulation model called CROPWAT. CROPWAT simulates the complex relationships of on-farm parameters of climate, soil and crop. The model was applied to simulate results of various water supply and irrigation management conditions. The study seeks to decipher knowing when to irrigate, i.e. the optimum stage in the drying cycle at which to apply water, and how much plant-available water the soil profile can hold.

5.1 INTRODUCTION

South Africa is the 30th driest nation in the whole world (Oyebode and Adeyemo 2014b) and hence, it is termed a ‘water stressed’ country. It is characterized by low average annual rainfall and falls within the semi-arid and arid region of the world. The current water demand is more than the available water for supply within the country.

The diverse uses of available water include: domestic, irrigation, industrial, recreation purposes and hydropower (Bieupoude, Azoumah and Neveu 2012).

Currently, South African government, in a report by the department of Water Affairs, stated that the sum of R700billion is needed to meet the country's growing demand for water (Crowley and van Vuuren 2013b). South Africa's water economy shows the typical characteristics of a mature water economy, which is characterized by a high and growing demand for water; intense competition for water between different sectors; environmental externality problems; a price inelastic, long-run supply of impounded water; and an increasingly expensive water supply projects (Statistics South Africa 2006).

According to a report by Nkondo *et al.* (2012), it was confirmed that Irrigation uses almost 60% of the consumptive water supply in South Africa. Therefore, there is need to optimize the available water resources in a judicious and beneficial manner. As a result of these, an optimization method or technique must be employed to effectively regulate and optimize the use of available water for irrigation purposes.

The optimal allocation of limited water resources for the planning and management of irrigated agriculture can be achieved by adopting computer-based models. Numerous simulation and optimization modeling approaches have been developed and used to solve the water allocation problems. The results derived from such studies have shown that optimization models have some deficiencies, but performs excellently when used in conjunction with simulation models (Singh 2014). The outcome of the combined use of these two approaches gives the best results.

5.1.1 Applications of Optimization models in irrigation scheduling

Diverse optimization methods have been adopted to prepare irrigation schedules around the world. For example, Saleem *et al.* (2013) proposed that a combination of crop water requirement (CWR) and local weather is useful in an optimization algorithm to compute an irrigation schedule. Among the optimization techniques employed for solving irrigation problems around the world are evolutionary algorithms. Evolutionary algorithms (EAs) go for discovery of the optima from a populace of solutions in parallel rather than from a single point. These gimmicks make them alluring for tending to complex design issues (Reddy and Kumar 2007).

Over the years, comprehensive studies have been conducted on the application of EAs for optimizing irrigation water allocation and scheduling. For example, Wardlaw and Bhaktikul (2004b) employed a genetic algorithm (GA) to the problem of irrigation scheduling and claimed better solution quality by scheduling supplies as close as possible to the Pareto front. Several other studies demonstrated the efficiency and the strength of GA approach as an optimization tool to provide good solutions for an irrigation scheduling problem.

Belaqziz *et al.* (2013a) propose a new methodology for irrigation scheduling optimization based on the stochastic search algorithm called Covariance Matrix Adaptation Evolution Strategy (CMA-ES) and applied it on the irrigation scheduling optimization of an irrigated sector located in the eastern part of the semi-arid Tensift plain in Morocco. The main objective of the study is to offer the irrigation managers a complete scheduling tool for irrigation rounds, including dates and times of opening and closing the canals to irrigate plots and the amount of water needed.

Azamathulla *et al.* (2008) conducted a study which involves the development and comparison of two models; a GA and Linear Programming (LP) to be applied to real-time reservoir operation in an existing Chiller reservoir system in Madhya Pradesh, India. The model was developed to obtain an optimal reservoir operating policy that incorporates field level decisions, while also deciding the appropriate time and amount of water to release from the reservoir. The GA model gives better yields when compared to the LP model. It was concluded that GAs are well suited to the solution of irrigation scheduling problems.

Also, Haq and Anwar (2014) applied GA to sequential irrigation scheduling problems. The study explores the potential of GA to solve large practical application problems. The rate, frequency and duration of water delivery are all fixed under the rotational irrigation schedule. Each farmer is supplied water at a specific period of time.

In the study, it was proved that delivery of irrigation water could be flexible distribution system and not fixed. The GA models performed well in sequential irrigation, it proved to be an efficient optimization tool especially for the contiguous irrigation scheduling problems.

According to Shang and Mao (2006), the limitations associated with optimization models when used for irrigation scheduling include; inability to give irrigation dates. All they can provide is the irrigation quota. A simulation model on the contrary, helps to simplify the changes in soil moisture and ET for the convenience of optimization.

5.1.2 Applications of Simulation models in irrigation scheduling

Simulation models on the other hand, include models of soil water balance, crop growth simulations and soil water dynamics. Simulation models are more advantageous because they provide an in-depth detail of the crop growth and ET. Simulation models are helpful to determine the effect of water stress on crop yield (Paredes *et al.* 2014). Several simulation models have been developed for the purpose of adequate irrigation scheduling operations around the world. Examples of simulation models applied to irrigation scheduling are model predictive control (MPC), developed and applied by Saleem *et al.* (2013). The system dynamics of MPC is based on water balance model which is used by many heuristic scheduling approaches. The MPC controller is designed for soil moisture deficit set-point tracking and also incorporates input and output constraints. Measured ET and precipitation data is used as an input into the model.

Also, AQUACROP is a crop growth simulation model developed by Food and Agricultural Organization (FAO). These models have been adopted by many researchers and produced excellent results. Paredes *et al.* (2014) applied AQUACROP to simulate the growth and crop water requirement of maize planted in Portugal. Another water balance simulation model used in irrigation scheduling operations is ISAREG.ISAREG is an irrigation scheduling simulation model that performs the soil water balance at the field scale. A detailed description of the model is given by Cai *et al.* (2009). It was applied to the irrigation schedule of wheat in Beijing, China.

A renowned simulation model is CROPWAT, which is a water balance model used to calculate crops and irrigation water requirements (Garg and Dadhich 2014). It was also designed by FAO, and approved for the design and management of irrigation schemes. It helps to plan irrigation schedules under different water supply conditions, either rain-fed or deficit irrigation (Kloss *et al.* 2012).

CROPWAT uses a daily soil-water balance to evaluate irrigation management practices and also develop irrigation schedules. The model is based on the FAO Irrigation and Drainage papers No. 56 "Crop evapotranspiration" and No. 33 "Yield response to water" (Popova and Pereira 2011). Calculations of the crop water requirements and irrigation requirements are carried out with inputs of climatic, crop and soil data. It has been adopted in irrigation scheduling operations and has produced great results too.

Furthermore, a simulation model was developed called *IrrigRotation*. It was developed by Rolim and Teixeira (2008). *IrrigRotation* is a soil water balance simulation model, which uses the dual crop coefficient methodology. It uses a daily time step in performing a continuous soil water balance simulation. This model overcomes the uncertainty of knowing the initial amount of water present in the soil profile at the beginning of the simulation. *IrrigRotation* has been tested in the Beja region, in Alentejo South of Portugal, and it provided irrigation requirements information based on the soil, crop, rotation scheme, climate and irrigation systems data.

5.1.3 Simulation-Optimization models in irrigation scheduling

When a combination of simulation and optimization techniques is adapted to irrigation scheduling problems, it overcomes all these limitations associated with either of the models. Some studies that adopted simulation - optimization of irrigation water allocation and planning are discussed below. Shang and Mao (2006) developed a simulation based optimization for the irrigation scheduling of winter wheat in North China. The aim of the model is to obtain a higher yield with limited volume of irrigation water application. It is also a model for irrigation timing. Wang and Cai (2009) uses Soil Water Atmosphere Plant (SWAT) model coupled with GA to prepare irrigation schedules for a corn plantation at Illinois. The study incorporated different types of weather forecast in preparing real-time irrigation scheduling. Kamble *et al.* (2013) used a combination of Soil-Water-Atmosphere-Plant (SWAP) simulation model and GA, an optimization technique to prepare an irrigation schedule for an irrigated cotton field in Netherlands.

The simulation-optimization approach proved that it has the potential to serve as an operational tool for irrigation scheduling purposes.Both studies were able to arrive at a viable irrigation schedules for their study areas.

5.1.4 Soil available water

The development of a proper rooting system and the uptake of the required amount of water from the soil are critical at every stage in plant growth (Kallestad *et al.* 2008). Too much or too little soil moisture can have direct effects on crop production. When the soil moisture exceeds the field capacity, it causes water logging in the soil and depresses oxidative processes in the root zone (Kamble *et al.* 2013). Field capacity (FC) is the soil moisture status after a saturated soil has been drained by gravity (Popova and Pereira 2011). On the other hand, if the soil moisture drops to a level below the permanent wilting point (PWP), then the rooting system cannot extract the moisture from the soil, because the soil is too dry. Hence, the available soil water (AW) is defined as: AW = FC-PWP (Isern, Abelló and Moreno 2012).

This chapter adopts a simulation approach for real-time optimal irrigation scheduling based on daily soil-water balance function. It provides a 5-day time-step irrigation schedule for potatoes in VIS, Northern Cape Province of South Africa. The optimization aspect of the study is presented in chapter six of this thesis.

5.2 MATERIAL AND METHOD

5.2.1 CROPWAT Simulation model

The predicted monthly ET_o values from the ANN network in chapter 4 of this thesis is one of the inputs into a crop growth and irrigation water simulation model called CROPWAT (Smith 1992). CROPWAT is a decision support tool (DSS) for estimating ET_C, soil moisture requirements for crops, yield losses under irrigation and rainfed conditions; and irrigation requirements for crops (Garg and Dadhich 2014). It was designed by FAO for the design and management of irrigation schemes. It helps to plan irrigation schedules under different water supply conditions, either rain-fed or deficit irrigation (Kloss *et al.* 2012).

CROPWAT uses a daily soil-water balance approach to evaluate irrigation management practices and also develop irrigation schedules. The model is based on the FAO Irrigation and Drainage papers No. 56 “Crop evapotranspiration” and No. 33 “Yield response to water” (Popova and Pereira 2011). Calculations of the crop water and irrigation requirements are carried out with inputs of climatic, crop and soil data.

According to Smith (1992), in order for CROPWAT to estimate crop water requirements (CWR), the model requires the following information or data; (a) ET_o values measured or predicted in real-time based on decade/monthly climatic data such as minimum and maximum air temperature, relative humidity, sunshine duration and windspeed (b) Rainfall data (daily/monthly/decade data) (c) Cropping pattern which consists of the planting date, crop coefficient data files (including Kc values, stage days, root depth, depletion fraction) and the area planted (0-100% of the total area).

For irrigation schedules, CROPWAT model requires information on: (a) soil type, total available soil moisture, maximum rooting depth, initial soil moisture depletion (% of total available moisture) (b) Scheduling criteria; several options can be selected regarding the calculation of application timing and application depth, or irrigate to return the soil back to field capacity when all the easily available moisture has been used. Marica (2012) gave a description of the formula used by CROPWAT model to calculate the CWR in equation (5.1).

$$CWR = ETo * Kc * area\,planted \tag{5.1}$$

Where Kc is the crop coefficient. This shows that the peak CWR in mm/day can be less than the peak ET_o value when less than 100% of the area is planted in the cropping pattern. Equation(5.2), which is given by Al-Najar (2011) calculates CWR as follows:

$$CWR = ETo * Kc - Pe \tag{5.2}$$

Where Pe is the effective rainfall. To calculate Pe, equation (5.3) is applied.

$$Pe = SF \times [0.70917 \times (Pr/25.4)^{0.82416} - 0.11556] \times 10^{0.000955\,ETc} \tag{5.3}$$

$$SF = 0.531747 + 0.295164\,(D/25.4) - 0.057697 \times (D/25.4)^2 + 0.003804 \times (D/25.4)^3 \quad (5.4)$$

Where D is the usable soil water storage (mm) and Pr is monthly rainfall (mm).

Total available soil water (TAM) is the maximum available water (mm) in the root zone of the crop while the readily available soil water (RAM) is the amount of water (mm) in the root zone that a plant can easily extract from the soil. Equation (5.5) gives the formula.

$$TAM = 1000\,(\theta FC - \theta WP)Zr(5)$$

$$RAM = \rho * TAM \quad (5.5)$$

Where $\theta FC$is the soil water content at fieldcapacity, $\theta WP$is the soil water content at wilting point, Zr is the root zone depth and ρ is the soil water depletion fraction.

Furthermore, CROPWAT adopts linear interpolation to estimate the average values of Kc in between each crop development stages within the growing season. The "Crop Kc" values are calculated as Kc * Crop Area, so if the crop covers only 50% of the area, the "Crop Kc" values will be half of the Kc values in the crop coefficient data file. In estimating the CWR, CROPWAT distributes the monthly total rainfall into equivalent daily values by using a continuous polynomial curve. The model also assumes that monthly rain falls into 6 rain storms, one every 5 days.

5.3 RESULTS AND DISCUSSION

In this chapter, real-time irrigation scheduling of potatoes was done in VIS, South Africa. The predicted monthly values of ET_o in chapter 4 was inserted into CROPWAT crop growth simulation model in conjunction with other required information such as rainfall data, cropping pattern, soil type and scheduling criteria.

Monthly rainfall, crop parameters and soil characteristics values were also inserted into the simulation model. Figure 16 shows the values of ET_o, rainfall and effective rainfall (Pe) for the year 2016, which is the planting year for this study. The planting date for potatoes on the farmland is 1st April, 2016 while the harvest date is 23rd August, 2016, making a total of 140 days.

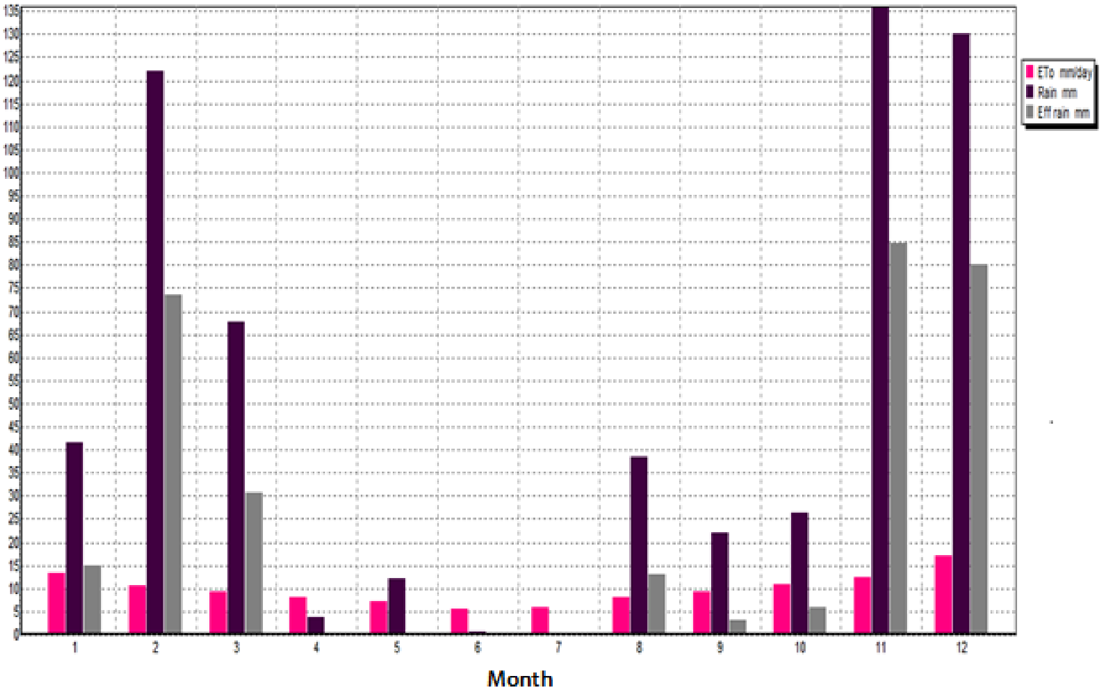

Figure 16: Values of ET_o, P*e* and Rainfall for year 2016

The soil type at VIS is described as Kalahari sand. It consists of mainly 75% sand, 15% clay and 10% silt (Ellington 2003). Table 10 presents the values of the crop water requirements and irrigation requirements calculated by CROPWAT decision support model.

Table10: Crop water requirement values

Month	**Decade**	**Stage**	**Kc coefficient**	**ETc (mm/day)**	**ETc (mm/day)**	**P*e* (mm/day)**	**Irrigation Requirement (mm/day)**
April	1	Initial	0.45	3.81	3.81	3.1	35.0
April	2	Initial	0.45	3.60	3.60	0.0	36.0
April	3	Initial	0.45	3.48	3.48	0.6	34.2
May	1	Deve	0.69	5.13	5.13	3.7	47.6
May	2	Deve	1.12	8.04	8.04	4.9	75.5
May	3	Deve	1.57	10.40	114.4	3.3	111.1
June	1	Mid	1.93	11.44	114.4	0.3	114.2
June	2	Mid	1.95	10.36	103.6	0.0	103.6
June	3	Mid	1.95	10.69	106.9	0.0	106.8
July	1	Mid	1.95	10.88	108.8	0.0	108.8
July	2	Mid	1.95	10.95	109.5	0.0	109.5
July	3	Late	1.87	11.94	131.3	0.1	131.2
August	1	Late	1.52	11.13	111.3	9.6	101.6
August	2	Late	1.17	9.45	94.5	14.4	80.1
August	3	Late	0.94	7.99	24.0	3.3	18.0

TOTAL					**1259.2**	**43.2**	**1213.2**

The growing period has been divided into stages of growth and the resultant crop coefficient (Kc) was multiplied by the ET_o values in order to calculate the value of crop evapotranspiration (ETc). A total value of 1259.2mm/day is the total crop evapotranspiration for the study. Also, the total irrigation requirement is 1213.2mm/day. This forms the CWR throughout the growing season. Figure 17 presents a graphical chart showing the values of ETc and Irrigation requirements.

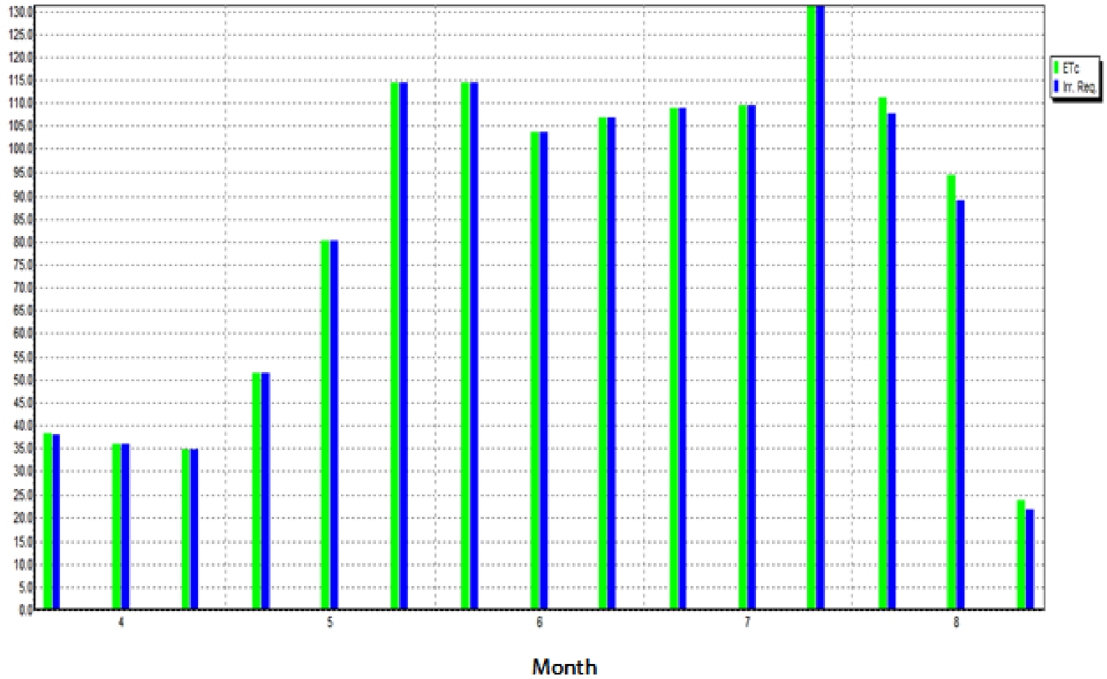

Figure 17: Values of ETc and irrigation requirement

From Figure 17, it can be observed that the values of ETc at the initial growth stage of potatoes are very low. This shows that potatoes require little amount of water at the initial growing stage and it increases gradually into the developmental stage and it is highest at the mid-stage of growth. CWR is at the optimal level during the mid-stage and the commencement of the late stage of growth. This is in consonance with the assertions of Jumman and Lecler (2009), that water are saved at the early stages of the crop growth cycle and also at the maturation and ripening stages. The resilience to water stress for the growth stages of potatoes have been identified by the model.

Figure 18 presents the values of depletion, RAM and TAM for this study. The depletion values are lowest at the initial stage of growth, and this increases as the crop grows. The depletion value is highest at the mid and late stages of growth with an average value of 38mm. This figure shows the soil water retention in the loamy clay soil present at the study area, it also shows the level at which the crop enters the wilting point, the amount of irrigation water to be applied per irrigation time that will bring the soil moisture to field capacity.

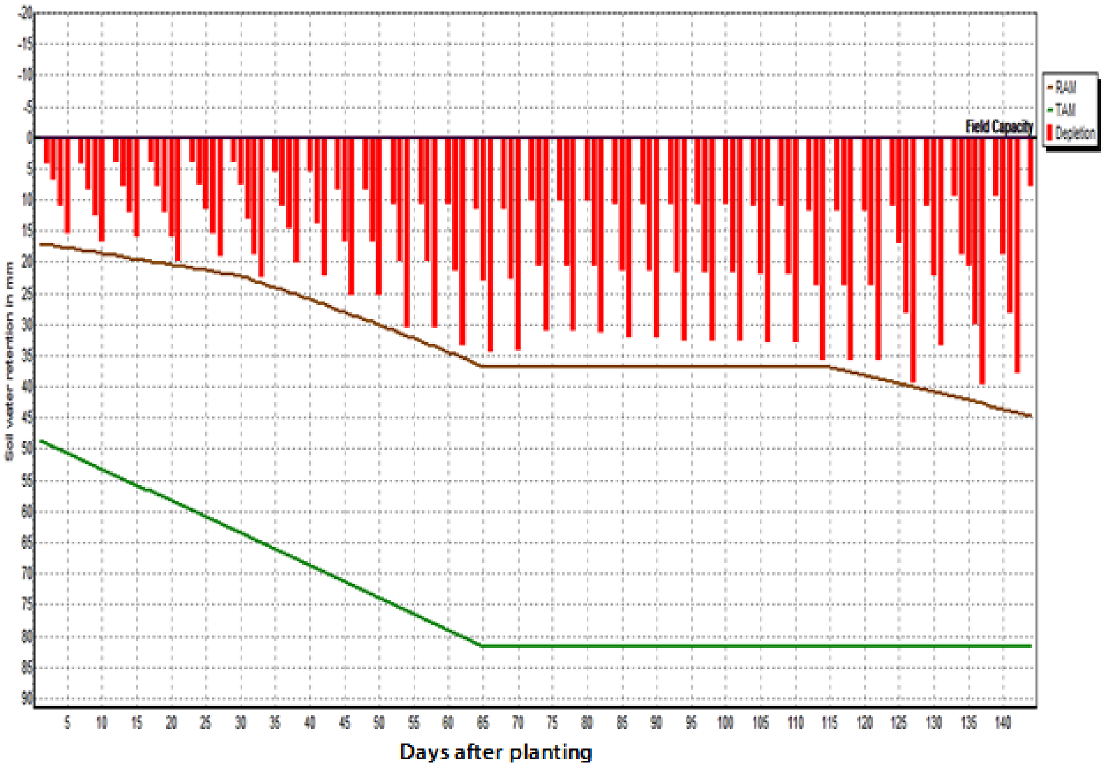

Figure 18: Irrigation schedule chart showing simulated **v**alues of RAM, TAW and depletion

The following are the summary of results obtained from the simulation operations: Total gross irrigation = 1824.2mm; Total net irrigation = 1276.9mm; Total rainfall = 48.2mm; Effective rainfall = 35.3mm; Total rainfall losses = 13mm; Actual water use by crop = 1248.5mm; Potential water use by crop = 1251.2mm; Actual irrigation requirement = 1215.9mm; Rainfall efficiency = 73.1%. The irrigation conditions are to irrigate at critical depletion and also refill soil to field capacity.

5.4 CONCLUSION

The real-time irrigation scheduling of potatoes is developed for VIS, South Africa. This is a study to determine the crop water requirement, irrigation water needs and irrigation schedules when potatoes are planted on an area of 100ha on the farmland within the irrigation scheme. Firstly, a real-time prediction of ET_o was done as advised by Safavi, Darzi and Mariño (2010); Popova and Pereira (2011) using ANN models. The result of the real-time ET_o was the input into a crop growth and simulation model called the CROPWAT model. This simulation model uses daily soil-water balance method to calculate the crop water requirements of the potatoes all through its planting season, which is between April 1st and 23rd August, 2016. It also helped in designing the irrigation schedules for the study. It was observed that the calculated total crop water needs of this study is 1259.2mm; net irrigation water requirement is 1276.9mm and this is spread over a 5-day irrigation time-step throughout the entire 140 days of cropping season. The outcome of this study provides a 5-day time step data and graphs on the status of soil moisture and irrigation water requirements, so that the farmer can be able to order water and irrigate appropriately. This accurate real-time irrigation scheduling system has allowed the farmer to make major water savings in order to prevent wastage of water resources in the farmland; which is a major objective of this study. Irrigation will only occur at the critical depletion point and refill is up to field capacity. Modeling results showed that estimated sowing; harvesting and irrigation application dates produced good estimates of crop evapotranspiration (ET_c) and soil moisture fluxes.

CHAPTER 6

OPTIMUM IRRIGATION WATER USEAND CROP YIELD USING COMBINED PARETO MULTI-OBJECTIVE DEIFFERENTIAL EVOLUTION

6.1 OVERVIEW

Adequate planning and management of water resources is highly essential in a water-stressed country like South Africa. Water policies that can aid the management and use of water in agricultural production with the aim of ensuring food security, employment opportunities as well as economic growth is of great value in ensuring sustainable use of freshwater. Without an iota of doubt, agricultural crop production is essential to societal development and economic growth in developing countries like South Africa, where the entire benefit, success and farming fortunes are proximately related. The first application of a novel combined Pareto multi-objective differential evolution (CPMDE) optimization algorithm for irrigation water use and crop yield management in a farmland in Vaalharts irrigation scheme (VIS), South Africa, is illustrated in this chapter. The main aim of this chapter is to demonstrate the first application of CPMDE to optimize crop yield under limited water availability while planting three different crop types on a farmland. The two objectives of the model are formulated to maximize total crop net benefit over a planting season while minimizing total irrigation water use. A set of non-dominated solutions with the high net benefits at lower irrigation water use and almost constant solution for the three crop types was obtained for the multi-objective optimization problem.

6.2 INTRODUCTION

South Africa, being a country with little rain, has been regarded as a water-stressed country (Oyebode, Adeyemo and Otieno 2014). This is the major reason why the freshwater resources of the country should be well managed for the long-term prosperity of the country. Low average rainfall has been the experience, and this has resulted in shortage of water supply because the demand is higher than supply. Also, one of the main responsibilities of government is to provide food security for its teeming population. This can only be achieved via irrigation, since rainfall events are very scarce in the country. Among the competing users of freshwater in South Africa, irrigation is the largest single user. It accounts for almost 60% of the annual available consumptive water in the country (Nkondo *et al.* 2012). Therefore, it is very important to optimize the water use for agricultural production, so that adequate productivity can be ensured. The available water must be scheduled in a way to avoid wastages due excessive irrigation water application, which will have an adverse effect on the crops and also the environment due to leaching of the nutrients within the soil profile. The optimal and judicious management of the country's freshwater resources serves as an entry point for this chapter.

Among South Africa's 70 million people, between 5 and 15 million South Africans lack basic food annually (Calzadilla *et al.* 2014). The primary aim of agricultural water resources management and crop production in any nation is to guarantee sufficient food resources for its entire population. Developing countries around the world have contributed notably to the population explosion globally (Singh 2014). World's population is expected to grow from approximately six billion in 1999 to between eight and eleven billion by 2050(USDA 2007).This increasing growth in human population has resulted in a higher demand for food and water resources (Oyebode, Adeyemo and Otieno 2014)

Despite this increase in population, the South African government has considered the agricultural sector strategic in food production, human survival, job creation and ensuring food security (SANTO 2013). Most commercial farmers in the country therefore depend solely on irrigation. The major dams in the region supply irrigation water to farmers at a price. Farmers buy water from Department of Water Affairs (DWA) which manages the dams and water resources in South Africa (Adeyemo and Otieno 2010b). Policies and strategies that can boost agricultural developing and productivity will help provide surplus food resources while simultaneously creating employment opportunities for the teeming population in the country.

Many studies have been undertaken to minimize the water use in agriculture especially irrigation water. In a report by DWA (2013a), it stated clearly that allocating water for use in the industrialized areas of South Africa rather than for irrigated agriculture, will, from an economic point of view, render higher returns. When water is allocated to industrialized areas at Gauteng, the economic gains are approximately 240 times more than those in the rural areas. Also, it implies that economically, it is better to allocate water to Gauteng (industrialized) economy rather than for irrigated agriculture. Furthermore, the report shows that when agricultural sector was considered economically, it was concluded that irrigation is an inefficient user of water in South Africa.

Irrigation, which is paramount for agricultural production uses more water to produce less output and also creates less employment per unit of water than any other sectors in the economy (Olofintoye 2015). This however does not imply that water should be taken away from irrigation, but rather that industrial activities should not be impeded by lack of water in favour of irrigated agriculture and also water should not be permanently allocated to less beneficial users to the possible future detriment of the economy (DWA 2013b). Therefore, policies that seek to minimize irrigation water uses and also maximize crop yield must be developed in the face of the water-stress challenge experienced by the agricultural water management sector in the country.

In optimizing irrigation water use, the objectives are conflicting in nature with many objectives that must be satisfied simultaneously. Therefore, irrigation water allocation is often handled in multi-objective framework to facilitate the development of suitable and sustainable strategies for practical implementation (Raju and Kumar 2004; Adeyemo and Otieno 2010b; Dai and Li 2013). Over the years, comprehensive studies have been conducted on the application of EAs for optimizing irrigation water allocation and scheduling and EAs have proved to be a very useful technique for deriving irrigation water schedules (Wardlaw and Bhaktikul 2004b, 2004a; Adeyemo, Otieno and Ndiritu 2008; Azamathulla *et al.* 2008; Mathur, Sharma and Pawde 2009; Casadesús *et al.* 2012; Belaqziz *et al.* 2013b; Kamble *et al.* 2013; Parsinejad *et al.* 2013; Haq and Anwar 2014).

A Genetic algorithm (GA) was developed by Wardlaw and Bhaktikul (2004a) to solve an irrigation scheduling problem. The objective of the study is to optimize the water use in an irrigation system fed on a rotational basis and this was applied to the Pugal branch canal in the Indira Ghandi Nahal Pariyonaja (IGNP) irrigation system located in North West India. Scheduling was based on a fixed amount of water demand within the constraints of canal system capacity alone, or by using soil moisture accounting models in determining water demands based on irrigation and hydro-meteorological conditions. The novelty in the work is developing a scheduling approach which combines both canal delivery scheduling with in-field soil moisture requirements. GA was combined with a deterministic soil moisture water balance model so as to make sure there is equal delivery of water throughout the various seasons within the irrigation canal systems. Under the canal scheduling modelling, the soil moisture was maintained between field capacity and wilting point while minimizing losses via drainage. Two approaches were considered in the GA formulations viz; 0-1 approach and the rotational approach, which is known as w*arabandi* in the indian subcontinent.

In the soil moisture modelling, a dual crop coefficient approach was adopted to account for water stress periods and resulting reductions in evapotranspiration. Water schedules were modelled under the soil water stress condition and non-stress condition; an appreciable comparison was made. The conclusion of their study is that GA produces feasible schedules under both the 0-1, and also *warabandi* approaches but a binary representation of canal water diversion periods is the most appropriate decision variable for the problem. The 0-1 approach provides a more efficient and equitable water use than the *warabandi* approach. GA proved to be capable of solving water scheduling problems including those which involves extreme conditions of water stress.

Recently, a new and novel EA algorithm called combined Pareto multi-objective differential evolution (CPMDE) algorithm was proposed by(Olofintoye, Adeyemo and Otieno 2014). The ability of CPMDE in solving unconstrained and constrained optimization problems was demonstrated and competitive results obtained from the benchmark and application of CPMDE suggest that it is a good alternative for solving real multi-objective optimization problems. This new algorithm was evaluated on tuneable problems by Adeyemo and Olofintoye (2014) and the only study where CPMDE algorithm had been used is the multi–objective optimization of an operating industrial wastewater treatment plant by Enitan *et al.* (2014).

This chapter presents the first application of CPMDE for the resolution of multi-objective crop yield and irrigation water use. The methodology is applied to a farmland in Vaalharts irrigation scheme (VIS), South Africa. The objectives of the model were formulated to maximize total net benefit of crops while minimizing irrigation water use. CPMDE was found useful in formulating sustainable policies pragmatic to the peculiar situation of managing the scarce freshwater resources for agricultural purposes in South Africa. Therefore, CPMDE is adoptable for solving irrigation water use problems.

6.3 METHODOLOGY

A new and novel evolutionary multi-objective algorithm called combined pareto multi-objective differential evolution (CPMDE) is proposed for solving multi-objective irrigation water use problems in this chapter. The algorithm combines methods of Pareto ranking and Pareto dominance selections to implement a novel generational selection scheme. The new scheme provides a systematic approach for controlling elitism of the population which results in the simultaneous creation of short solution vectors that are suitable for local search and long vectors suitable for global search. By incorporating combined Pareto procedures, CPMDE is able to adaptively balance exploitation of non-dominated solutions found with exploration of the search space. Thus, it is able to escape all local optima and converge to the global Pareto-optimal front. Results obtained from studies on the applications of CPMDE suggest it represents an improvement over the existing algorithm. Therefore, CPMDE presents a new tool that nations can adapt for the proper management of water resources towards the overall prosperity of their populace.

In CPMDE, boundary constraints are handled using the bounce-back strategy and this strategy replaces a vector that has exceeded one or more of its bounds by a valid vector that satisfies all boundary constraints(Olofintoye, Adeyemo and Otieno 2014). Major difference between the bounce-back strategy and random re-initialization is that the former takes the progress towards the optimum into account by selecting a parameter value that lies between the base vector parameter value and the bound being violated (Adeyemo and Olofintoye 2014). Equality and inequality constraints are handled using the constrained-domination technique suggested by (Deb 2001). DE/rand/1/bin variant of DE is used as the base for CPMDE. The CPMDE algorithm is summarized as follows (Olofintoye, Adeyemo and Otieno 2014):

1. Input the required DE parameters like number of individuals in the population (Np), mutation scale factor (F), crossover probability (Cr), maximum number of iterations/generations (gMax), number of objective functions (k), number of decision variables/parameters (D), upper and lower bounds of each variable, etc.
2. Initialize all solution vectors randomly within the limits of the variable bounds.
3. Set the generation counter, g =0
4. Generate a trial population of size Np using DE's mutation and crossover operations [26]
5. Perform a domination check on the combined trial and target population and mark all non-dominated solutions as "non-dominated" while marking others as "dominated".
6. Play domination tournament at each population index.
    i. If the trial solution is marked "non-dominated" and the target is marked "dominated" then the trial vector replaces the target vector.
    ii. If the trial solution is marked "dominated" and the target is marked "non-dominated" then the trial vector is discarded.
    iii. If both solutions are marked "dominated", then replace the target vector if it is dominated by the trial vector or if they are non-dominated with respect to each other.
    iv. If both vectors are marked "non-dominated", then note down the index and proceed to the next index. When all solutions marked "non-dominated" from steps i-iii above are installed in the next generation, then sort out all solutions noted in step iv one at a time using the harmonic average crowding distance measure [23]. The solution with a greater harmonic average distance is selected to proceed to the next generation.
7. Increase the generation counter, g, by 1. i.e. g = g+1.
8. If g <gMax, then go to step 4 above else go to step 9
9. Remove the dominated solutions in the last generation
10. Output the non-dominated solutions.

*Note domination checks are performed using the naive and slow method suggested by [27].

Source: (Olofintoye, Adeyemo and Otieno 2014)

6.3.1 Model formulation

The irrigation water use optimization problem in this study was conducted for a planting season at VIS. A farmland with an area of 1,000,000 m^2(100ha) and maximum water quota of 9140 m^3 per ha/annum was selected as a case study. Three different crops namely maize, groundnuts and potatoes are planted on the piece of land. In addition, an assumption that all the crops are not rainfed but rely solely on irrigation was adopted in this study. Formulation of the constrained multi-objective mathematical optimization problem follows.

6.3.1.1 Decision variables and objectives

The main aim of the study was to find the corresponding optimal crop mix and planting areas per crop while maximizing total net benefit (ZAR/m^2) and minimizing irrigation water use (m^3). The decision variable which represents the total net benefit is denoted by TNB_i (i = 1, 2, 3,) for maize, groundnuts and potatoes respectively. The objectives are formulated as follows:

Objective 1: Maximize total net benefits

Total net benefits (ZAR/m^2) is maximized to increase food production and employment on the farm. This has relative importance in terms of job creation and ensuring food security. Total net benefit is derived by multiplying the selling price (ZAR/ton) by the crop yield (ton/m^2).

Objective 2: Minimize irrigation water use

South Africa has been termed a water-stressed country and irrigation uses almost 60% of the available freshwater resources in the country (Adeyemo and Otieno 2010b; Nkondo *et al.* 2012), it is therefore pertinent to minimize irrigation water use. The multi-objective optimization equation for this problem which maximizes the total net benefit and minimizes total irrigation water use (WU) is presented in equation (6.1):

Maximize

$$TNB = \sum_{i=1}^{n}(Y_i * P_i * AR_i) - \sum_{i=1}^{n}(IN_i * AR_i * I_C)$$
$$+ \sum_{i=1}^{n}(AR_i * V_{Ci}) \cdots n = 3$$

Minimize $$WU = \sum_{i=1}^{n}(CWR_i \times AR_i)$$

Subject to

$$\sum_{i=1}^{n}(AR_i) \leq 1{,}000{,}000$$

$$100000 \leq AR_i \leq 700000$$

$$WU \leq 914000 \tag{6.1}$$

Where Y_i is the crop yield of the ith crop in (ton/m^2); P_i is the selling price of the ith crop in (ZAR/ton); AR_i is the planting area of the ith crop in (m^2); IN_i is the irrigation water need for the ith crop (ML/m^2); I_C is the irrigation or water cost (ZAR/ML) which is 8.77 cents/m^3 (Adeyemo and Otieno 2010a); V_C is the variable cost per m^2 for the ith crop (fertilizers, herbicides and sowing) (ZAR/m^2). *WU* is the total irrigation water use in (m^3) and CWR_i is the total annual estimated gross crop water requirements under flood irrigation, in (mm), for the ith crop, selected from Table 11.

6.3.1.2 Problem constraints

The bi-objectives mathematical crop yield optimization problem is subject to the following constraints:

Constraint 1: Total land area available.

The sum of areas AR_i where the crops are grown must not be greater than the total land area available for farming. This constraint is presented in equation (6.2):

$$A = \sum_{i=1}^{n} (AR_i) \leq 1{,}000{,}000 \quad (6.2)$$

Constraint 2: Minimum and maximum crop planting areas.

The minimum and maximum planting areas for each crop constitute the boundary constraints of the problem. Each crop is planted in at least 100000 $m^2$to avoid crop scarcity which may lead to hike in selling prices of food while the maximum planting areas ensure there will not be excessive surplus so that farmers will not have storage or selling problems(Adeyemo and Otieno 2010b). To compute the maximum crop planting areas, the following should be known:

Since the minimum planting area for each crop = 100,000 m^2, then the other 3 crops will occupy a minimum of (100,000 x 3) = 300,000 m^2. This leaves (1,000,000-300,000) = 700,000 m^2 as the maximum area available for a particular crop. Therefore, 700,000 m^2 is the maximum planting area for all the crops. The boundary constraint for the planting area is given in equation (6.3) as:

$$100000 \leq AR_i \leq 700000 \quad (6.3)$$

Table11: Total annual crop water requirement, yield and price for the three crops under consideration (Department of Agricultre 2013)

SN	**Crop**	**Yield (ton/ha)**	**Price (ZAR/ton)**	**Crop water requirement (mm)**
1	Maize	9.00	991.83	720
2	Ground nuts	4.50	2849.11	840
3	Potatoes	35.00	1744.00	1213

Constraint 3: Irrigation water release.

The amount of water available on the farm annually is limited by the amount of water released by the Department of Water Affairs. The volume of water supplied to VIS annually $0.914m^3/m^2$ ($9140m^3/ha$). Considering the $1,000,000m^2$(100ha) planting area considered for this study, therefore the maximum irrigation water release is $914,000m^3$of water annually. It is therefore required that total irrigation water use does not exceed the maximum that can be supplied by the feeder canal. This constraint is presented in equation (6.4):

$$WU \leq 914000 \tag{6.4}$$

6.3.2 Model solution and experimental setup

The mathematical model equations of the objective functions and the constraints listed in equations (6.1-6.5),for the constrained multi-objective crop yield optimization problem in this study were solved using a new and novel EMOA called CPMDE. The pseudo code for CPMDE by Olofintoye, Adeyemo and Otieno (2014) was encoded using visual basic for applications (VBA) to facilitate its application in resolving the crop yield optimization problem stated herein.

The population size for the algorithms was set at $N_p = 50$ as advised by Adeyemo, Bux and Otieno (2010)based on a study of the sensitivity analysis of DE algorithms. CPMDE algorithm was iterated for 1000 generations resulting in 50000 fitness computations, the crossover rate C_r was set at 0.95 while the mutation scaling factor F was set at 0.5 as advised by Storn and Price (1995) and Adeyemo and Otieno (2009c). DE/rand/1/bin variant of DE was implemented and the harmonic average distance for maintaining spread of solutions on the Pareto front of CPMDE was computed using the 2-nearest neighbours scheme.

6.3.3 Selecting the best compromise solution

The solution of multi-objective optimization problems (MOOP) results in a set of non-inferior solutions which are Pareto optimal solutions. No solution in this set can be considered better than any other in the absence of specialized information about the peculiarities of the problem at hand.

However, it is important that the decision maker chooses only one solution for final implementation. Compromise programming approach (CPA) is the recommended technique in making a final decision regarding a suitable operating policy concerning the problem being solved (Deb, Mohan and Mishra 2003). CPA picks a solution which is minimally located from a given reference point. In this study, the reference point is chosen as the ideal point which comprises the best of each of the m objectives. The best compromise solution (BCS) is the solution with a minimum lp-metric distance from a reference point z. l_p-metric is computed using equation (6.5). When p=2, the $l_2$metric specifies the Euclidean distance metric (Deb 2001; Olofintoye, Adeyemo and Otieno 2014).

$$l_p - metric: d(f, z) = \left(\sum_{m=1}^{M} \left| f_m(x) - z_m \right|^p \right)^{\frac{1}{p}} \quad \cdots \qquad (6.5)$$

The visual basic coded CPMDE helped in computing the Euclidean distance. The overall results for the 50 population solutions are presented in Table 12.

6.4 RESULTS AND DISCUSSION

The multi-objective crop yield problem of maximizing total net benefit while minimizing irrigation water use in a farmland in VIS was solved using CPMDE. Figure 19 presents the Pareto front obtained by CPMDE and the BCS which represents the 18th solution is indicated on this figure. Table 12 presents the details of the Pareto solutions obtained from the best run of CPMDE. Figure 20 presents the objective values for the final non-dominated solutions obtained in the best run of CPMDE while Figure 21 presents the corresponding planting areas for the three crops in the non-dominated solutions using CPMDE. Figure 22 presents the total crop planting areas for the three crops which form the BCS (solution 18) obtained by CPMDE.

The BCS is marked with boldface in Table 12.

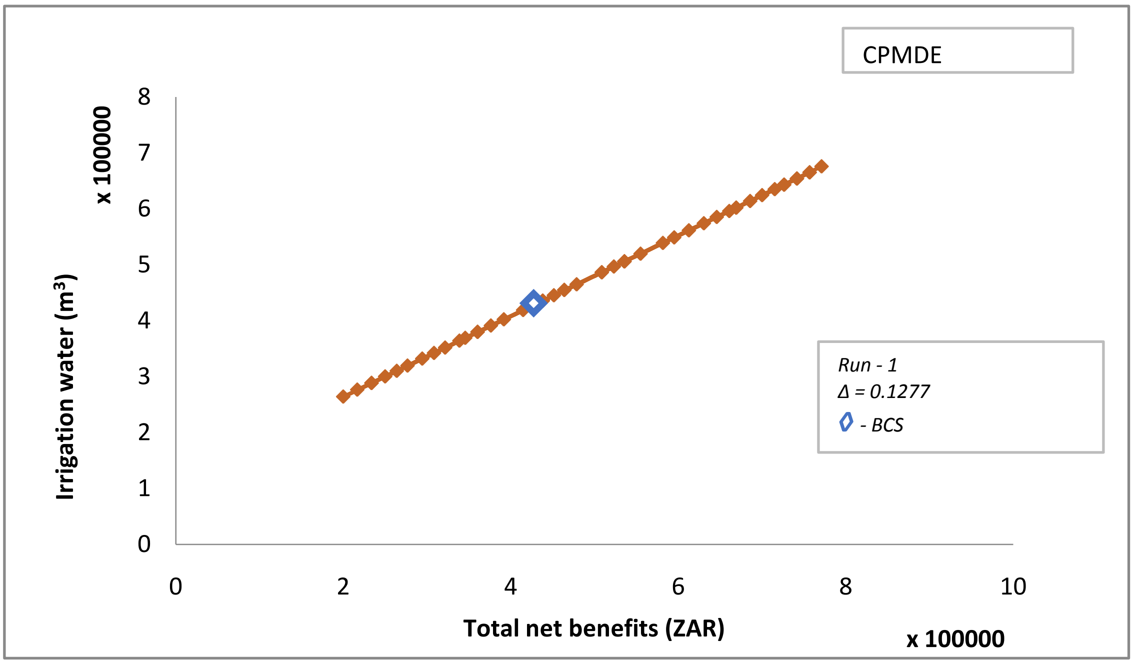

Figure 19: Pareto front obtained by CPMDE for the crop yield model when maximizing total net benefits and minimizing irrigation water.

Table 12: Details of Pareto solutions for the crop yield model when maximizing total net benefits and minimizing irrigation water.

Solution	Land area for each crop (m^2)			Total land area (m^2)	Total net benefits (ZAR)	Total Water Irrigation water (m^3)
	Maize	Ground nut	Potatoes			
1	619253.17	51324.00	50043.23	720620.4	770996.6	675774.56
2	443809.45	51250.65	50012.78	545072.88	595089.41	548648.09
3	263288.52	51384.23	50025.56	364698.31	414733.47	418843.99
4	494619.55	51237.45	50013.35	595870.35	645898.45	585243.51
5	431572.01	50000.12	50000.17	531572.3	581605.39	538795.78
6	404934.20	50000.08	50000.07	504934.35	554936.06	519556.11
7	240989.17	50716.77	50020.97	341726.91	391734.24	402166.12
8	225491.95	50736.05	50035.36	326263.36	376276.58	391061.52
9	564983.99	50059.44	50050.27	665093.7	715107.29	634954.97
10	50000.00	50000.00	50000.00	150000	200000	264000
11	*327374.44*	*51208.06*	*50011.84*	428594.34	478616.34	464787.92
12	518901.46	50081.48	50036.61	619019.55	669091.34	601881.23
13	209470.20	50805.84	50050.00	310326.04	360390.07	379708.38
14	276306.54	50000.00	50048.03	376354.57	426360.44	427038.43
15	358162.37	50476.59	50004.83	458643.79	508644	486286.34
16	385586.77	50000.00	50058.66	485645.43	535687.04	505807.95
17	288033.99	50079.64	50013.63	388127.26	438152.61	435524.58
18*	**403543.44**	**181542.00**	**352876.05**	**937961.49**	**767961.49**	**391061.52**
19	576191.58	50068.03	50015.33	676274.94	726306.35	643002.99
20	312049.94	51368.54	50057.74	413476.22	463880.77	454706.2
21	605562.30	51178.53	50021.57	706762.4	756763.86	665036.46
22	83574.58	50154.95	50022.58	183752.11	233766.98	288373.05
23	591597.23	50004.39	50002.97	691604.59	741619.77	653988.18
24	100001.18	50005.70	50018.62	200025.5	250035.21	300057.8
25	187372.62	51320.00	50010.24	288702.86	338709.34	364047.96
26	373036.76	50024.49	50000.41	473061.66	523065.65	496615.44
27	480428.07	50005.27	50016.68	580450.02	630467.28	573975.81
28	194280.14	51347.82	50012.82	295640.78	345643.19	369041.59
29	158328.57	50003.63	50019.89	258352.09	308367.19	342064.42
30	65267.70	51248.34	50070.55	166586.59	216734.97	276453.23
31	510584.81	50207.18	50008.64	610800.63	660831.56	595870.03
32	300765.30	50667.12	50027.85	401460.27	451471.68	445183.43
33	461082.53	51457.16	50025.57	562565.26	612609.75	561334.88
34	171296.51	50333.63	50014.96	271645.1	321645.54	351641.51
35	549821.15	50001.68	50012.48	649835.31	700013.28	624236.8
36	576191.58	50068.03	50015.33	676274.94	726306.35	643002.99
37	312049.94	51368.54	50057.74	413476.22	463880.77	454706.2
38	605562.30	51178.53	50021.57	706762.4	756763.86	665036.46
39	83574.58	50154.95	50022.58	183752.11	233766.98	288373.05
40	591597.23	50004.39	50002.97	691604.59	741619.77	653988.18
41	518901.46	50081.48	50036.61	619019.55	669091.34	601881.23
42	209470.20	50805.84	50050.00	310326.04	360390.07	379708.38
43	276306.54	50000.00	50048.03	376354.57	426360.44	427038.43
44	358162.37	50476.59	50004.83	458643.79	508644	486286.34
45	385586.77	50000.00	50058.66	485645.43	535687.04	505807.95
46	288033.99	50079.64	50013.63	388127.26	438152.61	435524.58
47	144318.15	50002.15	50000.01	244320.31	294323.91	331917.81
48	535676.52	50052.67	50003.21	635732.4	685738.86	613749.51
49	113816.22	50061.33	50023.77	213901.32	263902.92	310045.06
50	125527.36	51177.46	50013.92	226718.74	276727.44	319410.54

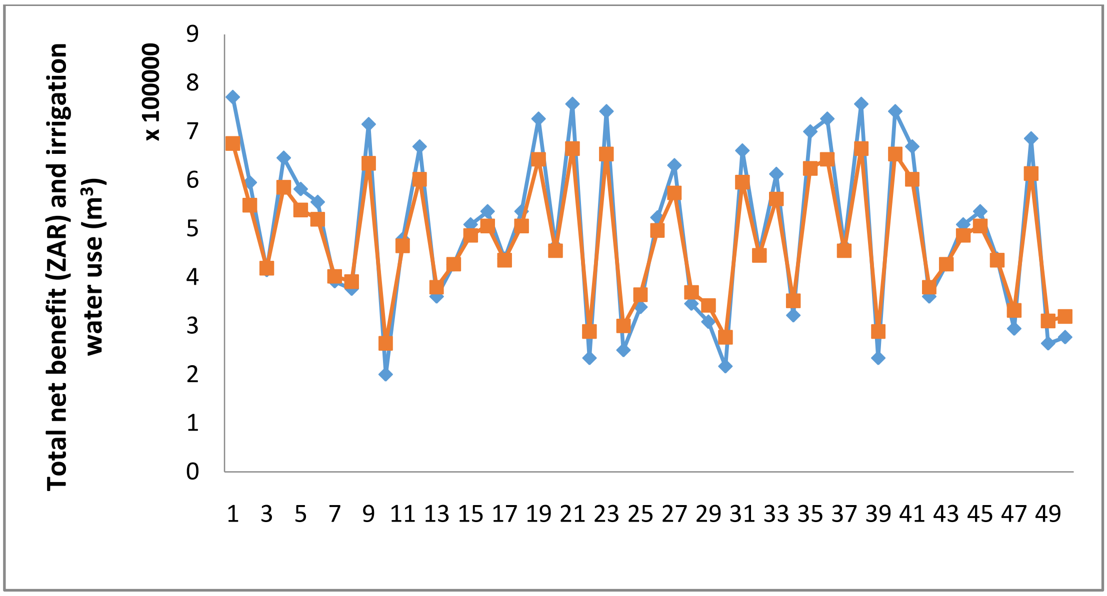

Figure 20: Non-dominated solutions for the crop yield model when maximizing total net benefit and minimizing irrigation water (BCS = 18).

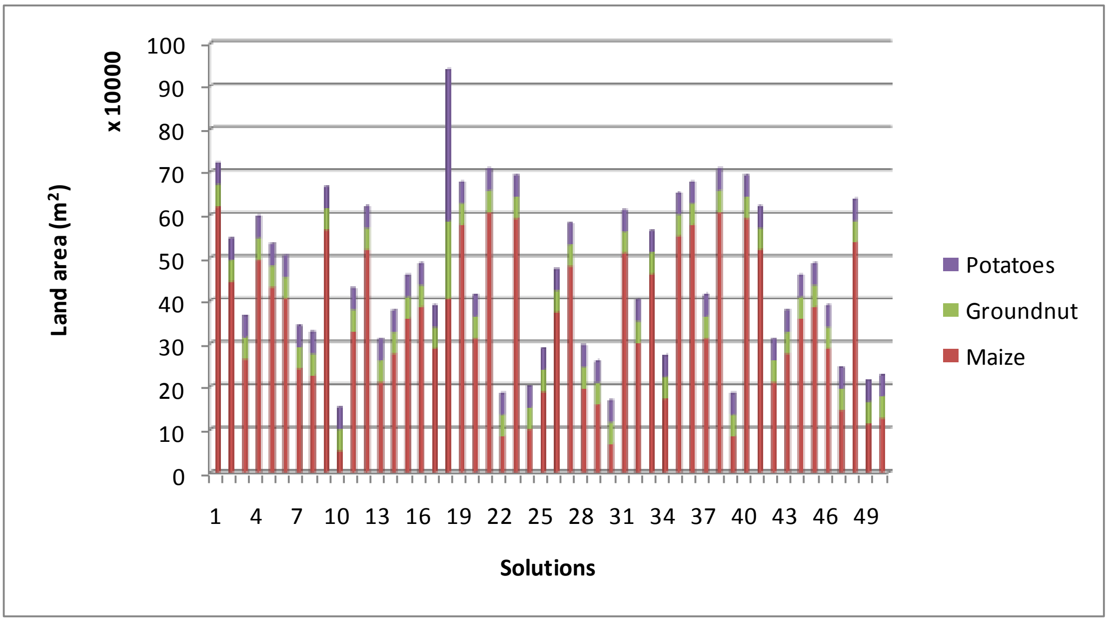

Figure 21: Different planting areas for the three crops in the non-dominated solutions using CPMDE.

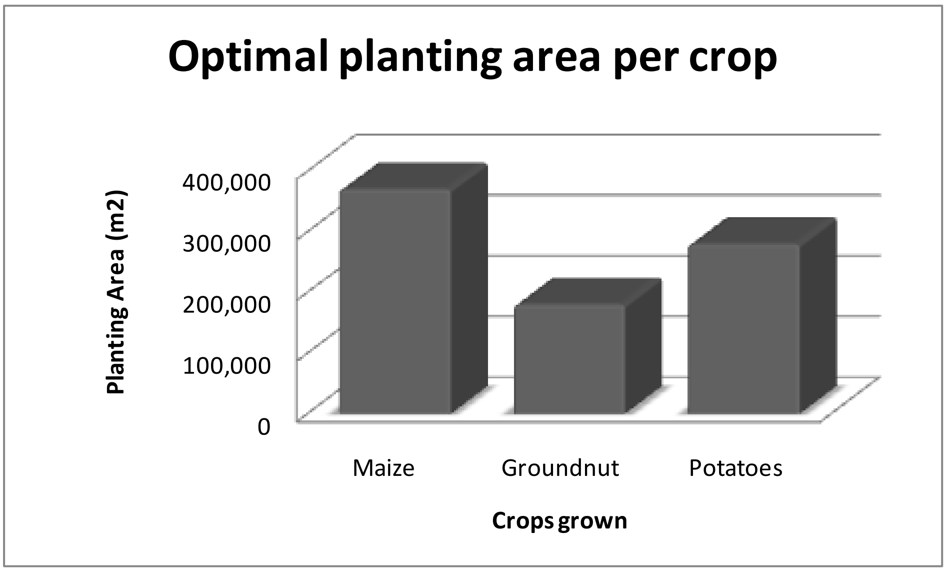

Figure 22: Optimal crop planting areas for maize, ground nut and potatoes corresponding to the best non dominated solution using CPMDE.

In this study, it was found out that the CPMDE algorithm performed excellently in finding optimal solutions to the crop yield problem at VIS, South Africa. In a single simulation run, CPMDE found quality Pareto solutions that provide trade-off between the conflicting objectives of the crop yield optimization problem. In the Pareto optimal solution set, each solution is not better than the others in all the objectives. In practice, the decision maker ultimately has to select one solution from this set for system implementation. All the solutions converged to Pareto front. Also, from the Pareto optimal set, it is evident that planting the crops within the optimal land area at the BCS, will reduce irrigation water use and hence, the total net benefit will be maximized. From a critical analysis of all the 50 solutions as presented in Table 12, solution 18 has the highest total net benefit of ZAR 767,961.49 generated from planting the three crops with total volume of irrigation water of 391,061.52 m^3, total planting areas of 937,961.49 m^2. This solution suggests that maize should be planted in 403543.44 m^2 land area, ground nut should be planted in 181542.00 m^2 in the farmland, while potatoes should be planted on 352876.05 m^2areas of land respectively.

The second best non dominated solution is solution 1 which has a total net benefit of ZAR 770,996.66 with irrigation water volume of 675,774.56 m^3 and total planting area of 720,620.4 m^2. The third best solution is solution 38 with total net benefit of ZAR 756,763.86, irrigation water volume of 665,036.46 $m^3$and total planting area of

706,762.4 m^2. Since the BCS is the solution which is minimally located from the ideal point which comprises the extremes of all the conflicting objectives, solution 18 is suggested for final implementation in this study. Among the three crops optimized, maize has the greatest land area, followed by potatoes. This shows that maize is more profitable in the VIS area than groundnut. This result is consistent with the results of (Adeyemo, Bux and Otieno 2010; Grove 2011).

6.5 CONCLUSION

The first application of a novel combined Pareto multi-objective differential evolution (CPMDE) optimization algorithm for irrigation water use and crop yield management in a farmland in Vaalharts irrigation scheme (VIS), South Africa, is illustrated in this chapter. The main aim of this chapter is to demonstrate the application of CPMDE to optimize crop yield under limited water availability while planting three different crop types on a farmland. The two objectives of the model are formulated to maximize total crop net benefit over a planting season while minimizing total irrigation water use. CPMDE generated a set of non-dominated solutions with the high net benefits at lower irrigation water use and almost constant solution for the three crop types was obtained for the multi-objective optimization problem. These solutions efficiently trade-off the objectives of maximizing total net benefit while minimizing irrigation water use in the farmland.

This study has successfully demonstrated the ability of CPMDE algorithm to generate non-dominated solutions along the Pareto-front of the selected problem and its ability to solve unconstrained, constrained and real-world optimization problems. From the generated Pareto optimal set, it is evident that planting the crops within the optimal land area at the BCS, will reduce irrigation water use and hence, the total net benefit will be maximized. The BCS (Figure 22) suggests that maize should be planted in 403543.44 m^2 land area, ground nut should be planted in 181542.00 m^2 in the farmland, while potatoes should be planted on 352876.05 m^{2}areas of land respectively. The cumulative planting area is 937961.49 m^2 and a cumulative of 391061.52 m^3 volume of irrigation water use. This has proved that CPMDE is suitable for solving multi-objective profit maximization and crop yield problems for the farmers as well as irrigation water use problems.

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 CONCLUSION

The need to make policies for adequate planning and management of water resources around the world has been the objective of several research works in recent years. Several hydrologic and optimization models for water resources management have been developed and applied to solve diverse real world problems. In the arid and semi-arid regions, water scarcity has been prevalent due to irregular average annual rainfall, which has characterized such region (Belaqziz *et al.* 2014). South Africa, being a water - stressed country falls within the semi-arid region, hence, the scarce nature of its water resources (Crowley and van Vuuren 2013a). In a rating of the driest countries in the world, South Africa was rated the 30th driest country in the world (Oyebode, Adeyemo and Otieno 2014) because it experiences low annual average rainfall. Water inadequacy in South Africa therefore calls for concerns in the management of existing facilities since the building of new facilities requires very high investments and are not recommended (Adeyemo 2011).

Hence, several heuristic optimization models with varying degrees of complexities have been widely applied for resolving water resources optimization and allocation problems. Prominent among these modeling application areas are crop growth, crop planning, irrigation planning and scheduling, hydrological systems, reservoir operations and other simulation studies (Ikudayisi and Adeyemo 2015). Above all, it is important to state that there exist some uncertainties about generating a one and only trustworthy and reliable optimization technique that can find a solution close to the global optimum in every situation (Deb 2001).

This study presents the management and optimization of irrigation water use for crops in a farm level at VIS, South Africa. The agricultural sector is the greatest user of available consumptive freshwater available for use in South Africa. It consumes about 60% of the total water use (Nkondo *et al.* 2012). Furthermore, the main goal of agricultural water resources management and crop production in any nation is to guarantee sufficient food resources for its teeming population. Food security has become a great concern around the world because of water scarcity experienced in the arid and semi-arid regions. In South Africa, majority of the crops produced rely solely on irrigation because of the erratic nature of rainfall within the country. Hence, it is very important to optimize the water use for this purpose. Also, the optimal and judicious management of the country's water resources serves as an entry point for this study.

Population growth in most developing countries have resulted in higher water demand for irrigation purposes since crop production must increase as well in order to feed the citizens. World's population is expected to grow from approximately six billion in 1999 to between eight and 11 billion by 2050. Human numbers are expected to increase by roughly 80 million people annually over the next 30 years(Olofintoye 2015). Between 5 and 15 million South Africans need food annually while many die of nutritional deficiencies (Calzadilla *et al.* 2014).

The VIS is the largest irrigation scheme in the whole world, hence it was chosen as the study area for this study. Weather and meteorological data between 1994 and 2014 were obtained both from South African Weather Service (SAWS) and Agricultural Research Council (ARC) in South Africa for this study. The data consist of six variables namely; minimum temperature (°C), maximum temperature (°C), rainfall (mm), relative humidity (%), and wind speed (m/s) and ET_o.

In order to calculate the crop water requirement (CWR) on the field or farmland, reference evapotranspiration (ET_o) is a major requirement. The estimation of ET_o is difficult most especially in the arid and semi-arid regions of developing countries, which is characterized with limited or no data at all. Therefore, in a way to model ET_o, it is important to find the correlation between the variables considered for estimating ET_o in order to determine the ones with the most significant effects on ET_o. This was done by using principal component analysis (PCA) and adaptive neuro-fuzzy inference systems (ANFIS). These techniques were adopted as data pre-processing methods before prediction of ET_o in real time was done. PCA was used to pre-screen the variables, while ANFIS was used as a post-screening technique for the said variables. It was concluded that ET_o increases with temperature and windspeed because the variables with the highest effect on ET_o are minimum temperature, maximum temperature and wind speed.

Also, eight artificial neural network models were developed and evaluated for the prediction of ET_o for the study area. The models were developed using feed-forward back propagation, and the number of neurons and hidden layers of each model were varied for determining the optimum network structure.Two statistical procedures, Pearson correlation coefficient (R) and root mean square error (RMSE) were used in selecting the optimal model. The second model (2), with notation (5-10-1), which is made up of five inputs, 10 neurons and one hidden layer was selected as the optimal model that is best suitable for predicting ET_0 in this study. It is concluded that ANN models with a single hidden layer performs better than models with multiple layers in prediction problems.

The real time irrigation scheduling of potatoes was developed using a crop growth simulation model called CROPWAT. This was to determine the 5-day time step soil moisture conditions for real-time water application for potatoes planted on a 100ha on the farmland. Irrigation scheduling and management is an important and innovating area which has been the subject of several research and studies in the last few decades. Scheduling involves the application of water to crops in the proper amount and at the appropriate time which will result in maximum crop yield and water use efficiency at the farm level. The study sought to know when, where and how much water to apply to an irrigated farmland. The planting date for potatoes on the farmland was 1st April, 2016 while the harvest date was 23rd August, 2016, making a total of 140 days. Throughout the growing season, the total crop water requirement was 1259.2mm; net irrigation water requirement was 1276.9mm and this is spread over a 5-day irrigation time-step throughout the entire 140 days of cropping season. The outcome of this study provides a 5-day time step data and graphs on the status of soil moisture and irrigation water requirements, so that the farmer can be able to order water and irrigate appropriately. This accurate real-time irrigation scheduling system allowed the farmer to make major water savings in order to prevent wastage of water resources in the farmland which is a major objective of this study. Irrigation will only occur at the critical depletion point and refill is up to field capacity. Modeling results showed that estimated sowing, harvesting and irrigation application dates produced good estimates of crop evapotranspiration (ET_c) and soil moisture fluxes.

Finally, a new and novel evolutionary multi-objective optimization algorithm, combined Pareto multi-objective differential evolution (CPMDE) was applied to optimize irrigation water use and crop yield on100ha VIS farmland. The algorithm combines methods of Pareto ranking and Pareto dominance selections to implement a novel generational selection scheme. The new scheme provides a systematic approach for controlling elitism of the population which results in the simultaneous creation of short solution vectors that are suitable for local search and long vectors suitable for global search. By incorporating combined Pareto procedures, CPMDE is able to adaptively balance exploitation of non-dominated solutions found with exploration of the search space. Thus, it is able to escape all local optima and converge to the global Pareto-optimal front. Results obtained from this study show that CPMDE algorithm performed excellently in finding optimal solutions to the crop yield problem at VIS, South Africa. In a single simulation run, CPMDE found quality Pareto solutions that provide trade-off between the conflicting objectives of the crop yield optimization problem. All the solutions converged to Pareto front. Also, from the Pareto optimal set, it is evident that planting the crops within the optimal land area at the BCS will reduce irrigation water use and hence, the total net benefit will be maximized.

The best solution (Figure 22) suggests that maize should be planted in 403543.44 m^2 land area, ground nut should be planted in 181542.00 m^2 in the farmland, while potatoes should be planted on 352876.05 m^2areas of land respectively. The cumulative planting area is 937961.49 m^2 and a cumulative of 391061.52 m^3 volume of irrigation water use. This has proved that CPMDE is suitable for solving multi-objective profit maximization and crop yield problems for the farmers as well as irrigation water use problems. This result is consistent with the results of (Adeyemo, Bux and Otieno 2010; Grove 2011).

The main aim of this study was to mathematically model irrigation of crops and also optimize irrigation water release in Vaalharts irrigation scheme (VIS) in South Africa. Real-time irrigation scheduling was to be developed with 5-day time-step, in order to prevent wastage of the scarce water resources on the irrigation farmlands. A new and novel evolutionary multi-objective optimization algorithm called combined Pareto multi-objective differential evolution (CPMDE) was to be applied to solve multi-objective water allocation and crop yield problems in VIS, South Africa. As mentioned in section 1.3, this study has four specific objectives which are:

1. To mathematically model and quantify the impact of reference evapotranspiration variables at Vaalharts irrigation scheme in South Africa**.**
2. To develop mathematical models that could be used for effective real time prediction of reference evapotranspiration in Vaalharts irrigation scheme using artificial neural networks (ANN).
3. To develop irrigation schedules and soil – moisture conditions for real-time water application for crops
4. To conceptualize and apply a novel multi-objective evolutionary algorithm for solving multi-objective optimisation problems to optimize irrigation water use and crop yield in the Vaalharts irrigation scheme of South Africa.

Specific objective 1 was achieved in chapter 3 where the local meteorological variables considered in estimating ET_o at VIS were mathematically modeled. This was done in order to quantify their impact on reference evapotranspiration at Vaalharts irrigation scheme in South Africa. It was found that temperature and windspeed increases with ET_o, hence they are the most important variable in the estimation of ET_o.

Specific objectives 2 was achieved in chapter 4, where eight artificial neural networks were developed and evaluated to get the optimal model for predicting reference evapotranspiration in VIS. The developed ANN models were designed using feed-forward back propagation. Number of neurons and hidden layers of each model were varied for determining the optimum network structure that best soothes the prediction. Each model has five inputs and one output. The optimal model was discovered using Pearson correlation coefficient (R) and root mean square (RMSE) before it was used to predict ET_o in the VIS for year 2016.

Objective 3 was achieved in chapter 5 where real-time irrigation scheduling of potatoes in VIS was designed. The predicted values of ET_o for year 2016 was part of the inputs needed by CROPWAT Simulation model. CROPWAT model was used to develop irrigation scheduling for a farmland in VIS using 5-day time step. Potatoes was the crop considered in the study because it is one of the staple crops grown on the VIS farmlands. However, the result shows that potatoes can be irrigated in 5-days interval without experiencing wilting of the crops due to lack of adequate soil moisture in the root zones of the crops.

Specific objective 4 was achieved in chapter 6 where a novel evolutionary algorithm called combined Pareto multi-objective differential evolution (CPMDE) optimization algorithm was applied to solve a problem of irrigation water use and crop yield management in a farmland in Vaalharts irrigation scheme (VIS), South Africa. This is the first time this new algorithm will be adapted to solve a problem of crop yield and irrigation water use. Since potatoes alone was considered in chapter 5, it was decided that two other crops grown in the study area should be added for optimization. This will help farmers to maximize their land and water use on the farmland. Hence, potatoes, groundnut and maize were optimized in chapter 6 of this thesis. It was found that maize is more profitable out of the three crops optimized. Therefore, all the objectives of this study have been achieved.

7.2 NOVELTIES AND CONTRIBUTIONS TO THE BODY OF KNOWLEDGE

The following novelties and contributions to the general body of knowledge are accomplished and published as enumerated in chapter one:

1. The use of a new and novel evolutionary multi-objective optimization algorithm (CPMDE) to solve a crop yield and irrigation water use problem. CPMDE represents an improvement over existing EA techniques because it has been tested on several tuneable problems and it outperformed other algorithms such as NSGA-II (Olofintoye, Adeyemo and Otieno 2014). The algorithm proposes a new selection methodology that provides a systematic approach for controlling elitism of the population which provides an adequate balance between exploitation of non-dominated solutions found and exploration of the decision search space. The studies herein provide the first applications of CPMDE in resolving water management problems in the agricultural sector in South Africa. Furthermore, since this study develops a system-theoretic algorithm, the application of the algorithm may be extended to solve problems in other strategic sectors.

2. The design of 5-day real-time irrigation schedule for VIS. Existing studies did weekly and daily irrigation schedules. 5-day real-time may bridge the gap between weekly and daily needs as improvement in yield may be attributed to apropos irrigation patterns.

3. Modeling of reference evapotranspiration variables in VIS using two comparative techniques namely PCA and ANFIS is another novel in this study. This was essential because it depicts the importance of the meteorological variables used in estimating ET_o and this was part of the factors considered while designing the ANN models in this thesis.

4. Major crops grown in the VIS scheme are maize, wheat and soybeans. This is a novel study to determine the crop water requirement, irrigation water needs and irrigation schedules when potatoes are planted on an area of 100ha on the farmland within the irrigation scheme.

7.3 RECOMMENDATIONS AND FUTURE RESEARCH

The following recommendations were made from the outcomes of the various studies.

(a) Countries in Sub-Saharan Africa should be encouraged to invest in irrigation projects and infrastructures so as to combat the ugly effect due to climate change.

(b) Countries in Sub-Saharan Africa should be encouraged to invest in research relating to climate change and data collection about water availability in their area so as to know the best sustainability and adaptability programme to be adopted.

(c) Since agricultural sector uses more water resources than domestic and industrial users, countries in Sub-Saharan Africa should give more emphasis to watershed management through rainwater harvesting and artificial recharge systems. Also they need to research into water efficient irrigation practices to save water.

(d) Since climate change is caused by emission of greenhouse gas particularly when carbon dioxide is released through the burning of fossil fuel. Countries in Sub-Saharan Africa should endeavour to guide against its reduction to the bearest minimum.

(e) Even though it has been shown that irrigation water demand increases with climate change, yet an adaptive measure must be considered in each country. Water managers must implement local adaptation strategies for resolving water stress.

The following are suggested areas for further research in order to improve the applicability of the methods developed in this work.

(f) This study focuses only on the Vaalharts irrigation scheme in South Africa, which was selected for being the largest in the country. Further research will be to employ CPMDE to optimise other real-world problems in other irrigation schemes within the country.
(g) This new CPMDE algorithm may be employed to solve problems in other sectors where optimization techniques in water management are needed.
(h) Further studies should be conducted on other crops to determine the optimum irrigation requirements for their growth.
(i) A computer application can be developed that will be user friendly. Farmers can use this in real time for irrigation of their crops. This will improve farming business and profitability.
(j) A decision support system can be generated for different farming areas in the country for real time irrigation of different crops.
(k) Other evolutionary algorithms can be compared with CPMDE to find out the best for different real world problems in areas such as reservoir operation, hydropower optimization, flood control and many other problem areas. scenarios.
(l) This study will be useful for future researchers because it describes in details the steps followed in the design of ANN models, it found the best configurations in terms of the number of layers and nodes for the optimal model. Furthermore, it provides a 5 – day schedule to farmers who use irrigation to grow their crops using potatoes as a test case. It has proved the capability of CPMDE in handling constrained multi-objective problems. Hence, it can be adopted to solve other real world problems. The best way to optimize land use and irrigation water on a farmland has been successfully demonstrated in this thesis.

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