Republic of Iraq
Ministry of Higher Education
and Scientific Research
Kerbala University
College of Engineering

Optimum Design of Layout for Sewer Networks System

A thesis submitted to the College of Engineering / Civil Engineering Department in partial fulfillment of the requirements for the degree of master of Science in Civil Engineering (Infrastructure Branch)

by

Zahraa Hussein Attiyah Al-Muzaffar

(B.Sc 2012)

Supervised by

Prof. Dr. Waqed H. Hassan Al-Mussawy

march **2019**

بِسْمِ اللَّهِ الرَّحْمَٰنِ الرَّحِيمِ

﴿ يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا مِنْكُمْ وَالَّذِينَ أُوتُوا الْعِلْمَ

دَرَجَاتٍ وَاللَّهُ بِمَا تَعْمَلُونَ خَبِيرٌ ﴾

صَدَقَ اللهُ العَلِيُّ العَظيم

سورة المجادلة/آيه(11)

Dedication

I dedicate this work

To my father and mother, who gave me affection and love; I say to them: you gave me life, hope, and the emergence of a passion for learning and knowledge

To my husband and the light of my life; my daughter "Rafif"

To my brothers, sisters, friends and the martyrs of Iraq

Also, to everyone who taught me a character and became a lamp illuminates the road ahead of me.

Zahraa

Acknowledgements

First of all, I would like to thank my God almighty, who granted me the power to finish this work.

This work would not have been possible without the assistance of many individuals. I am grateful to those people, who volunteered their time and advice, especially, my supervisor Prof. Dr. Waqed H. Hassan Al-Mussawy for his guidance, advice, invaluable remarks and fruitful discussions throughout the preparation of this work.

I would like to express my deep appreciation and gratitude to Engineer Safa'a Sabry Mohammed, my colleague from the College of Engineering, Kerbala University, for his assistance in numerous topics.

I also wish to express my deep appreciation and gratitude to Dr. Dhamyaa A. Al-Nasrawi from the Department of Computer Science, Kerbala University, for her assistance and valuable advice for in Genetic Algorithm part.

I would like to thank the faculty members of Kerbala University / College of Engineering and all members of the civil engineering department for all giving me the honor of attaining the master degree. And all thanks and gratitude to the department of GIS in the Directorate of the Karbala Sewers to give them the necessary data for the two case studies.

Finally, i would also like to express my deepest gratitude to my family for their support and encouragement.

Abstract

To optimize the layout of a sewer network, the feasible layouts of the network are firstly generated from directed or undirected base graph. Then, the best layout design (minimum cost with good system performance) is identified from among the numerous possible configurations subjected to constraints.

Genetic algorithms are often based on random beginnings, which are weak solutions. Therefore, the problem of how to provide good initial estimates for finding a solution that is automatically assigned is an ongoing research topic. For this purpose, this study proposes a new method hybrid Genetic Algorithm with Tree-Growing Algorithm (GA-TGA) technique, which uses a suitable growth algorithm, TGA, to avoid the problems associated with the configuring of the infeasible solutions. This will minimize the search space to provide a good initial population to implement the genetic algorithms.

Optimisation modelling is performed with a MATLAB (R2014a) code. The performance of seven different selection methods (RWS, RRWS, LRS, TRS, SUS, TOS and RMS), two different crossover methods (Order Crossover (OX) and Crossing Operator-Based Cloning (CX)), and different population sizes (number of solutions) (50, 100, 200, 300 and 500), have been examined using the proposed model to determine their impact on convergence behavior of the optimisation. Tournament Selection method (TOS) and Order Crossover (OX) proved to be the most effective in relation to the optimal layout design. With these methods as well as direct base graph resulted in the formation of a

feasible offspring population for the new generation, there is neither need to discard or repair infeasible solutions nor to apply penalty factors to the cost function.

Two benchmark examples (calibration examples) of sewer networks are used to test the proposed model. In the first example the proposed model found the minimum solution (5062.8 units) after 31 iterations and took about (3-5) min. to solve the example. It is clear from compared with previous studies the proposed (GA-TGA) model reaches the final solution with a number of generations less than the other methods. The study concluded that the proposed method is computationally efficient in terms of speed and is ease to implementation with identical objective function values.

Also, the cost savings achieved by the proposed model for the second example in comparison with the different design of models. It can be seen that the cost of the present model is 24.5% less from DDDP design model (Wen and Shih, 1983).

In order to determine the applicability of the proposed model with the practical networks in the local region, it is examined with two real case studies located in Karbala Holy city, and compared the cost of the manual designs with the designs obtained from the present model for networks. The percentages of saving were (13.05 %) and (7.123 %) for the first and second case studies respectively.

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List of Abbreviations

Symbols	Description
ACO	Ant Colony Optimisation
AGA	Adaptive Genetic Algorithm
BIE	Bounded Implicit Enumeration
CA	Cellular Automata
DDDP	discrete differential dynamic programing
DP	Dynamic Programming
EP	Evolutionary Programming
ERS	Exponential Ranking Selection
GA	Genetic Algorithm
GHCA	General Hybrid Cellular Automata
HP	Heuristic Programming
HS	Harmony Search
LP	Linear Programming
LRS	Linear Ranking Selection
NIDP	Non-uniform state Increment Dynamic Programming
NLP	Non-Linear Programming
OX	Order Crossover
PSO	Particle Swarm Optimisation
QP	Quadratic Programming
RMS	Random Selection
RRWS	Rank Roulette Wheel Selection
RWS	Roulette Wheel Selection
SA	Simulated Annealing
SSOM	Sewerage System Optimisation model
SUS	Stochastic Universal Sampling
SWMM	Name of package program (Storm Water Management model)
TGA	Tree Growing Algorithm
TOS	Tournament Selection
TRS	Truncation Selection
TS	Tabu Search

Chapter One

Introduction

1.1 Foreword

Rapid urbanization as well as population growth made it mandatory to enact pollution control laws and increase awareness towards cleanliness and sanitation. Hence, the problem of sewage collection and disposal, mainly, in the urban areas is becoming a major concern today. The significant fraction of the overall cost of waste disposal is in its initial development. This, as well as the need to reduce the cost, a reliable and cost efficient design for the sewerage system is necessary and has to be developed (Moeini and Afshar, 2012).

Networks form an important part of the infrastructure of any society. Physical networks such as water and gas pipelines, sewer, irrigation channels, electricity and telecommunication grids, are only some examples of the networks, which form valuable and costly assets of human beings. In each network structure, there are some nodes associated with some of the links created for a particular purpose.

Sewer network is an important infrastructure of any urban society that conveys wastewater from residential, commercial and industrial areas to the sewage treatment plant. The increase in population can consequently lead to an increase in water consumption resulting in wastewater generation. Wastewater flows are then collected through secondary sewer pipes and transported to the manholes to be then transported along main sewer pipes towards the system outlet. The construction of sewer networks is very expensive and needs to be designed accurately. Thus, introducing effective sewer network system with minimum cost is vital to handle the increase in wastewater generation.

Today's highly capitalized societies require " maximum benefit with minimum cost." (Geem, 2012). Achieving this goal will usually be based on optimisation techniques. Many problems in various fields were formulated as optimisation problems and they were solved using various optimisation algorithms. Over the decades, the application and development of optimisation models have attracted growing attention among engineers.

The design of a sewer network needs to solve two sequential subproblems: (1) optimal layout determination, (2) optimal hydraulic design of the network components. The latter includes the size of sewer pipes, depths of installation, slopes, and pumping facilities all of which are significantly under the influence of the layout configuration. The layout configuration is highly dependent on the size of the problem, outlet's location, the area extent and topography. The first step in designing an urban sewer network system is to find the optimal layout among many alternatives. Having a suitable and cost-effective sewer network design is normally interpreted as finding the solution for each problem that minimizes infrastructural cost, without violating operational requirements (Moeini and Afshar, 2012).

A sewer system layout is a sub-graph derived from a defined base graph of a city or village drainage system. In a base graph, all possible locations of manholes (vertices) and sewer lines (edges or links) are known and this graph is a joined cyclic graph. An undirected base graph can be drawn from the urban street configurations, barriers, outlets' locations topology. Supposedly, sewers pipes collect sewage flows gravitationally. Consequently, as a base, the designer relies on the topography of the area to follow the natural slope of the earth towards the outlet of the network. Most designers depend on their experiences and the decline of the region to get a near optimum layout of sewer networks compatible with the natural ground.

1.2 Statement of Problem

The sewer layout in flat areas influences significantly the final design, which is desired to be optimized for the construction and operational costs. In flat areas, the problem is different and it is difficult to be solved completely. The nonsignificant change in the topographical heights affects the designer's view to track the natural slopes of the earth and its gradient to a particular outlet. In such areas, there are often many possibilities for the sewers connectivity and for the network’s outlet location. The judgments and engineering experience applicable to steep areas are not sufficient to design a layout of sewer for flat areas in which the number of the feasible layouts increases exponentially with the number of sewers. For this purpose, utilizing optimisation methods are very helpful, at least for flat areas where traditional methods are inefficient.

1.3 Study Objective

The main objectives of this study are to find optimal layout design of sewer networks (directed and undirected base graph) to minimize the capital investment on infrastructure while ensuring good system performance under specific design criteria by developing a new model. For this purpose, a new hybridized (GA-TGA) technique is developed in the Genetic Algorithm.

1.4 Study Methodology

The following sequence steps have been followed to achieve the above objective:

1. Fieldwork:
   a. Selection the location of the case studies.
   b. Data collection and preparation, which include street layout plan, ground elevation, manual design for networks of cases study, and data for the construction of networks.

2. Theoretical:
   a. Formulation of the objective function, and defining the constraints of the objective function.
   b. Build a model by programming a code in MATLAB, using an efficient algorithm (Tree Growing Algorithm, TGA) that is able to generate all possible layouts.
   c. Genetic Algorithm (GA): An appropriate optimisation method is required to find the optimal layout design among many possible configurations that are subjected to the related constraints.
   d. Develope the GA by using different selection and crossover methods.

3. Apply the proposed model with benchmark examples and test different selection and crossover methods to find any methods more effective and best-performing for the proposed model.

4. After developing the proposed model, apply it with cases study in Kerbala city, Iraq.

1.5 Thesis Outline

- Chapter 1 Introduction: describes the relevance of the research topic, statement of problems, the objective of the study, the methodology of the current study, and outlines the present research.

- Chapter 2 Literature Review: describes a brief overview of the optimisation of sewerage system design, a basic introduction to three optimisation approaches that can be used for sewer system design as well as a summary about the research.
- Chapter 3 Theoretical Aspect: describes the layout theory for sewer design includes the flows estimation, design period, and a brief overview of Graph Theory. Also, it describes the theory of methods used in the model includes Evolutionary Technique (TGA) and Genetic Algorithm (GAs).
- Chapter 4 Formulation of Optimisation: explains the methodology of the work through three points, objective function, problem constraints, and formulation of new techniques model (GA-TGA).
- Chapter 5 Benchmark Problems and Case Study: presents the layout, and characteristics, for every benchmark problems and cases study.
- Chapter 6 Results and Discussion: presents and discusses the results obtained from the proposed model.
- Chapter 7 Conclusions and recommendations: this final chapter summarizes and discusses the main findings. It also includes recommendations for practitioners interested in practical applications and for researchers interested in exploring further the whole aspect of the optimum design of the layout for a sewer network.

Chapter Two

Literature Review

This chapter aims at providing a systematic and up-to-date review of achievements in sewer optimisation field. It also discusses problems and key issues in the context of future research needs in sewer optimisation. It also explains three approaches used to design a sewage collection network.

2.1 Historical View of Optimisation

The topic of optimal sewer design has been heavily studied. Its concept was first proposed in the mid-1960s (Deininger, 1966; Holland, 1966) when advances in the computer power shined a light on engineering research. Comprehensive cost-effective designs incorporating early simulation models and optimisation technologies became computationally tractable and flourished in the 1970s and 1980s (Guo et al., 2008). In the last two decades, due to increased consideration of water quality, sustainability and integrated management, a large number of applications have been implemented by using various advanced techniques. Indeed, research attention has been mainly paid to exploring new emerging optimisation techniques to boost optimisation performance.

2.2 Optimisation of Sewage System Design

In real projects, the layout and size optimisation are often solved separately, in which the layout is initially designed manually according to the engineering judgments. Then, a commercial program is used to design the sewer size. A great number of early various optimisation techniques were developed, including Linear Programming (LP), Non-linear Programming (NLP), Dynamic Programming (DP), Heuristic Programming (HP), Spreadsheet Method, and Cellular Automata (CA). These techniques seem to be inappropriate for delivering sophisticated and comprehensive sewer design solutions while (GA-TGA) model allows a good (though not necessarily optimal) solution to be produced for an optimization problem within a reasonable computation time without any loss of delicate characteristics of model and any requirement. In the early practice of using these techniques, the design problem was mostly handled as a pipe sizing and slope design problem for sewer networks with a fixed plan layout. Comparatively, little research has been involved with designing network layout, namely number and location of manholes because it significantly increases the complexity of the optimisation task (Walters, 1992). For systematic design of sewer networks layout, with or without optimisation, it is first of all required to have an efficient layout generator algorithm to overcome the problem complexities. The layout sub-problem belongs to a hard class of combinatorial mathematics and its solution ways are mostly found in the graph theory. In flat areas, the number of possible layouts exponentially increases with the number of sewers (Haghighi, 2013). The layout sub-problem is including several discrete and nonlinear constraints which also significantly grow with the problem size. These complexities make the layout subproblem intractable to be solved using common algorithms in the graph theory.

In general, three methods may be used to solve the sewer system design problem (Haghighi and Bakhshipour, 2012):

2.2.1 Full Enumeration Design

In this approach, all layout design alternatives are generated first to be then hydraulically designed. The best of the current designs will be selected in the final step. This approach is a very promising way to reach the global optimum; however, it is practical only for small networks. Sewer network layout design is a mathematical integration problem. By increasing the number of solutions, the computer time increases with the dimensions of the system. Adding the time required for the optimisation of sewers for each layout makes the application of this approach very limited in practice.

Pereira (1988) proposed a model, named DRENARP, which has several data files that allows input and permanent update of information. To solve the optimisation problem, DRENARP starts to reduce its size. To achieve this goal, the model generates a simplified network, excluding those branches that have a fixed direction of flow. After the generation of the layouts and the use of the genetic algorithm, a set of some least cost alternatives are re-evaluated for the purpose of achieving an optimal design.

Diogo et al., (2000) presented a global mathematical model for simultaneously obtaining the optimal layout and design of urban drainage systems for foul sewage and stormwater. The adopted global strategy combines and develops a sequence of optimal design and plan layout sub-problems. Dynamic programming is used as a very powerful technique, alongside simulated annealing and genetic algorithms in this discrete combinatorial optimisation problem of huge dimension. The resulting program was compatible with the practical applications, even for large and complex regional systems, allowing the optimal selection of drainage basins, pumping systems, wastewater treatment plants, sewer layout and diameters, as well as installation depths.

Weng and Liaw (2005) established a combinatorial optimisation model, called the Sewer System Optimisation Model for Layout and Hydraulics (GA/SSOM/LH). The modeling concept is to combine the fundamental principles of the GA, to the generation of possible network layouts, which can find the best sewer system layout by checking the overall least-cost hydraulic design of several possible alternate network layouts by the Sewerage System Optimisation model (SSOM). The Bounded Implicit Enumeration (BIE) is applied to determine the optimal size and slope for each. Hence the GA can evolve quickly generating an optimized system layout and ensuring a solution closer to the global optimum in a ‘fast’ manner. They concluded that the hybrid algorithms proved the suitability to solve the more complex optimisation problems at the sewer networks.

Diogo and Graveto (2006) presented that if specific limitations of the problem are properly exploited the optimal layout can be reached in a deterministic method, of course for small to medium systems. Basing on this, they proposed an adaptive algorithm to select the layout from an undirected base graph. Using that method, spanning trees of a base graph are extracted while many infeasible trees are avoided systematically. The optimal network is finally obtained by means of a simple economical comparison of all plan solutions having an optimized design. For large dimension networks, where the full enumeration design algorithm is not feasible, those investigators proposed the simulated annealing method.

2.2.2 Separate Design (*The Simplified Optimisation Method*)

In this approach, the two sub-problems are designed separately, in which the layout is designed manually or by definition of a simple objective function. This type is very common, especially in large networks. In the context of this approach many researchers developed their design algorithms, as follows,

Liebman (1967) used a simple search method for seeking improved layouts in gravity flow sewage collection networks. The method begins with a designer selected layout and attempts to find layouts with smaller total costs. A digital computer program is used to obtain the results.

Mays (1975) used dynamic programing (DP) and discrete differential dynamic programing (DDDP) to optimize the design of two hydraulic models of storm sewer systems. The first model was a serial sewer system while the second was a branched sewer system. They concluded that the DDDP approach is proffered to the DP approach for large systems because it requires less computer time and memory, even though a global optimum is not guaranteed. He also stated that there are four major factors that affect the efficiency of DDDP applied to sewer systems, namely, the location of the initial trial trajectory, the initial width of the corridor, the number of lattice points and the rate of reduction of state increment.

Bhave (1983) developed a method based on linear programming (LP) techniques and produced a locally optimal solution. Initially, based on classical transportation problem principles, a theory was developed to formulate an LP problem for obtaining design paths from the source nodes to the demand nodes and thereby for obtaining the design distribution graph for the entire distribution system. They concluded that the method is preferable to check the design feasibility constraints in which they are derived herein as this avoids checking the complicated transportation constraints if the earlier simpler constraints were not satisfied, and the design was not feasible.

Tekeli and Belkaya (1986) developed a layout generation algorithm LGA for generation of sanitary sewer layouts, using a standard shortest path algorithm. The results were as good as, or better than, the layouts recommended for networks with up to 70 manholes. Due to computer memory restrictions, the larger networks must be sub zoned for subsequent superposition. Guidelines were developed for sub-zoning as well as general implementation from testing of LGA with the various-sized network.

Elimam et al., (1989) applied linearized Linear Programming and Heuristics to design large-size networks (pipes sizes diameter and slope). Their approach provides continuous pipe diameters with partial flow condition and using modified Hazen-Williams formula. They concluded that the developed model had been extensively and successfully used to design several large sewer networks.

Charalambous and Elimani (1990) employed a Heuristic Algorithm to design sewer networks that can handle the introduction of lift stations and the use of standard diameters. They used either the

Manning or the modified Hazen-Williams hydraulic equation in the proposed model. They found that the Heuristic Algorithm provided good and logical (rather than optimal) designs of sewer networks. They also found that HP provides the flexibility for altering design parameters throughout avoiding the tedious tasks of performing the required engineering computations in choosing standard pipe diameters and their corresponding slopes.

Walters and Lohbeck (1993) proposed two of the alternative genetic algorithms for selecting the optimal sewer networks layout from the network-directed base graph. The first was a conventional binary string to represent the network layout. While the second method used a more efficient integer representation. Though, it was confirmed that a great interest is needed to determine the initial base graph to consider all the pipe connection restrictions and layout of the sewer. Also, the genetic algorithm techniques are shown to be very effective search procedures for the class of network optimisation problem investigated.

Walters and Smith (1995) developed a genetic algorithm with new sophisticated features to optimize the layout. An effective method called the tree-growing algorithm was integrated into the main solver for the production of random spanning trees. By identifying the root node and the connectivity decision variables, the tree-growing algorithm begins to form a spanning-tree in such a manner that the resulting tree converges to the root node.

Geem et al., (2000) developed a new heuristic algorithm to arrive at the optimal point near the global optimum with high probability. It mimics the improvisation of music players and is named Harmony Search (HS).

Afshar and Mariño (2006) used Ant Colony Algorithm ACO to find the optimal layout of sewer networks includes commercial pipe diameters and slope, partial flow condition and Manning formula. They used two different formulations to represent the optimal layout of sewer networks in the appropriate form required to apply the ant algorithm. In the first formulation, the selected link was taken as the decision points of the problem, and on the other formulation, the nodes of the network were taken as the decision points of the problem. They applied the proposed model to find the optimal layout of a sewer network for three benchmark problems. They concluded that ACO algorithm superior to other optimisation methods. They also concluded that the second formulation was superior to the first formulation for optimal layout of sewer networks.

Pan and Kao (2009) developed a model coupled GA with Quadratic Programming (QP) to solve optimal design of sewer networks problem. In that work, the non-linear functions were converted into quadratic forms and solved the issue by employing QP, which combined with GA. The QP calculated the excavation depths, slopes of pipe, and network cost for each chromosome. They concluded that the GA-QP model and DDDP alternatives might be inapplicable or impracticable.

Afshar (2010) applied partially constrained ACO algorithm, a parameter-free Continuous Ant Colony Optimisation (CACO) algorithm, respectively, for the optimal design of sewer networks includes size pipe diameters and slope. Two alternative formulations of the constrained algorithm are used to solve a test example and the results are presented and compared with those of the unconstrained approach. The methods are founed to be very effective in locating the optimal solution and efficient in terms of the convergence characteristics of the resulting algorithms. The proposed algorithms were also found to be relatively insensitive to the initial colony and size of the colony used compared to the original algorithm.

Haghighi and Bakhshipour (2012) developed an Adaptive Genetic Algorithm (AGA) to find the optimal design of sewer networks includes pipe diameter and slopes as well as indicates the pump. Through the present method, all the constraints of the sewer system were systematically monitored and focused on dealing with the discrete and non-linear constraints of the problem. Therefore, there was neither need for discarding or repairing infeasible chromosomes nor for applying penalty factors to the cost function. The researchers found that handling with the constraints of adaptive method computationally makes the optimisation more efficient in terms of reliability and speed.

Haghighi (2013) provide an adaptive layout generator algorithm named loop by loop cutting algorithm. The work of this method was to open the undirected base graph with a step by step procedure whilst systematically the constraints of the layout are met. This method is simply applied and can solve the complexities of the problem efficiently. By this method, the problem becomes rather unrestrained and possible to connect to any metaheuristic easily.

Indeed, when comparing the results with the previous studies, it was found that this algorithm is particularly useful for the design of urban sewage networks in flat areas.

Swamee and Sharma (2013) used Linear Programming (LP) technique to estimate the pipe diameters and sewer depths. They used Darcy-Weisbach formula as the resistance equation and commercially available pipes diameter directly in the problem formulation, without transforming nonlinear objective function or constraint equations into linear functions. They also incorporated commercially available pipe sizes directly in the problem formulation. Furthermore, they used the commercial sewer pipe sizes directly in the design of sewer system, which eliminates the problem of rounding off the estimated pipe sizes to the nearest commercial sizes as required in some optimisation techniques, which forfeits the purpose of system optimisation to a large extent. They focused equally on economic considerations and hydraulic feasibility and moving away from conventional design guidelines based only on self-cleaning velocity concepts for a node to node sewer link hydraulic design. At this stage the methodology has been developed for a sewer line having any number of links, which will be extended to a typical sewer network in future.

Afshar et al., (2016) improved the efficiency of a Cellular Automata (CA) to find the optimal design of sewer networks by employing adaptive refinement. In the proposed model, the continuous decision variables were discretized to turn the original mixed-integer problem to a discrete problem, which was then solved by a two-stage CA method. Therefore, an adaptive refinement approach was suggested to reduce the computational cost of the CA method without adverse effect on the final solution quality. They found that the proposed model resulted in a quality solution with much more reduction in the computational effort.

2.2.3 **Simultaneous Design** (the Coupled Method)

In which the layout configuration, sewer diameters and buried depths are simultaneously optimized. This approach is called an integrated optimisation model. It is ideal to obtain the global optimum design since the sub-problems are implicitly solved. However, the integration of the two subproblems into one model and the coupling an optimisation solver to that requires difficult formulations and particular design algorithms. Therefore, the process of solving becomes more difficult and involves heavy calculations (Haghighi, 2013).

Li and Matthew (1990) developed a new approach to improve urban sewerage networks in order to conclude the optimal selection of layout using the searching direction method and design optimisation of the layout provided by the discrete differential dynamic programming (DDDP). In this work, the configuration of the layout was enhanced through an iterative procedure while the network construction cost becomes cheaper and cheaper.

Afshar and Jabbari (2008) used - in their research - a genetic algorithm to find the optimal solution for the simultaneous layout and size of the pipes used in the network. The engineering principles were used to determine the extent of reliability. The method starts from the layout that containing all the possible links since the number of independent paths is considered between a source intersection and another, which is then distributed as a measure of reliability. This instantaneous method was tested using two benchmark examples considered in the literature for this type of study.

Moeini and Afshar (2012), (2013) used the Tree Growing Algorithm (TGA) and ACO algorithm for the simultaneous layout and pipe size determination of sewer networks. They used TGA to find the optimal layout while ACO algorithm to find size pipe diameters and pipe slope. They solved three benchmark problems with the proposed model. They concluded that the proposed model was efficient in finding the optimal layout and designing sewer networks.

Haghighi and Bakhshipour (2014) used an integrated optimisation model, in which the layout configured using the loop-by-loop cutting algorithm. The network was then hydraulically designed to sizing pipe diameters, for optimized cost function. The Tabu Search (TS) method was developed as a deterministic combinatorial metaheuristic coupled to the design solvers. The proposed plan was capable of adapting the search into possible parts of the problem resolution space add to solve subproblems of layout configuration and sizing of sewer simultaneously. They have found that using the integrated model for sewage network design becomes more efficient and systematic for design, and it is a very promising way to reach the optimal solution globally.

Rohani et al., (2015) proposed a General Hybrid Cellular Automata (GHCA) model that hybridised with two of the most reliable heuristic search methods, namely Genetic Algorithm (GA) and Ant Colony Optimisation Algorithm (ACOA), for the simultaneous optimal design of layout and size of pumped and/or gravity sewer networks. The heuristic search algorithms were used to create a trial layout for the network, while GHCA was used to design the network by determining the pipe diameters, pipe slopes. The results comparing to those of some current methods indicated that the proposed models, and in particular the ACOA-GHCA method, were more efficient and effective than some other methods for the optimum design of layout and size of sewer networks.

Navin and Mathur (2016) provided a new approach to optimally solve optimally the design problem and determine the size of the sewer network simultaneously. Generation algorithm has been introduced a predetermined number of trees extending to generate a predetermined number of sewer layouts from a base sewer network in order of increasing the length. The optimisation layouts have been created to improve the components of sewer sizing. It was found that optimal sewer layout for total system optimisation is one in which the total cumulative flow has a minimum value. The Modified Particle Swarm Optimisation (MPSO) algorithm has been used to determine the component sizes of the selected layouts optimally. The results showed the ability of the proposed method to find the optimal solution to the problem of the layout and design of the components of sewer networks.

Steele et al., (2016) developed a heuristic model for determining the optimal (minimum cost) layout and size of pipe design of a storm sewer network. The hierarchical procedure combines a sewer layout model formulated as a mixed-integer nonlinear programming (MINLP) problem, which is solved by using the General Algebraic Modeling System (GAMS) and the simulated annealing optimisation procedure for the pipe design of a generated layout that developed in Excel. The GAMS and the simulated annealing models were interfaced through linkage of Excel and GAMS. A sample scenario demonstrated that using these methods may allow for significant costs save while simultaneously reduce the time that is typically required to design and compared the multiple storm sewer networks.

A few researchers dealt with the problem of layout or specifically joint layout and size optimisation of sewer networks. For example; Argaman et al., (1973), as well as Mays and Wenzel (1976) used dynamic program (DP) for the optimum design of the sewer network with a single outlet using a simplifying assumption that for every pipe of the network in which the direction of flow was fixed. Also, Walters (1985) used DP for layout and size optimisation of the sewer networks. Li and Matthew (1990) proposed an overlapped approach to optimize the use of urban sewage networks system. Diogo and Graveto (2006) developed a complete enumeration model and a simulated annealing (SA) model for the layout and component of sizing optimisation of sewer networks.

A genetic algorithm (GA) is an unrestrained, natural technique. It has a random structure with a slow growth, which the reason behind the non-arithmetically effective when compared to other mathematical methods. With the increase in the number of constraints and decision variables, the weak point, which is related to speed, becomes more dangerous. However, hybrid optimisation models may be a useful remedy for this problem. Cisty (2010) proposed a combined model from a genetic algorithm (GA) and linear programming (LP), called GALP. Pan and Kao (2009) hybridized a GA with quadratic programming (QP), named GA-QP. Rohani and Afshar (2014) proposed a hybrid model that combines a GA with hybrid cellular automata (GHCA). Hassan et al., (2018) proposed GA-HP model. The Genetic Algorithm (GA) was applied to obtain the diameters of the pipes needed for the preliminary design of the network and the Heuristic Programming (HP) preliminary designs were used to obtain the optimum slope for those pipes and to determine other characteristics such as the velocity, depth of water, depths of excavation and the total cost of the network. The proposed hybrid approach addressed the above concerns by reducing the need for large numbers of generations as well as addressing the problem of random initial population for the GA.

2.3 Summary

In this research, for the layout design of sewer networks, a hybrid genetic algorithm was developed. The inner solver may be considered to be a tree-growing algorithm, combined with a genetic algorithm as the outer solver. The TGA based strategy was applied to quickly obtain a set of preliminary solutions from a directed, undirected, or partially directed base graph, which is then adopted as a good initial population for the genetic algorithm implemented. In this way, vast computation costs can be saved by providing the GA execution with a high-quality initial population, while a genetic algorithm method was used to find the optimum solution. Systematically, all constraints of the layout sub-problem were addressed.

The major advantage of using this hybrid (GA-TGA) method in this study instead GA in Walters (1995) lies in the fact that a GA, in this case, has a much smaller searching space than in a case when GA methodology was used alone, which has a great impact when trying to achieve better results and provides a faster convergence to reach the optimal solution. A two real-world example was used to illustrate the effectiveness of this technique.

Chapter Three

Theoretical Aspect

3.1 Wastewater Sources and Flowrate

The components that make up the wastewater flow and change accruing in the collection system may be classified into the following (Metcalf and Eddy, 2014):

- Domestic wastewater. Wastewater discharges from residence, commercial, institutional, and public facilities. Domestic wastewater is also known as sanitary wastewater.
- Industrial wastewater. Wastewater in which industrial wastes predominate.
- Infiltration / Inflow (I/I). Water that enters the collection system through indirect and direct means. Infiltration is extraneous water that enters the collection system through leaking joints, cracks, and breaks. Inflow is stormwater that enters the collection system from storm drain connections (catch basin), roof leaders, foundation and basement drains, or through an access port (manhole covers).
- Stormwater. Runoff resulting from rainfall and snowmelt.

Data can be used to estimate the average wastewater flow rates from various domestic, commercial, institutional, and industrial sources. Determining the flow of wastewater rates consists of five parts (Davis, 2010):

1. Selection the design period.
2. Population's estimation and industrial growth.

3. Estimation flow rates of the wastewater.
4. Estimation of inflow and infiltration.
5. Estimation of the variability of the wastewater flow rates.

3.1.1 Selection the Design Period

The future period for which the provision is made in designing the capacities of various components of the sewerage scheme is known as the design period. The design period depends upon the ease and difficulty in expansion, amount and availability of investment, anticipated rate of population growth, including shifts in communities, industries and commercial investments, hydraulic constraints of the systems designed, and life of the material and equipment. Table (3-1) illustrates the design periods used for practice and the average life expectancy.

Table (3-1): Design periods for wastewater works (Davis, 2010).

Type of facility	Characteristics	Design period, yr	Life expectancy, yr
Treatment plants			
Fixed facilities	Difficult and expensive to enlarge/replace	20 - 25	50 +
Equipment	Easy to refurbish/replace	10 - 15	10 - 20
Collection systems			
Trunk lines and interceptors > 60 cm	Replacement is expensive and difficult	20 - 25	60 +
Laterals and mains ≤ 30 cm	Easy to refurbish/replace	To full development[a]	40 - 50

[a] Full development (also called "build-out") means that the land area being serviced is completely occupied by houses and/or commercial and institutional facilities.

3.1.2 Estimation of Wastewater Flows

a- Domestic wastewater flow

I. Residential areas: For new developments or newly sewered area, wastewater flowrates are derived from an analysis of population data and estimated per capita wastewater flowrates from similar communities. The quantity of domestic wastewater from an area will generally be about (60) to (90) per cent of the water supplied to the area (Steel, 1979). The higher percentages apply to cold countries which have cold weather. In warm, dry climates where water is used for evaporative cooling of homes and landscape irrigation for example lawn sprinkling, the lower percentage is more likely (Metcalf and Eddy, 2014). Hence, if the community used a water is known, the probable output of domestic wastewater can be estimated. Estimation of wastewater facilities should allow for future growth of the area. Glumrb (2004) recommended that the volume of flowrates from wastewater network system could be determined depending on the average domestic daily flow rate of (75-380) lcpd (liters per capita per day). In addition, wastewater flowrates that come from industrial, institutional and commercial services. There are water saving devices, which greatly reduces the flow of sewage as shown in Table (3-2).

Table (3-2): Typical changes in water consumption with the use of water saving devices (AWWA, 1998).

Use	Without water conservation. Lpcd	With water conservation. Lpcd
Showers	50	42
Clothes washing	64	45
Toilets	73	35

II. Commercial areas: depending on the function of activity, unit flowrate for commercial facilities can vary widely because of the wide variations that have been observed. Flowrate was generally expressed in terms of quantity of flow per unit area [i.e.,$m^3/ha * d$]. Typical unit area flowrate allowances for commercial developments are normally ranged from (7.5 to $14\ m^3/ha * d$) (Metcalf and Eddy, 2014). Table (3-3) can be a basis for estimating commercial flows.

Table (3-3): Typical flow rates of wastewater from commercial sources in the United States (Metcalf and Eddy, 2014).

Source	Unit	Flow rate, L/unit . d	
		Range	Typical
Airport	Passenger	10 - 20	15
Apartment	Bedroom	380 - 570	450
Automobile service station	Vehicle	30 - 60	40
	Employee	35 - 60	50
Bar/cocktail lounge	Seal	45 - 95	80
	Employee	40 - 60	50
Boarding house	Person	95 - 250	170
Conference center	Person	40 - 60	30
Department store	Restroom	1,300 - 2,300	1,500
	Employee	30 - 60	40
Hotel	Guest	150 - 230	190
	Employee	30 - 60	40
Industrial building (sanitary wastewater only)	Employee	60 - 130	75
Laundry (self-service)	Machine	1,500 - 2,100	1,700
	Customer	170 - 210	190
Mobile home park	Mobile home	470 - 570	530
Motel with kitchen	Guest	210 - 340	230
Motel without kitchen	Guest	190 - 290	210
Office	Employee	25 - 60	50
Public restroom	User	10 - 20	15
Restaurant without bar	Customer	25 - 10	35
Restaurant with bar	Customer	35 - 15	40
Shopping center	Employee	25 - 50	40
	Parking space	5 - 10	8
Theater	Seal	10 - 15	10

III. Institutional facilities: typical flowrates from some institutional facilities are shown in Table (3-4). It is stressed that flowrates vary with the region.

Table (3-4): Typical flow rates of wastewater from institutional sources in the United States (Metcalf and Eddy, 2014).

Source	Unit	Flow rale, L/unit . d	
		Range	Typical
Assembly hall	Guest	10 - 20	IS
Hospital	Be d	660 - 1.500	1, 000
	Employee	20 - 60	4 0
Prison	Inmate	300 - 570	4 50
	Employee	20 - 60	4 0
School[a]			
With cafeteria, gym, and showers	Student	60 - 120	10 0
With cafeteria only	Student	40 - 80	6 0
School, boarding	Student	280 - 380	3 20

[a] Flow rates are L/unit-school day.

b- <u>Industrial wastewater flows</u>

Industrial flows will vary with the type and size of the industry, the degree of water reuse, and the on-site treatment methods that are used. When the type of industry and the water requirements are known. The wastewater flow could be estimated to be about 85-95 per cent of the water used. The typical design value for estimating wastewater flows from industrial areas with a few wet processes ranges from $(7.5 \text{ to } 14\ \mathrm{m^3/ha*d})$ for light industrial development and $(14 \text{ to } 28\ \mathrm{m^3/ha*d})$ for medium industrial development. While the specified type of industry is unknown, an allowance of (50 m^3/hectare/day = 0.58 l/hectare/sec) is often used (Metcalf and Eddy, 2014).

3.1.3 Infiltration and inflow

There is always some entry of groundwater into sewers through broken pipes, defective joints, and similar entry points. The amount of infiltration depends mostly on the groundwater level and the care exercised in the construction of the sewer. If the groundwater table is below the sewer, infiltration will occur only when the water is moving down through the soil. If the water table is high, infiltration rates of (3 to 15 $m^3/ha * d$ = 0.06 to 0.17 l/hectare/sec) of area sewer may occur. Infiltration is sometimes estimated to be between (0.1 to 10 m^3/day) per centimeter of diameter per kilometer of sewer (Linsley and Franzini, 1979). Estimation of the inflow from roof leaders and other sources must be based on local conditions.

3.1.4 Variation in Wastewater Flowrates

The flow of domestic and industrial wastewater varies throughout the day and year. The daily peak from small residential areas will usually occur in the midmorning and will vary from (200) to more than (500) percent of the average flow rate, depending on the number of people contributing. Commercial and industrial wastewater is delivered somewhat more uniformly throughout the day, with peak rates varying from (150) to (250) per cent of the flow rate (Linsley and Franzini, 1979).

Because the variation in wastewater flows will change with the size of the city, the amount of industrial wastewater and other local conditions, the typical values quoted above are only a guide. On the other hand, some designers use the following formula to estimate the maximum rate of domestic sewage flow from small areas (Steel, 1979):

$$\mathbf{M = 1 + \frac{14}{4 + P^{0.5}}} \qquad \dots \ \mathbf{3\text{-}1}$$

in which **M** is the ratio of the maximum sewage flow to the average, and **P** is the population served in thousands. Some engineers use 22 as the numerator of the fraction. The ratio of the maximum sewage flow to the average flow **M** must be greater than 2.7.

3.2 Basic Graph Theory

The concept of a graph is relatively recent since it only formally appeared during the 20th century. Today, it has become essential in many fields, in particular in applied and fundamental computer science, in optimisation, and in algorithmic complexity. The study of graphs and their applications, therefore, provides an opportunity to deal with very diverse questions with numerous applications.

The layout of the sewer network is mathematically a graph with certain characteristics. Before addressing the issue, it is necessary to review some basic concepts and terminology in the graph theory. The graph theory is the main branch of discrete mathematics and studies the mathematical expression of graphs. With a focus on the scope of this work, and some graphics principles, mostly taken from (Fournier, 2009) are summarized as below:

i. **Undirected base graph:** An undirected base graph **G** is defined by two finite sets: a non-void set **X** of elements called vertices, a set **E** of elements called edges Figure (3-1)a. Herein, the vertices are manholes and the edges are sewer pipe. Also, the number of **X** and **E** is represented by **n** and **m** respectively.

ii. **Directed base graph:** A directed base graph, brief to a digraph is defined by two finite sets: a non-empty set **X** of vertices and a set **A** of directed edges, with an ordered pair (x, y) where **y** is named the head and **x** is called the tail Figure (3-1)b. In a classification, digraphs may be defined as cyclic digraphs including loops or double edges, and acyclic digraphs in the absence of loops. This is referred to as the latter also tree digraph as shown in Figure (3-1)c.

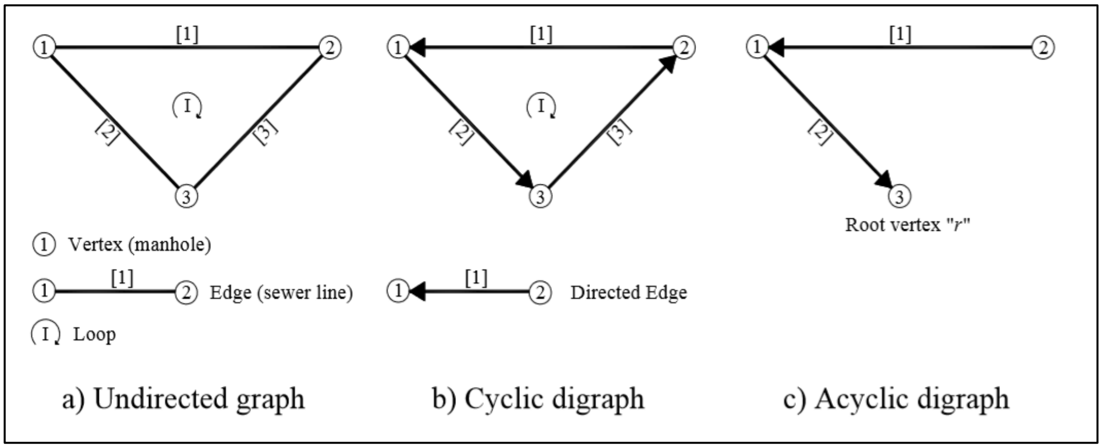


Figure (3-1) Principles of the Graph Theory (Haghighi, A. (2013)).

iii. **Spanning trees:** A spanning tree of graph **G** is a tree sub-graph, including all vertices. By definition, a connected graph **G** has (at least) one spanning tree.

iv. **Root:** Vertex **r** is the root of a digraph **G**, such as vertex 3 in Figure (3-1)c, such that there is for any vertex **x** of **G** a directed path from **x** to **r**. In general, a digraph may have several roots.

Using these definitions, an urban sewer system layout is a sub-graph derived from a predefined base graph. Depending on the previously applied methods for creating the layout sub-graph, the base graph can be considered as a directed (Walters and Lohbeck, 1993) or undirected (Walters and Smith, 1995); (Diogo and Graveto, 2006). In the base graph, all discharge probabilities are included such that manholes (vertices) and sewer pipes (edge), to form a connected cyclic graph. With regard to street alignments, barriers, topography, waterways, outlet location and existing sewer networks in the city, the undirected base graph can be drawn as Figure (3-2a). Probably, each manhole in the base graph is linked with the neighbouring manholes to direct the wastewater flow toward. A directed base graph reduces greatly the number of the possible layouts that can be formed as shown in Figure (3-2b).

a- b-

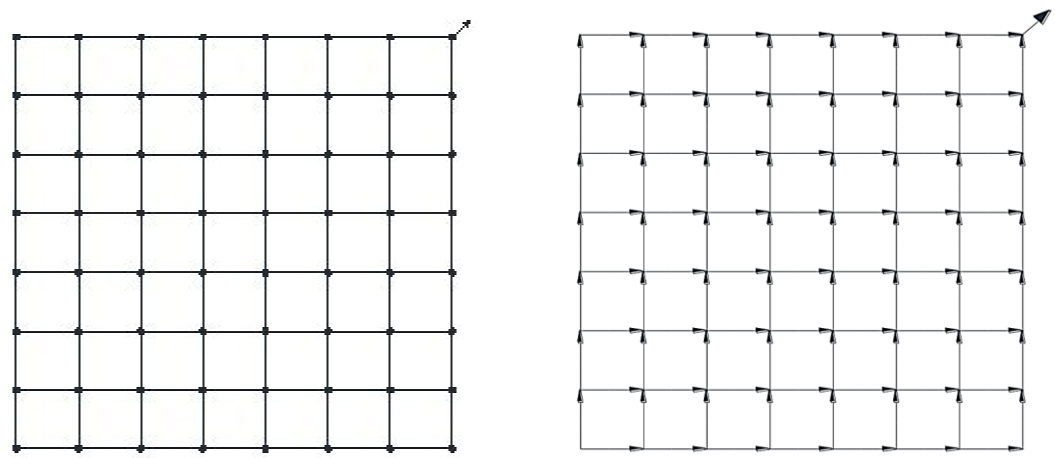


Figure (3-2) Base graph a) Undirected, B) Directed (Walters and Smith, 1995).

It is possible to calculate the total number of trees that can be formed from a base graph by the method described by Trent (1954). Assume the base graph has (N + 1) nodes. The number of trees that can be formed is equal to the determinant of the square matrix T, size N,

i.e. $$\mathbf{n\ tree} = |\mathbf{T}| \qquad \ldots\ \mathbf{3\text{-}2}$$

where: **n tree** = number of connected trees.

and the elements or **T** are

$\mathbf{T_{ii}}$= number of links intersecting at node i

$\mathbf{T_{ij}}$= - 1 *(number of links connecting i and j)

The matrix has a smaller by one size than the number of nodes as information from one node is redundant.

As an example, for the base graph of Figure (3-3)

$$T = \begin{bmatrix} 2 & -1 & 0 \\ -1 & 3 & -1 \\ 0 & -1 & 2 \end{bmatrix} \quad \text{... } \mathbf{3\text{-}3}$$

giving n tree = |T| = 8

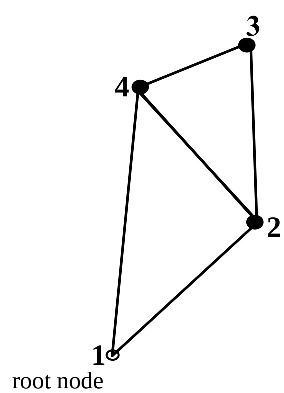


Figure (3-3) Undirected base graph.

The number of trees expands rapidly with increasing network size, for example, the base graphs of Figure (3-2a), there are 1.26×10^{26} possible different layouts that can be generated. Each one is a feasible solution to the problem (Walters and Smith, 1995).

3.3 Tree-Growing Algorithm

An effective method is used within the formation of the initial population of solutions. The main characteristic of this algorithm is generating a connected spanning tree from the directed, undirected, or partially directed basic graph. It should be noted here that the trees generated from this algorithm are not distributed randomly throughout the space of solution, which means all solutions are possible. The type of tree generated by the algorithm is very important because it is biased towards the production of networks that diverge from the root and this is similar to the natural growth of the plant and of most engineering tree networks including flow. The tree growing algorithm included within the main model is used to create the possible trees similar to layouts from the base layout of the sewer network, and has the additional benefit of permitting fast creation of trees to be biased towards trees that have a sensible engineering structure, which adds high efficiency to the current optimisation model (Walters and Smith, 1995).

3.3.1 Performance of the Tree Growing Algorithm

A very simple tree growing example is shown in Figure (3-4). When using the algorithm, the first growing pipe will give either layout A_1 or A_2, with equal probability. Also when the second pipe grows, four layouts will produce with equal probability, B_1 to B_4. Finally, the third pipe will result in one of the eight equal-probability layouts C_1 to C_8. However, out of the eight layouts, there are only four different layouts, D, E, F, and G, occurring respectively 1,3,3,1 times. Hence, the probabilities for the formation of D, E, F, and G by the algorithm are 0.125, 0.375, 0.375, 0.125 respectively, the preferred choice being toward the solutions of the sensible engineering of E and F. A random tree generator would truly result in equal-probabilities for all four layouts (Walter and Smith, 1995).

$$\text{probability } (\mathbf{p_i}) = \frac{\mathbf{f_i}}{\sum_{j=1}^{n} \mathbf{f_j}} \qquad \textbf{... 3-4}$$

$\mathbf{f_i}$ = individual's fitness

n = denotes to the population size in terms of the number of individuals.

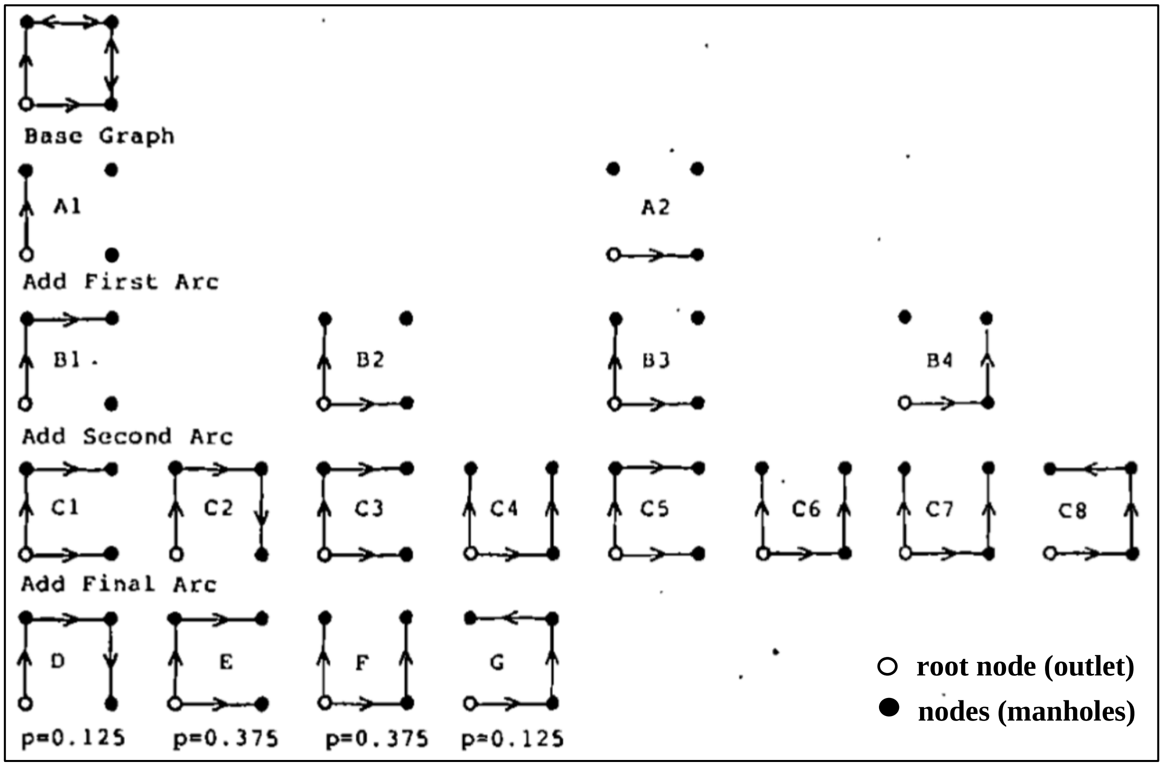


Figure (3-4) Steps performance of the tree-growing algorithm (Walter and Smith, 1995).

3.3.2 The Algorithm of Grow a Tree

The following algorithm was devised to grow a tree:

Three vectors **C**, **A** and **AA** are used to implement the tree growing algorithm in which:

C = the set of nodes contained within the growing tree.

A = the set of sewer pipes within the growing tree.

AA = the set of edges adjacent to the growing tree, any one of which has an equal chance of forming the next branch.

1. Starting from the Root-Node and identify it (N_r),
2. Initialize C = [N_r],
3. Initialize A = 0,
4. Initialize AA = [edges in base graph connected to root node],
5. Choose a randomly edge from the set of edges of (AA) and identify it (a).
6. Update (A) by adding edge (a), A = A + [a],
7. Identify the other node of edge (a) as the newly connected node (N) and consider it the root node.
8. Update (C) by adding node (N), C=C+[N].
9. Identify edges, ac(i), connected to (N) in base graph, excluding edge (a).
10. Update AA, by removing edge (a) and any newly infeasible edges, and adding any of edges ac(i) that are feasible candidates. This is further explained as follows:
    a) AA = AA - a (remove newly connected edge from list),
    b) For each ac (i), is ac (i) in AA already?
        - ❖ Yes: AA = AA - [ac (i)] (remove ac (i) from list, a tree is now such that adding ac (i) would cause a loop),
        - ❖ No: Are both end nodes of ac (i) in C?

- Yes: AA = AA (leave list unaltered and go to step (10b) to ac (i+1) , as adding ac (i) would cause a loop in the tree),
- No: is ac (i) in the correct direction?
  - Yes: AA = AA + [ac (i)] (add ac (i) to list).
  - No: AA = AA

11. Repeat from step (5) until added the required edges to make the tree-growing algorithm.

The process defined above leads to the construction of a spanning tree layout out of base layout defined. Here, sewer network has a tree-like layout. Therefore, the tree growing algorithm is used in an incremental manner to construct feasible tree-like layouts out of the base layout. The use of TGA for tree network construction has already been attempted for the layout optimisation of tree pipe network.

3.4 Genetic Algorithms (GAs)

3.4.1 Key Elements

Genes: Genes are the basic units “instructions” for building the genetic algorithms. Genes may represent a possible solution to a problem without actually being a solution as shown in Figure (3-5).

Individuals (chromosomes): An individual is a single solution involved currently in the search process. Each individual is named a chromosome or string. A chromosome is a sequence of genes, compared to chromosomes in natural systems. A chromosome is a main key element, which that the genetic algorithm dealing with.

Populations (initial solutions): A population is a group of individuals currently involved in research. There are two main concepts for populations used in GAs.

1. The initial population generation.
2. The size of the population.

The size of the population depends on the difficulty of the problem. Often, this is done on a random population initialized. Preferably, the initial population must be a gene pool as much as possible in order to be able to discover all the area of the search.

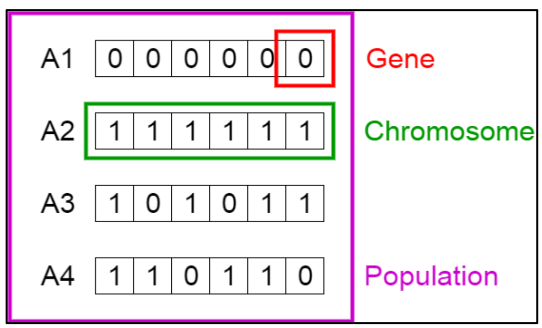


Figure (3-5) Element in the genetic algorithm (Mallawaarachchi, V., 2017).

3.4.2 Foreword on the Genetic Algorithms

Since the 1960s, there has been increasing interest in imitating living beings to develop powerful algorithms for difficult optimisation problems. A term now in common use to refer to such techniques is **evolutionary computation**. The best known algorithms in this class include genetic algorithms, developed by (Holland, 1975). Holland proposed GA as a heuristic method based on “Survival of the Fittest”.

The science that deals with the mechanisms responsible for similarities and differences in a species are called Genetics. The word “genetics” is derived from the Greek word “genesis” meaning “to grow” or “to become” (Sivanandam and Deepa, 2007).

Genetic Algorithms (GAs) are adaptive methods, which may be used to solve the search and optimisation problems by finding the optimal solution(s) to a given computational problem that maximizes or minimizes a particular function. Mitchell (1998) used the word "search" to describe what GAs do. It is important at this point to compare this meaning of "search" with its other meanings in computer science. There are at least three meanings of "search":

(1) Search for stored data: The problem is here to efficiently retrieve information stored in computer memory.
(2) Search for paths to goals: The problem is here to efficiently find a set of actions that will move from a given initial state to a given goal.
(3) Search for solutions: This is a more general class of search than "search for paths to goals." The idea is to efficiently find a solution to a problem in a large space of candidate solutions.

3.4.3 Features of Genetic Algorithms

GAs differ from other conventional optimisation processes in:

1. GAs work with a coding of the parameter set, not the parameters themselves.
2. GAs search from a population of points, not a single point.
3. GAs use objective function information, not derivatives or other auxiliary knowledge.
4. GAs use probabilistic transition rules, not deterministic rules.

They are based on the genetic processes of biological organisms. Over many generations, natural populations evolve according to the principles of natural selection and "survival of the fittest" first clearly stated by Charles Darwin in The Origin of Species (Beasley, Bull and Martin, 1993).

As given in (Gen and Cheng, 2000), there are five basic components to a genetic algorithm:

1. A genetic representation of solutions to the problem.
2. A way to create an initial population of solutions.
3. An evaluation function rating solutions in terms of the fitness function.
4. Genetic operators that alter the genetic composition of children during reproduction, (Selection, Crossover and Mutation).
5. Values for parameters of genetic algorithms.

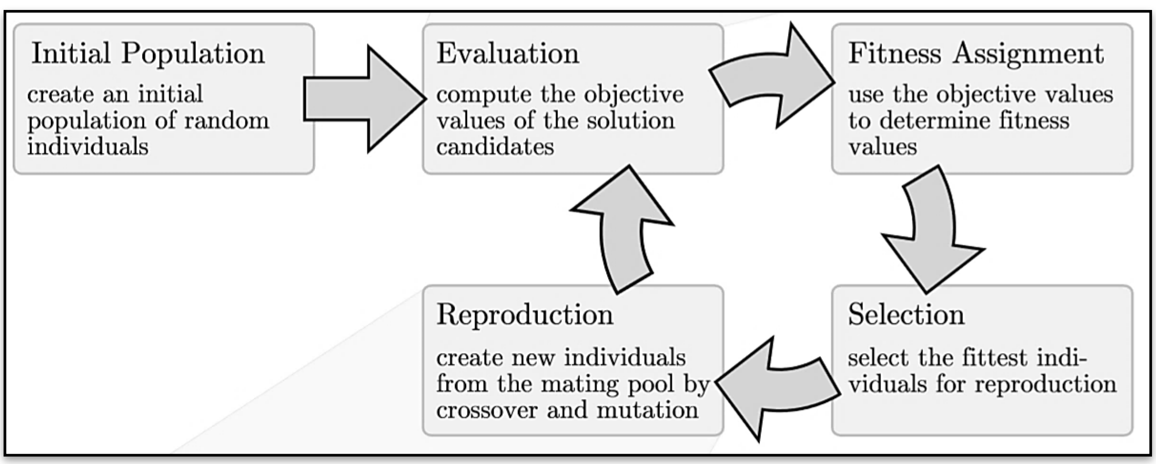


Figure (3-6) The basic cycle of genetic algorithms (Weise, 2009).

Individuals or chromosomes are represented in the population as strings of binary digits. There are other types of representations that can be used such as real, integer and tree representations based on the problem to be solved. Genetic operators are applied to modify the composition of chromosomes in order to generate children (or individuals in the next generation) that differ from their parents (or individuals in the previous generation) by mixing the two chromosomes together to create two new children and then mutates a chromosome's existing genetic information to form a new chromosome as shown in Figure (3-6). Three major operations used in the genetic algorithm are Selection, Crossover and Mutation. Convergence is obtained to reach a near to optimal solution after a certain number of generations, after a fixed time, or if there has been no improvement for, say, the last 10 generations.

3.5 Basic Principles of Genetic Algorithm

Before a GA can be run, a suitable coding or representation, for the problem must be devised. There is also require to a fitness function, which assigns a figure of merit to each coded solution. During the run, parents must be selected for reproduction and recombined to create offspring. These aspects are described below:

3.5.1 Coding or Representation

Typically, all search and optimisation algorithms deal with solutions, each of which represented replicate of the original problem. Therefore, the solution must be able to achieve it fully in practice. This means either that it is manufactured in the laboratory or in a workshop, or it can be used to solve a puzzle or as a control strategy and so on. The solution is a vector of real value that determines the dimensions of the main parameters of the problem, this is common in most engineering problems. In some cases, the complex problem can be made ease by selecting the coding that works appropriately and efficiently with the specific algorithm (Back, Fogel and Michalewicz, 2000).

An individual is a single solution while a population is a set of individuals at an instant of the searching process. An individual is defined by a chromosome. A chromosome stores genetic information (called phenotype) for an individual as shown in Figure (3-7). The key issue when using GAs is the encoding of a solution to the problem. The issue has been investigated in many aspects, such as mapping characters from genotype space to phenotype space when individuals are decoded into solution and metamorphosis properties when individuals are manipulated by genetic operators.

a- A binary string of n-bits representation   b- Real-value representation

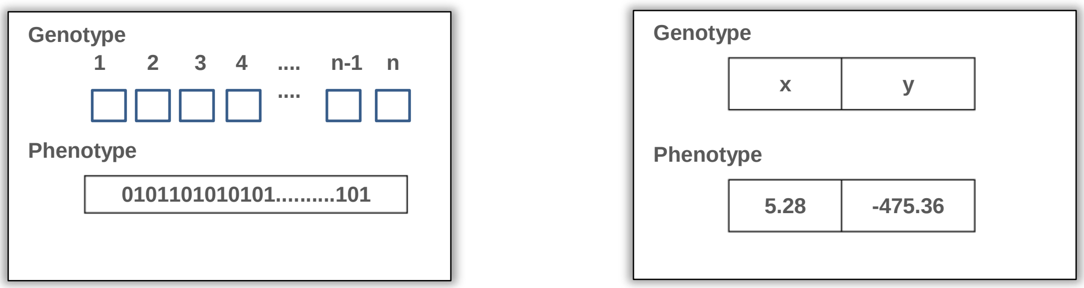


Figure (3-7) Representation of a Chromosome.

According to what kind of symbol is used as the alleles of a gene, the encoding methods can be classified follows:

- **Binary encoding**: Representing a gene in terms of bits (0s and 1s).

Chromosome A	101100101100101011100101
Chromosome B	111111100000110000011111

Figure (3-8) Binary encoding.

- **Real-number encoding**: Representing a gene in terms of values or symbols or string. It can be anything connected to the problem.

Chromosome A	1.2324 5.3243 0.4556 2.3293 2.4545
Chromosome B	ABDJEIFJDHDIERJFDLDFLFEGT
Chromosome C	(back), (back), (right), (forward), (left)

Figure (3-9) Real-number encoding.

- **Integer or literal permutation encoding (order encoding)**: Representing a sequence of elements. It can be used in ordering problems, such as the travelling salesman problem or task ordering problem.

Chromosome A	1 5 3 2 6 4 7 9 8
Chromosome B	8 5 6 7 2 3 1 4 9

Figure (3-10) Order encoding.

- **General data structure encoding (tree encoding):** Representing in the form of a tree of objects. is used mainly for evolving programs or expressions, for genetic programming.

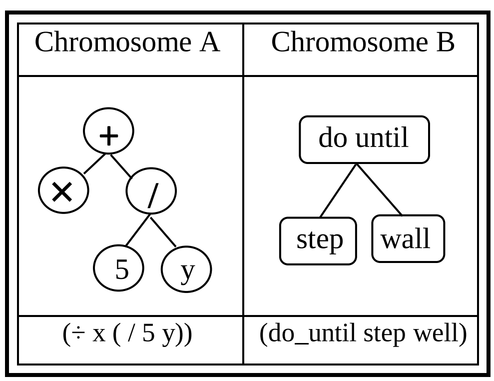


Figure (3-11) Tree encoding.

Real-number encoding is best used for function optimisation problems (Gen and Cheng, 2000). It is most suitable for optimisation in a continuous search space. Herein; used integer encoding (order encoding) to encoding layout problem.

3.5.2 Fitness Function

Evaluate the fitness of each chromosome by knowing its fitness function. To calculate the fitness of the chromosome must first be encoded and then find the objective function (in this study the cost) of it. The fitness not only indicates how good the solution is, but also corresponds to how close the chromosome is to the optimal one. For maximization problems, the fitness function can be considered to be the same as the objective function, for minimization problems, the number of such transformations are possible. The following fitness is often used:

$$\mathbf{F(i)} = \frac{\mathbf{1}}{\textbf{objective function } (\mathbf{i})} \qquad \ldots \textbf{3-5}$$

The fitness function F(i) must be more sensitive than just detecting what is a ‘good’ chromosome versus a ‘bad’ chromosome: it needs to accurately score the chromosomes based on a range of fitness values, so that a somewhat complete solution can be distinguished from a more complete solution (Mohammed, 2014).

The highest fitness value is considered the best solution and the least value the poorest solution. If the problem is to minimize the cost, then high-cost solutions will have low fitness, and low-cost solutions will have high fitness. For the proposed model, a value of 1.0 is used for the lowest-cost member and 0.0 for the highest-cost member, with intermediate solutions that have linear fitness interpolated between these values.

3.5.3 Selection

The process of choosing two individuals from the original population for reproduction in an evolutionary process is called selection. proportional selection is one of the common forms for selection. The name indicates that this approach involves the establishment of a number of offspring in proportion with the fitness of the individual. This method was suggested and analyzed by Holland (1975). It has been widely used in many applications of evolutionary algorithms.

The operator's selection in exploiting the characteristics of the best candidate solutions is aimed at improving these solutions in all generations. The selection operator is the most important parameter that may affect the performance of the GA. The operator directs the genetic search to promising areas in the search space. In selection, the fitness values of individuals are taken into account only.

During the literature review many selection methods have been proposed in the proposed model and seven different selection techniques will be used in the genetic algorithm. These techniques are presented here, namely: the Roulette Wheel Selection (RWS), the Rank Roulette Wheel Selection (RRWS), the Linear Rank Selection (LRS), the Stochastic Universal Sampling (SUS), the Tournament Selection (TOS), the Truncation Selection (TRS) and the Random selection (RMS). A brief description of each method of selection will be used, as follows:

3.5.3.1 Roulette Wheel Selection (RWS)

The roulette wheel is the simplest and traditional random selection method proposed by the Holland (1975). It is classified under a proportional selection as individuals select on the basis of a probability proportionate with their fitness. The roulette selection principle is a linear search through the roulette wheel with slots in the wheel weighted in proportion to the fitness values of the individual. All chromosomes (individuals) are placed in the population on the roulette wheel according to the value of their fitness (Goldberg and Deb, 1991). Assigned to each individual a part on the roulette wheel. The size of each part in the roulette wheel is proportional to the value of an individual's fitness, The higher the value, the greater the part. Then, the virtual roulette wheel is spin. Then selected the individual corresponding to the part on which roulette wheel stops, as shown in the Figure (3-12). The process is repeated until the desired number of individuals is selected. Individuals with higher fitness have more probability of selection. This may lead to biased selection towards high fitness individuals. It can also possibly miss the best individuals of a population. There is no guarantee that good individuals will find their way into the next generation. Roulette wheel selection uses exploitation technique in its approach.

The conspicuous characteristic of this selection method is In fact, every member (i) of the current population is given the probability (p_i) of being selected (Hancock, 2000), proportional with its fitness (f_i)

$$\mathbf{p_i = \frac{f_i}{\sum_{j=1}^{n} f_j}} \qquad \text{... 3-6}$$

Where **n** denotes to the population size in terms of the number of individuals.

It is very important to referring to the known disadvantage in this technique, which is the risk of rapid convergence premature of the GA to a local optimum, since the existence of a dominant individual who always wins the competition and selects as a parent.

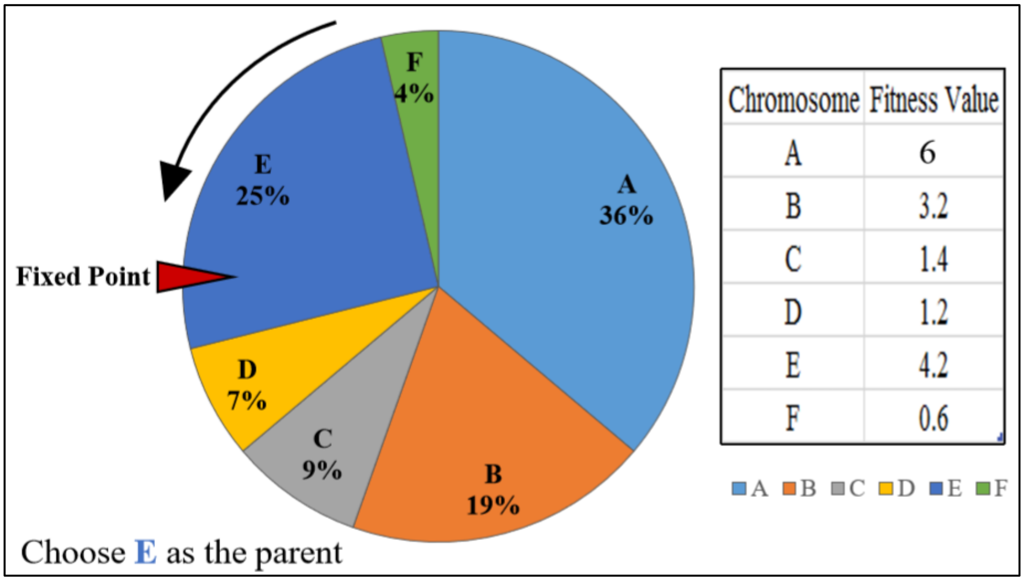
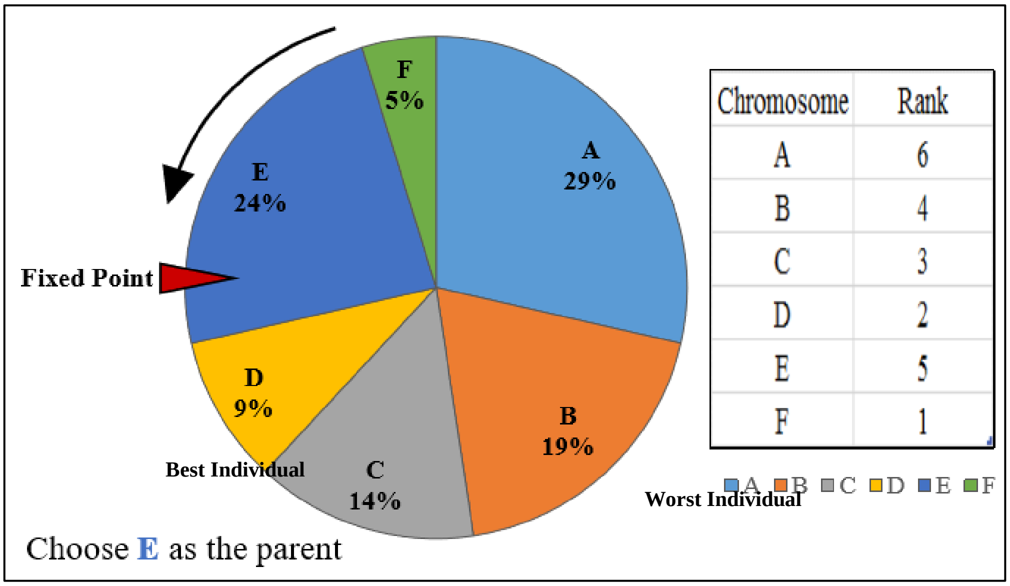


Figure (3-12) Roulette-wheel selection mechanism.

3.5.3.2 Rank Roulette Wheel Selection (RRWS)

Rank selection sorts the population first according to fitness value and ranks them. Rank **N** is assigned to the best individual and rank 1 to the worst one. Then, every chromosome is allocated a selection probability with respect to its rank (Baker, 1985). Individuals are selected as per their selection probability. Rank selection is an explorative technique of selection. It prevents too quick convergence and differs from roulette wheel selection in terms of selection pressure. It overcomes the scaling problems like stagnation or premature convergence.

Ranking controls selective pressure by the uniform method of scaling across the population. Rank selection behaves in a more robust manner than other methods. The Figure (3-13) shown the Rank Roulette Wheel selection method.



Chromosome	Rank
A	6
B	4
C	3
D	2
E	5
F	1

Figure (3-13) Rank Roulette Wheel Selection mechanism.

3.5.3.3 Linear Rank Selection (LRS)

The ranking selection method was originally proposed by Baker to avoid serious disadvantages of proportional selection (Baker, 1985). By linear ranking, selective pressure can be controlled more directly than by scaling, thus significantly speeding up the search process. Linear ranking allocates a selection probability to each individual that is proportional to the individual's rank where the rank of the least fit is defined to be zero and the rank of the most fit is defined to be $\mu-1$, given a population of size μ. To generate an algorithm, linear selection can be applied by identifying a single parameter $\boldsymbol{\beta}$ rank, and the expected number of offspring to be allocated to the best individual in each generation. The probability of selecting each individual **i** is defined as follows:

$$\mathrm{Pr}_{\mathrm{lin\_rank}}(i) = \frac{\alpha_{\mathrm{rank}} + [\mathrm{rank}(i)/(\mu - 1)](\beta_{\mathrm{rank}} - \alpha_{\mathrm{rank}})}{\mu} \qquad \ldots\mathbf{3\text{-}7}$$

where $\propto_{\mathrm{rank}} = 2 - \beta_{\mathrm{rank}}$, and $1 \leq \beta_{\mathrm{rank}} \leq 2$. That is, the expected number of offspring of the best individual is no more than twice that of the population average. This illustrates how the ranking can avoid premature convergence caused by individuals ‘super’.

3.5.3.4 Stochastic Universal Sampling (SUS)

The stochastic universal selection was developed by Baker (Baker, 1987). It is a single phase selection algorithm with minimum spread and zero bias. It is performed by sizing the slots of a weighted roulette wheel, placing equally spaced markers along the outside of the wheel, and spinning the wheel once; the number of copies an individual receives is then calculated by counting the number of markers that fall in its slot. The algorithm is O(n) because only a single pass is needed through the list after the sum of the function values is calculated.

It exhibits less variance than repeated calls to roulette wheel selection. The individuals are mapped to contiguous segments of a line, such that each individual’s segment is equal in size to its fitness exactly as in roulette-wheel selection. Here equally spaced pointers are placed over the line, as many as there are individuals to be selected as shown in the Figure (3-14).

Stochastic universal selection ensures a selection of offspring, which is closer to what is deserved than roulette wheel selection. Stochastic Universal Selection can be used to make any number of selections. It is preferred in situations where more than one sample is to be drawn from the distribution.

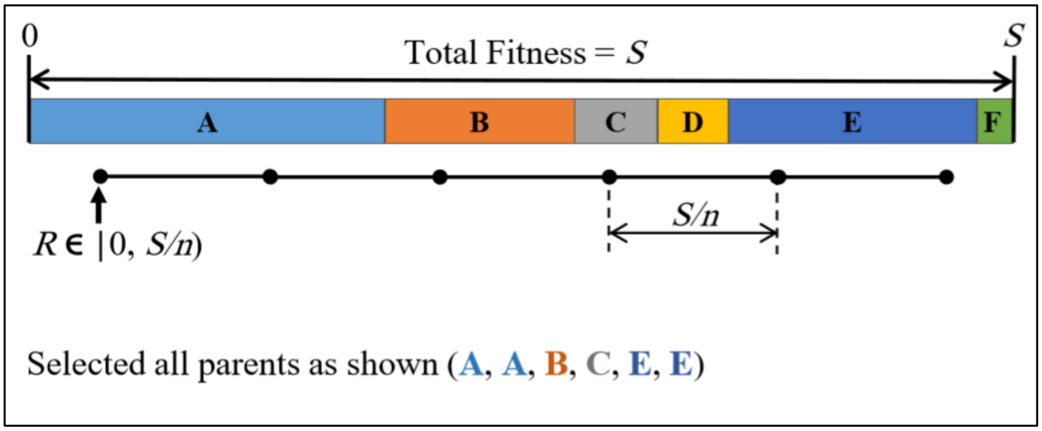


Figure (3-14) Stochastic Universal Sampling mechanism (Baker, 1987) .

Stochastic universal selection ensures a selection of offspring, which is closer to what is deserved than roulette wheel selection. Stochastic Universal Selection can be used to make any number of selections. It is preferred in situations where more than one sample is to be drawn from the distribution.

3.5.3.5 Tournament Selection (TOS)

Tournament selection is a variant of rank based selection methods. Its principle consists in randomly selecting a set of **k** individuals, so that they are withdrawn from the population with or without replacement. These individuals represent a group that are then ranked according to their relative fitness and the fittest individual is selected for reproduction. The whole process is repeated **n** times for the entire population as shown in figure (3-15).

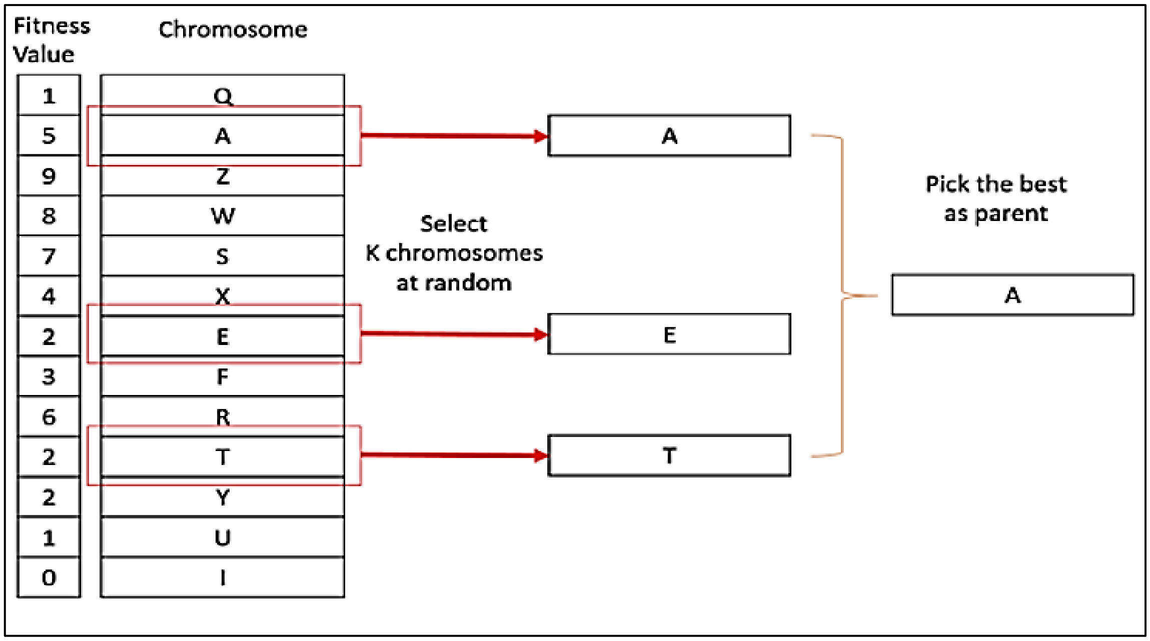


Figure (3-15) Tournament Selection mechanism.

3.5.3.6 Truncation Selection (TRS)

The truncation selection is a very simple technique that orders the candidate solutions of each population according to their fitness. Then, only a certain portion **P** of the fittest individuals is selected and reproduced **1/p** times. It is less used in practice than other techniques, except for a very large population. **P** indicates the proportion of the population to be selected as parents and takes values ranging from 50% - 10%. Individuals below threshold do not produce offsprings (Hancock, 2000).

3.5.3.7 Random Selection (RMS)

In this strategy, it is randomly select parents from the existing population. There is no selection pressure towards fitter individuals and therefore this strategy is usually avoided.

3.5.4 Crossover in Trees

Crossover, which also called recombination, is a genetic operator used to combine the genetic information of two parents to generate new offspring. Like its counterpart in nature, crossover produces new individuals that have some parts of both parent’s genetic material. Crossover takings in three steps:

- The crossover operator selects a pair of individual-strings to mate randomly.
- Selection a cross site along the string length randomly
- Finally, swap the position values between the two crossover strings after the cross point location.

This means that the simplest method to implement this is by randomly selecting some point of crossover and copying everything before the point of the first parent and then copying everything after the crossing point of the other parent. Two techniques of crossover in trees (used in this study) are discussed as follows:

3.5.4.1 Order Crossover (OX)

Order crossover was proposed by (Davis, 1985). In order to avoid the illegal connection among nodes, the crossover is only operated on the node dimension. The operation is on any two individuals. It is not difficult to imagine that the crossover will dramatically change the tree structure among generations. However, it is useful for the exploration of the evolutionary process (Zhou and Gen, 2003).

The OX operator acts as follows: it copies a part of the child chromosome from the first parent and constructs the remaining part from the second parent. More precisely, cut point is randomly selected, and the part of the first parent located before this cut point is copied to the child. The remaining positions in the child are then filled one at a time, starting after the cut point by copy the remaining unused numbers from the second parent to the first child. It can use two cut point, for instance, let the two parents and the two cut points (|) be as follows:

$$p_1 = (1\ 2\ 3 \mid 5\ 4\ 6\ 7 \mid 8\ 9),$$
$$p_2 = (4\ 5\ 2 \mid 1\ 8\ 7\ 6 \mid 9\ 3).$$

Then the first child C_1 is:

$$C_1 = (2\ 1\ 8 \mid 5\ 4\ 6\ 7 \mid 9\ 3).$$

If we exchange the roles of the two parents P_1 and P_2, we can obtain the second child C_2:

$$C_2 = (3\ 5\ 4 \mid 1\ 8\ 7\ 6 \mid 9\ 2).$$

3.5.4.2 Modified Crossing Operator-Based Cloning (CX)

The operator of crossing produces new ‘child’ (son) from two parents. This study propose to clone one of the parents. When this method is applied to the spanning tree, the son first identicals to one parent and then inherits a random link from the other parent, provided that it does not create cycles in the son's tree (Ghoualmi-zine and Mahmoudi, 2010). In this section, give the specification of proposed operators and a pseudo algorithm for each one is given. The method will be modified to suit the proposed model. As shown in the following steps:

Generation algorithm of Son1

Step1: All links of the first parent to the first son are copied. The number of links (genes) can be inherited.

Son1 ← Parent1 (Cloning Parent)

Step 2: At randomly, a link (i , j) is removed from the son's tree, with the condition that this link does not exist in the second parent in which the son's tree will be divided into two sets.

Step 3: Then select a link from Parent 2 with the condition that this link with the same upstream node of eliminating link. then add this link to Son1 in order to connect the two sets of the tree. If no link in Parent 2 verifies the previous condition then stop the elimination of link (i, j) from Son1 and Go to step 2.

Step 4: If no link can be eliminated from son 1 or number of the inherited links equal to N, then stop otherwise go to step 2.

Generation algorithm of Son2

Follow the same steps as previous 1), 2), 3) with the following variation in step 1:

Son2← Parent2 (Cloning Parent2)

(Thus, Son2 inherits links from Parent1.)

3.5.5 Mutation

Chromosomes are subjected to mutation after crossover. The main advantage of the mutation is to prevent the algorithm from being stuck at the local minimum. It provides new genetic structures in the population where the individual's units are randomly modified. There are many different forms of mutations for different types of representation. One of the most important parameters in the technique of mutation is mutation's probability (Pm). The probability of a mutation determines the number of times that parts of the chromosomes will mutate. If the mutation will not occur, the offspring will be copied directly after the crossover without any modification. If the mutation occurs, one or more of the chromosome building units will be changed. The entire chromosome will change if the probability of the mutation is 100%, and nothing will change if it is 0%. The mutation should not occur too much, because the genetic algorithm will change to random search in fact.

3.5.6 Values for parameters

There are some operating parameters in the GA program, i.e. the population size, the maximum number of generations, the probability of the jump mutation, the probability of uniform crossover, and etc., of a GA run. They are related to the convergence of the evolutionary process, which should be set by a heuristic rule, to shorten the computation time. For this case study, GA algorithm parameters with the routine integer coding, were chosen as follows: the number of populations is (50-500); the mating rate is 0.9 (a typical crossover probability lies between 0.75 and 0.95); the mutation rate is 0.5; the objective of optimisation is 1/cost, which fits the requirements for the “Minimizing” and “Nonnegative” fitness function, etc.

Chapter Four

Formulation of Optimisation Problem

Optimisation problems are often specified using a particular form. First, the design variables are listed. Then, the objectives are given, and finally, the constraints are given. Computer algorithms are to search the design space of a computer model. The design variables are adjusted by an algorithm in order to achieve objectives and satisfy constraints and formulation of new techniques model. The formulation of the optimum layout design of sewer networks will be illustrated in this section.

4.1 Objective Function

The definition of a linear objective function depends on some weights or cost values appointed to pipes within the base graph of the network. Therefore, many methods can be operating to resolve the raised linear problem as found in Rosen (2003) and Fournier (2009). Herein, the layout of the sewer sub-problem appears to be similar to the shortest path problems. However, the layout sub-problem is very complicated and intractable to resolve by common linear methods. In urban drain systems, the weight of every sewer pipe is that its construction cost value, which could be a function of the diameter of the sewer and depth of installation remain unknown. In simplified cost functions, like what was suggested by Walters and Lohbeck (1993), pipe weights are defined by a nonlinear and concave function of sewer length and discharge. In spite of these simplifications, the accumulated discharge of the pipe in a sewer network is not known at first, before the layout is designed. In other words, the system cost is obtained implicitly with the layout configuration. As a result, the layout sub-problem is nonlinear and typical linear optimisation models cannot be so used.

It is assumed that the cost of the pipe in the sewer network should be proportional to its length, and a concave function of the pipe's flow. It should be observed, initially, that the flow along the sewer pipe is unknown and depends on the layout design. In principle, any form of cost function could be applied, but, for simplicity, the following equation can be used (Walter and Smith, 1995):

$$\boldsymbol{Min.\ C} = \sum_{i=1}^{n} \boldsymbol{L}_i \sqrt{\boldsymbol{Q}_i} \qquad \text{… 4-1}$$

where $\boldsymbol{C}$ = the layout objective function per units cost,

$\boldsymbol{L}$ = length of sewer pipe (m),

$\boldsymbol{Q}$ =The cumulative flow rate of the sewer pipe obtained from the layout configuration (m^3/s),

$\boldsymbol{n}$ = number of sewer lines

The flow in each pipe in the sewer network equals a sum of flow rates for the previous manholes. The above equation represents the real state. The cost per unit capacity for a sewer pipe reduces when the pipe increases in capacity, which shows the cost is a nonlinear, concave function of capacity.

4.2 Constraints

The configuration of a sewerage system in urban areas is a sub-graph derived from a previously defined base graph. Initially, the base graph can be considered as a directed or undirected based on the method used to create the layout sub-graphs. The base graph includes all the drainage possibilities from the manholes (vertices) and sewer pipes (edge), which in turn form a connected cyclic graph. The base graph shall take into account the alignments of the streets, barriers, watercourses, the location of the outlet and existing sewage pipes in the city. In addition, each manhole in the base graph is connected to adjacent manholes according to the direction of wastewater flow. However, there are a number of basic constraints that must be fulfilled to generate the feasible layouts from a base graph, as in the following:

1- The graph should be acyclic, with the configuration being a tree layout.
2- In the layout configuration, all manholes (vertices) must be involved in the tree; that means the layout is a spanning tree.
3- In the layout configuration, all sewers (edges) must be involved in the tree because each one of them is draining sewage for a particular street.
4- The drainage system has an outlet (root) to which the spanning tree should be directed.
5- It can enter more than one sewer pipe in a manhole, but it must exit out of one sewer pipe directed towards the outlet except for the root manhole.

All the network constraints are automatically satisfied in the tree-growing algorithm and the resulting layout is therefore feasible.

These limitations make the present problem more complex than those common in the problem of spanning trees in graphs theory.

4.3 Formulation of the Model

Firstly, similar to the natural evolutionary process, GAs take a large number of generations to achieve performance improvement, with increased computational costs for complex systems. Secondly, many forms of GA rely on randomly generated initial populations which are often poor solutions. Therefore, the approach can be prohibitively time-consuming especially for designing large networks (Yufeng et al., 2017).

The proposed approach goes some way to handling problems related to configuring solutions that are infeasible. A main innovative element is in the method for generation of the initial population from feasible solutions by a suitable growth algorithm. This is described previously in this study in addition to the methods for selection of parents and crossover which guarantee that a feasible offspring population can be formed for the new generation. This mechanism leads to faster convergence to reach the optimal solution, with a more detailed explanation about the present model presented below:

1- **Coding the variables of design**: One of the requirements of genetic algorithms is that any experimental solution to the layout design problem is represented by a specific length-encoded string similar to the chromosome structure of the genetic code. This is achieved by selecting a map between the values of the design variables and a set of encoded substrings with the number of bits needed, depending on the system of coding used. Herein; used integer encoding (order encoding) to encoding layout problem. The intuitive idea of encoding a tree solution is to use a two-dimensional structure for its genetic representation. One dimension encodes the number of pipes; another dimension encodes the name of the pipe. Therefore, we may have an (n×2) matrix to represent a chromosome for an n-node tree. The genes in the second dimension take a permutation with integers from **1** to **n** exclusively, the gene includes two alleles one allele upstream node and another downstream node. As shown in the Figure (4-1):

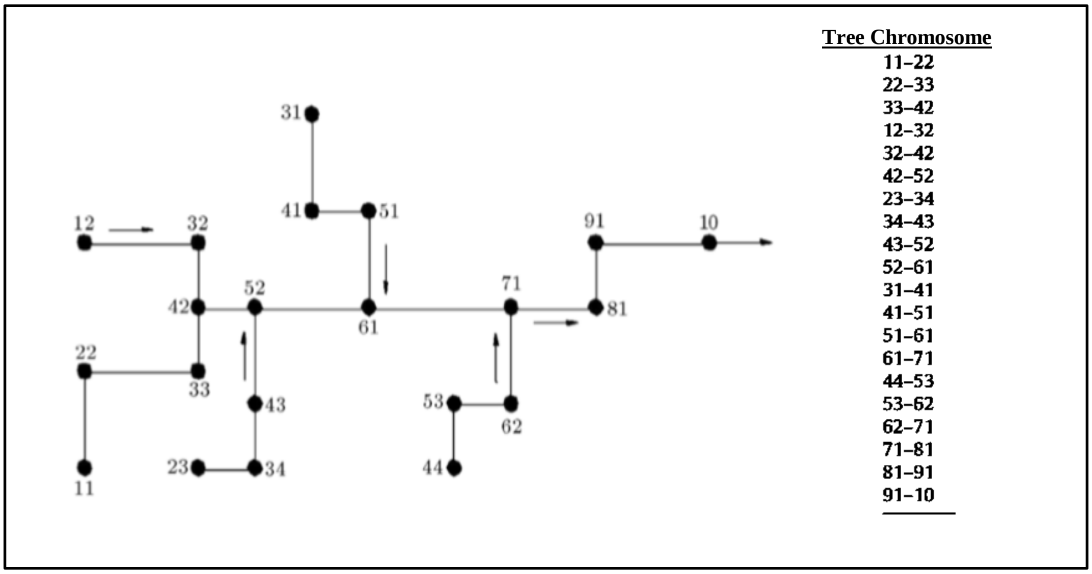


Figure (4-1) Encoding the layout of the proposed model.

2- **Calling sub-routine the TGA to generate the initial population:** The initial population represents the important part of the algorithm. It is the path that the GA will take towards the near optimal solution. Therefore, It is expected to increase the efficiency performance of GA, if the search algorithm can detect optimal initial solutions rather than random solutions. The differences in this model are that the technique used to research the space to discover the solutions in the first place must be more efficient than the initial population in GA to be effective as shown in Figure (4-2). Therefore, the seeding of a GA has to be completed with a minimal number of model evaluations whilst representing the best benefit to the algorithm. To achieve this, a hybrid (GA-TGA) approach is proposed that used the initial power of the TGA without sacrificing the ability of the GA to find solutions that match or exceed the exact requirements of the optimisation. The major advantage that the TGA has over other search techniques is that the process, in fact, has a bias towards generating trees which have a structure diverging from the root, a characteristic of natural growth in trees and root systems and of economically engineered sewage networks. This inherent bias towards sensible engineering solutions seems to add greatly to the efficiency of the optimisation model.

3- **Fitness account:** in this step the fitness function has been computed for each layout in the population. It is described as the inverse of the total cost of each layout's network. The highest fitness value is considered the best solution and the least value, the poorest solution.

4- **Generation of a new population:** to generate a new population by repeating the following steps until the new population is complete:

i. **Selection**: two parent chromosomes are selected from a population according to their fitness (the better the fitness, the bigger the chance of being selected). This work considered seven different selection methods.

ii. **Crossover**: the process of selecting two parents of the solutions and production of children (offspring). Creating a better offspring than the parents is achieved by applying the crossover operator to a mating pool. Here, two different crossover methods were considered where Pc=0.9: Order Crossover (OX), proposed by Davis (1985), and Crossing Operator-Based Cloning (CX), used by Ghoualmi-zine and Mahmoudi (2010).

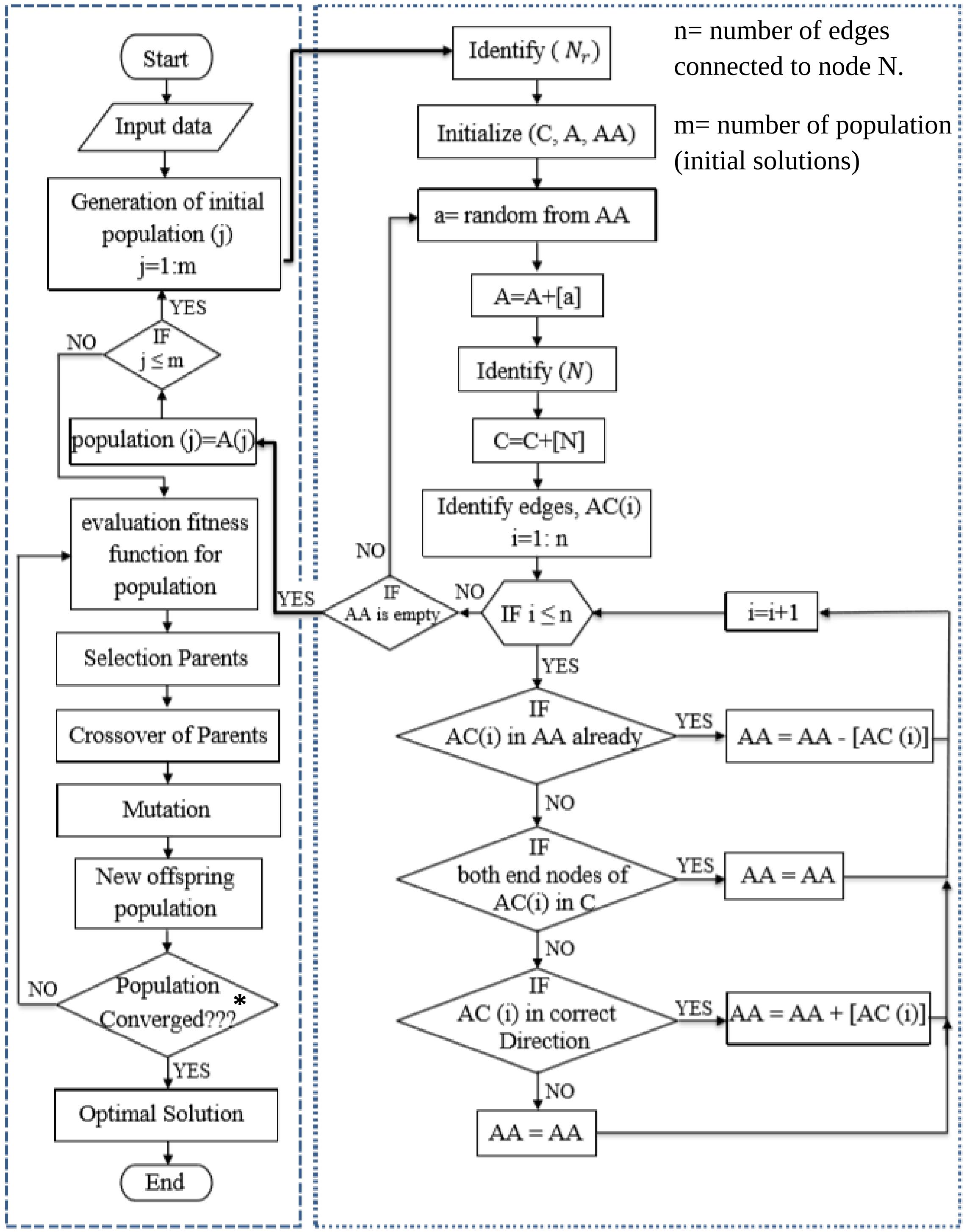
iii. **Mutation**: offspring are subject to a mutation after crossover. The benefit of a mutation is to prevent the algorithm from being trapped at the local minimum, which occurs through the formation of a new genetic structure in the population resulting from random modification of some of its genes in strings. In an integer encoding GA, randomized mutations change the value of the selected gene to the random integer value between coded genes of chromosomes, Here, a random mutation operator with Pm = 0.5 is employed by which only one gene in a chromosome is randomly selected for mutation.

iv. **Replace Current Population with New Generation:** replaces the current population with a new generation of solutions in the basic generation of the algorithm. In general, the average fitness of the new population will be greater than the previous population, due to the crucial process of special selection of the fitter members as parents.

v. **Convergence criterion of the model**: throughout the evolution, the cost of the present best design converges more or less approximately to the real minimum. Making new generations and evaluating the fitness of their members ought to ideally continue until the global optimum is known. However, since the global optimum is not usually known, another standard must be used to terminate the program. The evolution could be terminated, as an example, after a certain number of generations, after a fixed time, or if there has been no improvement for, say, the last 10 generations. The other possibility is to continue until all solutions are almost identical. In every generation, there is a rapid improvement in the beginning. Later on, the best solutions can be achieved only from time to time. However, even if there has been no improvement for several generations, the new optimum may be produced suddenly, which makes the selection of termination criterion difficult. For this work, genetic algorithms have been terminated if no new optimisation has been detected.

The advantage of using this hybrid method consists in the fact that a GA, in this case, has a much smaller searching space than in a case when GA methodology is used alone which has a great impact when trying to achieve better results.

The efficiency of the algorithm can be changed by allowing one or more of the best solutions from one generation to continue in the next generation. This approach prevents the best solution being lost from generation to generation and can significantly increase the initial rate of convergence towards the optimal solution. However, the rapid convergence is not necessarily desirable, as this will increase the chance or end of action at the local level and is not globally optimal.



Genetic Algorithm　　　　Sub-Routine TGA to generation initial population

***Population converged after a certain number of generations, after a fixed time, or if there has been no improvement for, say, the last 10 generations.**

Figure (4-2) Flowchart of the proposed model.

Chapter Five

Benchmark Problems and Cases Study

This chapter presents the layout and characteristics for benchmark problems, which are used to evaluate the performance of the new model (GA-TGA). Indeed, the cases study are also given, which are used to determine the applicability the proposed model to practical networks in the local region.

5.1 Benchmark Examples

5.1.1 First Benchmark Example

To considers the minimum cost problem of layout and to demonstrate the convergence ability of the proposed model testing it in an example of the tree from the regular grid (8*8 node) base graph which can be **undirected** and **directed** as shown in Figure (5-1). Originally proposed and solved by Walters and Smith (1995) using Evolutionary Programming (EP). The coordinates of the nodes and the nodal flow rate are shown in Table (5-1). The location of the outlet node is as specified in the figure.

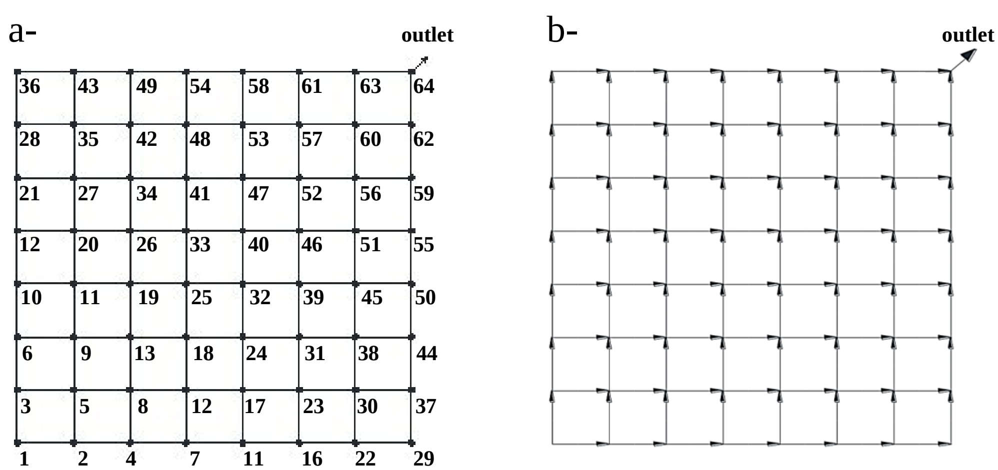


Figure (5-1) Base graph of the first example a) undirected, b) directed (Walters and Smith, 1995).

Table (5-1): Base graph for a regular grid (8 x 8 node) example (Walters and Smith, 1995).

Node	X	Y	Flowrate units	Upstream* Nodes		Node	X	Y	Flowrate units	Upstream* Nodes	
1	0	0	10	2	3	33	30	40	10	40	41
2	10	0	20	4	5	34	20	50	20	41	42
3	0	10	10	5	6	35	10	60	10	42	43
4	20	0	20	7	8	36	0	70	20	43	
5	10	10	10	8	9	37	70	10	10	44	
6	0	20	20	9	10	38	60	20	20	44	45
7	30	0	10	11	12	39	50	30	10	45	46
8	20	10	20	12	13	40	40	40	20	46	47
9	10	20	10	13	14	41	30	50	10	47	48
10	0	30	20	14	15	42	20	60	20	48	49
11	40	0	10	16	17	43	10	70	10	49	
12	30	10	20	17	18	44	70	20	20	50	
13	20	20	10	18	19	45	60	30	10	50	51
14	10	30	20	19	20	46	50	40	20	51	52
15	0	40	10	20	21	47	40	50	10	52	53
16	50	0	20	22	23	48	30	60	20	53	54
17	40	10	10	23	24	49	20	70	10	54	
18	30	20	20	24	25	50	70	30	20	55	
19	20	30	10	25	26	51	60	40	10	55	56
20	10	40	20	26	27	52	50	50	20	56	57
21	0	50	10	27	28	53	40	60	10	57	58
22	60	0	20	29	30	54	30	70	20	58	
23	50	10	10	30	31	55	70	40	10	59	
24	40	20	20	31	32	56	60	50	20	59	60
25	30	30	10	32	33	57	50	60	10	60	61
26	20	40	20	33	34	58	40	70	20	61	
27	10	50	10	34	35	59	70	50	10	62	
28	0	60	20	35	36	60	60	60	20	62	63
29	70	0	10	37		61	50	70	10	63	
30	60	10	20	37	38	62	70	60	20	64	
31	50	20	10	38	39	63	60	70	10	64	
32	40	30	20	39	40	64	70	70	0		

*based on arbitrary initial flow directions.

Walter and Smith (1995) used this example to test the developed Evolutionary Programming EP (or Evolutionary Design) for optimal layout of tree networks and compared with the GA of (Walters and Lohbeck, 1993).

The example was later solved by many researchers; (Geem, Z.W., Kim, T.G. and Kim, 2000) and (Afshar and Mariño, 2006) to test the Harmony Search HS and the Ant Algorithm method ACO, respectively.

5.1.2 Second Benchmark Example

This example will be designed using the proposed (GA-TGA) model as a benchmark example. It was introduced and solved originally with the Discrete Differential Dynamic Programming (DDDP) model by Wen and Shih (1983), then, after which the Non-uniform state Increment Dynamic Programming (NIDP) model, which achieve a new optimal solution, saving 15% of the total construction cost (Orth and Hsu, 1986), Weng and Liaw (2005) established a combinatorial optimisation model for Sewer System Layout with Applied Genetic Algorithm (GA/SSOM/LH), to find an optimal design for a real urban sewer system. A sewer system contains 72 sewer stages (pipes) and 73 manholes a directed base graph as seen in Figure (5-2) was prepared for the problem that is also used in this study more details are also found in the cited reference..

The layout design problem is considered here, but an attempt will be made to include the design of the sewer's size, to proves the minimizing in objective function (cost) directly minimize the term of $L\sqrt{Q}$ for each sewer pipe that leads to minimize the pipe sizes and depths of installation indirectly, and to provide a complete optimal design package. Based on this information, the example will be resolved in two stages. Using a proposed model in the first sub-problem, the optimal layout is required in the initial base graph. After that, the Genetic Algorithm with Heuristic Programming (GA-HP) technique used to design. The principle of (GA-HP) in (Hassan et al., 2017) in which some essential details of the method are found. A (GA-HP) model is employed herein to solve the sewer design sub-problem after obtaining the optimal layout by the proposed model.

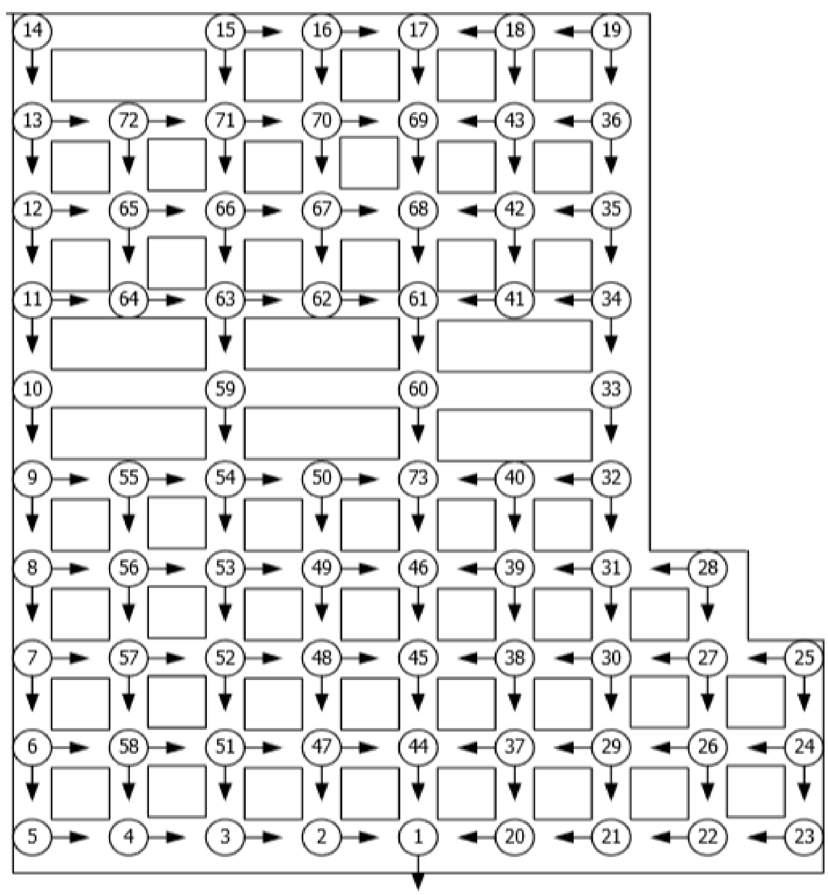


Figure (5-2) The street layout plan of 73 nodes (Weng and Liaw, 2005)***.***

5.2 Cases Study

In this study, two case studies will be used, that are located in Karbala city, Iraq. Karbala is located in the central region of Iraq on the edge of the eastern plateau bank, west of the Euphrates river. The city is located between longitudes (43˚ 15′ 0″ E - 44˚ 15′ 0″ E), and latitudes (32˚ 7′ 30″ N - 32˚ 46′ 5″ N) as shown in Figure (5-3). It is bordered to the north and west by Anbar province, to the south by Najaf province, to the east and northeast by Babil province. Karbala is one of the main cities of the Islamic holy shrines characterized by its standing historical, cultural and specificity urban in Iraq position. Two major city center shrines of Imam Hussein and Imam Abbas peace be upon them exist in the middle center of the city. Karbala city is located within the most densely populated geographical regions in Iraq (ICTR, 2011). The ground level to the city is about (30-44) meters above sea level.

The city of Karbala was chosen for several reasons. Approximately, there is no significant change in terrain heights therefore can be assumed it to be a flat area. In such areas, there is often a lot of possibilities for connecting sewers networks and the location of the network outlet.

Figure (5-3) shows the location of the two case studies which were chosen to study in this research. Two case study is called Al-Amil district, and Al-Hur district.

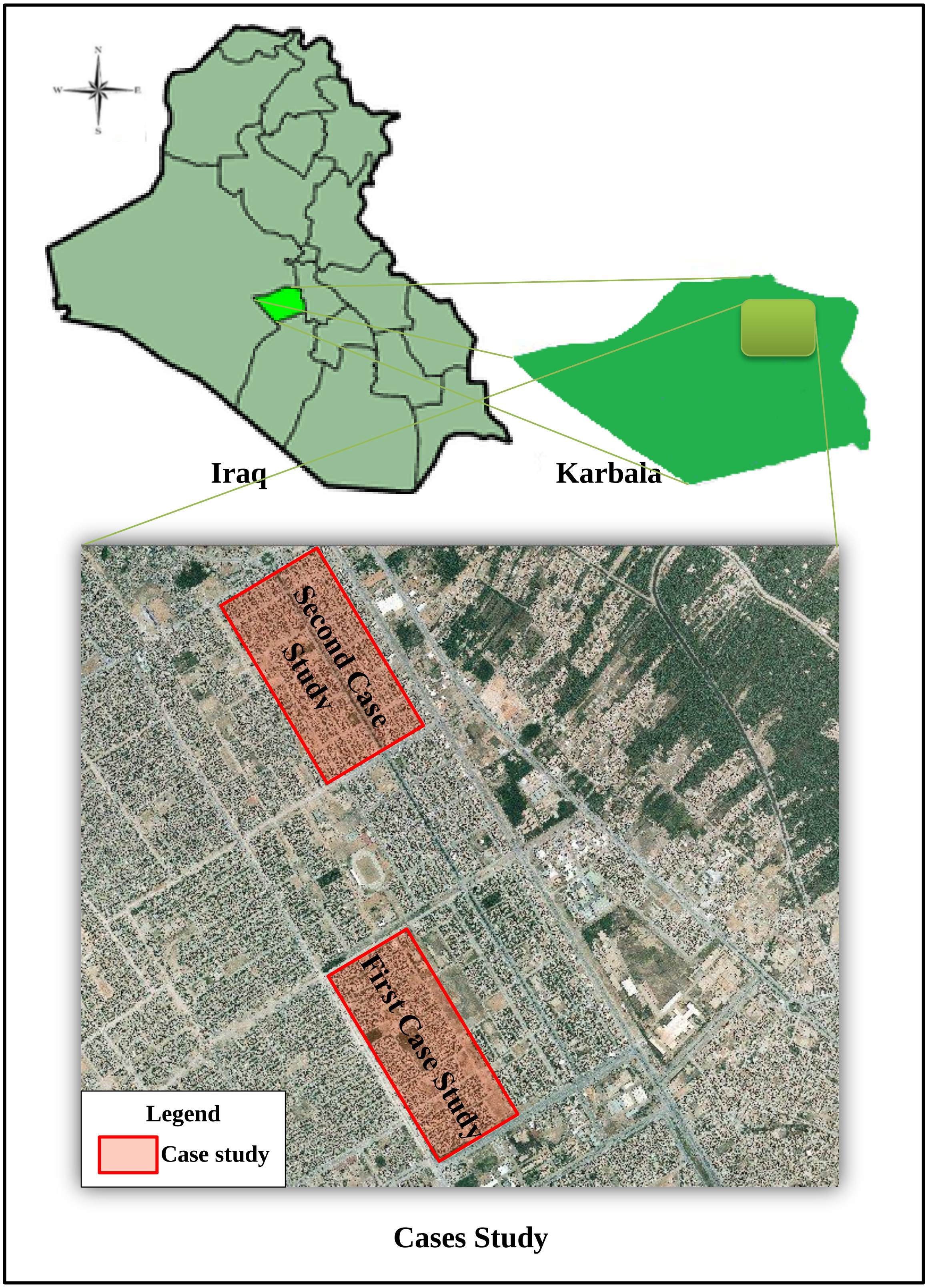


Figure (5-3) Geographical location of the case studies area relative to Karbala, Iraq.

5.2.1 First Case Study

The first case study located in the city center, first sector from Al-Amil quarter. It is located between latitudes 32˚ 36′ 51″ N, and longitudes 43˚ 59′ 48″ E. It forms about (0.485) km^2 as shown in Figure (5-3). It provided by the sewer network, which includes 216 nodes and 215 pipes, the total length of the network (8.227 km), and the layout of the present network shown in Figure (5-4). When using the objective function (equation (4-1) described in chapter four) to calculate the total cost of actual design for the layout of the network as build, a total cost was obtained equal 450.92 units.

Table (5-2) presents the data characteristics as a build for this network and information of actual layout design by manually. The discharge per pipe was calculated based on the population of the area served, and the average daily water consumption per capita. Taking into consideration infiltration from water table and inflow from manholes cover.

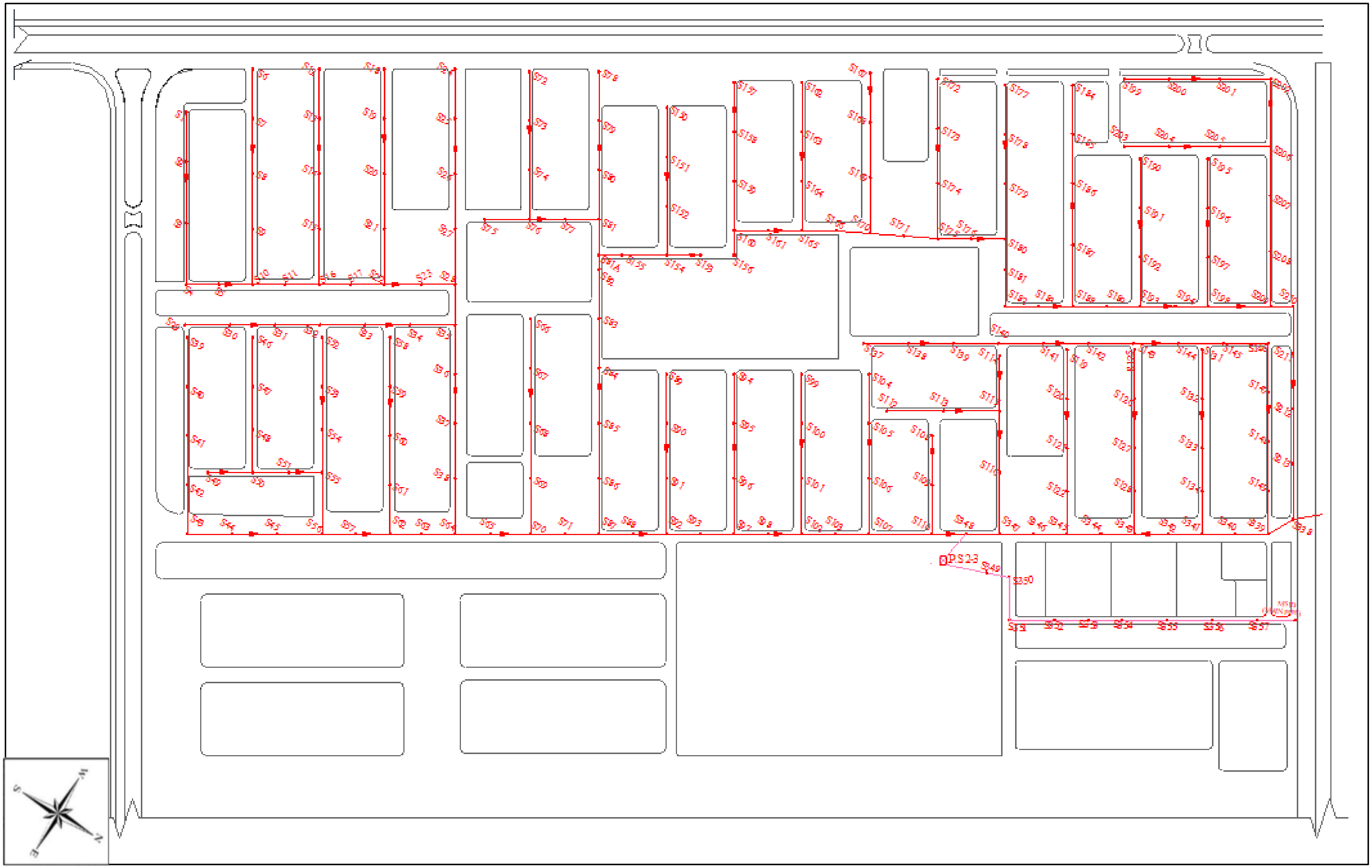


Figure (5-4) Existing layout of the Al-Amil district (GIS-DKS, 2017).

Table (5-2): Manual design for the first case study (GIS-DKS, 2017).

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
1 2	40	0.000355	103 107	30	0.014660
2 3	50	0.000790	104 105	40	0.000355
3 4	50	0.001224	105 106	45	0.000746
4 5	29	0.001474	106 107	45	0.001137
5 10	30	0.001735	107 110	56	0.016276
6 7	40	0.000355	108 109	40	0.000355
7 8	45	0.000746	109 110	40	0.000703
8 9	45	0.001137	110 348	30	0.017230
9 10	45	0.001527	112 113	50	0.000443
10 11	29	0.003506	113 115	50	0.000877
11 16	30	0.003766	114 115	45	0.000399
12 13	40	0.000355	115 116	50	0.001701
13 14	45	0.000746	116 347	50	0.002135
14 15	45	0.001137	119 120	40	0.000355
15 16	45	0.001527	120 121	40	0.000703
16 17	28	0.005528	121 122	35	0.001006
17 22	30	0.005789	122 345	35	0.001310
18 19	40	0.000355	125 126	40	0.000355
19 20	45	0.000746	126 127	40	0.000703
20 21	45	0.001137	127 128	35	0.001006
21 22	45	0.001527	128 343	35	0.001310
22 23	33	0.007595	131 132	40	0.000355
23 28	30	0.007855	132 133	40	0.000703
24 25	40	0.000355	133 134	35	0.001006
25 26	45	0.000746	134 341	35	0.001310
26 27	45	0.001137	137 138	40	0.000355
27 28	45	0.001527	138 139	40	0.002873
28 35	33	0.009660	139 140	40	0.003220
29 30	40	0.000355	140 141	40	0.003567
30 31	40	0.000703	141 142	40	0.003914
31 32	40	0.001050	142 143	40	0.004262
32 33	40	0.001397	143 144	40	0.004609
33 34	40	0.001744	144 145	40	0.004956
34 35	40	0.002091	145 146	40	0.005303
35 36	40	0.012091	146 147	40	0.005650

Table (5-2): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
36 37	40	0.012439	147 148	40	0.005998
37 38	45	0.012830	148 149	40	0.006345
38 64	45	0.013220	149 339	35	0.006648
39 40	40	0.000355	157 158	40	0.000355
40 41	40	0.000703	158 159	40	0.000703
41 42	40	0.001050	159 160	40	0.001050
42 43	40	0.001397	156 160	20	0.000181
43 44	40	0.001744	160 161	30	0.001483
44 45	40	0.002091	161 165	30	0.001744
45 56	40	0.002439	162 163	40	0.000355
46 47	40	0.000355	163 164	40	0.000703
47 48	35	0.000659	164 165	40	0.001050
48 50	35	0.000963	165 166	30	0.003046
49 50	40	0.000355	166 170	30	0.003306
50 51	32	0.001588	167 168	40	0.000355
51 55	30	0.001848	168 169	45	0.000746
52 53	40	0.000355	169 170	45	0.001137
53 54	35	0.000659	170 171	30	0.004695
54 55	35	0.000963	171 175	30	0.004955
55 56	50	0.003238	172 173	40	0.000355
56 57	30	0.005928	173 174	45	0.000746
57 62	30	0.006188	174 175	45	0.001137
58 59	40	0.000355	175 176	30	0.006344
59 60	40	0.000703	176 180	30	0.006605
60 61	40	0.001050	177 178	40	0.000355
61 62	40	0.001397	178 179	40	0.000703
62 63	28	0.007820	179 180	45	0.001093
63 64	30	0.008080	180 181	25	0.008124
64 65	32	0.021570	181 182	30	0.008384
65 70	35	0.021874	182 183	30	0.008645
66 67	40	0.000355	183 188	30	0.008905
67 68	45	0.000746	184 185	40	0.000355
68 69	45	0.001137	185 186	40	0.000703
69 70	45	0.001527	186 187	50	0.001137
70 71	31	0.023662	187 188	50	0.001571

Table (5-2): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
72 73	40	0.000355	188 189	30	0.010728
73 74	40	0.000703	189 193	30	0.010988
74 76	40	0.001050	190 191	40	0.000355
75 76	40	0.000355	191 192	40	0.000703
76 77	32	0.003844	192 193	40	0.001050
77 81	30	0.004105	193 194	30	0.012291
78 79	40	0.000355	194 198	30	0.012551
79 80	40	0.000703	195 196	40	0.000355
80 81	40	0.001050	196 197	40	0.000703
81 81A	29	0.005398	197 198	40	0.001050
150 151	40	0.000355	198 209	56	0.014080
151 152	40	0.000703	199 200	40	0.000355
152 154	40	0.001050	200 201	45	0.000746
153 154	30	0.000268	201 202	45	0.001137
154 155	40	0.001657	202 206	55	0.001615
155 81A	20	0.001830	203 204	40	0.000355
81A 82	12	0.007324	204 205	45	0.000746
82 83	40	0.007673	205 206	45	0.001137
83 84	40	0.008020	206 207	40	0.003090
84 85	45	0.008411	207 208	45	0.003828
85 86	45	0.008802	208 209	45	0.004956
86 87	45	0.009192	209 210	20	0.019200
87 88	30	0.009452	210 211	38	0.019531
88 92	30	0.009712	211 212	45	0.019922
89 90	40	0.000355	212 213	45	0.020312
90 91	45	0.000746	213 338	45	0.020703
91 92	45	0.001137	338 339	25	0.020919
92 93	30	0.011101	339 340	30	0.027820
93 97	30	0.011362	340 341	29	0.028072
94 95	40	0.000355	341 342	30	0.029634
95 96	45	0.000746	342 343	30	0.029895
96 97	45	0.001137	343 344	30	0.031457
97 98	30	0.012751	344 345	30	0.031718
98 102	30	0.013011	345 346	30	0.035450
99 100	40	0.000355	346 347	30	0.035711

Table (5-2): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
100101	45	0.000746	347348	30	0.038098
101102	45	0.001137	348349	30	0.055320
102103	30	0.014400			

5.2.2 Second Case Study

The second case study located in Al-hur subdistrict. It forms about (0.521) km^2 as shown in Figure (5-3). It includes 309 nodes and 308 pipes, the total length of the network (11.313 km), and the layout of network present such as Figure (5-5). When using the objective function (equation (4-1) described in chapter four) to calculate the total cost of manual design for the layout of the network as build a total cost was obtained equal 673.28 units. Table (5-3) presents the data characteristics as a build for this network and information of actual layout design by manually.

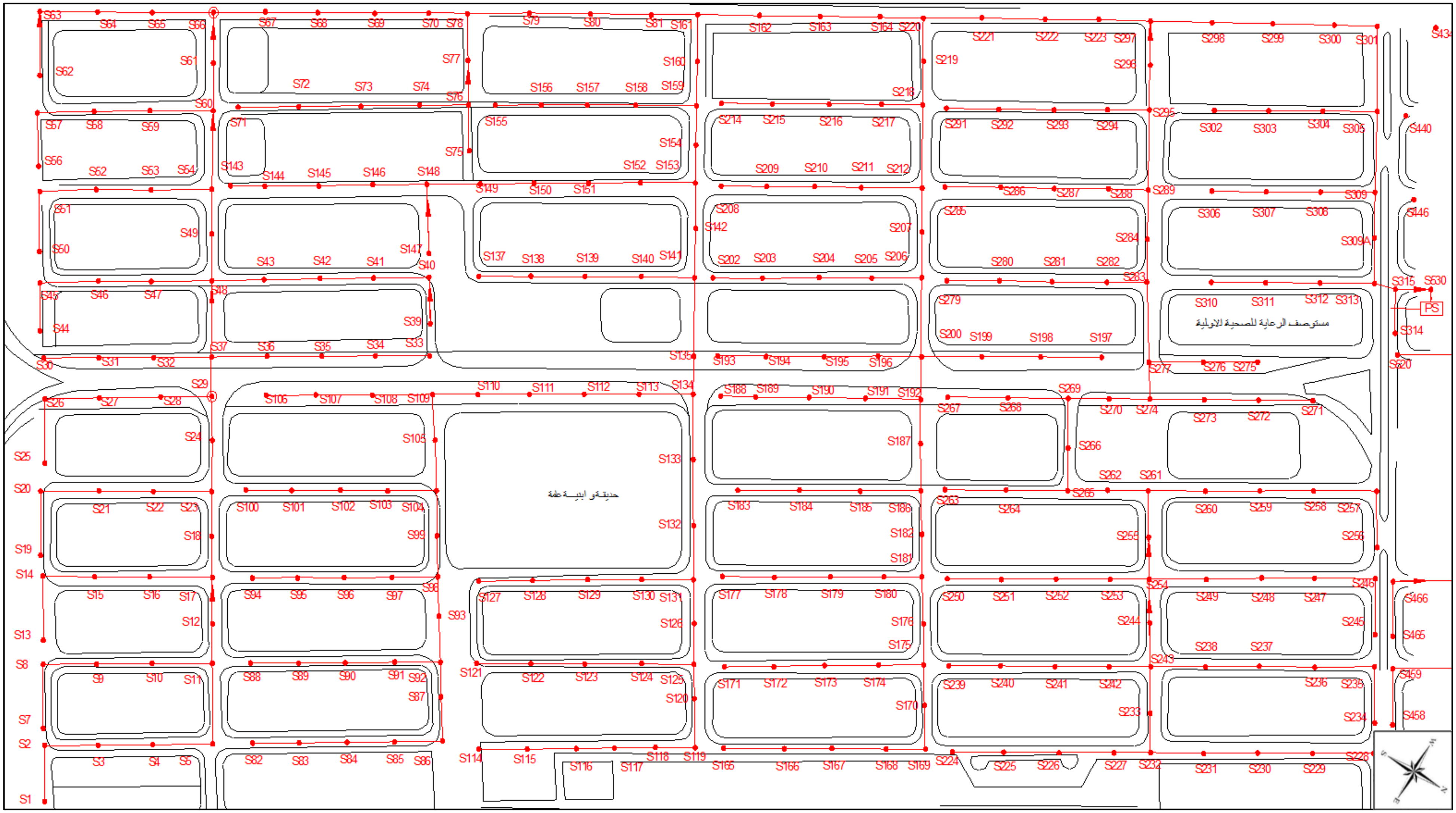


Figure (5-5) Existing layout of Al-Hur district (GIS-DKS, 2017).

Table (5-3): Manual design for the second case study (GIS-DKS, 2017).

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
1 2	35	0.000311632	160 161	30	0.024709491
2 3	40	0.000659144	161 162	45	0.035630498
3 4	40	0.001006366	162 163	45	0.036021123
4 5	45	0.00139728	163 164	45	0.036411748
5 11	50	0.001831597	164 220	30	0.036671296
7 8	40	0.000355324	165 166	45	0.000399016
8 9	40	0.000702546	166 167	35	0.000702257
9 10	40	0.001049769	167 168	40	0.001049769
10 11	45	0.001440683	168 169	30	0.001309606
11 12	25	0.003479456	169 170	25	0.001526331
12 17	30	0.003740162	170 175	25	0.001743345
13 14	40	0.000355324	171 172	35	0.000311632
14 15	38	0.000685069	172 173	35	0.000615451
15 16	40	0.001032407	173 174	40	0.000962963
16 17	45	0.001423322	174 175	35	0.001266493
17 18	25	0.005371817	175 176	25	0.003219039
18 23	28	0.005615046	176 181	30	0.003479745
19 20	40	0.000355324	177 178	40	0.000355324
20 21	43	0.000728762	178 179	40	0.000702546
21 22	40	0.00107581	179 180	40	0.001049769
22 23	43	0.001449248	180 181	28	0.00129213
23 24	30	0.007316551	181 182	28	0.005007407
24 29	28	0.007559491	182 186	28	0.005250463
25 26	40	0.000355324	183 184	45	0.000399016
26 27	40	0.000702546	184 185	45	0.000789641
27 28	45	0.001093461	185 186	45	0.001180266
28 29	38	0.001422917	186 187	30	0.00668287
29 37	25	0.009191262	187 192	30	0.006943287
30 31	40	0.000355324	188 189	25	0.000224248
31 32	40	0.000702546	189 190	40	0.000572338
32 37	40	0.001049769	190 191	40	0.00091956
33 34	40	0.000355324	191 192	40	0.001266782
34 35	40	0.000702546	192 200	25	0.008418692
35 36	40	0.001049769	193 194	35	0.000311632
36 37	40	0.001396991	194 195	40	0.000659144
37 48	48	0.012039815	195 196	40	0.001006366

Table (5-3): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
39 40	30	0.00026794	196 200	30	0.001266204
40 41	40	0.000615741	197 198	45	0.000399016
41 42	40	0.000962963	198 199	40	0.000745949
42 43	40	0.001310185	199 200	45	0.001136863
43 48	40	0.001657407	200 206	50	0.011241319
44 45	30	0.00026794	202 203	35	0.000311632
45 46	40	0.000615741	203 204	40	0.000659144
46 47	40	0.000962963	204 205	40	0.001006366
47 48	45	0.001353877	205 206	35	0.001309896
48 49	30	0.015293981	206 207	28	0.012785185
49 54	28	0.015536921	207 212	28	0.013028241
50 51	38	0.000337847	208 209	35	0.000311632
51 52	40	0.000685185	209 210	35	0.000615451
52 53	40	0.001032407	210 211	35	0.000919271
53 54	45	0.001423322	211 212	40	0.001266782
54 60	50	0.001857639	212 218	52	0.014739699
56 57	35	0.000311632	214 215	40	0.000355324
57 58	40	0.000659144	215 216	40	0.000702546
58 59	40	0.001006366	216 217	40	0.001049769
59 60	45	0.00139728	217 218	30	0.001309606
60 61	30	0.003505787	218 219	26	0.016265972
61 66	30	0.003766204	219 220	26	0.016491667
62 63	40	0.000355324	220 221	45	0.053547164
63 64	40	0.000702546	221 222	45	0.053937789
64 65	40	0.001049769	222 223	40	0.054284722
65 66	45	0.001440683	223 297	38	0.054614468
66 67	40	0.005546296	224 225	38	0.000337847
67 68	40	0.005893519	225 226	40	0.000685185
68 69	40	0.006240741	226 227	40	0.001032407
69 70	40	0.006587963	272 232	27	0.00126603
70 78	28	0.006830324	228 229	45	0.000399016
71 72	45	0.000399016	229 230	40	0.000745949
72 73	45	0.000789641	230 231	40	0.001093171
73 74	45	0.001180266	231 232	40	0.001440394
74 76	36	0.001492245	232 233	25	0.00291522
75 76	28	0.000250463	233 243	30	0.003175926

Table (5-3): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
76 77	28	0.001977894	234 235	35	0.000311632
77 78	30	0.002238426	235 236	45	0.000702836
78 79	45	0.009452836	236 237	40	0.001049769
79 80	45	0.009843461	237 238	40	0.001396991
80 81	45	0.010234086	238 243	40	0.001744213
81 161	35	0.010537326	239 240	38	0.000337847
82 83	35	0.000311632	240 241	40	0.000685185
83 84	35	0.000615451	241 242	40	0.001032407
84 85	35	0.000919271	242 243	30	0.001292245
85 86	35	0.00122309	243 244	27	0.006430961
86 87	28	0.001465741	244 254	27	0.006665336
87 92	20	0.001638889	245 246	35	0.000311632
88 89	35	0.000311632	246 247	45	0.000702836
89 90	30	0.000571759	247 248	40	0.001049769
90 91	35	0.000875868	248 249	40	0.001396991
91 92	35	0.001179688	249 254	40	0.001744213
92 93	28	0.003054282	250 251	40	0.000355324
93 98	25	0.003271123	251 252	40	0.000702546
94 95	35	0.000311632	252 253	40	0.001049769
95 96	35	0.000615451	253 254	30	0.001309606
96 97	35	0.000311632	254 255	26	0.009929167
97 98	35	0.00122309	255 261	30	0.009972801
98 99	25	0.004703414	256 257	35	0.000311632
99 104	28	0.004946644	257 258	45	0.000702836
100 101	35	0.000311632	258 259	40	0.001049769
101 102	35	0.000615451	259 260	40	0.001396991
102 103	35	0.000919271	260 261	40	0.001744213
103 104	35	0.00122309	261 262	30	0.011969329
104 105	30	0.006422454	262 265	30	0.012229745
105 109	28	0.006665394	263 264	45	0.000399016
106 107	35	0.000311632	264 265	45	0.000789641
107 108	40	0.000355324	265 266	25	0.01322772
108 109	45	0.000746238	266 274	30	0.013488426
109 110	35	0.007707465	267 268	45	0.000399016
110 111	40	0.008054977	268 269	45	0.000789641
111 112	40	0.008402199	269 270	30	0.014530093

Table (5-3): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
112 113	40	0.008749421	270 274	30	0.014790509
113 134	40	0.009096644	271 272	40	0.000355324
114 115	35	0.000311632	272 273	40	0.000702546
115 116	35	0.000615451	273 274	40	0.001049769
116 117	28	0.000858102	274 277	25	0.029529803
117 118	30	0.001118634	275 276	40	0.000355324
118 119	30	0.001379051	276 277	40	0.000702546
119 120	30	0.001639468	277 283	50	0.030659722
120 125	20	0.0018125	279 280	40	0.000355324
121 122	40	0.000355324	280 281	40	0.000702546
122 123	40	0.000702546	281 282	40	0.001049769
123 124	40	0.001049769	282 283	30	0.001309606
124 125	40	0.001396991	283 284	25	0.032177373
125 126	25	0.003418692	284 289	30	0.032438079
126 131	28	0.003661921	285 286	40	0.000355324
127 128	40	0.000355324	286 287	40	0.000702546
128 129	40	0.000702546	287 288	40	0.001049769
129 130	40	0.001049769	288 289	30	0.001309606
130 131	38	0.001379514	289 295	50	0.034175347
131 132	35	0.005337674	291 292	40	0.000355324
132 133	40	0.007131944	292 293	40	0.000702546
133 134	40	0.007479167	293 294	40	0.001049769
134 135	25	0.016783854	294 295	30	0.001309606
135 141	50	0.017219329	295 296	28	0.035719213
137 138	40	0.000355324	296 297	28	0.035962269
138 139	40	0.000702546	297 298	45	0.090960359
139 140	40	0.001049769	298 299	45	0.091350984
140 141	40	0.001396991	299 300	45	0.091741609
141 142	30	0.018867477	300 301	30	0.092001157
142 153	28	0.019110417	301 305	51	0.092445081
143 144	25	0.000224248	302 303	40	0.000355324
144 145	40	0.000572338	303 304	40	0.000702546
145 146	40	0.00091956	304 305	40	0.001049769
146 148	40	0.001266782	305 309	50	0.093920718
147 148	45	0.000399016	306 307	40	0.000355324
148 149	40	0.00200463	307 308	40	0.000702546

Table (5-3): Continued.

Link from to	Length (m)	Q design (m^3/s)	Link from to	Length (m)	Q design (m^3/s)
149 150	40	0.002351852	308 309	40	0.001049769
150 151	40	0.002699074	309 309A	28	0.095204167
151 152	40	0.003046296	309 A313	28	0.095447222
152 153	40	0.003393519	310 311	40	0.001802083
153 154	25	0.022712674	311 312	40	0.002149306
154 159	25	0.022929688	312 313	40	0.002496528
155 156	35	0.000311632	314 315	28	0.000250463
156 157	35	0.000615451	313 315	15	0.098065104
157 158	35	0.000919271	315 530	26	0.098534491
158 159	45	0.001310475			
159 160	25	0.024448785			

Chapter Six

Results and Discussion

The hybrid genetic algorithm developed in this study can be employed to solve several hypothetical as well as real actual problems as a part of the validation and testing of the proposed model (GA-TGA). All the results of applying the proposed model for two benchmarks and two cases study will be illustrated in this chapter.

6.1 Application of a GA-TGA model for the first benchmark example

The performance of the present GA-TGA model is discussed in this example with **directed** and **undirected** base graph into three steps such as follows:

1- Evaluate the selection methods: discuss the results obtained from the proposed model with different selection methods.
2- Evaluate the crossover methods: discuss the results obtained from the proposed model with different crossover methods.
3- Evaluate the size of population: discuss the results obtained from the proposed model with different size of population.

6.1.1 Directed Base Graph

The directed base graph is very useful in the design of sewer networks. The directed base graph reduces greatly the number of possible layouts that can be formed. The performance of the proposed method in the direct base graph in Figure (5-1b), can be evaluated through the following stages:

6.1.1.1 Evaluate Selection Methods

In this section, the present model is tested to find the optimal design of a sewer network for the first benchmark example with different selection methods for Genetic Algorithm. The results are obtained with an Order Crossover method (OX), the probability of crossover (Pc) = 0.9, and the one gene mutation per chromosome, the probability of mutation (Pm) = 0.5.

Figure (6-1) illustrates the convergence curves for a number of generations during the evolutionary process to reach the optimal solution cost by GA-TGA method, with Rank Roulette Wheel Selection (RRWS) method for the directed base graph of the first benchmark example. This method can avoid premature convergence and eliminate the need to scale fitness values, but it can be computationally expensive due to the need of sorting populations. The figure also shows the minimum cost of 5218 units of the optimal design was obtained after 54 generations. This value of the objective function was the same value, which found by Walters and Smith (1995). It is the global minimum cost value that can be obtained in this example.

Figure (6-2) shows the convergence curves for a number of generations during the evolutionary process to reach the optimal solution cost by GA-TGA with Linear Ranking Selection (LRS) method for the directed base graph of the first benchmark example. This method uses the scaled the fitness function between known intervals based on the rank of fitness function as mentioned previously in chapter three. The minimum cost of 5218 units for the optimal design was obtained after 60 generations.

Figure (6-3) shows the convergence curves for a number of generations during the evolutionary process to reach the optimal solution cost by GA-TGA with Truncation Selection (TRS) method for the directed base graph of the first benchmark example. Through the chart shown, this method improve the proposed model to find the optimal solution faster from the previous methods in which obtained the minimum cost 5218 units for the optimal design after 25 generations.

Figure (6-4) also shows the typical convergence curve for a number of generations during the evolutionary process to reach the optimal solution cost by GA-TGA with Tournament Selection (TOS) method for the directed base graph of first sewer network example. Through the results, this method proved powerful and effective to find the optimal solution in which the minimum cost 5218 units for the optimal design was obtained after only 13 generations.

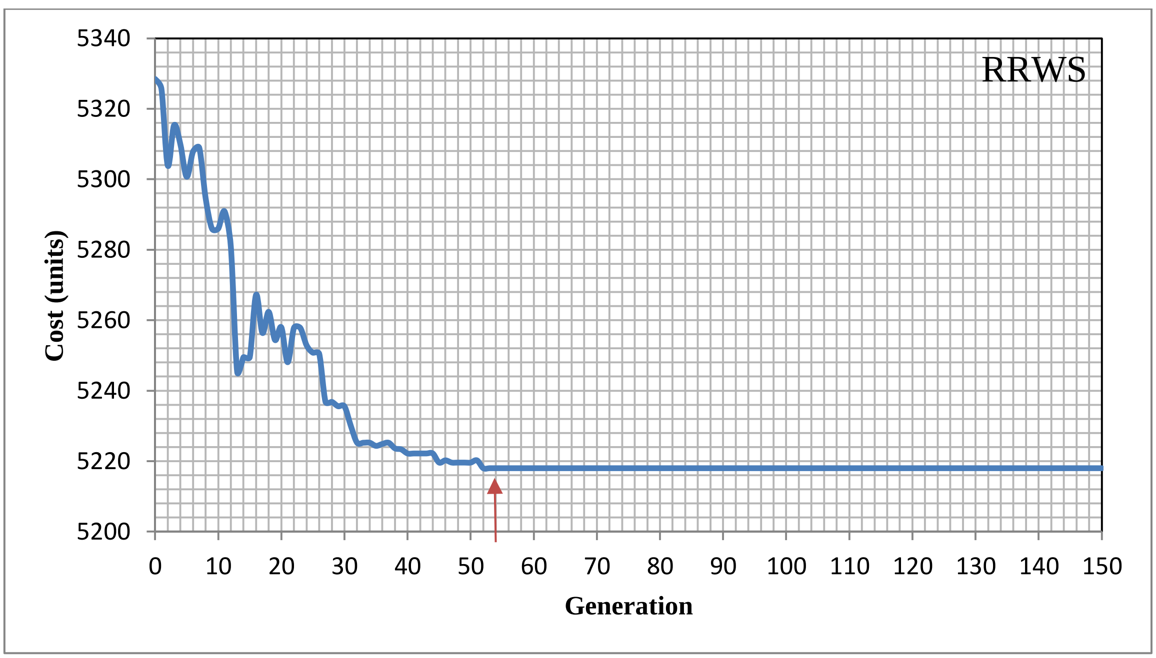


Figure (6-1) The convergence curve for RRWS method by the present model for the directed base graph of the first example.

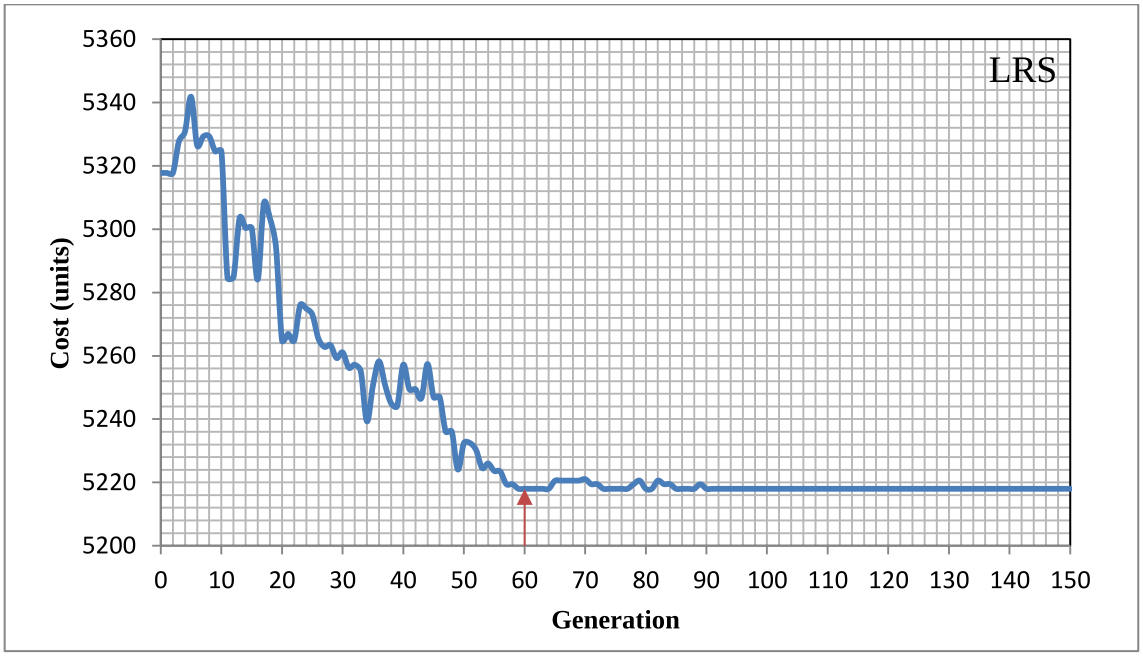


Figure (6-2) The convergence curve for (LRS) method by the present model for the directed base graph of the first example.

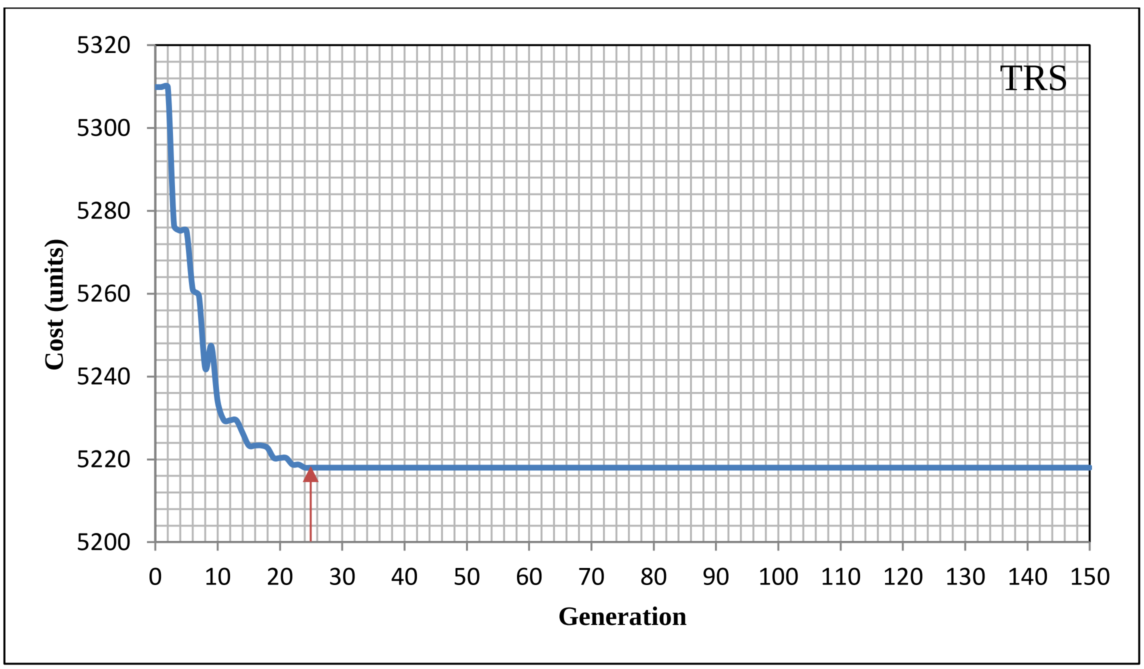


Figure (6-3) The convergence curve for (TRS) method by the present model for the directed base graph of the first example.

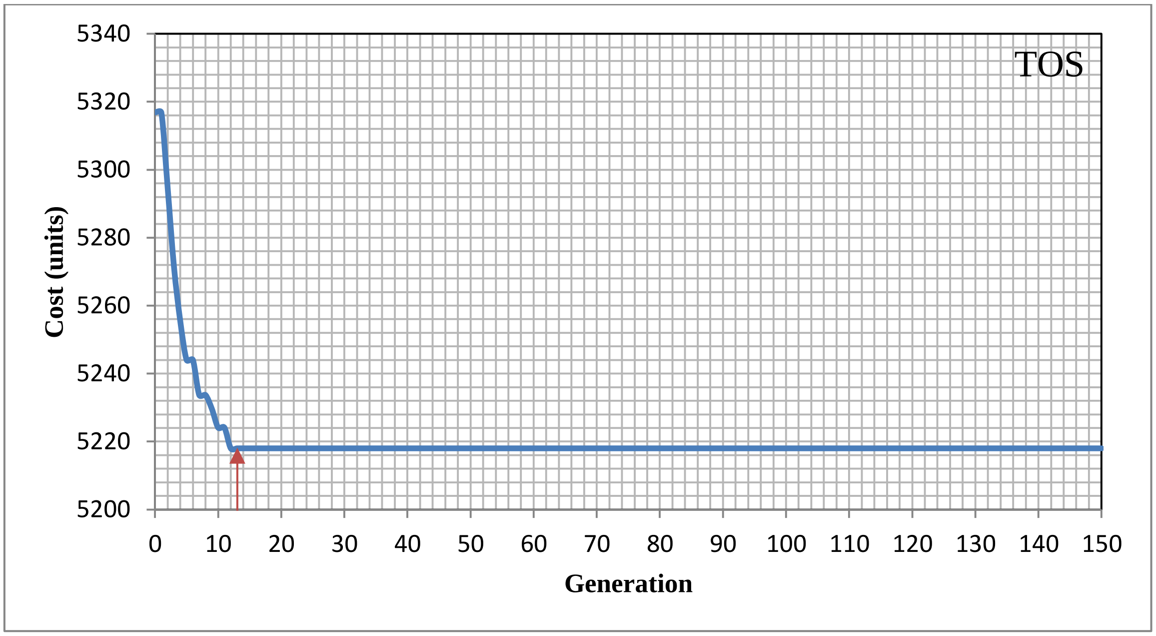


Figure (6-4) The convergence curve for (TOS) method by the present model for the directed base graph of the first example.

Figures (6-5 to 6-7) show the typical convergence curve for a number of generations during the evolutionary process to reach the optimal solution cost by GA-TGA method with the RWS, SUS and RMS selection methods respectively. It is clear from Figure (6-5) that it is not guaranteed to find the globally optimal solution and it can be substantially slower than previous selection methods. This is because the initial population contains one or two very fit but not the best individuals and the rest of the population are not good. Then, these fit individuals will quickly dominate the whole population and prevent the population from exploring other potentially better individuals. Such a strong domination causes a very high loss of genetic diversity, which is definitely not advantageous for the optimisation process. On the other hand, if individuals in a population have very similar fitness values, it will be very difficult for the population to move towards a better one since selection probabilities for fit and unfit individuals are very similar. The best optimal design for the first example 5250.3 units was obtained after 728 generations.

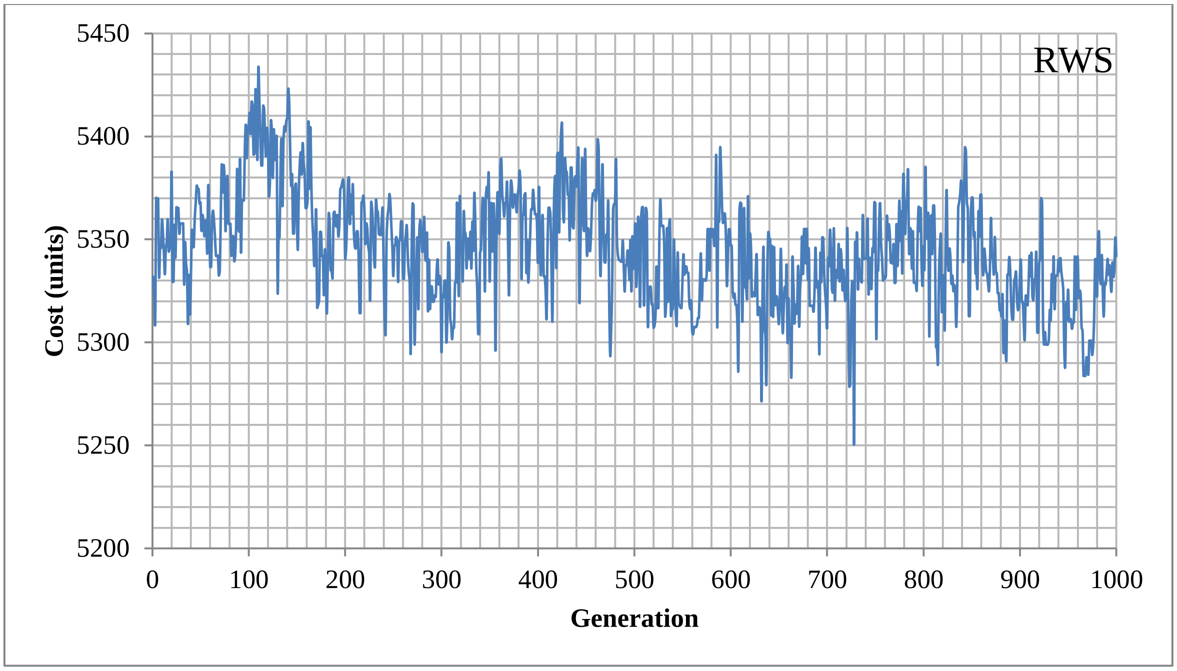


Figure (6-5) The convergence curve for (RWS) method by the present model for the directed base graph of the first example.

Figure (6-6) shows the optimum cost solution for Stochastic Universal Sampling (SUS) method, the existence of more than one optimal solution for the problem with the little disparity between it, but The cost of minimum solution 5268.7 units was obtained after 577 generations.

Figure (6-7) shows the optimum cost solution for Random Selection (RMS) method. The cost for the minimum solution was 5288.15 units obtained after 106 generations.

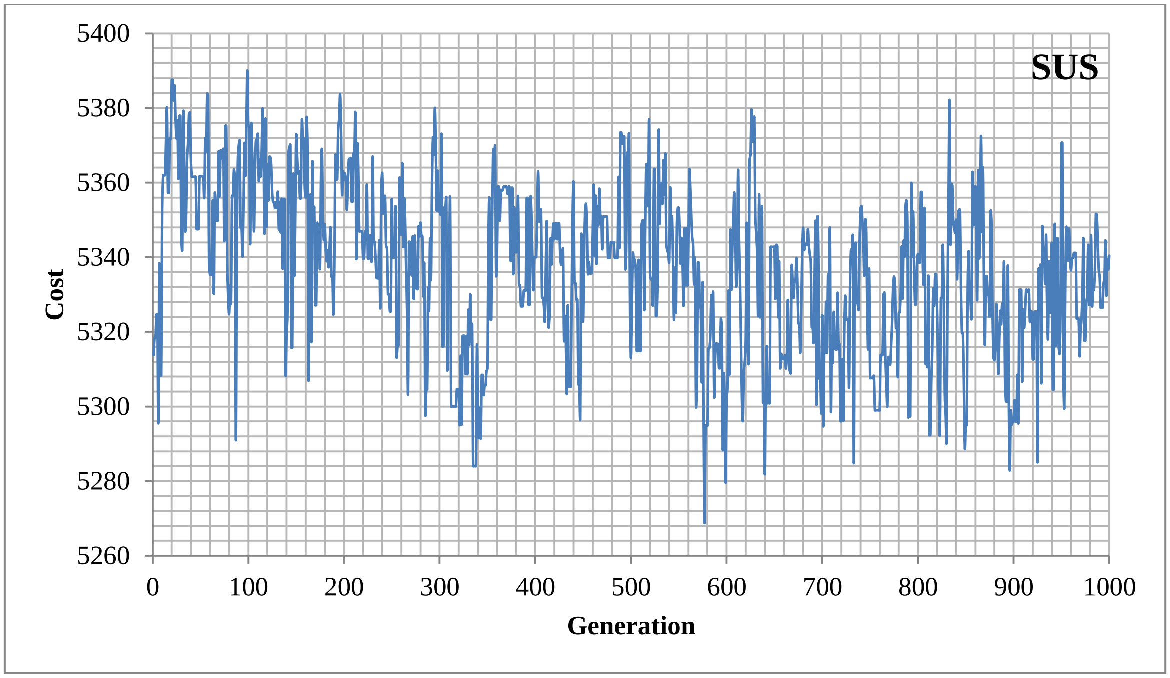


Figure (6-6) The convergence curve for (SUS) method by the present model for the directed base graph of the first example.

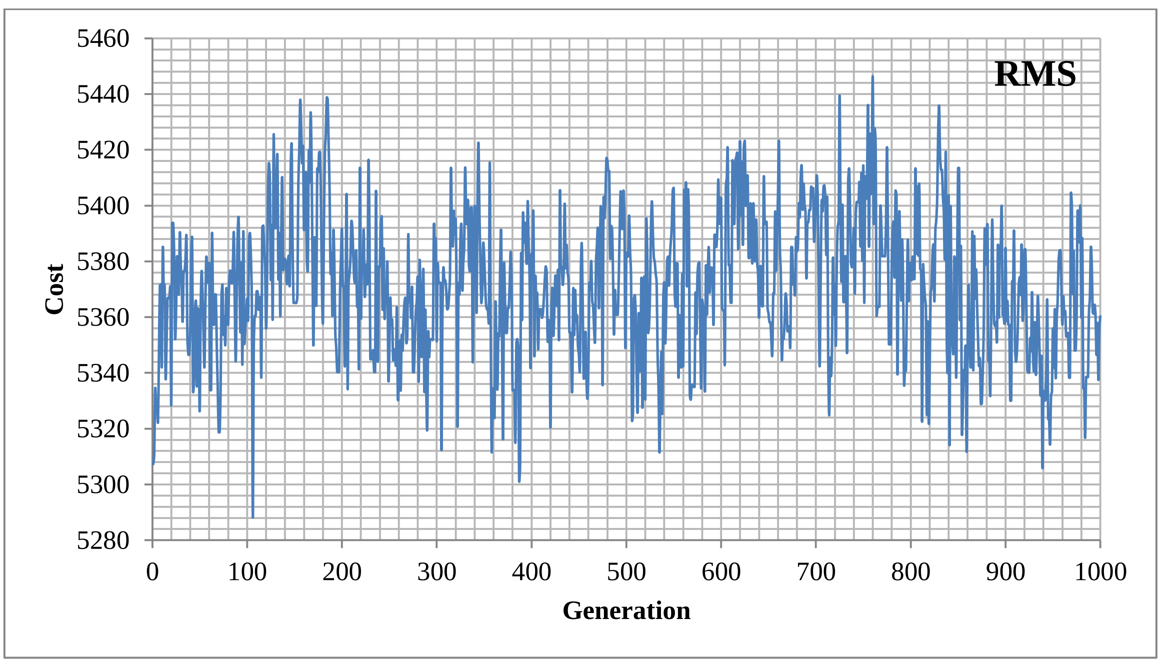


Figure (6-7) The convergence curve for (RMS) method by the present model for the directed base graph of the first example.

It is clear from the foregoing that the number of generations required to reach the final solution is improving with different selection methods. The total cost of the optimum design after 54, 61, 24 and 13 generations was obtained for RRWS, LRS, TRS and TOS selection methods, respectively. The four methods could be reached to the optimum solution (5218 units) but with different generation numbers. The optimum objective function of solution 5218 units was obtained with the Tournament selection (TOS) method, within 13 generations this is the best and fastest method of selection for the GA-TGA model because it reduced in computational effort and time. As for the RRWS, SUS and RMS selection methods, the results of the three methods show that the data are irregular so these methods do not work with the proposed model as shown in Table (6-1).

Table (6-1) The number of generation and min. cost for different selection methods

Method of selection	Generation	Min. cost (units)
RRWS	54	5218
LRS	60	5218
TRS	25	5218
TOS	13	5218
RWS	728	5250.3
SUS	577	5268..7
RMS	106	5288.15

6.1.1.2 Evaluate the Crossover Methods

Shows figure (6-8) the convergence curves for a number of generations during the evolutionary process to reach the optimal solution cost, with two different methods of crossover for a directed base graph of the first benchmark example. The following results are obtained with TOS method (Pc = 0.9) because it provided the best performance compared to other methods, and a one gene mutation per chromosome with a probability of mutation Pm = 0.5. It is clear that the two methods could be reached to the optimum solution, but with different generation numbers. The optimal design was obtained at a total cost of 5218 units after 13 and 38 generations, for Order Crossover on Nodes (OX) and Crossing Operator Based Cloning (CX) methods, respectively. It has been concluded that OX is the best method of crossover in the present model as it found the optimal solution after only 13 generations.

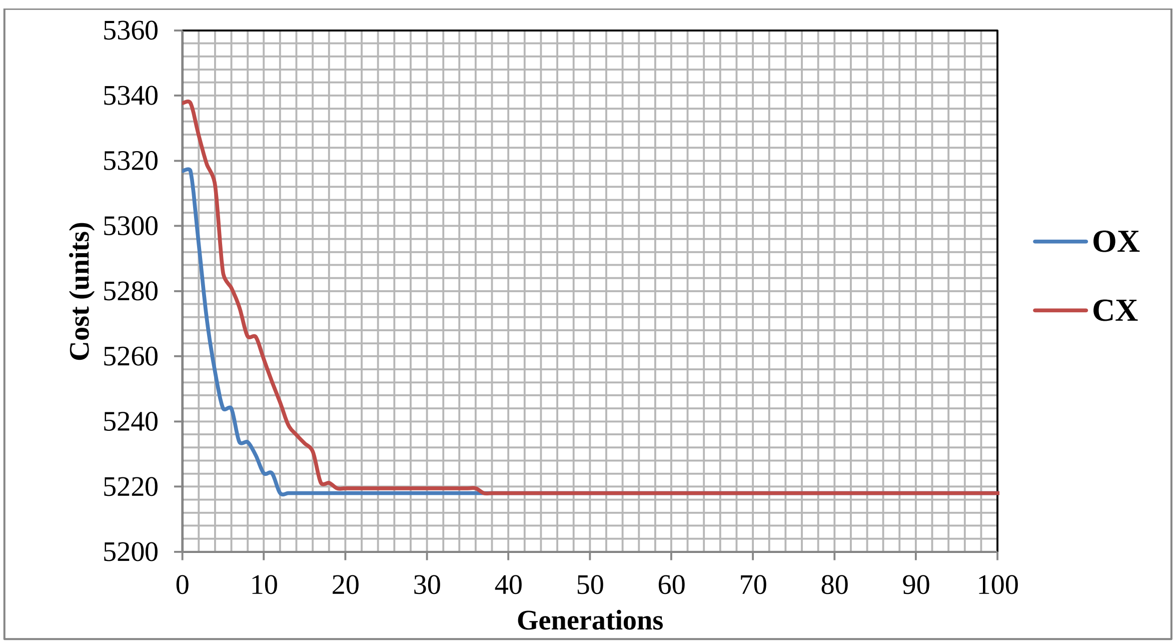


Figure (6-8) The convergence characteristics for two different crossover methods with TOS method by the present model.

6.1.1.3 Evaluate Different Size of Population

Figure (6-9) shows the influences of the size of the population on the performance of the present model during the evolutionary process, for a directed base graph of the first benchmark example. The result was obtained with a TOS method, OX method (Pc = 0.9), and a one gene mutation per chromosome with a probability of mutation Pm = 0.5. As expected, the increase in the size of the population improves the quality of the final solution. For the optimal design the minimum cost (5218 unit) was obtained after 24, 20, 13, 19 and 17 generations, for population sizes of 50, 100, 200, 300 and 500, respectively. Clearly, the increase in the population size may reduce the selection probability of the best member for crossover. Especially at the large networks as in real networks.

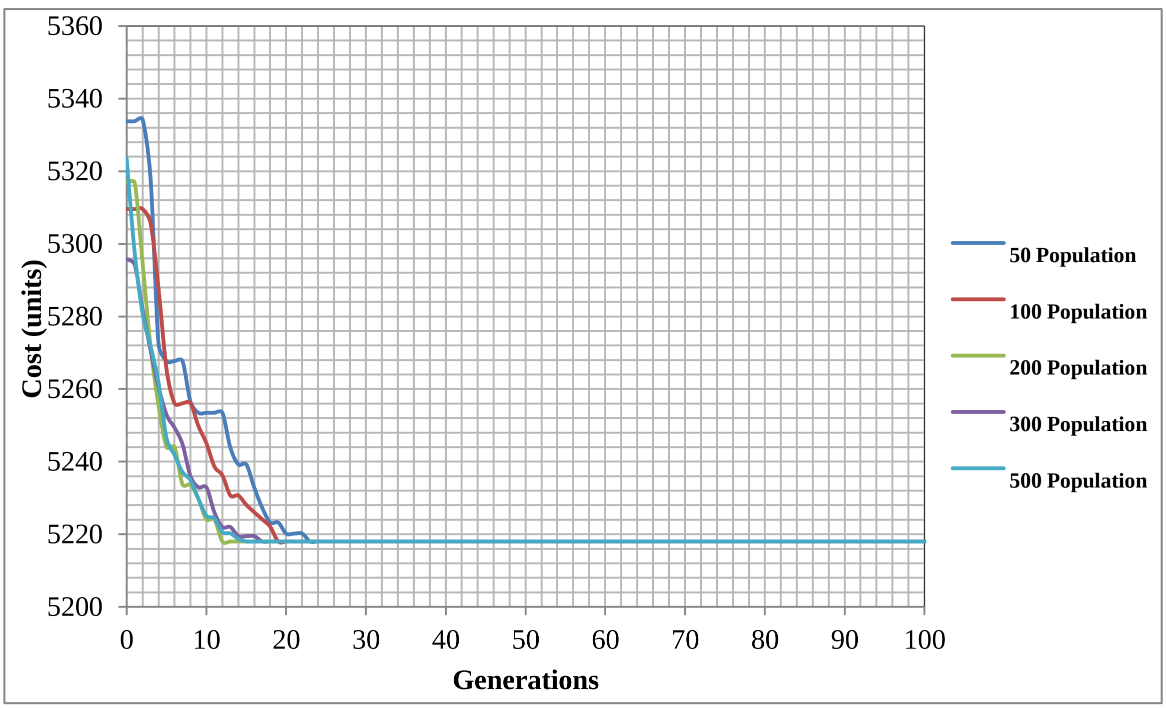


Figure (6-9) The convergence characteristics for different sizes of the population with TOS method by the present model.

Originally, the directed base graph of this example was examined using the Genetic Algorithm method described by Walters and Lohbeck (1993), the minimum cost was found to be 5218 units. Applied the proposed model by running the program repeatedly revealed the same solution (5218 units) only after 13 generations for two layouts of the network. This result was obtained with TOS and OX, as shown in Figure (6-10).

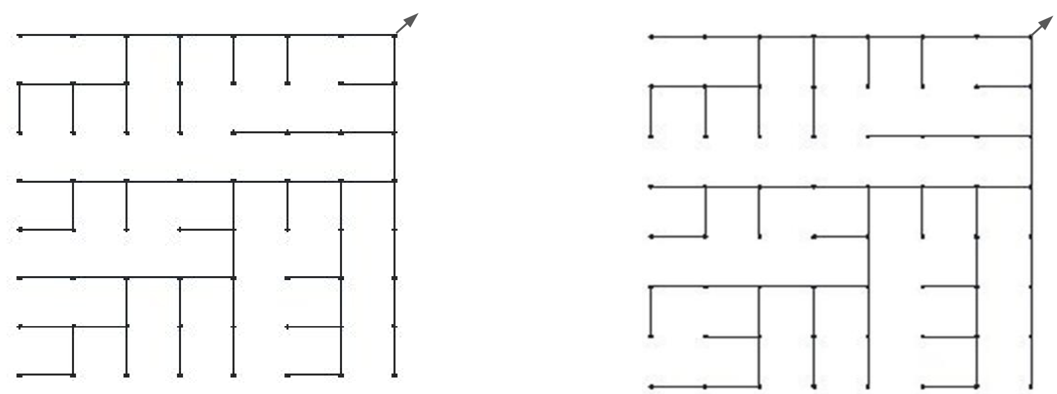


Figure (6-10) Two layout of the same minimum cost (5218 units) obtained from the proposed model.

6.1.2 Undirected Base Graph

The type of undirected method considered to be more difficult and complicated from other methods due to the huge feasible solutions. In the undirected base graph of this example in Figure (5-1a) that described in chapter five, it can generate 1.26×10^{26} possible different layouts, in which each one is a feasible solution to the planning problem (Walters and Lohbeck, 1993).

6.1.2.1 Evaluate Selection Methods

Figure (6-11) illustrates the convergence curves for a number of generations during the evolutionary process to reach the optimal solution cost, with the RRS, TRS and TOS methods for the undirected base graph of the first benchmark example. The following results were obtained with an order crossover method (Pc = 0.9), and a one gene mutation per chromosome with a probability of mutation Pm = 0.5. As expected, the number of generations required to reached the final solution is improved by using different methods of selection. All methods could be reach to the optimum solution 5062.8 units, but with different generation numbers. The optimal design cost (5062.8 units) was obtained after 96, 51 and 31 generations, for the selection methods RRS, TRS and TOS, respectively. Also, TOS method showed much faster than the other used selection methods. It was obtained the best result (5062.8 units) with the method of selecting the TOS, within 31 generations. So the TOS method is the best method to selection in this model. As for the RRWS, LRS, SUS and RMS selection methods, the results of these four methods are irregular data so these methods do not work with the proposed model.

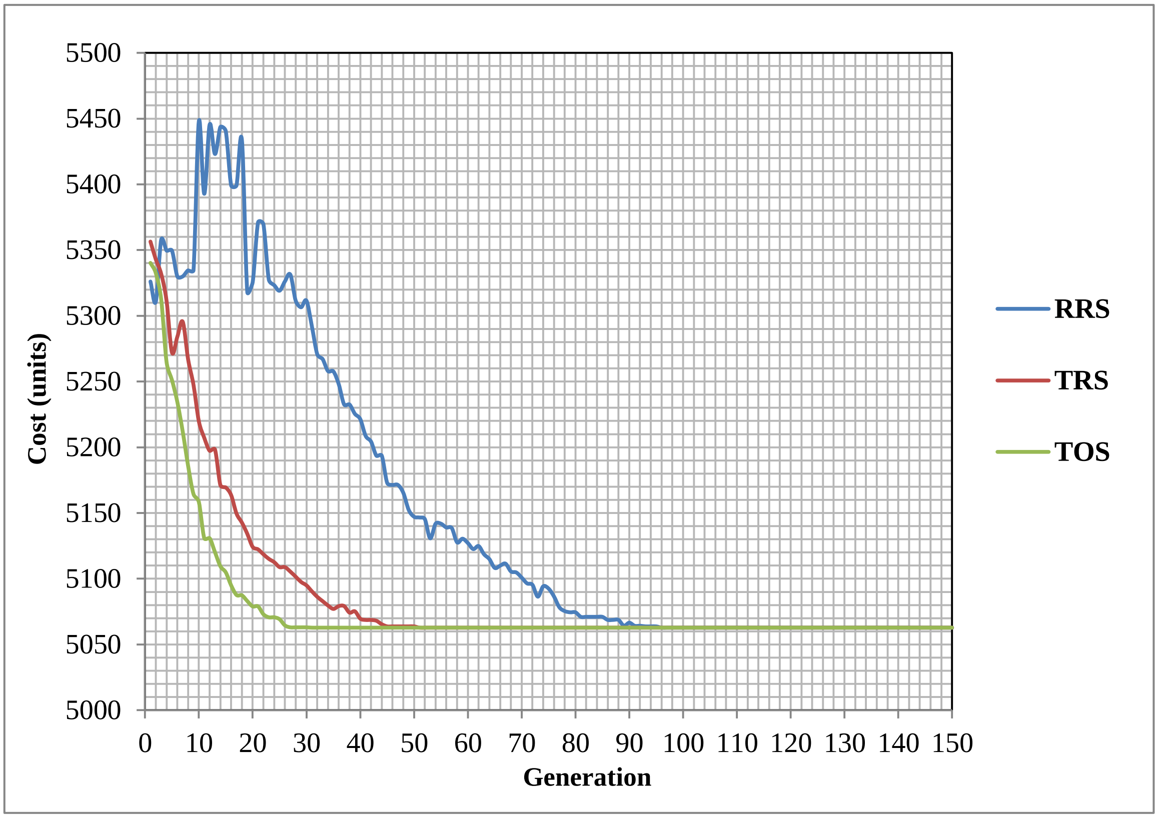


Figure (6-11) The convergence characteristics of generations for different methods of selection by the present model.

6.1.2.2 Evaluate Crossover methods

Figure (6-12) illustrates the convergence curves for a number of generations during the evolutionary process to reach the optimal solution cost, with two different methods of crossover for the undirected base graph of the first benchmark example. The following results were obtained with TOS method, Pc = 0.9, and a one gene mutation per chromosome with a probability of mutation Pm = 0.5. It's clear the two methods could be reached to the optimum solution 5062.8 units, but with different generation numbers. The optimal design was obtained after 31 and 41 generations, for

Order Crossover on Nodes (OX) and Crossing Operator Based Cloning (CX) methods, respectively. Thus, OX method is the best method of crossover in the proposed model because it reaches the optimum solution after only 31 generation.

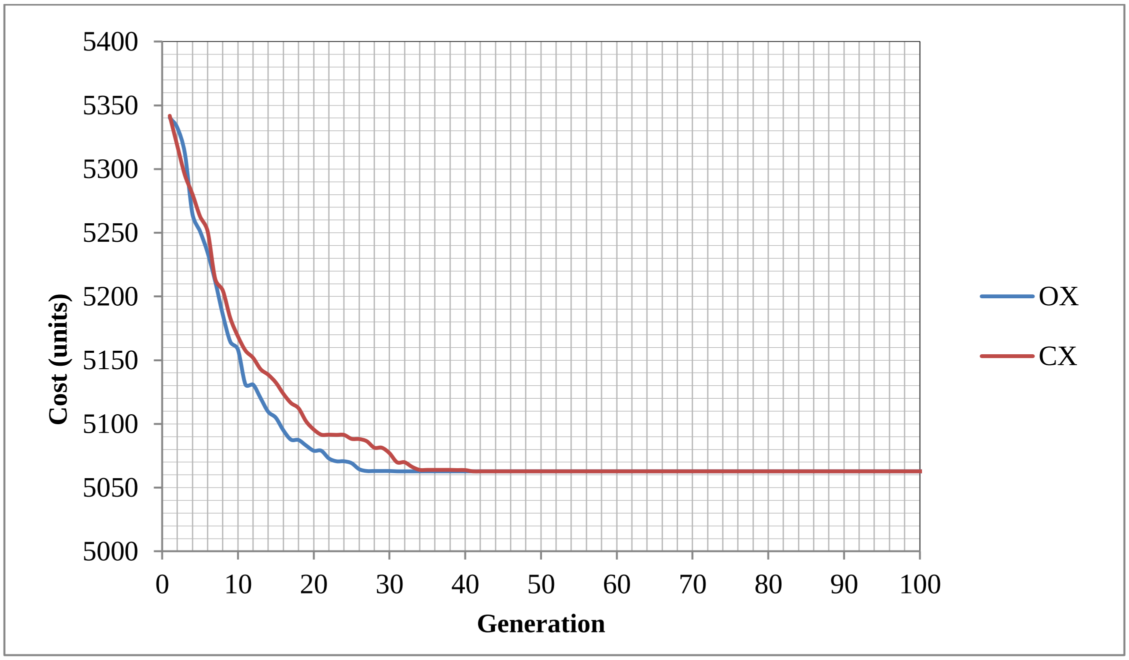


Figure (6-12) The convergence characteristics of generations for two different crossover methods with TOS method by the present model.

6.1.2.3 Evaluate Different Size of Population

Finally, Figure (6-13) illustrates the influences of the size of the population on the performance of the present model during the evolutionary process, for the undirected base graph of the first benchmark example. The following results were obtained with a TOS method, OX method (Pc = 0.9), and a one gene mutation per chromosome with a probability of mutation Pm = 0.5. For the optimal design, the minimum cost of 5062.8 units was obtained after 92, 38, 31, 32 and 45 generations, for population sizes of 50, 100, 200, 300 and 500, respectively. Clearly, the increase in the population size may reduce the selection probability of the best member for crossover.

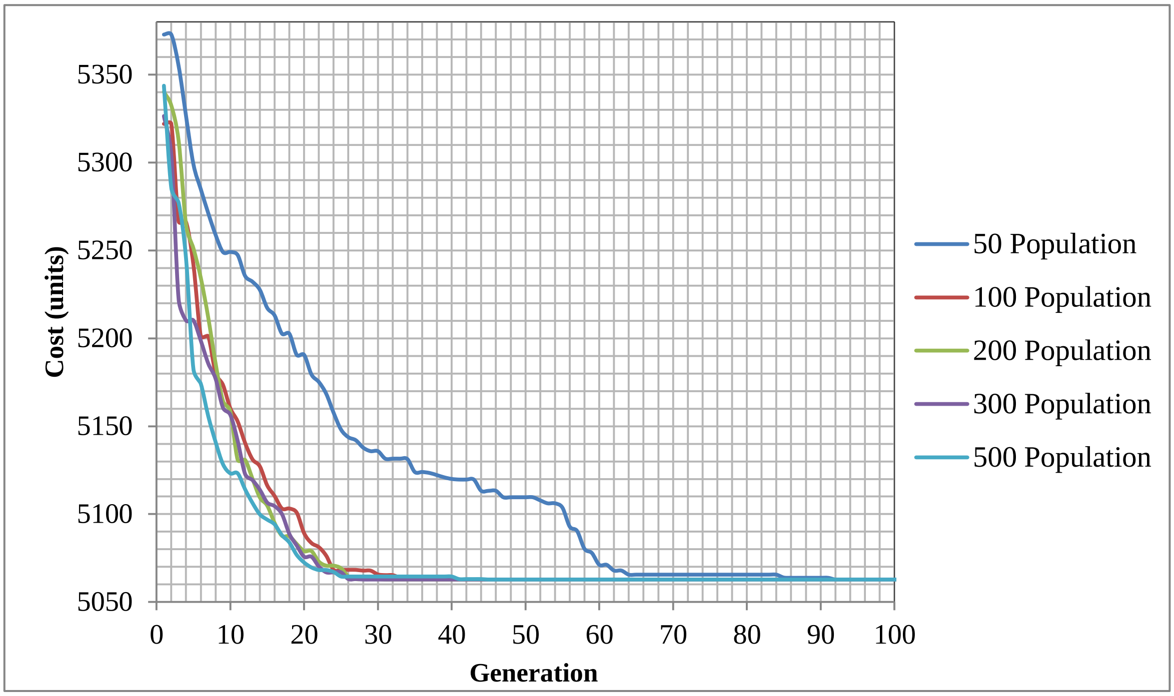
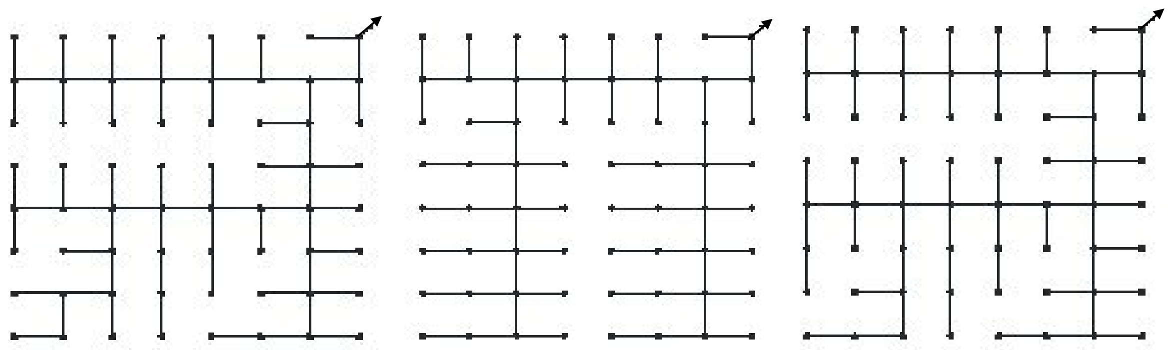


Figure (6-13) The convergence characteristics of generations for different sizes of the population with TOS method by present model.

Originally, the undirected base graph of the first example was proposed and solved by Walters and Smith (1995) using Evolutionary Progresses EP. Later solved by many researchers; (Geem et al., 2000) and (Afshar and Mariño, 2006) to test the Harmony Search HS and the Ant Colony Algorithm method ACO, respectively. By repeatedly running the program with TOS and OX methods, a minimum cost 5062.8 units was obtained, exactly the same as the optimal solutions cost obtained from EP, HS and ACO shown in Figure (6-14c), but EP produced a reasonable solution within 3200 generations, HS found the same solution after 1497 generations and ACO found the same solution after 4880 generations, while the proposed model found the same solution only after 31 iterations and took about (3-5) min to solve the example. It is clear from the above that the proposed (GA-TGA) model reaches the final solution with a number of generations less than the other methods, and moreover, the number of generations is very small compared to all other methods as shown in Table (6-2).

In order to illustrate the performance of the proposed method, Figure (6-14) shows the top three solutions with its costs from the proposed model (GA-TGA) computations.



a) Cost = 5064.5 units b) Cost = 5063.3 c) Cost = 5062.8 units

Figure (6-14) (a) Third Best Solution; (b) Second Best Solution; and (c) The Best Solution.

Table (6-2) first benchmark problem compared with other researchers

Undirected base graph			
Model	**Method**	**Cost (units)**	**No. of Evaluation**
Walter and Smith (1995)	EP	5062.8	3200
Geem, Z.W., Kim, T.G. and Kim, 2000	HS	5062.8	1497
(Afshar and Mariño, 2006	ACO	5062.8	4880
Present model	GA-TGA	5062.8	31
Directed base graph			
Walters and Lohbeck (1993)	EP	5218	—
Present model	GA-TGA	5218	13

6.2 Application of a GA-TGA model for the second benchmark example

Figure (6-15) shows the performance of the proposed GA-TGA model with the second benchmark example. The result was obtained with a Tournament selection method (TOS), Order crossover (OX) were the best method worked with a present model in previous benchmark example, the probability of crossover Pc = 0.9, one-gene mutation per chromosome, the probability of mutation Pm = 0.5, and population size equal to 200 chromosomes. Repeatedly running the program with TOS and OX methods the optimum layout with minimum cost equal 2.45497E5 units is gained in only 12 generations, while when using the objective function (equation (4-1) described in chapter four) to calculate the cost of each of the layouts obtained from using the DDDP model, and The GA/SSOM/LH model as shown in Figures (6-16)b and (6-16)c, the results obtained 2.47182E5 units, and 2.51469E5 units respectively. Compared with the optimum solutions obtained from other methods the cost of the present model is lower, Figure (6-16)d shows layout obtained from the proposed model.

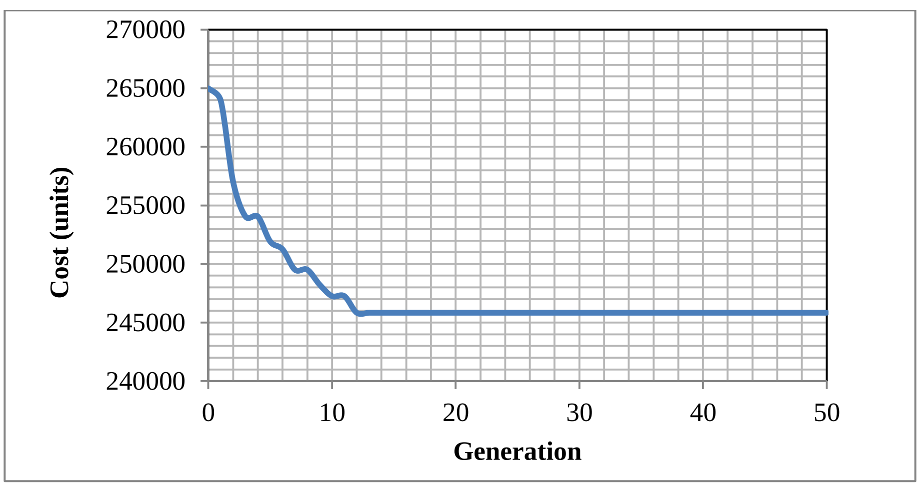
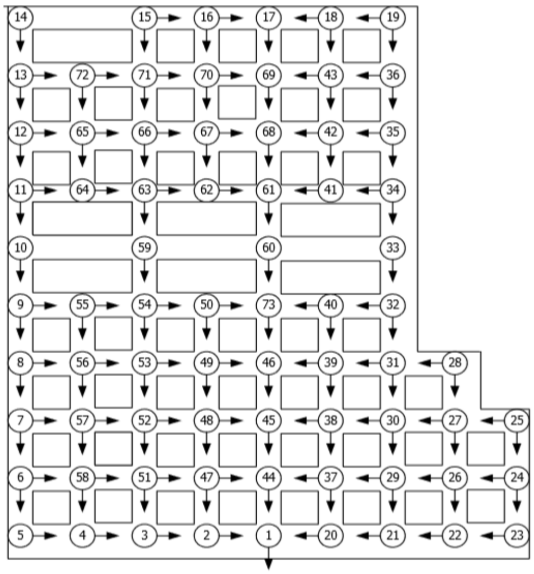
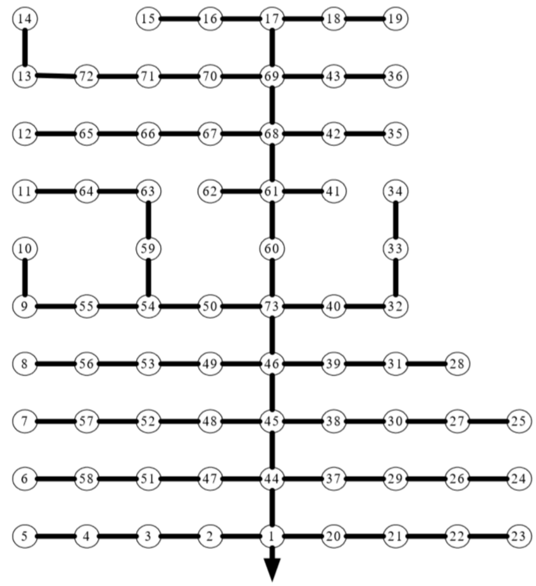


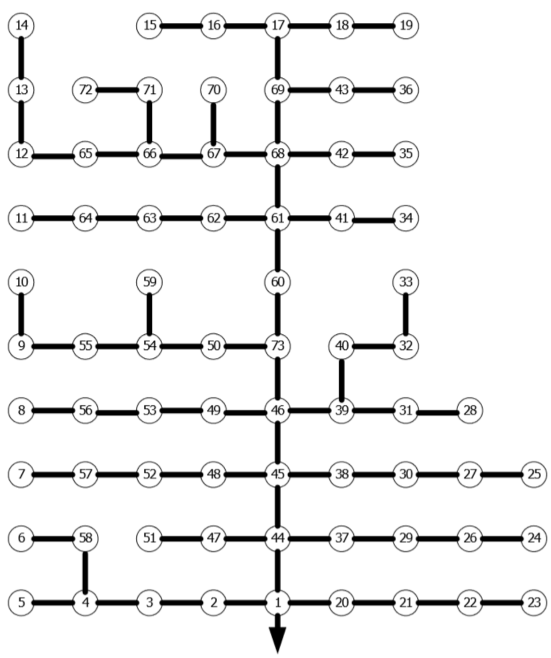
Figure (6-15) The optimum cost solution by the proposed GA-TGA model for second benchmark example.



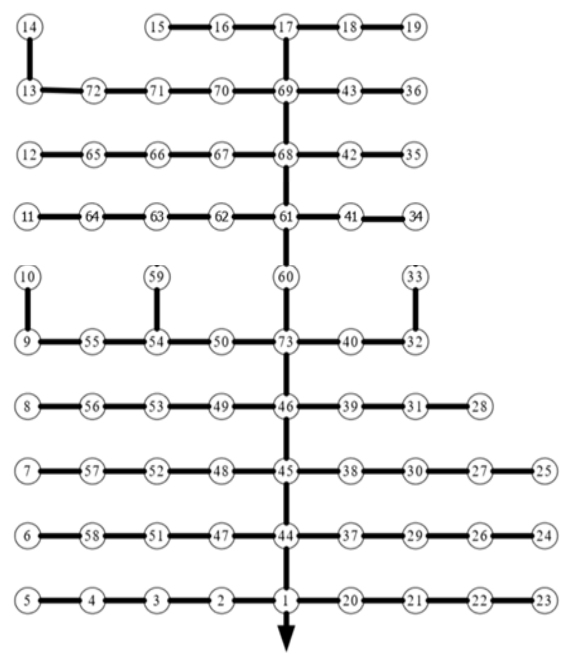
a-The street layout plan of 73 nodes (Weng and Liaw, 2005).



b- Layout obtained using DDDP model (Wen and Shih, 1983).



c- Layout obtained using GA/SSOM/LH model (Weng and Liaw, 2005).



d- Layout obtained using present model

Figure (6-16) Optimum designs for the second benchmark example.

In order to consider the problem with general forms, the constriction cost of sewer networks will be obtained from hydraulic design. The layout problem was considered here and an attempt will be made to design the size of pipes. However, there is no guarantee that the method will reach the global optimal solution. It also seems that for flat areas, the simplified objective function is used as a suitable standard to optimised individually the layout sub-problem.

Table (6-3) shows the results of the application different of optimisation methods. The last three results have been optimized by the (GA-HP). Also, the table shows the cost savings achieved by the proposed model in comparison with the different design of models. It can be seen that the cost of the present model is 24.5%, 3.6%, and 1.36% less, from alternative 1, 3, and 4 respectively, and requiring much less computational effort, while alternative 2 less than proposed model because the first is an integrated optimisation model that solves the two sub-problems simultaneously. Therefore, the proposed algorithm is very promising to be part of an integrated and global optimisation model in future research. The characteristics of the best layouts solution obtained from hydraulic design for last three alternatives designed by GA-HP hydraulic model are shown in Tables (6-4), (6-5) and (6-6), respectively.

Table (6-3): Optimisation methods and optimal sewer networks cost for the second benchmark example.

Number	Alternative	Cost (NT$)
1	DDDP design model (Wen and Shih, 1983)	1,752,050
2	GA/SSOM/LH design model (Weng and Liaw, 2005)	1,297,820
3	GA-HP design, layout created by DDDP model	1,372,884
4	GA-HP design, layout created by GA/SSOM/LH model	1,341,579
5	GA-HP design, layout created by proposed (GA-TGA) model.	1,323,342

Table (6-4): The Results obtained with the GA-HP design and layout created by DDDP model.

Manhole		Flowrate	Length	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	CMD	M	%	M	U/S	D/S	U/S	D/S	M/S
1	1	20884.4	0	0	0	0	0	4.81	4.81	0
2	1	1159	80	0.44	0.2	1.69	1.34	4.79	4.81	0.65
3	2	747.3	80	0.47	0.2	2.06	1.69	4.79	4.79	0.60
4	3	461.1	80	0.67	0.2	2.59	2.06	4.74	4.79	0.60
5	4	160.5	80	1.58	0.2	3.86	2.59	4.76	4.74	0.60
6	58	301.1	80	0.94	0.2	4.08	3.33	4.98	4.83	0.60
7	57	295	80	0.95	0.2	3.90	3.14	4.8	4.75	0.60
8	56	307.1	80	0.92	0.2	3.90	3.16	4.8	5	0.60
9	55	719.2	82	0.50	0.25	2.35	1.94	4.9	5.05	0.60
10	9	396.4	78	0.80	0.25	2.98	2.35	4.9	4.9	0.60
11	64	554.9	80	0.58	0.2	4.00	3.54	4.9	5	0.60
12	65	301.1	80	0.94	0.2	3.62	2.87	4.9	5.25	0.60
13	72	786.6	80	0.45	0.2	3.04	2.68	5.07	5.2	0.60
14	13	337	133	0.86	0.2	4.18	3.04	5.08	5.07	0.60
15	16	496.1	80	0.63	0.2	4.32	3.82	5.22	5.25	0.60
16	17	803.3	80	0.44	0.2	3.82	3.46	5.25	5.3	0.60
17	69	1560.3	135	0.44	0.2	2.81	2.21	5.3	5.45	0.68
18	17	496.1	80	0.63	0.2	3.31	2.81	5.35	5.3	0.60
19	18	172.9	80	1.49	0.2	4.50	3.31	5.4	5.35	0.60
20	1	1105.1	75	0.44	0.2	1.67	1.34	4.77	4.81	0.64
21	20	691	80	0.49	0.2	2.06	1.67	4.77	4.77	0.60
22	21	402.4	80	0.74	0.2	2.66	2.06	4.74	4.77	0.60
23	22	129.2	60	1.90	0.2	3.80	2.66	4.7	4.74	0.60
24	26	258.8	70	1.06	0.2	3.87	3.13	4.77	4.77	0.60

Table (6-4): Continued.

Manhole		Flowrate	Length	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	CMD	M	%	M	U/S	D/S	U/S	D/S	M/S
25	27	129.2	78	1.90	0.2	3.87	2.39	4.77	4.86	0.60
26	29	769.8	80	0.46	0.2	3.13	2.76	4.77	4.87	0.60
27	30	530.9	90	0.60	0.2	2.39	1.85	4.86	4.93	0.60
28	31	154.2	80	1.64	0.2	4.12	2.81	5.02	5.02	0.60
29	37	1292.5	80	0.44	0.2	2.76	2.41	4.87	4.81	0.66
30	38	1056.4	80	0.44	0.2	1.85	1.50	4.93	4.84	0.64
31	39	588.4	80	0.55	0.2	2.81	2.37	5.02	5.01	0.60
32	10	1034.6	81	0.38	0.25	3.28	2.98	5.05	5.05	0.60
33	32	724.8	78	0.48	0.2	3.65	3.28	5.05	5.05	0.60
34	33	360.9	80	0.81	0.2	4.30	3.65	5.2	5.05	0.60
35	12	313.1	80	0.91	0.2	4.35	3.62	5.25	5.3	0.60
36	43	319.1	80	0.89	0.2	4.35	3.63	5.25	5.35	0.60
37	44	1791.9	80	0.33	0.25	2.41	2.15	4.81	4.81	0.65
38	45	1555.1	80	0.44	0.2	1.50	1.14	4.84	4.91	0.68
39	46	1132.1	80	0.44	0.2	2.37	2.02	5.01	5.01	0.65
40	73	1303.2	90	0.44	0.2	4.15	3.75	5.05	5.05	0.67
41	61	325.1	78	0.88	0.2	4.30	3.61	5.2	5.2	0.60
42	68	886.6	80	0.44	0.2	4.40	4.05	5.3	5.3	0.61
43	69	892.1	80	0.44	0.2	3.63	3.28	5.35	5.45	0.61
44	1	19613.8	124	0.42	0.5	0.43	-0.09	4.81	4.81	1.22
45	44	17078.9	115	0.32	0.5	0.80	0.43	4.91	4.81	1.06
46	45	14678	120	0.24	0.5	1.09	0.80	5.01	4.91	0.91
47	44	1888.5	80	0.33	0.25	2.63	2.37	4.85	4.81	0.66
48	45	1832.6	80	0.33	0.25	2.43	2.17	4.82	4.91	0.65
49	46	1901.2	90	0.33	0.25	2.46	2.16	5.01	5.01	0.66
50	73	3509.7	90	0.17	0.4	1.45	1.30	5.1	5.05	0.61
51	47	1371.9	80	0.44	0.2	2.98	2.63	4.78	4.85	0.67
52	48	1345.5	80	0.44	0.2	2.79	2.43	4.81	4.82	0.67
53	49	1395.6	80	0.44	0.2	2.81	2.46	5	5.01	0.67
54	50	3277.1	80	0.17	0.4	1.59	1.45	5.1	5.1	0.60
55	54	991	90	0.39	0.25	1.94	1.59	5.05	5.1	0.60
56	53	867.2	80	0.44	0.2	3.16	2.81	5	5	0.61
57	52	836.7	80	0.44	0.2	3.14	2.79	4.75	4.81	0.60
58	51	853.4	80	0.44	0.2	3.33	2.98	4.83	4.78	0.61
59	54	1913.8	78	0.33	0.25	2.78	2.53	5	5.1	0.66
60	73	8589.9	78	0.15	0.45	1.43	1.31	5.1	5.05	0.68
61	60	8092.8	80	0.15	0.45	1.55	1.43	5.2	5.1	0.68
62	61	325.1	80	0.88	0.2	4.10	3.40	5	5.2	0.60
63	59	1255.3	78	0.44	0.2	3.12	2.78	5.1	5	0.66

Table (6-4): Continued.

Manhole From	Manhole to	Flowrate CMD	Length M	Slope %	Diameter M	Crown Elevation(M) U/S	Crown Elevation(M) D/S	Ground Elevation(M) U/S	Ground Elevation(M) D/S	Velocity M/S
64	63	645.6	80	0.52	0.2	3.54	3.12	5	5.1	0.60
65	66	864.5	80	0.44	0.2	2.87	2.52	5.25	5.4	0.61
66	67	1403.5	80	0.44	0.2	2.52	2.17	5.4	5.35	0.67
67	68	1918.9	80	0.33	0.25	2.17	1.91	5.35	5.3	0.66
68	61	7213.6	130	0.15	0.45	1.74	1.55	5.3	5.2	0.68
69	68	4699.7	120	0.21	0.35	1.99	1.74	5.45	5.3	0.68
70	69	2244	80	0.22	0.35	2.17	1.99	5.45	5.45	0.60
71	70	1730.5	80	0.27	0.3	2.38	2.17	5.4	5.45	0.60
72	71	1050.9	80	0.37	0.25	2.68	2.38	5.2	5.4	0.60
73	46	12414	124	0.17	0.5	1.30	1.09	5.05	5.01	0.77

Table (6-5): The Results obtained with the GA-HP design and layout created by GA/SSOM/LH model.

Manhole From	Manhole to	Length M	Flowrate CMD	Slope %	Diameter M	Crown Elevation(M) U/S	Crown Elevation(M) D/S	Ground Elevation(M) U/S	Ground Elevation(M) D/S	Velocity M/S
1	1	0	20884.4	0	0	0	0	4.81	4.81	0
2	1	80	1908.8	0.86	0.25	2.07	1.81	4.79	4.81	0.66
3	2	80	1523.9	0.45	0.25	2.33	2.07	4.79	4.79	0.63
4	3	80	1260.6	1.49	0.25	2.59	2.33	4.74	4.79	0.60
5	4	80	160.5	0.63	0.2	3.86	2.59	4.76	4.74	0.60
6	58	80	301.1	0.94	0.2	4.08	3.33	4.98	4.83	0.60
7	57	80	295	0.37	0.2	3.90	3.14	4.8	4.75	0.60
8	56	80	307.1	0.89	0.2	3.90	3.16	4.8	5	0.60
9	55	82	719.2	0.63	0.2	3.41	3.02	4.9	5.05	0.60
10	9	78	396.4	0.44	0.2	4.00	3.41	4.9	4.9	0.60
11	64	80	354.9	0.44	0.2	4.00	3.34	4.9	5	0.60
12	65	80	1050.9	0.28	0.25	2.48	2.19	4.9	5.25	0.60
13	12	120	786.6	0.82	0.2	3.03	2.48	5.07	4.9	0.60
14	13	135	337	0.44	0.2	4.18	3.03	5.08	5.07	0.60
15	16	80	496.1	0.33	0.2	4.32	3.82	5.22	5.25	0.60
16	17	80	803.3	0.53	0.2	3.82	3.46	5.25	5.3	0.60
17	69	135	1560.3	0.19	0.25	2.81	2.37	5.3	5.45	0.63
18	17	80	496.1	0.91	0.2	3.31	2.81	5.35	5.3	0.60
19	18	80	172.9	0.52	0.2	4.50	3.31	5.4	5.35	0.60
20	1	75	1105.1	0.75	0.2	1.67	1.34	4.77	4.81	0.64
21	20	80	691	0.26	0.2	2.06	1.67	4.77	4.77	0.60
22	21	80	402.4	0.17	0.2	2.66	2.06	4.74	4.77	0.60
23	22	60	129.2	0.44	0.2	3.80	2.66	4.7	4.74	0.60

Table (6-5): Continued.

Manhole		Length	Flowrate	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	M	CMD	%	M	U/S	D/S	U/S	D/S	M/S
24	26	70	258.8	0.44	0.2	3.87	3.13	4.77	4.77	0.60
25	27	78	129.2	0.81	0.2	3.87	2.39	4.77	4.86	0.60
26	29	80	769.8	0.48	0.2	3.13	2.76	4.77	4.87	0.60
27	30	90	530.9	0.15	0.2	2.39	1.85	4.86	4.93	0.60
28	31	80	154.2	0.44	0.2	4.12	2.81	5.02	5.02	0.60
29	37	80	1292.5	0.51	0.2	2.76	2.41	4.87	4.81	0.66
30	38	80	1056.4	0.46	0.2	1.85	1.50	4.93	4.84	0.64
31	39	80	588.4	0.44	0.2	2.81	2.37	5.02	5.01	0.60
32	40	84	713.6	0.92	0.2	3.56	3.15	5.05	5.05	0.60
33	32	78	390.5	0.76	0.2	4.15	3.56	5.05	5.05	0.60
34	41	82	360.9	0.95	0.2	4.30	3.64	5.2	5.2	0.60
35	42	80	313.1	0.13	0.2	4.35	3.62	5.25	5.3	0.60
36	43	80	319.1	0.33	0.2	4.35	3.63	5.25	5.35	0.60
37	44	80	1791.9	0.44	0.25	2.41	2.15	4.81	4.81	0.65
38	45	80	1555.1	0.48	0.2	1.50	1.14	4.84	4.91	0.68
39	46	80	2009.6	1.64	0.25	2.37	2.11	5.01	5.01	0.66
40	39	100	991	1.90	0.2	3.15	2.71	5.05	5.01	0.63
41	61	78	662.6	0.44	0.2	3.64	3.24	5.2	5.2	0.60
42	68	80	886.6	0.13	0.2	3.62	3.27	5.3	5.3	0.61
43	69	80	892.1	0.33	0.2	3.63	3.28	5.35	5.45	0.61
44	1	124	19140	0.44	0.5	0.43	-0.07	4.81	4.81	1.19
45	44	115	17078.9	0.44	0.5	0.80	0.43	4.91	4.81	1.06
46	45	120	14678	0.55	0.5	1.08	0.80	5.01	4.91	0.91
47	44	80	1137.5	0.60	0.2	3.43	3.08	4.85	4.81	0.65
48	45	80	1832.6	1.06	0.25	2.43	2.17	4.82	4.91	0.65
49	46	90	1901.2	0.94	0.25	2.46	2.16	5.01	5.01	0.66
50	73	90	2475	0.44	0.25	2.36	2.07	5.1	5.05	0.68
51	47	80	582.7	0.15	0.2	3.88	3.43	4.78	4.85	0.60
52	48	80	1345.5	0.33	0.2	2.79	2.43	4.81	4.82	0.67
53	49	80	1395.6	0.33	0.2	2.81	2.46	5	5.01	0.67
54	50	80	2229.2	0.44	0.25	2.63	2.36	5.1	5.1	0.68
55	54	90	991	0.46	0.2	3.02	2.63	5.05	5.1	0.63
56	53	80	867.2	1.90	0.2	3.16	2.81	5	5	0.61
57	52	80	836.7	0.44	0.2	3.14	2.79	4.75	4.81	0.60
58	4	124	853.4	1.58	0.2	3.33	2.78	4.83	4.78	0.61
59	54	78	758.6	0.56	0.2	4.10	3.74	5	5.1	0.60
60	73	78	9659.1	0.33	0.5	1.37	1.27	5.1	5.05	0.68
61	60	80	9174.2	0.24	0.5	1.48	1.37	5.2	5.1	0.68
62	61	80	1529.1	0.44	0.2	2.58	2.23	5	5.2	0.68

Table (6-5): Continued.

Manhole		Length	Flowrate	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	M	CMD	%	M	U/S	D/S	U/S	D/S	M/S
63	62	80	1255.3	0.44	0.2	2.93	2.58	5.1	5	0.66
64	63	80	645.6	0.74	0.2	3.34	2.93	5	5.1	0.60
65	66	80	1570.7	0.33	0.3	2.19	1.96	5.25	5.4	0.60
66	67	80	2942.3	0.44	0.4	1.96	1.81	5.4	5.35	0.60
67	68	80	3881.2	0.32	0.4	1.81	1.67	5.35	5.3	0.62
68	61	130	7213.6	0.33	0.45	1.67	1.48	5.3	5.2	0.68
69	68	120	2818.2	0.49	0.3	2.37	2.06	5.45	5.3	0.66
70	67	120	617.1	0.33	0.2	4.55	3.91	5.45	5.35	0.60
71	66	120	1034.6	0.40	0.2	3.55	3.02	5.4	5.4	0.63
72	71	80	301.1	0.44	0.2	4.30	3.55	5.2	5.4	0.60
73	46	124	11797.7	0.33	0.5	1.27	1.08	5.05	5.01	0.73

Table (6-6): The Results obtained with the GA-HP design and layout created by proposed (GA-TGA) model

Manhole		Flowrate	Length	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	CMD	M	%	M	U/S	D/S	U/S	D/S	M/S
1	1	20884.9	0	0	0	0	0	4.81	4.81	0
2	1	1055.4	80	0.86	0.2	1.60	1.25	4.79	4.81	0.64
3	2	670.5	80	0.45	0.2	2.01	1.60	4.79	4.79	0.60
4	3	407.2	80	0.36	0.2	2.59	2.01	4.74	4.79	0.60
5	4	160.5	80	1.49	0.2	3.86	2.59	4.76	4.74	0.60
6	58	301.1	80	0.63	0.2	4.08	3.33	4.98	4.83	0.60
7	57	295	80	1.04	0.2	3.90	3.14	4.8	4.75	0.60
8	56	307.1	80	0.26	0.2	3.90	3.16	4.8	5	0.60
9	55	719.2	82	0.89	0.2	3.41	3.02	4.9	5.05	0.60
10	9	396.4	78	0.63	0.2	4.00	3.41	4.9	4.9	0.60
11	64	354.9	80	0.44	0.2	4.00	3.34	4.9	5	0.60
12	65	264.3	80	0.45	0.2	4.00	3.17	4.9	5.25	0.60
13	72	786.6	80	0.82	0.2	3.04	2.68	5.07	5.2	0.60
14	13	337	133	0.21	0.2	4.18	3.04	5.08	5.07	0.60
15	16	496.1	80	0.44	0.2	4.32	3.82	5.22	5.25	0.60
16	17	803.3	80	0.44	0.2	3.82	3.46	5.25	5.3	0.60
17	69	1560.8	135	0.44	0.2	2.81	2.21	5.3	5.45	0.68
18	17	496.6	80	0.91	0.2	3.31	2.81	5.35	5.3	0.60
19	18	172.9	80	0.52	0.2	4.50	3.31	5.4	5.35	0.60
20	1	1105.1	75	0.75	0.2	1.67	1.34	4.77	4.81	0.64
21	20	691	80	0.15	0.2	2.06	1.67	4.77	4.77	0.60
22	21	402.4	80	0.44	0.2	2.66	2.06	4.74	4.77	0.60

Table (6-6): Continued.

Manhole		Flowrate	Length	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	CMD	M	%	M	U/S	D/S	U/S	D/S	M/S
23	22	129.2	60	0.44	0.2	3.80	2.66	4.7	4.74	0.60
24	26	258.8	70	0.44	0.2	3.87	3.13	4.77	4.77	0.60
25	27	129.2	78	0.81	0.2	3.87	2.39	4.77	4.86	0.60
26	29	769.8	80	0.48	0.2	3.13	2.76	4.77	4.87	0.60
27	30	530.9	90	0.15	0.2	2.39	1.85	4.86	4.93	0.60
28	31	154.2	80	0.44	0.2	4.12	2.81	5.02	5.02	0.60
29	37	1292.5	80	0.51	0.2	2.76	2.41	4.87	4.81	0.66
30	38	1056.4	80	0.46	0.2	1.85	1.50	4.93	4.84	0.64
31	39	588.4	80	0.44	0.2	2.81	2.37	5.02	5.01	0.60
32	40	713.6	81	0.76	0.2	3.56	3.17	5.05	5.05	0.60
33	32	390.5	78	0.92	0.2	4.15	3.56	5.05	5.05	0.60
34	41	360.9	80	0.95	0.2	4.30	3.65	5.2	5.2	0.60
35	42	313.1	80	0.13	0.2	4.35	3.62	5.25	5.3	0.60
36	43	319.1	80	0.33	0.2	4.35	3.63	5.25	5.35	0.60
37	44	1791.9	80	0.48	0.25	2.41	2.15	4.81	4.81	0.65
38	45	1555.1	80	0.44	0.2	1.50	1.14	4.84	4.91	0.68
39	46	1018.6	80	1.64	0.2	2.37	2.02	5.01	5.01	0.63
40	73	991	90	1.90	0.2	3.17	2.77	5.05	5.05	0.63
41	61	662.6	78	0.94	0.2	3.65	3.26	5.2	5.2	0.60
42	68	886.6	80	0.44	0.2	3.62	3.27	5.3	5.3	0.61
43	69	892.1	80	0.13	0.2	3.63	3.28	5.35	5.45	0.61
44	1	19993.9	124	0.33	0.5	0.56	0.01	4.81	4.81	1.24
45	44	17079.4	115	0.44	0.5	0.93	0.56	4.91	4.81	1.06
46	45	14678.5	120	0.44	0.5	1.21	0.93	5.01	4.91	0.91
47	44	1990.9	80	0.55	0.25	2.63	2.37	4.85	4.81	0.66
48	45	1832.6	80	0.60	0.25	2.43	2.17	4.82	4.91	0.65
49	46	1901.2	90	1.06	0.25	2.46	2.16	5.01	5.01	0.66
50	73	2475	90	0.44	0.25	2.36	2.07	5.1	5.05	0.68
51	47	1436.1	80	0.44	0.2	2.98	2.63	4.78	4.85	0.68
52	48	1345.5	80	0.18	0.2	2.79	2.43	4.81	4.82	0.67
53	49	1395.6	80	0.33	0.2	2.81	2.46	5	5.01	0.67
54	50	2229.2	80	0.44	0.25	2.63	2.36	5.1	5.1	0.68
55	54	991	90	0.44	0.2	3.02	2.63	5.05	5.1	0.63
56	53	867.2	80	0.46	0.2	3.16	2.81	5	5	0.61
57	52	836.7	80	1.90	0.2	3.14	2.79	4.75	4.81	0.60
58	51	853.4	80	1.58	0.2	3.33	2.98	4.83	4.78	0.61
59	54	758.6	78	0.44	0.2	4.10	3.74	5	5.1	0.60
60	73	9659.6	78	0.33	0.5	1.54	1.44	5.1	5.05	0.68
61	60	9174.7	80	0.24	0.5	1.64	1.54	5.2	5.1	0.68

Table (6-6): Continued.

Manhole		Flowrate	Length	Slope	Diameter	Crown Elevation(M)		Ground Elevation(M)		Velocity
From	to	CMD	M	%	M	U/S	D/S	U/S	D/S	M/S
62	61	1529.1	80	0.44	0.2	2.59	2.23	5	5.2	0.68
63	62	1255.3	78	0.44	0.2	2.93	2.59	5.1	5	0.66
64	63	645.6	80	0.74	0.2	3.34	2.93	5	5.1	0.60
65	66	784.1	80	0.74	0.2	3.17	2.80	5.25	5.4	0.60
66	67	1121.1	80	0.33	0.2	2.80	2.45	5.4	5.35	0.65
67	68	1442.9	80	0.32	0.2	2.45	2.10	5.35	5.3	0.68
68	61	7214.1	130	0.33	0.45	1.84	1.64	5.3	5.2	0.68
69	68	5257	120	0.49	0.45	2.02	1.84	5.45	5.3	0.63
70	69	2438.3	80	0.50	0.35	2.19	2.02	5.45	5.45	0.60
71	70	1821.2	80	0.44	0.3	2.39	2.19	5.4	5.45	0.60
72	71	1087.7	80	0.44	0.25	2.68	2.39	5.2	5.4	0.60
73	46	12789.2	124	0.44	0.5	1.44	1.21	5.05	5.01	0.80

6.3 Application of a GA-TGA model for the Cases Study

The performance of the previously present model with two benchmarks problems found the Tournament selection method (TOS) and the Order crossover (OX) method to be the most effective among the several methods in the relation of optimum layout design.

In this section, the performance of the GA-TGA model will test for networks assumed as flat areas to find the optimum layout design of sewer networks and compare it with the actual design (as build) in terms of cost.

The first case study was a relatively small network includes 216 manholes and 215 pipes. The mechanism of operation of the proposed model is carried out on the main sewer pipes for the network of the case study to find the shortest path and then attaching the sub-pipes on the main sewer pipes to get the layout with the shortest path to less cost. According to the proposed GA-TGA model the optimum layout with minimum cost about 392.0 units is shown in Figure (6-17). While, when using the objective function to calculate the cost of the layout obtained from existing layout (as build) in Figure (5-4) in chapter five, the results obtained 450.9 units, resulting in a reduction of about 13.05 %. This reduction is relatively suitable because of the initial cost of establishing sewerage networks, which is an important part of the city's infrastructure. Table (6-7) presents the data characteristics for optimum layout design of the first case study by the proposed model.

Figure (6-17) Optimum layout of the first case study obtained by the proposed model.

Table (6-7): Optimum layout design for the first case study by the proposed model.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
1 2	40	0.000355	100 101	45	0.000746
2 3	50	0.000790	101 102	45	0.001137
3 4	50	0.001224	102 103	30	0.014400
4 5	29	0.001474	103 107	30	0.014660
5 10	30	0.001735	104 105	40	0.000355
6 7	40	0.000355	105 106	45	0.000746
7 8	45	0.000746	106 107	45	0.001137
8 9	45	0.001137	107 110	56	0.016276
9 10	45	0.001527	108 109	40	0.000355
10 11	29	0.003506	109 110	40	0.000703
11 16	30	0.003766	110 348	30	0.017230
12 13	40	0.000355	112 113	50	0.000443
13 14	45	0.000746	113 115	50	0.000877
14 15	45	0.001137	115 116	50	0.025299
15 16	45	0.001527	116 347	50	0.025734
16 17	28	0.005528	119 120	40	0.000355
17 22	30	0.005789	120 121	40	0.000703
18 19	40	0.000355	121 122	35	0.001006
19 20	45	0.000746	122 345	35	0.001310
20 21	45	0.001137	125 126	40	0.000355
21 22	45	0.001527	126 127	40	0.000703
22 23	33	0.007595	127 128	35	0.001006
23 28	30	0.007855	128 343	35	0.001310
24 25	40	0.000355	131 132	40	0.000355
25 26	45	0.000746	132 133	40	0.000703
26 27	45	0.001137	133 134	35	0.001006
27 28	45	0.001527	134 341	35	0.001310
28 35	33	0.009660	137 138	40	0.000355
29 30	40	0.000355	138 139	40	0.002873
30 31	40	0.000703	139 140	40	0.003220
31 32	40	0.001050	145 144	45	0.000399
32 33	40	0.001397	144 143	40	0.000746
33 34	40	0.001744	143 142	40	0.001093
34 35	40	0.002091	142 141	40	0.001440
35 36	40	0.012091	141 140	40	0.001788
36 37	40	0.012439	140 115	55	0.023998
37 38	45	0.012830	146 147	35	0.000312
38 64	45	0.013220	147 148	40	0.000659
39 40	40	0.000355	148 149	40	0.001006
40 41	40	0.000703	149 339	35	0.001310
41 42	40	0.001050	157 158	40	0.000355
42 43	40	0.001397	158 159	40	0.000703
43 44	40	0.001744	159 160	40	0.001050
44 45	40	0.002091	156 160	20	0.000181
45 56	40	0.002439	160 161	30	0.001483
46 47	40	0.000355	161 165	30	0.001744

Table (6-7): Continued.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
47 48	35	0.000659	162 163	40	0.000355
48 50	35	0.000963	163 164	40	0.000703
49 50	40	0.000355	164 165	40	0.001050
50 51	32	0.001588	165 166	30	0.003046
51 55	30	0.001848	166 170	30	0.003306
52 53	40	0.000355	167 168	40	0.000355
53 54	35	0.000659	168 169	45	0.000746
54 55	35	0.000963	169 170	45	0.001137
55 56	50	0.003238	170 171	30	0.004695
56 57	30	0.005928	171 175	30	0.004955
57 62	30	0.006188	172 173	40	0.000355
58 59	40	0.000355	173 174	45	0.000746
59 60	40	0.000703	174 175	45	0.001137
60 61	40	0.001050	175 176	30	0.006344
61 62	40	0.001397	176 180	30	0.006605
62 63	28	0.007820	177 178	40	0.000355
63 64	30	0.008080	178 179	40	0.000703
64 65	32	0.021570	179 180	45	0.001093
65 70	35	0.021874	180 181	25	0.008124
66 67	40	0.000355	181 182	30	0.008384
67 68	45	0.000746	183 182	30	0.009886
68 69	45	0.001137	188 183	30	0.009626
69 70	45	0.001527	184 185	50	0.001970
70 71	31	0.023662	185 186	40	0.003845
72 73	40	0.000355	186 187	50	0.004280
73 74	40	0.000703	187 188	50	0.004714
74 76	40	0.001050	189 188	30	0.004660
75 76	40	0.000355	193 189	30	0.004400
76 77	32	0.003844	190 191	40	0.000355
77 81	30	0.004105	191 192	40	0.000703
78 79	40	0.000355	192 193	40	0.001050
79 80	40	0.000703	194 193	30	0.003098
80 81	40	0.001050	198 194	30	0.002837
81 81A	29	0.005398	195 196	40	0.000355
150 151	40	0.000355	196 197	40	0.000703
151 152	40	0.000703	197 198	40	0.001050
152 154	40	0.001050	209 198	56	0.001537
153 154	30	0.000268	182 140	30.5	0.018528
154 155	40	0.001657	202 201	45	0.000399
155 81A	20	0.001830	201 200	45	0.000790
81A 82	12	0.007324	200 199	40	0.001137
82 83	40	0.007673	199 184	46	0.001536
83 84	40	0.008020	206 205	45	0.000399
84 85	45	0.008411	205 204	45	0.000790
85 86	45	0.008802	204 203	40	0.001137
86 87	45	0.009192	203 185	46	0.001536

Table (6-7): Continued.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
87 88	30	0.009452	206A 207	30	0.000268
88 92	30	0.009712	207 208	45	0.000659
89 90	40	0.000355	208 209	45	0.001050
90 91	45	0.000746	339 340	30	0.001570
91 92	45	0.001137	340 341	29	0.001822
92 93	30	0.011101	341 342	30	0.003384
93 97	30	0.011362	342 343	30	0.003645
94 95	40	0.000355	343 344	30	0.005207
95 96	45	0.000746	344 345	30	0.005468
96 97	45	0.001137	345 346	30	0.009200
97 98	30	0.012751	346 347	30	0.009461
98 102	30	0.013011	347 348	30	0.035446
99 100	40	0.000355	348 349	30	0.052668

The second case study was relatively large network includes 309 manholes and 308 pipes. According to the proposed GA-TGA model the optimum layout with minimum cost about 625.329 units. as shown in Figure (6-18). While, when using the objective function to calculate the cost of the layout obtained from existing layout in Figure (5-5), the results obtained 673.285 units, resulting in a reduction of about 7.123 %. Table (6-8) presents the data characteristics for optimum layout design of the first case study by the proposed model.

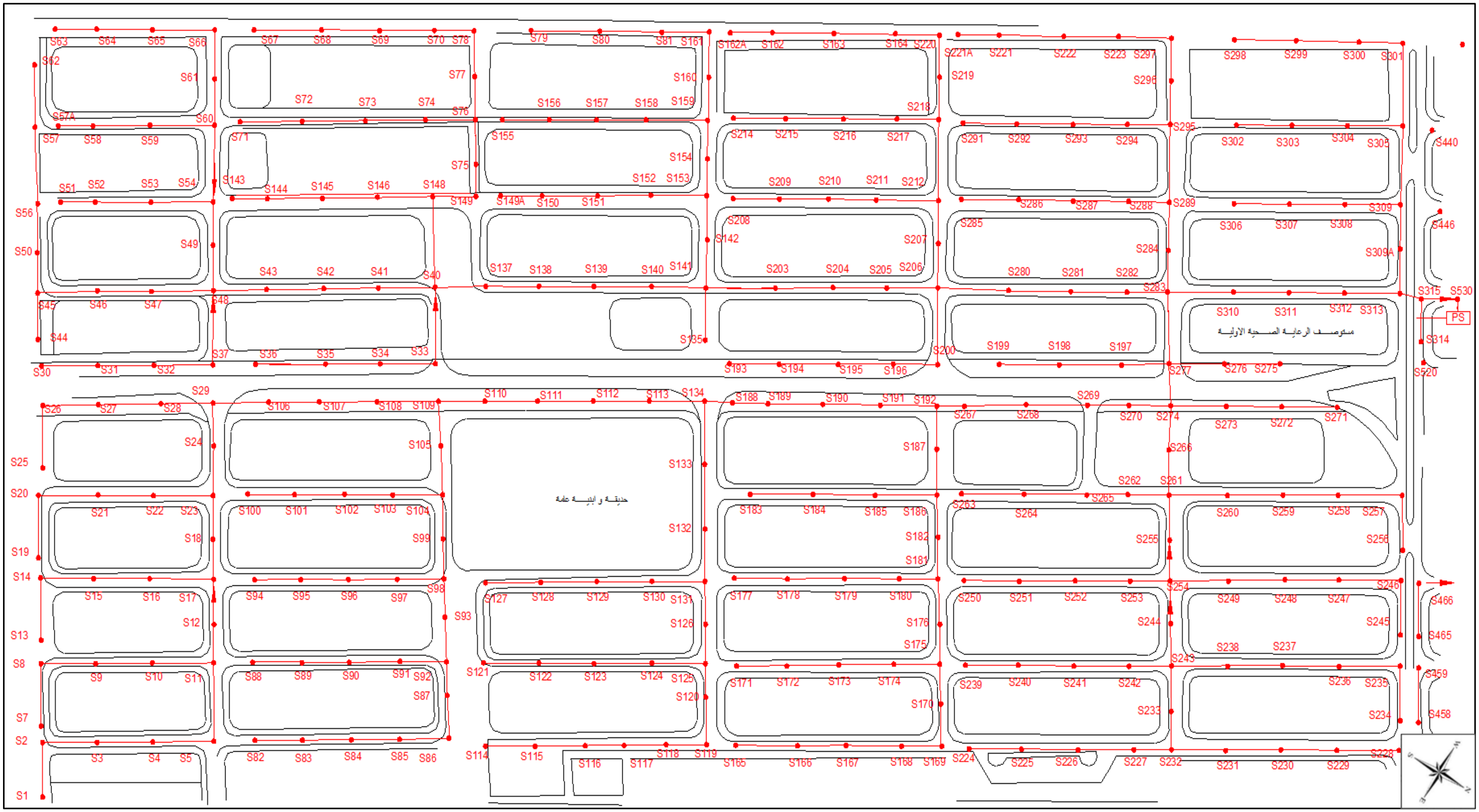


Figure (6-18) Optimum layout of the second case study obtained by the proposed model.

Table (6-8): Optimum layout design for the second case study by the proposed model.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
1 2	35	0.0003116	266 274	30	0.0134884
2 3	40	0.0006591	274 277	27	0.0002417
3 4	40	0.0010064	271 272	40	0.0003553
4 5	45	0.0013973	272 273	40	0.0007025
5 11	50	0.0018316	273 274	40	0.0010498
7 8	40	0.0003553	274 277	27	0.0507423
8 9	40	0.0007025	62 57	40	0.0003553
9 10	40	0.0010498	57 56	48	0.0007725
10 11	45	0.0014407	56 50	30	0.0010318
11 12	25	0.0034795	50 45	25	0.0012486
12 17	30	0.0037402	44 45	30	0.0002679
13 14	40	0.0003553	45 46	40	0.0018571
14 15	38	0.0006851	46 47	40	0.0022043
15 16	40	0.0010324	47 48	45	0.0025952
16 17	45	0.0014233	63 64	30	0.0002679
17 18	25	0.0053718	64 65	40	0.0006157
18 23	28	0.0056150	65 66	45	0.0010067
19 20	40	0.0003553	66 61	30	0.0012662
20 21	43	0.0007288	61 60	30	0.0015266
21 22	40	0.0010758	57A 58	25	0.0002242
22 23	43	0.0014492	58 59	40	0.0005723
23 24	30	0.0073166	59 60	45	0.0009633
24 29	28	0.0075595	60 54	50	0.0029167
25 26	40	0.0003553	51 52	25	0.0002242
26 27	40	0.0007025	52 53	40	0.0005723
27 28	45	0.0010935	53 54	45	0.0009633
28 29	38	0.0014229	54 49	28	0.0041133
29 106	40	0.0093223	49 48	30	0.0043738
106 107	40	0.0096696	30 31	40	0.0003553
107 108	40	0.0100168	31 32	40	0.0007025
108 109	40	0.0103640	32 37	40	0.0010498
82 83	35	0.0003116	37 48	48	0.0014669
83 84	35	0.0006155	48 43	40	0.0087668
84 85	35	0.0009193	43 42	40	0.0091140
85 86	35	0.0012231	42 41	40	0.0094612
86 87	28	0.0014657	41 40	40	0.0098084
87 92	20	0.0016389	36 35	50	0.0004427
88 89	35	0.0003116	35 34	40	0.0007894
89 90	30	0.0005718	34 33	40	0.0011366
90 91	35	0.0008759	33 40	50	0.0015712

Table (6-8): Continued.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
91 92	35	0.0011797	67 68	50	0.0004427
92 93	28	0.0030543	68 69	40	0.0007894
93 98	25	0.0032711	69 70	40	0.0011366
94 95	35	0.0003116	70 78	28	0.0013789
95 96	35	0.0006155	78 77	30	0.0016395
96 97	35	0.0003116	77 76	28	0.0018824
97 98	35	0.0012231	71 72	45	0.0003990
98 99	25	0.0047034	72 73	45	0.0007896
99 104	28	0.0049466	73 74	45	0.0011803
100 101	35	0.0003116	74 76	36	0.0014922
101 102	35	0.0006155	76 75	28	0.0036098
102 103	35	0.0009193	75 149	20	0.0037830
103 104	35	0.0012231	149 148	30	0.0040440
104 105	30	0.0064225	143 144	25	0.0002242
105 109	28	0.0066654	144 145	40	0.0005723
109 110	30	0.0172818	145 146	40	0.0009196
110 111	40	0.0176296	146 148	40	0.0012668
111 112	40	0.0179769	148 40	50	0.0057378
112 113	40	0.0183241	40 137	35	0.0174036
113 134	40	0.0186713	137 138	40	0.0177512
114 115	35	0.0003116	138 139	40	0.0180984
115 116	35	0.0006155	139 140	40	0.0184456
116 117	28	0.0008581	140 141	40	0.0187928
117 118	30	0.0011186	79 80	50	0.0004427
118 119	30	0.0013791	80 81	45	0.0008330
119 120	30	0.0016395	81 161	35	0.0011363
120 125	20	0.0018125	161 160	30	0.0013964
121 122	40	0.0003553	160 159	28	0.0016394
122 123	40	0.0007025	155 156	35	0.0003116
123 124	40	0.0010498	156 157	35	0.0006155
124 125	40	0.0013970	157 158	35	0.0009193
125 126	25	0.0034187	158 159	45	0.0013105
126 131	28	0.0036619	159 154	25	0.0031583
127 128	40	0.0003553	154 153	25	0.0033753
128 129	40	0.0007025	149A 150	30	0.0002679
129 130	40	0.0010498	150 151	40	0.0006157
130 131	38	0.0013795	151 152	40	0.0009630
131 132	35	0.0053377	152 153	40	0.0013102
132 133	40	0.0071319	153 142	28	0.0049206
133 134	40	0.0074792	142 141	30	0.0051811

Table (6-8): Continued.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
134 188	20	0.0263148	135 141	30	0.0002679
165 166	45	0.0003990	141 203	50	0.0246615
166 167	35	0.0007023	203 204	40	0.0250081
167 168	40	0.0010498	204 205	40	0.0253553
168 169	30	0.0013096	205 206	35	0.0256589
169 170	25	0.0015263	193 194	35	0.0003116
170 175	25	0.0017433	194 195	40	0.0006591
171 172	35	0.0003116	195 196	40	0.0010064
172 173	35	0.0006155	196 200	30	0.0012662
173 174	40	0.0009630	200 206	50	0.0017014
174 175	35	0.0012665	162A 162	30	0.0002679
175 176	25	0.0032190	162 163	30	0.0005284
176 181	30	0.0034797	163 164	45	0.0009198
177 178	40	0.0003553	164 220	30	0.0011794
178 179	40	0.0007025	220 219	25	0.0013961
179 180	40	0.0010498	219 218	25	0.0016131
180 181	28	0.0012921	214 215	40	0.0003553
181 182	28	0.0050074	215 216	40	0.0007025
182 186	28	0.0052505	216 217	40	0.0010498
183 184	45	0.0003990	217 218	30	0.0013096
184 185	45	0.0007896	218 212	50	0.0033507
185 186	45	0.0011803	208 209	35	0.0003116
186 187	30	0.0066829	209 210	35	0.0006155
187 192	30	0.0069433	210 211	35	0.0009193
188 189	25	0.0265321	211 212	40	0.0012668
189 190	40	0.0268802	212 207	28	0.0048512
190 191	40	0.0272274	207 206	28	0.0050942
191 192	40	0.0275747	206 280	50	0.0328733
192 267	20	0.0346829	280 281	45	0.0332636
267 268	45	0.0350749	281 282	40	0.0336105
268 269	45	0.0354656	282 283	30	0.0338704
269 270	30	0.0357251	199 198	45	0.0003990
270 274	30	0.0359855	198 197	45	0.0007896
224 225	38	0.0003378	197 277	35	0.0010929
225 226	40	0.0006852	275 276	40	0.0003553
226 227	40	0.0010324	276 277	40	0.0007025
227 232	27	0.0012660	277 283	40	0.0528698
228 229	45	0.0003990	221A 221	30	0.0002679
229 230	40	0.0007459	221 222	40	0.0006157
230 231	40	0.0010932	222 223	40	0.0009630

Table (6-8): Continued.

Pipe From to	Length (m)	Q design (m^3/s)	Pipe From to	Length (m)	Q design (m^3/s)
231 232	40	0.0014404	223 297	38	0.0012927
232 233	25	0.0029152	297 296	28	0.0015352
233 243	30	0.0031759	296 295	28	0.0017782
234 235	35	0.0003116	291 292	40	0.0003553
235 236	45	0.0007028	292 293	40	0.0007025
236 237	40	0.0010498	293 294	40	0.0010498
237 238	40	0.0013970	294 295	30	0.0013096
238 243	40	0.0017442	295 289	48	0.0034981
239 240	38	0.0003378	285 286	40	0.0003553
240 241	40	0.0006852	286 287	40	0.0007025
241 242	40	0.0010324	287 288	40	0.0010498
242 243	30	0.0012922	288 289	30	0.0013096
243 244	27	0.0064310	289 284	30	0.0050596
244 254	27	0.0066653	284 283	25	0.0052763
245 246	35	0.0003116	283 310	48	0.0924189
246 247	45	0.0007028	298 299	45	0.0003990
247 248	40	0.0010498	299 300	45	0.0007896
248 249	40	0.0013970	300 301	30	0.0010492
249 254	40	0.0017442	301 305	51	0.0014931
250 251	40	0.0003553	302 303	40	0.0003553
251 252	40	0.0007025	303 304	40	0.0007025
252 253	40	0.0010498	304 305	40	0.0010498
253 254	30	0.0013096	305 309	50	0.0029688
254 255	26	0.0099292	306 307	40	0.0003553
255 261	30	0.0099728	307 308	40	0.0007025
256 257	35	0.0003116	308 309	40	0.0010498
257 258	45	0.0007028	309 309A	28	0.0042522
258 259	40	0.0010498	309A 313	28	0.0048425
259 260	40	0.0013970	310 311	40	0.0942124
260 261	40	0.0017442	311 312	40	0.0945596
261 262	30	0.0119693	312 313	40	0.0949068
262 265	30	0.0122297	314 315	28	0.0002505
263 264	45	0.0003990	313 315	15	0.0998707
264 265	45	0.0007896	315 530	26	0.0946803
265 266	25	0.0132277			

Chapter Seven

Conclusions and Recommendations

7.1 Conclusions

The configuration of layout study as the first sub-problem greatly influences the design specifications. The sub-problem of layout design belongs to a solid category of mathematics and the methods of solving them are often found in the graph theory. In flat areas, the number of feasible layouts increases with the number of sewers (Haghighi, 2013).

The present study accomplishes the objective of developing an efficient algorithm for the optimal layout design of a sewer system. A hybrid Genetic Algorithm (GA-TGA) model was proposed to get the optimal layout design for sewer networks. A highly effective algorithm was adopted to determine near optimum layouts for selected tree networks from undirected or directed base graphs to provide a good initial population for the genetic algorithm. A new approach has been described based on TGA as a seed of GAs for layout design optimisation problems. A number of conclusions were reached by studying and analyzing the results as follows:

1- The proposed model uses a hybrid combination of TGA and GA technologies to produce better solutions for convergence behavior of the optimisation.
2- All sewer layout's constraints were achieved during the proposed method. This leads to neither need to discard or repair infeasible chromosomes nor to apply penalty factors to the cost function.

3- The hybridization provides a fast solver that can also be successful in finding the global solution.

4- The performance of the different methods of selection (RWS, LRS, RRS, TRS, SUS, RMS and TOS), different methods of crossover (OX, CX), and different population sizes (50, 100, 200, 300 and 500), has been tested using the present model (GA-TGA) to determine their impact on convergence behavior. For the first benchmark example, the GA-TGA required less generation (iterations) than that required by other methods with same minimum cost. The TOS and the OX method proved to be the most efficient with regard to optimum design.

5- In the second benchmark example, although the separate optimisation method used here is not global, it is computationally very effective and easy to apply. Also, it showed a solving this benchmark example is that the simplified method is not far from the optimal global level, but is even closer to that compared to previous works. However, the proposed algorithm is very promising to join in an integrated and global optimisation model in future research.

6- In the case studies, the savings percentage obtained through the optimal design by using the proposed GA-TGA model indicate that the model is well performing.

7- In order to ensure the efficiency of the proposed GA-TGA model for the design of large networks, it was examined with two case studies located in Karbala Holy city, then compared the cost of the manual designs with the designs obtained from this model for networks. The saving percentage was (13.05 %) and (7.123 %) for relatively small and large networks, respectively.

7.2 Recommendations

1- Design of sewer network by combining the proposed model (GA-TGA) with the Genetic Algorithm with Heuristic Programming (GA-HP) technique to provide an integrated and global optimisation model in future research.

2- Developing the proposed model to be a visual program user-friendly to be used for the design of real networks in the future.

3- Developing the proposed GA-TGA model to design layout of water distribution networks.

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الخلاصة

لتحسين تخطيط شبكات الصرف الصحي ، أولاً ، يتم إنشاء التخطيطات المجدية للشبكة من الرسم البياني الأساسي الموجه أو غير الموجه ، ثم يتم تحديد أفضل تصميم للتخطيط من بين العديد من التكوينات المحتملة خاضعة للقيود.

تعتمد الخوارزميات الجينية (Genetic Algorithms) في الغالب على بدايات عشوائية ، وهي حلول ضعيفة. ولذلك ، فإن مشكلة كيفية توفير تقديرات أولية جيدة لإيجاد حل يتم تعيينه تلقائيًا هي موضوع بحث مستمر. لهذا الغرض ، تقترح هذه الدراسة خوارزمية جينية هجينة جديدة (GA-TGA)، والتي تستخدم خوارزمية نمو مناسبة ، TGA، لتجنب المشاكل المرتبطة بتكوين الحلول غير المجدية التي تؤدي إلى تقليل فضاء البحث لتوفير مجموعة أولية جيدة لتشغيل الخوارزميات الجينية.

تم استخدام برنامج الماتلاب (MATLAB) لتنفيذ نموذج الأمثلية (GA-TGA). وقد اختبر النموذج المقترح لتحديد تأثير سلوك التقارب للحل الأمثل من خلال أداء سبعة طرق مختلفة لأختيار الابوين ,(RWS, RRWS, LRS, TRS, SUS, TOS, RMS)، وطريقتين مختلفتين لتزاوج الكروموسومات (Order Crossover (OX), Crossing Operator-Based Cloning). ومختلف حجم للسكان (50 ، 100 ، 200 ، 300 ، 500)، أثبتت طريقة الأختيار (Tournament Selection TOS) وطريقة التزاوج (Order Crossover OX) أعلى كفاءة فيما يتعلق بتصميم المخطط الأمثل. وعندما استخدمت هذه الطرق مع الرسم البياني الأساسي المباشر نتج عنها تكوين مجموعة سكانية ممكنة للجيل الجديد، لا توجد فيه حاجة لتخليص أو إصلاح الحلول غير القابلة للتطبيق ولا لتطبيق عوامل العقاب على وظيفة التكلفة. يتم استخدام نموذجين قياسيين لشبكات الصرف الصحي لاختبار النموذج المقترح (GA-TGA). ثم تتم مناقشة النتائج ومقارنتها مع الدراسات السابقة. وقد استنتج أن الطريقة فعالة من حيث السرعة والكفاءة ومن السهل تنفيذها بنفس قيم الوظيفة الموضوعية (Objective Function).

من أجل تحديد قابلية تطبيق النموذج المقترح على الشبكات العملية في المنطقة المحلية ، تم فحصه مع حالتين دراسيتين واقعتين في مدينة كربلاء المقدسة ، ثم قارنت تكلفة التصاميم اليدوية

الفعلية مع التصاميم التي تم الحصول عليها من النموذج الحالي للشبكات. وكانت نسب الادخار (13.05 ٪) و (7.123 ٪) للحالة الدراسية الأولى والثانية على التوالي.

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة كربلاء / كلية الهندسة

التصميم الأمثل للتخطيط لنظام شبكات الصرف الصحي

رسالة مقدمة إلى كلية الهندسة / قسم الهندسة المدنية كجزء من متطلبات نيل
درجة الماجستير في علوم الهندسة المدنية (فرع البنى التحتية)

من قبل
زهراء حسين عطية المظفر
(بكالوريوس هندسة مدني 2012)

بإشراف
أ.د. واقد حميد حسن الموسوي

آذار 2019