REAL TIME OPTIMAL WATER ALLOCATION IN THE ORANGE RIVER CATCHMENT IN SOUTH AFRICA.

Submitted in fulfilment of the requirements of the degree of

Doctor of Engineering: Civil Engineering

in the Faculty of Engineering and the Built Environment at

Durban University of Technology

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FEBRUARY 2015

ABSTRACT

The planning and management of water resources systems often involve formulation and establishment of optimal operating policies and the study of trade-off between different objectives. Due to the intricate nature of water resources management tasks, several models with varying degrees of complexities have been developed and applied for resolving water resources optimisation and allocation problems. Nevertheless, there still exist uncertainties about finding a generally consistent and trustworthy method that can find solutions which are very close to the global optimum in all scenarios.

This study presents the development and application of a new evolutionary multi-objective optimisation algorithm, combined Pareto multi-objective differential evolution (CPMDE). 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. The performance of CPMDE was compared with 14 state-of-the-art evolutionary multi-objective optimisation algorithms. A total of ten test problems and three real world problems were considered in the benchmark of the algorithm. Findings suggest that the new algorithm presents an improvement in convergence to global Pareto-optimal fronts especially on deceptive multi-modal functions where CPMDE clearly outperformed all other algorithms in convergence and diversity. The convergence metric on this problem was several orders of magnitude better than those of the other algorithms. Competitive results obtained from the benchmark of CPMDE suggest that it is a good alternative for solving real multi-objective optimisation problems. Also, values of a variance statistics further indicate that CPMDE is reliable and stable in finding solutions and converging to Pareto-optimal fronts in multi-objective optimisation problems.

CPMDE was applied to resolve water allocation problems in the Orange River catchment in South Africa. Results obtained from the applications of CPMDE suggest it represents an improvement over some existing methods. CPMDE was applied to resolve water allocation problems in the agricultural and power sectors in South Africa. These sectors are strategic in forging economic growth, sustaining technological developments and contributing further to the overall development of the nation. They are also germane in capacitating the South African government's commitment towards equity and poverty eradication and ensuring food security.

Harnessing more hydropower from existing water sources within the frontier of the country is germane in capacitating the South African Government's commitment to reduction of the countries' greenhouse gas emissions and transition to a low-carbon economy while meeting a national target of 3 725 megawatts by 2030. Application of CPMDE algorithm in the behavioural analysis of the Vanderkloof reservoir showed an increase of 20 310 MWH in energy generation corresponding to a 3.2 percent increase. On analysis of storage trajectories over the operating period, it was found that the real time analysis incorporating a hybrid between CPMDE and ANN offers a procedure with a high ability to minimize deviation from target storage under the prevailing water stress condition. Overall, the real time analysis provides an improvement of 49.32 percent over the current practice. Further analysis involving starting the simulation with a proposed higher storage volume suggests that 728.53 GWH of annual energy may be generated from the reservoir under medium flow condition without system failure as opposed to 629 GWH produced from current practice. This corresponds to a 13.66 percent increase in energy generation. It was however noted that the water resources of the dam is not in excess. The water in the dam is just enough to meet all current demands. This calls for proper management policies for future operation of the reservoir to guard against excessive storage depletions.

The study herein also involved the development of a decision support system for the daily operation of the Vanderkloof reservoir. This provides a low cost solution methodology suitable for the sustainable operation of the Vanderkloof dam in South

Africa. Adopting real time optimisation strategies may be beneficial to the operation of reservoirs. Findings from the study herein indicate that the new algorithm represents an improvement over existing methods. Therefore, CPMDE presents a new tool that nations can adapt for the proper management of water resources towards the overall prosperity of their populace.

DECLARATION

I hereby declare that the work reported in this thesis "**Real time optimal water allocation in the Orange River catchment in South Africa**" 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, conference papers, book chapters and workshop 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.

Oluwatosin Onaopemipo OLOFINTOYE.

DEDICATION

"…And all thy children shall be taught of the LORD
and great shall be the peace of thy children…"

To:

…the keeper of time…

…the true source of divine inspiration…

…the curator of wisdom, knowledge and understanding…

….the custodian of the spirit of power, love and of a sound mind…

…my ever-loving FATHER and reason for my existence…

To the Almighty God for his sustenance.

ACKNOWLEDGEMENTS

Foremost, my profound gratitude goes to the Almighty GOD (The Father, Son and Holy Spirit) 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 individuals and institutions that played significant roles in driving this research work towards a successful completion.

My indefatigable supervisor, Professor Josiah Adeyemo for his useful pieces of advice, constructive criticism, guidance, patience, unflinching support, encouragements and painstakingly guiding and directing me towards the successful completion of my doctorate. Professor Adeyemo, you are a true source of inspiration, a symbol of excellence. Iron sharpens iron. Indeed, success is contagious. You are unique and the best among supervisors! I bless the Lord for the privileged opportunity of working with you. The solid academic foundation you bestowed, I believe is sufficient to see me through all future challenges that may arise along my path to greatness in my career. May God bless you and your family.

Professor Fred Otieno, for co-supervising this work and for your fatherly guidance. Real fathers are very rare. I am blessed to have a real father who displays his care with so much sincerity and ease. I especially thank you for providing useful guidance in the application for bursaries, conference attendance and other financial support necessary for the completion of this work.

My wonderful parents, Professor Joseph Olofintoye and Mrs Cecilia Olofintoye (Late), for the outstanding upbringing and solid academic foundation you bestowed. I am forever grateful to you. I also appreciate my fantastic siblings, Seun and Blessing, for their unflinching support. You stand out among real brothers!

Professor Bolaji Sule for the very solid academic foundation you gave me during my masters study. I found it very useful in completing this task. I especially appreciate you for releasing me to go out and acquire an international education though we had worked previously on a doctoral project for a year. I know it was not easy but I perceive you saw the future and made a right decision. You are a father indeed.

Professor and Mrs Bariki and Dr Adeleke for the door God opened through you. You are true parents. May the Almighty Father bless and reward you and your families.

My pastors, Pastor and Mrs Adejimi and Pastor (Mrs) Ajibade and their families for your prayers, spiritual guidance, godly counsels and moral support you gave during the course of the work.

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. I appreciate the Faculty of Engineering and the Built Environment and deanship for the student support during the programme. May God move the faculty forward.

My unreserved appreciation goes to the entire staff of the Civil Engineering and Water resources and Environmental Engineering departments, University of Ilorin, Nigeria, for their support throughout the program and for being a reliable family. I also appreciate University of Ilorin for the staff development award granted me to complete this doctorate program. University of Ilorin is truly “Better by Far!”

My sincere thanks to Jane Mogaswa of the Department of Water Affairs, South Africa, for her assistance in obtaining data and other information necessary for the completion of this research work.

I appreciate the Lawals (Mrs Sarah Lawal, Toba, Happiness, Mary, Samuel and Femi) for their sacrificial inputs. You have been a pillar indeed. A lovely family. May the Almighty reward your labour of love.

I appreciate friends that were friends indeed.

Oluwafunmibi, OreofeJesu and Oluwaseyi. I wonder how you sweet little daughters understood that daddy needed to study hard to be able to afford a better life for you, all and sundry. Indeed, you are taught of the Lord. I appreciate you and thank the LORD for giving you to us.

"… A virtuous woman, who can find? … For her price is far above rupees". My loving wife, Roseline Olofintoye - thank you for being a friend and life companion. I appreciate your moral support and indefatigable commitment to my 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 love you.

Finally, to all who have contributed immensely in one way or the other to the optimal success of this research, but who due to space constraint on the Pareto front could not be explicitly mentioned in real time, I say a BIG thank you. All other protocols are hereby accurately observed. May God bless you all, Amen.

Oluwatosin OLOFINTOYE.

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LIST OF ABBREVIATIONS

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BCS	Best Compromise Solution
CPA	Compromise Programming Approach
CPMDE	Combined Pareto Multi-objective Differential Evolution
DAFF	Department of Agriculture, Forestry and Fisheries
DE	Differential Evolution
DOE	Department of Energy
DSS	Decision Support System
DUT	Durban University of Technology
DWA	Department of Water Affairs
EA	Evolutionary Algorithm
EGA	Enhanced GA
EMOA	Evolutionary Multi-Objective Algorithms
ES	Evolution Strategy
ESKOM	Electrical Company of South Africa
ESV	Existing Storage Volume
FCC	Flood Control Curve
GA	Genetic Algorithm
GAO	Genetic Algorithm Optimisation
GHG	Green House Gases
GP	Genetic Programming

GUI	Graphical User Interface
KANGAL	Kanpur Genetic Algorithm Laboratory
LGP	Linear Genetic Programming
LISP	List Programming
LLCW	Low-Level Contaminated Water
MATLAB	Matrix Laboratory
MDEA	Multi-objective Differential Evolution Algorithm
MNN	Modular Neural Network
MODE	Multi Objective Differential Evolution
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOOP	Multi-Objective Optimisation Problem
MOPSO	Multi-Objective Particle Swarm Optimisation
NF	Neuro Fuzzy
NSGA-II	Elitist Non-dominates Sorting Genetic Algorithm
OWNT	Optimal Water Network Topology
PDE	Partial Differential Equation
RMSE	Root Mean Square Error
SI	Scatter Index
TUB	Technical University of Berlin
USGS	US Geological Survey
VanResOp	Vanderkloof Reservoir Operation
VBA	Visual Basic for Applications

VIS	Vaalharts Irrigation Scheme
WHO	World Health Organization
WRC	South African Water Research Commission
WRPM	Water Resource Planning Model

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

1.1.1 Introduction

Water scarcity has emerged a global issue in recent times. This ominous situation is further being exacerbated by escalating water demands due to unprecedented population growths, unsustainable urban developments and recently anthropogenic climate change among other factors (Hamid and Khan 2003; Olofintoye, Adeyemo and Otieno 2012). As the global population grows and demands for food and energy increase, the pressure on freshwater ecosystems intensifies. In addition, the main effects of climate change are likely to be felt through changes to the hydrologic cycle with resultant effects on the environment, national developments and socio-economic growth (Quesne, Pegram and Heyden 2007). It is therefore pertinent to encourage the development of management strategies that facilitate proper management of limited water resources while sensitising people of all nations of the perils posed by indiscriminate and unsustainable use of water which may lead to significant depletion of freshwater resources.

According to Otieno and Ochieng (2004), South Africa, currently categorized as a water stressed country and recently ranked the 30th driest country in the world (Crowley and Vuuren 2013), is forecasted to experience physical water scarcity by the year 2025 with an annual freshwater availability of less than 1000 m^3 per capita. Hence, the efficient use and allocation of available water resources with the aim of ensuring continuous availability of water calls for proper planning, design, operation, allocation, optimisation and management of available water resources using sustainable advanced techniques. This study develops a novel evolutionary algorithm called combined Pareto multi-objective differential evolution (CPMDE) which is an evolutionary multi-objective optimisation algorithm. It further investigates its applicability for optimisation in solving water allocation problems in the Orange River catchment in South Africa.

1.1.2 Agricultural and energy as strategic sectors in South Africa

In the face of the water stress besetting South Africa as a nation with its attendant challenges to the environment and quality of human life, the agricultural (SANTO 2013) and power (SIDALA 2010) sectors have been considered strategic and germane in capacitating the South African government's commitment towards equity and poverty eradication and ensuring food security. The agricultural sector is expected to guarantee food security in the nation while simultaneously creating employment opportunities for the teeming population, thereby forging national socio-economic development necessary for re-launching South African economy (SANTO 2013). Therefore, efforts are being geared towards developing and promoting productivity in this sector.

A recent study indicates that in South Africa, the agricultural sector is the largest consumer of freshwater through irrigation (Adeyemo 2009). Other studies (DWA 1995b, 2010) have however reported that despite the numerous benefits associated with irrigated agriculture, the agricultural sector is relatively an inefficient user of water. For instance, results of an analysis by DWA (1995b), indicate that allocating water for use in the industrialised areas of South Africa rather than for irrigated agriculture, will, from an economic point of view, render higher returns. Substantial differences in the order of 80 to 1 were also found with respect to employment opportunities. This implies a clear economic preference for using water in the Gauteng (industrialised) economy rather than for irrigated agriculture in the Orange River catchment. 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 caution should be exercised not to permanently commit water to less beneficial uses to the possible future detriment of the economy (DWA 1995b). Hence, studies have been undertaken to minimize the water use in agriculture especially irrigation water so as to achieve optimum crop production.

In efforts to stem the effects of power shortages arising from escalating energy demands brought about by rapid urbanization and industrial development, the power sector has been considered strategic in forging economic growth, sustaining technological development and contributing further to the overall development of the nations (Ajenifuja 2009). The electrical company of South Africa (Eskom), responsible for the generation, distribution, control and management of electricity in the country, produces roughly 95 percent of the electricity in the republic. Due to the fact that South Africa is rich in coal, 90 percent of Eskom's electricity is produced by coal fired thermal power plants. The Gariep and Vanderkloof hydropower installations in the Orange River basin are operated between two to four hours per day to generate peaking power. Studies have shown that electricity produced from the Orange River Hydro stations is half as cheap as the ones sourced from Eskom's thermal power plants (ESKOM 2010).

Due to growing global concerns about anthropogenic climate change and environmental degradation brought about partly due to indiscriminate burning of fossil fuels, current global policies are pushing toward the reduction of greenhouse gases (GHG) emissions to help reduce the rate at which the earth is warming. Also, in line with international agreements, the South African Government is committed to four percent of estimated electricity demand being met by renewable energy resources by 2013 (SIDALA 2010). This is expected to result in over 200 000 fewer kilogrammes of particulate matter being emitted into the air annually (ESKOM 2010).

Recent studies have shown that GHG emission factors for hydropower plants are typically 30-60 times less than factors for fossil fuel generation, taking into account emissions from decaying biomass in reservoirs, (Ajenifuja 2009). Hence, strategies aimed at harnessing more hydropower from existing water sources within the frontier of the country is germane in capacitating the South African Government's commitment to reduction of the country's GHG emissions and transition to a low-carbon economy while meeting a national target of 3 725 megawatts by 2030 (SIDALA 2010; DOE 2014).

It has been reported that the objectives of maximizing hydropower from reservoirs are often in conflict with the objectives of irrigation (Salami 2007). While hydropower generation requires that the reservoir be 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 2008). Therefore, strategies aimed at maximizing power generation within the constraints of agricultural crop production and water demands are germane in forging economic growth in South Africa.

1.1.3 Evolutionary algorithms in water resources management

Evolutionary algorithms (EAs) are population-based meta-heuristic optimisation 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 optimisation problems (Price, Storn and Lampinen 2005).

In recent times, methods of EAs have found widespread use in the fields of water resources single and multi-objective optimisation due to their robustness in the resolution of such problems (Cai, McKinney and Lasdon 2001; Yuan *et al.* 2008; Selle and Muttil 2010). The applications of EAs for solving water resources optimisation problems in the agricultural and power sectors have also been widely reported in the literature (Reddy and Kumar 2007; Salami 2007; Reddy and Kumar 2008; Adeyemo and Otieno 2009c; Madsen *et al.* 2009) and they have indeed been found excellent in solving water management problems in these sectors. A comprehensive review of the state-of-the-art on applications of EAs in solving water resources optimisation problems is provided by Olofintoye, Adeyemo and Otieno (2013b).

In this study, the applications of an EA in resolving multi-objective water resources allocation problems in the agricultural and power sectors in South Africa are demonstrated. Results obtained further demonstrate that resolution of multi-objective water resources problems using EAs is beneficial to economic growth and development of the nation.

1.2 STATEMENT OF THE PROBLEM

Several heuristic algorithms have been applied in resolving water resources optimisation problems, yet there still exist some uncertainties about finding a generally trustworthy method that can consistently find solutions which are really close to the global optimum of the problems in all circumstances (Kerkez *et al.* 2010). Therefore, further research aimed at developing single and multi-objective evolutionary optimisation procedures that integrate resource planning of available resources and the simultaneous management of various demands or allocation is still needed in the fields of water resources planning and management.

1.3 STUDY OBJECTIVES

The main objective of this study was to develop a new evolutionary multi-objective optimisation algorithm and apply it to solve multi-objective water allocation problems in the agricultural and power sectors in the Orange River catchment in South Africa. Specific objectives of the study are:

1. To develop and conceptualize a novel multi-objective evolutionary algorithm for solving multi-objective mathematical optimisation problems and apply the developed method in water resources management in the Orange River catchment in South Africa.
2. To benchmark the developed algorithm with existing state-of-the-art algorithms using standard benchmark problems and standardized performance metrics to evaluate its performance and adaptability for solving real world optimisation problems.

3. To solve a multi-objective crop planning problem by using the newly developed multi-objective algorithm to optimise planting areas for given crops under land and water constraints

4. To adopt an existing framework for solving problems of water allocation to users in real time. In contrast to futuristic scheduling models that have been applied, the real time approach will integrate model-based information and decision support system for water resources allocation as they occur in the present.

5. To develop a decision support system (DSS) by encoding the real time framework into a computer application package using visual basic for applications. This will make its application user friendly.

6. To apply the DSS to reservoir operations by investigating real time multi-objective water allocation for hydropower generation from the Vanderkloof dam.

1.4 SIGNIFICANCE OF THE STUDY

In keeping in line with the South African government's commitment towards equity and poverty eradication and ensuring food security, the results of this study will help in making recommendations to policy makers, related stakeholders and decision makers in the agricultural and energy sectors in South Africa. This will help them in making concerted efforts towards developing relevant approaches to managing water in different regions across the country. It will also aid operators of reservoir systems in the country in planning future operations of dams.

The results of the study will lead to recommendations on water management which will facilitate optimising the use of available resources and help protect and maximize the revenue generated from the limited available water resources. Outputs from this research will be useful to national water management institutions like South African Water Research Commission (WRC), Department of Water Affairs (DWA), Department of Agriculture, Forestry and Fisheries (DAFF), Department of Energy

(DOE) and Eskom. It will also help in making recommendations to policy makers and authorities in other water related industries.

This study develops a system-theoretic algorithm. The application of the algorithm may therefore be extended to solve problems in other strategic sectors. Publications from this research may also be useful to scholars undertaking researches in a similar field.

1.5 LIMITATIONS OF THE STUDY

The accuracy of this study may possibly be influenced by accuracy of data as the data used was extracted from record books; due to possible human errors, the accuracy of the data may not be totally ascertained. This study was also limited by the availability of real time demand data as this could not be accessed during the period of the work. However available daily hydrology of the reservoir was used to operate the dam on a daily basis. Investigation of the operation of the reservoir using real time hydrologic and demand data is hereby left for further studies when relevant information will be available.

1.6 SCOPE OF THE STUDY

The applications of developed models in this study is restricted to solving water allocation problems in agricultural and power sectors in South Africa. Two study areas were chosen for investigation. Models were developed for solving a crop planning problem in a farmland in Vaalharts irrigation scheme (VIS), South Africa. VIS is one of the largest irrigation schemes in the world covering 369.50 square kilometres in the Northern Cape Province of South Africa (VIS 2013). The scheme is supplied with water abstracted from Vaal River, which is the main tributary of the Orange River that provides water to the Vaal River Supply Area (DWA 1995b). Real time optimisation of the Vanderkloof reservoir is also carried out in this study.

This study is limited to the application of Differential evolution (DE) algorithm in resolving water allocation problems in the study areas. DE is extended in developing the new evolutionary algorithm in this study. The choice of DE is due to its numerous advantages reported in the literature. Moreover, there exists a study on the application of multi-objective DE in resolving crop planning problem in VIS. This facilitated further benchmark of the algorithm developed herein.

1.7 STUDY AREAS

Vaalharts irrigation scheme and the Vanderkloof reservoir are selected as relevant study areas in this research. These study areas are strategic to agricultural production and power generation in South Africa. These sectors are vital in forging socio-economic growth and overall development of the country. Since this thesis presents a compilation of manuscripts where each chapter presents an individual study done during the course of the research, full description of the relevant study areas are presented in respective chapters.

1.8 OUTLINE OF THE THESIS

This thesis presents manuscripts that were prepared, compiled or published during the course of the research work. The thesis is organized into seven chapters. The work starts with a general introduction in chapter 1. Water scarcity as a main issue in water resources management in South Africa is discussed. The application of evolutionary optimisation algorithm in water resources management is also discussed and proposed for resolving water allocation problems in the agricultural and power sectors in South Africa. The statement of the problem, study objectives, significance and limitations of the study are also presented. This thesis does not incorporate an elaborate literature review but rather, literature review relevant to each chapter is given in respective chapters. However, chapter 2 gives a comprehensive review of the state-of-the-art on some applications of some existing evolutionary optimisation algorithms in water resources management. This serves to provide a general introduction to the field.

In chapter 3, a novel evolutionary multi-objective optimisation algorithm is developed. The new algorithm is called combined Pareto multi-objective differential evolution (CPMDE). The ability of CPMDE in solving unconstrained, constrained and real world optimisation problems is demonstrated. Competitive results obtained from the benchmark of CPMDE suggest that it is a good alternative for solving real multi-objective optimisation problems. Following an argument that some test problems used in benchmarking evolutionary algorithms are not tuneable and it is difficult to establish the feature of an algorithm that is being tested, CPMDE is further tested using tuneable multi-objective test problems in chapter 4 and applied to solve another real world engineering design problem. Results obtained from further benchmark of the algorithm corroborate the efficacy of CPMDE as an efficient method of multi-objective optimisation algorithm.

Based on the results of successful benchmark of the algorithm in chapters 3 and 4, CPMDE is applied to solve a multi-objective crop planning problem in Vaalharts irrigation scheme in chapter 5. Here, a comparative study with existing state-of-the-art algorithms is also made. Findings of the study suggest that CPMDE is a good alternative suitable for resolving crop planning and other related water resources management problems in a multi-crop environment with limited freshwater for irrigation in a water-stressed country like South Africa.

In chapter 6, a framework for real time water allocation is adopted for operation of the Vanderkloof reservoir in the Orange River catchment. This framework involved the coupling of a data driven artificial neural network (ANN) model and CPMDE to form a hybrid for hydrological simulation and multi-objective numerical optimisation of hydropower production from the Vanderkloof dam in real time. It was found that the hybrid ANN-CPMDE real time reservoir operation methodology provides a low cost solution methodology suitable for the sustainable operation of the Vanderkloof dam in South Africa.

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.

Literature review relevant to each study is incorporated in respective chapters and each chapter is concluded by the details of research output(s) from the chapter. Also, because this thesis is a compilation of manuscripts, some repetitions between chapters are unavoidable.

1.9 PUBLICATIONS

A total of 22 research articles were prepared during the course of this work. In all, five book chapters, five journal articles, 10 conference papers/ presentations and two workshop papers were written. All the five book chapters have appeared in print. Two of the journal papers have been published. One has been accepted for publication while two are under review in reputable academic journals at the time of filing this report. Five of the conference papers were presented at local conferences while five were presented at international conferences. Two workshop papers were also presented at an institutional workshop. Articles prepared during this work are listed hereunder.

(a) Book chapters

[1] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2014. A Combined Pareto Differential Evolution Approach for Multi-objective Optimization. In: Schütze, O., Coello Coello C.A., Tantar, A., Tantar, E., Bouvry, P., Moral, P. D. and Legrand, P. eds. *EVOLVE-A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation III*. Switzerland: Springer International Publishing, 213-231.

[2] Adeyemo, J. and **Olofintoye, O.** 2014. Optimized Fourier Approximation Models for Estimating Monthly Streamflow in the Vanderkloof Dam, South Africa. In: Tantar, A., Tantar, E., Sun, J., Zhang, W., Ding, Q., Schütze, O., Emmerich, M., Legrand, P., Moral, P. D. and Coello Coello C.A. eds. *EVOLVE - A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation V*. Switzerland: Springer International Publishing, 293-306.

[3] Enitan, A., Adeyemo, J., **Olofintoye, O.**, Bux, F. and Swalaha, F. M. 2014. Multi-objective Optimization of Methane Producing UASB Reactor Using a Combined Pareto Multi–objective Differential Evolution Algorithm (CPMDE). In: Tantar, A., Tantar, E., Sun, J., Zhang, W., Ding, Q., Schütze, O., Emmerich, M., Legrand, P., Moral, P. D. and Coello Coello C.A. eds. *EVOLVE - A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation V*. Switzerland: Springer International Publishing, 321-334.

[4] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2013. Evolutionary algorithms and water resources optimization. In: Schütze, O., Coello Coello C.A., Tantar, A., Tantar, E., Bouvry, P., Moral, P. D. and Legrand, P. eds. *EVOLVE-A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation II*. Berlin: Springer Berlin Heidelberg, 491-506.

[5] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2012. Impact of Regional Climate Change on Freshwater Resources and Operation of the Vanderkloof Dam System in South Africa. In: Singh, B. R. ed. *Global Warming – Impacts and Future Perspective*. Croatia: InTech, 165-184.

(b) Journal Articles

[6] Adeyemo, J. A. and **Olofintoye, O. O.** 2014. Evaluation of Combined Pareto Multiobjective Differential Evolution on Tuneable Problems. *International Journal of Simulation Modelling*, 13 (3): 276-287.

[7] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2015. Real-time optimal water allocation for daily hydropower generation from the Vanderkloof dam, South Africa. *Applied soft computing*, 2015. *Under review*.

[8] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2015. Optimum crop planning using Combined Pareto Multi-objective Differential Evolution. *Journal of the South African Institution of Civil Engineering*, 2015. *Under review*.

[9] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2013. Precipitation-runoff process modelling using artificial neural networks. *Scientific Research and Essays*, 8 (25). August, *2013. Accepted for publication.*

[10] **Olofintoye, O.** and Adeyemo, J. 2011. The role of global warming in the reservoir storage drop at Kainji dam in Nigeria. *International Journal of Physical Sciences* 6(19): 4614-4620.

(c) Conference papers

[11] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2014. Real-Time Hydropower Generation from the Vanderkloof Dam, South Africa. *International Journal of Arts & Sciences' (IJAS) American Canadian Conference for Academic Disciplines*. Ryerson University, Toronto, Canada, 19 – 22 May 2014.

[12] Adeyemo, J. and **Olofintoye, O.** 2014. Resolution of Multiobjective water supply problems in the Vanderkloof dam. *International Journal of Arts & Sciences' (IJAS) American Canadian Conference for Academic Disciplines*. Harvard Medical School, Boston, Massachusetts, USA, 26 to 30 May 2014.

[13] Adeyemo, J. and **Olofintoye, O.** 2012. Application of hybrid models in water resources management. In: Proceedings of *EVOLVE international conference 2012*. CINVESTAV-IPN, Mexico City, Mexico, 07 – 09 August, 2012.

[14] **Olofintoye, O.** and Adeyemo, J. 2012. Development and Assessment of a Fourier Approximation Model for the Prediction of annual Rainfall in Ilorin, Nigeria. In: Proceedings of *Water Institute of Southern Africa Biennial Conference and Exhibition* Cape Town, South Africa, 05 – 09 May, 2012.

[15] Adeyemo, J. and **Olofintoye, O.** 2012. Impact of regional climate change on the rainfall and inflow of the Vanderkloof dam in South Africa. In: Proceedings of *Water Footprint: Water Institute of Southern Africa Biennial Conference and Exhibition*. International Conference Center, Cape Town, 05 – 09 May, 2012.

[16] Adeyemo, J., **Olofintoye, O.** and Otieno, F. 2012. Artificial neural networks for Precipitation-runoff process modelling. In: Proceedings of *Water Footprint: Water Institute of Southern Africa Biennial Conference and Exhibition*. International Conference Center, Cape Town, 05 – 09 May, 2012.

[17] Adeyemo, J. and **Olofintoye, O.** 2012. Impact of global warming on Vanderkloof dam catchment. *21st century watershed technology conference and workshop: Improving water quality and environment*. Hotel Palace Bari, Italy, May 26th- June 1st, 2012.

[18] Adeyemo, J., **Olofintoye, O.** and Moyo, S. 2011. Differential evolution for the minimum weight design for framed structures. In: Proceedings of *Joint Congress of the South African and American Mathematical Societies*. Nelson Mandela Metropolitan University, Port Elizabeth, Eastern Cape, South Africa., 29 November – 3 December, 2011.

[19] **Olofintoye, O.** and Adeyemo, J. 2011. A potential application of nanotechnology for the prediction of maximum rainfall. In: Proceedings of *Fourth African Regional Conference of Vice Chancellors, Deans of Science, Engineering and Technology, (COVIDSET 2011)*. Birchwood Hotel, Johannesburg, South Africa., 23 – 25 November, 2011.

[20] **Olofintoye, O. O.** and Adeyemo, J. A. 2011. Development of a Micro-Mobile Program for Application in Wastewater Treatment. In: Proceedings of *Humboldt-Kollege International Conference (Ogbomoso 2011)*. Ladoke Akintola University of Technology, Ogbomoso, Nigeria, 4-7 July 2011.

(d) Workshop papers

[21] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2012. A novel multi-objective evolutionary algorithm for real-time water allocation in the Orange River catchment in South Africa. Paper presented at the *Institutional research day 2012*. Steve Biko campus library complex, Durban University of Technology, Durban, South Africa, 15th November, 2012.

[22] Adeyemo, J., Otieno, F. and **Olofintoye, O.** 2012. Performance evaluation of Multi-Objective Differential Evolution Algorithm (MDEA) strategies for water resources management. Paper presented at the *Institutional research day 2012*. Steve Biko campus library complex, Durban University of Technology, Durban, South Africa, 15th November, 2012.

CHAPTER 2

EVOLUTIONARY ALGORITHMS AND WATER RESOURCES OPTIMISATION

2.1 OVERVIEW

Heuristic optimisation models with varying degrees of complexities have been widely applied for resolving water resources optimisation and allocation problems. Nevertheless there still exist uncertainties about finding a generally consistent and trustworthy method that can find solutions which are really close to the global optimum in all circumstances. This chapter makes a review of some of the numerous evolutionary optimisation algorithms available to water resources planners and managers. Evolutionary algorithms have been found propitious and useful in facilitating critical water management decisions and are becoming promising global optimisation tools for major real world applications. Further research aimed at developing optimisation models for water resources planning, management and optimisation is therefore necessary.

2.2 INTRODUCTION

Water is a natural resource that is essential for good health and the survival of all kinds of lives on earth. Less than one percent of the water of the earth is available as freshwater on land. The rest is contained either in the oceans or in form of frozen ice on mountain tops and glaciers (Srinivasulu and Jain 2006). Under pressure from population explosion, urbanization, extravagant lifestyles, climate change, intensive agriculture and industrialization, water is fast becoming a scarce resource. This is evident from the fact that a lack of water to meet daily needs is a reality for one in three people around the world today. Health consequences of water scarcity and its impact on daily life pose a threat to national growth and impede international development (WHO 2009). It is absolutely necessary therefore, to sensitise people of all nations about the imminent danger posed by mismanagement which may result in the depletion of limited freshwater resources and the impact this will have on people and the ecosystems on which they depend.

From the earliest times, water resources management and allocation had been on the basis of social criteria, maintaining the community by ensuring that water is available for human consumption, sanitation and food production (Dinar, Rosegrant and Meinzen-Dick 1997). In some cases, there had existed rigid water right policies in which water was allocated to users according to their rights without taking into account economic efficiency in water use (Reca *et al.* 2001). However, with the trend in population growth and its attributes and continuous pollution of the available water sources, there has been increased pressure on the available water resource resulting in increased conflict over its allocation and a further stress on this resource leading to scarcity (Otieno and Ochieng 2004). In some other cases, existing hydrologic policies for resolving deficit had often aimed at increasing water resources through the construction of more hydraulic regulation or retention works, mainly large dams. Societies have invested capital in infrastructure to maintain this allocation. Yet social changes, further population growth and water pollution has made water scarcity more widespread than ever before. Thus inefficient use of water, poor cost recovery for operating and maintenance expenses, the mounting cost of developing new water sources and problems with the quality of service in agency-managed systems has led to a search for alternatives that make water allocation and management more efficient (Dinar, Rosegrant and Meinzen-Dick 1997). This has oftentimes led to amendments in existing water management policies.

Water inadequacy in most countries calls for concern in the management of existing facilities since the building of new facilities requires very high investments (Adeyemo and Otieno 2010). If available water resources are not utilised efficiently and effectively, water demand may eventually exceed available supply, ultimately leading to artificial drought situations in several places on the globe in the near future. Therefore, employing advanced water use forecasting and optimisation models that integrate resource planning of available supply and the simultaneous management of various demands or allocations is of paramount importance in the field of water resources planning and management (Srinivasulu and Jain 2006).

Awareness of increasing water scarcity has driven efforts to model global water resources for improved insight into water resources infrastructures and management strategies (Sangodoyin and Adeyemo 2004; Olofintoye, Sule and Salami 2009; Davies and Simonovic 2011; Olofintoye and Adeyemo 2011b; Olofintoye and Salami 2011). Developing strategies that facilitate the efficient use of available water resources have been the subject of many studies in the field of water resources planning and management (Sniedovich 1978; Reca *et al.* 2001; Shangguan *et al.* 2002; Adeyemo and Otieno 2009b). Several optimisation techniques that attempt to propound ways of mitigating or resolving water resources allocation problems have been reported in several studies (Babel, Gupta and Nayak 2005; Fernandes and Schreider 2009; Otieno and Adeyemo 2010).

In recent times, methods of evolutionary algorithms (EAs) have found widespread use in the fields of water resources single and multi-objective optimisation due to their robustness in the resolution of such problems (Cai, McKinney and Lasdon 2001; Yuan *et al.* 2008; Selle and Muttil 2010; Olofintoye, Adeyemo and Otieno 2013b; Adeyemo and Olofintoye 2014a; Enitan *et al.* 2014). Evolutionary algorithms are population-based meta-heuristic optimisation procedures that use biology-inspired mechanisms like mutation, crossover, natural selection and survival of the fittest in order to refine a set of solution candidates 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 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. 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). The superiority of EAs in the solution of 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 WATER RESOURCES MANAGEMENT USING GENETIC ALGORITHMS

Genetic algorithms are a subclass of evolutionary algorithms where the elements of the search space are encoded using binary strings or arrays of other elementary types, although versions of GAs that employ the use or real valued parameters are now available (Weise 2009). In a GA setup, possible individual solutions to a mathematical optimisation problem are represented by strings of genetic factors called chromosomes. A set of individuals make up a generation. The generation is allowed to evolve through genetic operations of selection, crossover and mutation till a global optimum solution is obtained (Cho, Seok Sung and Ryong Ha 2004). The successful applications of GAs in the solution of water resources management problems have been reported in several studies (Kerachian and Karamouz 2007; Wang, Chang and Chen 2009; Wang *et al.* 2011).

Lavric *et al.,* (2004) presented an approach of genetic algorithm optimisation (GAO) for generating optimal water network topology (OWNT) with an objective to minimize total low-level contaminated water (LLCW) consumption. The algorithm was applied to water systems with multiple pollutants and several LLCW sources, considering only one resource at a time and complying with all restrictions. The OWNT was viewed as an oriented graph, starting from unit operations with the lowest level of contaminants at entrance using an ordering rule based either on the load or the maximum LLCW consumption. A mathematical model based on the total and contaminant species mass balances, together with the input and output units' constraints was developed and solved using the GAO. Each internal flow defined the genes on a chromosomal representation of the decision variable. The individual chromosomes were interbred according to their frequency of selection, using one-point crossover method, then mutation was applied to randomly selected members of the new generation. Comparison of the results with a method of mathematical programming showed that the performance of the GAO was satisfactory, thus the GAO could be used as an alternative for minimizing total LLCW consumption in water network topologies.

It has been observed that water quality of most large rivers in South Korea is poor due to industrialization and pollution due to the high population resident in the cities. Also, seasonal variation in river flow is very large. In the drought season, low flows lead to an increase in the pollution level. Pollution is a serious problem in the middle and lower parts of the rivers because many industrial facilities and large populated cities are located around them. It was especially noted that in the Youngsan river basin, one of the most polluted rivers in South Korea, water quality has depreciated due to heavy pollutant loads from Kwangju city and surrounding areas. In the past, wastewater treatment policy for polluted rivers in Korea has been, first of all, to construct secondary treatment plants for untreated areas and secondarily, to construct advanced treatment plants for the river sections whose water quality is impaired. Unfortunately, the water quality goal of the ministry of environment was not met. Thus, Cho, Seok Sung and Ryong Ha, (2004), in a study to achieve water quality goals and wastewater treatment cost optimisation in the affected river basin, developed a mathematical water quality management model integrating a genetic algorithm.

In the study, total wastewater treatment costs in the basin were calculated as the sum of the treatment cost for each plant, which was based on the treatment type. Treatment cost for a wastewater treatment plant is the sum of the annual repayment for capital construction costs and annual operation-and-management costs. In calculating the annual repayment for capital costs, the construction costs of already completed plants were not included but the construction costs for the new plants and the additional costs for the capacity expansion and the upgrade of existing plants were included. An amortization period of 20 years and a social discount rate of 11.3 percent were used in the study. Pollution source, land use, geographic features and measured water quality data of the river basin were incorporated into the ArcView geographic information system database to facilitate the selection of treatment type and computation of treatment cost for 26 wastewater treatment plant in the river basin.

In applying GA to resolve the water quality management problem, the chromosome was designed in such a way that the genes represented the treatment level at each wastewater treatment plant. A careful selection of proper genetic operators among various kinds of genetic operators was made. The chromosomes were encoded using a system of binary digits. In the optimisation process of the GA, a population of 90 chromosomes was used; crossover and mutation probabilities were set at 80 percent and 1 percent respectively. The algorithm was iterated for 100 generations. The fitness of the chromosomes were evaluated using the results of the forecasts of water quality and treatment cost. The fitness value was represented as the inverse of the sum of the total treatment cost and the penalty. A penalty was given whenever the water quality goal is violated, the fitness value is modified by linear scaling. Linear scaling was used for the proper selection of the parents. The modified fitness values of the chromosomes were used for selecting parents that will produce offspring for the next generation. Results from four scenarios that do not use the GA were compared with the results of the management model using the GA. It was found that the results based on the GA were much better than those for the other four scenarios from the viewpoint of the achievement of water quality goals and cost optimisation. It was therefore concluded that GA could be an alternative to other mathematical programming methods which have been applied in regional wastewater treatment cost optimisation.

Lavric, Lancu and Pleayu (2005) proposed the use of a hybrid technique based on an improved GA, to solve the optimisation problem of finding the minimum water supply concomitantly with the water network topology ensuring the maximum water reuse. The hybrid character of the algorithm is given by the local reshape of the chromosome at the gene level to cope with the mass balance restrictions, while the improvement of the GA is given by the shrinking neighbourhood cloning strategy which favours the individuals surrounding the best-so-far solution. The GA optimisation uses each network's internal flow as a gene, assembling the topology into a chromosome. The boundary constraints in terms of minimum and maximum allowable flows for each gene are satisfied during population generation by simply rejecting genes lying outside the feasible domain. The individuals were interbred according to their frequency of selection using the one-point crossover method and then mutations were applied to randomly selected individuals. The algorithm was tested on test problems from literature and was proven to have better performance after which it was used to solve the more difficult problem of finding an optimal topology of the wastewater network when multiple contaminated water sources are considered. A mathematical model describing each unit operation based on total and contaminant species' mass balances, together with input and output constraints was developed and solved using the algorithm. The topology of the wastewater network was encoded by an oriented graph which was adequately represented by an upper triangular matrix in which the units lay on the diagonal positions. Finally, the algorithm was encoded in an easy to use software which facilitates the computation of the optimal topology of the unit operations' network and the minimum supply water consumption, observing the imposed inlet and outlet constraints.

In a study employing the use of an enhanced genetic algorithm (EGA) for bi-objective pump scheduling in a water supply system, Wang, Chang and Chen (2009) argued that when a cost-effective water distribution system is to be designed, the best way is to plan a profitable schedule for a set of pump combination. Frequently however, existing infrastructures more often than not are not allowed to be altered or reconstructed. Thus, without modifying the infrastructure, the overall cost can still be cut down by using a good pumping schedule. Moreover, a good pump scheduling scheme is a feasible and economic way to save pumping cost. This is because there is no need to destroy the current infrastructure and the existing pumps and pipelines still can contribute to daily efficient water distribution. Therefore, the only thing that needs to be redesign is a good schedule, namely that, if possible, the pumps had better be operated in the night time.

Wang, Chang and Chen (2009) further argued that in areas where groundwater is the sole water resource, it should be used temperately because depleting groundwater may cause land subsidence, an environmental change that can hardly be recovered. This situation may be avoided through artificial mediation through improved pumping by pumping water intermittently. Thus by developing an eco-aware schedule, land subsidence caused by over-pumping groundwater can be slowed down. Therefore, an eco-aware objective was considered in the proposed model such that the final resulting schedules can be not only cost-effective but also environmental conscious. A good pumping scheme therefore, should be a trade-off between environmental benefits and maintenance cost.

In the study, a GA-based pump scheduling scheme in which pumps need to be used intermittently was proposed. In this scheme, a GA-based local search is proposed to enhance the intensification force, i.e., the exploitation of the accumulated search experience. A real number chromosome encoding was also employed to meet the needs of the real world problem. Two selection operators were employed in the selection procedure: one for single-objective optimisation and one for bi-objective optimisation. For the single-objective optimisation (i.e., cost optimisation), the roulette wheel selection is considered while for the bi-objective optimisation (i.e., cost and subsidence), a Pareto fitness ranking was used to guide the selection procedure. A single-point crossover operator was employed in which a pump is randomly chosen as a crossover point and tail parts of two solutions are exchanged to produce two new offspring. Five heuristic mutation procedures were employed to access vectors points in the search space. The evolutionary population size N_p was set at 100 and the number of generations, gMax at 1000. The crossover rate and mutation rate used in all methods were 0.9 and 0.5, respectively.

Unlike traditional GA methods, the proposed EGA has two merits. First a method of greedy selection is employed to obtain a near-optimal solution at the beginning and to accelerate the convergence speed. In comparison to conventional methods, the proposed scheme generates a higher quality population. Therefore, only a few iterations are needed to achieve desired convergence. Second, a binary local search is developed according to the properties of the problem. With this local search, each chromosome can converge at the local minimum in its neighbourhood such that promising solutions are not ignored by the proposed scheme.

To ease the computational tedium involved in the research, the proposed algorithm was implemented using Delphi 7, a powerful rapid application development tool. Final results showed that the schedule did not only achieve lower cost but also gained more environmental benefits. In concluding the study, Wang, Chang and Chen (2009), suggested that future researches should focus on accelerating the convergence speed of the EGA.

2.4 WATER RESOURCES MANAGEMENT USING DIFFERENTIAL EVOLUTION

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 optimisation 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 (Price, Storn and Lampinen 2005). In recent years, DE has gradually become more popular and has been used in many practical cases, mainly because it has demonstrated good robust convergence properties and is principally easy to understand (Yuan *et al.* 2008; Goudos *et al.* 2011; Lu *et al.* 2011). For instance, Adeyemo and Otieno (2010) presented four strategies of a multi-objective differential evolution algorithm (MDEA) to demonstrate the potential of maximizing the farmer's total net income despite the water shortage problems in South Africa. MDEA is a multi-objective evolutionary algorithm based on the original DE algorithm proposed by Price and Storn (1997). In the study, four strategies of MDEA namely, MDEA1, MDEA2, MDEA3 and MDEA4 were adopted to solve a multi-objective crop planning model with multiple constraints in a farmland in the Vaalharts irrigation scheme (VIS). VIS covers about 36,950 ha and is located in the east of Fhaap Plateau on the Northern Cape and North West province borders in South Africa. The three objectives of the model were to minimize the total irrigation water (m^3) and to maximize both the total net income in South African Rand (ZAR) from farming and the total agricultural output in tons. Four crops namely maize, groundnut, Lucerne and Peacan nut were planted with each crop planted in at least 5000m^2 of land. Monthly estimated of gross irrigation water requirements for the crops were computed following standard procedures. The volume of total irrigation water to be used for irrigating the four crops on the farm is minimized due to shortage of water in the study area.

Numerical results produced quality non-dominated solutions which converged to Pareto optimal fronts. MDEA1 and MDEA2 strategies with binomial crossover method were found to be better for solving the crop planning problem than MDEA3 and MDEA4 strategies with exponential crossover method. It was observed that MDEA, which handles multiple constraints using a penalty function proposed by Deb, (2001), runs faster with more quality Pareto optimal solutions when tested on benchmark problems. All the four strategies of MDEA namely, MDEA1, MDEA2, MDEA3 and MDEA4 found non-dominated solutions that converge to the Pareto fronts. The solutions were also diverse on the Pareto fronts. Thus, it was concluded that the four strategies of MDEA are effective and robust multi-objective optimisation algorithms for solving multi-objective models in water resources management especially in water deficient countries like South Africa.

According to Karterakis *et al.,* (2007), the multiple uses of coastal water resources and the necessity of maintaining them in good quality require rational design and management. The water quality deterioration due to seawater intrusion that is observed in the coastal aquifers, especially during the summer season, has been identified as the main environmental problem of coastal these regions.

In an attempt to design an optimal pumping scheme in the coastal aquifer of Hersonissos in Crete, to ensure water adequacy during the summer season without enhancing the already intense seawater intrusion problem in the region, Karterakis *et al.,* (2007) understudied the optimal management of freshwater resources in coastal regions based on environmental criteria with focus on the determination of an optimal pumping scheme. This will ensure adequacy of portable water supply in coastal regions without deteriorating the quality of freshwater due to seawater intrusion.

The objective of the management model was formulated to maximize total extracted freshwater volume from five preselected pumping locations (production wells). Constraints that ensure no further intrusion of the seawater front were imposed at ten preselected observation locations where the calculated hydraulic head should be greater than a specified value at the end of a 10-year management period. Restrictions for all the five production wells regarding the maximum allowable extracting rates were also imposed and summarized in a mathematical model. First, a simplex method was used to solve the constrained optimisation problem; a piecewise linearization of the non-linear optimisation problem was obtained by sequential implementation of the simplex algorithm. Secondly, the solution of the non-linear optimisation problem was obtained using a DE algorithm. In the implementation presented in the study, the constraints were combined with the objective function as penalty terms to form a fitness function which is minimized using DE. A comparison of the results obtained by the two different optimisation approaches was performed and a sensitivity analysis was employed in order to examine the influence of the active pumping wells in the evolution of the seawater intrusion front along the coastline. The solutions provided by the two methods were similar for values of the volume flow rates and the values of the sensitivity analyses. However, a discrepancy between the two solutions was observed at a particular pumping well location where the simplex method, contrary to the DE algorithm, provided a zero value for the corresponding volume flow rate. Additionally, as the sensitivity analysis demonstrated, the simplex solution shows a much higher sensitivity at the well compared to the DE solution, which seems more robust.

2.5 WATER RESOURCES MANAGEMENT USING EVOLUTION STRATEGY

Evolution strategy (ES) was developed in 1963 by Ingo Rechenberg and Hans-Paul Schwefel at the Technical University of Berlin (TUB) while solving an engineering optimisation problem. ES like GA is a stochastic search heuristic based on ideas of adaptation and evolution and is conceptually similar to natural evolution (Mirghani *et al.,* 2009). An ES is an effective continuous function optimiser in part because it encodes parameters as floating-point numbers and manipulates them with arithmetic operators. ES primarily uses mutation and selection as search operators. These operators are applied iteratively (Price, Storn and Lampinen 2005). The uses of ES as function optimisers have been reported in studies (Berlich and Kunze 2004; Kanoun, Troltzsch and Trankler 2006; Navale and Nelson 2010).

Mirghani *et al.,* (2009) in a study aimed at finding solutions to groundwater contaminant source identification problems argued that groundwater contaminant source identification is important in environmental forensics and characterization of contamination for the purposes of regulatory enforcement and liability assessment. Further, groundwater characterisation can be classified as an inverse problem which involves the resolution of unknown system characteristics from observed data. Inverse problems are difficult to solve due to their natural ill-posedness and computational intractability. In the study, a simulation–optimisation approach that couples a numerical pollutant transport simulation model with an evolution strategy search algorithm was adopted for solution of the inverse problem. In a simulation–optimisation approach, the simulation model is coupled loosely or tightly with an optimisation technique to determine the model inputs that best represent the observed data.

The research considered three-dimensional heterogeneous and homogeneous flow field problems with four to seven unknown parameters to be estimated, with the contaminant source located within the aquifer. The solution method uses a loosely coupled simulation–optimisation approach. In the context of the problem, source locations and historical contaminant release schedules were the unknowns and were resolved from the spatially and temporally distributed observations collected at the contaminant monitoring wells. The main objective was to enhance the efficiency of the simulation–optimisation approach utilizing high performance technologies that minimizes the overall computation time for solving groundwater inverse problems. A parallelization approach that exploits the fine and coarse grained parallelism exhibited by simulation–optimisation frameworks was employed to improve the simulation model's efficiency and reduce forward model computation time. A forward model, represented by a system of partial differential equations (PDEs) was used to describe the transport processes of the groundwater system and to define the relationship between system inputs and outputs. This numerical transport model is then solved iteratively during the evolutionary search. Several variations of a groundwater source identification problem were examined and the fitness function was evaluated in terms of solution quality and computational performance. A population size of 128 vectors was used for the ES-based procedure, which was executed for 10 generations, to estimate the computation time.

The results indicate that while ES performs adequately for all scenarios investigated, the performance was affected by problem complexity i.e. number of decision variables used to characterize the source. It was however found that the parallel simulation–optimisation framework with the optimal configuration reduces the simulation time drastically from days to minutes when compared to a serial implementation method. The process involved in the study were computationally intensive since several hundreds to thousands of forward model evaluations are typically required for solutions to be found, hence the computational experiments were performed on the TeraGrid cluster, a mainframe computer available at the National Centre for Supercomputing Applications.

2.6 WATER RESOURCES MANAGEMENT USING GENETIC PROGRAMMING

Genetic programming (GP) is a class of evolutionary algorithm that automatically creates computer programs to perform a selected task using the principle of Darwinian natural selection. GP is a robust, dynamic and fast growing discipline and has been successfully applied and verified in the field of water resources engineering (Aytek, Asce and Alp 2008; Ghorbani *et al.* 2010; Nasseri, Moeini and Tabesh 2011).

Shiri and Kisi, (2010) in a study to investigated best-fit models for predicting groundwater depth in Bondville and Perry, understudied the ability of GP and adaptive neuro-fuzzy inference system (ANFIS) techniques for groundwater depth forecasting. Five GP and ANFIS models comprising various combinations of water table depth values were developed to forecast one, two and three-day ahead water table depths. Comparison of the accuracy of the models were made based of the root mean square errors (RMSE), scatter index (SI), variance account for (VAF) and coefficient of determination (R^2) statistics. Results showed that the GP and ANFIS models could be employed successfully in forecasting water table depth fluctuations. However, GP was found to be superior to ANFIS in accuracy and provided explicit mathematical expressions for the problem.

A machine code-based genetic programming for suspended sediment concentration estimation in the flow of a river at Jagual, Puerto Rico, was developed by Kisi and Guven (2010). The study proposed an application of linear genetic programming (LGP) which is an extension to GP technique, for suspended sediment concentration estimation. The authors argued that accurate estimation of suspended sediment concentration carried by a river is important with respect to channel navigability, reservoir filling, hydroelectric-equipment longevity, river aesthetics, fish habitat, scientific interests and many water resources projects. Underestimating sediment yield ultimately results in insufficient reservoir capacity. Hence, to acquire an appropriate reservoir design and operation, it is mandatory to determine sediment yield accurately.

The study by Kisi and Guven (2010), utilised the LGP variant of GP which operates directly on binary machine code strings that are perturbed directly in memory and are executed directly without passing through an interpreter during fitness calculation. This results in a significant speedup compared with interpreting systems. The main characteristic of LGP in comparison to tree-based GP is that expressions of a functional programming language (for example LISP) are substituted by programs of an imperative language (like C). The main aim of the study was to develop an explicit formulation based on LGP to accurately estimate suspended sediment concentration.

The evolutionary algorithm adopted for the LGP applies tournament selection and puts a low selection pressure on the individuals by allowing only two individuals to participate in a tournament. The loser of each tournament is replaced by a copy of the winner. In the crossover scheme adopted, a segment of random position and random length is selected in each of the two parents and exchanged. If one of the resulting children exceeds the maximum length, crossover is aborted and restarted with exchanging equally sized segments. The crossover points only occur between instructions. A mutation operation that randomly replaces instruction identifier, variables, or constants by equivalents from valid ranges was adopted. High mutation rates were found to produce better results. The length of initial population of feasible programs was 64 instructions per program and the maximum number of instructions allowed per program was set to 256. The LGP algorithm was iterated for 10,000 generations.

Daily streamflow and suspended sediment concentration data from two stations, Rio Valenciano and Quebrada Blanca, operated by the US Geological Survey (USGS) were used as case studies. The performance of LGP was compared with those of the adaptive neuro-fuzzy, neural networks and rating curve models employed in previous studies. Comparison of the results indicated that the LGP performs better than the neuro-fuzzy, neural networks and rating curve models based on the root mean square errors (RMSE) and determination coefficient (R^2) statistics. Unlike the neuro fuzzy (NF) and ANN which are black-box models, the LGP model presents a simple explicit mathematical formulation. It was concluded that LGP, which is relatively simpler than NF and ANN can be successfully employed in modelling daily suspended sediment concentrations in rivers.

Sreekanth and Datta, (2010) developed surrogate models for evolving multi-objective management strategies for saltwater intrusion in coastal aquifers. Two different surrogate models, one based on GP and the other based on modular neural network (MNN) were developed and linked to a multi-objective genetic algorithm (MOGA) to derive the optimum pumping strategy for coastal aquifer management, considering two objectives. The surrogate models were trained and tested then used to predict the salinity concentrations at different locations resulting from groundwater extraction. A two-stage training strategy was implemented for training the surrogate models. Surrogate models were initially trained with input patterns selected uniformly from the entire search space and optimal management strategies based on the model predictions were derived from the management model. A search space adaptation and model retraining was also performed by identifying a modified search space near the initial optimal solution based on the relative importance of the variables in salinity prediction. The performance of the methodologies using GP and MNN based surrogate models were compared for an illustrative study area. It was found that the developed GP models had lesser uncertainty compared to MNN models and the number of parameters used in the GP model was lesser than that used in the MNN models. Results also showed that the GP based model were better suited for optimisation using an adaptive search space.

2.7 CONCLUSION

Optimisation models with varying degrees of complexities have been widely applied for resolving water resources optimisation and allocation problems. In recent times, procedures based on heuristic EAs have found wide spread applications in the fields of water resources planning, management and optimisation. This chapter made a review of some of the numerous evolutionary optimisation algorithms available to water resources planners and managers. Several heuristic algorithms have been applied in resolving water resources optimisation problems, yet there still exist some uncertainties about finding a generally trustworthy method that can consistently find solutions which are really close to the global optimum of the problems in all circumstances (Kerkez *et al.* 2010). The choice of optimisation model is almost arbitrary as no physical basis is available to rationalize the use of any particular algorithm. Search for the proper optimisation function has been the subject of several studies (Chen and Fu 2005; Khademi *et al.* 2009; Cisty 2010).

EAs have been found propitious and useful in facilitating critical water management decisions and are becoming promising global optimisation tools for major real world applications. Therefore, developing single and multi-objective evolutionary optimisation procedures that integrate resource planning of available resources and the simultaneous management of various demands or allocation is a topic that is still open for further research in the field of water resources planning and management. Further research aimed at developing evolutionary optimisation algorithms for water resources planning, management and optimisation is therefore necessary.

2.8 RESEARCH OUTPUTS

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[2] Adeyemo, J. and **Olofintoye, O.** 2014. Optimized Fourier Approximation Models for Estimating Monthly Streamflow in the Vanderkloof Dam, South Africa. In: Tantar, A., Tantar, E., Sun, J., Zhang, W., Ding, Q., Schütze, O., Emmerich, M., Legrand, P., Moral, P. D. and Coello Coello C.A. eds. *EVOLVE - A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation V*. Switzerland: Springer International Publishing, 293-306.

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CHAPTER 3

A COMBINED PARETO DIFFERENTIAL EVOLUTION APPROACH FOR MULTI-OBJECTIVE OPTIMISATION

3.1 OVERVIEW

In recent years, methods of multi-objective evolutionary algorithms (MOEAs) have been developed to solve problems involving the satisfaction of multiple objectives within the limits of certain constraints, yet there still exists some uncertainty about finding a generally trustworthy method that can consistently find solutions which are really close to desired objectives in all situations. In this chapter, a combined Pareto multi-objective differential evolution (CPMDE) algorithm is presented. The algorithm combines methods of Pareto ranking and Pareto dominance selections to implement a novel selection scheme at each generation. The ability of CPMDE in solving unconstrained, constrained and real-world optimisation problems was demonstrated. Competitive results obtained from benchmarking CPMDE suggest that it is a good alternative for solving real multi-objective optimisation problems.

3.2 INTRODUCTION

Optimisation problems are ubiquitous in engineering and the sciences. Simply put, optimisation is an attempt to maximize a system's desirable properties while simultaneously minimizing its undesirable characteristics (Price, Storn and Lampinen 2005). Optimisation also refers to the art 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 (Babu, Chakole and Syed-Mubeen 2005). 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 2001). In the solution of MOOPs, the aim is to simultaneously optimise a set of conflicting objectives to obtain a group of alternative trade-off solutions called Pareto-optimal or non-inferior solutions which must be considered equivalent in the absence of specialized information concerning the relative importance of the objectives (Fan, Lampinen and Levy 2006; Deb 2011).

Differential evolution (DE) is a stochastic direct search evolution strategy optimisation method that is fairly fast and reasonably robust. Since its inception in the 90's, DE has found practical applications in the solution of scientific optimisation problems (Adeyemo and Olofintoye 2012). Due to its reported successes, its uses have been extended to other types of problem domains, including multi-objective optimisation (Price, Storn and Lampinen 2005; Mezura-Montes, Reyes-Sierra and Coello 2008). In recent times, several researches extending the application of DE for finding solutions in the multi-objective problem domains have been reported in the literature (Babu and Jehan 2003; Angira and Babu 2005; Adeyemo and Otieno 2009a). For example, Fan, Lampinen and Levy (2006) presented and validated a new differential evolution method for multi-objective optimisation. In their study, a new selection scheme was designed to replace the existing one to enable DE applicable to solve either single objective or multi-objective optimisation problems. In their selection scheme, the trial population vector is compared with its counterpart in the current population. If the trial candidate dominates the current population member it will survive to the next generation and replace the current population vector, otherwise the current population member is retained. They suggest that if the trial solution is worse than the target solution in any of the objectives, it should be discarded. The method was validated using three multi-objective benchmark optimisation problems. Simulation results show that the approach is capable of generating an approximated Pareto-front for the selected problems. To further examine the practical applicability of the proposed method, it was used to optimise a prototype air mixer subject to two objectives. Results show that the new DE approach can handle practical multi-objective problems successfully.

A comprehensive survey of the state-of-the-art on methods of multi-objective optimisation using differential evolution is provided by Mezura-Montes, Reyes-Sierra and Coello (2008). In the survey, methods that adjust the selection scheme of traditional DE to implement new selection schemes for multi-objective optimisation are broadly categorized as either methods employing Pareto-ranking or Pareto-dominance approaches. Methods of Pareto-ranking for multi-objective DE assign ranks to each solution in the combined trial and target population based on their non-domination levels. Solutions on the best non-dominated front are assigned a rank of '1'; the solutions in the next set are assigned '2' and so on. Algorithms using this method often select all solutions with the best ranks for propagation to the next generation. In Pareto-dominance method for DE, ranks are not assigned, rather, a solution that wins the domination contest at an index proceeds to the next generation (Mezura-Montes, Reyes-Sierra and Coello 2008). In this chapter, a novel multi-objective evolutionary algorithm (MOEA) which incorporates DE as its base algorithm is proposed. The algorithm combines the Pareto-ranking and Pareto-dominance approaches in a unique way to implement a novel selection scheme at each generation. Hence, it is named combined Pareto multi-objective differential evolution (CPMDE). Results obtained from benchmarking CPMDE show its promises as an excellent alternative method of MOEA.

3.3 COMBINED PARETO MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION

At each generation of CPMDE, the combined population of trial and target solutions are checked and non-dominated solutions (i.e. solutions on the best non-dominated front - with rank '1') are marked as 'non-dominated' while others are marked 'dominated'. After generating a trial population, tournaments are played between trial solutions and their counterparts in the target population at the same index. Four scenarios emerge: 1) if the trial solution is marked 'non-dominated' and the target is marked 'dominated' then the trial vector replaces the target vector and the target vector is discarded. 2) If the trial solution is marked 'dominated' and the target is marked 'non-dominated' then the trial vector is discarded. 3) If both solutions are marked 'dominated' then we resort to the method of Pareto-dominance selection where the trial vector replaces the target vector if it dominates the target or if they are non-dominated with respect to each other. 4) If both vectors are marked 'non-dominated', then a harmonic average crowding distance measure suggested by Huang *et al.* (2005) is employed to select the solution that will proceed to the next generation. Furthermore, the crowding tournament is delayed until all solutions marked 'non-dominated' in the first three scenarios are installed in the next generation after which non-dominated solutions at the remaining indices are sorted out one at a time.

3.3.1 CPMDE algorithm

The step-by-step procedure of the proposed CPMDE can be summarized in the following algorithm listing:

---

1. Input the required DE parameters like number of individuals in the population (Np), mutation scaling factor (F), crossover probability (Cr), maximum number of iterations/generations (gMax), number of objective functions (M), number of decision variables/parameters (d) and upper and lower bounds of each variable.
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 (Price, Storn and Lampinen 2005).
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 tournaments at each population index. Tournaments are played by comparing trial and target solutions at the same index.
    i. If the trial solution is marked 'non-dominated' and the target is marked 'dominated' then the trial vector replaces the target vector and the target vector is discarded.
    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 with the trial 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 (Huang *et al.* 2005). 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 Deb (2001).

3.3.2 Visualizing the effect of the combined Pareto selection procedures on the difference vector distribution

DE is based on evolution using difference vectors; therefore the difference vector distribution affects the optimisation process (Price, Storn and Lampinen 2005). The impact of the distribution of difference vectors on algorithm performance is illustrated as follows: Figure 1a shows a hypothetical distribution of 12 vectors in a bi-objective optimisation problem where both objectives are minimized. Vectors 1-6 are assumed to be target vectors while vectors A-F are the trial vectors. Figure 1b shows the ranks of the solutions. In order to fill the six slots in the next generation, it is further assumed that solutions 1, 2, 3 compete against A, B, C while solutions 4, 5, 6 compete against D, E, F respectively. Following these assumptions, algorithms based solely on Pareto ranking selection (PRS), (e.g. NSGA-II) will select solutions 1-6 as parents for the next generation (Figure 2a), while the procedure of CPMDE selects solutions 1, 2, 3 because they have a rank of '1' as parents for the next generation. This serves to provide a direction for the search. Also solution D will replace solution 4 while E will replace solution 5 because they are non-dominated with respect to each other though solutions 4 and 5 lies on a front with a better non-dominated rank (Figure 2b). Figures 3a and 3b present the difference vector distributions obtained by PRS and CPMDE.

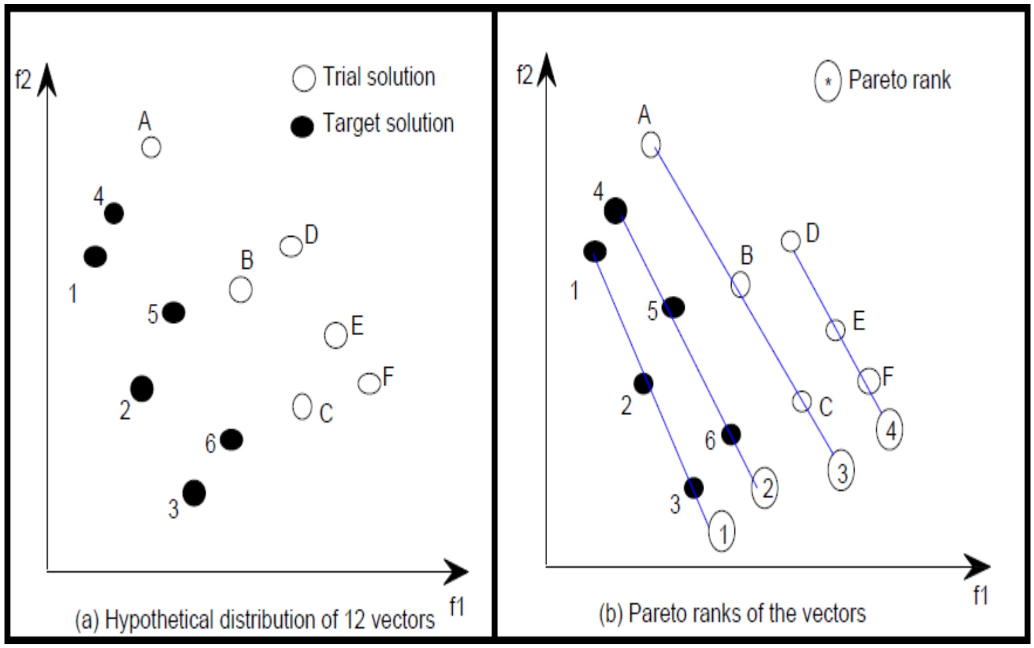


Figure 1: Hypothetical distribution of 12 vectors and their Pareto ranks.

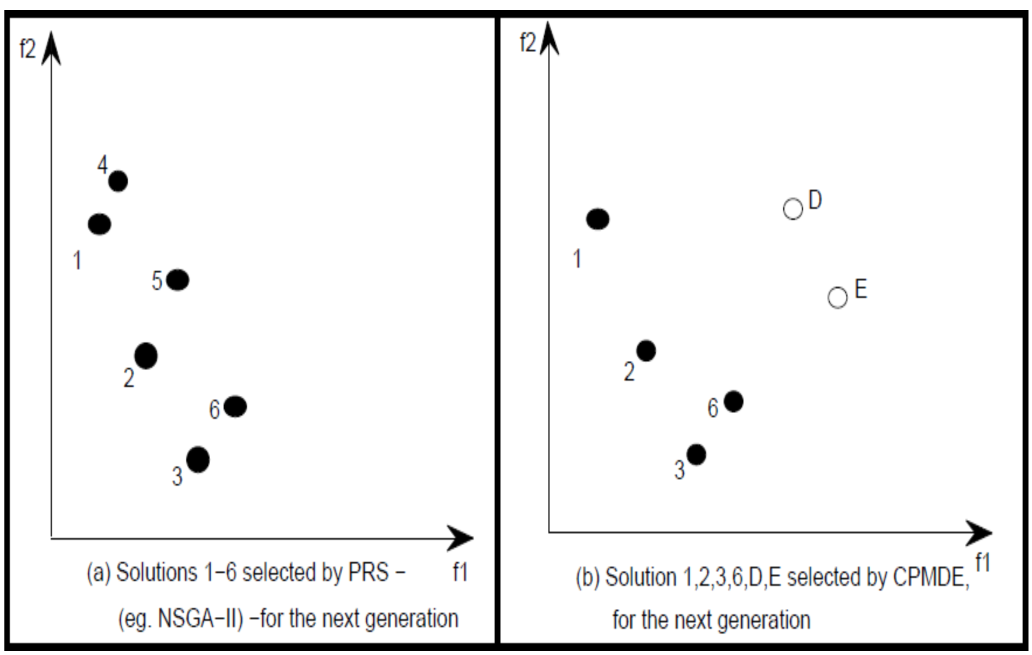


Figure 2: Solutions selected by PRS and CPMDE for the next generation.

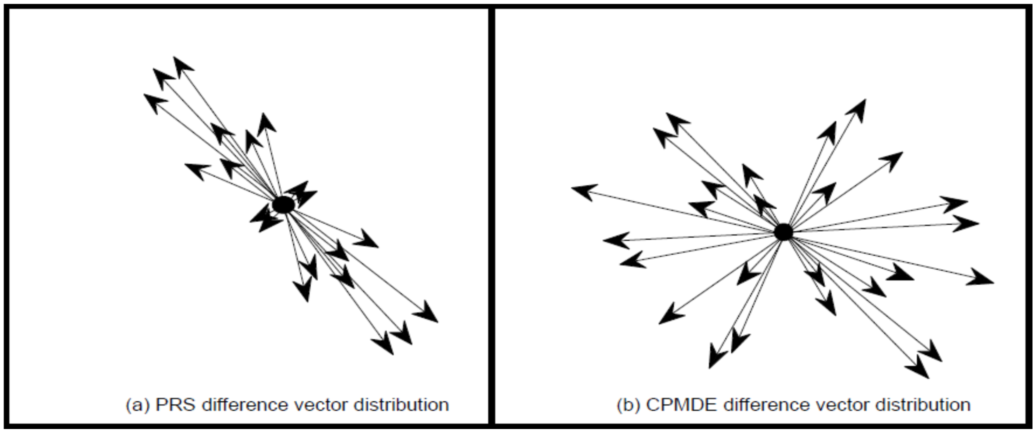


Figure 3: Difference vector distributions produced by PRS and CPMDE.

Inspection of Figure 3a shows that the sheaf of vector difference produced by PRS algorithms like NSGA-II contains some short vectors suitable for local search. The longer vectors are however aligned somewhat longitudinally to the best non-dominated front found. Figure 3b shows that controlling elitism of the pool by allowing solutions on lower ranks to proceed to the next generation, the difference vector distribution of CPMDE can be made to contain some short vectors suitable for local search and long vectors which are traverse to the fronts and suitable for a global search. Figure 4a shows that Perturbation with the difference vector distribution of procedures based solely on Pareto ranking selection like NSGA-II has a propensity to get attracted to a local optimal front while those of CPMDE are able to escape local fronts in the early generations Figure 4b.

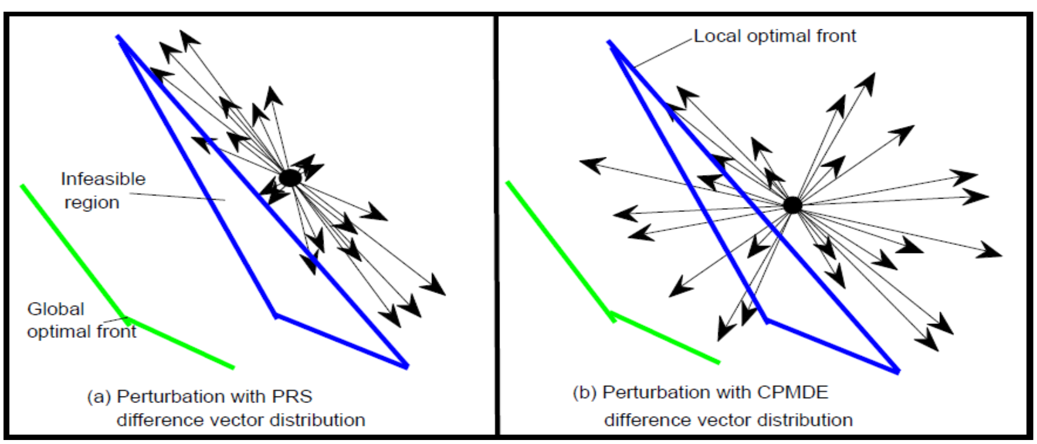


Figure 4: Perturbation using PRS and CPMDE difference vector distributions.

3.3.3 Promoting diversity among solutions in the obtained non-dominated set

In order to obtain a diverse set of solutions in the obtained non-dominated front, CPMDE employs the harmonic average crowding distance measure suggested by Huang *et al.* (2005) to select the solution that will proceed to the next generation when both solutions lie on the best non-dominated front. This method harmonizes the average distances of all k-nearest neighbours around a solution. The harmonic average distance d, is computed using equation (3.1) (Huang *et al.* 2005):

$$d = \frac{k}{\frac{1}{d_1} + \frac{1}{d_2} + \cdots + \frac{1}{d_k}} \qquad \ldots.\ (3.1)$$

where d_1, d_2, …, d_k are the Euclidean distances of k nearest neighbouring solutions and k is the number of nearest solutions. If one of the distances is very large and other distances are all small, the harmonic average distance will still be small. In this way, influence of outliers on the computation of crowding degree may be overcome. Solutions with higher harmonic average distances are better (Huang *et al.* 2005). Furthermore, at higher iterations, the harmonic distance measure ensures uniform distribution of solutions on the non-dominated front.

3.3.4 Handling constraints in CPMDE

3.3.4.1 Variable bound constraints

In CPMDE, boundary constraints are handled using the bounce-back strategy. This strategy replaces a vector that has exceeded one or more of its bounds by a valid vector that satisfies all boundary constraints. In contrasts to random re-initialization, the bounce-back strategy 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 (Price, Storn and Lampinen 2005).

3.3.4.2 Equality and inequality constraints

Equality and inequality constraints are handled using the constrained-domination technique suggested by Deb (2001). A solution $x^{(i)}$ is said to constrained-dominate another solution $x^{(j)}$, if any of the following conditions is true:

i. Solution $x^{(i)}$ is feasible and solution $x^{(j)}$ is not feasible.

ii. Solutions $x^{(i)}$ and $x^{(j)}$ are both infeasible, but solution $x^{(i)}$ has a smaller overall constraint violation.

iii. Solutions $x^{(i)}$ and $x^{(j)}$ are feasible and solution $x^{(i)}$ dominates solution $x^{(j)}$.

3.4 BENCHMARKING CPMDE

The performance of CPMDE was compared with 6 state-of-the-art MOEAs on four unconstrained benchmark test beds. The performance of CPMDE was also compared on one constrained test problem and assessed on a three-objective optimisation problem. Furthermore, the performance of CPMDE on an engineering cantilever design problem is demonstrated. Other algorithms used in benchmarking CPMDE in this study include NSGA-II (real coded), NSGA-II (binary coded), SPEA, PAES, MODE-E (MODE with external archive and crowding distance measure) and MOPSO.

3.4.1 Benchmark test problems

Four test problems: SCH, FON, KUR and ZDT4 were used for evaluating the performance of CPMDE on unconstrained optimisation problems. These are common difficult benchmark problems used in the literatures (Deb *et al.* 2002; Angira and Babu 2005; Huang *et al.* 2005; Reddy and Kumar 2007). These are bi-objective problems in which both objectives are to be minimized. Each problem poses a different type of difficulty to MOEAs. SCH is a single variable problem having a convex Pareto-optimal front. This is the simplest of the test problems. FON is an n-variable problem having a non-convex Pareto-optimal front. The 3-variable version is adopted in this study. The non-convexity of the front is the major difficulty posed here. KUR is a 3-variable problem having a number of disconnected Pareto-optimal fronts. Finding uniform spread of solutions on all discontinuous regions is the challenge in this problem. ZDT4 is a 10-variable problem with 21^9 local optimal fronts. Escaping all local non-dominated fronts to converge to the global optimal front is a real challenge in this problem.

To evaluate the performance of CPMDE on constrained optimisation problem, the problem TNK is used (Deb *et al.* 2002). This is a bi-objective problem with two constraints. Both of the objectives are to be minimized. TNK has a non-convex, discontinuous Pareto-optimal front. Finding uniform spread of solutions on all segments while satisfying both constraints is a challenge in this problem.

Theoretical MOEA optimisation studies generally consider a small number of objectives. The bi-objective case is by far the most studied. Real world MOEA applications, by contrast, are frequently more ambitious, with the number of treated criteria reaching double figures in some cases (Purshouse and Fleming 2003). Hence, the performance of CPMDE was evaluated on test problem DTLZ2 to demonstrate its effectiveness in solving problems involving more than two objectives. The 3-objective version of the test problem is adopted in this study. The definitions and descriptions of all test functions are taken from literatures (Deb 2001; Purshouse and Fleming 2003; Reddy and Kumar 2007; Adeyemo and Otieno 2009a) and summarized in Table1.

3.4.2 Performance measures

Various performance measures for evaluating MOEA performance have been suggested and implemented (Deb 2001). For example, Schutze *et al.* (2012) proposed a method for finding good Hausdorff approximations of Pareto fronts using an averaged Hausdorff distance measure (Δp). The measure Δp is a performance indicator in multi-objective evolutionary optimisation which simultaneously takes into account proximity to the true Pareto front and uniform spread of solutions. Hence, it efficiently combines both spread and convergence measures in a single performance metric. The proposed methodology has further been found useful in MOEA evaluations (Rudolph, Trautmann and Schutze 2012; Trautmann *et al.* 2012). However, in order to provide a uniform basis for comparison of MOEAs used in this study, two performance measures reported in the published studies were adopted (Deb *et al.* 2002; Huang *et al.* 2005). Convergence metric is used to evaluate convergence to the global Pareto-optimal front while diversity metric is employed to measure the spread of solutions on the obtained non-dominated front.

Table 1: Summary of benchmark test problems.

Problem/ Comments	n	Variable bounds	Objective functions and constraints	Pareto optimal solutions
SCH Convex, Unconstrained	1	[-10^3,10^3]	$f_1(x) = x^2$ $f_2(x) = (x-2)^2$	$x \in [0,2]$
FON Non-convex, Unconstrained	3	[-4,4]	$f_1(x) = 1 - \exp\left(-\sum_{i=1}^{3}\left(x_i - \frac{1}{\sqrt{3}}\right)^2\right)$ $f_1(x) = 1 - \exp\left(-\sum_{i=1}^{3}\left(x_i + \frac{1}{\sqrt{3}}\right)^2\right)$	$x_1 = x_2 = x_3$ $\in \left[-\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}\right]$
KUR Non-convex, Unconstrained, Discontinuous	3	[-5,5]	$f_1(x) = \sum_{i=1}^{n-1}\left(-10\exp\left(-0.2\sqrt{x_i^2 + x_{i+1}^2}\right)\right)$ $f_2(x) = \sum_{i}^{n}\left(\mid x_i \mid^{0.8} + 5\sin x_i^3\right)$	(refer: [Deb,2001])
ZDT4 Convex, Unconstrained, Deceptive, Multiple Local- Pareto fronts	10	$x_1 \in [0,1]$ $x_i \in [-5,5$ $i = 2,3,\ldots,$	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{\left(\frac{x_1}{g(x)}\right)}\right]$ $g(x) = 1 + 10(n-1) + \sum_{i=2}^{n}\left(x_i^2 - 10\cos(4\pi x_i)\right)$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,3,\ldots,n$
DTLZ2 Three- objectives, Unconstrained	12	[0,1]	$f_1(x) = (1 + g(x))\cos(x_1\pi/2)\cos(x_2\pi/2)$ $f_2(x) = (1 + g(x))\cos(x_1\pi/2)\sin(x_2\pi/2)$ $f_3(x) = (1 + g(x))\sin(x_1\pi/2)$ $g(x) = \sum_{3}^{n}(x_i - 0.5)^2$	$x_1, x_2 \in [0,1]$ $x_i = 0.5$ $i = 3,4,\ldots,n$
TNK Non-convex, Constrained, Discontinuous	2	$x_i \in [0,\pi]$ $i = 1,2$	$f_1(x) = x_1$; $f_2(x) = x_2$ *Subject to:* $g_1(x) = -x_1^2 - x_2^2 + 1 + 0.1\cos\left(16\arctan\left(\frac{x_1}{x_2}\right)\right) \le 0$ $g_2(x) = (x_1 - 0.5)^2 + (x_2 - 0.5)^2 \le 0.5$	

3.4.2.1 Convergence metric

This is the average distance of the non-dominated set of solutions in Q from a set P*of Pareto-optimal solutions. It is computed using equation (3.2). According to Deb (2001) an algorithm with a smaller value of convergence metric Υ gives a closer convergence to the Pareto front.

$$\Upsilon = \frac{\sum_{j=1}^{|Q|} d_j}{|Q|} \quad \text{.... (3.2)}$$

where d_j is the Euclidean distance (in the objective space) between the solution $j \in Q$ and the nearest member of P*.

3.4.2.2 Spread/Diversity metric

This metric measures the extent and spread of solutions in the obtained non-dominated front. It is computed using equation (3.3):

$$\Delta = \frac{\sum_{m=1}^{M} d_m^e + \sum_{i=1}^{|Q|-1} \left(d_i - \overline{d}\right)}{\sum_{m=1}^{M} d_m^e + (|Q|-1)\overline{d}} \quad \text{.... (3.3)}$$

where d_i is the Euclidean distance (in the objective space) between consecutive solutions in the obtained non-dominated front Q, and $\overline{d}$ is the average of these distances. M is the number of objectives. The parameter d_m^e is the Euclidean distances between the extreme solutions of the Pareto front P* and the boundary solution of the obtained non-dominated front Q with respect to each objective m. An algorithm with a smaller value of diversity metric Δ provides a better spread of solutions on the Pareto front (Deb 2001).

3.4.3 Sensitivity analysis

A sensitivity analysis was performed to determine the best combination of crossover rate Cr and mutation scaling factor F that will be the best for CPMDE in solving optimization problems. Cr was varied from 0.0 to 1.0 at a step of 0.05 while F was varied from 0.1 to 0.9 at a step of 0.05. It was found that the best combination for these parameters is when Cr lies between 0.25 – 0.35 or 0.8 – 0.95 while F ranges from 0.25 – 0.6. The bifurcation in the values of Cr has also been observed by Price, Storn and Lampinen (2005) who suggest that functions solvable with low Cr were decomposable while functions requiring high values of Cr were not. The best combination for Cr, and F was found to be when Cr = F = 0.3 for the test problems.

3.4.4 Experimental setup

In this study, DE/rand/1/bin variant of DE was used as the base for CPMDE. Cr and F were set at 0.3. Population size Np was set to 100 and the algorithm was run for a maximum number of generations, gMax = 250 to give a total of 25000 fitness computations. A set of 500 uniformly spaced solutions were taken from the Pareto-optimal set for computation of all metrics. Averages and variances of metric values over 10 runs are reported in this study. For test problem TNK, gMax was set at 500 generations. Harmonic average crowding distances are computed using two nearest neighbours.

3.4.5 Cantilever design problem

To demonstrate the applicability of CPMDE in solving real-world optimisation problems, the algorithm was applied to design a cantilever beam. A problem originally studied by Deb (2001) using NSGA-II and further studied by Adeyemo and Otieno (2009a) using MDEA is adopted here. A schematic representation of a cantilever beam is depicted in Figure 5.

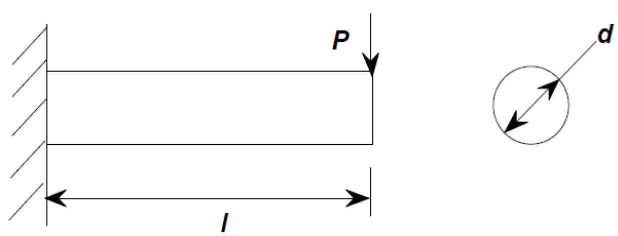


Figure 5: A schematic diagram of a cantilever beam. Source: Adapted, Deb, (2001).

This problem has two decision variables of diameter (d) and length (l). The beam is designed to carry an end load P. There are two conflicting objectives that should be minimized; the weight of the beam f_1 and end deflection f_2. Minimizing the weight, f_1, will result in an optimum solution that will have small dimensions of d and l. If the dimensions are small, the beam will not be adequately rigid and the end deflection of the beam will be large. If on the other hand, the beam is minimized for end deflection, the dimensions of the beam will be large, thereby making the weight of the beam to be large. There are two constraints in this design problem. 1) The maximum stress, σ_{max} must be less than the allowable strength S_y and 2) the end deflection δ must be smaller than a specified limit of δ_{max}. The two-objective constrained optimisation problem for the two decision variables d(mm) and l(mm) is formulated as follows (Deb 2001):

Objective function 1 (Minimize weight): $f_1(d,l) = \rho \dfrac{\pi d^2}{4} l$

Objective function 2 (Minimize deflection): $f_2(d,l) = \delta = \dfrac{64Pl^3}{3E\pi d^4}$

Subject to: $\sigma_{\max} \le S_y, \quad \delta \le \delta_{\max}$

Bound constraints: $10 \le d \le 50mm, \quad 200 \le l \le 1000mm$

$$where: \sigma_{\max} = \frac{32Pl}{\pi d^3}$$

ρ, P, d and l are the density, force, diameter and length respectively. The following parameter values are used: ρ = 7800 kg/m3, P = 1 KN, E = 207 GPa, S_y = 300 MPa and δ_{max} = 5 mm. On this problem, the following settings are used for CPMDE: Cr = 0.9, F = 0.5, Np = 100 and gMax = 300.

3.5 RESULTS

The mean and variance of the convergence metric on the unconstrained test beds over 10 runs of CPMDE are reported in Table 2 while those of the diversity metric are presented in Table 3. The performance metrics for MOPSO on the test problem ZDT4 is not available. The authors reported that this algorithm failed on this multi modal test bed. Reported values of convergence and diversity metrics for other algorithms used in benchmarking CPMDE are taken from correlative literatures (Deb *et al.* 2002; Adeyemo and Otieno 2009a) and presented in the respective tables. Best mean results are shown in boldface.

Figure 6 depicts the convergence of the non-dominated front obtained by CPMDE to the true Pareto-optimal front in problems SCH, FON, KUR and ZDT4. The values of the test metrics are indicated on the respective plots. Figure 7 shows the performance of NSGA-II and CPMDE, respectively, for 500 generations on the TNK problem. Figure 8 shows the results obtained by NSGA-II, MODE, MDEA and CPMDE on the cantilever beam design problem while Figure 9 depicts the convergence of solutions obtained by CPMDE to the true Pareto optimal surface of test problem DTLZ2.

Table 2: Convergence metrics on unconstrained test beds.

Algorithm	Convergence metric			
	SCH	FON	KUR	ZDT4
NSGA-II (real coded)	0.003391±0.000000	0.001931±0.000000	0.028964±0.000018	0.513053±0.118460
NSGA-II (binary coded)	0.002833±0.000001	0.002571±0.000000	0.028951±0.000016	3.227636±7.307630
SPEA	0.003465±0.000000	0.010611±0.000005	0.049077±0.000081	9.513615±11.321067
PAES	**0.001313**±0.000003	0.151263±0.000905	0.057323±0.011989	0.854816±0.527238
MODE-E	0.006502±0.000000	0.003031±0.000000	0.030819±0.000008	0.030689±0.004867
MOPSO	0.006603±0.000000	0.002157±0.000000	0.030858±0.000032	N/A
CPMDE	0.003273±0.000000	**0.001646**±0.000000	**0.017632**±0.000002	**0.000731**±0.000000

Table 3: Diversity metrics on unconstrained test beds.

Algorithm	Diversity metric			
	SCH	FON	KUR	ZDT4
NSGA-II (real coded)	0.477899±0.003471	0.378065±0.000639	0.411477±0.000992	0.702612±0.064648
NSGA-II (binary coded)	0.449265±0.002062	0.395131±0.001314	0.442195±0.001498	0.479475±0.009841
SPEA	0.818346±0.004497	0.804113±0.002961	0.880424±0.009066	0.732097±0.011284
PAES	1.063288±0.002868	1.162528±0.008945	1.079838±0.013772	0.870458±0.101399
MODE-E	0.347156±0.001160	**0.220099**±0.000393	**0.401911**±0.000545	0.338330±0.003676
MOPSO	0.594483±0.002670	0.595938±0.002150	0.620227±0.002170	N/A
CPMDE	**0.156397**±0.000102	0.308420±0.000749	0.402617±0.001025	**0.203378**±0.000400

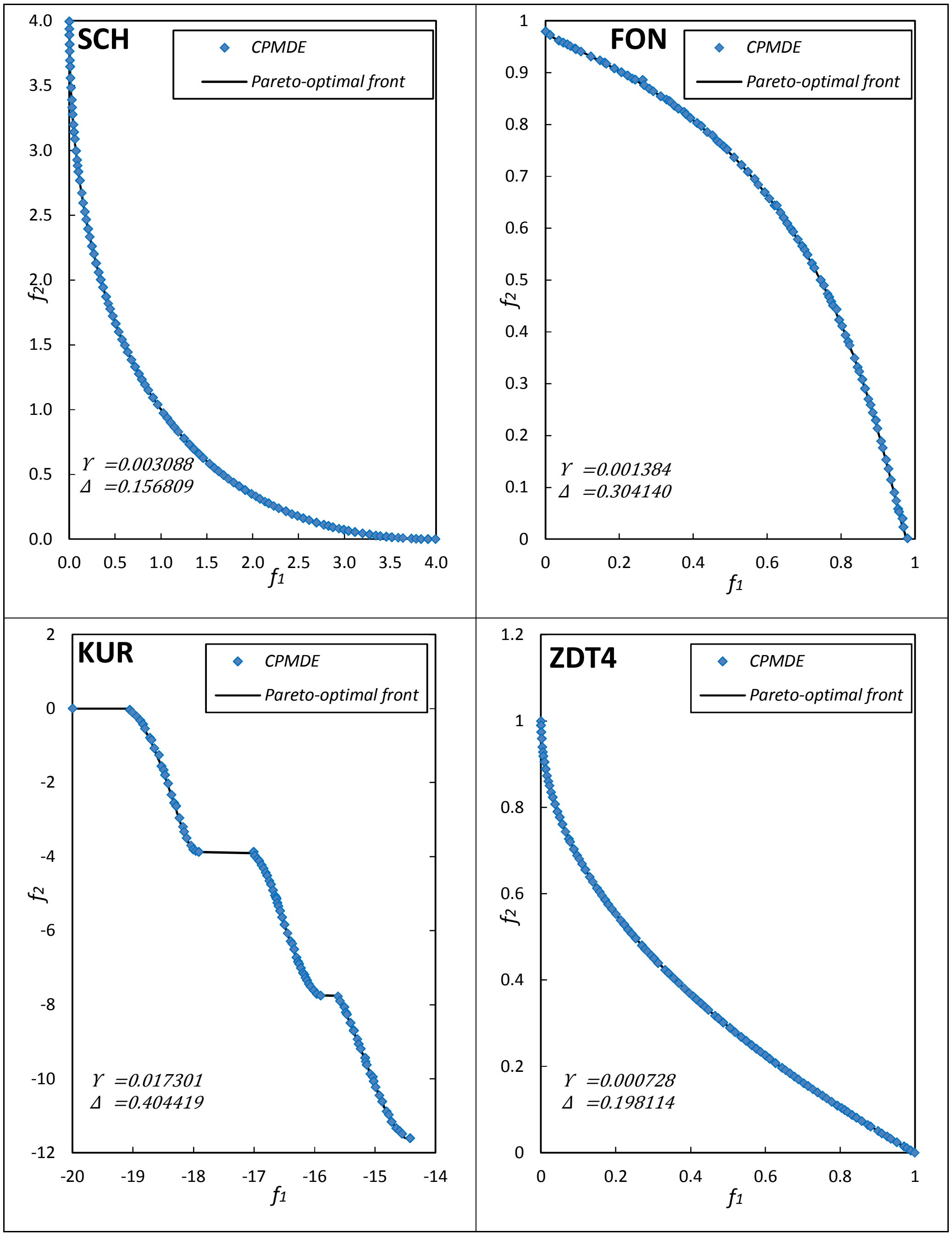
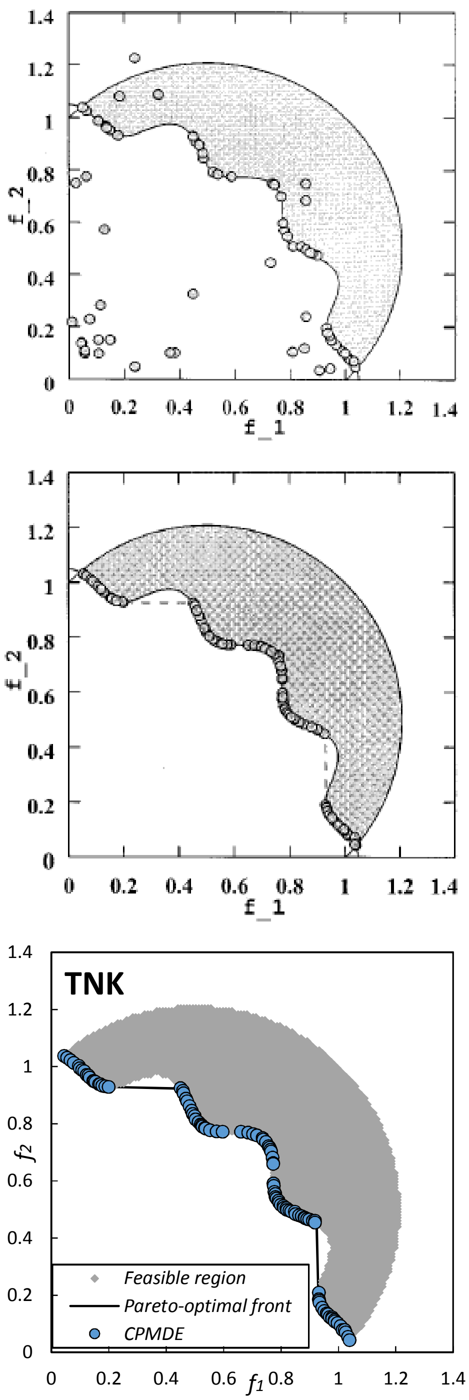


Figure 6: Convergence of CPMDE non-dominated front to the true Pareto-optimal front in problems SCH, FON, KUR and ZDT4.

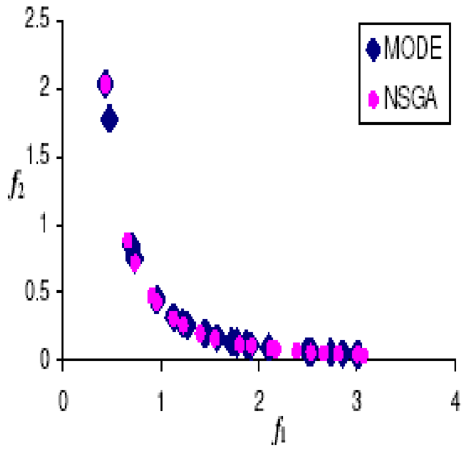


(a)
Obtained non-dominated solutions with RTS based NSGA-II on constrained problem TNK.
Source: Adapted from Deb et al., (2002)

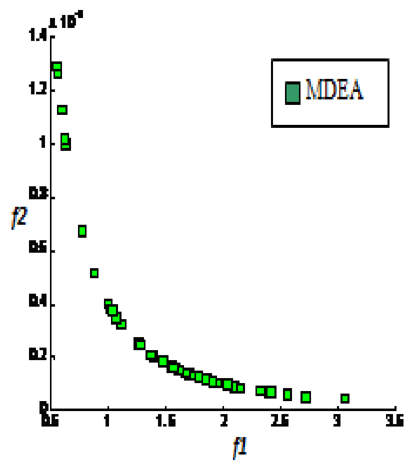
(b)
Obtained non-dominated solutions with constraint domination based NSGA-II on constrained problem TNK.
Source: Adapted from Deb et al., (2002)

(c)
Obtained non-dominated solutions with constraint domination based CPMDE on constrained problem TNK.

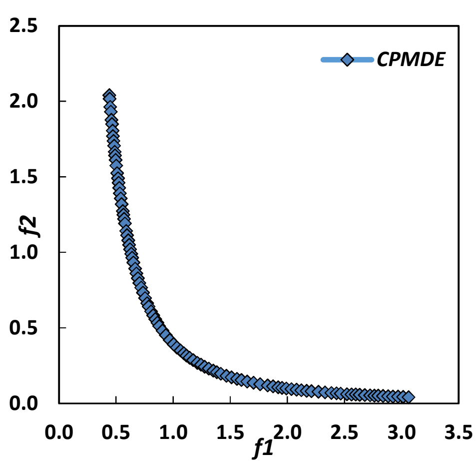
Figure 7: Performance of NSGA-II and CPMDE on test problem TNK for 500 iterations.



(a)
Non-dominated solutions obtained by MODE and NSGA-II for the cantilever beam design problem.
Source: Adeyemo and Otieno, (2009)



(b)
Non-dominated solutions obtained by MDEA for the cantilever beam design problem.
Source: Adeyemo and Otieno, (2009)



(c)
Non-dominated solutions obtained by CPMDE for the cantilever beam design problem.

Figure 8: The results of MODE, NSGA, MDEA and CPMDE for cantilever design problem.

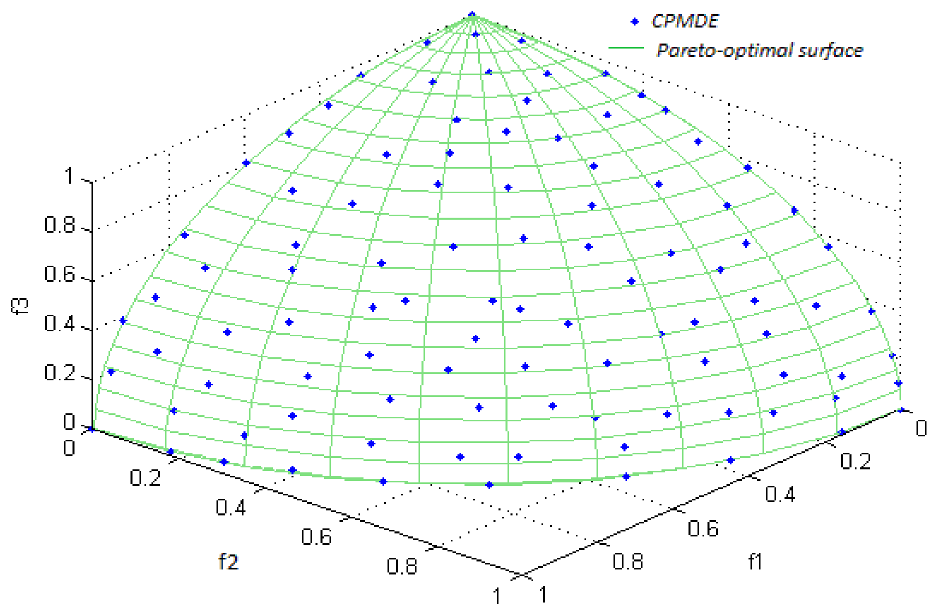


Figure 9: Convergence of CPMDE to the true Pareto-optimal surface of DTLZ2.

3.6 DISCUSSION OF RESULTS

From the results in Tables 2 and 3, it is found that CPMDE performed well in converging to the Pareto front of SCH. It produced the third best result for convergence metric and the best result for diversity metric (Υ=0.003273, Δ=0.156397). PAES performed best on this test bed (Υ=0.001313), the performance of CPMDE is therefore comparable with other algorithms on this problem. CPMDE outperformed all other algorithms in converging to the Pareto front of test beds FON and KUR as it produced convergence metrics of Υ=0.001646 and Υ=0.017632 respectively. However, MODE-E produced better values of diversity metrics on this bed while CPMDE was the runner up in both cases. It can be said that the performance of CPMDE is comparable to MODE-E and better than the other algorithms on these test beds.

The strength of CPMDE in converging to the global Pareto-optimal front in deceptive multi-modal functions is amply demonstrated on test problem ZDT4. Here, CPMDE outperformed all other algorithms in convergence and diversity (Υ=0.000731, Δ=0.203378). The runner-up in this case is MODE-E with metrics (Υ=0.030689, Δ=0.338330). The convergence metric for CPMDE on this problem is several orders of magnitude lesser than those of the other algorithms. On all unconstrained problems except KUR, CPMDE produces variance values of zero (Table 2) and a value of 0.000002 for test problem KUR. This suggests that CPMDE is reliable and stable in converging to the Pareto-optimal fronts of these beds.

By inspection, Figure 7 shows that CPMDE performs better than NSGA-II employing the RTS constraint handling technique on problem TNK. The performance of CPMDE is comparable to the performance of NSGA-II employing the constraint domination technique. This suggests that the constraint domination approach employed by CPMDE for handling constraints is adequate. CPMDE was also able to find uniform spread of solutions on all segments of the discontinuous Pareto front of this problem.

Comparison of results of CPMDE with results obtained by MDEA, MODE and NSGA on an engineering cantilever design problem (Figure 8) indicates that the non-dominated solutions generated by CPMDE are comparable to those of MODE, NSGA and MDEA which are recent state-of-the-art MOEAs. CPMDE produced quality non dominated solutions along the Pareto front. This shows that CPMDE can perform well on real-world engineering problems. From inspection of Figure 9, it is evident that the non-dominated solutions obtained by CPMDE are very close to and well distributed on the true Pareto-optimal surface of test problem DTLZ2. Therefore, CPMDE may be applied to solve optimisation problems involving more than two objectives.

3.7 CONCLUSION

In this chapter, a combined Pareto multi-objective differential evolution (CPMDE) multi-objective evolutionary algorithm is proposed. By incorporating combined Pareto procedures to implement a novel selection scheme at each generation, 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. It was found that CPMDE could converge to the Pareto-optimal front of constrained and unconstrained optimisation problems.

The ability of CPMDE to converge to the global Pareto-optimal front in deceptive multi-modal functions is amply demonstrated on test problem ZDT4 which has 21 billion local optimal fronts. Among the seven algorithms compared in this study, CPMDE produced the best convergence in three out of four, and best diversity in two out of four unconstrained test beds. Also, the variances of the metrics suggest that the algorithm is stable in finding optimal solutions on the test beds.

The ability of CPMDE in solving constrained optimisation problems and optimisation problems involving more than two objectives was also demonstrated. Furthermore, CPMDE was applied to solve a real-world problem where its ability to solve such problems was demonstrated. Competitive results obtained from the benchmark and application of CPMDE suggest that it is a good alternative for solving multi-objective optimisation problems. Therefore, CPMDE is adoptable as a method of MOEA for solving real-world MOOPs.

3.8 RESAERCH OUTPUTS

[1] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2014. A Combined Pareto Differential Evolution Approach for Multi-objective Optimisation. In: Schütze, O., Coello Coello C.A., Tantar, A., Tantar, E., Bouvry, P., Moral, P. D. and Legrand, P. eds. *EVOLVE- A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation III*. Switzerland: Springer International Publishing, 213-231.

[2] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2012. A novel multi-objective evolutionary algorithm for real time water allocation in the Orange River catchment in South Africa. Paper presented at the *Institutional research day 2012*. Steve Biko campus library complex, Durban University of Technology, Durban, South Africa, 15th November, 2012.

CHAPTER 4

PERFORMANCE EVALUATION OF COMBINED PARETO MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION ON TUNEABLE MULTI-OBJECTIVE TEST BEDS

4.1 OVERVIEW

Many optimisation problems in engineering involve the satisfaction of multiple objectives within the limits of certain constraints. Methods of evolutionary multi-objective algorithms (EMOAs) have been proposed and applied to solve such problems. Recently, a combined Pareto multi-objective differential evolution (CPMDE) algorithm was proposed. The algorithm combines Pareto selection procedures for multi-objective differential evolution to implement a novel selection scheme. The ability of CPMDE in solving unconstrained, constrained and real optimisation problems was demonstrated and competitive results obtained from the application of CPMDE suggest that it is a good alternative for solving multi-objective optimisation problems. In this chapter, CPMDE is further tested using tuneable multi-objective test problems and applied to solve a real world engineering design problem. Results obtained herein further corroborate the efficacy of CPMDE in multi-objective optimisation.

4.2 INTRODUCTION

In most practical decision-making problems, the presence of multiple objectives or multiple criteria is evident (Deb 2001). Due to the multi-criteria nature of most real-world problems, multi-objective optimisation problems (MOOPs) are very common particularly in engineering and scientific designs and applications. MOOPs involve multiple often conflicting objectives, which are to be optimised simultaneously. There is no single optimal solution to this class of problems; rather, the solution consists of a group of alternative trade-off solutions called Pareto-optimal or non-inferior solutions which must be considered equivalent in the absence of specialized information concerning the relative importance of the objectives (Deb 2011; Zhou *et al.* 2011).

Evolutionary algorithms (EAs) are population-based meta-heuristic optimisation algorithms that use biology-inspired mechanisms like mutation, crossover, natural selection and survival of the fittest in order to refine a set of solution candidates iteratively. EAs have often performed well approximating solutions to all types of problems because they ideally do not make any assumption about the underlying fitness landscape (Weise 2009; Olofintoye, Adeyemo and Otieno 2013b). Since EAs deal with a group of candidate solutions, it seems natural to use them in MOOPs to find a group of optimal solutions. Indeed, the applications of evolutionary multi-objective algorithms (EMOAs) to the solution of real world MOOPs have been demonstrated and they have been found very efficient in solving these classes of problems (Reddy and Kumar 2007; Mezura-Montes, Reyes-Sierra and Coello 2008; Qin *et al.* 2010). The development of the theory of EMOA in recent years has spurred researches in the field of development of EMOAs for the solution of real-world problems. Over the past decades, several studies involving the extension of evolutionary algorithms to solve multi-objective numerical optimisation problems have been reported (Fonseca and Fleming 1993; Knowles and Corne 1999; Deb *et al.* 2002).

Differential evolution (DE) is currently one of the most popular heuristics being used for solving single-objective optimisation problems in continuous search spaces. Due to its reported successes on a myriad of problems, its use has been extended to other types of problem domains, including multi-objective optimisation (Price, Storn and Lampinen 2005; Mezura-Montes, Reyes-Sierra and Coello 2008). In recent times, several researches extending the application of DE for finding solutions in the multi-objective problem domains have been reported in the literatures (Abbass and Sarker 2002; Babu and Jehan 2003; Adeyemo and Otieno 2009a; Ali, Siarry and Pant 2012). For instance, Robic and Filipic (2005) proposed three strategies of a Pareto-based differential evolution for multi-objective optimisation (DEMO). The suggested strategies are DEMO/parent, DEMO/closest/dec and DEMO/closest/obj. In DEMO/parent, a child replaces the parent at the same index if it dominates that parent while in DEMO/closest/dec, the child replaces the closest parent to it in the decision space. DEMO/closest/obj replaces a parent with a child in the objective function space.

The performances of the strategies of DEMO were compared with six other methods of EMOAs on five benchmark test beds. It was found that DEMO outperformed the other algorithms especially those based on other EAs such as genetic algorithm (GA) and evolution strategies (ES). It was thus concluded that DEMO may be adopted as an alternative for solving MOOPs.

In chapter 3 (also available in Olofintoye, Adeyemo and Otieno (2014a)), a combined Pareto multi-objective differential evolution (CPMDE) algorithm is introduced. The algorithm combines Pareto selection procedures for multi-objective differential evolution to implement a novel selection scheme at each generation. The performance of CPMDE was evaluated using common difficult test problems obtained from multi-objective evolutionary computation literatures. The ability of the algorithm in solving unconstrained, constrained and real optimisation problems was demonstrated and competitive results obtained from its application suggest that it is a good alternative for solving multi-objective optimisation problems. However, Deb (2001) has argued that most of these test problems are not tuneable and it is difficult to establish the feature of an algorithm that has been tested. Based on this argument, the author presented a systematic procedure of designing test problems for unconstrained and constrained multi-objective evolutionary optimisation and constructed a set of six difficult test problems. These problems have further been studied by researcher in the field (Fonseca and Fleming 1993; Deb *et al.* 2002; Robic and Filipic 2005; Adeyemo and Otieno 2009a). Motivated by the preceding argument, CPMDE is further tested using five (continuous) tuneable unconstrained multi-objective test problems and one constrained test problem. Furthermore, CPMDE is applied to solve a real world engineering design problem. Results obtained herein further corroborate the efficacy of CPMDE in solving multi-objective optimisation problems. A thorough discussion on CPMDE can be found in Olofintoye, Adeyemo and Otieno (2014a).

4.3 THE CPMDE ALGORITHM

In CPMDE, the combined population of trial and target solutions at the end of every iteration is checked for non-dominated solutions. Solutions that will proceed to the next generation are selected using a combined Pareto ranking and Pareto dominance selection scheme (Mezura-Montes, Reyes-Sierra and Coello 2008). Diversity among solutions in the obtained non-dominated set is promoted using a harmonic average crowding distance measure (Huang *et al.* 2005). Furthermore, boundary constraints are handled using the bounce-back strategy (Price, Storn and Lampinen 2005) while equality and inequality constraints are handled using the constrained-domination technique suggested by Deb (2001). The CPMDE algorithm is summarized in section 3.3.1 of this report. A rigorous discussion on CPMDE can be found in Olofintoye, Adeyemo and Otieno (2014a) and in chapter 3 of this report.

4.4 EVALUATING AND BENCHMARKING CPMDE

The performance of CPMDE is compared with 13 state-of-the-art EMOAs on five unconstrained benchmark test beds and one constrained test problem. Furthermore, the performance of CPMDE on an engineering two-bar truss design problem is demonstrated. Other algorithms used in benchmarking CPMDE in this study include NSGA-II (real coded), NSGA-II (binary coded), SPEA, PAES, PDEA, MODE, MODE-E (MODE with external archive and crowding distance measure), MOPSO, SDE, DEMO/parent, DEMO/closest/dec, DEMO/closest/obj and MDEA.

4.4.1 Description of benchmark test problems

Five Zitzler-Deb-Thiele (ZDT1, ZDT2, ZDT3, ZDT4 and ZDT6) test problems, which are common tuneable difficult benchmark problems used in the literatures (Deb *et al.* 2002; Madavan 2002; Xue, Sanderson and Graves 2003; Robic and Filipic 2005) are chosen for evaluating the performance of CPMDE on unconstrained optimisation problems. These are bi-objective problems in which both objectives are to be minimized. Each problem poses a different type of difficulty to EMOAs. The definitions and descriptions of all test functions are taken from literatures (Deb 2001; Robic and Filipic 2005; Reddy and Kumar 2007; Adeyemo and Otieno 2009a) and summarized in Table 4.

ZDT1 is a 30-variable problem having a convex Pareto-optimal front. The difficulty an EMOA may face on this problem is in tackling the large number of decision variables. ZDT2 is also a 30-variable problem but has a non-convex Pareto-optimal front. The non-convexity of the front is the major difficulty posed here.

Table 4: Description of benchmark test beds.

Problem	n	Variable bounds	Objective functions and constraints	Pareto-Optimal solutions	Comments
ZDT1	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left(1 - \sqrt{f_1(x)/g(x)}\right)$ $g(x) = 1 + 9(\sum_{i=2}^{n} x_i) \big/ (n-1)$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,3,\ldots,n$	Convex
ZDT2	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left(1 - (f_1(x)/g(x))^2\right)$ $g(x) = 1 + 9(\sum_{i=2}^{n} x_i) \big/ (n-1)$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,3,\ldots,n$	Non-convex
ZDT3	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \left[\sqrt{\frac{x_1}{g(x)}}\right] - \frac{x_1}{g(x)}\sin(10\pi x_1)\right]$ $g(x) = 1 + 9(\sum_{i=2}^{n} x_i) \big/ (n-1)$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,3,\ldots,n$	Convex, Discontinuous, Not all points in $0 \le x_I \le 1$ lie on the Pareto-optimal front
ZDT4	10	$x_1 \in [0,1]$ $x_i \in [-5,5]$ $i = 2,3,\ldots,n$	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{\left(\frac{x_1}{g(x)}\right)}\right]$ $g(x) = 1 + 10(n-1) + \sum_{i=2}^{n}\left(x_i^2 - 10\cos(4\pi x_i)\right)$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,3,\ldots,n$	Convex, Deceptive, Multiple local Optimal fronts
ZDT6	10	[0,1]	$f_1(x) = 1 - e^{-4x_1}\sin^6(6\pi x_1)$ $f_2(x) = g(x)\left[1 - \left(\frac{f_1(x)}{g(x)}\right)^2\right]$ $g(x) = 1 + \frac{9}{n-1}\sum_{i=2}^{n} x_i$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,3,\ldots,n$	Nonconvex, Nonuniformly spaced solutions on Pareto front, Low density of solutions near Pareto front.
CONSTR	10	$x_1 \in [0.1,1]$ $x_2 \in [0,5]$	$f_1(x) = x_1$ $f_2(x) = \frac{1 + x_2}{x_1}$ *Subject to:* $g_1(x) = x_2 + 9x_1 \ge 6$ $g_2(x) = -x_2 + 9x_1 \ge 1$	$0.39 \le x_1 \le 0.67$ $: x_2 = 6 - 9x_1$ *and* $0.67 \le x_1 \le 1.00$ $: x_2 = 0$	Convex, Constrained, Segmented Pareto front

ZDT3 is a 30-variable problem having a number of disconnected Pareto-optimal fronts. Finding uniform spread of solutions on all discontinuous regions is the challenge in this problem. ZDT4 is a 10-variable problem with 21^9 local optimal fronts. Escaping all local non-dominated fronts to converge to the global optimal front is a real challenge in this problem. ZDT6 is a 10-variable problem having a non-convex Pareto-optimal front with non-uniform distribution of solutions on the front. Finding a uniform spread of solution on this non-convex front poses a challenge to EMOAs.

To evaluate the performance of CPMDE on constrained optimisation problems, the problem CONSTR is used (Deb 2001; Reddy and Kumar 2007). This is a bi-objective problem with two constraints. Both of the objectives are to be minimized. CONSTR has a convex Pareto-optimal front with two distinct segments. Finding uniform spread of solutions on both segments while satisfying both constraints is a challenge in this problem.

4.4.2 Performance measures

Performance measures that exist for EMOA evaluation are multifarious (Zhou *et al.* 2011; Schutze *et al.* 2012). However, in order to provide a uniform basis for comparison of EMOAs used in this chapter, the three performance measures reported in the published studies were adopted (Deb *et al.* 2002; Robic and Filipic 2005; Adeyemo and Otieno 2009a). The generational distance and convergence metric are used to evaluate convergence to the global Pareto-optimal front while the diversity metric is employed to measure the spread of solutions on the obtained non-dominated front.

4.4.2.1 Generational distance

This is the average distance of the non-dominated set of solutions in a set Q from a set of chosen Pareto-optimal solutions. It is computed using equation (4.1):

$$GD = \frac{\left(\sum_{i=1}^{|Q|} d_i^p\right)^{\frac{1}{p}}}{|Q|} \qquad \text{…. (4.1)}$$

For $p = 2$, d_i is the Euclidean distance (in the objective space) between the solutions of Q and the nearest member in the true Pareto-front. An algorithm having a small value of GD is gives a better convergence to the Pareto front (Deb 2001).

4.4.2.2 Convergence metric

This is a special case of the GD where $p = 1$. Convergence metric is computed using equation (3.2) in section 3.4.2.1 of this report (Robic and Filipic 2005):

4.4.2.3 Diversity metric

This metric measures the extent and spread of solutions in the obtained non-dominated front. It is computed using equation (3.3) in section 3.4.2.2 of this report. An algorithm with a smaller value of diversity metric (Δ) gives a better spread of solutions on the Pareto front (Deb 2001).

4.4.3 Experimental setup

In this study, DE/rand/1/bin variant of DE was used as the base for CPMDE. The cross over rate, Cr and mutation scaling factor, F were set at 0.3. Population size Np was set to 100 and the algorithm was run for a maximum number of generations, gMax = 250. A set of 500 uniformly spaced solutions were taken from the Pareto-optimal set for computation of all metrics. Averages and variances of metric values over 10 runs are reported in this study. For comparison of the performance of CPMDE with NSGA-II on the problem CONSTR, the following parameters are used: Cr = F = 0.3, Np = 40 and gMax = 200. Harmonic average crowding distances are computed using the two nearest neighbours on either sides of a solution.

4.4.4 Two-bar truss design problem

To demonstrate the applicability of CPMDE in solving real-world optimisation problems, the algorithm was applied to design a two-bar truss system. A problem originally studied by Palli *et al.* (1998) using the ϵ-constraint method and further studied by Deb, Pratap and Moitra (2000) using NSGA-II is adopted here. A schematic representation of the two-bar truss is depicted in Figure 10.

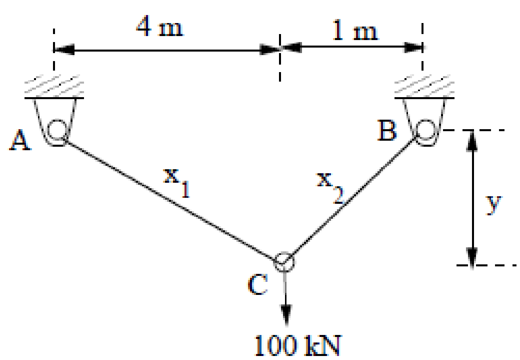


Figure 10: A Schematic Diagram of a Two-Bar Truss.
Source: (Deb, Pratap and Moitra 2000)

The truss is designed to carry a certain load without elastic failure. Thus, in addition to the objective of designing the truss for minimum volume (which is equivalent to designing for minimum cost of fabrication); there are additional objectives of minimizing stresses in each of the two members AC and BC. The two-objective constrained optimisation problem for three decision variables y (vertical distance between B and C in m), x_1 (cross-sectional area of AC in m^2) and x_2 (cross-sectional area of BC in m^2) is formulated as follows (Deb, Pratap and Moitra 2000):

Objective function 1 (Minimize volume):	$f_1(x_1, x_2, y) = x_1\sqrt{16+y^2} + x_2\sqrt{1+y^2}$
Objective function 2 (Minimize stress):	$f_2(x_1, x_2, y) = \max(\sigma_{AC,}\sigma_{BC})$
	$where: \sigma_{AC} = \dfrac{20\sqrt{16+y^2}}{yx_1}, \qquad \sigma_{BC} = \dfrac{80\sqrt{1+y^2}}{yx_2}$
Subject to:	$\max(\sigma_{AC,}\sigma_{BC}) \le 1(10^5)$
Bound constraints:	$1 \le y \le 3, \qquad 0 \le x_1, x_2 \le 0.01$

σ_{AC} and σ_{BC} are the stresses in members AC and BC respectively. On this problem, the following settings are used for CPMDE: Cr = 0.9, F = 0.5, Np = 100 and *gMax* = 100.

4.5 RESULTS AND DISCUSSION

The mean and variance of the convergence metric on the unconstrained test beds, over 10 runs of CPMDE are reported in Table 5 while those of the diversity metric are presented in Table 6. The convergence metric for PDEA was not available; therefore for comparative study on this algorithm, the available generational distance metric is extracted from literatures and presented alongside those of DEMO and CPMDE in Table 7. Diversity metrics for MODE on all test functions are not available because they were not calculated in the original study. Also, the performance metric for MOPSO on test problem ZDT4 is not available. The authors reported that this algorithm failed on this test bed. Reported values of generational distances, convergence and diversity metrics for other algorithms used in benchmarking CPMDE are taken from correlative literatures (Deb *et al.* 2002; Madavan 2002; Xue, Sanderson and Graves 2003; Robic and Filipic 2005; Adeyemo and Otieno 2009a) and presented in the respective tables. Best mean results are shown in boldface. Figure 11 depicts the convergence of the obtained non-dominated front to the true Pareto-optimal front in problems ZDT1, ZDT2, ZDT3, ZDT4, ZDT6 and CONSTR respectively. The values of the test metrics are indicated on the respective plots. Figure 12 shows the performance of NSGA-II and CPMDE, respectively, for 200 generations on the CONSTR problem. Figure 13 shows the results obtained by NSGA-II and CPMDE on the two-bar truss design problem.

Table 5: Convergence metrics on unconstrained test beds.

Algorithm	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
NSGA-II (real coded)	0.033482±0.004750	0.072391±0.031689	0.114500±0.004940	0.513053±0.118460	0.296564±0.013135
NSGA-II (binary coded)	0.000894±0.000000	0.000824±0.000000	0.043411±0.000042	3.227636±7.307630	7.806798±0.001667
SPEA	0.001799±0.000001	0.001339±0.000000	0.047517±0.000047	7.340299±6.572516	0.221138±0.000449
PAES	0.082085±0.008679	0.126276±0.036877	0.023872±0.000010	0.854816±0.527238	0.085469±0.006664
PDEA	N/A	N/A	N/A	N/A	N/A
MODE	0.005800±0.000000	0.005500±0.000000	0.021560±0.000000	0.638950±0.500200	0.026230±0.000861
MODE-E	0.001999±0.000000	0.001554±0.000000	0.002642±0.000000	0.030689±0.004867	0.005998±0.000005
MOPSO	0.019659±0.000012	0.017093±0.000133	0.030469±0.000067	N/A	0.751692±0.151000
SDE	0.002741±0.000385	0.002203±0.000297	0.002741±0.000120	0.100100±0.446200	0.000624±0.000060
DEMO/parent	0.001083±0.000113	0.000755±0.000045	0.001178±0.000059	0.001037±0.000134	0.000629±0.000044
DEMO /closest/dec	0.001113±0.000134	0.000820±0.000042	0.001197±0.000091	0.001016±0.000091	0.000630±0.000021
DEMO /closest/obj	0.001132±0.000136	0.000780±0.000035	0.001236±0.000091	0.041012±0.063920	0.000642±0.000029
MDEA	0.000921±0.000005	**0.000640**±0.000000	0.001139±0.000024	0.048962±0.536358	**0.000436**±0.000055
CPMDE	**0.000755**±0.000000	0.000775±0.000000	**0.000916**±0.000000	**0.000731**±0.000000	0.000584±0.000000

Table 6: Diversity metrics on unconstrained test beds.

Algorithm	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
NSGA-II (real coded)	0.390307±0.001876	0.430776±0.004721	0.738540±0.019706	0.702612±0.064648	0.668025±0.009923
NSGA-II (binary coded)	0.463292±0.041622	0.435112±0.024607	0.575606±0.005078	0.479475±0.009841	0.644477±0.035042
SPEA	0.784525±0.004440	0.755184±0.004521	0.672938±0.003587	0.798463±0.014616	0.849389±0.002713
PAES	1.229794±0.000742	1.165942±0.007682	0.789920±0.001653	0.870458±0.101399	1.153052±0.003916
PDEA	0.298567±0.000742	0.317958±0.001389	0.623812±0.000225	0.840852±0.035741	0.473074±0.021721
MODE	N/A	N/A	N/A	N/A	N/A
MODE-E	0.306235±0.001130	0.298449±0.000580	0.504275±0.000200	0.338330±0.003676	0.335594±0.019000
MOPSO	0.586728±0.001480	0.689580±0.038200	0.594200±0.001150	N/A	0.935686±0.018500
SDE	0.382890±0.001435	0.345780±0.003900	0.525770±0.043030	0.436300±0.110000	0.361100±0.036100
DEMO/parent	0.325237±0.030249	0.329151±0.032408	0.309436±0.018603	0.359905±0.037672	0.442308±0.039255
DEMO /closest/dec	0.319230±0.031350	0.335178±0.016985	0.324934±0.029648	0.359600±0.026977	0.461174±0.035289
DEMO /closest/obj	0.306770±0.025465	0.326821±0.021083	0.328873±0.019142	0.407225±0.094851	0.458641±0.031362
MDEA	0.283708±0.002938	0.450482±0.004211	**0.299354**±0.023309	0.406382±0.062308	0.305245±0.019407
CPMDE	**0.241173**±0.000077	**0.266395**±0.000379	0.353734±0.000522	**0.203378**±0.000400	**0.217533**±0.000234

Table 7: Generational distance metrics on unconstrained test beds.

Algorithm	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
PDEA	0.000615±0.000000	0.000652±0.000000	0.000563±0.000000	0.618258±0.826881	0.023886±0.003294
DEMO/parent	0.000230±0.000048	0.000091±0.000004	0.000156±0.000007	0.000202±0.000053	0.000074±0.000004
DEMO /closest/dec	0.000242±0.000028	0.000097±0.000004	0.000162±0.000013	0.000179±0.000048	0.000075±0.000002
DEMO /closest/obj	0.000243±0.000050	0.000092±0.000004	0.000169±0.000017	0.004262±0.006545	0.000076±0.000003
CPMDE	**0.000086**±0.000000	**0.000087**±0.000000	**0.000107**±0.000000	**0.000085**±0.000000	**0.000068**±0.000000

From the results in Tables 5 - 7, it is evident that CPMDE outperformed all other algorithms on ZDT1 test bed as it produced the minimum values of all test metrics in all cases(ϒ=0.000755, GD=0.000086, Δ=0.241173). Binary coded NSGA-II performed second with respect to convergence (ϒ=0.000894) while MDEA was the second best with respect to diversity (Δ=0.283708). MDEA and DEMO/parent showed slightly better convergence property on ZDT2, however, CPMDE performed best with respect to diversity preservation on this test bed, reporting a value of Δ=0.266395. Therefore the performance of CPMDE on this problem is comparable to MDEA and DEMO but better than those of other algorithms. Table 5 shows that CPMDE performed best in converging to the Pareto-optimal front of ZDT3 with a convergence metric, ϒ=0.000916. However, the reported diversity metric for MDEA and all versions of DEMO were better. Hence, the performance of CPMDE is comparable with MDEA and DEMO on this test bed. The advantage of CPMDE in converging to the global Pareto-optimal front in deceptive multi-modal functions is amply demonstrated on test problem ZDT4. Here, CPMDE outperformed all other algorithms in convergence and diversity (ϒ=0.000731, GD=0.000085, Δ=0.203378). The runner-ups in this case are DEMO/closest/dec (ϒ=0.001016) on convergence and MODE-E on diversity (Δ=0.338330). The convergence metric on this problem is clearly smaller than those of other algorithms. On ZDT6, CPMDE performed second best with a convergence metric (ϒ=0.000584) which is slightly higher than 0.000436 reported for MDEA. However, CPMDE produced the best diversity (Δ=0.217533) on this problem. On all unconstrained problems, CPMDE produces variance values of zero for convergence metrics and generational distances (Tables 5 and 7). This suggests that CPMDE is reliable and stable in converging to the true Pareto front on these test beds.

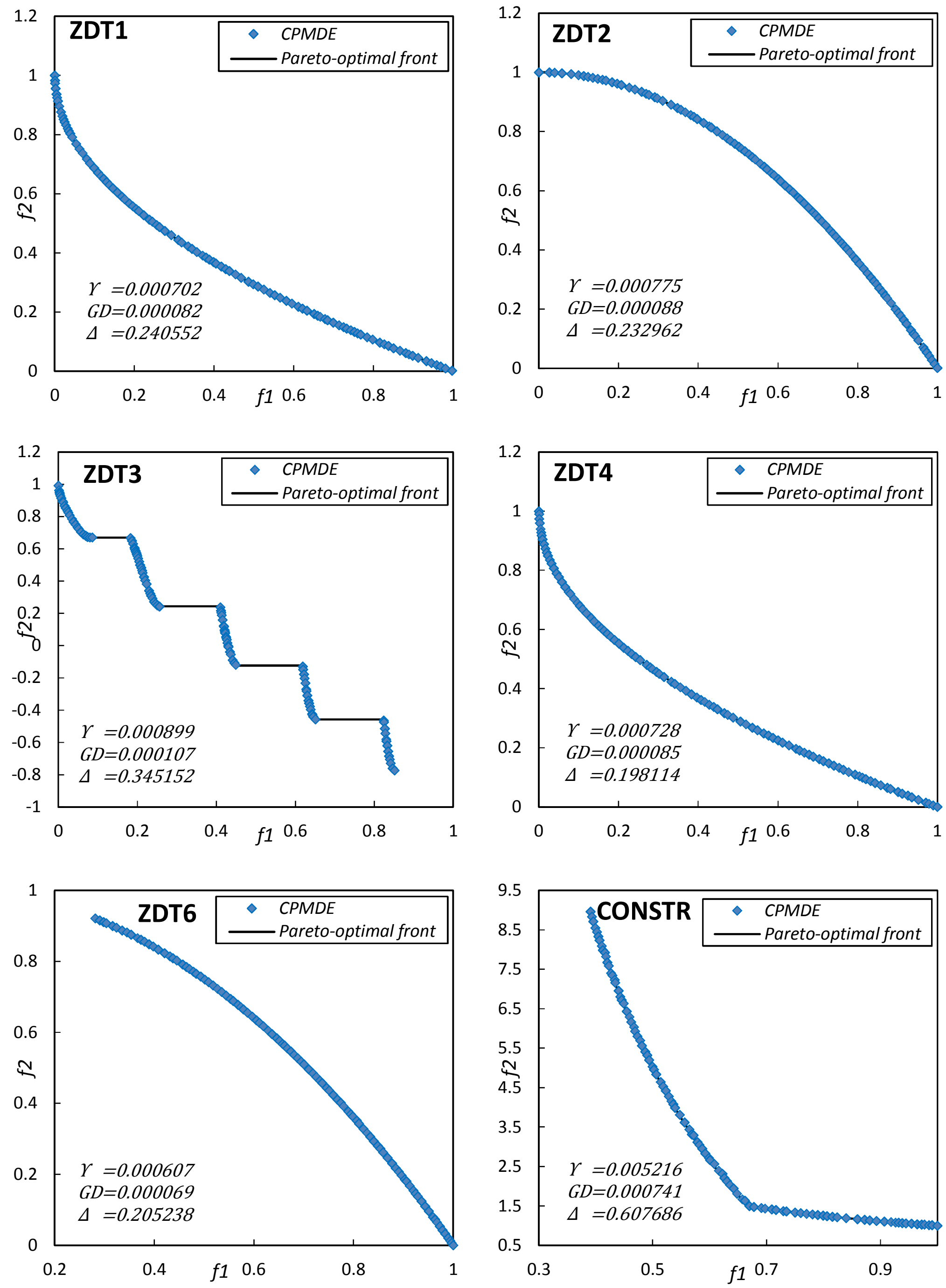
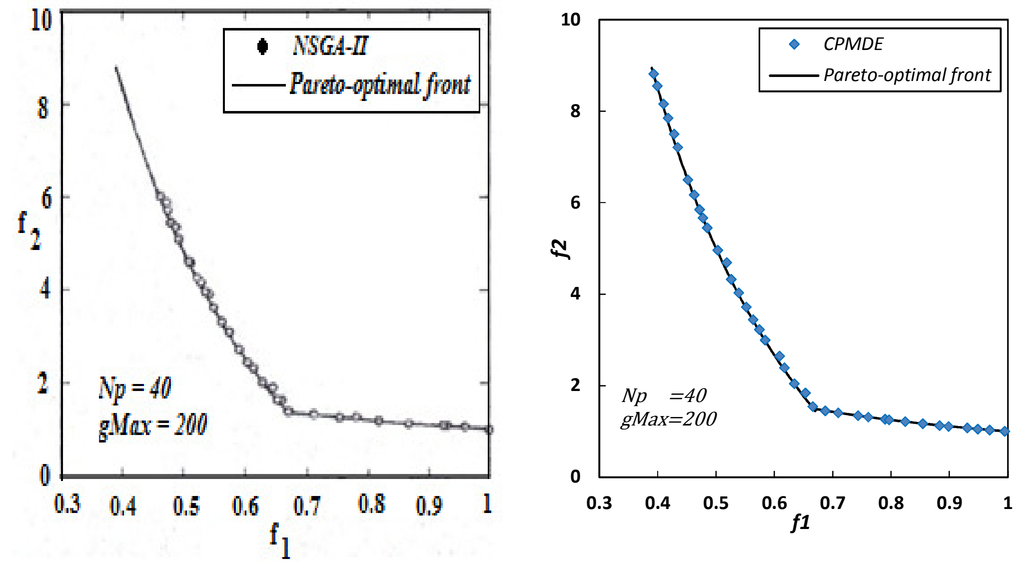
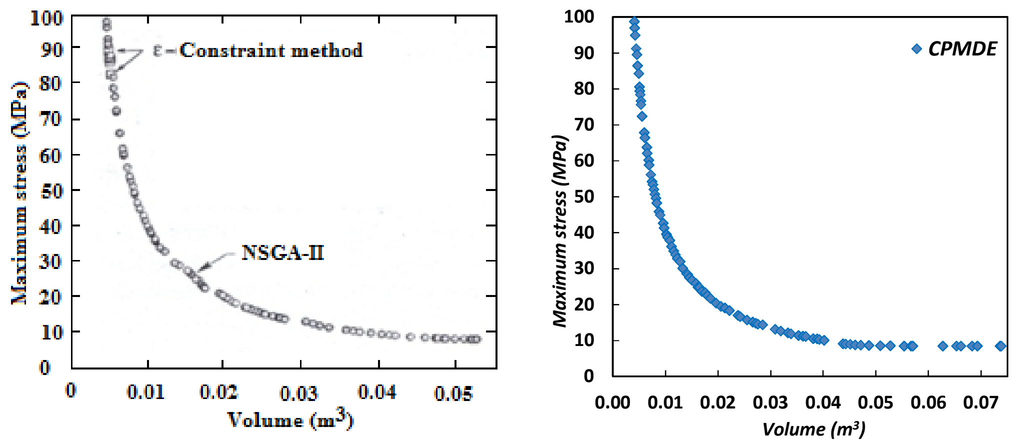


Figure 11: Convergence of CPMDE Non-dominated Front to the True Pareto-optimal Front in Test Problems ZDT1, ZDT2, ZDT3, ZDT4, ZDT6 and CONSTR.



Source: Adapted from (Deb 2001)

Figure 12: Performance of NSGA-II and CPMDE on Test Problem CONSTR, 200 iterations.



Source: Adapted from (Deb 2001)

Figure 13: Performance of NSGA-II and CPMDE on a Two-bar Truss Design Problem.

By inspection, Figure 12 shows that while NSGA-II was able to produce solutions covering roughly 80 percent of the Pareto-optimal front for 200 iterations on the CONSTR test problem, CPMDE spanned the entire front with better convergence property. Therefore, CPMDE outperforms NSGA-II which is one of the state-of-the-art algorithms on this problem.

On the two-bar truss design problem, ϵ-constraint found only five solutions with spread (0.004445m^3, 89983 kPa) - (0.004833m^3, 83268 kPa) while NSGA-II found many solutions in the range (0.00407 m^3, 99755 kPa) - (0.05304 m^3, 8439 kPa). CPMDE was also able to find many solutions spanning the range (0.00408m^3,98787kPa) - (0.07384m^3, 8433kPa). If minimization of stress is important, NSGA-II finds a solution with stress as low as 8439 kPa, whereas the ϵ-constraint method found a solution with minimum stress of 83268 kPa, an order of magnitude higher than that found in NSGA-II (Deb *et al.* 2002). CPMDE found a solution with minimum stress of 8433kPa which is slightly less than that found by NSGA-II, thus, the performance of CPMDE is comparable with NSGA-II on this problem. CPMDE produces many quality non-dominated solutions on the Pareto-optimal front of this problem in a single simulation run (Figure 13). This shows that CPMDE can perform well on real-world engineering problems.

4.6 CONCLUSION

A benchmark of Combined Pareto multi-objective differential evolution (CPMDE) on tuneable multi-objective test problems is presented in this chapter. The ability of CPMDE in solving constrained and real multi-objective optimisation problems was also illustrated. The ability of CPMDE to converge to the global Pareto-optimal front in deceptive multi-modal functions is amply demonstrated on test problem ZDT4 which has 21 billion local optimal fronts. Among the 14 algorithms compared in this study, CPMDE produced the best convergence in three out of the five and best diversity in four out of five unconstrained test beds. Also, the variances of the metrics suggest that the algorithm is stable on the test beds. Furthermore, CPMDE was applied to solve a real-world problem where its efficacy on such problems was confirmed. Competitive results obtained from the application of CPMDE suggest that it is a good alternative for solving multi-objective optimisation problems. Therefore, this study further corroborates that CPMDE is adoptable as a method of EMOA for solving real-world MOOPs.

4.7 RESEARCH OUTPUTS

[1] Adeyemo, J. A. and **Olofintoye, O. O.** 2014. Evaluation of Combined Pareto Multiobjective Differential Evolution on Tuneable Problems. *International Journal of Simulation Modelling*, 13 (3): 276-287.

[2] Adeyemo, J., **Olofintoye, O.** and Moyo, S. 2011. Differential evolution for the minimum weight design for framed structures. In: Proceedings of *Joint Congress of the South African and American Mathematical Societies*. Nelson Mandela Metropolitan University, Port Elizabeth, Eastern Cape, South Africa., 29 November – 3 December, 2011.

CHAPTER 5

OPTIMUM CROP PLANNING USING COMBINED PARETO MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION

5.1 OVERVIEW

Formulating adoptable policies congenial to adequate management of water in agricultural production and planning with aims of ensuring food security while providing employment opportunities is of great practical value in ensuring sustainable use of freshwater in a water-stressed country like South Africa. The application of a novel combined Pareto multi-objective differential evolution (CPMDE) optimisation algorithm for water resources and crop planning 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 crop planning under limited water availability. The two objectives of the model are formulates to maximize total crop planting area while minimizing total irrigation water use. CPMDE found quality Pareto solutions specifying the recommended planting areas for each of the four crops modelled in the study area. Furthermore, Competitive results obtained from a benchmark of CPMDE with two state-of-the-art multi-objective optimisation algorithms (NSGA-II and MDEA) suggest that it is a good alternative suitable for resolving crop planning and other related water resources management problems in a multi-crop environment with limited freshwater for irrigation in a water-stressed country like South Africa.

5.2 INTRODUCTION

The main goal of agricultural water resources management and crop production in any nation is to guarantee sufficient food resources for its teeming population. Most developing countries have contributed notably to the drastic population increase worldwide over the last hundred years. Recent analyses show that world’s population is currently growing by over 80 million people each year and is projected to exceed six billion by the year 2000 (USDA 2008). 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. These levels of increases are unprecedented in human history and create challenges to the environment and quality of human life. Furthermore, the increasing growth in human population has resulted in an inevitable upsurge in demand for food and water resources as well as for arable acreage (Rose 2014).

Recent analysis of population in the Orange River basin which houses major cities that form the main economic hub of South Africa shows that the total population in the catchment is expected to grow at an annual rate of 1.64 percent from 719 821 in 1980 to 1 271 229 in 2015. For the period 1995 to 2015 in particular, a higher growth rate of 1.78 percent per annum is speculated (DWA 1995b). Against the backdrop of recent population explosion and its attendant challenges to the environment and quality of human life, the agricultural sector has been considered strategic in subsistence, survival, development and in re-launching South African economy as it has relative importance in terms of job creation and ensuring food security (SANTO 2013). Efforts are being geared towards developing and promoting productivity in the agricultural sector and the food processing industries with aims of providing surplus food resources while simultaneously creating employment opportunities for the teeming population in the region. 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 (Perret, Anseeuw and Mathebula 2005). Hence, developing policies that maximize arable acreage for agricultural crop production are of great practical importance to the economy of the nation.

The need to manage limited freshwater resources in arid and semi-arid regions is of paramount importance to stakeholders and decision-makers in the water resources management sector, most especially in this era of climatic vicissitude. South Africa, being a water-stressed country and the 30th driest in the world (Crowley and Vuuren 2013), has not been left out in formulating sustainable policies and strategic plans aimed at ensuring continuous availability of freshwater. South Africa is a dry country with erratic rainfall throughout the year. She receives less than 500 mm rain on average annually over about two-third of its area (Adeyemo 2009). 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 2009).

Agriculture uses more than half of surface water in South Africa. Many studies have been undertaken to minimize the water use in agriculture especially irrigation water. For instance, results of a recent analysis by DWA (1995), indicate that allocating water for use in the industrialised areas of South Africa rather than for irrigated agriculture, will, from an economic point of view, render higher returns. The economic gains of applying water to industrialised areas are approximately 240 times more than those in the source areas. Substantial differences, in the order of 80 to 1, were also found with respect to employment opportunities. This implies a clear economic preference for using water in the Gauteng (industrialised) economy rather than for irrigated agriculture in the Orange River catchment. Furthermore, results obtained from economic analyses indicate that agriculture as a general economic sector, and irrigation as a specific sub sector, are relatively inefficient users of water. The agricultural sector utilises significantly more water to produce output and creates less employment per unit of water than any other sectors in the economy (DWA 1995b). 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 caution should be exercised not to permanently commit water to less beneficial uses to the possible future detriment of the economy (DWA 1995b). Hence, in the face of the water-stress challenge besetting agricultural water management in the country, operational policies that seek to minimize irrigation water uses are highly desirable.

Crop planning is the engagement of acreage by several crops planted yearly and their spatial dispersion in the allocated farmland (Joannon *et al.* 2008). Crop planning in a water scarce country like South Africa is a serious challenge. Under a multi-crop environment, various crops compete for the available water whenever the water available is less than the irrigation demands. In water-scarce conditions, the deficit allocation among the competing crops has significant influence on irrigation system performance (Reddy and Kumar 2008). Crop planning objectives are conflicting in nature with many objectives that must be satisfied simultaneously. Therefore, crop planning is often handled in multi-objective framework to facilitate the development of suitable and sustainable strategies for practical implementation (Raju, Kumar and Duckstein 2006; Adeyemo 2009). Sundry methods employing the application of evolutionary multi-objective optimisation algorithms (EMOA) have been found useful for resolving crop planning problems with encouraging results. For instance, Sarker and Ray (2009) adopted methodologies of a proposed evolutionary multi-objective constrained algorithm and an existing method of multi-objective genetic algorithm for resolving multi-objective crop planning models. The new EMOA found quality non-dominated solutions which represent adoptable crop planning policies for application in real-world situations. It was concluded that methods of EMOAs are adoptable as suitable alternatives for solving multi-objective crop planning models. Several studies implementing the application of EMOAs in the solution of multi-objective crop planning models have also been reported in the literature (Reddy and Kumar 2008; Brunelli and Lücken 2009; Adeyemo and Otieno 2010).

Recently, combined Pareto multi-objective differential evolution (CPMDE) algorithm was proposed by Olofintoye, Adeyemo and Otieno (2014a). The ability of CPMDE in solving unconstrained and constrained optimisation 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 optimisation problems (MOOP). This chapter presents the first application of CPMDE for the resolution of multi-objective crop planning models. The methodology is applied to a farmland in Vaalharts irrigation scheme (VIS), South Africa. The objectives of the model were formulated to maximize farmland areas for crop production while minimizing irrigation water use. CPMDE was found useful in formulating sustainable policies pragmatic to the peculiar situation in the Orange River basin in South Africa described in the preceding paragraphs. Therefore, CPMDE is adoptable for solving crop planning problems.

5.3 METHODOLOGY

A new EMOA, CPMDE is proposed for solving multi-objective crop planning models in this chapter. The performance of CPMDE is compared with two state-of-the-art EMOAs; multi-objective differential evolution algorithm (MDEA) and elitist non dominated sorting genetic algorithm (NSGA-II). CPMDE and MDEA are based on differential evolution (DE) algorithm while NSGA-II is based on genetic algorithm (GA). In particular, this study revisits an earlier study by Adeyemo and Otieno (2009c) to facilitate comparison of the performance of CPMDE with MDEA on this problem. NSGA-II was also chosen for comparison because it has successfully been employed in previous crop planning studies (Sarker and Ray 2009). In particular, because this study involves a comparative study with an existing study (Adeyemo and Otieno 2009c), the crop planning models developed in the earlier study are adopted here and no new crop planning models are developed.

5.3.1 Study area

The models in this study are adapted to solve crop planning problem in a 771,000 m^2 farmland in Vaalharts irrigation scheme (VIS), South Africa. Water resources in VIS is managed by Vaalharts water user association (Grove 2006). VIS is one of the largest irrigation schemes in the world covering about 369.50 square kilometres in the Northern Cape Province of South Africa. It lies east of Fhaap Plateau located in a summer rainfall climatic zone on latitude 28°01′S and longitude 24°43′E (VIS 2013). The area experiences paucity of rainfall with an average rainfall of about 442 mm per annum (Grove 2006; Adeyemo 2009) which makes irrigation important in the area. There is significant difference between the maximum and minimum temperatures as the seasons change. Temperatures ranges between 17.4 °C - 32.7 °C in January to a minimum of about 2.4 °C in July which is the coldest month (Grove 2006).

The scheme is supplied with water abstracted from Vaal River, which is the main tributary of the Orange River that provides water to the Vaal River supply area (DWA 1995b). Water abstracted at Vaalharts diversion weir along the Vaal River, about 8 km upstream of Warrenton, is conveyed through a 1 176km long network of canals. This system provides irrigation water to a total of 39 820 ha scheduled land and industrial water to six towns (VIS 2013). Irrigation water is supplied to 680 commercial farmers in the scheme. Water is supplied to farmers through feeder canals with capacities of 150 m^3 per hour for 5½ days per week. The water quota for irrigation in the scheme is 9 140 m^3 per ha/annum. Common crops grown in the area include wheat/barley, maize, groundnuts, cotton and other permanent crops like lucerne, pecan nuts, grapes, olives and some other fruits (Grove 2006; Adeyemo 2009). A map of the study area is presented in Figure 14.

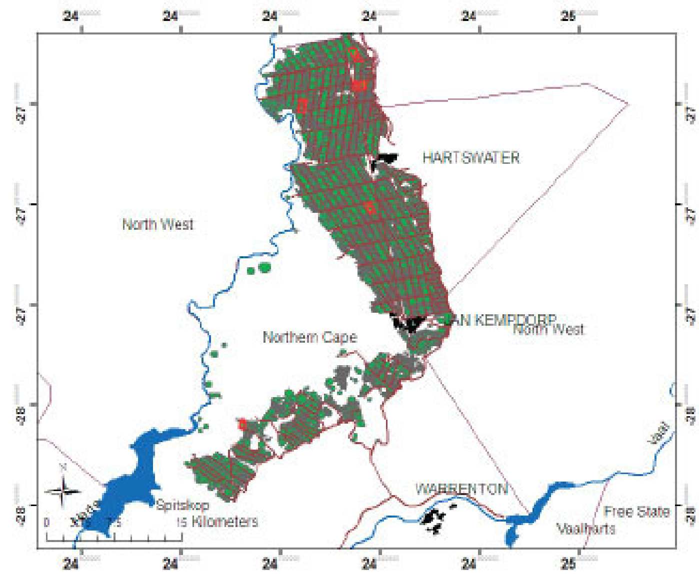


Figure 14: Vaalharts irrigation scheme.
Source: Rensburg et al. (2011)

5.3.2 Model formulation

The crop planning optimisation problem in this study was conducted for a planting season at VIS. A farmland with an area of 771 000 m^2 and maximum water quota of 9140 m^3 per ha/annum was selected as a case study. Four different crops namely maize, groundnuts, lucerne and pecan nuts are planted on the piece of land. In addition, an assumption that all the crops are not rainfed but rely solely on irrigation (Adeyemo and Otieno 2009c) was adopted in this study. Formulation of the constrained multi-objective mathematical optimisation problem follows.

5.3.2.1 Decision variables and objectives

The main aim of the study was to find the corresponding planting areas where each of the four crops should be planted to maximize the total planting area (m^2) while the farmer is minimizing irrigation water use (m^3). The decision variable which represents an area of land where a crop is planted is denoted A_i, (i = 1, 2, 3, 4) for maize, groundnuts, lucerne and pecan nuts respectively. The objectives are formulated as follows:

Objective 1: Maximize total planting area

Total planting area (A) in 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. Moreover abundant food supply will invariably result in cheaper food prices for South Africans. The mathematical model maximizing the total planting area is presented in equation (5.1):

$$\text{Maximize} \quad A = \sum_{i=1}^{n} (A_i) \qquad ; n = 4 \qquad \ldots.\ (5.1)$$

A_i is the area of land in m^2 where the i^{th} crop is grown.

Objective 2: Minimize irrigation water use

South Africa has emerged a water-stressed country and agriculture has been reported to consume more than half of the freshwater resources in the country (Olofintoye, Adeyemo and Otieno 2012), it is therefore pertinent to minimize irrigation water use. This will afford the use of more water for profitable ventures like water transfer to Gauteng for industrial uses. Besides, formulating policies that minimizes irrigation water use within the limits of supply constraints encourages efficient use of water for irrigation which can help in sustainable development of agriculture (Reddy and Kumar 2008). The mathematical model equation minimizing total irrigation water use is presented in equation (5.2):

$$\text{Minimize} \quad vol = \sum_{i=1}^{n} (CWR_i \times A_i) \qquad \ldots.\ (5.2)$$

where vol 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 crop i, selected from Table 8.

5.3.2.2 Problem constraints

The bi-objectives mathematical crop planning optimisation problem is subject to the following constraints:

Constraint 1: Total land area available.

The sum of areas A_i where the crops are grown must not be greater than the total land area available for farming. This constraint is presented in equation (5.3):

$$A = \sum_{i=1}^{n} (A_i) \leq 771000 \qquad \ldots (5.3)$$

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 50 000 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 2009). Yields in excess of storage when demand is less than supply creates storage and selling problems which cause a drop in selling prices of crops. This invariably results in loss to the farmer. Computation of maximum crop planting areas used for optimisation in this study is as follows:

Since the minimum planting area for each crop = 50000 m^2 *Then the other 3 crops will occupy a minimum of (50000 x 3) = 150000 m^2* This leaves (771000 – 150000) = 621000 *m^2 as the maximum area available for a particular crop.* *Therefore,* 621000 *m^2 is chosen as the maximum planting area for all the crops.*

The boundary constraints for this problem is therefore specified in equation (5.4) as:

$$50000 \leq A_i \leq 621000 \qquad \ldots (5.4)$$

Table 8: Crop water requirement and planting areas for the crops.

SN	Crop	Crop water requirement (mm)
1	Maize	720
2	Ground nuts	840
3	Lucerne	1800
4	Pecan nuts	1920

Source: Grove (2006)

Constraint 3: Irrigation canal capacity.

The amount of water available on the farm annually is limited by the capacity of the irrigation canal. Water is supplied to the farm through a feeder canals with a maximum capacity of 150 m^3 per hour for 5½ days in a week (Grove 2006; Adeyemo and Otieno 2009c). To avail consistency in computation, the canal capacity is converted to volumetric units, m^3 as follows (Adeyemo and Otieno 2009c):

Amount of water available per day = 150 m^3/hour x 24 hours = 3600 m^3daily *Water available for 5½ days per week = 5.5 x 3600 = 19800 m^3weekly* Therefore *Water available for a month = 4 x 19800 =* 79200 m^3 monthly *Hence, the canal is able to supply a maximum of (79200 x 12) = 950400 m^3 of water annually*

It is thus required that total irrigation water use do not exceed the maximum that can be supplied by the feeder canal. This constraint is presented in equation (5.5):

$$vol \leq 950400 \qquad \dots. (5.5)$$

5.3.3 Model solution EMOAs and experimental setup

The mathematical model equations (5.1 – 5.5) representing the constrained multi-objective crop planning optimisation problem in this study were solved using three methods of EMOAs namely, NGSA-II, MDEA and CPMDE. An open source MATLAB program encoding the original version of the pseudo code for NSGA-II developed at the Kanpur genetic algorithm laboratory (KANGAL), India, by Deb *et al.* (2002) and made available online from the repository of Seshadri (2009) was downloaded for use in this study. MATLAB files encoding MDEA were also developed using the pseudo code for MDEA available from the repository of the developers (Adeyemo 2009), while the pseudo code for CPMDE (Olofintoye, Adeyemo and Otieno 2014a; Adeyemo and Olofintoye 2014c) was encoded using visual basic for applications (VBA) to facilitate its application in resolving the crop planning optimisation problem stated herein.

The population size for all the algorithms was set at N_p = 40 based on sensitivity analysis from an earlier study by Adeyemo and Otieno (2009c). All algorithms were iterated for 1000 generations resulting in 40 000 fitness computations for each algorithm. Furthermore, 10 independent runs were made for each algorithm to facilitate statistical comparison of these algorithms on this problem. For NSGA-II, the crossover probability P_c was set to 0.9 while the mutation probability was set to ¼ as recommended by Deb *et al.* (2002). For MDEA and CPMDE both implementing DE algorithm, 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 for both MDEA and CPMDE. Harmonic average distance for maintaining spread of solutions on the Pareto front of CPMDE was computed using the 2-nearest neighbours scheme.

5.3.4 Comparison of solution methodologies

The performance of CPMDE in comparison with NSGA-II and MDEA was evaluated using three performance metrics viz. Set coverage metric, spread metric and non-parametric Wilcoxon's signed rank test. Set coverage was used to provide an indication of convergence to true Pareto front while spread metric was computed to give an indication of how well an algorithm finds solution spanning the entire Pareto front. The Wilcoxon signed rank test was adopted to determine if there is a statistical significant difference in the performance of the algorithms.

5.3.4.1 Set Coverage metric (SC)

This metric may be used to compare the performance of EMOAs in situations where a priori information about the true Pareto front is not available. The set coverage metric SC (A, B) calculates the proportion of solutions in set B which are weakly dominated by solutions of set A. A metric value of 1 means all members of B are dominated while 0 indicates that no member of set B is dominated by any solution in set A (Deb 2001; Reddy and Kumar 2007). If SC (A, B) < SC (B, A), then solutions in B are less dominated by solutions in A. Therefore solutions in B are closer to the true Pareto front than solutions in set A. The expression for computing this metric is presented in equation (5.6):

$$SC(A,B) = \frac{\left|\{b \in B \,|\, \exists a \in A : a \preceq b\}\right|}{|B|} \quad \ldots. (5.6)$$

5.3.4.2 Spread metric (Δ)

This metric measures the extent and spread of solutions in the obtained non-dominated front. It is computed using equation (3.3) in section 3.4.2.2 of this report. An algorithm with a smaller value of diversity metric Δ provides a better spread of solutions on the Pareto front (Deb 2001). In this study, the extreme solutions are taken as the extremes found in the combined runs of the algorithm.

5.3.4.3 Wilcoxon's signed rank test

The results of metrics obtained by CPMDE were analysed statistically with those of NSGA-II and MDEA using the non-parametric Wilcoxon's signed ranks test (Garcia *et al.* 2009; Ali, Siarry and Pant 2012). A multiple-problem analysis model is adopted. This is a pair wise test aims at detecting significant difference between the performances of two EMOAs. The null hypothesis for Wilcoxon's test is $H_0 : \Theta_D = 0$; in the underlying populations represented by the two samples of results, the median of the difference scores equals zero. The alternative hypothesis is $H_1 : \Theta_D \neq 0$. In this test, the difference between the performance scores of two models on i^{th} out of N functions are ranked according to their absolute values; average ranks are assigned in case of ties. Let R^+ be the sum of ranks for the functions on which the second algorithm (CPMDE, herein) outperformed the first and R^- the sum of ranks for the opposite. Let T be the smallest of the sums, $T = \min(R^+, R^-)$. If T is less than or equal to the value of the distribution of Wilcoxon for N degrees of freedom, the null hypothesis of equality of means is rejected. The p-value associated to a comparison is performed by means of the normal approximation for the Wilcoxon T statistics. In this study, SPSS software package was used for computing the p values. The critical value for the Wilcoxon's signed rank test at the 95 percent level of significance is 0.05, which implies that if the p-value is greater than 0.05, there is no significant difference between the performances of the models (Garcia *et al.* 2009; Lowry 2013; Adeyemo and Olofintoye 2014a).

5.3.5 Selecting the best compromise solution

In contrast to single objective optimisation problems where the solution is a single vector that comprises of decision variable values representing the global optimum of the problem, solution of multi-objective optimisation problems (MOOP) results in a set of non-inferior solutions which are Pareto optimal. 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. From a practical standpoint however, a decision maker needs only one solution for final implementation. Deb (2001) has suggested a compromise programming approach (CPA) to facilitate choosing of a final operating policy when specialized information concerning the problem being solved is available. 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 l_p metric distance from a reference point z. l_p metric is computed using equation (5.7) (Deb 2001; Reddy and Kumar 2007). When p=2, the l_2 metric specifies the Euclidean distance metric.

$$l_p - metric: d(f,z) = \left(\sum_{m=1}^{M} \left| f_m(x) - z_m \right|^p \right)^{\frac{1}{p}} \quad \dots (5.7)$$

5.4 RESULTS

The multi-objective crop planning problem of maximizing total planting area while minimizing irrigation water use in a farmland in VIS was solved using NGSA-II, MDEA and CPMDE. Figure 15 depicts the Pareto front obtained by CPMDE. The BCS is indicated on this figure. Figure 16 shows the Pareto front obtained by NSGA-II while Figure 17 depicts that obtained by MDEA. Figure 18 is a replication of the Pareto front obtained by MDEA from an earlier study (Adeyemo and Otieno 2009c). Plots in Figures 15 – 17 were made based on runs with the best values of diversity metrics in Table 11. Figure 19 presents the objective values for the final non-dominated solutions obtained in the best run of CPMDE while Figure 20 shows the corresponding crop planting areas for the BCS obtained by CPMDE. Table 9 presents the details of the Pareto solutions obtained from the best run of CPMDE. Numbers set in boldface indicate new solutions that lie outside the clusters of solutions found by MDEA in an earlier study by Adeyemo and Otieno (2009c). The BCS marked with an asterisk (solution 29) is set in *italics.* This also lies outside the range of solutions found from earlier study and therefore also set in boldface. Table 10 presents the results of the computation of set coverage metrics while Table 11 presents the values of diversity metrics. A very high values of infinity (INF) is assigned for the diversity metric in Table 11 in cases where an algorithm could not find a feasible solution to the problem. The summaries of the statistical Wilcoxon signed rank test in benchmarking the performance of CPMDE with NSGA-II and MDEA using the set coverage and diversity metrics are presented in Tables 12 and 13 respectively.

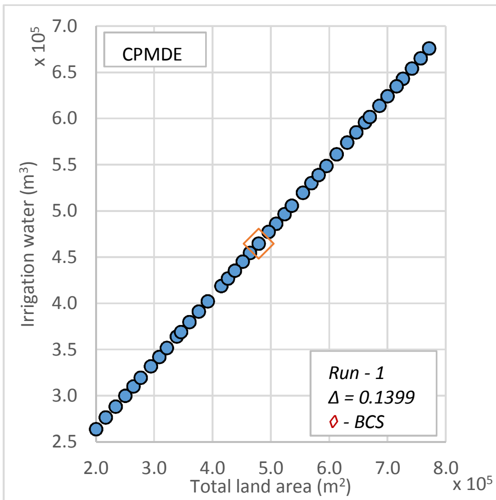


Figure 15: Pareto front obtained by CPMDE for the crop planning model when maximizing total planting area and minimizing irrigation water.

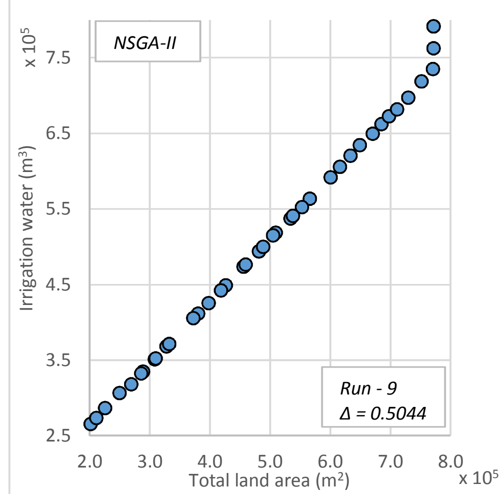


Figure 16: Pareto front obtained by NSGA-II for the crop planning model when maximizing total planting area and minimizing irrigation water.

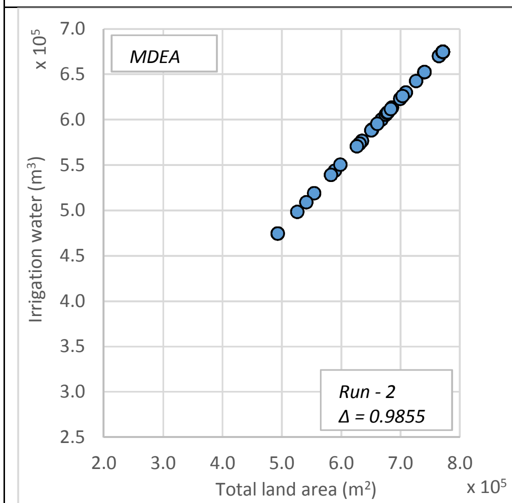


Figure 17: Pareto front obtained by MDEA for the crop planning model when maximizing total planting area and minimizing irrigation water.

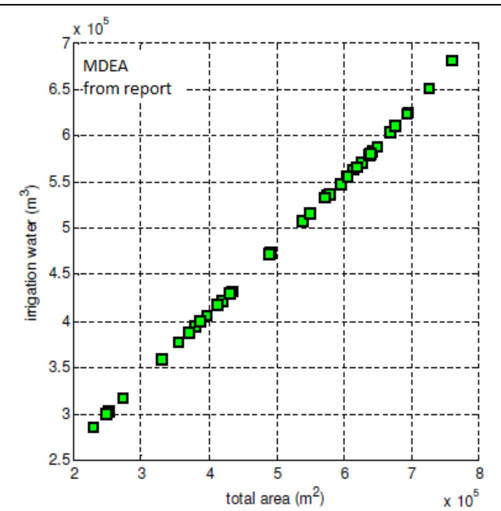


Figure 18: Pareto front obtained by MDEA from previous study.
Source:Adeyemo and Otieno (2009c).

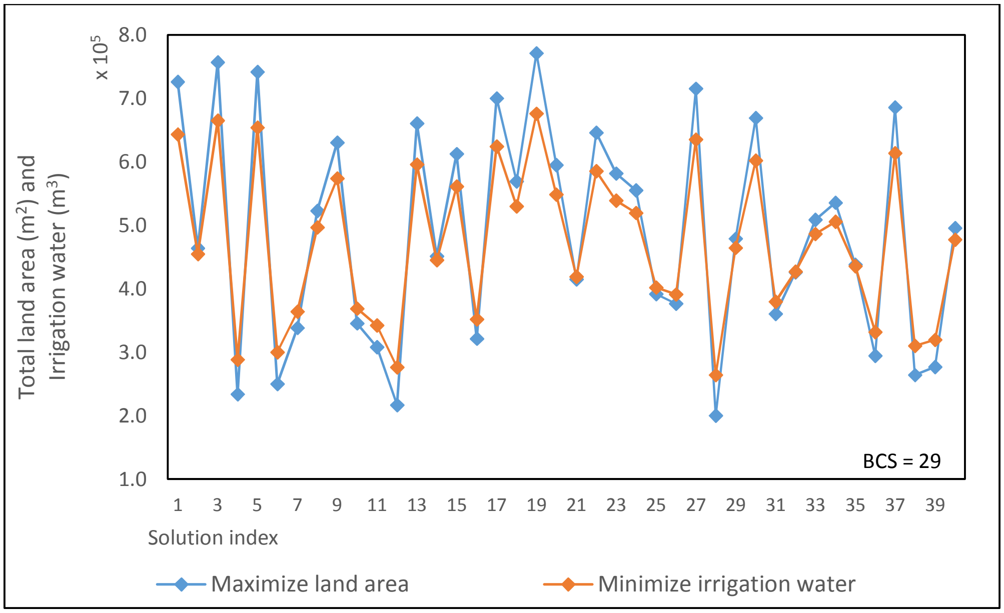


Figure 19: Non-dominated solutions for the crop planning model when maximizing total planting area and minimizing irrigation water using CPMDE.

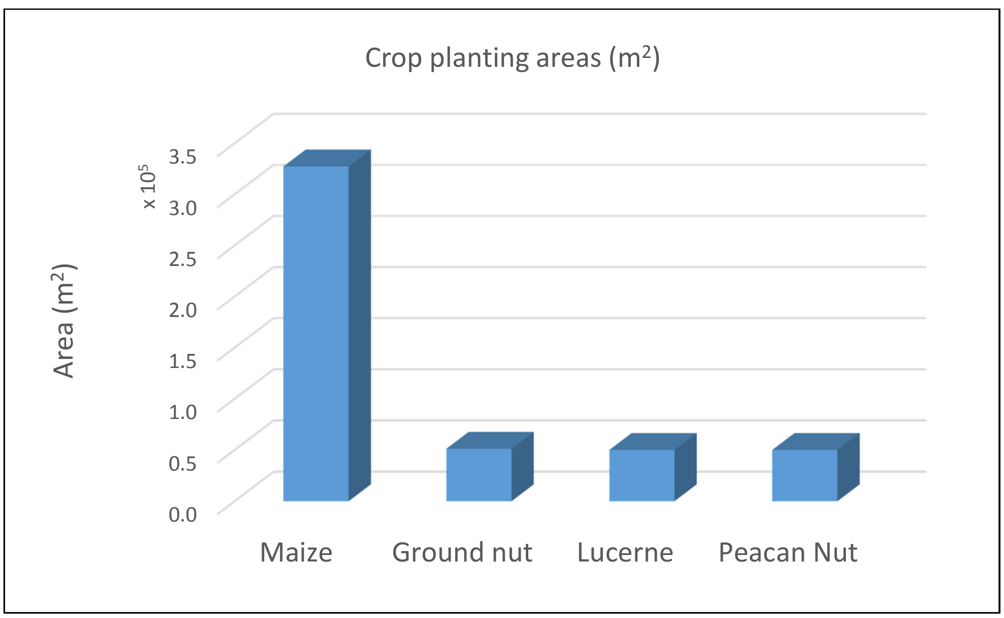


Figure 20: Optimal crop planting areas for maize, ground nut, lucerne and peacan nut using CPMDE.

Table 9: Details of Pareto solutions for the crop planning model when maximizing total planting area while minimizing irrigation water.

Solution	Land area for each crop (m^2)				Total Land Area (m^2)	Total Water Irrigation water (m^3)
	Maize	Ground nut	Lucerne	Pecan Nut		
1	**576191.58**	**50068.03**	**50015.33**	**50031.41**	**726306.35**	**643002.99**
2	**312049.94**	**51368.54**	**50057.74**	**50404.55**	**463880.77**	**454706.20**
3	**605562.30**	**51178.53**	**50021.57**	**50001.47**	**756763.86**	**665036.46**
4	83574.58	50154.95	50022.58	50014.88	233766.98	288373.05
5	**591597.23**	**50004.39**	**50002.97**	**50015.18**	**741619.77**	**653988.18**
6	100001.18	50005.70	50018.62	50009.71	250035.21	300057.80
7	187372.62	51320.00	50010.24	50006.48	338709.34	364047.96
8	**373036.76**	**50024.49**	**50000.41**	**50003.99**	**523065.65**	**496615.44**
9	480428.07	50005.27	50016.68	50017.27	630467.28	573975.81
10	194280.14	51347.82	50012.82	50002.42	345643.19	369041.59
11	**158328.57**	**50003.63**	**50019.89**	**50015.10**	**308367.19**	**342064.42**
12	**65267.70**	**51248.34**	**50070.55**	**50148.38**	**216734.97**	**276453.23**
13	510584.81	50207.18	50008.64	50030.93	660831.56	595870.03
14	**300765.30**	**50667.12**	**50027.85**	**50011.41**	**451471.68**	**445183.43**
15	461082.53	51457.16	50025.57	50044.49	612609.75	561334.88
16	171296.51	50333.63	50014.96	50000.44	321645.54	351641.51
17	**549821.15**	**50001.68**	**50012.48**	**50177.97**	**700013.28**	**624236.80**
18	418456.27	50716.81	50047.05	50008.19	569228.32	529991.05
19	**619253.17**	**51324.00**	**50043.23**	**50376.20**	**770996.60**	**675774.56**
20	443809.45	51250.65	50012.78	50016.53	595089.41	548648.09
21	263288.52	51384.23	50025.56	50035.15	414733.47	418843.99
22	494619.55	51237.45	50013.35	50028.10	645898.45	585243.51
23	431572.01	50000.12	50000.17	50033.09	581605.39	538795.78
24	404934.20	50000.08	50000.07	50001.72	554936.06	519556.11
25	240989.17	50716.77	50020.97	50007.33	391734.24	402166.12
26	225491.95	50736.05	50035.36	50013.22	376276.58	391061.52
27	**564983.99**	**50059.44**	**50050.27**	**50013.59**	**715107.29**	**634954.97**
28	**50000.00**	**50000.00**	**50000.00**	**50000.00**	**200000.00**	**264000.00**
29*	***327374.44***	***51208.06***	***50011.84***	***50022.00***	***478616.34***	***464787.92***
30	518901.46	50081.48	50036.61	50071.79	669091.34	601881.23
31	209470.20	50805.84	50050.00	50064.03	360390.07	379708.38
32	276306.54	50000.00	50048.03	50005.87	426360.44	427038.43
33	**358162.37**	**50476.59**	**50004.83**	**50000.22**	**508644.00**	**486286.34**
34	**385586.77**	**50000.00**	**50058.66**	**50041.61**	**535687.04**	**505807.95**
35	288033.99	50079.64	50013.63	50025.35	438152.61	435524.58
36	**144318.15**	**50002.15**	**50000.01**	**50003.60**	**294323.91**	**331917.81**
37	535676.52	50052.67	50003.21	50006.45	685738.86	613749.51
38	113816.22	50061.33	50023.77	50001.60	263902.92	310045.06
39	**125527.36**	**51177.46**	**50013.92**	**50008.70**	**276727.44**	**319410.54**
40	**344929.67**	**51031.54**	**50015.86**	**50021.88**	**495998.95**	**477286.42**

Table 10: Set coverage metrics for the crop planning problem.

Run	*SC*(M, C)	*SC*(C,M)	*SC*(N,C)	*SC*(C,N)
1	0.025	0.100	0.000	0.975
2	0.025	0.000	0.000	1.000
3	0.025	0.025	0.000	0.850
4	0.025	0.000	0.000	0.825
5	0.025	0.000	0.000	0.425
6	0.025	0.050	0.000	1.000
7	0.025	0.050	0.000	0.725
8	0.025	0.075	0.000	0.975
9	0.050	0.000	0.000	0.800
10	0.025	0.025	0.000	1.000
NSGA-II (N)	*MDEA (M)*	*CPMDE (C)*		

Table 11: Diversity metrics for the crop planning problem.

Run	CPMDE	MDEA	NSGA-II
1	0.1399	1.0955	0.6118
2	0.1810	0.9855	INF
3	0.1977	1.3097	0.5155
4	0.2144	1.1543	0.5417
5	0.1781	1.0903	0.5241
6	0.1608	1.1309	INF
7	0.1940	1.1084	0.6237
8	0.2399	1.0955	0.5806
9	0.2014	1.0807	0.5044
10	0.1748	1.3097	INF

Table 12: Results of Wilcoxon test on set coverage metric.

CPMDE	R+	R-	Z	p-value
MDEA	4	4	3.590	0.719
NSGA -II	10	0	-2.810	0.005

Table 13: Results of Wilcoxon test on spread metric

CPMDE	R+	R-	Z	p-value
MDEA	10	0	-2.803	0.005
NSGA -II	10	0	-2.803	0.005

5.5 DISCUSSION OF RESULTS

The findings in this study indicate that in general all the algorithm performed well in finding optimal solutions to the problem stated herein. In a single simulation run, CPMDE found quality Pareto solutions that provide trade-off between the conflicting objectives of the crop planning optimisation problem. All the solutions converged to Pareto front. The solutions are also diverse on the Pareto front. From the analysis of the 40 non-dominated solutions in the Pareto optimal set (Figure 15), it is evident that total planting area is directly proportional to irrigation water use. In reality, increasing planting area invariably results in an increase in irrigation water use. The BCS (see Figures 15, 19, 20 and Table 9) suggests that maize should be planted in 327 374.44 m^2 land area, ground nut should be grown in 51 208.06 m^2 in the farmland, while lucerne and peacan nuts should be cultivated in 50 011.84 m^2 and 50 022.00 m^2 areas of land respectively. This results in total cultivated land of 478 616.34 m^2 and a cumulative of 464 787.92 m^3 volume of irrigation water use. Analysis of the BCS indicate that maize is planted in an area roughly six times more than those of the other crops while the other crops are planted in approximately equal areas of land. This suggests that maize is more lucrative in the study area. These results are consistent with the findings of Adeyemo and Otieno (2009c). The total planting areas of land for all the solutions range from a minimum of 200 000.00 m^2 (solution 28) to a maximum of 770 996.60 m^2 (solution 19), which correspond to volumes of 264 000.00 m^3 and 675 774.56 m^3 irrigation water use respectively (see Figure 19 and Table 9). Solution 28 suggests that all crops be planted on an area of 50 000 m^2 while solution 19 indicates that maize, ground nut, Lucerne and pecan nut should be grown in farmland areas of 619 253.17 m^2, 51 324.00 m^2, 50 043.23 m^2 and 50 376.20 m^2 respectively. Since the BCS is the solution which is minimally located from the ideal point which comprises the extremes of all the conflicting objectives, solution 29 is suggested for final implementation in this study.

NSGA-II was able to generate optimal solutions close to the Pareto front in most of the runs of the algorithm. This indicates that the algorithm is adoptable for solving the crop planning problem. However, by inspection, a vertical section consisting of three solutions is seen in the extreme right of the Pareto front generated by NSGA-II (Figure 16). The solution just below the 750 000 m^3 irrigation water use in this vertical section is better than the two solutions above this threshold. While this solution has a lower value of water use, the trio have equal values of cultivated land. Therefore the two solutions above the 750 000 m^3 water use threshold in the vertical section are not part of the Pareto front. This vertical section indicates that the algorithm was not able to fine-tune all the solutions to converge to Pareto front before the end of the iteration. Also, it was observed that in 3 out of the 10 runs of the algorithm (see runs 2, 6 and 10 in Table 11) NSGA-II was not able to find feasible solutions to the problem. On the average, NSGA-II couldn't find feasible solutions in 30 percent of the trials in solving the problem herein. This phenomenon has also been observed by Sarker and Ray (2009) who reported that NSGA-II experienced difficulties in finding feasible solutions to a complex crop planning multi-objective optimisation problem. This problem may probably be resolved by solving the starting point problem (Price, Storn and Lampinen 2005). This involves writing special procedures that ensures that at least one feasible solution if found before iteration commences. Also, increasing the number of iterations cycles may be beneficial in the application of this algorithm in solving these types of problems.

Analysis of results show that CPMDE demonstrates good convergence ability. Inspection of Table 10 shows that CPMDE demonstrated better convergence ability when compared to NSGA-II on this problem. None of the Pareto solutions obtained from the runs of CPMDE are worse than those of NSGA-II in all the 10 runs (SC(N, C)=0 in all cases). Also in all cases of spread metric computation (Table 11), CPMDE produced lower values of the metric. Results of the Wilcoxon signed rank test in Tables 12 and 13 also indicate that there is a significant difference in the performances of the algorithm at the 95 percent level of significance. CPMDE performed reasonably well in converging to Pareto front ($Z=-2.810$, $p=0.005$ in Table 12) and in finding good spread of solutions on the front ($Z=-2.803$, $p=0.005$ in Table 13).

MDEA achieved fast convergence to Pareto front in all runs of the algorithm. This suggests that the algorithm is also adoptable for solving crop planning problems.

Visual inspection of Figures 15 and 17 however shows that while MDEA produced solutions covering roughly half the length of the Pareto front for 1000 iterations on the crop planning problem, CPMDE generated solutions that spanned the entire front with better convergence property. Also, analysis in an earlier study (Adeyemo and Otieno 2009c) produced a fragmented Pareto front consisting of three main clusters (See Figure 18). Based on sizes of total planting areas, the first cluster is from total planting area of 220 000 m^2 to 270 000 m^2, the second cluster ranges from 320 000 m^2 to 450,000 m^2, while the third cluster spanned planting areas between 550 000 m^2 and 700 000 m^2. In Table 9, new solutions found lying outside these three clusters are indicated in boldface. CPMDE found 18 new solutions which lie outside the reported clusters found by MDEA. This corresponds to roughly 45 percent of the entire Pareto front. Thus, whereas MDEA found solutions covering approximately 55 percent of the entire Pareto front, NSGA-II and CPMDE found solutions spanning the entire front (see Figures 15, 16, 17 and 18).

The difference in the appearance of the Pareto fronts in Figures 17 and 18 also indicates instability in the ability of MDEA in maintaining spread of solutions on the Pareto front. While some runs generated fronts similar to Figure 17, others generated fronts similar to that in Figure 18. Computation of average spread of the runs however indicated that the algorithm finds solutions covering roughly half of the front in all cases. Figure 17 was chosen for presentation as it has the lowest value of diversity metric in all the runs. MDEA was not consistent in finding quality Pareto solutions spanning the front probably due to the fact that the algorithm does not explicitly incorporate a mechanism for preserving diversity on the generated non-dominated front (Deb 2001; Huang *et al.* 2005; Ali, Siarry and Pant 2012; Olofintoye, Adeyemo and Otieno 2014a).

Values of set coverage metrics for the 10 runs of the algorithms in Table 10 indicate that CPMDE and MDEA performed equally in converging to Pareto front in two cases (runs 3 and 10), MDEA outperformed CPMDE in four runs (2, 4, 5 and 9), while CPMDE performed better in four cases (runs 1, 6, 7 and 8). However, in all the 10 cases of spread metric computation (Table 11), CPMDE produced better spread of solutions on the Pareto front than MDEA. From the results of the Wilcoxon signed rank test in Tables 12, there is no significant difference in the performances of the CPMDE and MDEA in converging to the Pareto front at the 95 percent level of significance (Z=3.590, p=0.719). However, Table 13 shows that there is significant difference in the performances of the algorithms in finding good spread of solutions on the Pareto front (Z=-2.803, p=0.005). Here CPMDE was able to generate better spread of solutions on the Pareto-optimal front.

5.6 CONCLUSION

Proper water resources management in agricultural crop production and planning with aims of ensuring food security while providing employment opportunities is paramount to ensuring sustainable use of freshwater in a water-stressed country like South Africa. In this chapter, the application of a novel multi-objective optimisation algorithm (CPMDE) for water resources and crop planning management in VIS is illustrated. It is shown that CPMDE can be successfully employed to search the feasible solution space for a complex cropping pattern that involves multiple objectives and multiple constraints. CPMDE generated adoptable quality Pareto-optimal solutions corresponding to the recommended planting areas for the four different crops modelled in the study area. These solutions efficiently trade-off the objectives of maximizing total planting area while minimizing irrigation water use in the farmland. It is hereby suggested that the generated Pareto solutions be further investigated and adopted as crop production policies for use in the study area.

The study and interpretation of the solutions of multi-objective crop planning optimisation models using three methodologies of EMOAs was also investigated. The application of a method of multi-objective genetic algorithm (NSGA-II) and two techniques of multi-objective differential evolution (CPMDE and MDEA) in resolving multi-objective crop planning models were compared. A benchmark of solution methodologies show that CPMDE can be ranked in the class of state-of-the-art algorithms like NSGA-II and MDEA based on results of evaluations using set coverage metric, spread metric and a non-parametric Wilcoxon signed rank test.

The two goals in multi-objective optimisation are to discover solutions as close to the Pareto front as possible while finding solutions as diverse as possible on the front. A good multi-objective evolutionary algorithm will be known if both goals are satisfied (Deb 2001; Adeyemo 2009). Whereas MDEA was able to achieve close convergence to the Pareto front, it was not stable in finding good spread of solutions on the front. Therefore, it is advised that diversity should be preserved when using this algorithm henceforth.

Competitive results obtained from the application and benchmark of CPMDE herein suggest that it is a good alternative suitable for resolving crop planning and other related water resources management problems in a multi-crop environment with limited freshwater for irrigation in a water scarce country like South Africa. In this chapter, it has been established that CPMDE (Olofintoye, Adeyemo and Otieno 2014a) performs reasonably well when compared with MDEA (Adeyemo and Otieno 2009a) and NSGA-II (Deb *et al.* 2002) which are two state-of-the-art algorithms, in finding solutions to the water resource management problem stated herein. The findings in this study therefore, further confirms that CPMDE is adoptable as a method of EMOA for the analysis and resolution of real-world mathematical multi-objective water resources optimisation models.

5.7 RESEARCH OUTPUTS

[1] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2015. Optimum crop planning using Combined Pareto Multi-objective Differential Evolution. *Journal of the South African Institution of Civil Engineering*, 2015. *Under review*.

[2] Adeyemo, J., Otieno, F. and **Olofintoye, O.** 2012. Performance evaluation of Multi-Objective Differential Evolution Algorithm (MDEA) strategies for water resources management. Paper presented at the *Institutional research day 2012*. Steve Biko campus library complex, Durban University of Technology, Durban, South Africa, 15th November, 2012.

CHAPTER 6

REAL TIME OPTIMAL WATER ALLOCATION FOR DAILY HYDROPOWER GENERATION FROM THE VANDERKLOOF DAM, SOUTH AFRICA

6.1 OVERVIEW

Against the backdrop of power shortages arising from escalating energy demands due to rapid global urbanization and industrial development, the power sector has been considered strategic in forging economic growth, sustaining technological development and contributing further to the overall development of the nations. Unfavourable conditions experienced by communities as a result of power failures due to shortage of supplies have driven efforts worldwide in search of improved techniques propitious to sustainable reservoir optimisation and operations for power generation.

Recent studies have established that combining accurate reservoir inflow forecasting models with optimisation technologies can provide more efficient and balanced solutions for operating multi-purpose reservoir systems. This has often produced improvements in the economy of hydropower generation (Ngo 2006; Madsen *et al.* 2009). This chapter presents the coupling of a data driven artificial neural network (ANN) model with a novel combined Pareto multi-objective differential evolution (CPMDE) for hydrological simulation and multi-objective numerical optimisation of hydropower production from the Vanderkloof dam in real time. Results from the application of the real time model indicate that 728.53 GWH of annual energy may be generated from the reservoir without system failure under medium flow condition. It was also found that the real time method developed in this study indicates a 49.32 percent improvement in performance over current practice. It is concluded that the hybrid ANN-CPMDE real time reservoir operation methodology suggested herein provides a low cost solution methodology suitable for sustainable operation of the Vanderkloof reservoir in South Africa. This suggests that adopting real time optimisation strategies may be beneficial to operation of reservoirs.

6.2 INTRODUCTION

Since the advent of the industrial revolution in the mid-1700s, the global community has continuously witnessed a systematic increase in technological development, industrialization and rapid urbanization. This has inevitably led to an unprecedented increase in energy demands worldwide. In a true global perspective of the demand, it is being generally accepted that the countries of the world are experiencing "energy crisis" and are therefore, constantly developing cutting edge strategies aimed at satisfying the exponential growth in the demand (Ajenifuja 2009; Awoyemi 2010).

Against the backdrop of rapid urbanization and industrial developments worldwide with their attendant challenges of skyrocketing energy demands, the power sector has been considered strategic in forging economic growth, sustaining technological development and contributing further to the overall development of the nations (Ajenifuja 2009). The electrical company (Eskom), is responsible for generating, distributing, controlling and managing electricity in South Africa. Eskom Holdings Limited generates roughly 95 percent of the electricity in the republic and is among the largest producers of electricity in the world. South Africa is rich in coal and 90 percent of Eskom's electricity is produced by coal fired thermal power stations. The Gariep and Vanderkloof hydropower installations in the Orange River basin are used to produce based energy during periods of high flows and occasionally operated between two to four hours a day to generate peaking power especially in periods of low flows. Studies have however shown that electricity produced from the Orange River hydropower stations is half as cheap as the ones sourced from Eskom's thermal power plants (ESKOM 2010).

Concerns about global climate change have prompted calls for action at every level of government and across many sectors of economy and society. It has become pertinent to establish suites of coordinated activities that will examine the serious and sweeping issues associated with global climate change and provide advice on possible mitigations to stem the tide of global warming and environmental degradation (McBean and Motiee 2008; Olofintoye and Adeyemo 2011b; Adeyemo, Olofintoye and Otieno 2012; Olofintoye, Adeyemo and Otieno 2012). Recent anthropogenic global warming has been attributed to unsustainable industrialization which releases greenhouse gases (GHG), technological development, urbanization, deforestation and indiscriminate burning of fossil fuels among other factors (Odjugo 2009). Current global policies are therefore pushing toward the reduction of GHG emissions to help reduce the rate at which the earth is warming. For instance, the Energy Act of 2007 passed by the state of Minnesota aims to reduce GHG emissions by 15 percent by 2012, 30 percent by 2025 and 80 percent by 2050 (Awoyemi 2010). Also, in line with international agreements (DOE 2014), the South African Government is committed to 4 percent of estimated electricity demand being met by renewable energy resources by 2013. This is expected to result in over 200 000 fewer kilogrammes of particulate matter being emitted into the air annually (ESKOM 2010). Due to high costs of maintenance and operation, pollution and environmental degradation problems associated with the operation of thermal power plants, it is expedient to seek other forms of energy which are cheaper, renewable, greener and sustainable in South Africa (SIDALA 2010).

According to Ajenifuja (2009), recent studies have confirmed that GHG emission factors for hydropower plants are typically 30-60 times lesser than factors for fossil fuel generation, taking into account emissions from decaying biomass in reservoirs. Further research has also shown that development of about half of the world's economically feasible hydropower potential could reduce GHG emissions by roughly 13 percent. Hydropower at present supplies approximately 20 percent of the world's electricity. If all economically feasible hydropower potentials are developed, hydropower could substitute fossil-fuelled thermal plants and reduce global carbon dioxide pollution by up to 7 million tons/year. Hence, strategies aimed at harnessing more hydropower from existing water sources within the frontier of the country is germane in capacitating the South African Government's commitment to reduction of the countries' GHG emissions and transition to a low-carbon economy while meeting a national target of 3 725 megawatts by 2030 (SIDALA 2010; DOE 2014).

As a result of their outstanding advantages, the first half of the 20^{th} century witnessed exceptional growths in the use of hydropower. Today, it stands as the most significant of renewable and sustainable source for electrical power production globally (Paish 2002). In operation, hydroelectric power plants produce no direct waste and have considerably lower output levels of GHG than fossil fuel powered energy plants. They also have longer economic lives and lower operating and labour costs (Ajenifuja 2009; SIDALA 2010). However, notwithstanding their excellent performances and numerous advantages, construction of new water resources structures, mainly large dams for hydropower generation is very expensive and are therefore highly opposed (Adeyemo 2009; Loucks and Bee 2005). Furthermore, building of new dams are often accompanied by various environmental challenges like net loss of total streamflow due to increased evaporation from reservoir surface and seepage under structures, changes in the ecology of watershed and river systems, displacement of humans and human settlements, inundation of arable agricultural lands, land use changes and other environmental degradation problems (WCD 2001; Loucks and Bee 2005; Aremu and Adebara 2007; Salami 2007). Therefore, management of existing water resources facilities using efficient cutting edge techniques is of paramount importance in water resources management. Studies have shown that even small improvements in the operating policies of existing water related structures often lead to large benefits for many consumers (Adeyemo 2009; Madsen *et al.* 2009; Bosona and Gebresenbet 2010).

Results from recent researches have demonstrated that the combination of accurate reservoir inflow forecasting and numerical optimisation techniques can provide more efficient and balanced solutions for operation of multi-purpose reservoir systems and thereby improve the economy of hydropower production (Madsen and Skotner 2005; Ngo 2006; Madsen *et al.* 2009; Adeyemo and Olofintoye 2012; Olofintoye, Adeyemo and Otieno 2014b). This chapter presents the coupling of a data driven artificial neural network (ANN) model and a novel combined Pareto multi-objective differential evolution (CPMDE) algorithm for hydrological simulation and multi-objective optimisation of hydropower production from the Vanderkloof dam in real time. ANN is employed to forecast daily reservoir inflow while CPMDE is used to generate Pareto-optimal policies for daily operation of the reservoir. The optimisation problem considers the trade-off between a short-term objective in terms of maximizing hydropower production within the forecast period and a long-term objective in terms of minimizing deviations from the optimised storage control curve.

6.3 METHODOLOGY

This study adopts a forecast-optimisation framework suggested by (Ngo 2006) for real time operation of reservoir systems. This framework has been applied for resolving reservoir operations and has been found useful in generating quality optimal solutions for operating reservoir systems (Madsen and Skotner 2005; Richaud *et al.* 2011). In this chapter, the forecast-optimisation framework is applied to daily operation of Vanderkloof dam in South Africa. An ANN forecast model was developed to predict daily reservoir inflows while CPMDE is used to generate Pareto-optimal policies for daily operation of the reservoir. CPMDE is a new evolutionary multi-objective optimisation algorithm (EMOA) proposed by Olofintoye, Adeyemo and Otieno (2014a). The ability of CPMDE in solving unconstrained and constrained optimisation problems has been demonstrated and competitive results obtained from the benchmark and application of CPMDE suggest that it is a good alternative for solving real multi-objective optimisation problems (MOOP) (Olofintoye, Adeyemo and Otieno 2013a; Adeyemo and Olofintoye 2014b; Adeyemo and Olofintoye 2014c; Enitan *et al.* 2014; Olofintoye, Adeyemo and Otieno 2014a, 2014b).

At the beginning of each day, forecast is made about the expected inflow based on inflows obtained in past three consecutive days. The reservoir is optimised based on the expected reservoir inflow and releases for the particular day are made. In particular, the methodology is applied for operating the Vanderkloof reservoir with the aim of investigating the feasibility of generating hydropower throughout the day over the operating period. The method was applied to the operating period from May 1, 2012 to April 30, 2013. The decision date for reservoir operation in South Africa is May 1 when reservoir operating analysis is undertaken to decide how the reservoir should be operated in the coming year (Mugumo 2011; DWA 2013). It was observed that the reservoir was able to meet all demands without failing throughout the planning period. To gauge the performance of the proposed methodology, actual release decisions made over the operating period were extracted and used to estimate actual power generation over the operating period.

6.3.1 Data

Climatic, hydrologic, reservoir characteristics and operation, water demand, flood control curves, storage control and characteristics relations, turbine and power plant characteristics, canal and penstock discharge data for the Vanderkloof dam were obtained from the Department of Water Affairs (DWA) and Eskom. These agencies are responsible for the measurement, control and storage of hydrologic and other relevant information about major dams and hydropower plants in South Africa. Data from these agencies are regarded the best that could be found anywhere in the republic (Mugumo 2011; Mugumo, Ndiritu and Sinha 2013).

6.3.2 Study area

The methodology in this study is adapted to the operation of the Vanderkloof reservoir and power plant in South Africa. Vanderkloof dam along the Orange River is a multipurpose reservoir for flood control, irrigation, hydropower generation and recreation activities in that order of importance (Adeyemo 2009). The dam is located in a summer rainfall climatic zone in the country. It is situated near Petrusville in the Northern Cape province of South Africa on latitude 29.99222°S and longitude 24.73167°E (Adeyemo and Olofintoye 2014a).

Vanderkloof forms the second largest storage reservoir in South Africa with a capacity of about 3 200 million m^3 and a surface area approximately 133.43 square kilometres when full. It is an important part of the Orange River Project (ORP). Water entering the dam is either released downstream through the two installed hydropower generators or transferred through the Vanderkloof main canal having a discharge capacity of $57m^3/_s$. The main canal supplies water to the Ramah branch canal and the Orange-Riet canal. The Orange-Riet canal transfers water to the Riet River basin where it is used to irrigate about 29 086 ha of agricultural land (Adeyemo and Olofintoye 2014a; DWA 2013).

The penstock inlet at 1 150.80 metres above sea level (m.a.s.l), defines the minimum operating level for hydropower generation while the irrigation canal outlet at 1 147.78 m.a.s.l, slightly lower than the penstock inlet defines the minimum operating level for the reservoir. (Adeyemo 2009; Mugumo 2011; DWA 2013; Mugumo, Ndiritu and

Sinha 2013). Eskom's hydroelectric power station is situated within the dam wall. The station houses two turbo generators with efficiencies rated at approximately 92.41 percent. These machines are located in an underground cavern below the dam wall on the left flank of the river at an average elevation of 1 089 m.a.s.l. The combined capacity of the two installed generators is 240 MW at 120 MW each at a maximum discharge of about 200 $m^3/_s$ and a total of 400 $m^3/_s$. The minimum net generating head for hydropower at the station is about 54 m while the average tail water elevation is roughly 1 095.95 m.a.s.l (Adeyemo 2009; ESKOM 2010; Mugumo 2011).

The operating policy for the reservoir requires that all releases to areas downstream of the dam be channelled through the turbines to meet demands downstream of the dam while maximizing hydropower generation. Figure 21 shows the general layout of the dam.

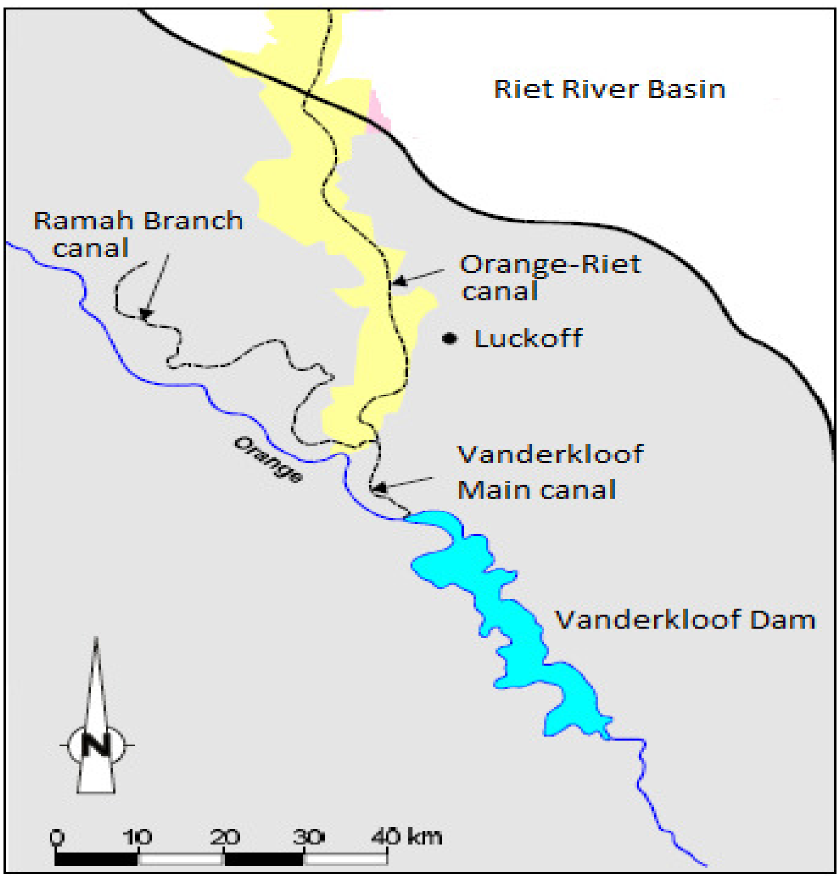


Figure 21: General layout of Vanderkloof dam, South Africa.
Source: Adapted from DWA (1995a)

6.3.3 Reservoir inflow modelling and forecasting

Historical streamflow data was necessary for development of daily reservoir inflow forecast model for daily operation of the reservoir. The nature of data collected for this purpose is streamflow volume in mega litres (Ml) recorded for every day of the year. This was converted to mega cubic meter (Mm^3) for use in the analysis herein. A period spanning 36 years of data (1977 – 2013) was used in the analysis.

This study implements the system-theoretic modelling approach through the adoption of an ANN modelling technique for the purpose of forecasting daily reservoir inflows. The main advantages of modelling input-output relations using ANNs lie in their abilities to simulate linear, non-linear and time varying systems where the modeller does not require a detailed knowledge about the complex physical processes driving the predictor-response system (Jeong and Kim 2005; Kalteh 2007).

While conceptual hydrological models have proved their importance in understanding hydrological processes, their implementation and calibration often present various difficulties. Oftentimes they are found to be too complex, data intensive and cumbersome to use. This therefore calls for the use of simpler system-theoretic models like ANNs which establish relations between input and output variables without considering the intricate physical laws governing the hydrological process (Rajurkar, Kothyari and Chaube 2002).

In particular, Mugumo (2011) and Mugumo, Ndiritu and Sinha (2013) have argued that the conceptual South African water resource planning model (WRPM) currently used to simulate stochastic streamflow into the Vanderkloof reservoir is overly complex. The intricacy and non-user friendly structure of the model limit its application and hence there is need to develop simpler models capable of achieving the same task. Consequently, Mugumo (2011) developed an ANN model to forecast monthly streamflows necessary for the monthly operation of the dam. It was found that the ANN forecast model performed favourably well in predicting monthly inflows into the reservoir.

The applicability of ANN methodology for modelling daily streamflows into reservoirs has also been demonstrated by several authors with encouraging results. Moreover, studies have further shown that ANNs provide a systematic approach for reservoir inflow forecast and represent an improvement in prediction accuracy over their conventional conceptual counterparts (Kalteh 2007; Dorum *et al.* 2010; Abdulkadir 2011).

The structure adopted for the ANN model in this study is a multiple input single output (MISO) ANN with a single hidden layer (Rajurkar, Kothyari and Chaube 2002). The universal approximation theorem of ANN modelling states that an ANN model with only one layer of hidden unit suffices to approximate any function with finitely many discontinuities to arbitrary precision, provided the activation functions of the hidden units are non-linear (Krose and Smagt 1996). A feed-forward network having a single layer of hidden units with logistic sigmoid activation functions and an output unit with pure-line function is used herein. Specifically, this ANN-MISO structure has been used by Mugumo (2011), Mugumo, Ndiritu and Sinha (2013), and Oyebode and Adeyemo (2014) to forecast monthly streamflows in the Vanderkloof dam.

An assumption that the streamflow phenomenon is governed by a Markov process is also adopted in formulating the ANN model in this study. In a Markovian flow process, the flow in a given time period is assumed to depend on a series of antecedent flows and a random component. One explanation for adopting this assumption in modelling streamflow might be that a high flow in one time period will build up groundwater level and thus provide a tendency towards another high flow in the next period. Similarly, groundwater will be depleted during periods of low flows and so a low flow may be expected to be followed by another low flow (Salami 2007). Markovian flow model assumption has been adopted by several authors in developing models for reservoir inflow forecasts (Campolo, Andreussi and Soldati 1999; Salami 2007; Mugumo 2011).

Through a preliminary sensitivity analysis (Mugumo 2011), it was found that the best configuration for the ANN model forecasting daily streamflow into the Vanderkloof dam based on available historical daily data is a model with three input nodes, five hidden nodes and one output node. The input nodes represent flow 1-day ago (Q_{t-1}), flow 2-days ago (Q_{t-2}) and flow 3-days ago (Q_{t-3}) while the forecast flow which is a function of flows in the past 3 days is presented on the output node (Q_t). The detail and configuration of the ANN model developed for daily streamflow forecast into the Vanderkloof dam in this study is presented in Figure 22.

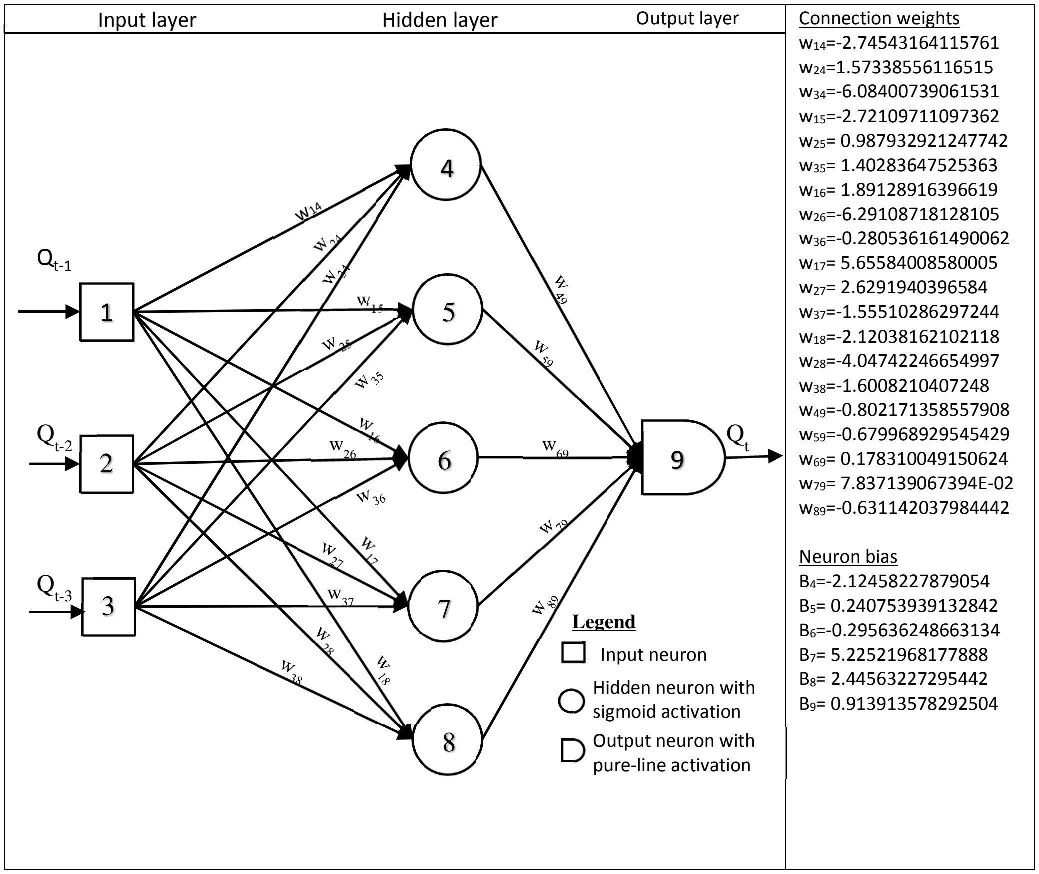


Figure 22: Detail and configuration of ANN daily streamflow forecast model for Vanderkloof dam

The development of the ANN streamflow forecast model was carried out in accordance with standard procedure (Krose and Smagt 1996; Kalteh 2007; Oyebode and Adeyemo 2014). An exhaustive review investigating the role of ANNs for hydrological modelling is reported by the American Society of Civil Engineers (Rajurkar, Kothyari and Chaube 2002). Details on ANN structuring for streamflow modelling is also available in Mugumo (2011) and Oyebode and Adeyemo (2014). Also, applications of

ANN-based streamflow modelling are widely reported in the hydrological literature (Campolo, Andreussi and Soldati 1999; Rajurkar, Kothyari and Chaube 2002; Mugumo 2011; Oyebode and Adeyemo 2014). Hence, details of ANN model development are not repeated here as the main focus of this study is to optimise daily reservoir operation for hydropower production, while ANN is only adopted for daily streamflow forecast.

6.3.4 Development of reservoir storage relationships

Storage relationships are important in reservoir operations. These relationships are useful in computation of reservoir storage head and surface area necessary for the estimation of generating head for hydropower and lake evaporation in each time period. The two storage relationships developed in this study are storage-elevation and storage-area equations.

Reservoir characteristics design data of the reservoir (DWA 1995a) were used in the development of these relationships. Exponential, linear, logarithmic, polynomial and power functions were fitted to determine the best model for the storage relationships (Salami 2007; Ajenifuja 2009). It was found that polynomial models of degree six best define the storage relationships of the Vanderkloof dam based on high values of coefficient of determination, R^2.

The Polyfit() function of MATLAB engineering software was used in fitting the polynomial models. This function embeds a subroutine that automatically determines the condition of the model. If it is reported that the model is ill-condition then the model either under fits or over fits the data points. The results from the fit in this study were reported to be well-conditioned which indicate that the models are adoptable for use in determining the storage head and storage surface areas. In applying these models, the existing storage first need to be divided by 1000 then the resulting elevation is multiplied by 1000 while the resulting surface area from the model is multiplied by 100. This is due to the mathematical transformations employed in the development of the models. Figure 23 shows the developed storage-elevation model while Figure 24 presents the storage-surface area model.

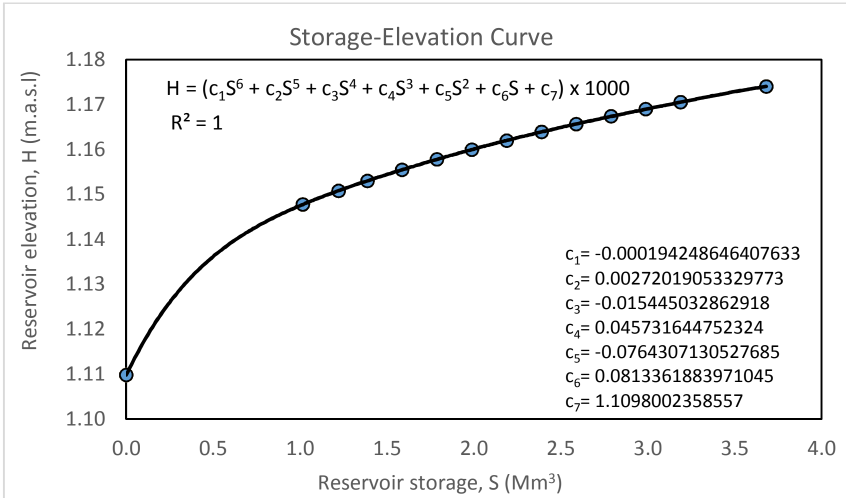


Figure 23: Storage-elevation curve for Vanderkloof reservoir.

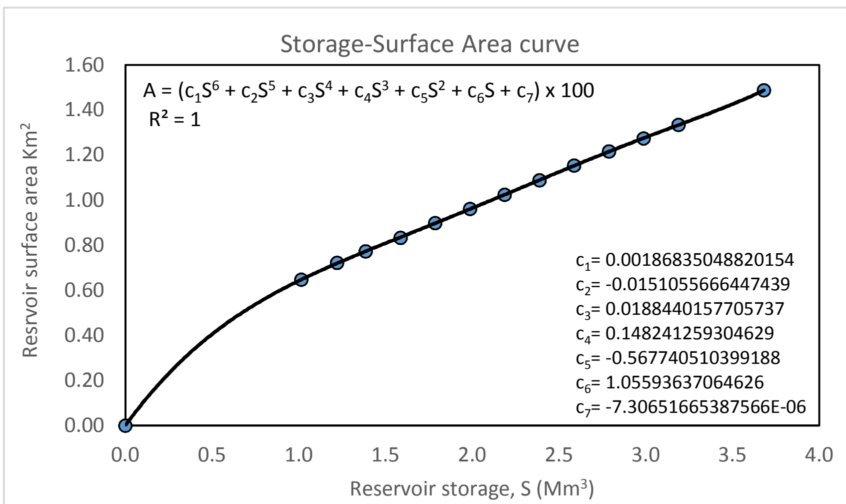


Figure 24: Storage-surface area curve for Vanderkloof reservoir.

6.3.5 Model formulation for real time optimal reservoir operation

The methodology in this study was adopted for daily operation of Vanderkloof dam for the 2012 – 2013 operating period. This period was chosen because it was the most recent operating period with complete data in the available dataset as at the time this study was performed. A preliminary frequency analysis of annual streamflows also shows that the flow in this period is categorized among the medium flows. Operating a reservoir without failure under a medium flow condition indicates that the reservoir will perform reliably at least 75 percent of the time (Scott and Smith 1997). This study inspects the scenario of application of the proposed model against existing practice. Formulation of the real time constrained multi-objective mathematical reservoir optimisation problem follows.

6.3.5.1 Decision variable and objectives

The main aim of the study was to determine the daily water releases into the main canal and the turbines that would maximize daily hydropower generation while satisfying the existing canal and irrigation demands. The existing monthly water demands on the reservoir are specified by DWA (2010) and are presented in Table14. These values are converted to daily demands by dividing by the number of days in the month for the analysis in this study.

The releases were also constrained to satisfy the maximum specified water supply deficit rate. The chosen decision variable for analysis herein is the reservoir storage at the end of the day, S_{End} (Mm^3). This facilitates the computation of the total daily reservoir release R_{cts} (Mm^3) using the mass balance equation. R_{cts} comprise the sum of the releases to the main canal R_c (Mm^3), turbine release R_t (Mm^3) and the reservoir overspill R_s (Mm^3). Once a decision on total release is made in each iteration of the optimisation algorithm, the breakdown of the release is specified as follows:

- If release is less than the total demand for the day, there is a deficit in water supply. A deficit rate is computed and the turbine and canal demands are supplied at the computed deficit level.
- If the release meets the turbine and canal demands then satisfy the canal demand and allot any extra water to the turbine to maximize hydropower production. Here, hydropower generation takes precedence over irrigation because DWA (1995) has noted that agriculture as a general economic sector and irrigation as a specific sub sector are relative inefficient users of water compared to other economic sectors. Hence industrial activities should not be impeded by lack of water in favour of irrigated agriculture.

- When the turbine has been satisfied to full capacity and yet there is still extra water, assign the extra to the canal to avoid wastage of water that may result from spill from the reservoir.
- The reservoir is allowed to spill only when the hydro turbines and canal have been satisfied to capacity and yet there is excess water over the overspill crest.

Table 14: Monthly water demands and hydrology of Vanderkloof dam, South Africa.

Month	Monthly water demands (Mm^3)			Hydrology	
	Power Plant	Main canal	Total	Net Evaporation depth (mm)	Flood control Volume FCC (Mm^3)
May	81.69	4.10	**85.79**	102	3120.142
Jun	79.06	2.47	**81.53**	81	3143.088
Jul	88.84	9.92	**98.76**	93	3159.342
Aug	130.65	19.92	**150.57**	123	3173.684
Sep	193.83	37.86	**231.69**	176	3174.322
Oct	234.91	48.12	**283.03**	230	3160.617
Nov	232.95	49.66	**282.61**	269	3135.121
Dec	274.99	32.36	**307.35**	313	3110.580
Jan	263.21	50.95	**314.16**	315	3088.271
Feb	197.23	37.6	**234.83**	256	3087.952
Mar	178.51	26.35	**204.86**	191	3093.689
Apr	124.26	10.71	**134.97**	132	3104.844
Total	**2080.13**	**330.02**	**2410.15**	**2281**	

Source: DWA (2010)

The objectives for the real time operation of the Vanderkloof reservoir for daily generation of hydropower are formulated as follows:

Objective 1: Maximize daily hydropower production.

Usually, hydropower generation is the cheapest form of electricity generation. It has also been observed that electricity produced from the Orange River Hydro stations is half as cheap as the ones sourced from Eskom's thermal power stations (ESKOM 2010). Hence, daily hydropower generation from the dam is maximized with the aim of generating electricity for the citizens at a cheaper cost. This is in line with the commitment of the government of South Africa towards equity and poverty eradication (SIDALA 2010). Furthermore, this underpins the South African

Government's commitment to reduction of the countries' GHG emissions and transition to a low carbon economy in line with international agreements (DOE 2014). The mathematical model equation for maximizing hydropower production from reservoirs is presented in equation (6.1) (Loucks and Bee 2005; Salami 2007; Ajenifuja 2009):

$$Maximize \quad Hp = 2.725 \, R_t H \varepsilon \qquad \ldots (6.1)$$

Where, Hp is hydropower production in the day in megawatt hours (MWH). R_t is the volume of water released through the hydropower turbine during the day in mega meter cube (Mm^3), Ɛ is the turbine efficiency in converting the mechanical energy of water to electrical energy and H is the average hydropower generating head in the day in metres (m). H is specified as the vertical distance between the water surface elevation in the reservoir that is the source of the flow through the turbines and the maximum of either the turbine elevation or the tail water elevation (Loucks and Bee 2005).

Objective 2: Minimize deviation from optimised flood control curve.

The second important objective in real time optimal hydropower generation from reservoirs is minimizing deviation from monthly target storage specified by the flood control rule curve (FCC) (Ngo 2006; Madsen *et al.* 2009). This aims to retain enough water in the reservoir and keep the storage head as high as possible for power generation in subsequent days. This objective is in conflict with the objective of maximizing hydropower generation in the day when the existing reservoir storage is below the target storage. Increasing the power output in a single day will result in fast fall of upstream water level, thus the average generating head is depressed and the total volume of water and generating head for future generation of hydropower is decreased.

The objective of minimizing deviation from optimised FCC also serves as an automatic switch between flood control when the reservoir is above the FCC and provision of inherent hedging against reservoir failure when the existing water level is far below the FCC (Ngo 2006). The mathematical model equation for minimizing deviation from optimised FCC is given in equation (6.2):

$$Minimize \ \Delta S = \left| S_{End} - FCC_m \right| \quad .... (6.2)$$

Where, ΔS is the deviation from target flood control storage (Mm^3), S_{End} is the storage volume (Mm^3) in the reservoir at the end of the day after all releases have been made and all losses computed. FCC_m is the flood control target volume for a day existing in an operating month m (m = 1, 2, … , 12). The values of FCC_m for Vanderkloof dam are specified by DWA and are presented in Table 14.

6.3.5.2 Problem constraints

The bi-objective real time reservoir optimisation problem of maximizing daily hydropower production while minimizing deviation from the optimised flood control curve is subject to the following constraints:

Constraint 1: Mass balance or storage continuity equation:

The mass balance equation defining the relationship between inflow and outflow variables at the reservoir site must be satisfied. The storage continuity equation is presented in equation (6.3) (Loucks and Bee 2005; Salami 2007). Equations (6.4, 6.5 and 6.6) gives details of the terms in equation 6.3.

$$S_{End} = S_{Start} + Q - E_{net} - R_{cts} - Ls \quad .... (6.3)$$

where;

$$R_{cts} = (R_c + R_t + R_s) \quad .... (6.4)$$

$$E_{net} = (E - P) \quad .... (6.5)$$

$$Ls = 0 \quad .... (6.6)$$

where S_{End} is the reservoir storage at the end of the day as defined in equation (2), S_{Start} is the existing storage volume in the reservoir at the beginning of the day, Q is the streamflow into the reservoir during the day, P is precipitation on the reservoir surface during the day, E is gross evaporation from the reservoir surface, Ls is seepage loss, R_c , R_t and R_s are daily reservoir releases as previously defined. All variables are measured in volumetric units of mega cubic metres (Mm^3). Since the reservoir is stable and has been in operation for a long time, seepage losses are assumed to be negligible in this study. The reservoir inflow Q is obtained from forecast using the ANN model developed in section 6.3.3.

For the analysis herein, daily net evaporation values are used. Values of monthly average net evaporation depth (mm) have been complied by DWA (1995a) for analysis of the reservoir. These values were obtained from historical records by subtracting the values of monthly reservoir precipitation from gross evaporation and averaged over the length of the historical record. These values are presented in Table 14. Daily net evaporation depth is obtained by dividing the monthly value by the number of days in the specified month. Net evaporation volume E_{net} (Mm^3) is obtained by multiplying the daily evaporation loss depth by the average surface area of the reservoir during the operating day.

Constraint 2: Limits on reservoir storage:

The storage volume in the reservoir is allowed to vary only between the minimum and maximum permissible storages. This constraint is specified in equation (6.7):

$$S_{\min} \le S_{End} \le S_{\max} \quad \text{.... (6.7)}$$

Where, S_{min} (Mm^3) is the minimum permissible storage volume and S_{max} (Mm^3) is the reservoir capacity. Because this study aims to investigate the feasibility of generating hydropower from the dam without failure, S_{min} is set to the minimum operating storage volume for hydropower generation at the reservoir (1 222.1 Mm^3). The flood control rule curve is a hard boundary constraints which should not be crossed during long term reservoir operation and planning. However, during day-to-day or real time operation of reservoirs, the flood rule curve may be crossed temporarily during reservoir spilling (Savenije 1995; Mugumo 2011). Therefore, S_{max} (3188.6 Mm^3) is used as the maximum permissible storage volume instead of values from the FCC in the real time analysis herein.

Constraint 3: Limits on releases through the turbines and canal:

The values of daily releases through the turbines and main canal must lie between the minimum and maximum releases allowed through these outlets. The South African Department of Water Affairs (DWA) has adopted a maximum water supply deficit rate of 20 percent to cushion the frequency and severity of shortages in operating the reservoir (DWA 2010). This implies that water supplied through these reservoir outlets must meet at least 80 percent of the demands in the supply areas. This specifies the minimum releases. Maximum release through these outlets are specified by the discharge capacity of the respective outlet. These constraints are presented in equations (6.8) and (6.9):

$$0.8D_c \leq R_c \leq C_c \quad \text{.... (6.8)}$$
$$0.8D_t \leq R_t \leq T_c \quad \text{.... (6.9)}$$

where, D_c and D_t (Mm^3) are daily canal and turbine demands respectively. These daily demands are computed by dividing the monthly demands in Table 14 by the number of days in the respective month. C_c is the maximum volumetric daily discharge of the main canal (4.9248 Mm^3) while T_c (Mm^3) is the daily discharge capacity of the turbines (34.56 Mm^3).

Constraint 4: Hydropower plant capacity:

The maximum electrical energy that can be produced from a hydropower generating plant at any time is limited by installed plant capacity *P* (MW) and the plant factor *f*. The plant factor is a measure of hydroelectric power plant use and is usually dictated by the characteristics of the power system supply and demand. The total energy produced (MWH) during any period cannot exceed the product of the plant factor *f*, the number of hours in the period *h* and the plant capacity *P*, as defined in equation (6.10.) (Loucks and Bee 2005; Salami 2007):

$$Hp \leq (Hp_{\max} = Phf) \quad \text{.... (6.10.)}$$

Hp_{max} is the cap on hydropower that can be generated in the day in megawatt hours (MWH). Since this study investigates the feasibility of generating hydropower throughout the day, it is assumed that the plant will be in full use and power generated from the plant will be fully consumed. Therefore, a plant factor, $f = 1.0$ is assumed in this study. The time step for the real time optimisation herein is a day, hence h = 24 hours is used. The plant capacity of the Vanderkoolf power plant is 240 MW.

6.3.6 Model solution and experimental setup

The mathematical model equations (6.1 – 6.10) representing the constrained multi-objective real time reservoir optimisation problem were solved using CPMDE which is a new methods of EMOA proposed by Olofintoye, Adeyemo and Otieno (2014a). The pseudo code for CPMDE was encoded using visual basic for applications (VBA) to facilitate its application in resolving the real time reservoir operation problem stated herein. The population of solution vectors was set at $N_p = 10$. This is based on the advice by Storn and Price (1995) that a minimum population size 10 times the number of decision variables suffices in the application of methodologies based on DE. The algorithm was iterated for 3000 generations for each day in the real time analysis herein. Crossover rate C_r was set at 0.90 while the mutation scaling factor F was set at 0.60 as advised by Storn and Price (1995). Harmonic average distance for maintaining spread of solutions on the Pareto front was computed using the two-nearest neighbour scheme.

6.3.7 Selection of daily reservoir operating policy

Application of CPMDE for real time multi-objective optimisation of the daily operation of Vanderkoolf reservoir produces a set of 10 non-inferior solutions representing feasible daily optimal operating policies. These policies trade-off power generation against storage depletion and reservoir storage head drop. These set of non-inferior solutions are Pareto-optimal and no solution in the set can be considered better than any other in the absence of specialized information regarding the nature of the problem at hand (Deb 2001; Huang *et al.* 2005; Reddy and Kumar 2007). These provide a basis for choosing a preferred solution that balances short-term and long-term objectives taking other considerations into account. Based on these results, the operator can express his/her preference to choose the most suitable solution in the set of Pareto-optimal solutions.

In order to select daily best compromise solutions (BCS) for the real time analysis of the reservoir in this study, the existing release restriction policies for the reservoir (Mugumo 2011) were used in collaboration with a compromise programming approach (CPA) suggested by Deb (2001). CPA (see section 5.3.5) selects a solution which is minimally located from a given reference point as the BCS. Figure 25 shows the current release restriction policy that are used for operating the reservoir. The penstock elevation at 1 150.8 m.a.s.l specifies the minimum operating level for hydropower generation. This corresponds to a storage of 1 222.1 Mm^3. Hydropower can only be generated from the dam when storage is above the minimum operating level for hydropower generation, that is, when the reservoir storage is in zone 1 or zone 2. For the purpose of the real time study herein, the release restriction policy is applied in determining the daily reference point as follows:

- If the existing storage volume (ESV) at the beginning of the day is in zone 2 which is the restriction zone, releases are reduced by a restriction factor to hedge against complete depletion of storage in the reservoir. This helps in ensuring that there will be water in the reservoir for hydropower generation in the future. The restriction factor depends on how depleted reservoir is at the present day and is computed as a linear interpolation between the maximum and minimum storage volume of this zone.
- If ESV resides in the lower part of the normal operating zone, that is, in the lower part of zone 1, the storage is considered to be far below the FCC but above the restriction zone. The aim here is to release just enough water to meet the full daily demands of the turbine and canal. Here no extra water is allocated to downstream users so as to aid in build-up of storage in the reservoir. This zone is defined as the zone with storage volume 40 Mm^3 less than the storage defined by the corresponding FCC.
- If ESV is in the upper part of the normal operating zone but below the FCC, then storage is considered to be in the vicinity of the FCC. In this zone, the aim is to operate the reservoir in a steady state mode while keeping reservoir storage in the vicinity of the FCC. Here, the release is made as close as possible to the inflow as possible. The operating rule in this zone is to release the total forecasted inflow or 100 percent of the total demand, whichever is greater. This zone is defined as the zone with storage volume less than the storage defined by the corresponding FCC by not more than 40 Mm^3. The combined discharge capacity of the canal and turbine is 39.4848 Mm^3. This is approximated to 40 Mm^3 in this study to define storage within the vicinity of the FCC.

- If the reservoir storage is above the FCC then the reservoir is operated in flood control mode. Releases are made to avoid spillage and safeguard the structure. The aim in this scenario is to release the total forecasted inflow or 100 percent of the total demand whichever is greater plus the excess storage above the FCC. This helps to deplete the storage to fall below the FCC.

VAN DER KLOOF DAM			
Reduced Level (m)	**Zone Volume** (million m^3)	**Capacity** (million m^3)	**LEVEL**
1 1750.50		3 187.07	Full Supply Level
ZONE 1 1 153.00	**ZONE 1** **1 802.13**	**ZONE 1** 1 386.47	Normal Operation
ZONE 2 1 150.80	**ZONE 2** **1 64.37**	**ZONE 2** 1 222.10	Only Eskom
ZONE 3 1 147.78	**ZONE 3** **206.70**	**ZONE 3** 1 015.40	Releases
ZONE 4 1 128.45	**ZONE 4** **809.92**	**ZONE 4** 205.48	Low Level Storage
Low Level Storage 1 071.00	**Low Level Storage** **205.48**	**Low Level Storage** 0.00	Bottom

Figure 25: Release restriction policy for Vanderkloof dam (Mugumo 2011).

6.3.8 Operation scenarios.

Three operation scenarios were investigated in this study. In the first scenario, the behaviour of the reservoir was inspected under existing current practice. The existing storage volumes and actual reservoir releases made were used to compute power generation and investigate the behaviour of the reservoir over the operating period. This scenario starts with a low storage based on the data of actual operation of the dam. The other two scenarios adopt the methodology developed in this study to investigate the performance of the reservoir under two different starting storage volumes. The starting storages investigated herein are low starting storage and high starting storage. First simulations through the operating period were carried out using an initial starting storage of 2 689.536 Mm^3. This was the ESV at the beginning of the operating period according to the available data. This resulted from the current operation of the system. This scenario is considered a low starting storage case as the initial volume was about 430 Mm^3 short of the value specified by the optimised FCC. A final storage volume of 3 107.898 Mm^3 was obtained at the end of the operating period. This represents the initial starting storage for the next operating season. This volume, which is about 12.243 Mm^3 short of the expected starting storage, was then used to rerun the simulation over the operating period. This scenario is considered as a high starting storage scenario. Results show that the starting storage of the reservoir affects the amount of power that can be generated from the reservoir over the operating period.

6.3.9 Development of a decision support system (DSS) for real time operation of the Vanderkloof reservoir.

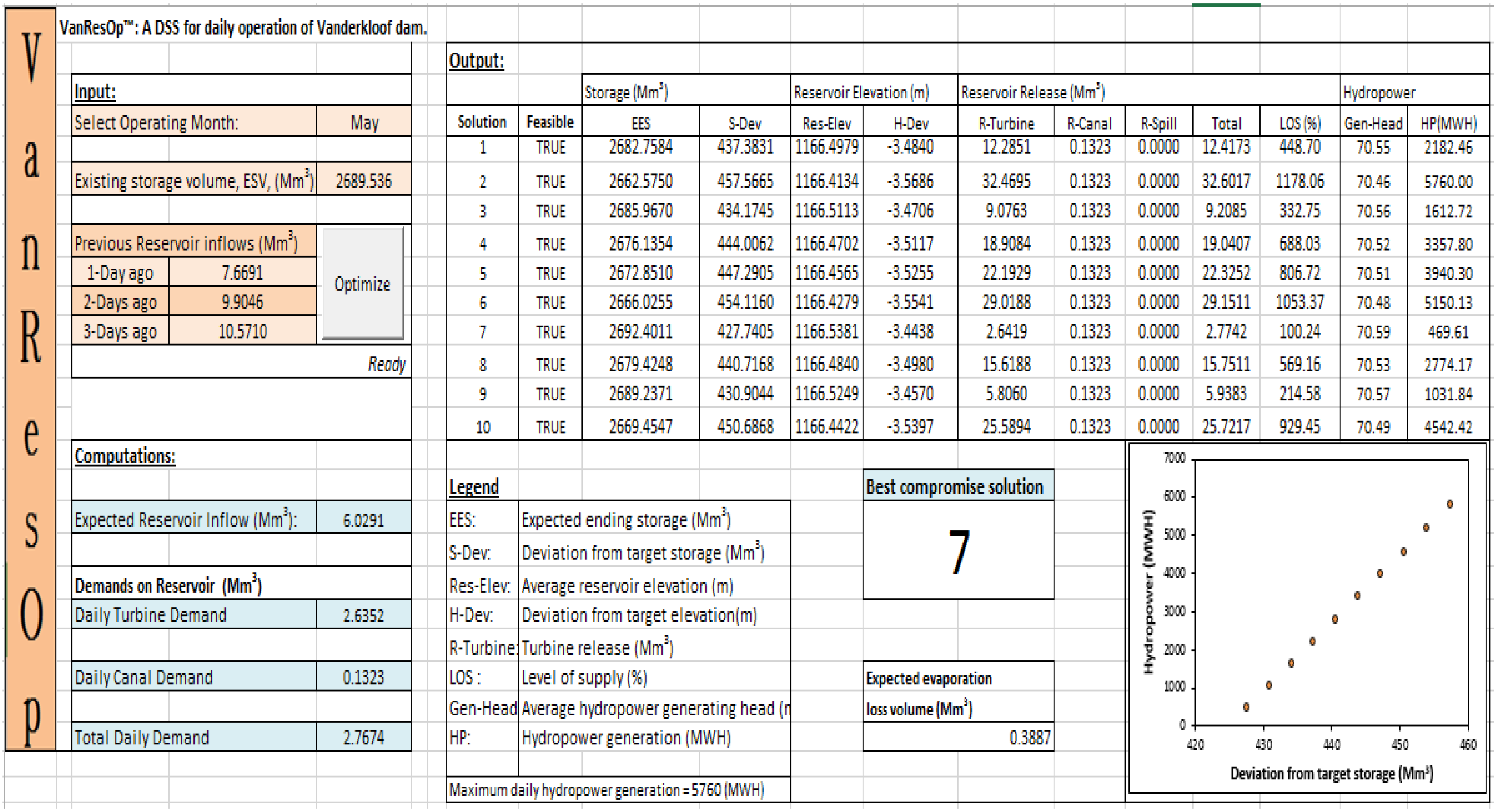
Analyses in hydrological studies often require handling large volumes of data and rigorous computations. Developing software/expert systems for this purpose may help reduce the cumbersome computational tedium involved to a great extent (Islam and Kumar 2003; Olofintoye and Adeyemo 2011c). The advent of personal computers and the development of standardized programming platforms have spurred engineers and scientists worldwide into developing software applications for the solution of unique engineering and scientific problems (Olofintoye and Adeyemo 2011a). Several studies reporting the development and applications of computer programs or software for the solution of engineering and water resources problems have been cited in the literature (Vivoni *et al.* 2002; Islam and Kumar 2003; Raji 2004; Morin *et al.* 2006; Olofintoye, Salami and Jimoh 2009).

According to Loucks and Bee (2005), developing and implementing a decision support system (DSS) for water resource management may offer great benefits in making critical water allocation decisions. These interactive modelling and display technologies can, within limits, adapt to the level of information needed and can give decision-makers some control over data input, model operation and data output (Loucks and Bee 2005).

Mugumo (2011), while operating the Vanderkloof reservoir noted a general absence of a software which is versatile in data manipulation, user friendliness and at the same time specifically tailored toward reservoir operations. The author further recommended development of a software or DSS dedicated to water resource management and reservoir operations, especially in South Africa. Hence, in this study, the models and all relevant information for the daily operations of the Vanderkloof as presented in the methodology, were compiled into a user friendly software application program using visual basic for applications (VBA) embedded in Microsoft Excel. This resulted in the development of a new software program called VanResOp for real time operation of Vanderkloof dam in South Africa. The acronym is formed by taking preceding letters as follows: **Van**derkloof **Res**ervoir **Op**eration. VanResOp represents a DSS that generates daily optimal operating policies for the Vanderkloof reservoir. The user interface of the DSS is presented in Figure 26.

The DSS takes as input the current month, ESV at the beginning of the operation day, and flows into the reservoir in the past three days. These are entered into respective cells in the input section on the interface, following which the user clicks on the 'Optimize' button. VanResOp undertakes all necessary calculations incorporating the details in the methodology section herein and produces as set of 10 daily Pareto-optimal solutions which represent feasible operating policies for the reservoir. These provide a basis from which a decision maker may choose from to operate the dam for a particular day. Details of the optimal solutions are presented in the output section. A graph showing the Pareto front of the solutions is also shown in the lower right corner of the interface while the suggested best compromise policy is displayed in the best compromise section near the centre of the user interface (Figure 26).

The DSS was specifically developed using VBA in Microsoft Excel due to the excellent data manipulation ability and user friendliness of Microsoft Excel. Users familiar with Microsoft Excel need not spend excessive time in learning to use and apply a new user interface.



VanResOp™: A DSS for daily operation of Vanderkloof dam.

VanResOp

Input:

Select Operating Month:	May
Existing storage volume, ESV, (Mm³)	2689.536
Previous Reservoir inflows (Mm³)	
1-Day ago	7.6691
2-Days ago	9.9046
3-Days ago	10.5710

Optimize

Ready

Computations:

Expected Reservoir Inflow (Mm³):	6.0291
Demands on Reservoir (Mm³)	
Daily Turbine Demand	2.6352
Daily Canal Demand	0.1323
Total Daily Demand	2.7674

Output:

		Storage (Mm³)		Reservoir Elevation (m)		Reservoir Release (Mm³)					Hydropower	
Solution	Feasible	EES	S-Dev	Res-Elev	H-Dev	R-Turbine	R-Canal	R-Spill	Total	LOS (%)	Gen-Head	HP(MWH)
1	TRUE	2682.7584	437.3831	1166.4979	-3.4840	12.2851	0.1323	0.0000	12.4173	448.70	70.55	2182.46
2	TRUE	2662.5750	457.5665	1166.4134	-3.5686	32.4695	0.1323	0.0000	32.6017	1178.06	70.46	5760.00
3	TRUE	2685.9670	434.1745	1166.5113	-3.4706	9.0763	0.1323	0.0000	9.2085	332.75	70.56	1612.72
4	TRUE	2676.1354	444.0062	1166.4702	-3.5117	18.9084	0.1323	0.0000	19.0407	688.03	70.52	3357.80
5	TRUE	2672.8510	447.2905	1166.4565	-3.5255	22.1929	0.1323	0.0000	22.3252	806.72	70.51	3940.30
6	TRUE	2666.0255	454.1160	1166.4279	-3.5541	29.0188	0.1323	0.0000	29.1511	1053.37	70.48	5150.13
7	TRUE	2692.4011	427.7405	1166.5381	-3.4438	2.6419	0.1323	0.0000	2.7742	100.24	70.59	469.61
8	TRUE	2679.4248	440.7168	1166.4840	-3.4980	15.6188	0.1323	0.0000	15.7511	569.16	70.53	2774.17
9	TRUE	2689.2371	430.9044	1166.5249	-3.4570	5.8060	0.1323	0.0000	5.9383	214.58	70.57	1031.84
10	TRUE	2669.4547	450.6868	1166.4422	-3.5397	25.5894	0.1323	0.0000	25.7217	929.45	70.49	4542.42

Legend

EES:	Expected ending storage (Mm³)
S-Dev:	Deviation from target storage (Mm³)
Res-Elev:	Average reservoir elevation (m)
H-Dev:	Deviation from target elevation(m)
R-Turbine:	Turbine release (Mm³)
LOS :	Level of supply (%)
Gen-Head	Average hydropower generating head (m
HP:	Hydropower generation (MWH)

Maximum daily hydropower generation = 5760 (MWH)

Best compromise solution
7

Expected evaporation loss volume (Mm³)
0.3887

Figure 26: Graphical user interface (GUI) of VanResOp

VanResOp was employed to perform a real time behavioural analysis of the reservoir over the operating period. This facilitated the investigation of the feasibility of daily hydropower generation from the Vanderkloof reservoir under normal flow conditions. VanResOp may be available in the future on request from the repository of Durban University of Technology (DUT), South Africa.

6.4 RESULTS

The real time multi-objective reservoir operation problem of maximizing daily hydropower generation while meeting long term objectives in terms of minimizing deviations from the optimised flood control curve at the same time satisfying existing water demands riparian to the river, was solved using an ANN-CPMDE hybrid solution technique. ANN was employed to forecast daily reservoir inflow while CPMDE was used to optimise the daily operation of the reservoir to obtained daily Pareto-optimal solutions representing feasible daily operating policies for the dam. Figure 27 shows the fit of the ANN forecast model over the operating period used in this study. The sum of daily hydropower produced in each month are presented in Figure 28 while Figure 29 shows the daily storage trajectories over the operating period.

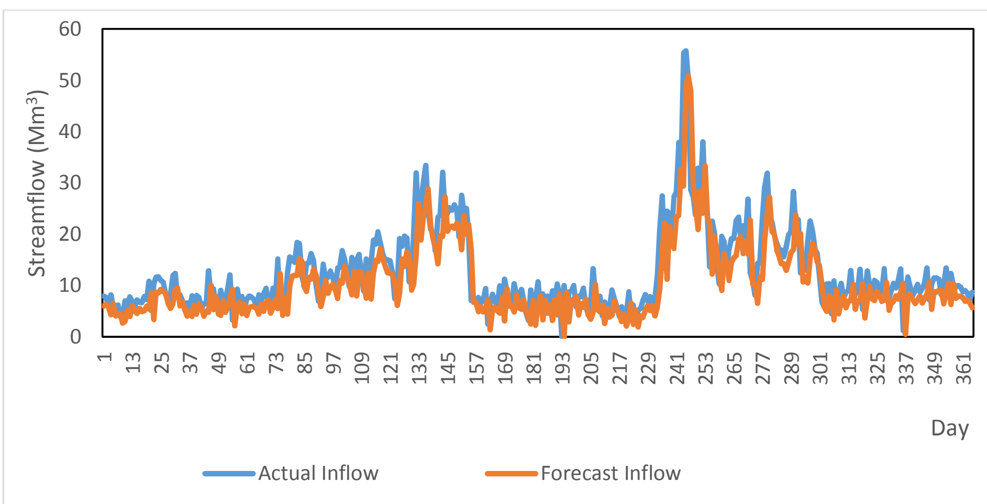


Figure 27: Fit of the ANN streamflow forecast model over the operating period.

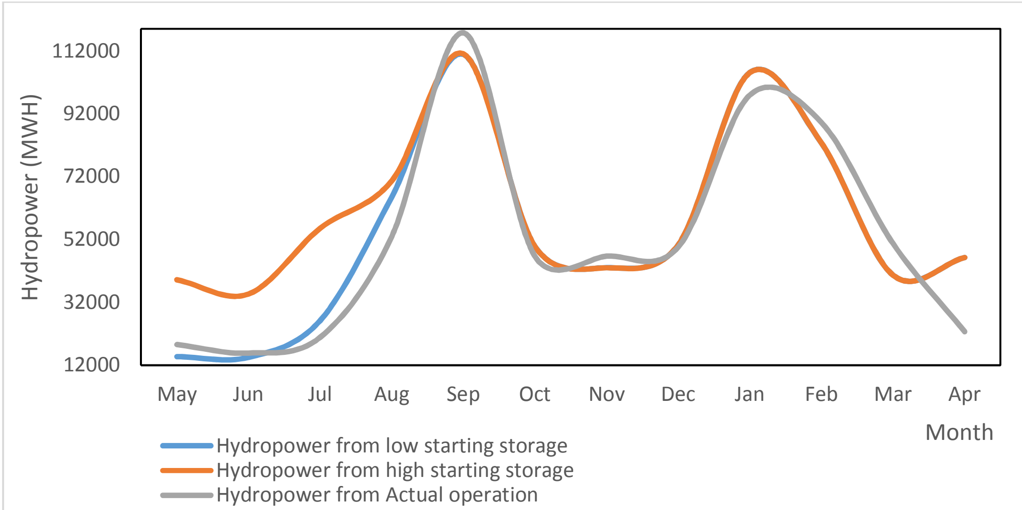


Figure 28: Cumulative monthly hydropower production over the operating period.

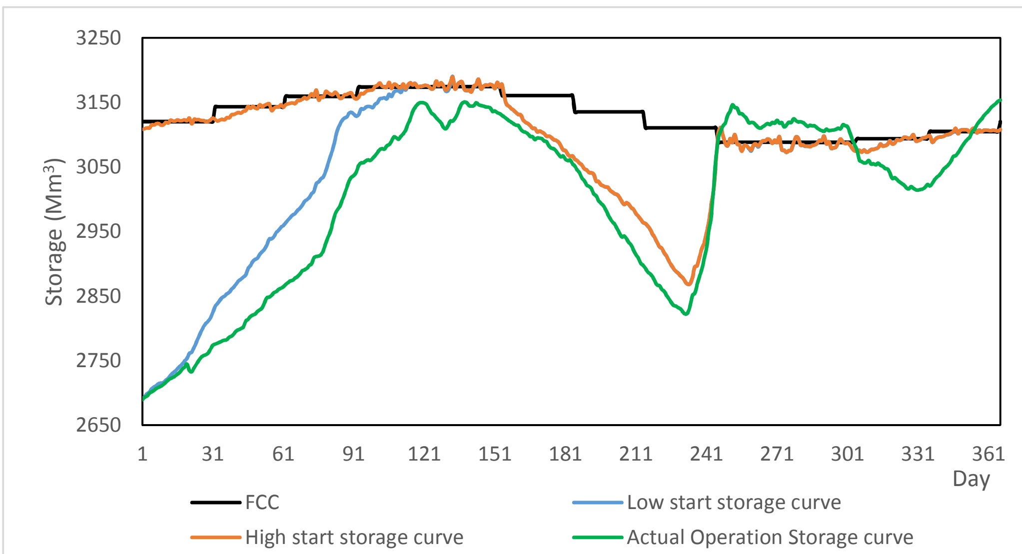


Figure 29: Reservoir storage trajectories over the operating period.

6.5 DISCUSSION OF RESULTS

Figure 27 shows that the developed ANN streamflow forecast model produces good generalization of the underlying phenomenon generating the inflow dataset. This further proves the ability of ANN in modelling hydrological processes. The model exhibits a good representation of the streamflow dynamics of the Vandekloof reservoir as it was able to adequately reproduce the inflow pattern with a substantial degree of accuracy. This also suggests that the assumption of a Markovian flow process in the selection of input variables for the model is adequate. The satisfactory performance of the network further corroborates the authenticity of the universal approximation theorem for ANN that a three layered feed-forward neural networks is sufficient for most hydrological modelling and forecast applications. The fact that an ANN with a simple network architecture, that is, a three layered ANN network with three neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer could satisfactorily simulate reservoir inflow in this study also demonstrates the power and applicability of ANNs in operating complex reservoir systems.

Simulation through the operating period using well balanced optimised solutions shows a general pattern in possible hydropower generation from the dam. Figure 28 shows two peak periods for hydropower generation corresponding to periods of peak streamflow into the reservoir. The higher of the peaks for possible hydropower generation occurs during the spring months (around August – October) while the lower peak occurs during the summer months (December – February). Rainfall and consequently streamflow into the reservoir are generally higher in the summer months than the spring months, however it was observed (Figure 28) from real time simulation, that the peak hydropower generated during spring (111.035 GWH) is slightly higher than that generated in summer (105.063 GWH). This is probably due to the fact that the FCC (Figure 29) restricts storage volume during the high inflow period so as to reserve storage space necessary for flood control during the flood season. This consequently enforces reservoir operations to maintain lower storage heads during this period even though much water is available for power generation.

The reservoir storage specified by the FCC for the month of September (3 120.14 Mm^3) corresponds to a generating head approximately 74.5 m, while storage specified for January (3088.27 Mm^3) corresponds to a generating head of about 73.8 m. According to Salami, (2007), the amount of water in storage may sometimes not be as important as the depth of water in the reservoir. This is because potential energy which is ultimately converted to mechanical energy for power generation is a function of elevation and must be sufficiently high to do useful work. Therefore, it may be said that more power is produced in spring due to high inflows and higher reservoir elevations specified by the FCC.

The season from October to December is marked by significant drop in reservoir storage and hydropower generation due to low inflows (Figures 28 and 29). Although the FCC specifies high storage values during this season, flows during this period are generally low thereby resulting in significant deviation in storage from that specified by the FCC and consequently a drop in hydropower generating head. From the result of the analysis however, it was found that it is still possible to generate a low amount of energy (minimum of 43.01 GWH) despite the prolonged period of low streamflow. The period between March and July is also accompanied by low flows, however, due to pockets of high flows during this season it is possible to maintain a high head. In order to maintain high heads in this period however, reservoir releases have to be restricted, thus resulting in lower hydropower generation.

The current practice in operating the dam requires that the turbines should be operated at full capacity when storage is above the FCC until storage drops below the FCC. When storage is significantly depleted, restriction rules (Figure 25) are applied to hedge against further depletion (DWA 2010; Mugumo 2011). No rule specifies the exact amount of water to discharge on daily basis. Unlike the procedures of the current practice, the real time methodology produces optimal policies that specify the exact amount of water to release thus providing guidance facilitating the daily operation of the reservoir.

Examination of Figure 28 shows that while starting with a low storage, the power generated from actual operations and real time analysis were roughly equal in the first two months (May-June). In the following two months (July-August), power production using the real time methodology was generally higher while in September power generation from real time operation was slightly lower. Performance of the system was roughly the same through the period of low flows (October to December). After the low flow period, the real time application method was able to recover faster and produced higher power in the second peak generation period (January).

While the real time method was able to balance power generation towards the end of the operating period (March – April), actual operations witnessed a significant drop in power production and storage fluctuations (Figure 29) probably in an attempt to keep the reservoir full in anticipation of the next operating period. A difference in power production of about 23.6 GWH was observed between the performance of the real time methodology and the actual operation in this period. The total power generated from actual operation of the dam over the planning period was 629 GWH. In applying the real time method, it was observed that the dam generated 649.31 GWH over the operating period. This difference of 20.31 GWH in power production indicates an increase of about 3.2 percent in power generation. This suggests that power production from the dam may be improved by adopting real time strategies.

The advantage of employing the real time methodology is amply evident from inspection of the storage trajectories over the operating period (Figure 29). While the real time method was able to recover from storage depletion in about four months, the actual operation of the reservoir indicates that the dam did not recover storage until eight months (Figure 29). The failure of the dam to recover before the period of extended low flows led to a further depletion of the reservoir during the low flow period. This depletion was in the range of 50 Mm^3 more than the depletion observed from the application of the real time methodology. Due to this high depletion, it is evident that the operator applied strict hedging rules which brought the storage above the FCC within 3 months after the low flows. While this was useful in keeping the reservoir storage high, it reduced the power produced during this period as the operation of the reservoir was not optimal (Figure 28). Further attempt to keep the reservoir around the FCC resulted in the fluctuations observed towards the end of the operating period as there was no methodology in place to specify optimal daily release from the reservoir.

Figure 29 shows that while it was possible to minimize deviations from target storages and keep storage as close to the FCC as possible by applying the real time methodology, significant deviations from the FCC were observed during the actual operation over the operating period. An average cumulative storage deviation of 95.4

Mm^3 was observed during operations using the proposed real time methodology while about 139.4 Mm^3 resulted from actual operations. This difference of 44 Mm^3 indicates a decrease of 46.12 percent in deviation from target storage. Therefore, it may be said that the real time methodology presents a method that is roughly 46.12 percent times better than the actual operations in minimizing deviations from reservoir target storage volumes.

From further analysis of results of simulation over the operating period, it was observed that the starting storage of the reservoir significantly affects the amount of hydropower that can be generated over the period. Total annual hydropower production reduces with reducing starting storage volumes. Starting real time simulation with a storage volume of 2 689.536 Mm^3 which is roughly 14 percent short of the expected starting storage, produced a total annual power of 649.31 GWH, while starting with a higher volume (3 107.898 Mm^3), roughly 0.4 percent short of the volume specified by the FCC produced about 728.53 GWH of annual energy. This difference in power generation of about 79.23 GWH indicates an increase of about 11 percent in power generation.

From Figures 28 and 29, it is evident that when simulation is started with a low storage volume, power production is restricted while a systematic attempt is made to build reservoir storage and hydropower generating head. Examination of real time operations in these Figures (28 and 29) shows that it took about 112 days (almost 4 months) for the reservoir to recover from a storage shortage of only 14 percent to be at par with the operation started with a high storage volume. However, the reservoir was able to recover before the prolonged period of low reservoir inflows. It was further observed that once the reservoir recovered storage, operations follow the same pattern to the end of the operating season. Furthermore, it was noted that if the reservoir is able to maintain its storage head close to the FCC before the low flows, it will ultimately recover from storage depletion after the low flows period and maintain a high head into the next operating season.

The low starting storage that was 14 percent short of the expected starting storage specified by the FCC, resulted from the current operation of the reservoir. However, by applying the real time reservoir operation methodology suggested herein under a medium flow condition, the reservoir was able to systematically recover from storage depletion and maintain a high head into the following operating season. This suggests that adopting real time cutting edge technologies for the operation of Vanderkloof dam may be beneficial for future operation of the reservoir.

Results from the real time reservoir analysis in this study indicate that under a medium flow condition with a high reservoir storage volume at the beginning of the operating period, it is possible to generate hydropower on a daily basis from the reservoir without a failure of the system. An average of 1.26 GWH/day could be generated in the month of May, 1.15 GWH/day in June while 1.79 GWH/day could be produced in July. Average daily power generation of 2.28 GWH/day is possible in August, 3.70 GWH/day in September, 1.60 GWH/day in October and 1.43 GWH/day may be generated in November. Mean daily hydropower generation in December is 1.62 GWH/day while an average of 3.39 GWH/day and 2.95 GWH/day can be produced in January and February respectively. Daily average energy of 1.31 GWH/day may be generated in March while 1.54 GWH/day is possible in the month of April. Minimum power generation (1.15 GWH/day) occurs in June while maximum generation (3.70 GWH/day) occurs in September. A total of 728.53 GWH of annual energy may be generated under medium flow condition when the reservoir is full at the beginning of the operating period.

It was also observed that storage was maintained above critical levels and at no time did storage fall to the restriction zone throughout the simulation. The deficit rate was zero in all the days of the operating period and there was no need for water rationing. Also, the reservoir was 99.6 percent full at the end of the operating period. This suggests that the hydrology of the dam can sustain its current water demands under the prevailing climate situation. This is consistent with the findings of (Adeyemo, Olofintoye and Otieno 2012; Olofintoye, Adeyemo and Otieno 2012) that hydropower generation from the dam and water supplies to other sectors are is still sustainable under the prevailing climate condition. However, the fact that the dam took a period of about four months to recover from a storage depletion of only 14 percent indicates that the water resources of the dam is not in excess. The water in the dam is just enough to meet all current demands. This calls for proper management policies for future operation of the reservoir to guard against excessive storage depletions.

The findings of this study are also consistent with the findings of Mugumo (2011), Mugumo, Ndiritu and Sinha (2013), and Olofintoye, Adeyemo and Otieno (2014b) that if water in the reservoir is properly managed, hydropower can be sourced from the Vanderkloof dam over the operating period without system failure. However, Mugumo (2011) investigated the operation of the dam using monthly streamflows and not real time reservoir inflows as used in this study.

The results from the analysis in this study also support the findings of Madsen and Skotner (2005), Richaud *et al.* (2011) and Ngo (2006) that the combination of accurate reservoir inflow forecasting and optimisation technology for real time operation of reservoirs, can provide more efficient and balanced solutions for operating reservoirs to improve the economy of hydropower production. For instance while operating the Hoa Binh reservoir in Vietnam, Madsen *et al.* (2009) observed an increase in power generation of about 210 GWH per annum while implementing a real time methodology. In this study, an increase of 3.2 percent in power generation and 46.12 percent in ability to minimize deviations from storage targets were observed. This indicates that the real-time reservoir operation methodology applied herein may represent an improvement of up to 49.32 percent in performance over current practices.

The real time reservoir operation in this study involved averaging monthly values to obtain daily values by dividing by the number of days in a month since real time data was not readily available. This may possibly impact on the accuracy of the study. Investigation of the reservoir using exact real time data is left for further studies when relevant information will be available.

6.6 CONCLUSION

Water scarcity has emerged a global issue in recent times. The situation is being further exacerbated by escalating water demands while available water resources are limited, population explosion, unsustainable urbanization and in recent times anthropogenic climate change among other factors (Hamid and Khan 2003; Olofintoye, Adeyemo and Otieno 2012). This has driven efforts worldwide in search of improved techniques propitious to proper water allocation planning and reservoir optimisation and management operations. A real time reservoir behavioural analysis was performed to inspect the feasibility of daily hydropower generation from the Vanderkloof reservoir under normal flow conditions. A hybrid between a data driven artificial neural network (ANN) model and a novel combined Pareto multi-objective differential evolution (CPMDE) was employed for hydrological simulation and numerical multi-objective optimisation of hydropower production from the dam in real time. ANN was adopted to forecast real time streamflows while CPMDE was employed to search the decision space for feasible Pareto-optimal solutions representing daily operating policies for the reservoir. These Pareto solutions trade-off the short term and long term objectives and provide a basis from which a decision maker may choose from to operate the dam in real time and subsequently gauge system performance. Results from the application of the real time model indicate that 728.53 GWH of annual energy may be generated from the reservoir under medium flow condition without system failure. Storage was maintained above critical levels while the reservoir supplied the full demands on the dam throughout the operating period. This indicates that the system yield is sufficient and there is no immediate need to augment the system (Mugumo 2011; Olofintoye, Adeyemo and Otieno 2012; Mugumo, Ndiritu and Sinha 2013). However, the long period required for storage recovery when the dam is depleted suggests that the water resources of the dam are not in excess. Hence, effective water management strategies for future operation of the reservoir to guard against excessive storage depletions are needed.

Generating daily hydropower from the dam will provide electricity for the citizens at a cheaper cost. This aligns with the South Africa government's commitment towards poverty eradication and reduction of the countries' greenhouse gas emissions to conform to international standards and reduce the country's contribution to anthropogenic global climate change. Results of simulation in this study indicate that it took the reservoir close to four months to recover from a storage depletion of only 14 percent. This is due to the fact that the reservoir is located in a semi-arid region with low rainfalls. Hence methodologies that encourage indiscriminate allocation of water which may lead to significant storage depletions should be avoided. Findings from the application of the real time methodology suggested herein show that the reservoir could systematically recover from storage depletion and maintain a high storage head into the next operating season. Therefore, the hybrid ANN-CPMDE real time reservoir operation technique suggested herein provides a low cost solution methodology suitable for the sustainable operation of the Vanderkloof reservoir in South Africa. Results from the application of real time method developed in this study indicate a 49.32 percent improvement in performance over current practices. Recommendation is hereby made to stakeholders, policy makers and operators of the reservoir to further investigate, embrace and adopt cutting edge real time optimisation systems which may be beneficial to future operation of the reservoir. The real time optimisation of the reservoir was investigated under normal flow conditions, this indicates that the reservoir will perform successfully at least 75 percent of the time. Investigation of the reservoir under drought condition is hereby left for further studies.

6.7 RESEARCH OUTPUTS

[1] **Olofintoye, O.**, Adeyemo, J. and Otieno, F. 2015. Real time optimal water allocation for daily hydropower generation from the Vanderkloof dam, South Africa. *Applied soft computing*, 2015. *Under review*.

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CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 CONCLUSION

The search for accurate and reliable hydrologic and optimisation models for water resources management has been the point of much discussion in previous researches with promising applications in many areas of human endeavours such as crop growth, irrigation planning, hydrological systems, reservoir operations and other simulation studies (Lennox *et al.* 2003; Olofintoye 2007). Water inadequacy in most countries calls for concerns in the management of existing facilities since the building of new facilities requires very high investments and are highly opposed (Adeyemo 2009; Adeyemo and Otieno 2010). Hence, several heuristic optimisation models with varying degrees of complexities have been widely applied for resolving water resources optimisation and allocation problems. Nevertheless there still exist uncertainties about finding a generally consistent and trustworthy method that can find solutions which are really close to the global optimum in all circumstances (Olofintoye, Adeyemo and Otieno (2013b).

In this study, a new evolutionary algorithm (CPMDE) was developed and applied to resolve water allocation problems in the Orange River catchment in South Africa. Results obtained from the applications of CPMDE suggest it represents an improvement over some existing methods. CPMDE combines methods of Pareto ranking and Pareto dominance selections to implement a novel and unique selection scheme at every generation. The new scheme introduces 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. CPMDE was benchmarked against 14 state-of-the-art evolutionary multi-objective optimisation algorithms. Findings suggest that the new algorithm presents an improvement in convergence to global Pareto-optimal fronts especially on deceptive multi-modal functions. Competitive results obtained from the benchmark of CPMDE suggest that it is a good alternative for solving real multi-objective optimisation problems. Results from a rigorous comparison of solution methodologies using standardized performance metrics and a statistical Wilcoxon signed rank test further show that CPMDE can be ranked in the class of recent and standardized state-of-the-art evolutionary multi-objective algorithms.

CPMDE was applied to resolve water allocation problems in the agricultural and power sectors in South Africa. The results suggest that these methodologies are applicable in other countries with similar or different climate and conditions. The agricultural and power sectors have been considered strategic and germane in capacitating the South African government's commitment towards equity and poverty eradication and ensuring food security. On a crop planning problem, CPMDE found 18 new policies that were not found in an earlier study. This indicates that the algorithm represents an improvement of roughly 45 percent over an existing method that has been formerly applied.

The results of application of CPMDE in the real time behavioural analysis of the Vanderkloof reservoir showed an additional 20.31 GWH of energy corresponding to an increase of 3.2 percent in power generation. Analysis of storage trajectories over the operating period showed an increase in ability to minimize deviation from target storage. Overall, the real time analysis provides an improvement of 49.32 percent over the current practice. Further analysis involving starting the simulation with high storage volume suggests that 728.53 GWH of annual energy may be generated from the reservoir under medium flow condition without system failure. This corresponds to an 11 percent increase in energy generation.

It is concluded that a hybrid ANN-CPMDE real time reservoir operation methodology suggested herein provides a low cost solution methodology suitable for the sustainable operation of the Vanderkloof dam in South Africa. This suggests that adopting real time optimisation strategies may be beneficial to operation of reservoirs. Therefore, CPMDE presents a new tool nations can adapt for the proper management of water resource towards the overall prosperity of their populace.

The main objective of this study was to develop a new evolutionary multi-objective optimisation algorithm and apply it to solve multi-objective water allocation problems in the agricultural and power sectors in the Orange River catchment in South Africa. As mentioned in chapter 1, this study has six specific objectives which were:

1. To develop and conceptualize a novel multi-objective evolutionary algorithm for solving multi-objective mathematical optimisation problems and apply the developed method in water resources management in the Orange River catchment in South Africa.
2. To benchmark the developed algorithm with existing state-of-the-art algorithms using standard benchmark problems and standardized performance metrics to evaluate its performance and adaptability for solving real world optimisation problems.
3. To solve a multi-objective crop planning problem by using the newly developed multi-objective algorithm to optimise planting areas for given crops under land and water constraints

4. To adopt an existing framework for solving problems of water allocation to users in real time.

5. To develop a decision support system (DSS) by encoding the real time framework into a computer application package using visual basic for applications.

6. To apply the DSS to reservoir operations by investigating real time multi-objective water allocation for hydropower generation from the Vanderkloof dam.

Specific objective 1 was addressed in chapters 3 and 4 where a novel evolutionary multi-objective optimisation algorithm (CPMDE) was developed. This algorithm was later employed in resolving strategic water resources optimisation problems in Chapters 5 and 6. Benchmark of CPMDE on standardized benchmark test beds was achieved in chapters 3 and 4. Chapter 5 further provides a benchmark of the algorithm using a real world multi-objective crop planning problem. Hence, specific objectives

2 and 3 are satisfied. In chapter 6, specific objectives 4, 5 and 6 where achieved. In the chapter, a simulation-optimisation framework for solving real time optimal water allocation problems was adopted. The specifics of the framework in this study involved combining CPMDE with ANN to form a useful hybrid for real time operation of Vanderkloof dam for power generation under irrigation and existing riparian demand constraints. The ANN-CPMDE hybrid was implemented in a new DSS called VanResOp to facilitate is application for real time operation of the reservoir. VanResOp was the employed to investigate the feasibility of daily power generation from the Vanderkloof dam over the operating period. Results showed that the DSS was useful in generating optimal policies that facilitate the daily operation of the dam. 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 development of a novel evolutionary multi-objective optimisation algorithm (CPMDE) that represents an improvement over existing techniques. 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 and power sectors 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. Development of a new DSS (VanResOp) that incorporates model based information for the real time operation of Vanderkloof dam.
3. Development of ANN-CPMDE heuristic hybrid for real time operation of the Vanderkloof reservoir.

7.3 RECOMMENDATIONS AND FUTURE RESEARCH

The following recommendations suggest areas for further research to improve the applicability of the methods developed in this work.

- Gariep and Vanderkloof dams are the two most important dams along the Orange River. This study focuses only on the Vanderkloof dam because it is the last in the series and therefore captures the operation of the Gariep dam upstream. Furthermore, it serves as the last valve in the river system up to the river mouth. Further research will be to employ CPMDE to optimise the combined operations of these dams to satisfy the conflicting objectives of hydropower, irrigation, flood control and municipal and industrial water supply in real time.
- Upgrade of VanResOp to capture the operation of the Gariep dam and other important water structures within the river system may be considered for further studies.
- This study was also limited by the availability of real time demand data. Investigation of the reservoir using real time hydrology and demands is hereby left for further studies when relevant information becomes readily available.
- The real time optimisation of the reservoir in this study was investigated under normal flow conditions. This indicates that the reservoir will perform successfully at least 75 percent of the time. Investigation of the reservoir under drought condition is hereby left for further studies.
- The Orange River is shared among three riparian countries i.e. Lesotho, Namibia and South Africa. Due to the trans-boundary nature of the basin, there is a need to manage the water resources of the river in such a way as to avoid conflicts among these countries and minimize water shortages especially in Namibia, which lies at the tail end of the basin. The decision making algorithm proposed in this research work was applied for water resources management only in the context of South Africa. Application of CPMDE for resolving real time multi-objective water resources conflicts among the countries riparian to the river is left for further studies.

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