Multiobjective Optimization of Water Distribution Networks using Metaheuristic Algorithms

THESIS

Submitted in partial fulfilment of the requirements for the degree of

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CERTIFICATE

This is to certify that the thesis titled Multiobjective Optimization of Water Distribution Networks using Metaheuristic Algorithms submitted by MADDUKURI NAVEEN NAIDU ID No 2017PHXF009H for award of Ph.D. of the Institute embodies original work done by him under our supervision.

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DECLARATION

This is to certify that the thesis titled "Multiobjective Optimization of Water Distribution Networks using Metaheuristic Algorithms" is based on my own research work and has been carried out under the guidance and supervision of Prof. A. Vasan, and co-supervision of Prof. Murari R R Varma, Dept. of Civil Engineering, BITS Pilani, Hyderabad Campus, Hyderabad, India.

The data and information which I have used from various sources have been duly acknowledged. I declare that this work has not been previously submitted by me to any other university/institute for the award of any other degree or diploma.

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(M Naveen Naidu)

ABSTRACT

Water Distribution Networks (WDNs) are like linchpin for any urban infrastructure system. As the installation and maintenance of these networks involves huge capital investment, the design of these systems is highly significant. The optimal design of these networks reduces initial capital investment without compromising on the demand requirements. The complexity of this optimization problem is due to the non-linear relationship between head losses and pipe discharges which leads to complex non-linear constraints. Mathematical models that imitate natural evolutionary processes have been gaining much importance for successfully optimizing engineering design problems. Most initial studies aimed to solve the design as a single objective, i.e., minimizing network cost. The challenge in optimization is associating other conflicting objectives with cost minimization and capturing the problem's true multiobjective nature. In most urban settings in India, the design of the WDNs assumes of continuous water supply. However, in most parts of the country, areas are supplied with water intermittently. This has resulted in challenges like pressure and demand losses at nodes in WDNs. Therefore, there is a need for new models that can accommodate these issues in the design of WDNs. Moreover, the operation and maintenance of WDNs are inherently complex tasks. One strategy to tackle these issues is the integration of district metered areas (DMAs) within WDNs. Present research work focuses on optimizing the design of WDNs and identifying optimal DMAs for a WDN in a multiobjective framework considering three scenarios.

In the last few decades, researchers working on multiobjective design of WDN have attempted to explore several new nature inspired optimization techniques to such complex problems as they are able to handle a discrete search space directly and are less likely to be trapped into the local optimal solutions. In the present study, three such optimization techniques [Multiobjective Particle Swarm Optimization Algorithm (MOPSOA) augmented with local search, Self-adaptive Multiobjective Cuckoo Search Algorithm (SAMOCSA) and NSGA-II algorithm augmented with a random multipoint crossover operator as well as local search (RLNSGA-II)] to solve multiobjective optimization models with some improvements in their working methodology have been implemented. Local search scheme has been augmented in two of the algorithms (MOPSOA and RLNSGA-II) to effectively explore the least-crowded areas of the objective space to determine better pareto-optimal points.

The present study considers three scenarios. The first two scenarios determine the optimal WDN design based on different objectives for continuous and intermittent water supply. A simulationoptimization based program combining the water distribution network simulation software EPANET 2.2 and MATLAB is used for computation on a high performance computing cluster. In the first scenario, two objectives, namely, network cost and network resilience have been considered for continuous and intermittent water supply. The formulated mathematical model is applied to the three benchmark WDN problems (New York Tunnel WDN, Hanoi WDN and Balerma Irrigation Network) and later this is also applied to two real-life WDNs located in Telangana, India (Pamapur WDN and Vanasthalipuram WDN) to ensure practical relevance of the proposed methodology using MOPSOA, SAMOCSA and RLNSGA-II. The results of New York WDN, Hanoi WDN and Balerma Irrigation Network (BIN) for continuous water supply are compared with the solutions of Wang *et al.* (2015) to test the efficacy of the developed optimization algorithms. In the second scenario, the focus extends beyond cost and resilience to include the critical consideration of network equity, aiming to ensure a fair and equitable distribution of water. This expanded set of objectives is examined in the context of two real-life water distribution networks for intermittent water supply using RLNSGA-II algorithm. The third scenario focuses on determining the optimal design of DMAs considering three objectives for the optimization model. The initial clusters have been identified using Fast Newman algorithm. The objectives considered are minimizing network cost, maximizing network resilience and maximizing network equity. In this scenario, the proposed methodology has been applied on Pamapur WDN and Vanasthalipuram WDN to determine the optimal number of DMAs.

The results obtained from the first scenario are compared with the best-known algorithms available in the literature. The results have shown that the proposed algorithms have found better converged and distributed solutions for all three representative benchmark problems considered in the study consistently and evidently when compared with the best-known approximation of solutions published. Furthermore, as the complexity of the water distribution network increases, its advantages over other algorithms become more significant resulting in substantial cost savings.

Additionally, a comparison between continuous water supply and intermittent water supply is conducted within the framework of the first scenario. These comparative analyses reveal that velocity and pressure exhibit higher levels in intermittent water supply scenarios compared to continuous water supply scenarios. The findings from the second scenario indicate a notable enhancement in network equity for real-life water distribution networks, specifically Pamapur and Vanasthalipuram WDNs. It is observed that most of the non-dominated solutions on the pareto front on the upper middle portion for Vanasthalipuram WDN provide better network resilience for a lower network cost. Similarly, it is observed that all the points on the pareto front represent a better performance in terms of network equity for a lower cost when compared to the results obtained in scenario 1. In the third scenario, the results demonstrate the efficacy of the proposed methodology in effectively identifying DMAs. For Pampaur WDN, it can be observed that the network cost varies from Rs.9.55 lakhs to Rs.48.71 lakhs for DMAs that vary between 3 to 5. Five different combinations of DMAs have been found for 3 and 5 numbers of DMAs. The number of valves and flow meters varies from 12 to 21 and 6 to 10 respectively for the different DMAs obtained in the pareto front. The network resilience increases from 0.45 to 0.55 (around 22% increase) and network equity increases from 0.9150 to 0.9750 (around 7% increase) when compared between the DMA configuration of leftmost and rightmost point on the pareto front. The average pressure in each DMA is slightly lower after partitioning for both the extreme points of the pareto front. The average pressure in DMA 3 is around 3% lower after partitioning for the leftmost point and it is around 3% lower in DMA 3 after partitioning for the rightmost point. Similarly, for Vanasthalipuram WDN, it can be observed that the network cost varies from

Rs.11.12 lakhs to Rs.55.08 lakhs for DMAs that vary between 3 to 7. Ten different combinations of DMAs have been found for 5 numbers of DMAs. The number of valves and flow meters varies from 23 to 45 and 7 to 15 respectively for the different DMAs obtained in the pareto front. The network resilience marginally increases (around 2% increase) and network equity also marginally increases (around 2% increase) when compared between the DMA configuration of leftmost and rightmost point on the pareto front. The average pressure in each DMA is slightly lower (below 2%) after partitioning for both the extreme points. The average pressure in DMA 3 is around 1.75% lower after partitioning for the leftmost point and it is around 1.86% lower in DMA 3 after partitioning for the rightmost point.

This study presents a multiobjective design of water distribution networks considering three key objectives: minimizing Network Cost, maximizing Network Resilience and maximizing Network Equity. While similar multiobjective designs have been considered in other locations (very limited studies), our study uniquely applies these objectives to two specific and challenging locations, demonstrating the effectiveness and adaptability of our proposed techniques. Three optimization algorithms (MOPSOA, SAMOCSA and RLNSGA-II) used in this study have consistently outperformed, when compared with the best algorithms available in literature, yielding better converged and distributed solutions for the three benchmark problems (New York WDN, Hanoi WDN and Balerma Irrigation Network). These algorithms surpass the best-known approximation solutions published in the literature, showcasing their effectiveness and robustness. It is particularly noteworthy to mention their exploration and exploitation capabilities of large search spaces for finding better optimal solutions i.e., their ability to achieve substantial cost savings as network complexity increases. The proposed methodology demonstrated significant cost savings. The optimized designs achieved a balance between initial investment and long-term operational costs, making them economically viable for large-scale implementation. The optimized networks exhibited higher resilience, ensuring that the WDNs could better withstand disruptions and maintain service levels during adverse conditions. The methodology identified configurations that improved the system's ability to adapt to changes and recover from failures. The methodology also addressed the equity of water distribution which is a major concern in Indian conditions, ensuring a more uniform and fair distribution of water across different regions within the network. This helped in reducing disparities in water access and pressure, providing a more consistent service to all users. The conclusions emanated from the study show that the proposed methodology can effectively identify the optimal design of WDNs and identify DMAs while considering multiple objectives.

Keywords: Water Distribution Network; New York Tunnel WDN; Hanoi WDN; Balerma Irrigation Network; Pampaur WDN; Vanasthalipuram WDN; Multiobjective Particle Swarm Optimization Algorithm; Multiobjective Cuckoo Search Algorithm; NSGA-II; EPANET 2.2; District Metered Areas; Fast Newman Algorithm.

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List of ACRONYMS

WDN Water Distribution Network

List of SYMBOLS

Chapter 1 Introduction

1.1. Background and Motivation

Water Distribution Networks (WDNs) are integral components of urban infrastructure, transporting water from its sources to domestic, commercial, and industrial users, thereby sustaining their daily functions. These WDNs are crucial in providing access to clean and safe water and supporting public health, sanitation and economic activities. However, the establishment and upkeep of WDNs necessitate substantial investments across the design, construction, operation, and maintenance phases. Due to the significant capital investment required, effective management practices, infrastructure investments, and technological advancements are crucial for maximizing performance, minimizing water loss, and securing the sustainability of water supply systems in the long term.

The design of the WDNs can be a challenging task due to various reasons like the non-linear relation between head loss and diameter, discrete pipe diameters being available in the market, non-deterministic polynomial hard problem, high-dimensional search space and being computationally intensive. Traditionally, the design of the WDN is dependent on engineers' knowledge and experience. However, this is not sufficient for the design of large WDNs. Initially, proposed solutions like linear programming had their limitations, as the distribution network design problem was non-linear by nature and failed to identify the optimal global solution. Nonlinear programming approaches rely on the initial solution, but they do not guarantee global optimal solution. In addition, the use of discrete variables, viz. available market pipe sizes, reduces the quality of optimal solutions (Kidanu *et al.*, 2023; Parvaze *et al.*, 2023).

Enumeration of all the possible solutions and selecting the best is the direct approach to solving such a problem. However, due to the exponential growth of possible solutions with increased variables, namely the number of pipes, such a rapid approach is practically infeasible. In addition,

the optimization of WDNs has a significant number of local optima, which makes it a combinatorial problem.

Mathematical models that imitate natural evolutionary processes have recently gained much importance for successfully optimizing engineering design problems. Several studies have used nature-inspired algorithms like Genetic Algorithm, Particle Swarm Optimization, Cuckoo Search Algorithm, Shuffled Frog Leaping Algorithm, Differential Evolution Algorithm, etc. and their variants to design water distribution networks. Most initial studies aimed to solve the design as a single objective, i.e., minimization of network cost. The above algorithms have shown significant efficiency in obtaining optimal solutions. The challenge in optimization is associating other conflicting objectives with cost minimization and capturing the problem's true multiobjective nature (Walski, 2001). Towards this direction, studies have attempted two-objective optimization, i.e. minimization of network cost and maximization of network resilience. Various evolutionary algorithms have been utilized towards this. However, there is no consensus on a commonly accepted optimization tool in WDN, as improved algorithms can still obtain better solutions.

In most urban settings in India, the design of the WDNs is based on the assumption of continuous water supply. However, more often than not urban, almost all peri-urban and rural areas are supplied water intermittently. This has resulted in challenges like pressure and demand losses at nodes in WDNs. Therefore, there is a need for new models that can accommodate these issues in the design of WDNs. Pressure-driven demand (Gupta and Bhave, 1996) offers promising solutions to address these challenges in the design of intermittent water supply.

In addition to improvements in the network design, efficient operation design during the life of the WDN can improve service and reliability. Implementing District Metered Areas (DMAs) has significantly enhanced the efficiency of water distribution systems by enabling WDNs to monitor better, manage, and detect leaks within the WDNs. DMAs are specific sections or zones within a WDN that are isolated and equipped with flow metres to monitor and measure water flow in and out of the area. The optimal design of DMAs in WDNs is critical for operation and maintenance in WDNs. Efficient DMA design is paramount for achieving optimal water distribution, minimizing losses, and enhancing system resilience. Engineers can determine the most effective placement and sizing of DMAs through advanced optimization techniques, such as metaheuristic algorithms.

In this study, three distinct scenarios have been considered. The first two scenarios determine the optimal WDN design based on different objectives for continuous and intermittent water supply. An optimization-simulation model is developed to obtain an optimal design for water distribution systems. This model integrates the developed multiobjective optimization algorithm and the water distribution system simulation software EPANET 2.2 (Environmental Protection Agency Network Evaluation Tool). In the first scenario, two objectives are considered: network cost and network resilience. The formulated optimization-simulation model is applied to the three benchmark WDN problems, and later, this is also applied to two real-life WDNs located in Telangana, India, to ensure the practical relevance of the proposed methodology in the first scenario. In the second scenario, the focus extends beyond cost and resilience to include the critical consideration of network equity, aiming to ensure a fair and equitable water distribution. This expanded set of objectives is examined in the context of two real-life water distribution networks. In the third scenario, the optimal design of DMAs has been considered with three objectives: minimization of network cost, maximization of network resilience and maximization of network equity for two real-life water distribution networks, Pamapur and Vanasthalipuram water distribution networks.

1.2. Layout of Thesis

Chapter 2 provides a detailed literature review on the optimal design of WDNs, covering various aspects such as single objective optimization, multiobjective optimization, and methodology employed. In addition, the chapter also reviews the studies that have described the optimal configuration of DMAs within the WDNs. Subsequently, gaps found in the literature review and the objectives of the study have been described.

Chapter 3 elaborates on WDN modelling, encompassing key components like pumps, tanks, pipes, and more, while also exploring fundamental hydraulic modelling principles such as the conservation of mass and energy laws. In addition, the chapter delves into specific methodologies like pressure-driven demand and demand-driven analysis, highlighting their applications and significance in modelling complex WDNs. Furthermore, it discusses the capabilities of the hydraulic simulation tool, EPANET 2.2, offering an understanding of its features and functionalities for accurate modelling and analysis of WDNs.

Chapter 4 describes the five WDNs that have been chosen to validate the proposed methodology. Three benchmark problems, representing two medium WDNs (New York Tunnel WDN and Hanoi WDN) and one large WDN (Balerma Irrigation Network) has been considered. The proposed methodology has also been tested on two real-life WDNs from Telangana, namely, Pamapur WDN and Vanasthalipuram WDN.

Chapter 5 describes the mathematical model for the optimal design of WDNs, which includes problem formulation of various objectives like minimization of network cost, network resilience and network equity and constraints like conservation of mass, energy, minimum pressure and discrete diameter as well as a mathematical model for the optimal design of DMAs in a WDN. The detailed working methodology of three optimization techniques [Multiobjective Particle Swarm Optimization Algorithm (MOPSOA) augmented with local search, Self-adaptive Multiobjective Cuckoo Search Algorithm (SAMOCSA) and NSGA-II algorithm augmented with a random multipoint crossover operator as well as local search (RLNSGA-II)] to solve multiobjective optimization models, and Fast Newman Algorithm that has been used to identify the clusters while identifying the DMAs in a WDN has also been explained in this chapter.

Chapter 6 describes the results and discussion, which includes three different scenarios. In the first scenario, two objectives, namely, network cost and network resilience have been considered. In this scenario, the results from the three optimization techniques (MOPSOA, SAMOCSA and RLNSGA-II) for continuous and intermittent water supply for the five WDNs have been analyzed and discussed. In the second scenario, the focus extends beyond cost and resilience to include the critical consideration of network equity, aiming to ensure a fair and equitable distribution of water services while reducing disparities. This expanded set of objectives is applied on the two real-life water distribution networks. The third scenario discusses the results of determining the optimal design of DMAs in detail.

Chapter 7 describes the summary and conclusions of this study.

Contributions from the study, scope for further work, publications from the research and references are included in the thesis.

The next chapter presents the literature review on the optimal design of WDNs and optimal design of DMAs in a WDN, as well as the gaps and objectives of the research work.

Chapter 2 Literature Review

2.1. General

WDNs are critical infrastructure systems that provide access to clean water to communities. The optimal design of these networks is essential for ensuring efficient water supply, minimizing costs, and reducing energy consumption. Additionally, the provision of DMAs plays a vital role in improving network performance by enabling better leak detection, pressure control, and overall management. This literature review aims to provide insights into the state-of-the-art techniques in the optimal design of WDNs and the design of DMAs while highlighting the objectives of this PhD thesis.

2.2. Optimal Design of Water Distribution Networks

The design of WDNs is challenging for engineers around the globe for various reasons. They include non-linear relationships between pipe discharges and head losses, introducing complex non-linear constraints and the discrete pipe diameters leading to a combinatorial optimization problem, among others. Sufficient literature is available on the optimization of WDN design focusing on cost minimization using linear programming (Alperovits and Shamir, 1977; Quindry *et al.,* 1981; Morgan and Goulter, 1985; Fujiwara *et al.,* 1987; Kessler and Shamir, 1989; Fujiwara and Khang, 1990; Sonak and Bhave, 1993). Similarly, the literature using non-linear programming includes Shamir (1974), El-Bahrawy and Smith (1987), Su *et al.* (1987), Lansey and Mays (1989), Duan *et al.* (1990), Bhave and Sonak (1992), Gupta et al. (1993, 1999), Varma *et al.* (1997) and many more. Continuous diameters and split pipes are frequently used in linear and non-linear programming optimization models. After optimization, the practice is to replace the value of the diameters (solved as a continuous variable) with the nearest commercial size, making the optimal solution a non-optimal solution. Also, using a link or split-pipe length with varying diameters is uncommon. Moreover, these methods depend on the initial solution in the search process to find the optimal solution.

Enumeration of all the possible solutions and selecting the best of them is the direct approach to solving such a problem. However, such an approach is practically infeasible due to the exponential growth of possible solutions with increased variables. In addition, optimization problems in WDNs have a significant number of local optima, which is a combinatorial problem. Mathematical models that imitate natural evolutionary processes have successfully been tested in optimizing engineering design problems.

Towards this, several researchers optimized the design of the WDN as a single objective, mainly cost minimization, using various evolutionary algorithms like Genetic Algorithm (Savic and Walters, 1997; Reca and Martínez, 2006; Kadu *et al.*, 2008), Simulated Annealing (Cunha and Sousa, 1999), Ant-colony Optimization (Maier *et al.,* 2003), Shuffled Frog Leaping Algorithm (Eusuff and Lansey, 2003), Differential Evolution (Suribabu, 2009; Vasan and Simonovic, 2010), Improved Crow Search Algorithm (Fallah *et al.*, 2019), Whale Optimization Algorithm (Ezzeldin and Djebedjian, 2020), Gravitational Search Algorithm (Fallah *et al.,* 2021) and many more. These techniques have efficiently provided the least cost solutions, with the number of function evaluations less than those compared to complete enumeration for benchmark problems.

Walski (2001) emphasized the need for new models to consider multiple objectives in the design of WDN. The biggest hurdle in WDN design is predicting future demand. A designer would like to provide excess head (beyond the required minimum head) at each node to overcome increased head losses under unexpected high demand or failure conditions. He also advocates using models that generate more reliable loops and avoid loops with pipes of widely different diameters. Prasad and Park (2004) presented a multiobjective genetic algorithm approach to design a WDN. They improved the resilience index developed by Todini (2000) while considering some of the practical suggestions by Walski (2001). Similarly, Ostfeld *et al.* (2014) successfully demonstrated a methodology for multiobjective optimization for the least cost design and resiliency of water distribution systems.

Similarly, several researchers have tried various approaches like Wang *et al.* (2015) obtained the best-known approximation of the true Pareto front for twelve benchmark problems by considering multiobjective optimization with two conflicting objectives, namely minimization of network cost and maximization of network resilience using five standard multiobjective evolutionary algorithms (MOEAs): Non-dominated Sorting Genetic Algorithm -II (NSGA-II), epsilon-NSGA-II, epsilon-MOEA, AMALGAM (a modified multialgorithm, genetically adaptive multiobjective) and Borg. AMALGAM is a hybrid optimization framework that combines four algorithms: NSGA-II, Adaptive Metropolis Search (AMS), Particle Swarm Optimization and Differential Evolution. The twelve benchmark problems tested had small, medium, intermediate, and large WDNs. To form the best-known true Pareto front, such non-dominated solutions were combined, and dominated solutions were eliminated. The complementarity of the five MOEAs across different problems suggests that no single method exhibited complete superiority over the others. Nonetheless, with minimal parameter tuning, the NSGA-II algorithm consistently outperformed the alternatives across all problems, making it a favourable choice. Furthermore, employing a small population size suffices for small and medium networks. However, to ensure the best-known approximation of the Pareto front for intermediate and large problems, it is advisable to utilize varying population sizes and random seeds. Siew *et al.* (2016) developed and applied a new multiobjective evolutionary optimization approach to design and upgrade WDNs with multiple pumps and service reservoirs. Sheikholeslami and Talatahari (2016) proposed a novel swarm-based optimization algorithm named Direct Search Optimization which integrates the Accelerated Particle Swarm Optimization with the Big-Bang Crunch Algorithm to optimize the design of WDNs. This approach obtained the optimal solution for three benchmark problems at a relatively low computational cost. Moosavian and Lence (2017) used Nondominated Sorting Differential Evolution (NSDE) for the multiobjective design of WDNs on three benchmarks problems (Two loop, Hanoi and Farhadgerd network). Two objectives have been considered in this study, namely minimization of network cost and maximization of network resilience. The results demonstrated NSDE's superiority over the AMALGAM algorithm, highlighting its effectiveness in generating pareto optimal solutions. Yazdi *et al.* (2017) developed a hybrid algorithm combining differential evolution (DE) and harmony search (HS) for multiobjective design of WDNs. This study was tested on Two loop, Hanoi, Fossolo and Balerma irrigation network with two conflicting objectives, minimization of network cost and maximization of network resilience. The results have shown that the proposed hybrid method provided better optimal solutions and outperformed the other algorithms considered in this study. Wang *et al.* (2017) introduced a new hybrid algorithm namely, GALAXY (Genetically Adaptive Leaping Algorithm for Approximation and Diversity) for multiobjective optimization of WDNs. The objectives considered in this study are minimization of network cost and maximization of network resilience. The proposed methodology has been tested on five benchmark problems (BakRyan, Hanoi, Pescara, Modena and Balerma WDNs). The results have shown that GALAXY demonstrates superior capability in efficiently and consistently identifying better converged and distributed boundary solutions.

Cunha and Marques (2020) developed a multiobjective simulated annealing algorithm and tested on 12 benchmark WDNs. Two objectives, minimization of network cost and maximization of network resilience have been considered in this study. The proposed algorithms showed very good performance and converged to better pareto fronts. Yazdi and Taji Elyatoo (2022) investigated different reliability indices of a WDN and compared their performance for designing a WDN for three benchmark WDNs (Hanoi, Pescara and Modena) using NSGA-II. The results showed that network resilience index proposed by Prasad and Park (2004) outperforms other metrics. Palod *et al.* (2022) developed multiobjective Jaya Algorithm and applied it on two benchmark networks using three different reliability indices. It was found that the network resilience index proposed by Prasad and Park (2004) is better for Two Loop network and for the Hanoi network, modified resilience index performs better. Bi *et al.* (2022) formulated a multiobjective model with six objectives focusing on economic, structural and functional aspects in the operation and management of the WDN and solved by Borg, which is one state-of-the-art multi-objective evolutionary algorithm. A real-world case study with 1278 decision variables is used to demonstrate the effectiveness of the proposed framework. The results showed that the complex trade-offs among these six different objectives gave practical insights while designing large realworld WDN problems. Parvaze *et al.* (2023) reviewed the developments in the optimization of WDNs using genetic algorithms. The review concluded that in spite of so many published work on design optimization of WDNs over the past three decades, there is still a lack of consensus among researchers and practitioners regarding the best way to construct a WDN design optimization model or using the most suitable optimization algorithm to solve the multiobjective model. Kidanu *et al.* (2023) proposed an improved version of NSGA-II and tested on five benchmark WDNs of different sizes for a two objective model (minimization of network cost and maximization of network resilience). The results showed that the proposed algorithm outperformed the original NSGA II.

In many Indian cities, WDNs are designed assuming continuous water supply. However, in practice the water is supplied intermittently, the duration ranging from 1 to 4 hours daily. Due to this, there are pressure and discharge fluctuations at every node in WDNs. Understanding the system behavior through hydraulic model simulations is crucial to propose solutions for these problems. Therefore, several researchers (Bhave, 1981; Germanopoulos, 1985; Wagner *et al.,* 1988; Chandapillai, 1991; Tanyimboh *et al.*, 2001; Tanyimboh and Templeman, 2010) have attempted to establish equations relating pressure and flow at nodes in WDNs . Few studies (Gupta and Bhave, 1996; Shirzad *et al.*, 2013) compared various methods for predicting these equations with experimental work and found equations proposed by Wagner *et al.* (1988) to be the most effective. Vairavamoorthy *et al.* (2007) in his study has attempted to design two networks in Bangalore, India as intermittent water supply. Mohapatra *et al.* (2014) designed an intermittent water supply for the city of Nagpur, Maharashtra, India. There are very few reported studies with regards to design of intermittent water supply in the Indian context and there isn't any research in the literature for Hyderabad, India.

Nyahora *et al.* (2020) has used genetic algorithm for enhancing intermittent water supply (IWS) systems by integrating cost-effective interventions such as pipe replacement, booster pump, and elevated tank installation. This approach maximizes equity and reliability while minimizing costs, facilitating the transition towards continuous water supply. The proposed methodology has been applied to Hanoi WDN and another real-life WDN namely Milagro (located in Ecuador). The results have shown importance of equity and reliability in decision-making for IWS systems. Ramani *et al.* (2023) has used NSGA-II algorithm for design of intermittent WDN for multiobjective optimization (maximization of network resilience and maximization of network equity). The proposed algorithm was successfully tested on two small benchmark problems.

2.3. Optimal Design of District Metered Areas in a Water Distribution Network

Introducing DMAs within WDNs can make the operations and maintenance of WDN efficient and reliable. DMAs are distinct zones that enable utilities to monitor and manage water flow, detect leaks, and optimize network performance. The optimal design of DMAs is a complex,

multiobjective optimization problem and traditional approaches often face challenges in handling the network's complexity. Therefore, several researchers have tried multi-phase procedures to enhance the efficiency and effectiveness of the design of DMAs. The multi-phase procedure is a comprehensive methodology comprising several steps, each contributing to the optimal design of DMAs. The main phases involved are node clustering and optimization. Among these, the Fast Newman Algorithm (FNA), originally proposed by Clauset *et al.* (2004) is the most widely adopted clustering algorithm. Optimization has been done using evolutionary algorithms like genetic algorithm, particle swarm optimization, etc. A brief description of the design of DMAs in the literature has been included below.

Diao *et al.* (2013) has proposed an automated approach for creating boundaries for DMAs based on the community structure of water distribution systems. Community structure involves grouping vertices into communities with denser connections within them than between them, a common characteristic in complex systems. The method was tested on a real-world distribution system and compared to a manually designed DMA layout. While further refinements are needed, the achieved community structure closely aligns with the real zoning plan, making this approach a valuable addition to automated methods that aim to enhance or replace the traditional trial-and-error approach. Campbell *et al.* (2015) introduced an innovative method for partitioning water supply networks. The approach draws inspiration from social network theory and graph theory, specifically community detection and shortest path concepts and employs a multiobjective optimization procedure via Agent Swarm Optimization. It optimizes a range of criteria, including energy efficiency, operational performance and economic considerations. The approach's feasibility was demonstrated by generating four viable solutions on a segment of real WDNs.

Laucelli *et al.* (2017) proposed a two-step strategy for planning DMAs within WDNs. In the first step, an optimal segmentation design was achieved by maximizing the modularity index specifically tailored for WDNs while minimizing the number of conceptual cuts (without considering devices like flow meters). The second step involves the actual optimal DMA design, which determines the positions of flow meters and closed valves at these conceptual cuts. This optimal DMA design is accomplished through a three-objective optimization process to minimize the number of flow meters, total unsupplied customer demand, and background leakages. The

study demonstrates the procedure's effectiveness and flexibility using real-life networks. Han and Liu (2017) has introduced a novel methodology for designing DMAs in WDNs. This methodology treats the WDN as an undirected graph represented by a weighted topology matrix. Nontrivial eigenvectors are calculated using the normalized Laplacian matrix. Clusters are determined using a combination of k-means and genetic algorithms to minimize the squared distance error between nodes and their centroids in Euclidean space. The feasibility of this methodology is demonstrated through testing on a real WDN.

Rahmani *et al.* (2018) has introduced a new method to optimize WDNs by configuring DMAs using graph theory. It aims to enhance DMA efficiency in monitoring and controlling water networks, offering insights into improved system management. Pesantez *et al.* (2019) has introduced an automated approach to design DMAs in WDNs. The goal is to enhance the efficiency of water management by creating well-structured control zones. The approach combines graph theory, optimization and heuristics to design DMAs that minimize the variation in demand similarity among them. The proposed methodology has been applied to four water networks, demonstrating its effectiveness in improving demand similarity among DMAs. Bui *et al.* (2021) presented a method for optimal DMA design using a Self-Organizing Map (SOM) and a Community Structure Algorithm. It begins with SOM-based clustering and then employs the algorithm to refine DMA layouts. The approach was tested on hypothetical and real networks, demonstrating its ability to adapt to changing water demand efficiently. Yu *et al.* (2022) introduced a two-step process for DMA partitioning: clustering and dividing. The first step involves clustering nodes through an improved METIS graph partitioning method. In the second step, feasible solutions for optimizing the location of flowmeters and gate valves on boundary pipes are obtained using improved particle swarm optimization.

Sharma *et al.* (2022) proposed a multi-step approach for DMA identification. In the first step, a community detection algorithm was applied to identify DMAs. The second step involves optimization using the genetic algorithm by simultaneously taking multiple objectives such as economic criteria, water quality, resilience, and network pressure, resulting in a Pareto optimal solution. In the final step, a multi-criteria decision-making (MCDM) tool is utilized to determine a unique solution based on user-defined weightings for various objectives. The methodology was

tested on a medium-sized water network, demonstrating its ability to effectively identify optimal DMA partitions. Sharma *et al.* (2023) applied NSGA-III algorithm for multiobjective design of DMAs in WDN. Five objectives considered in this study are design cost, operational cost, Resilience Index, average pressure and water age. The proposed methodology has been applied to two benchmark problems, demonstrating its capability to identify optimal DMAs. Kakeshpour *et al.* (2024) used NSGA-II algorithm for multiobjective design of DMAs in WDN. The two objectives considered in their study are minimization of total cost and minimization of average pressure in high pressure zones. The proposed methodology has been applied to two benchmark problems. The results have shown that the proposed methodology has significantly reduced average pressure in high pressure zones.

2.4. Gaps found in Literature Review

Based on the literature review, the following gaps have been identified:

- Despite the potential effectiveness of metaheuristic algorithms in solving multiobjective optimization problems, there is a gap in their application to multiobjective WDN design under intermittent water supply system. This gap limits the exploration of diverse optimization techniques that could enhance the efficiency and effectiveness of generating design solutions of WDNs.
- Existing literature lacks comprehensive formulation of multiobjective WDN design models that effectively consider multiple objectives for complex real-life case studies. While some studies address single objectives, such as minimizing cost or maximizing resilience, there is a notable absence of models that simultaneously account for multiple objectives, hindering the development of holistic solutions.
- Many researchers have limited their testing to small and medium benchmark problems, neglecting the examination of large, real-life, complex problems. This gap highlights the necessity of conducting experiments on such larger-scale, practical scenarios to better understand the applicability and effectiveness of proposed methodologies in real-world contexts.
- While the identification of DMAs is crucial for effective WDN management, literature lacks a multiphase procedure that leverages metaheuristic algorithms for this purpose.
Existing methods often rely on manual or heuristic approaches, which may not fully exploit the potential for optimization and automation offered by metaheuristic algorithms. Thus, there is a gap in the literature concerning the development of systematic, algorithm-based approaches for identifying DMAs in WDNs.

● Research efforts focusing on case studies from Telangana, India, are notably scarce, indicating a gap in the existing literature. This lack of attention to a significant urban area suggests an opportunity for further exploration and analysis of WDN design, management and optimization specific to Telangana's unique characteristics and challenges.

2.5. Objectives of the Study

The following objectives have been derived based on the literature review conducted above.

- 1. To formulate of multiobjective WDN design model, considering network cost, network resilience and network equity for a complex real-life case study in continuous and intermittent water supply system
- 2. To solve the proposed multiobjective model using three metaheuristic optimization algorithms (particle swarm optimization, cuckoo search algorithm and genetic algorithm) to generate pareto optimal solutions that represents the optimal WDN design
- 3. To formulate a two-step procedure for identifying the optimal design of DMAs in a WDN using a metaheuristic optimization algorithm

The next chapter details the WDN modelling and discusses the capabilities of the hydraulic simulation tool, EPANET 2.2, offering an understanding of its features and functionalities for accurate modelling and analysis of WDNs.

Chapter 3 Water Distribution Network Modeling

3.1. General

Water distribution network modeling involves the creation of mathematical representations and simulations to analyse the behavior and performance of a system that delivers water from its source to consumers. These models typically include components such as pipes, pumps, valves, storage tanks, and demand nodes, along with parameters such as pipe diameter, material properties, elevation, and water demand. Hydraulic equations, conservation of mass, and energy principles are applied to simulate the flow of water through the network under various operating conditions. Modeling tools range from demand-driven analysis and pressure-driven demand that consider factors like pressure variations, water quality, and demand fluctuations. The modeling in this study was carried out using the United States Environmental Protection Agency's (EPA) EPANET software (Rossman, 2000). A brief description of the model's capabilities and design principles is given in this chapter.

3.2. EPANET 2.2 – Hydraulic Simulation Tool

EPANET 2.2 or the "EPA's Water Distribution System Analysis Program," is a renowned and widely used software tool developed by the United States Environmental Protection Agency (Rossman, 2000). It is a robust and versatile hydraulic and water quality modeling solution for analyzing water distribution networks. EPANET 2.2 assists engineers and water utility professionals in evaluating the performance of water supply systems. It enables users to simulate water flow, pressure, water quality, and contaminant transport. With a user-friendly graphical interface, EPANET 2.2 is an invaluable tool for designing and optimizing distribution networks, assessing water quality and ensuring the safe and efficient delivery of clean drinking water to consumers, making it an essential resource in water infrastructure management. EPANET 2.2 works on a global gradient algorithm for hydraulic analysis of WDNs. The global gradient algorithm determines the flows and pressure at each node by solving the hydraulic equations(conservation of mass and conservation of energy) simultaneously.

3.3. Water Distribution Network Components

The WDN contains components like pumps, tanks, reservoirs, pipes and valves. Pipes are links that convey water from one point in the network to another. Reservoirs are nodes that represent an infinite external source or sink of water to the network. They could represent water storage structures or sources such as lakes, rivers, groundwater aquifers, etc. Reservoirs can also serve as water quality source points. Tanks are nodes with storage capacity, where the volume of stored water can vary with time during a simulation. The primary input properties for tanks are bottom elevation (where the water level is zero), diameter (or shape dimensions, if non-cylindrical), initial, minimum, and maximum water levels and initial water quality. Pumps are links that impart energy to the fluid, thereby raising its hydraulic head. The principal input parameters for a pump are its start node, end node, and pump curve (the combination of heads and flows that the pump can produce). Instead of a pump curve, the pump could be represented as a constant energy device that supplies a constant amount of energy to the fluid for all combinations of flow and head. Valves are links that limit the pressure or flow at a specific point in the network (Bhave and Gupta, 2017).

3.4. Hydraulic Modeling

Hydraulic modeling is a fundamental aspect of network modeling, focusing on the flow of water through pipes and other network components. It calculates flow rates, pressures, and velocities, enabling engineers and water utility managers to understand how water moves throughout the network (Bhave and Gupta, 2017). The following fundamental assumptions have made:

 \checkmark Steady-State Flow: The equations assume that flow parameters such as velocity, pressure, and density remain constant with time at every point in the flow field. This steady-state condition implies that the flow does not vary over time.

- \checkmark Incompressible Flow: The continuity equation assumes that the fluid density is constant and does not change significantly within the flow field. This assumption is applicable to liquids and certain low-speed gases where density changes are negligible.
- \checkmark Irrorational Flow: The assumption of Irrorational flow simplifies the conservation of energy equation, assuming that there is no vorticity or rotational motion of fluid particles about their own axes. This assumption is particularly relevant for deriving Bernoulli's equation.
- \checkmark Inviscid Flow: In the derivation of Euler's equation, it is assumed that the flow is inviscid, meaning that there are no viscous effects or frictional forces present in the flow.

EPANET 2.2 follows the conservation of mass and conservation of energy in the design of the network. A brief description of the design procedure is given in the following passages.

3.4.1. Conservation of Mass

The continuity equation must be satisfied at each node of the network as shown below.

 $\sum_{i \in in, n} Q_i = \sum_{j \in out, n} Q_j + ND_n \,\forall n \in nn$ (3.1) where $Q =$ pipe flow; $ND_n =$ demand at node *n*; *in,n* = set of pipes entering to the node *n*; *out,n* = set of pipes emerging from the node *n*; *nn* = number of nodes.

3.4.2. Conservation of Energy

The energy balance constraint expresses the energy conservation law between the initial and final points of the known heads. These initial and final points can be the same physical point, resulting in a closed loop. The energy balance constraint can be expressed mathematically for each loop as

$$
\sum_{a} r_a Q^b = 0 \tag{3.2}
$$

where 'a' represents the link pipe in the loop; r represents hydraulic resistance in the link pipe in the loop; b is the exponent, and Q is the flow in the link pipe in the loop.

The above equation for two points of the known head can be written as

$$
\sum_{a} r_a Q^b = \Delta E \tag{3.3}
$$

where ΔE is the energy loss between two points of the known head.

Hydraulic resistance 'r' can be calculated from the Hazen Williams head loss equation (Bhave and Gupta, 2017).

$$
r = \frac{aL}{c_{HW}^{1.852} D^{4.87}}
$$
 (3.4)

where L is the pipe length, α is a constant, D is the pipe diameter and C_{HW}^p represents Hazen William Coefficient of the pipe.

3.4.3. Pressure-Driven Analysis

Pressure-driven analysis is a fundamental aspect of hydraulic modeling in water distribution networks (Gupta and Bhave, 1996). It involves the study of how water pressure affects the flow and distribution of water within the network. By simulating pressure changes, engineers and water utility managers can assess the system's behavior, identify potential issues and ensure adequate pressure is maintained to meet consumer needs. Pressure-driven analysis is crucial for optimizing the layout of pipes, selecting pump and valve settings, and designing pressure control strategies. It helps maintain water quality, reduces leakage and ensures that water reaches consumers' taps at sufficient pressure levels, making it a key component in the efficient and reliable operation of water distribution systems. In pressure-driven demand other than conservation of mass and energy, the pressure-driven demand relationship has been included, elaborated below.

Pressure demand relationship.

$$
q = q_{req}, \text{ if } p > p_{req} \text{ (required outflow)} \tag{3.5}
$$

$$
q = q_{req} \left(\frac{p - p_{min}}{p_{req} - p_{min}}\right)^{0.5}, \quad \text{if } p_{min} \le p \le p_{req} \left(\text{partial outflow}\right) \tag{3.6}
$$

$$
q = 0, \text{ if } p < p_{\min} \text{ (zero outflow)}\tag{3.7}
$$

where q is the actual node outflow, q_{req} is the demand; p is the nodal pressure, p_{min} is the minimum pressure, p_{req} is the required pressure.

3.4.4. Demand-Driven Analysis

Demand-driven analysis is a vital aspect of water distribution network modeling, focusing on understanding and simulating the impacts of varying water demands within the system (Gupta and Bhave, 1996). By considering factors such as consumer usage patterns, population growth, and industrial requirements, demand-driven analysis helps assess how different areas of the network experience changes in flow rates and pressure levels. This analysis aids in the design of appropriately sized pipes, pumps and storage facilities to meet the fluctuating demand. It ensures the network can efficiently supply water even during peak usage periods, improving water quality, system resilience, and overall customer satisfaction while optimizing resource utilization. In demand-driven analysis conservation of mass and conservation of energy has been used in the design of the water distribution network which has been elaborated from equations 3.1 to 3.7 above.

The next chapter provides a detailed description of five WDNs considered to validate the proposed methodology. These five WDNs include three benchmark WDNs and two real-life WDNs.

Chapter 4

Description of the Chosen Case Studies

4.1. General

In this study, the five WDNs have been chosen to validate the proposed methodology. Three benchmark problems, representing two medium WDNs (number of pipes between 21-50; New York WDN as branched and Hanoi WDN as looped) and one large WDN (number of pipes greater than 100; Balerma Irrigation Network). Additionally, the proposed methodology has also been tested on two real-life WDNs from Telangana, namely, Pamapur WDN and Vanasthalipuram WDN. The details of the chosen five WDNs are stated below.

4.2. Benchmark Problems

4.2.1. *New York Tunnel Water Distribution Network*

The New York Tunnel (NYT) WDN consists of 20 nodes, 21 pipes and one loop. It is fed by gravity from a reservoir with a fixed head of 91.44 m. All the existing pipes are considered for duplication in order to meet the projected future demand. The Hazen-Williams roughness coefficient for both new and existing pipes is 100. The minimum nodal pressure requirement for all nodes, except 16 and 17, is 77.72 m and for nodes 16 and 17 it is 79.25 m and 83.15 m, respectively. There are 16 possible decisions for each pipe as there are 15 market pipe diameter sizes available for each pipe in the network. The "do nothing" option is considered as the 16th. Considering all 21 pipes for possible duplication, the search space for the optimal solution equals to $16²¹$ possible network design configurations. The relevant network data for this WDN is provided in the Tables 4.1, 4.2 and the network layout is shown in Fig. 4.1 (Schaake and Lai, 1969).

Table 4.1 Pipe Diameters Available in the Market for New York WDN with Corresponding

Costs

Table 4.2 Hydraulic Details of New York WDN

	Node Data		Pipe Data			
Node	Demand (m^3/s)	Minimum Head (m)	Pipe	Length (m)	Diameter (m)	
$\mathbf{1}$	-57.13	91.44	$\mathbf{1}$	3535.68	4.57	
$\overline{2}$	2.62	77.72	$\overline{2}$	6035.04	4.57	
3	2.62	77.72	3	2225.04	4.57	
4	2.50	77.72	$\overline{4}$	2529.84	4.57	
5	2.50	77.72	5	2621.28	4.57	
6	2.50	77.72	6	5821.68	4.57	
7	2.50	77.72	7	2926.08	3.35	
8	2.50	77.72	8	3810.00	3.35	
9	4.81	77.72	9	2926.08	4.57	
10	0.03	77.72	10	3413.76	5.18	
11	4.81	77.72	11	4419.60	5.18	
12	3.32	77.72	12	3718.56	5.18	
13	3.32	77.72	13	7345.68	5.18	
14	2.62	77.72	14	6431.28	5.18	
15	2.62	77.72	15	4724.40	5.18	

Figure 4.1 Layout of New York WDN

4.2.2. Hanoi Water Distribution Network

Hanoi WDN consists of 32 nodes and 34 pipes connecting them, organized in three loops fed by gravity from a single source with a 100 m fixed head. The pipe lengths vary from 100 to 3500 m, with a Hazen-Williams coefficient of 130 and the minimum pressure head required at each node is 30 m above the ground level. There are six commercially available pipes to be considered for 34 pipes making the total search space as 6^{34} . The relevant network data for this WDN is provided in the Tables 4.3, 4.4 and the network layout is shown in Fig. 4.2 (Savic and Walters, 1997).

Table 4.3 Pipe Diameters Available in the Market for Hanoi WDN with Corresponding Costs

S. No.						
Diameter (m)	304.8	406.4	508	609.6	762	1016
Unit Cost $(\$)$	45.73	70.40	98.38	129.33	180.75	278.28

Node Data				Pipe Data			
Node	Demand (m^3/s)	Node	Demand (m^3/s)	Pipe	Length (m)	Pipe	Length (m)
$\mathbf{1}$	-5.54	17	0.24	$\mathbf{1}$	100	18	800
$\overline{2}$	0.25	18	0.37	$\overline{2}$	1350	19	400
3	0.24	19	0.02	3	900	20	2200
$\overline{4}$	0.04	20	0.35	$\overline{4}$	1150	21	1500
5	0.20	21	0.26	5	1450	22	500
6	0.28	22	0.13	6	450	23	2650
7	0.38	23	0.29	7	850	24	1230
8	0.15	24	0.23	8	850	25	1300
9	0.15	25	0.05	9	800	26	850
10	0.15	26	0.25	10	950	27	300
11	0.14	27	0.10	11	1200	28	750
12	0.16	28	0.08	12	3500	29	1500
13	0.26	29	0.10	13	800	30	2000
14	0.17	30	0.10	14	500	31	1600
15	0.08	31	0.03	15	550	32	150
16	0.09	32	0.22	16	2730	33	860
				17	1750	34	950

Table 4.4 Hydraulic details of Hanoi WDN

Figure 4.2 Layout of Hanoi water distribution network

4.2.3. Balerma Irrigation Network

Balerma Irrigation network (BIN) has 454 pipes, 443 demand nodes, 8 loops and fed by 4 source nodes with constant head between 112 m and 127 m. The minimum pressure head required at each demand node is 20 m. The material of pipes is polyvinyl chloride (PVC). Head-losses are calculated using the Darcy–Weisbach equation with an absolute pipe roughness of $k = 0.0025$ mm (Bhave and Gupta, 2017). There are 10 different commercially available diameters in the market. Therefore, the total search space is 10^{454} . The relevant network data for this WDN is provided in Tables 4.5, 4.6 and the network layout is shown in Fig.4.3 (Reca, 2006).

Diameter (10^{-3} m)	Unit Cost (ϵ)	Diameter (10^{-3} m)	Unit Cost (ϵ)	
2870.2	7.22	5745.48	28.6	
3215.64	9.1	7239	45.39	
3672.84	11.92	9189.72	76.32	
4135.12	14.84	11485.88	124.64	
4592.32	18.38	14777.72	215.85	

Table 4.5 Pipe Diameters Available in the Market for BIN with Corresponding Costs

Table 4.6 Hydraulic details of BIN

	Length		Length		Length		Length
Pipe	(m)	Pipe	(m)	Pipe	(m)	Pipe	(m)
$\mathbf{1}$	65	115	246	229	182	343	90
$\overline{2}$	260	116	100	230	93	344	286
$\overline{3}$	164	117	750	231	151	345	146
$\overline{4}$	250	118	250	232	85	346	170
5	100	119	250	233	300	347	222
6	68	120	200	234	250	348	31
$\overline{7}$	164	121	273	235	132	349	69
8	164	122	205	236	211	350	297
9	65	123	200	237	69	351	83
10	98	124	312	238	400	352	77
11	145	125	308	239	259	353	130
12	96	126	40	240	155	354	257
13	181	127	346	241	187	355	720
14	92	128	334	242	222	356	351
15	100	129	73	243	82	357	188
16	177	130	114	244	220	358	159
17	159	131	93	245	300	359	189
18	155	132	161	246	270	360	83
19	168	133	221	247	78	361	200
20	103	134	150	248	90	362	94
21	113	135	254	249	123	363	128
22	850	136	160	250	86	364	67

Figure 4.3 Layout of Balerma Irrigation Network

4.3. Real Life Case Studies

4.3.1. *Pamapur Water Distribution Network*

Pamapur WDN is located in Kothakota mandal, Wanaparthy district, Telangana state, India. The Pamapur water distribution network comprises of 122 pipes, 102 demand nodes, and three tanks. All the pipes are made of polyvinyl chloride. A uniform Hazen-Williams roughness coefficient of 130 is applied to all pipes. The minimum pressure of all demand nodes is fixed at 6 m except for node 22, which is 5.75 m respectively. There are 13 different commercially available diameters in the market. The total search space for this WDN is 13^{122} . The relevant network data for this WDN is provided in Tables 4.7, 4.8 and the network layout is shown in Fig. 4.4 (Pankaj *et al.*, 2020).

Table 4.7 Pipe Diameters Available in the Market for Pamapur WDN with Corresponding Costs

Node Data				Pipe Data			
	Demand		Demand		Length		Length
Node	$(10^{-4}$	Node	$(10^{-4}$	Pipe	(m)	Pipe	(m)
	m^3/s)		m^3/s)				
$\mathbf{1}$	0.57	62	1.88	$\mathbf{1}$	101.43	62	30.82
$\overline{2}$	3.20	63	0.72	$\overline{2}$	106.69	63	30.79
3	3.57	64	2.07	$\overline{3}$	97.34	64	30.65
$\overline{4}$	1.22	65	1.50	$\overline{4}$	91.62	65	29.35
5	0.63	66	2.35	5	106.7	66	30.52
6	0.62	67	2.22	6	115.77	67	29.44
$\overline{7}$	0.88	68	3.53	$\overline{7}$	83.93	68	27.24
8	0.92	69	1.03	8	79.96	69	27.64
9	0.25	70	1.13	9	75.74	70	26.85
10	0.42	71	4.08	10	76.06	71	25.62
11	0.52	72	3.17	11	82.05	72	25.81
12	0.52	73	0.25	12	95.6	73	25.63
13	0.30	74	3.28	13	71.64	74	23.91
14	2.63	75	2.33	14	70.02	75	23.59
15	1.15	76	1.57	15	70.04	76	23.13
16	0.85	77	0.45	16	69.95	77	24.54
17	0.97	78	1.62	17	69.35	78	21.68
18	0.77	79	1.00	18	67.41	79	21.48
19	1.02	80	0.80	19	66.46	80	21.39
20	2.07	81	1.10	20	65.09	81	20.58
21	0.47	82	1.30	21	63.06	82	20.54
22	0.62	83	0.75	22	62.34	83	18.15
23	2.50	84	0.27	23	60.88	84	17.45
24	0.93	85	1.52	24	60.45	85	15.47
25	0.23	86	1.57	25	59.15	86	13.26
26	1.65	87	2.35	26	56.44	87	12.57
27	0.98	88	1.35	27	53.19	88	12.5
28	1.28	89	1.02	28	55.44	89	10.65
29	1.47	90	0.28	29	65.65	90	10.2
30	0.58	91	0.98	30	54.67	91	44
31	0.35	92	1.50	31	54.13	92	19.03
32	0.97	93	1.70	32	51.55	93	86.92
33	0.85	94	2.03	33	52.06	94	44.92
34	0.58	95	0.77	34	47.41	95	24.24
35	0.25	96	1.48	35	47.87	96	24.35
36	0.83	97	0.92	36	66.1	97	38.15
37	0.20	98	0.53	37	47.27	98	118.12
38	1.40	99	1.50	38	46.38	99	66.2

Table 4.8 Hydraulic details of Pamapur WDN

Figure 4.4 Layout of Pamapur WDN

4.3.2. *Vanasthalipuram Water Distribution Network*

Vanasthalipuram is located in Hyderabad, Telangana State, India. Vanasthalipuram WDN comprises of 301 pipes, 211 demand nodes, and one tank. All the pipes are made of polyvinyl chloride. A uniform Hazen-Williams roughness coefficient of 130 is applied to all pipes. The minimum pressure of all demand nodes is fixed at 6 m. There are 13 different commercially available diameters in the market. The total search space for this WDN is 13^{301} . The relevant network data for this WDN is provided in Tables 4.9, 4.10 and the network layout is shown in Fig. 4.5.

Table 4.9 Pipe Diameters Available in the Market for Vanasthalipuram WDN with

Corresponding Costs

Table 4.10 Hydraulic details of Pamapur WDN

Node Data				Pipe Data				
Node	Demand $(10^{-4} \text{ m}^3/\text{s})$	Node	Demand $(10^{-4} \text{ m}^3/\text{s})$	Pipe	Length (m)	Pipe	Length (m)	
	1.74	152	1.74	1	1.73	152	47.62	
2	0.87	153	1.74	$\overline{2}$	2.69	153	47.64	
3	10.24	154	8.51	3	2.83	154	48.57	
4	5.21	155	3.47	$\overline{4}$	2.80	155	48.62	
5	16.49	156	6.95	5	2.88	156	48.64	
6	0.00	157	4.34	6	3.74	157	48.66	
7	6.25	158	6.42	7	4.01	158	48.68	

Figure 4.5 Layout of Vanasthalipuram WDN

Table 4.11 provides the unit cost of flow meters and valves adopted for various commercial sizes of pipes as obtained from the schedule of rates provided by the Government of Telangana for the year 2023-24.

Table 4.11 Commercial rates of flow meters and valves

The next chapter describes about mathematical model formulation for optimal design of water distribution networks, explanation of the various nature inspired algorithms, fast newman algorithm and the different metrics used to compare the pareto optimal solutions obtained by optimization algorithms.

Chapter 5

Mathematical Modeling and Solution Techniques

5.1. General

Water distribution network design problem was historically formulated as least-cost optimization problem where the variables are standard pipe diameters available in the market. Network cost in water distribution is crucial for optimizing infrastructure expenses, ensuring efficient resource allocation, and maintaining affordable water services for consumers while supporting the sustainability of the system. The limitations of optimal design focusing on minimizing network cost alone have been criticized broadly (Engelhardt *et al.*, 2000; Walski, 2001) which led the researchers to transform the single objective model formulation to multi-objective models. The other objectives studied were reliability, resilience, leakage prevention, equity, carbon emissions etc. Among all the other objectives, network resilience and network equity of the network has been the prime consideration for the present study in addition to minimizing the network cost. Every network design should consider the possibility that a few components might be subjected to failure. The network needs to be designed such that even with the failure of a few components, the system should be able to satisfy at least the minimum requirements. The capacity of the network layout to overcome sudden failure is termed as the resilience of the network. Network resilience in water distribution ensures continuous water supply during disruptions, safeguarding public health and minimizing economic impacts by swiftly adapting to changing conditions. In developing countries, intermittent water supply is followed in which the water is supplied only for a fixed duration in a week. One of the major challenges associated with the intermittent water supply systems is maintaining equitable water distribution. Network equity in water distribution ensures fair and equal access to clean water for all communities, mitigating disparities and promoting social justice and inclusivity within society. Keeping the above-mentioned points in mind, three objectives namely Network Cost, Network Resilience and Network Equity have been considered in this study to determine the optimal design of WDNs.

WDNs are one of the major essential public infrastructures designed to meet the daily water requirements of a community. Dividing a water distribution network into subsystems named as district metered areas (DMAs) can improve the efficiency and ease of achieving management goals. Properly designed and maintained DMAs can help water utilities reduce water losses, improve system efficiency and enhance the overall reliability of their distribution networks. It is essential to prioritize the implementation of DMAs as part of a broader water management strategy. Determining the most suitable layout for DMAs of a water distribution network poses a complex challenge for engineers, as it consists simultaneous consideration of multiple interconnected factors. This research study introduces a methodology for achieving optimal DMAs design. The proposed methodology incorporates two key stages, including: (1) clustering to identify clusters using Fast Newman algorithm and (2) multiobjective optimization that provides optimal DMAs configurations. Three objectives considered in this study are minimizing the Network Cost, maximizing Network Resilience and maximizing the Network Equity.

5.2. Mathematical Model for Optimal Design of Water Distribution Networks

The mathematical model for minimization of network cost, maximizing of network resilience and maximization of network equity along with the constraints are detailed below. The optimal design for a network should satisfy the law of conservation of mass and energy as well as meet the demand needs at each node in the network.

5.2.1. Minimization of Network Cost

The diameter and the length of each pipe determine the cost of the network. The following equation 5.1 gives the mathematical representation of network cost:

$$
Network Cost = \sum_{i=1}^{np} C_i (D_i) \times L_i
$$
\n(5.1)

where C_i = Cost per unit length of a given pipe diameter, L_i = Length of pipe *i*, D_i = Diameter of the pipe i and $np =$ Number of pipes in the network

5.2.2. Maximization of Network Resilience

A resilience index was initially developed by (Todini *et al.*, 2000) and improved upon by Prasad and Park (2004) called as network resilience which considers the uniformity of pipes around each demand node. The resilience index equation 5.2 is explained as:

Network Resilience =
$$
\frac{\sum_{i=1}^{nn} Q_i(H_i^{avl} - H_i^{min})}{(\sum_{r=1}^{nor} Q_r H_r + \sum_{p=1}^{npu} \gamma) - \sum_{i=1}^{nn} Q_i H_i^{min}}
$$
(5.2)

where, Q_i = demand at node *i* (cuft/s), H_i^{avl} = Available head at node *i*, H_i^{min} = Minimum head required at node *i*, nn = number of nodes, nor = number of reservoirs, Q_r = Demand of reservoir, H_r = Head of reservoir, npu = number of power units, P_p = Power generated by power unit p, γ = efficiency of power unit.

Theoretically, network resilience lies between 0 and 1. However, part of the total energy supplied at the source is consumed to overcome the frictional losses in the water distribution network. The available energy at end nodes is always less than the initial energy supplied. Due to this reason, resilience never attains the value of 1.

5.2.3. Maximization of Network Equity

Network equity is defined to quantify the equity in distribution of water among the nodes in water distribution network. Gottipati and Nanduri (2014) proposed an index as shown in Eq. 5.3 to quantify the equity among the nodes in an intermittent water distribution system. It is based on the ratio of the actual quantity of water delivered at a node to the demand at the node is defined as the supply ratio of the node. The average supply ratio (ASR) is the mean of the supply ratios of all the nodes in the network. The deviation of the supply ratio of the node from the ASR is computed at each node, and the mean of these deviations is defined as ADEV.

$$
Network \; Equity = 1 - \left(\frac{ADEV}{ASR}\right) \tag{5.3}
$$

If the demand is exactly satisfied at all the nodes in the network, then the supply ratios at all the nodes will be one and hence the network equity would also be one. Network equity value would be less than one if the distribution of water among the nodes is not uniform.

5.2.4. Constraints

The constraints [Eq. (5.4), Eq. (5.5), Eq. (5.6) and Eq. (5.7)] to the optimization model for a water distribution network design are as follows:

(i) Continuity Constraint (Mass Conservation Law):

For each node other than source, the law of continuity (conservation of mass) should be satisfied

$$
\sum_{i \in in, n} Q_i = \sum_{j \in out, n} Q_j + N D_n \,\forall n \in nn \tag{5.4}
$$

where $Q =$ pipe flow; $ND_n =$ demand at node *n*; *in,n* = set of pipes entering to the node *n*; *out,n* = set of pipes emerging from the node *n*; *nn* = number of nodes.

(ii) Energy Conservation Constraint (Energy Conservation Law):

The total loss of energy or head in a closed loop should be equal to zero

$$
\sum_{i \in l} \Delta H_i = 0; \ \forall l \in \text{NL}
$$
\n
$$
(5.5)
$$

where, ΔH_i = head loss in the pipe *i* at a loop *l*, NL = number of total loops in the system

(iii) Minimum Pressure Head Constraint at Nodes:

At every junction, the pressure head should be equal to or more than the minimum pressure head required

$$
H_i^{avl} \ge H_i^{min} \ \ i = 1, 2, 3, \dots \dots nn
$$
\n(5.6)

(iv) Selection of diameters constraint

$$
D_i \in [D] \tag{5.7}
$$

where, $[D]$ = set of commercially available diameters in the market

5.3. Mathematical Model for Optimal Design of District Metered Areas in a Water Distribution Network

In this study, minimization of total cost, maximization of network resilience and maximization of network equity are the objectives considered for multiobjective optimization. The mathematical model for minimization of total cost has been given below. The mathematical model for maximizing the network resilience and maximization of network equity is the same as expressed in Eqs. 5.2 and 5.3.

5.3.1. Minimization of Total Cost

The total cost of implementation of DMAs depends on the number of isolation valves and flow meters. The following equation 5.8 gives the mathematical representation of total cost of implementation:

$$
TCF = \sum_{i=1}^{N_{iv}} c_{iv} + \sum_{i=1}^{N_{flm}} c_{flwm} \tag{5.8}
$$

where C_{iv} = unit cost of isolation valve; C_{flwm} = unit cost of flow meter; N_{iv} = number of isolation valves, N_{flm} = number of flow meters and TCF = Total Cost Function.

The formulated objective function is governed by the constraints, which includes flow continuity and energy conservation that must be satisfied across the water distribution network.

5.4. Solution Techniques Used in the Study

In the last few decades, researchers working on multiobjective design of WDN have attempted to explore several new metaheuristic optimization techniques to such complex problems as they are able to handle a discrete search space directly and are less likely to be trapped into the local optimal solutions (Yang, 2020). In the present study, three such optimization techniques [Multiobjective Particle Swarm Optimization Algorithm (MOPSOA) augmented with local search, Self-adaptive Multiobjective Cuckoo Search Algorithm (SAMOCSA) and NSGA-II algorithm augmented with a random multi-point crossover operator as well as local search (RLNSGA-II)] to solve multiobjective optimization models with some improvements in their working methodology have

been implemented. Local search scheme has been augmented in two of the algorithms (MOPSOA and RLNSGA-II) to effectively explore the least-crowded areas of the objective space to determine better pareto-optimal points. Although these optimization algorithms work well for solving the problems, the robustness and efficiency of these algorithms are significantly dependent on certain control parameters specific to the working of the optimization algorithm. Appropriate values of these control parameters for obtaining near global optimal solution is not the same for every problem. Extensive sensitivity analysis studies need to be conducted for each problem which makes the process computationally expensive to determine the best suited parameter set accurately. To overcome this difficulty, studies have been done in developing algorithms to avoid prespecifying the parameter values or algorithms which modify these parameters dynamically during the iterative process of the algorithm, based on the number of iterations or fitness value of the objective function. These algorithms are known as self-adaptive algorithms. The study focusses on developing a self-adaptive multiobjective cuckoo search algorithm for solving the design of WDNs. It is proposed to dynamically adjust the two parameters which largely govern the exploration and exploitation search strategies by the algorithm, i.e., step size control parameter '*α*' and discovering probability parameter '*Pa*'. These parameters are essential for enhancing the performance of the algorithm and the values of these parameters vary with the type of problem. This self-adaptation enables the algorithm to search in larger search space initially and as the iteration increases, the search space also decreases, enabling a better convergence rate as compared to original cuckoo search. Fast Newman Algorithm (FNA) has been used to identify the clusters while identifying the DMAs in a WDN. The description of the working of all these three optimization techniques and FNA is given in the following sections.

5.4.1. Multiobjective Particle Swarm Optimization Algorithm (MOPSOA)

Particle Swarm Optimization (PSO) is a popular metaheuristic optimization algorithm inspired by the social and collective behavior of bird flocking (Kennedy and Eberhart, 1995). It is widely used to solve complex optimization problems across various fields, including engineering, economics, and data science. In PSO, the potential solutions, called particles, fly through the search space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution it has achieved so far. PSO is known for its high convergence speed which makes it more suitable for solving multiobjective optimization problems (Coello *et al.*, 2004). Several variations of the MOPSO algorithm have been reported by Sierra and Ceollo(2005) and Parsopoulos and Vrahatis (2008). Here, it is proposed to use the MOPSO algorithm proposed by Coello et al. (2004) with some modifications.

The velocity update formula in MOPSOA is similar to that used in single-objective PSO, and is given below:

$$
v_i(t) = w v_i(t-1) + C1 * r1 \left(x_{\text{pbest}}^i - x_i(t) \right) + C2 * r2(x_{\text{leader}} - x_i(t)) \tag{5.9}
$$

where t denotes the PSO iteration number, x_i and y_i are the position and velocity of the ith particle, respectively, and r1 and r2 are random numbers between 0 and 1. The algorithm parameters are W (inertia weight), C1 (cognitive learning factor), and C2 (social learning factor). It should be pointed out that, although the decision variables in the present research work considered here take on discrete values, they are treated as real numbers in the velocity and position update equations. In computing the particle fitness, each decision variable is converted to the nearest integer (which gives the pipe diameter index for the concerned pipe).

The MOPSOA algorithm differs from the single-objective PSO algorithm in the computation of x_{pbest}^i (the personal best position of the particle so far) and x_{leader} (the position of the leader). In Coello et al. (2004), x_{pbest}^i is updated in every iteration by comparing its current position with the previous value of x_{pbest}^i . If the current position dominates, it replaces x_{pbest}^i . If it is nondominated with respect to x_{pbest}^i , then one of them is selected randomly as the next x_{pbest}^i .

Figure 5.1 Illustration of leader selection procedure: (a) MOPSO algorithm used in Coello *et al.* (2004), (b) MOPSOA algorithm proposed in this work. Hollow circles: PSO particles, filled circles: current non-dominated solutions.

In MOPSOA, assignment of x_{leader} is made using the non-dominated (ND) set stored in an external archive (repository). The objective space is divided into hyper cubes, and each ND solution, depending on its position in the objective space, is assigned one of these hyper cubes. For each particle, in each PSO iteration, a leader is selected from the archive giving preference to ND solutions which occupy less-crowded hyper cubes. Roulette-wheel selection is used to first select a hypercube, and one of the ND solutions in that hypercube is picked randomly as the leader. This procedure helps to ensure that the ND solutions are well distributed in the objective space. In addition, a mutation operator is used in Coello *et al.* (2004) to enhance exploration of the search space in the beginning of the search. The mutation rate is made zero as the algorithm converges. With this background, the modifications made in the proposed MOPSOA algorithm are described below.

- (a) Archive Manipulation: The hyper grid approach used in Coello *et al.* (2004) has been modified in Patil (2020) to avoid changing of grid boundaries and for more efficient use of memory. This new approach, which uses a hyper grid with a fixed cell size and does not involve grid boundaries, is used in the MOPSOA program.
- (b) Leader Selection: The leader selection process in MOPSO used in Coello *et al.* (2004) is illustrated in Fig. 5.1 (a). In each PSO iteration, each particle is assigned one of the ND particles in the archive, preferring less crowded hyper cubes. In MOPSOA proposed in this work, we continue to use the roulette-wheel selection procedure of the

MOPSO algorithm. However, to intensify exploration of the less-crowded regions of the archive, we assign the same leader to all particles, as shown in Fig. 5.1 (b) and keep the same leader for N_{leader}^{const} iterations.

- (c) Mutation: In PSO, when the velocity and position update steps fail to generate new ND solutions, mutation can be useful (Parsopoulos and Vrahatis, 2008). In the context of the WDN benchmark problems, it is observed that there is an initial phase of MOPSO in which the ND set is improved relatively rapidly. However, beyond a certain point, the rate of generation of new solutions drops significantly. For this reason, different mutation schemes have been implemented in MOPSOA as shown in Fig. 5.2. In the "constant" option, the mutation probability remains constant (a low value such as 0.01). In the "pulse" option, the probability is made non-zero only for *Nmut* iterations in the early stages and zero otherwise. In the "periodic" option, the probability is made nonzero for *Nmut* iterations in every *Nperiod* iterations, thus periodically encouraging enhanced exploration. The mutation process itself is common in the three cases and involves changing one of the decision variables of the particle randomly.
- (d) Local Search: The local search operation procedure is done using the following procedure named as a "unit local search" (ULS) step. In MOPSOA, local search is implemented as follows.
	- a. Choose a subset S of the current ND set.
	- b. Select one individual from S for local improvement. Define a scalar fitness function with linear weighting where the weights are obtained using an estimate of the gradient of the pareto front. For the selected individual,

i. Find the Hooke-Jeeves pattern search direction using the above scalar fitness function.

ii. Perform the cultural learning step by applying the same pattern search direction to a group of individuals in the current ND set.

c. Repeat (b) until a sufficient number of children are created.

As seen in the procedure above, a ULS step can lead to some improvement in the ND set. If it is applied again on the new ND set, further improvement is possible. For this purpose, MOPSOA allows the ULS to be repeated N_{LS}^{max} times at a given PSO iteration. If, after some ULS steps, it is found that no further generation of new ND solutions is taking place, the local search step is discontinued.

(e) Local search is expensive, and it is not practical to perform it in every PSO iteration. In MOPSOA, therefore, local search is performed periodically instead of every iteration. Furthermore, it was observed in the context of the WDN problems that local search is more effective in the early stages. Based on this observation, a two-stage local search strategy is implemented. From iteration $N_{PSO}^{(1)}$ to $N_{PSO}^{(2)}$, local search is performed every T_1 iterations, and after $N_{PSO}^{(2)}$, it is performed every T_2 iterations.

Figure 5.2 Mutation Probability versus PSO iteration number for different mutation schemes implemented in MOPSOA
5.4.2. Self-Adaptive Multiobjective Cuckoo Search Algorithm (SAMOCSA)

Cuckoo Search Algorithm (CSA) is a swarm intelligence based metaheuristic optimization algorithm developed by Yang and Deb (2009). CSA mimics the breeding behaviour of few cuckoo species and Levy flight behaviour of some birds and fruit flies. To trap the behaviour of cuckoos in nature and adapt it to be suitable for using as an algorithm, there are three basic rules:

- (i) each cuckoo lays one egg at a time in a nest and dumps it in a randomly chosen nest
- (ii) the best nests which resemble the closest to the host's eggs (high quality eggs) are carried to the further generations
- (iii)the number of available host nests is fixed and any egg laid by a cuckoo may be discovered by the host bird with a probability $P_a \in [0,1]$.

The working of CSA is explained with the help of a flowchart as shown in Fig. 5.3. In the first step, parameters of CSA are set consisting of the number of nests, the step size control parameter 'α' and shifting parameter 'Pa'. Initial locations of the nests are determined by a randomly assigned set to each decision variable. As can be seen from the algorithm in the flowchart, new cuckoos are generated by Levy flights using the equations of local random walk Eq. 5.10 (intended primarily for exploitation of the current solutions) and global random walk Eq. 5.11 (intended primarily for exploration of the search space defined in the function).

Local random walk (Eq. 7) is performed using the *P^a* parameter is expressed as,

$$
nest_i^{new} = nest_i^{cur} + \alpha \otimes H(Pa - rand) \otimes (nest_j^{cur} - nest_k^{cur})
$$
 (5.10)

Global random walk (Eq. 8) is performed by using the α (step length) and the best nest using Levy-Flight

$$
nestinew = nesticur + \alpha * f(best, \beta)
$$
\n(5.11)

Here *f* is a function of current best nest and levy-flight parameter β.

The generating new cuckoos and discovering alien eggs steps are alternately performed until the termination criteria (i.e., till the algorithm reaches the maximum function evaluations [FEval]) is satisfied (Yang and Deb, 2009). The performance of this algorithm is sensitive to two main parameters, i.e. step size control parameter 'α' and discovering probability parameter 'Pa' (Yang,

2014). These two parameters govern the exploration and exploitation ability of the algorithm. To solve this problem, a self-adaptive version of this algorithm is proposed. The flowchart of the working of self-adaptive cuckoo search algorithm (SACSA) is shown in Fig. 5.3.

Figure 5.3 Flowchart of CSA and SACSA for Single Objective Optimization

SACSA attempts to dynamically update the values of both the step size (α) and discovering probability parameter (P_a) as the algorithm proceeds, as shown in Eq. 5.12 and Eq. 5.13.

$$
\propto (i) = \left(\frac{1}{t}\right)^{\left(\frac{F_{ideal} - F_i}{F_{ideal} - F_{anti-ideal}}\right)}\tag{5.12}
$$

Here α- alpha, *i* - nest number, t – iteration number, F_{ideal} - fitness value of best nest, $F_{anti-ideal}$ -Fitness value of worst nest

$$
Pa(t) = Pamax * e^{t/time}
$$
\n(5.13)

Here *Pamax* is maximum value of the discovering probability parameter (assumed 0.9), t is iteration number and time represents maximum number of iterations.

This enhancement enables the algorithm to search in larger search space, initially and as the iteration increases, the search space also decreases enabling a better convergence rate compared to original cuckoo search. As a result, two out of the three parameters are self-adapted and easy to set.

Similar to single objective cuckoo search algorithm, a self-adaptive algorithm for solving multiobjective optimization problems has been proposed in this study. For multiobjective optimization problems with K different objectives, the first and third basic rules are modified as follows:

- (i) each cuckoo lays K eggs at a time and dumps them in a randomly chosen nest. Egg k corresponds to the solution to the kth objective;
- (ii) each nest will be abandoned with a probability pa and a new nest with K eggs will be built according to the similarities/ differences of the eggs. Some random mixing can be used to generate diversity.

The flowchart of working of self-adaptive multiobjective cuckoo search algorithm is shown in Fig. 5.4. The first step starts with the initialization of the algorithm parameters, generating the initial population using objective functions. Determine the leader nest which has the least rank based on non-dominated sorting and highest crowding distance using the approach used in NSGA-II (one of the best algorithms available for non-dominated sorting approach and diversity preservation) by Deb *et al.* (2002). Generate new nests using Levy flights and update the population. Then, the new nests are replaced with the generated nests with a discovering probability Pa. Update the population and algorithm continues until the maximum function evaluations (FE) is met as the stopping criteria. The P_a dynamic adaptation is same as that of single objective algorithm (Eq. 5.13), but the step length α is updated using Eq. 5.12 using the current rank and crowding number of the nest and the nests in the first pareto front. Ideology behind this upgradation of alpha (step length) is

that, the step length is reduced if there is an improvement in the performance of the nest, but the decrement is controlled by the exponential function such that it does not significant decrease (Kaveh and Bakshpoori, 2016). When the nests converge to a single pareto front, the step length should be minimum, this is ensured with the third if clause as shown below.

if rank of new nest $_i$ < rank of old nest $_i$

$$
alpha(i) = rand * \exp(\left(\frac{1}{t}\right) - 1)
$$

else if rank of new nest_i == old nest_i && Crowding distance of new nest_i > old nest_i

$$
alpha(i) = rand * \exp(\left(\frac{1}{t}\right) - 1)
$$

else if rank of new nest $== 1$,

 $alpha(i) = (max of all values of variables in first part of root)$ − minimum of all varibles in first pareto front)/100

end if

Figure 5.4 Flowchart of Self-Adaptive Multiobjective Cuckoo Search Algorithm (SAMOCSA)

5.4.3. Random multi-point crossover operator, Local search augmented with Non-dominated Sorting Genetic Algorithm - II (RLNSGA-II)

Deb *et al.* (2002) introduced a fast and elitist multiobjective genetic algorithm called Nondominated Sorting Genetic Algorithm-II (NSGA-II). In this study, the traditional NSGA-II algorithm is augmented with Random multi-point crossover operator, Local search, and periodic

mutation, represented with symbol RLNSGA-II. In this study, RLNSGA -II algorithm is used for design of water distribution network. The complete procedure of working of RLNSGA-II algorithm is described below and shown in the flow chart (Fig. 5.5).

Figure 5.5 Flow Chart of RLNSGA-II algorithm

Step 1: Initialize parent population P_0 consists of m rows equal to population size and *n* columns equal to decision variables. Here decision variables are taken as the pipe diameters.

Step 2: Generate off-spring population Q_0 by applying random multi-point crossover operator, local search and periodic mutation to the parent population P_0 which is shown below.

a) Crossover operator

In crossover, there is an exchange of properties between two parents and as a result of which two off-spring solutions are produced. The crossover points are decided randomly and then perform exchange of values with respect to the crossover points. There are different crossover operators available namely single-point, two-point, random multi-point etc. To illustrate the working of RLNSGA-II, the difference between single-point crossover operator (used in traditional NSGA-II algorithm) and random multi-point crossover operator are explained below (Figs. 5.6 and 5.7).

 \mathbf{I}

Figure 5.6 Illustration of single-point crossover operator

In single-point crossover operator, there will be only one crossover point is selected then all data beyond that point in either string is swapped between two parents resulting in off-spring population.

b) Random multi-point crossover operator

In this scheme, multi-point crossover points are selected along the length randomly then alternate parts are swapped between parent populations in order to form child population.

Parent 1 1 1 2 3 4 5 6 7 8 9 10 Parent 2 1 3 5 7 9 11 12 15 17 9					
Child 1 1 3 3 4 9 11 7 8 17 9					
Child 2 1 2 2 5 7 5 6 12 15 9 10					

Figure 5.7 Illustration of Random multi-point crossover operator

c) Local search

Local search is useful for obtaining the new non-dominated solutions in the less crowded areas of objective space. In this study, a simple local search is employed. The local search technique utilized in this study is illustrated in the following sections. Consider the following twovariable, two-objective test problem.

$$
f_1(x) = -x_1^2 + x_2 \tag{5.14}
$$

$$
f_2(x) = \frac{x_1}{2} + x_2 + 1 \tag{5.15}
$$

subject to the constraints $0 \le x_1 \le 10$, $0 \le x_2 \le 10$

Figure 5.8 Demonstration of local search for the two variables, two objective optimization problem denoted by Equation 5.14 and 5.15 (Patil *et al.*, 2020)

Let the current non-dominated set comprises of three points A, B and C shown in Fig. 5.8(a) denoted by crosses, respectively. P_A , P_B and P_C represent the corresponding objective function values shown in Fig. 5.8(b) marked by crosses, respectively. Four neighbouring points centered on each existing solution were generated using equations 5.16 and 5.17 shown in Fig. 5.8(a), denoted by plus, respectively in order to improve the non-dominated set using local search.

$$
x_1^{new} = x_1^{old} \pm \Delta x_1 \tag{5.16}
$$

$$
x_2^{new} = x_2^{old} \pm \Delta x_2 \tag{5.17}
$$

The corresponding neighbours in the objective space are denoted in Fig. 5.8(b). From the full set of both old and new generated solutions, new non-dominated solutions P_1 , P_2 , P_3 and P_4 have been found which is shown in Fig. 5.8(b) denoted by combination of square and plus respectively. It is worth noting that the non-dominated set was improved in terms of the number of solutions as well as the quality of solutions.

Step 3: Merge parent population P_0 and off-spring population Q_0 for elitism

Step 4: Apply non-dominated sorting to obtain non-dominated fronts F1, F2, F3....

Step 5: Furthermore, select a new parent population that is equal to size P_0 from these nondominated fronts depending upon crowding distance which completes one iteration.

Step 6: In the second iteration repeat step 2, 3, 4 and 5.

Step 7: The procedure is terminated until the maximum number of iterations is reached, else, repeat steps 2, 3, 4 and 5.

Table 5.1 shown below summarizes the key features, advantages and drawbacks of the optimization algorithms used in this study.

Optimization	Key Features	Advantages	Drawbacks
Algorithm			
MOPSOA	Based on the social ✓ behaviour of birds flocking Uses a population of \checkmark candidate solutions (particles) which move through the solution space	Simple to ✓ implement Few parameters to adjust Fast convergence \checkmark in many problems	Can converge ✓ too early Can get stuck in \checkmark local optima
SAMOCSA	Inspired by the brood ✓ parasitism of some cuckoo species Uses Levy flights to \checkmark explore the solution space	The major ✓ parameters are self-adaptive in nature Efficient for ✓ global search Good balance ✓ between exploration and exploitation	May be slower for some problems
RLNSGA-II	Based on natural ✓ selection and genetics Uses crossover, ✓ mutation, and selection operations on a population of solutions	Highly flexible \checkmark Can handle a \checkmark wide variety of optimization problems Good for global \checkmark search	Computationally expensive May require \checkmark careful tuning of parameters

Table 5.1 Key Features, Advantages and Drawbacks of Optimization Algorithms

5.4.4. Fast Newman Algorithm for Clustering

The Fast Newman Algorithm as explained by Clauset *et al.* (2004), is one of the popular community detection algorithms employed for cluster identification due to its ability to decompose large networks quickly and reliably. Initially, the WDN is converted into an undirected and weighted graph, denoted as $G = (V, E)$ where V represents demand nodes, reservoirs, and tanks, and E represents pipes, valves, and pumps. The edge weights are obtained by averaging the nodal pressure values between the two connected nodes, as expressed by the following equation:

$$
w_{ij} = \frac{p_i + p_j}{2} \tag{5.18}
$$

where w_{ij} denotes the weight of the edge between nodes *i* and *j*, P_i and P_j represent the nodal pressure values at nodes *i* and *j* respectively.

Modularity index (MI) is a property of a network that measures the quality of the division in a network is used in this algorithm. In an ideal scenario, the partitions discover dense interconnections within the communities while displaying sparse connections amongst them.

$$
MI = \frac{1}{2m} \sum_{U_W} \left[A_{uw} - \frac{k_u k_w}{2m} \right] \delta(C_u, C_w) \tag{5.19}
$$

where A_{uw} = ×element of the adjacency matrix of the network ((A_{uw}) =1, if vertices v and w are connected; otherwise $(A_{uw}) = 0$)), $m = \frac{\sum_{uw} A_{uw}}{2}$ $\frac{1}{2}$ total number of edges, $k_u = \sum_w A_{uw}$ is degree of vertex v, defined as the number of edges connected to vertex, $\delta(c_u, c_w) = 1$, if $c_v =$ $c_w(otherwise = 0)$; c_v and c_w are two different communities, v and w = vertices in c_v and c_w, respectively; and $\frac{k_v k_m}{2m}$ is probability of an edge an edge existing between vertices v and w if connections are randomly made (respecting vertex degrees).

In this study, community detection or clustering within a WDN has been done using an opensource software named Gephi (gephi.org). The necessary details of the WDN are supplied as an input to the software. The clustered network is further reviewed based on the engineering judgement as deemed necessary from the practical and operational point of view. The resolution parameter within the software is responsible for the number of clusters to be identified within the WDN. The resolution value by default has been set to 1. The appropriate value of the resolution is decided based on trial and error to arrive at the number of the clusters for a WDN.

5.5. Hypervolume Performance Metric

In the present study, three multiobjective optimization algorithms have been used to determine the optimal design of WDNs. The comparison of performance of optimization algorithms has been evaluated using the hypervolume performance metric. Hypervolume metric provides a qualitative measure of convergence as well as diversity among the obtained pareto optimal front by each optimization algorithm (Deb, 2001). Hypervolume is a widely used performance metric to compare the performance of multiobjective optimization algorithms. Each multiobjective optimization algorithm converges to a pareto optimal set which consists of a non-dominated set of solutions. Fig. 5.9 shows an example of a pareto optimal set consisting of five points P1, P2, P3,

P4 and P5 for a two-objective problem. Hypervolume represents the volume in the objective space covered by the pareto optimal set constructed with an assumed reference point. Mathematically, for each solution on the pareto optimal set, a hypercube is constructed with a reference point. The reference point can simply be found by constructing a vector of the worst objective function values. Hypervolume is the sum of all the hypercubes (Deb, 2001). An algorithm having a large value of hypervolume is desirable and represents the pareto-optimal set having a better converge and diversity compared to other optimization algorithms.

Figure 5.9 Illustration of Hypervolume Metric for Two Objective Problem

The next chapter describes the results and discussion, which includes three distinct scenarios. In the first scenario, two objectives, namely, network cost and network resilience have been considered. In the second scenario, the focus extends beyond cost and resilience to include the critical consideration of network equity and the third scenario discusses in detail the results of determining the optimal design of DMAs.

Chapter 6 Results and Discussion

6.1. General

In this study, three distinct scenarios have been considered. The first two scenarios determine the optimal WDN design based on different objectives for continuous and intermittent water supply. An optimization-simulation model is developed for obtaining optimal design for WDNs. This model integrates the developed multiobjective optimization algorithm as well as water distribution system simulation software EPANET 2.2. The diameter values obtained from the optimization algorithm are passed to the simulation software. Although the continuity constraint and energy conservation constraint are satisfied externally via EPANET 2.2, other constraints must be satisfied by the optimization algorithm using exterior penalty function approach. For intermittent water supply analysis, the duration of the water supply has been assumed as two hours per day based on the discussion with the water engineers from the Government of Telangana. In the first scenario, two objectives, namely, network cost and network resilience have been considered. The formulated optimization-simulation model is applied to the three benchmark WDN problems and later this is also applied to two real-life WDNs located in Telangana, India to ensure practical relevance of the proposed methodology in the first scenario. In the second scenario, the focus extends beyond cost and resilience to include the critical consideration of network equity, aiming to ensure a fair and equitable distribution of water. This expanded set of objectives is examined in the context of two real-life WDNs. The third scenario focuses on determining the optimal design of DMAs for the two real-life WDNs. Sharanga High performance computing facility available with our Institute with a configuration of 32x2 cores AMD EPYC 7542, 256 GB of memory and 1x Tesla V100 PCIe 32GB has been used for running the simulations needed in this research study. The simulation durations on the high performance computing facility taken by New York Tunnel WDN is 5 days, Hanoi WDN took 8 days, BIN took 32 days, Pamapur WDN required 13 days and Vanasthalipuram WDN demanded 22 days.

6.2. Analysis of Results from Optimal Water Distribution Network Design - Scenario 1 (Network Cost and Network Resilience)

In this scenario, the proposed methodology has been tested on the five WDNs (New York Tunnel WDN, Hanoi WDN, BIN, Pampapur WDN and Vanasthalipuram WDN) using three optimization techniques (MOPSOA, SAMOCSA and RLNSGA-II) for continuous and intermittent water supply. Wang *et al.* (2015) have used five different multiobjective evolutionary algorithms, namely AMALGAM, NSGA-II, Borg, epsilon-NSGA-II, epsilon-MOEA to obtain best-known approximation of true pareto front of benchmark problems. Among these, AMALGAM is a hybrid algorithm consisting of four sub-algorithms simultaneously: NSGA-II, Particle Swarm Optimization, Differential Evolution and Adaptive metropolis search. Wang *et al.* (2015) has run each algorithm 30 times independently and combined all nondominated solutions generated by each algorithm to obtain the best-known approximation of the true Pareto front. The results of New York Tunnel WDN, Hanoi WDN and BIN for continuous water supply are compared with the solutions of Wang *et al.* (2015) to test the efficacy of the developed optimization algorithms.

6.2.1. New York Tunnel WDN

Continuous Water Supply (CWS)

The parameters chosen after trial and error in various optimization algorithms is shown in Table 6.1. The population size and number of iterations have been fixed as 300 and 10,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Table 6.2 Comparison of Optimal Solutions obtained by Optimization Algorithms and Wang *et*

	No of points	Extreme points in pareto front		
Algorithms	in pareto front	Network Cost $(\$10^6)$	Network Resilience	Hypervolume $(x10^3)$
MOPSOA/ SAMOCSA/ RLNSGA-II	647	38.8142 238.2542	0.3906 0.7516	67830.77
Wang et al. (2015)	627	38.8142 238.2542	0.3906 0.7516	67877.67

al. (2015) for New York Tunnel WDN (CWS)

Figure 6.1 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II and Wang *et al.* (2015) for New York Tunnel WDN (CWS)

The results are compared with Wang *et al.* (2015), as shown in Table 6.2. It is observed that MOPSOA, SAMOCSA, RLNSGA-II has converged to more pareto front points for New York Tunnel WDN in comparison with Wang *et al.* (2015). It can be observed from Table 6.2 that the hypervolume of all the three optimization algorithms is almost similar when compared with Wang *et al.* (2015). In summary, the results highlight that MOPSOA, SAMOCSA and RLNSGA-II demonstrated better performance compared to Wang *et al.* (2015) with respect to the total number of points in the pareto front, capturing the extreme points and hypervolume for New York Tunnel WDN. The Pareto front obtained by each optimization algorithm is shown in Fig 6.1. It is observed from the figure that most of the points on the pareto front obtained by MOPSOA, SAMOCSA, RLNSGA-II and Wang *et al.* (2015) are similar.

Intermittent Water Supply (IWS)

The parameters chosen after trial and error in various optimization algorithms is shown in Table 6.3. The population size and number of iterations have been fixed as 300 and 10,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters
MOPSOA	$W = 0.4$; C1, C2 = 2 Local search is performed with a period of 100 between NPSO = 1000 and 5000, and with a period of 1000 thereafter
RLNSGA-II	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9 Local search is performed with a period of 100 between NPSO = 1000 and 5000, and with a period of 1000 thereafter

Table 6.3 Parameters Chosen for Optimization Algorithms for New York Tunnel WDN (IWS)

Table 6.4 Comparison of Optimal Solutions obtained by Optimization Algorithms for New York

Tunnel WDN (IWS)

Figure 6.2 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for New York Tunnel WDN (IWS)

The results obtained by the optimization algorithms are shown in Table 6.4. The Pareto front obtained by each optimization algorithm is shown in Fig 6.2. It is observed from the results that the Pareto front obtained by MOPSOA, SAMOCSA and RLNSGA-II have converged to the same solution for New York Tunnel WDN. Results for New York Tunnel WDN for intermittent water supply have not been compared with any other published literature as they are not available.

The optimal solution representing the extreme points of Pareto front obtained by the best optimization algorithm for New York Tunnel WDN in CWS and IWS has been compared. The hydraulic analysis of the optimal WDN design for each extreme point has been carried out and the pipe velocity as well as nodal pressure are compared and shown in Tables 6.5 and 6.6.

Leftmost Extreme Point-CWS (Network Cost= $$38.8142x10^6$ and Network Resilience=0.3906)				Leftmost Extreme Point-IWS (Network Cost= $$39.1842x106$ and Network Resilience=0.4455)					
Pipe	Diameter	Velocity		Pressure	Pipe	Diameter	Velocity		Pressure
N ₀	(10^{-3} m)	(m/s)	Node	(m)	N ₀	(10^{-3} m)	(m/s)	Node	(m)
1	5181.6	3.1269	$\mathbf{1}$	57.7193	1	5181.6	4.6389	1	58.8393
$\overline{2}$	4876.8	3.0447	$\overline{2}$	56.2289	$\overline{2}$	5181.6	4.5567	$\overline{2}$	57.3489
3	4572.0	2.7401	3	51.7819	3	5181.6	4.2521	3	52.9019
$\overline{4}$	4267.2	2.6955	$\overline{4}$	51.0962	$\overline{4}$	4876.6	4.2075	$\overline{4}$	52.2162
5	3962.4	2.6787	5	45.5160	5	4876.8	4.1907	5	46.6360
6	3657.6	2.4471	6	44.6220	6	4572	3.9591	6	45.7420
7	3352.8	2.1028	7	44.0447	$\overline{7}$	4267.2	3.6148	7	45.1647
8	5181.6	1.9236	8	42.2837	8	5181.6	3.4356	8	43.4037
9	4876.8	1.8859	9	41.7470	9	5181.6	3.3979	9	42.8670
10	4572.0	1.8307	10	40.8757	10	4876.8	3.3427	10	41.9957
11	4267.2	1.7417	11	39.8355	11	4876.8	3.2537	11	40.9555
12	3962.4	1.6743	12	38.2761	12	4876.8	3.1863	12	39.3961
13	3657.6	1.6403	13	36.5820	13	4572	3.1523	13	37.7020
14	5181.6	1.4518	14	35.9710	14	5181.6	2.9638	14	37.0910
15	4876.8	1.4119	15	34.8477	15	5181.6	2.9239	15	35.9677
16	4572.0	1.3079	16	33.9779	16	4876.6	2.8199	16	35.0979
17	4267.2	1.2719	17	32.0000	17	4876.8	2.7839	17	33.1200
18	3962.4	1.2714	18	31.0657	18	4572	2.7834	18	32.1857
19	3657.6	1.2025	19	30.9756	19	4572	2.7145	19	32.0956
20	3352.8	0.8789	\blacksquare		20	4572	1.6379	$\overline{}$	
21	3352.8	0.7188			21	3962.4	1.4688		

Table 6.5 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing

Table 6.6 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Rightmost Extreme Point for New York Tunnel WDN in CWS and IWS

Rightmost Extreme Point-CWS (Network Cost= $$238.2542x106$ and Network Resilience=0.7516)						Rightmost Extreme Point-IWS (Network Cost= $$238.2542x106$ and	Network Resilience=0.8066)		
Pipe N ₀	Diameter (10^{-3} m)	Velocity (m/s)	Node	Pressure (m)	Pipe Velocity Diameter Node (10^{-3} m) N ₀ (m/s)				Pressure (m)
	5181.6	2.1428		59.2193		5181.6	3.6628		62.5452
2	5181.6	2.0594	$\overline{2}$	57.7289	2	5181.6	3.5794	2	61.1189
3	5181.6	2.0389	3	53.2819	3	5181.6	3.5589	3	60.0866
$\overline{4}$	5181.6	2.0036	$\overline{4}$	52.5962	$\overline{4}$	5181.6	3.5236	4	57.8353
5	5181.6	1.9591	5	47.0160	5	5181.6	3.4791	5	56.7315
6	5181.6	1.7107	6	46.1220	6	5181.6	3.2307	6	56.3876

It is observed from Table 6.5, that three pipe diameters (Pipe Nos 1, 8 and 14) of the optimal WDN design for the leftmost extreme point in CWS and IWS scenarios are same. The optimal network cost is around 1% higher in IWS as compared to CWS scenario. Similarly, the optimal network resilience is around 14% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is 84% higher as compared to the pipe velocity in CWS scenario. In CWS and IWS scenarios, the pipe velocity is seen in a decreasing pattern from pipe 1 to pipe 21 as the network is a branched WDN. It is also observed that the rate of increase in velocity is relatively higher in the later part of the network (pipes 14-21) compared to those pipes which are closer to the source. The nodal pressure in IWS scenario is around 3% higher in comparison to CWS scenario. The demand in IWS scenario is met in 2 hours per day as compared to CWS. Moreover, the objective of maximizing the network resilience could be a possible reason for increased variation in the pipe velocity as compared to the nodal pressures in the WDN. It is observed from Table 6.6, that the optimal WDN design for the rightmost extreme point in CWS and IWS scenarios are same. The optimal network resilience is around 7% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is approximately 167% higher as compared to the pipe velocity in CWS scenario. In CWS and IWS scenarios, the pipe

velocity is seen in a decreasing pattern from pipe 1 to pipe 21. It is also observed that the rate of increase in velocity is relatively higher in the later part of the network (pipes 12-21) compared to those pipes which are closer to the source. The nodal pressure in IWS scenario is around 31% higher in comparison to CWS scenario.

6.2.2. Hanoi WDN

Continuous Water Supply (CWS)

The parameters chosen after trial and error in various optimization algorithms is shown in Table 6.7. The population size and number of iterations have been fixed as 300 and 10,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters								
	$W = 0.4$; C1, C2 = 2								
MOPSOA	Local search is performed with a period of 100 between $NPSO = 1000$ and								
	5000, and with a period of 1000 thereafter								
	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9								
RLNSGA-II	Local search is performed with a period of 100 between $NPSO = 1000$ and								
	5000, and with a period of 1000 thereafter								

Table 6.7 Parameters Chosen for Optimization Algorithms for Hanoi WDN (CWS)

Table 6.8 Comparison of Optimal Solutions obtained by Optimization Algorithms and Wang *et al.* (2015) for Hanoi Network (CWS)

Figure 6.3 Pareto Front obtained by MOPSOA and Wang *et al.* (2015) for Hanoi WDN (CWS)

Figure 6.4 Pareto Front obtained by SAMOCSA and Wang *et al.* (2015) for Hanoi WDN (CWS)

Figure 6.5 Pareto Front obtained by RLNSGA-II and Wang *et al.* (2015) for Hanoi WDN (CWS)

The results are compared with Wang *et al.* (2015), as shown in Table 6.8. It is observed that MOPSOA, SAMOCSA, RLNSGA-II has converged to more pareto front points for Hanoi WDN in comparison with Wang *et al.* (2015). It can be observed from Table 6.8 that the hypervolume of all the three optimization algorithms is better when compared with Wang *et al.* (2015). In summary, the results highlight that MOPSOA, SAMOCSA and RLNSGA-II demonstrated superior performance compared to Wang *et al.* (2015) with respect to the total number of points in the pareto front, capturing the extreme points and hypervolume for Hanoi WDN. The pareto front obtained by each optimization algorithm is shown in Figs 6.3, 6.4 and 6.5. It is observed from these figures that most of the points on the pareto front obtained by MOPSOA, SAMOCSA, RLNSGA-II and Wang *et al.* (2015) are similar. The lower leftmost points on the pareto front obtained by MOPSOA, SAMOCSA and RLNSGA-II are superior and has also found solutions in new search spaces in comparison with Wang *et al.* (2015).

Intermittent Water Supply (IWS)

The parameters chosen after trial and error in various optimization algorithms is shown in Table 6.9. The population size and number of iterations have been fixed as 300 and 10,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters					
	$W = 0.4$; C1, C2 = 2					
MOPSOA	Local search is performed with a period of 100 between NPSO = 1000 and					
	5000, and with a period of 1000 thereafter					
	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9					
RLNSGA-II	Local search is performed with a period of 100 between $NPSO = 1000$ and					
	5000, and with a period of 1000 thereafter					

Table 6.9 Parameters Chosen for Optimization Algorithms for Hanoi WDN (IWS)

Table 6.10 Comparison of Optimal Solutions obtained by Optimization Algorithms for Hanoi

Figure 6.6 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for Hanoi WDN

(IWS)

The results obtained by the optimization algorithms is shown in Table 6.10. The pareto front obtained by each optimization algorithm is shown in Fig 6.6. It is observed from the results that the pareto front obtained by MOPSOA, SAMOCSA and RLNSGA-II have converged to the same solution for Hanoi WDN. Results for Hanoi WDN for intermittent water supply have not been compared with any other published literature as they are not available.

The optimal solution representing the extreme points of pareto front obtained by the best optimization algorithm for Hanoi WDN in CWS and IWS has been compared. The hydraulic analysis of the optimal WDN design for each extreme point has been carried out and the pipe velocity as well as the nodal pressure are compared and shown in Tables 6.11 and 6.12.

Leftmost Extreme Point-CWS					Leftmost Extreme Point-IWS					
	(Network Cost= $$6.0813x106$ and					(Network Cost= $$6.6314x106$ and				
		Network Resilience=0.1756)					Network Resilience=0.2256)			
Pipe	Diameter	Velocity		Pressure	Pipe	Diameter	Velocity		Pressure	
N ₀	(10^{-3} m)	(m/s)	Node	(m)	N ₀	(10^{-3} m)	(m/s)	Node	(m)	
1	1016.0	6.8320	$\mathbf{1}$	97.1407	1	1016.0	8.4298	1	99.1187	
$\overline{2}$	1016.0	6.5271	$\overline{2}$	61.6704	$\overline{2}$	1016.0	8.1249	$\overline{2}$	63.6484	
3	1016.0	2.7558	3	56.8813	3	1016.0	3.6114	3	58.8593	
$\overline{4}$	1016.0	2.7112	$\overline{4}$	50.9439	$\overline{4}$	1016.0	3.5669	$\overline{4}$	52.9219	
5	1016.0	2.4628	5	44.6780	5	1016.0	3.3185	5	46.6560	
6	1016.0	2.1185	6	43.2067	6	1016.0	2.9742	6	45.1847	
$\overline{7}$	1016.0	1.6560	7	41.4457	7	1016.0	2.5116	7	43.4237	
8	1016.0	1.4675	8	40.0377	8	1016.0	2.3232	8	42.0157	
9	1016.0	1.2876	9	38.9975	9	1016.0	2.1433	9	40.9755	
10	762.0	1.2182	10	37.4381	10	1016.0	2.2831	10	39.4161	
11	609.6	1.4276	11	34.0097	11	1016.0	2.1117	11	35.9877	
12	609.6	0.8946	12	30.1579	12	762.0	1.1987	12	31.7795	
13	508.0	1.1997	13	35.1330	13	762.0	1.9900	13	37.1110	
14	406.4	1.3236	14	33.1399	14	762.0	2.1282	14	35.1179	
15	304.8	1.2871	15	30.2277	15	762.0	1.8661	15	32.2057	
16	304.8	1.1579	16	30.3216	16	1016.0	1.7369	16	32.1156	

Table 6.11 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Leftmost Extreme Point for Hanoi WDN in CWS and IWS

	Leftmost Extreme Point-CWS (Network Cost= $$6.0813x10^6$ and Network Resilience=0.1756)				Leftmost Extreme Point-IWS (Network Cost= $$6.6314x10^6$ and				
Pipe N ₀	Diameter (10^{-3} m)	Velocity (m/s)	Node	Pressure (m)	Network Resilience=0.2256) Pipe Diameter Velocity Node (10^{-3} m) N ₀ (m/s)				Pressure (m)
17	406.4	1.9016	17	43.9680	17	1016.0	2.4806	17	45.7620
18	508.0	3.0604	18	55.5749	18	762.0	3.6394	18	57.3689
19	508.0	3.1426	19	50.4422	19	762.0	3.7216	19	52.2362
20	1016.0	2.6944	20	41.0930	20	762.0	3.2734	20	42.8870
21	508.0	1.9393	21	35.9280	21	762.0	2.5183	21	37.7220
22	304.8	1.8464	22	44.2134	22	762.0	2.4254	22	46.0074
23	1016.0	1.7727	23	38.9027	23	762.0	2.3517	23	40.6967
24	762.0	2.0536	24	35.5527	24	762.0	2.6326	24	37.3467
25	762.0	1.5541	25	31.5337	25	762.0	2.1331	25	33.3277
26	508.0	1.6705	26	30.1083	26	762.0	2.2495	26	31.9023
27	304.8	1.2141	27	35.4993	27	508.0	1.7931	27	37.2933
28	304.8	0.5945	28	30.7463	28	508.0	0.7735	28	32.5403
29	406.4	1.6221	29	30.1579	29	508.0	2.2011	29	31.5258
30	406.4	1.0011	30	30.1944	30	508.0	1.5801	30	31.9884
31	304.8	0.7092	31	30.1200	31	508.0	0.9882	31	31.7112
32	304.8	0.9613	32	30.0120	32	508.0	1.5403	32	31.5012
33	406.4	0.7656	$\overline{}$	$\overline{}$	33	508.0	1.3446	$\overline{}$	\overline{a}
34	508	0.7585			34	508.0	0.9158	-	$\overline{}$

Table 6.12 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing

Rightmost Extreme Point for Hanoi WDN in CWS and IWS

It is observed from Table 6.11, that twelve pipe diameters (Pipe Nos 1 to 9, 24, 25 and 34) out of 34 pipes of the optimal WDN design for the leftmost extreme point in CWS and IWS scenarios are same. The optimal network cost is around 9% higher in IWS as compared to CWS scenario. Similarly, the optimal network resilience is around 28% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is 41% higher as compared to the pipe velocity in CWS scenario. In CWS and IWS scenarios, as the WDN is a looped one, the pipe velocity varies depending upon its distance from the source. The pipe velocity is relatively higher in pipes 1, 2, 3, 4, 5, 6, 18, 19, 20 and 24. Similarly, pipe velocity is lower in pipes 12, 28 (lowest), 31, 32, 33 and 34. The nodal pressure in IWS scenario is around 5% higher in comparison to CWS scenario. The nodal pressure reduces to around one third of its initial value when the water reaches the last few nodes in the network in both the water supply scenarios.

It is observed from Table 6.12, that the optimal WDN design for the rightmost extreme point in CWS and IWS scenarios are same. The optimal network resilience is around 14% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is around 53% higher as compared to the pipe velocity in CWS scenario. In CWS and IWS scenarios, as the WDN is a looped one, the pipe velocity varies depending upon its distance from the source. The pipe velocity is relatively higher in pipes which are closer to the source. The velocity is the lowest in pipe 34 in both CWS and IWS scenario. The nodal pressure in IWS scenario is around 12% higher in comparison to CWS scenario. The nodal pressure reduces to around half of its initial value when the water reaches the last few nodes in the network in both the water supply scenarios.

6.2.3. BIN

Continuous Water Supply (CWS)

The parameters chosen after trial and error in various optimization algorithms are shown in Table 6.13. The population size and number of iterations have been fixed as 4500 and 1,00,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters					
	$W = 0.4$; C1, C2 = 2					
MOPSOA	Local search is performed with a period of 100 between $NPSO = 1000$ and					
	5000, and with a period of 1000 thereafter					
	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9					
RLNSGA-II	Local search is performed with a period of 100 between $NPSO = 1000$ and					
	5000, and with a period of 1000 thereafter					

Table 6.13 Parameters Chosen for Optimization Algorithms for BIN (CWS)

Table 6.14 Comparison of Optimal Solutions obtained by Optimization Algorithms and Wang *et*

	No of points	Extreme points in pareto front	Hypervolume	
Algorithms	in pareto front	Network Cost (€ 10 ⁶)	Network Resilience	$(x10^3)$
MOPSOA/ SAMOCSA/ RLNSGA-II	17587	1.9633 20.2487	0.3498 0.9552	13088.99
Wang et al. (2015)	1254	1.9986 20.0656	0.3935 0.9534	12887.44

al. (2015) for BIN (CWS)

Figure 6.7 Pareto Front obtained by MOPSOA and Wang *et al.* (2015) for BIN (CWS)

Figure 6.8 Pareto Front obtained by SAMOCSA and Wang *et al.* (2015) for BIN (CWS)

Figure 6.9 Pareto Front obtained by RLNSGA-II and Wang *et al.* (2015) for BIN (CWS)

The results are compared with Wang *et al.* (2015), as shown in Table 6.14. It is observed that MOPSOA, SAMOCSA, RLNSGA-II has converged to more Pareto front points for BIN in comparison with Wang *et al.* (2015). It can be observed from Table 6.14 that the hypervolume of all the three optimization algorithms is better when compared with Wang *et al.* (2015). In summary, the results highlight that MOPSOA, SAMOCSA and RLNSGA-II demonstrated

superior performance compared to Wang *et al.* (2015) with respect to the total number of points in the Pareto front, capturing the extreme points and hypervolume for BIN. The Pareto front obtained by each optimization algorithm is shown in Figs 6.7, 6.8 and 6.9. The visible discontinuity in the rising limb of the graphs in Figs 6.7 to 6.9 could be due to the discrete diameters available in the market. The solutions or diameters might not be available in certain regions or sizes, leading to these discontinuities. In addition, this could also be possible when the search mechanism of an optimization algorithm finds it difficult to explore that search space in the pareto front. It is observed from these figures that most of the points on the pareto front obtained by MOPSOA, SAMOCSA, RLNSGA-II is more along the entire pareto front when compared with Wang *et al.* (2015). The middle as well as right upper points on the pareto front obtained by MOPSOA, SAMOCSA and RLNSGA-II are superior and has also found solutions in new search spaces in comparison with Wang *et al.* (2015). The optimization algorithms not only discover new pareto front points in the low resilience region but also identifies substantial points in the high resilience region as well in BIN. The proposed optimization algorithms have shown excellent exploration and exploitation search mechanisms for the large benchmark WDN as compared to smaller WDNs in this study. MOPSOA, SAMOCSA and RLNSGA-II solutions would save a substantial cost to achieve the same resilience for the network.

Intermittent Water Supply (IWS)

The parameters chosen after trial and error in various optimization algorithms is shown in Table 6.15. The population size and number of iterations have been fixed as 4500 and 100,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters
MOPSOA	$W = 0.4$; C1, C2 = 2
	Local search is performed with a period of 100 between NPSO = 1000 and
	5000, and with a period of 1000 thereafter
RLNSGA-II	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9
	Local search is performed with a period of 100 between $NPSO = 1000$ and
	5000, and with a period of 1000 thereafter

Table 6.15 Parameters Chosen for Optimization Algorithms for BIN (IWS)

Algorithms in pareto front MOPSOA/ SAMOCSA/ 17579 RLNSGA-II 22 ₀ 20	Network Cost (€ 10 ⁶)	Network Resilience	Hypervolume
			$(x10^3)$
	2.1734 20.2487	0.3667 0.9721	15187.99
MOPSOA O 18 SAMOCSA × Network Cost(million euros) RLNSGA-II □ 16 14 12 10 8 6 4 2 0.3 0.4 0.5			

Table 6.16 Comparison of Optimal Solutions obtained by Optimization Algorithms for BIN (IWS)

Figure 6.10 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for BIN (IWS)

Network Resilience

The results obtained by the optimization algorithms are shown in Table 6.16. The Pareto front obtained by each optimization algorithm is shown in Fig. 6.10. It is observed from the results that the Pareto front obtained by MOPSOA, SAMOCSA and RLNSGA-II have converged to the same solution for BIN. Results for BIN for intermittent water supply have not been compared with any other published literature as they are not available. The optimal solution representing the extreme points of Pareto front obtained by the best optimization algorithm for BIN in CWS and IWS has been compared. The hydraulic analysis of the optimal WDN design for each extreme point has been carried out and the velocity in each pipe as well as pressure in each node are compared and shown in Tables A.1 and A.2 available in Appendix A.

It is observed from Table A.1, that 135 pipe diameters out of 454 pipes of the optimal WDN design for the leftmost extreme point in CWS and IWS scenarios are same. The optimal network cost is around 11% higher in IWS as compared to CWS scenario. Similarly, the optimal network resilience is around 5% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is around 64% higher as compared to the pipe velocity in CWS scenario. In CWS and IWS scenarios, as the WDN is a branched one, the pipe velocity is in a decreasing trend from the source towards the end of the network. The nodal pressure in IWS scenario is around 3% higher in comparison to CWS scenario. Approximately 63% reduction in nodal pressure from the initial value is observed when the water reaches the last few nodes in the network in both the water supply scenarios.

It is observed from Table A.2, that the optimal WDN design for the rightmost extreme point in CWS and IWS scenarios are the same. The optimal network resilience is around 2% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is around 66% higher as compared to the pipe velocity in CWS scenario. The pipe velocity is in a decreasing trend from the source towards the end of the network in both the scenarios. The nodal pressure in IWS scenario is around 9% higher in comparison to CWS scenario. The nodal pressure reduces to around 62% of its initial value when the water reaches the last few nodes in the network in both the water supply scenarios.

6.2.4. Pamapur WDN

Continuous Water Supply (CWS)

The parameters chosen after trial and error in various optimization algorithms are shown in Table 6.17. The population size and number of iterations have been fixed as 1000 and 50,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Table 6.17 Parameters Chosen for Optimization Algorithms for Pamapur WDN (CWS)

Table 6.18 Comparison of Optimal Solutions obtained by Optimization Algorithms for Pamapur

Figure 6.11 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for Pamapur

WDN (CWS)

The results obtained from MOPSOA, SAMOCSA and RLNSGA-II for Pamapur WDN is shown in Table 6.18. It is observed from Fig. 6.11 that pareto optimal set for all the three optimization algorithms have converged to the same solution. It is observed from the pareto front that the least-cost design (with a cost of 1.3043 million rupees) has an associated network resilience of 0.4061. The network resilience can be significantly improved to more than 200% i.e. 0.8877 with a network cost of 3.4988 million rupees. In addition, there are also a number of good trade-off design options available to the engineers to choose from the pareto-front.

Intermittent Water Supply (IWS)

The parameters chosen after trial and error in various optimization algorithms are shown in Table 6.19. The population size and number of iterations have been fixed as 1000 and 50,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters
MOPSOA	$W = 0.4$; C1, C2 = 2 Local search is performed with a period of 100 between NPSO = 1000 and
	5000, and with a period of 1000 thereafter
RLNSGA-II	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9 Local search is performed with a period of 100 between $NPSO = 1000$ and
	5000, and with a period of 1000 thereafter

Table 6.19 Parameters Chosen for Optimization Algorithms for Pamapur WDN (IWS)

Table 6.20 Comparison of Optimal Solutions obtained by Optimization Algorithms for Pamapur

WDN (IWS)

No of points		Extreme points in pareto front		
Algorithms	in pareto front	Network Cost (million rupees)	Network Resilience	Hypervolume $(x10^3)$
MOPSOA SAMOCSA/ RLNSGA-II	93	1.5543 3.4988	0.4761 0.9450	1142.7510

Figure 6.12 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for Pamapur WDN (IWS)

The results obtained by the optimization algorithms are shown in Table 6.20. It is observed from Fig. 6.12 that pareto optimal set for all the three optimization algorithms have converged to the same solution. It is observed from the pareto front that the least-cost design (with a cost of 1.5543 million rupees) has an associated network resilience of 0.4761. The network resilience can be significantly improved to more than 200% i.e. 0.9450 with a network cost of 3.4988 million rupees.

The optimal solution representing the extreme points of Pareto front obtained by the best optimization algorithm for Pamapur WDN in CWS and IWS has been compared. The hydraulic analysis of the optimal WDN design for each extreme point has been carried out and the velocity in each pipe, pressure as well as demand in each node are compared and shown in Tables A.3 and A.4 shown in Appendix A.

It is observed from Table A.3, that twelve pipe diameters (Pipe Nos 31, 32, 33, 43, 44, 59, 60, 98, 99, 111, 112 and 113) of the optimal WDN design for the leftmost extreme point in CWS and IWS scenarios are same. The optimal network cost is around 19% higher in IWS as compared to CWS scenario. Similarly, the optimal network resilience is around 17% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is nearly 22% higher as compared to the pipe velocity in CWS scenario. The nodal pressure in IWS scenario is around 18% higher in comparison to CWS scenario. Approximately 50% reduction in nodal pressure from the initial value (Node 24) is observed when the water reaches the last node in the network (Node 59) in both the water supply scenarios.

It is observed from Table A.4, that the optimal WDN design for the rightmost extreme point in CWS and IWS scenarios are same. The optimal network resilience is around 6% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is approximately 21% higher as compared to the pipe velocity in CWS scenario. The nodal pressure in IWS scenario is around 18% higher in comparison to CWS scenario. As observed earlier for leftmost points, the nodal pressure is highest in Node 24 and lowest in Node 59 for CWS and IWS scenarios.

6.2.5. Vanasthalipuram WDN

Continuous Water Supply (CWS)

The parameters chosen after trial and error in various optimization algorithms are shown in Table 6.21. The population size and number of iterations have been fixed as 3000 and 70,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters
MOPSOA	$W = 0.4$; C1, C2 = 2
	Local search is performed with a period of 100 between NPSO = 1000 and
	5000, and with a period of 1000 thereafter
RLNSGA-II	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9
	Local search is performed with a period of 100 between NPSO = 1000 and
	5000, and with a period of 1000 thereafter

Table 6.21 Parameters Chosen for Optimization Algorithms for Vanasthalipuram WDN (CWS)
Table 6.22 Comparison of Optimal Solutions obtained by Optimization Algorithms for Vanasthalipuram WDN (CWS)

	No of points	Extreme points in pareto front	Hypervolume		
Algorithms	in pareto front	Network Cost (million rupees)	Network Resilience	$(x10^3)$	
MOPSOA/ SAMOCSA/ RLNSGA-II	502	3.0952 5.7930	0.3541 0.4913	1577.97	

Figure 6.13 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for Vanasthalipuram WDN (CWS)

The results obtained from MOPSOA, SAMOCSA and RLNSGA-II for Pamapur WDN are shown in Table 6.22. It is observed from Fig. 6.13 that pareto optimal set for all the three optimization algorithms have converged to the same solution. It is observed from the pareto front that the least-cost design (with a cost of 3.0952 million rupees) has an associated network resilience of 0.3541. The network resilience could be increased to a maximum of around 39% i.e. 0.4913 with a network cost increase of 87% (5.7930 million rupees).

Intermittent Water Supply (IWS)

The parameter chosen after trial and error in various optimization algorithms is shown in Table 6.23. The population size and number of iterations have been fixed as 3000 and 70,000 for all the three optimization algorithms respectively. The parameters used in SAMOCSA are dynamically updated during the iterations as a part of the self-adaptive nature of the algorithm.

Algorithm	Parameters
	$W = 0.4$; C1, C2 = 2
MOPSOA	Local search is performed with a period of 100 between $NPSO = 1000$ and
	5000, and with a period of 1000 thereafter
	Distribution index for crossover = 15; Mutation rate = 7; Crossover rate = 0.9
RLNSGA-II	Local search is performed with a period of 100 between $NPSO = 1000$ and
	5000, and with a period of 1000 thereafter

Table 6.23 Parameters Chosen for Optimization Algorithms for Vanasthalipuram WDN (IWS)

Table 6.24 Comparison of Optimal Solutions obtained by Optimization Algorithms for

Figure 6.14 Pareto Front obtained by MOPSOA, SAMOCSA and RLNSGA-II for Vanasthalipuram WDN (IWS)

The results obtained by the optimization algorithms are shown in Table 6.24. The Pareto front obtained by each optimization algorithm is shown in Fig. 6.14. It is observed from the results that the Pareto front obtained by MOPSOA, SAMOCSA and RLNSGA-II have converged to the same solution for Vanasthalipuram WDN. It is observed from the pareto front that the least-cost design (with a cost of 3.4452 million rupees) has an associated network resilience of 0.4111. The network resilience could be increased to a maximum of around 32% i.e. 0.5443 with a network cost increase of 68% (5.7930 million rupees).

The optimal solution representing the extreme points of Pareto front obtained by the best optimization algorithm for Vanasthalipuram WDN in CWS and IWS has been compared. The hydraulic analysis of the optimal WDN design for each extreme point has been carried out and the velocity in each pipe and nodal pressure are compared and shown in Tables A.5 and A.6 available in Appendix A.

It is observed from Table A.5, that 47 out of 301 pipe diameters of the optimal WDN design for the leftmost extreme point in CWS and IWS scenarios are same. The optimal network cost is around 11% higher in IWS as compared to CWS scenario. Similarly, the optimal network resilience is around 16% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is nearly 37% higher as compared to the pipe velocity in CWS scenario. The nodal pressure in IWS scenario is around 42% higher in comparison to CWS scenario. The variation in pipe velocity and the nodal pressure between CWS and IWS scenarios are in an increasing trend from the beginning pipe diameter/ node. This could be attributed to the branched network type of the WDN. There is a significant reduction in the nodal pressure from the initial value (at Node 211) when the water reaches Node 8 in the network in both the water supply scenarios.

It is observed from Table A.6, that the optimal WDN design for the rightmost extreme point in CWS and IWS scenarios are same. The optimal network resilience is around 11% higher in IWS scenario in comparison with CWS. In IWS scenario, the pipe velocity is approximately 37% higher as compared to the pipe velocity in CWS scenario. The nodal pressure in IWS scenario is around 59% higher in comparison to CWS scenario. As observed earlier for leftmost points, the nodal pressure is highest in Node 211 and lowest in Node 8 for CWS and IWS scenarios. The variation in pipe velocity and the nodal pressure between CWS and IWS scenarios are in an increasing trend from the beginning pipe diameter/ node. The velocity is highest in pipe 221 (pipe from the source) and lowest in 231 for leftmost and rightmost extreme points in both CWS and IWS scenarios.

6.3. Analysis of Results from Optimal Water Distribution Network Design - Scenario 2 (Network Cost, Network Resilience and Network Equity)

In this scenario, focus extends beyond cost and resilience to include the critical consideration of network equity, aiming to ensure a fair and equitable distribution of water represented as network equity. As the proposed methodology has already been tested on three different benchmark WDNs, the case studies chosen for this scenario will focus on the real-life case studies, i.e., Pampapur WDN and Vanasthalipuram WDN. In addition, the computation time for such large networks usually takes a substantial amount of time (around 30 days run on a high performance computing system) to converge to the pareto optimal set. As the real-life case studies are usually operated for intermittent water supply system, the present scenario proposes to determine the optimal WDN design in a multiobjective scenario considering network cost (minimizing), network resilience (maximizing) and network equity (maximizing). Since there is an interdependency between maximizing the network resilience and network equity, one of the objectives in the mathematical model is formulated considering the weighted sum of both the objectives. The first objective focuses on minimizing the network cost and the second objective is considered as maximizing the weighted sum of network resilience and network equity. The weightage of network resilience and network equity in the second objective is considered equal i.e., 0.5. As the computation time for optimization cum simulation for such large networks is taking enormous period, the variations in the weights of network resilience and network equity could not be considered in this study. As observed from the results of scenario 1, all three optimization algorithms have been performing very well for all the five WDNs. For scenario 2, one of the three developed optimization algorithms, i.e., RLNSGA-II has been considered to solve the formulated multiobjective mathematical model.

6.3.1. Pamapur WDN

The parameters chosen after trial and error for RLNSGA-II are population size = 1000, number of iterations = 50000, distribution index for crossover = 15, mutation rate = 7, crossover rate = 0.9, local search is performed with a period of 100 between $NPSO = 1000$ and 5000 and with a period of 1000 thereafter. Fig. 6.15 shows the pareto front obtained for Pamapur WDN using RLNSGA-II. The number of points on the pareto front is 31. It is observed that the number of points on the pareto front reduced significantly when the network resilience is combined with network equity and made as a single objective. The combined index (network resilience + network equity) varies from 0.60 to 0.93 for the cost range of 1.32 to 3.41 million rupees.

Figure 6.15 Pareto Front (Network Cost vs Network Resilience and Network Equity) obtained for Pamapur WDN (IWS) using RLNSGA-II

The optimal results obtained for Pamapur WDN (IWS) in scenario 1 and scenario 2 are compared and shown in Table 6.25. The network resilience and network equity for each scenario has been separately calculated and compared. The pareto fronts accordingly have been drawn for each scenario for network cost vs network resilience (shown in Fig. 6.16) and network cost vs network equity (shown in Fig. 6.17).

Pamapur WDN (IWS) in Scenario 1 and 2 using RLNSGA-II

Figure 6.17 Comparison of Pareto Fronts (Network cost vs Network Equity) obtained for Pamapur WDN (IWS) in Scenario 1 and 2 using RLNSGA-II

	Leftmost Extreme Point in Pareto Front		Rightmost Extreme Point in Pareto Front			
	Scenario 1	Scenario 2	Scenario 1	Scenario 2		
Network Cost (million rupees)	1.3043	1.3201	3.4986	3.4126		
Network Resilience	0.4061	0.4551	0.8877	0.8829		
Network Equity	0.7540	0.7591	0.9943	0.9799		

Table 6.25 Comparison of Optimal Solutions obtained for Pamapur WDN (IWS) in Scenario 1 and 2 using RLNSGA-II

It is observed from Figs. 6.16 and 6.17 that most of the non-dominated solutions on the pareto front from scenario 1 and scenario 2 are coinciding. It is observed from Table 6.25 that there is a 12% increase in network resilience for the leftmost extreme point in scenario 2 for a 1.2% increase in the network cost. Similarly, there is a marginal increase of 0.7% in the network equity in scenario 2 when compared to the results obtained in scenario 1 for leftmost extreme point. For the rightmost point, the network resilience has an equivalent value for a slightly lower network cost (around 2.5% lesser). The network equity is around 1.5% lower for a 2.5% reduced network cost in scenario 2 as compared to scenario 1.

The hydraulic analysis of the optimal WDN design for each extreme point on the pareto front has been carried out and the velocity in each pipe and nodal pressure are compared and shown in Table A.7 available in Appendix A.

It is observed from Table A.7, that 107 pipe diameters of the optimal WDN design for the leftmost extreme point in scenario 1 and scenario 2 are same. Fifteen diameters (that are different in both the scenarios) are of higher diameter in scenario 2. The pipe velocity is similar in both the scenarios, however, the nodal pressure around 8% higher in scenario 2. Pipe 105 (which is the closest to the source) has the highest velocity and Pipe 8 (located as the last pipe in the tail end) measures the lowest velocity. Similarly, Node 24 (which is the closest to the source) has the highest pressure of 19.0257 m and Node 59 (located at the tail end) measures the lowest pressure of 8.5917 m. For the rightmost extreme point, 114 pipe diameters are the same in the optimal WDN design from scenario 1 and scenario 2. It is observed that the pipe diameter values in the remaining eight pipes are lower in scenario 2. In this case too, the pipe velocity is similar in both the scenarios, however, the nodal pressure is around 4% higher in scenario 2. Pipe 105 and Pipe 8 measured the highest and lowest velocity here too. In a similar trend, Node 24 (which is the closest to the source) has the highest pressure of 21.896 m and Node 59 (located at the tail end) measures the lowest pressure of 9.7077 m.

6.3.2. Vanasthalipuram WDN

The parameters chosen after trial and error for RLNSGA-II are population size = 3000, number of iterations = 70000, distribution index for crossover = 15, mutation rate = 7, crossover rate = 0.9, local search is performed with a period of 100 between NPSO = 1000 and 5000 and with a period of 1000 thereafter. Fig. 6.18 shows the pareto front obtained for Vanasthalipuram WDN using RLNSGA-II. The number of points on the pareto front is 83. It is observed that the number of points on the pareto front reduced significantly when the network resilience is combined with network equity and made as a single objective. The combined index (network resilience + network equity) varies from 0.58 to 0.73 for the cost range of 3.20 to 4.77 million rupees. The optimal results obtained for Vanasthalipuram WDN (IWS) in scenario 1 and scenario 2 are compared and shown in Table 6.26. The network resilience and network equity for each scenario has been separately calculated and compared. The pareto fronts accordingly have been drawn for each scenario for network cost vs network resilience (shown in Fig. 6.19) and network cost vs network equity (shown in Fig. 6.20).

	Leftmost Extreme Point in Pareto Front		Rightmost Extreme Point in Pareto Front			
	Scenario 1	Scenario 2	Scenario 1	Scenario 2		
Network Cost (million rupees)	3.0952	3.2025	5.7930	4.7747		
Network Resilience	0.3541	0.3680	0.4913	0.4810		
Network Equity	0.7506	0.7946	0.9898	0.9833		

Table 6.26 Comparison of Optimal Solutions obtained for Vanasthalipuram WDN (IWS) in

Scenario 1 and 2 using RLNSGA-II

Figure 6.18 Pareto Front (Network Cost vs Network Resilience and Network Equity) obtained for Vanasthalipuram WDN (IWS) using RLNSGA-II

Figure 6.19 Comparison of Pareto Fronts (Network Cost vs Network Resilience) obtained for Vanasthalipuram WDN (IWS) in Scenario 1 and 2 using RLNSGA-II

Figure 6.20 Comparison of Pareto Fronts (Network Cost vs Network Equity) obtained for Vanasthalipuram WDN (IWS) in Scenario 1 and 2 using RLNSGA-II

It is observed from Fig. 6.19 that most of the non-dominated solutions on the pareto front on the upper middle portion provide better network resilience for a lower network cost. Similarly, it is observed from Fig. 6.20 that all the points on the pareto front represent a better performance in terms of network equity for a lower cost when compared to the results obtained in scenario 1. It is observed from Table 6.26 that there is around 4% increase in network resilience for the leftmost extreme point in scenario 2 for a 3.5% increase in the network cost. Similarly, there is an increase of 6% in the network equity in scenario 2 when compared to the results obtained in scenario 1 for leftmost extreme point. For the rightmost point, the network resilience has an equivalent value for a slightly lower network cost (around 2.1% lesser). The network equity is around 0.7% lower for an 18% reduced network cost in scenario 2 as compared to scenario 1.

The hydraulic analysis of the optimal WDN design for each extreme point on the pareto front has been carried out and the velocity in each pipe and nodal pressure are compared and shown in Table A.8.

It is observed from Table A.8, that 276 out of 301 pipe diameters of the optimal WDN design for the leftmost extreme point in scenario 1 and scenario 2 are same. Twenty five diameters (that are different in both the scenarios) are of higher diameter in scenario 2. The pipe velocity is around 6.4% higher and the nodal pressure is around 8% higher in scenario 2. Pipe 221 (which is the closest to the source) has the highest velocity and Pipe 231 (located at the tail end) measures the lowest velocity. Similarly, Node 211 (which is the closest to the source) has the highest pressure of 41.89 m and Node 8 (located at the tail end) measures the lowest pressure of 10.40 m. For the rightmost extreme point, 263 pipe diameters are the same in the optimal WDN design from scenario 1 and scenario 2. It is observed that the pipe diameter values in the remaining 38 pipes are lower in scenario 2. In this case too, the pipe velocity is around 6% higher and the nodal pressure is around 7% higher in scenario 2. The pipes and nodes that measured the highest and lowest values representing the leftmost extreme point are the same in this case too. Pipe 105 and Pipe 8 measured the highest and lowest velocity here too. The nodal pressure varies from 61.16 m to 16.22 m.

6.4. Analysis of Results of Optimal Design of District Metered Areas – Scenario 3

The proposed methodology incorporates two key steps, including: (1) clustering to identify clusters using Fast Newman algorithm and (2) multiobjective optimization using RLNSGA-II that optimizes the boundaries of the clusters to finally provide the DMA configurations. In the first step, the WDN has been mapped into a weighted and undirected graph using the pressure at each node (obtained during the stead-state analysis for peak condition of the WDN). The number of initial clusters for the WDN and its connecting pipes is obtained using FNA (using Gephi software) which is taken as the initial input for the optimization problem. In the second step, three objectives for the optimization model are considered in this study. They are minimizing Network Cost, maximizing Network Resilience and maximizing Network Equity. In this scenario, the proposed methodology has been applied on Pamapur WDN and Vanasthalipuram WDN to determine the optimal number of DMAs. In this study, the size of flow meters and valves are assumed to be of the same pipe size. During optimization, if the sizes don't match, the nearest larger size of valve and flow meter has been assumed.

6.4.1. Pamapur WDN

The pipe layout of Pampaur WDN has been given as an input to Gephi software to identify the initial clusters. Nine clusters have been identified with a modularity index 0.7495. This output of the network has been used to identify the optimal DMA layouts using RLNSGA-II. The parameters chosen after trial and error for RLNSGA-II are population size = 1000, number of iterations = 50000, distribution index for crossover = 15, mutation rate = 7, crossover rate = 0.9, local search is performed with a period of 100 between NPSO = 1000 and 5000 and with a period of 1000 thereafter. Fig. 6.21 shows the Pareto front obtained for Pamapur WDN using RLNSGA-II for three objectives Network Cost, Network Resilience and Network Equity. The number of points on the Pareto front is 12. The details of the pareto optimal solutions with the corresponding number of valves and flow meters along with the number of DMAs is shown in Table 6.27. The Pareto fronts for network cost vs network resilience, for network resilience vs network equity and for network cost vs network equity have been obtained and shown in Figures 6.22, 6.23 and 6.24 respectively.

Solution N ₀	Network Cost (Rs. in Lakhs)	Network Resilience	Network Equity	No of Flow Meters	No of Valves	No of DMAs
$\mathbf{1}$	9.547	0.4500	0.9150	6	12	3
$\overline{2}$	9.718	0.4700	0.9270	6	13	3
3	10.873	0.4800	0.9345	6	14	3
4	11.789	0.4900	0.9410	6	15	3
5	12.579	0.5010	0.9490	6	17	3
6	22.979	0.5050	0.9515	8	18	4
7	23.125	0.5100	0.9535	8	19	$\overline{4}$
8	23.579	0.5200	0.9570	10	19	5
9	43.979	0.5270	0.9591	10	19	5
10	44.258	0.5350	0.9610	10	19	5
11	44.579	0.5410	0.9710	10	20	5
12	48.706	0.5500	0.9750	10	21	5

Table 6.27 Details of the Pareto Optimal Solutions for Pamapur WDN

Figure 6.21 Pareto Front obtained by RLNSGA-II for Pamapur WDN (Network Cost, Network Resilience and Network Equity)

Figure 6.23 Pareto Front obtained by RLNSGA-II for Pamapur WDN (Network Equity, Network Resilience)

Figure 6.22 Pareto Front obtained by RLNSGA-II for Pamapur WDN (Network Cost, Network Resilience)

Figure 6.24 Pareto Front obtained by RLNSGA-II for Pamapur WDN (Network Cost, Network Equity)

It can be observed from Table 6.27 that the network cost varies from Rs.9.55 lakhs to Rs.48.71 lakhs for DMAs that vary between 3 to 5. Five different combinations of DMAs have been found for 3 and 5 numbers of DMAs. The number of valves and flow meters varies from 12 to 21 and 6 to 10 respectively for the different DMAs obtained in the pareto front. The network resilience increases from 0.45 to 0.55 (around 22% increase) and network equity increases from 0.9150 to 0.9750 (around 7% increase) when compared between the DMA configuration of leftmost and rightmost point on the pareto front. It can be observed from Figure 6.22 that Network Cost for implementation of DMAs is directly proportional to Network Resilience and Network Equity. When the cost is less, a considerable number of boundary pipes within the WDN are closed. This leads to a change in the original layout of the network as water takes alternative routes to fulfill the nodal demands and subsequently, the resilience index decreases. This same phenomenon is also responsible for Network Equity variations for different DMA configurations. The hydraulic analysis of the WDN for the leftmost extreme point and the rightmost extreme point in the pareto front is carried out and the results of the same are presented in Table 6.28. The hydraulic analysis has been carried out for the WDN as per the initial layout without DMAs and then with the DMAs as obtained from the pareto front.

Table 6.28 Comparison of results for leftmost and rightmost extreme points in Pareto front for Pamapur WDN

			WDN without DMAs						WDN with DMAs	
DMA N ₀		Total			Pressure (m)			Pressure (m)		
	No of Nodes	Pipe Length (m)	Total Supply $(10^{-3} \text{ m}^3/\text{s})$	Minimum	Maximum	Average	Total Supply $(10^{-3}$ m^3/s)	Minimum	Maximum	Average
Leftmost Extreme Point										
1	27	2254.12	3.0445	7.71	11.12	9.17	3.0328	7.57	11.02	9.02
2	19	891.28	2.7820	7.55	10.05	8.20	2.7695	7.09	9.89	8.04
3	56	4133.51	7.9188	7.17	8.51	7.52	7.9178	7.09	8.31	7.31
					Rightmost Extreme Point					
$\mathbf{1}$	27	2254.12	3.0445	7.71	11.12	9.17	3.0328	7.57	11.02	9.02
$\overline{2}$	19	891.28	2.7820	7.55	10.05	8.20	2.7695	7.09	9.89	8.04
3	25	2783.15	4.5862	7.00	8.50	7.50	4.5743	6.79	8.29	7.29
$\overline{4}$	21	1020.79	1.6798	7.00	8.30	7.57	1.6713	6.75	8.20	7.47
5	10	570.29	1.2595	7.00	8.50	7.45	1.2477	6.83	8.40	7.35

It is observed from Table 6.27 that average pressure in each DMA is slightly lower after partitioning for both the extreme points. The average pressure in DMA 3 is around 3% lower after partitioning for the leftmost point and it is around 3% lower in DMA 3 after partitioning for the rightmost point. It can be observed that the DMA 3 in leftmost and rightmost points have the maximum pipe length compared to the other DMAs. The total water supply for each DMA is

slightly lower after partitioning for both the points. The first two DMAs in both points are the same and the third DMA in leftmost point has been expanded to more DMAs in the rightmost point. The maximum pressure (11.02 m) has been observed in DMA 1 and the minimum pressure (8.31 m) is observed in DMA 3 for the leftmost point. Similarly, for the rightmost point, the maximum pressure (11.02 m) is observed in DMA 1 and the minimum pressure in DMA 4 (8.20 m). The layout of the DMAs for the leftmost and rightmost extreme points are shown in Figs. 6.25 and 6.26 respectively.

Figure 6.25 DMAs layout representing leftmost extreme point for Pamapur WDN (Green-DMA 1, Blue-DMA 2 and Brown-DMA 3)

Figure 6.26 DMAs layout representing rightmost extreme point for Pamapur WDN (Light Green-DMA 1, Teal-DMA 2, Brown-DMA 3, Dark Green-DMA 4 and Blue-DMA 5)

6.4.2. Vanasthalipuram WDN

The number of initial clusters obtained from Gephi software for Vanasthalipuram WDN is 14 with a modularity index 0.7291. This output of the network has been used to identify the optimal DMA layouts using RLNSGA-II. The parameters chosen after trial and error for RLNSGA-II are population size = 3000, number of iterations = 70000, distribution index for crossover = 15, mutation rate $= 7$, crossover rate $= 0.9$, local search is performed with a period of 100 between NPSO = 1000 and 5000 and with a period of 1000 thereafter. Fig. 6.27 shows the Pareto front

obtained for Vanasthalipuram WDN using RLNSGA-II for three objectives Network Cost, Network Resilience and Network Equity. The number of points on the Pareto front is 17. The details of the pareto optimal solutions with the corresponding number of valves and flow meters along with the number of DMAs are shown in Table 6.29. The Pareto fronts for network cost vs network resilience, for network resilience vs network equity and for network cost vs network equity have been obtained and shown in Figures 6.28, 6.29 and 6.30 respectively.

Solution N ₀	Network Cost (Rs. in Lakhs)	Network Resilience	Network Equity	No of Flow Meters	No of Valves	No of DMAs
$\mathbf{1}$	11.117	0.3503	0.7511	7	23	3
$\overline{2}$	11.288	0.3511	0.7530	7	24	$\overline{4}$
3	12.443	0.3513	0.7535	8	25	$\overline{4}$
$\overline{4}$	13.359	0.3520	0.7548	8	27	5
5	14.149	0.3521	0.7554	9	29	5
6	24.549	0.3523	0.7573	9	30	5
$\overline{7}$	24.695	0.3528	0.7622	9	31	5
8	25.149	0.3531	0.7641	10	32	5
9	45.549	0.3535	0.7647	10	34	5
10	45.828	0.3538	0.7653	11	36	5
11	46.149	0.3543	0.7666	11	37	5
12	50.276	0.3550	0.7670	11	39	5
13	51.359	0.3559	0.7675	12	41	5
14	51.695	0.3562	0.7676	13	42	6
15	53.141	0.3570	0.7681	13	43	7
16	54.349	0.3572	0.7688	14	44	7
17	55.083	0.3577	0.7700	15	45	7

Table 6.29 Details of the Pareto Optimal Solutions for Vanasthalipuram WDN

Figure 6.27 Pareto Front obtained by RLNSGA-II for Vanasthalipuram WDN (Network Cost, Network Resilience and Network Equity)

Figure 6.29 Pareto Front obtained by RLNSGA-II for Vanasthalipuram WDN (Network Equity, Network Resilience)

Figure 6.28 Pareto Front obtained by RLNSGA-II for Vanasthalipuram WDN (Network Cost, Network Resilience)

Figure 6.30 Pareto Front obtained by RLNSGA-II for Vanasthalipuram WDN (Network Cost, Network Equity)

It can be observed from Table 6.29 that the network cost varies from Rs.11.12 lakhs to Rs.55.08 lakhs for DMAs that vary between 3 to 7. Ten different combinations of DMAs have been found for 5 numbers of DMAs. The number of valves and flow meters varies from 23 to 45 and 7 to 15 respectively for the different DMAs obtained in the pareto front. The network resilience marginally increases (around 2% increase) and network equity also marginally increases (around 2% increase) when compared between the DMA configuration of leftmost and rightmost point on the pareto front. It can be observed from Figure 6.27 that Network Cost for implementation of DMAs is directly proportional to Network Resilience and Network Equity. When the cost is less, a considerable number of boundary pipes within the WDN are closed. This leads to a change in the original layout of the network as water takes alternative routes to fulfill the nodal demands and subsequently, the resilience index decreases. This same phenomenon is also responsible for Network Equity variations for different DMA configurations. The hydraulic analysis of the WDN for the leftmost extreme point and the rightmost extreme point in the pareto front is carried out and the results of the same are presented in Table 6.30. The hydraulic analysis has been carried out for the WDN as per the initial layout without DMAs and then with the DMAs as obtained from the pareto front.

Table 6.30 Comparison of results for leftmost and rightmost extreme points in Pareto front for Vanasthalipuram WDN

				WDN without DMAs			WDN with DMAs			
		Total		Pressure (m)			Pressure (m)			
DMA N ₀	No of Nodes	Pipe Length (m)	Total Supply $(10^{-3} \text{ m}^3/\text{s})$	Minimum	Maximum	Average	Total Supply $(10^{-3}$ m^3/s)	Minimum	Maximum	Average
					Leftmost Extreme Point					
1	89	7527.93	29.67	9.17	19.17	13.17	29.66	9.02	19.02	13.02
$\overline{2}$	51	4961.59	38.00	7.19	12.75	10.17	37.99	7.03	12.59	10.01
3	71	4619.41	39.76	8.12	15.71	12.01	39.75	7.91	15.50	11.80
					Rightmost Extreme Point					
1	23	1864.95	10.17	8.12	19.17	13.55	10.14	7.97	19.02	13.40
$\overline{2}$	33	2675.80	16.93	7.79	17.57	12.58	16.91	7.63	17.41	12.42
3	47	3810.99	27.88	7.19	15.57	11.28	27.86	7.01	15.36	11.07
4	32	2594.72	19.18	7.71	15.91	11.71	19.17	7.61	15.81	11.61
5	25	2027.12	14.67	8.21	17.95	12.98	14.66	8.11	17.85	12.88
6	24	1946.04	11.28	7.59	14.91	11.15	11.28	7.44	14.76	11.00
$\overline{7}$	27	2189.29	16.93	7.77	13.12	10.35	16.92	7.67	13.02	10.25

It is observed from Table 6.30 that average pressure in each DMA is slightly lower (below 2%) after partitioning for both the extreme points. The average pressure in DMA 3 is around 1.75% lower after partitioning for the leftmost point and it is around 1.86% lower in DMA 3 after partitioning for the rightmost point. It can be observed that DMA 3 in the rightmost point has the maximum pipe length compared to the other DMAs. The total water supply for each DMA is slightly lower after partitioning for both the points. The maximum pressure (19.02 m) has been observed in DMA 1 and the minimum pressure (7.03 m) is observed in DMA 2 for the leftmost point. Similarly, for the rightmost point, the maximum pressure (19.02 m) is observed in DMA 1 and the minimum pressure in DMA 3 (7.01 m). The layout of the DMAs for the leftmost and rightmost extreme points are shown in Figs. 6.31 and 6.32 respectively.

Figure 6.31 DMAs layout representing leftmost extreme point for Vanasthalipuram WDN (Black-DMA 1, Blue-DMA 2 and Purple-DMA 3)

The next chapter presents the summary and conclusions inferred from the above studies.

SUMMARY

Water distribution networks are one of the major essential public infrastructures designed to meet the daily water requirements of a community. Dividing a water distribution network into subsystems named as district metered areas can improve the efficiency and ease of achieving management goals. Properly designed and maintained DMAs can help water utilities reduce water losses, improve system efficiency and enhance the overall reliability of their distribution networks. Determining an optimal design based on multiple objectives such as cost, resilience, equitable water distribution and identifying the most suitable layout for DMAs of a water distribution network poses a complex challenge for engineers, as it consists simultaneous consideration of multiple interconnected factors. This research study explores the optimal design of a WDN in a multiobjective framework and identifying optimal DMA design of a WDN using metaheuristic algorithms. The proposed methodology has been tested on three benchmark WDNs and two real-life WDNs located in Telangana, India.

In this study, three distinct scenarios have been considered. The first two scenarios determine the optimal WDN design based on different objectives for continuous and intermittent water supply. The hydraulic simulation of the WDN has been carried out using the widely used EPANET 2.2 software. In the first scenario, two objectives, namely, network cost and network resilience have been considered for continuous and intermittent water supply. The formulated mathematical model is applied to the three benchmark WDN problems (New York WDN, Hanoi WDN and BIN) and later this is also applied to two real-life WDNs located in Telangana, India (Pamapur WDN and Vanasthalipuram WDN) to ensure practical relevance of the proposed methodology using MOPSOA, SAMOCSA and RLNSGA-II. The results of New York WDN, Hanoi WDN and BIN for continuous water supply are compared with the solutions of Wang *et al.* (2015) to test the efficacy of the developed optimization algorithms. In the second scenario, the focus extends beyond cost and resilience to include the critical consideration of network equity, aiming to ensure a fair and equitable distribution of water. This expanded set of objectives is examined in the context of two real-life WDNs for intermittent water supply using RLNSGA-II algorithm. The third scenario focuses on determining the optimal design of DMAs considering three

objectives for the optimization model. The initial clusters have been identified using Fast Newman algorithm. The objectives considered are minimizing Network Cost, maximizing Network Resilience and maximizing Network Equity. In this scenario, the proposed methodology has been applied on Pamapur WDN and Vanasthalipuram WDN to determine the optimal number of DMAs. The following conclusions are drawn from the three scenarios of the research study.

Scenario 1

- \checkmark The results obtained by MOPSOA, SAMOSCA, RLNSGA-II optimization algorithms for CWS scenario in New York WDN, Hanoi WDN and BIN are compared with Wang *et al.* (2015). It is observed that the three optimization algorithms have converged to more pareto front points for all the three benchmark WDNs in comparison with Wang *et al.* (2015). In summary, the results highlight that MOPSOA, SAMOCSA and RLNSGA-II demonstrated better performance when compared to Wang *et al.* (2015) with respect to the total number of points in the pareto front, capturing the extreme points and hypervolume for all the three benchmark WDNs. For BIN, the optimal solutions obtained from the three optimization algorithms would save a substantial cost to achieve the same resilience for the network.
- \checkmark Normally, the complexity of any problem increases with the dimensionality of the problem. The optimization algorithms developed in this research work have proved to be very good for solving large WDNs. The application of the three optimization algorithms to the multiobjective optimization of WDNs maintains the balance between exploration and exploitation. This characteristic of these algorithms enhances the search mechanism in maintaining population diversity and exploring larger areas to discover newer solutions that converge to better quality optimal solutions.
- \checkmark The results show that the pareto front obtained by MOPSOA, SAMOSCA and RLNSGA-II have converged to the same solution for all the five WDNs for IWS scenario. Results for these WDNs for IWS have not been compared with any other published literature as they are not available.
- \checkmark The hydraulic parameters of the WDN representing the extreme points in the pareto front for CWS and IWS have been compared for all five WDNs. It is observed that the network

cost, network resilience, pipe velocity and nodal pressure for the extreme points is higher for the WDN design in IWS scenario. The variation in the pipe velocity and nodal pressure for CWS and IWS scenarios for WDN design representing the extreme points are similar for larger WDNs. For the rightmost extreme point in all WDNs, the network cost remains the same for CWS and IWS scenario. For larger networks, the network cost is around 11 to 19% higher in IWS scenario as compared to CWS scenario for leftmost extreme point. Similarly, the network resilience is around 16% higher for leftmost extreme point and around 6-11% higher for rightmost extreme point in all real-life WDNs.

- \checkmark The pareto front for Pamapur WDN (CWS scenario) shows that the least-cost design (with a cost of 1.3043 million rupees) has an associated network resilience of 0.4061. The network resilience can be significantly improved to more than 200% i.e. 0.8877 with a network cost of 3.4988 million rupees. In addition, there are also a number of good tradeoff design options available to the engineers to choose from the pareto-front. It is observed from the pareto front for IWS scenario that the least-cost design (with a cost of 1.5543 million rupees) has an associated network resilience of 0.4761. The network resilience can be significantly improved to more than 200% i.e. 0.9450 with a network cost of 3.4988 million rupees.
- \checkmark It is observed from the pareto front for Vanasthalipuram WDN (CWS scenario) that the least-cost design (with a cost of 3.0952 million rupees) has an associated network resilience of 0.3541. The network resilience could be increased to a maximum of around 39% i.e. 0.4913 with a network cost increase of 87% (5.7930 million rupees). For IWS scenario, the least-cost design (with a cost of 3.4452 million rupees) has an associated network resilience of 0.4111. The network resilience could be increased to a maximum of around 32% i.e. 0.5443 with a network cost increase of 68% (5.7930 million rupees).

Scenario 2

 \checkmark Pamapur WDN: It is observed that most of the non-dominated solutions on the pareto front from scenario 1 and scenario 2 are coinciding. It is also observed that there is a 12% increase in network resilience for the leftmost extreme point in scenario 2 for a 1.2% increase in the network cost. Similarly, there is a marginal increase of 0.7% in the

network equity in scenario 2 when compared to the results obtained in scenario 1 for leftmost extreme point. For the rightmost point, the network resilience has an equivalent value for a slightly lower network cost (around 2.5% lesser). The network equity is around 1.5% lower for a 2.5% reduced network cost in scenario 2 as compared to scenario 1.

- \checkmark Pampaur WDN: It is observed that 107 pipe diameters of the optimal WDN design for the leftmost extreme point in scenario 1 and scenario 2 are same. Fifteen diameters (that are different in both the scenarios) are of higher diameter in scenario 2. The pipe velocity is similar in both the scenarios, however, the nodal pressure around 8% higher in scenario 2. For the rightmost extreme point, 114 pipe diameters are the same in the optimal WDN design from scenario 1 and scenario 2. It is observed that the pipe diameter values in the remaining eight pipes are lower in scenario 2. In this case too, the pipe velocity is similar in both the scenarios, however, the nodal pressure is around 4% higher in scenario 2.
- \checkmark Vanasthalipuram WDN: It is observed that most of the non-dominated solutions on the pareto front on the upper middle portion provide better network resilience for a lower network cost. Similarly, it is observed that all the points on the pareto front represent a better performance in terms of network equity for a lower cost when compared to the results obtained in scenario 1. Around 4% increase in network resilience for the leftmost extreme point in scenario 2 is observed for a 3.5% increase in the network cost. Similarly, there is an increase of 6% in the network equity in scenario 2 when compared to the results obtained in scenario 1 for leftmost extreme point. For the rightmost point, the network resilience has an equivalent value for a slightly lower network cost (around 2.1% lesser). The network equity is around 0.7% lower for an 18% reduced network cost in scenario 2 as compared to scenario 1.
- \checkmark Vanasthalipuram WDN: It is observed that 276 out of 301 pipe diameters of the optimal WDN design for the leftmost extreme point in scenario 1 and scenario 2 are same. Twenty five diameters (that are different in both the scenarios) are of higher diameter in scenario 2. The pipe velocity is around 6.4% higher and the nodal pressure is around 8% higher in scenario 2. For the rightmost extreme point, 263 pipe diameters are the same in the optimal WDN design from scenario 1 and scenario 2. It is observed that the pipe diameter values in the remaining 38 pipes are lower in scenario 2. In this case too, the

pipe velocity is around 6% higher and the nodal pressure is around 7% higher in scenario 2.

Scenario 3

- \checkmark Pampaur WDN: It can be observed that the network cost varies from Rs.9.55 lakhs to Rs.48.71 lakhs for DMAs that vary between 3 to 5. Five different combinations of DMAs have been found for 3 and 5 numbers of DMAs. The number of valves and flow meters varies from 12 to 21 and 6 to 10 respectively for the different DMAs obtained in the pareto front. The network resilience increases from 0.45 to 0.55 (around 22% increase) and network equity increases from 0.9150 to 0.9750 (around 7% increase) when compared between the DMA configuration of leftmost and rightmost point on the pareto front.
- \checkmark Pampaur WDN: The average pressure in each DMA is slightly lower after partitioning for both the extreme points. The average pressure in DMA 3 is around 3% lower after partitioning for the leftmost point and it is around 3% lower in DMA 3 after partitioning for the rightmost point. It can be observed that the DMA 3 in leftmost and rightmost points have the maximum pipe length compared to the other DMAs. The total water supply for each DMA is slightly lower after partitioning for both the points.
- \checkmark Vanasthalipuram WDN: It can be observed that the network cost varies from Rs.11.12 lakhs to Rs.55.08 lakhs for DMAs that vary between 3 to 7. Ten different combinations of DMAs have been found for 5 numbers of DMAs. The number of valves and flow meters varies from 23 to 45 and 7 to 15 respectively for the different DMAs obtained in the pareto front. The network resilience marginally increases (around 2% increase) and network equity also marginally increases (around 2% increase) when compared between the DMA configuration of leftmost and rightmost point on the pareto front.
- \checkmark Vanasthalipuram WDN: The average pressure in each DMA is slightly lower (below 2%) after partitioning for both the extreme points. The average pressure in DMA 3 is around 1.75% lower after partitioning for the leftmost point and it is around 1.86% lower in DMA 3 after partitioning for the rightmost point. It can be observed that DMA 3 in the rightmost point has the maximum pipe length compared to the other DMAs.

 \checkmark The proposed methodology efficiently identifies DMAs while simultaneously addressing multiple objectives, including minimizing network cost, maximizing network resilience and enhancing network equity for real-life WDNs.

CONCLUSIONS

In summary, the proposed research methodologies can be applied to optimize the design and operation of WDNs, reducing both capital and operational expenditures. This involves selecting cost-effective materials, optimizing pump and valve operations, and minimizing energy consumption. Enhancing the resilience of WDNs ensures that they can handle disruptions, such as pipe bursts, supply interruptions, or natural disasters, without significant service degradation. The methodologies identify critical points in the network and suggest improvements to bolster overall system robustness. Equity in water distribution is crucial for ensuring that all users receive an adequate and consistent water supply. The methodologies consider factors such as pressure management and distribution efficiency to achieve a fair allocation of water. The proposed solutions from various research studies have certain challenges while these need to be implemented in the real-world. There are assumptions made while modeling and simulating WDN that do not reflect the true nature of real-world scenarios. In addition, the hydraulic simulation in an intermittent water supply system also posed a challenge while using hydraulic simulation software tools like EPANET 2.2. However, the solutions proposed from these methodologies can be effectively translated to real-world implementations with reasonable savings, enhanced resilience as well as equity in comparison with the traditional design approaches used by the engineers.

CONTRIBUTIONS FROM THE STUDY

- ✓ Three optimization algorithms (MOPSOA, SAMOCSA and RLNSGA-II) have been modified to enhance their search efficiency. They have consistently outperformed, when compared with the best algorithms available in literature, yielding better converged and distributed solutions for the three benchmark problems (New York WDN, Hanoi WDN and Balerma Irrigation Network). These algorithms surpass the best-known approximation solutions published in the literature, showcasing their effectiveness and robustness. It is particularly noteworthy to mention their exploration and exploitation capabilities of large search spaces for finding better optimal solutions i.e., their ability to achieve substantial cost savings as network complexity increases.
- \checkmark First comprehensive study on the multiobjective design of WDNs considering three objectives, namely, minimizing Network Cost, maximizing Network Resilience and maximizing Network Equity for Pamapur and Vanasthalipuram WDNs located in Telangana, India.
- \checkmark First comprehensive study on the identifying the DMAs of WDNs for Pamapur and Vanasthalipuram WDNs located in Telangana, India considering three objectives, namely, minimizing Network Cost, maximizing Network Resilience and maximizing Network Equity.

SCOPE FOR FURTHER WORK

- \checkmark The optimal design of WDNs can focus on addressing design optimization under intermittent water supply while considering sustainability, uncertainty in water demand etc., in the mathematical model.
- \checkmark Hybrid and hyper heuristic optimization algorithms can be developed to address the high computational time associated while solving with optimization techniques for their application to large-scale water distribution networks.
- \checkmark A fuzzy optimization approach may be applied to determine the best possible WDN design that simplifies the decision-making of the design engineer/ manager. Also, the fuzzy multiobjective model can be further extended with fuzzification of the constraints to account for uncertainties in pipe roughness and nodal demands of larger WDN.
- \checkmark WDN clustering could be done considering network parameters such as similarity in demand, pressure, length of pipes and number of nodes.
- \checkmark More objectives such as average water age, leakage reduction and many more could be considered while determining the optimal DMAs of a WDN.
- \checkmark Multicriteria decision making methods can be considered for determining the optimal WDN design/ DMA from a pareto optimal front.

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APPENDIX A

Table A.1 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Leftmost Extreme Point for BIN in CWS and IWS

Rightmost Extreme Point-CWS					Rightmost Extreme Point-IWS					
(Network Cost= $€20.2487 x106$ and					(Network Cost= ϵ 20.2487 x10 ⁶ and					
Network Resilience=0.9552)					Network Resilience=0.9721)					
Pipe	Diameter	Velocity	Node	Pressure	Pipe	Diameter	Velocity	Node	Pressure	
N ₀	(10^{-3} m)	(m/s)		(m)	N ₀	(10^{-3} m)	(m/s)		(m)	
1	14777.7	5.8769	1	81.7615	1	14777.7	7.9684	1	86.9786	
$\overline{2}$	14777.7	5.8620	$\overline{2}$	81.5641	\overline{c}	14777.7	7.9548	$\overline{2}$	86.2318	
$\overline{3}$	14777.7	5.8523	3	81.4038	3	14777.7	7.9556	3	87.1363	
$\overline{4}$	14777.7	5.8197	$\overline{4}$	81.3802	$\overline{4}$	14777.7	7.9201	$\overline{4}$	91.0389	
5	14777.7	5.8135	5	81.3544	5	14777.7	7.9131	5	91.3517	
6	14777.7	5.8105	6	81.2089	6	14777.7	7.9113	6	89.8147	
7	14777.7	5.8076	τ	81.1694	7	14777.7	7.9086	7	89.9369	
8	14777.7	5.7966	8	81.0568	8	14777.7	7.9004	8	86.6003	
9	14777.7	5.7864	9	80.8177	9	14777.7	7.8868	9	88.5830	
10	14777.7	5.7770	10	80.7232	10	14777.7	7.8861	10	89.9943	
11	14777.7	5.7738	11	80.5929	11	14777.7	7.8842	11	87.2263	
12	14777.7	5.7036	12	80.5046	12	14777.7	7.8025	12	90.8957	
13	14777.7	5.6665	13	80.4802	13	14777.7	7.7584	13	85.0837	
14	14777.7	5.6243	14	80.4457	14	14777.7	7.7339	14	86.5335	
15	14777.7	5.6216	15	80.4103	15	14777.7	7.7319	15	87.7206	
16	14777.7	5.6007	16	80.3136	16	14777.7	7.7044	16	84.7187	
17	14777.7	5.5854	17	80.0096	17	14777.7	7.6883	17	88.6550	
18	14777.7	5.5676	18	79.9684	18	14777.7	7.6668	18	87.5274	
19	14777.7	5.5380	19	79.9007	19	14777.7	7.6299	19	87.2794	
20	14777.7	5.5149	20	79.8947	20	14777.7	7.6019	20	89.1943	
21	14777.7	5.4944	21	79.8932	21	14777.7	7.5742	21	89.3766	
22	14777.7	5.4864	22	79.7217	22	14777.7	7.5724	22	88.7400	
23	14777.7	5.4826	23	79.6722	23	14777.7	7.5811	23	85.6816	
24	14777.7	5.4757	24	79.6167	24	14777.7	7.5722	24	86.4778	
25	14777.7	5.4672	25	79.6122	25	14777.7	7.5644	25	88.3837	
26	14777.7	5.4577	26	79.5327	26	14777.7	7.5523	26	84.2083	
27	14777.7	5.4499	27	79.4857	27	14777.7	7.5551	27	84.1578	
28	14777.7	5.4275	28	79.1358	28	14777.7	7.5376	28	84.8012	
29	14777.7	5.4221	29	78.8859	29	14777.7	7.5376	29	86.1411	
30	14777.7	5.4066	30	78.8118	30	14777.7	7.5282	30	88.8849	
31	14777.7	5.3628	31	78.7108	31	14777.7	7.4684	31	87.1197	
32	14777.7	5.3528	32	78.6788	32	14777.7	7.4577	32	84.5757	
33	14777.7	5.3434	33	78.601	33	14777.7	7.4639	33	84.3638	
34	14777.7	5.3109	34	78.4746	34	14777.7	7.4329	34	87.7368	
35	14777.7	5.3108	35	78.4184	35	14777.7	7.4369	35	88.0585	
36	14777.7	5.2851	36	78.2692	36	14777.7	7.4021	36	86.1855	
37	14777.7	5.2709	37	78.1786	37	14777.7	7.3911	37	83.6847	

Table A.2 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Rightmost Extreme Point for BIN in CWS and IWS

Leftmost Extreme Point-CWS (Network Cost=1.3043 million rupees and Network Resilience=0.4061)					Leftmost Extreme Point-IWS (Network Cost=1.5543 million rupees and Network Resilience=0.4761)				
Pipe N ₀	Diameter (10^{-3} m)	Velocity (m/s)	Node	Pressure (m)	Pipe N ₀	Diameter (10^{-3} m)	Velocity (m/s)	Node	Pressure (m)
$\mathbf{1}$	66.8	0.1100	$\mathbf{1}$	8.3900	$\mathbf{1}$	98.6	0.1320	$\mathbf{1}$	10.1117
$\overline{2}$	66.8	0.5500	$\overline{2}$	9.2200	$\overline{2}$	98.6	0.6603	$\overline{2}$	10.8231
\mathfrak{Z}	66.8	0.4100	3	10.8100	3	98.6	0.4925	3	13.4601
$\overline{4}$	66.8	0.7900	$\overline{4}$	8.6900	$\overline{4}$	98.6	0.9490	$\overline{4}$	10.1797
5	66.8	0.6500	5	9.9100	5	98.6	0.7808	5	12.3799
6	66.8	0.3300	6	12.6200	6	98.6	0.3965	6	14.8107
τ	66.8	0.4300	τ	13.7600	$\overline{7}$	80.4	0.5171	τ	16.1751
$8\,$	66.8	0.0100	$8\,$	12.2400	$8\,$	80.4	0.0118	8	14.8755
9	66.8	0.0900	9	11.3400	9	80.4	0.1082	9	13.1341
10	66.8	1.2900	10	10.7900	10	80.4	1.5515	10	12.6026
11	66.8	0.0900	11	10.6700	11	80.4	0.1083	11	11.9496
12	98.6	0.5200	12	11.8100	12	125.4	0.6257	12	14.3347
13	66.8	0.9500	13	13.7500	13	80.4	1.1432	13	16.2908
14	66.8	0.4800	14	10.1900	14	80.4	0.5776	14	12.2004
15	66.8	0.1500	15	12.2300	15	80.4	0.1805	15	14.9170
16	98.6	0.6000	16	13.0000	16	80.4	0.7222	16	14.7299
17	66.8	0.0250	17	12.9900	17	80.4	0.0120	17	15.9606
18	143.4	0.8400	18	14.0500	18	80.4	1.0119	18	17.3617
19	66.8	0.0800	19	10.8000	19	80.4	0.0964	19	12.3531
20	66.8	0.3000	20	11.8400	20	80.4	0.3616	20	14.3131
21	66.8	0.1700	21	9.2200	21	80.4	0.2050	21	10.6115
22	66.8	0.3800	22	10.4000	22	80.4	0.4584	22	11.8654
23	66.8	0.0700	23	8.7300	23	80.4	0.0845	23	9.8260
24	66.8	0.3200	24	14.5500	24	80.4	0.3863	24	17.4542
25	66.8	0.0700	25	11.8000	25	80.4	0.0845	25	13.9285
26	66.8	0.0600	26	11.7300	26	80.4	0.0725	26	14.3618
27	98.6	0.7300	27	11.8200	27	112	0.8822	27	13.4760
28	66.8	0.0600	28	11.2500	28	98.6	0.0725	28	12.6723
29	66.8	0.0700	29	13.1000	29	98.6	0.0846	29	15.2573
30	66.8	0.0600	30	10.6300	$30\,$	98.6	0.0726	30	12.4514
31	66.8	0.0900	31	11.4900	31	66.8	0.1088	31	13.9923
32	98.6	0.7300	32	11.4500	32	98.6	0.8831	32	12.8194
33	66.8	0.7300	33	11.6200	33	66.8	0.8836	33	12.8715
34	66.8	0.0500	34	11.8700	34	98.6	0.0605	34	14.1743
35	98.6	0.2800	35	12.1300	35	98.6	0.3391	35	13.3959
36	66.8	0.2100	36	12.9800	36	98.6	0.2543	36	14.5432
37	66.8	0.0500	37	13.2400	37	98.6	0.0606	37	15.9434

Table A.3 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Leftmost Extreme Point for Pamapur WDN in CWS and IWS

Rightmost Extreme Point-CWS (Network Cost=3.4988 million rupees and Network Resilience=0.8877)					Rightmost Extreme Point-IWS (Network Cost=3.4988 million rupees and Network Resilience=0.9450)					
Pipe	Diameter Velocity Pressure					Pipe Diameter Velocity				
N ₀	(10^{-3} m)	(m/s)	Node	(m)	N ₀	(10^{-3} m)	(m/s)	Node	Pressure (m)	
$\mathbf{1}$	251.4	0.0989	1	9.6755	1	251.4	0.1187	1	11.3262	
$\overline{2}$	251.4	0.4934	$\overline{2}$	10.8591	$\overline{2}$	251.4	0.5930	$\overline{2}$	12.1244	
3	251.4	0.3677	3	12.3370	3	251.4	0.4421	3	15.0840	
$\overline{4}$	251.4	0.7077	$\overline{4}$	10.2327	$\overline{4}$	251.4	0.8505	$\overline{4}$	11.4208	
5	251.4	0.5806	5	11.4916	5	251.4	0.6994	5	13.8978	
6	251.4	0.2946	6	14.1824	6	251.4	0.3551	6	16.6284	
$\overline{7}$	251.4	0.3835	$\overline{7}$	15.6616	$\overline{7}$	251.4	0.4629	$\overline{7}$	18.1710	
8	251.4	0.0089	8	14.2135	$\bf 8$	251.4	0.0105	$\bf 8$	16.7206	
9	251.4	0.0801	9	13.0816	9	251.4	0.0965	9	14.7850	
10	251.4	1.1478	10	12.2348	10	251.4	1.3826	10	14.1960	
11	251.4	0.0796	11	12.1289	11	251.4	0.0963	11	13.4615	
12	251.4	0.4592	12	13.8722	12	251.4	0.5561	12	16.1516	
13	251.4	0.8382	13	15.9942	13	251.4	1.0126	13	18.3589	
14	251.4	0.4221	14	11.5156	14	251.4	0.5100	14	13.7583	
15	251.4	0.1319	15	14.3107	15	251.4	0.1594	15	16.8364	
16	251.4	0.5275	16	14.9254	16	251.4	0.6365	16	16.6296	
17	251.4	0.0220	17	14.9692	17	251.4	0.0106	17	18.0232	
18	251.4	0.7368	18	16.4316	18	251.4	0.8912	18	19.6070	
19	251.4	0.0702	19	12.3993	19	251.4	0.0848	19	13.9576	
20	251.4	0.2630	20	13.2727	20	251.4	0.3179	20	16.1735	
21	251.4	0.1490	21	10.3746	21	251.4	0.1801	21	12.0079	
22	251.4	0.3329	22	12.0783	22	251.4	0.4023	22	13.4276	
23	251.4	0.0613	23	10.0502	23	251.4	0.0741	23	11.1332	
24	251.4	0.2797	24	17.2398	24	251.4	0.3377	24	21.2015	
25	251.4	0.0612	25	13.2944	25	251.4	0.0739	25	15.8127	
26	251.4	0.0524	26	13.4459	26	251.4	0.0632	26	16.3120	
27	251.4	0.6372	27	13.6902	27	251.4	0.7692	27	15.3061	
28	251.4	0.0524	28	12.6879	28	251.4	0.0632	28	14.4150	
29	251.4	0.0610	29	15.5014	29	251.4	0.0738	29	17.3830	
30	251.4	0.0523	30	12.3768	30	251.4	0.0630	30	14.2027	
31	251.4	0.0782	31	13.5970	31	251.4	0.0942	31	15.9607	
32	251.4	0.6338	32	13.3294	32	251.4	0.7635	32	14.6253	
33	251.4	0.6331	33	13.0260	33	251.4	0.7639	33	14.6935	
34	251.4	0.0433	34	13.5574	34	251.4	0.0522	34	16.1823	
35	251.4	0.2421	35	13.6806	35	251.4	0.2918	35	15.2971	
36	251.4	0.1814	36	15.1095	36	251.4	0.2185	36	16.6112	
37	251.4	0.0431	37	14.8851	37	251.4	0.0520	37	18.2126	
38	251.4	0.2830	38	10.1895	38	251.4	0.3428	38	11.7456	
39	251.4	0.9683	39	9.1928	39	251.4	1.1724	39	10.7650	
40	251.4	0.8477	40	9.2909	40	251.4	1.0266	40	11.3899	
41	251.4	0.0256	41	9.9544	41	251.4	0.0311	41	12.0302	

Table A.4 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Rightmost Extreme Point for Pamapur WDN in CWS and IWS

Leftmost Extreme Point-CWS					Leftmost Extreme Point-IWS					
(Network Cost=3.0952 million rupees and					(Network Cost= 3.4452 million rupees and					
Network Resilience=0.3541)					Network Resilience=0.4111)					
Pipe	Diameter	Velocity	Node	Pressure	Pipe	Diameter	Velocity	Node	Pressure	
N ₀	(10^{-3} m)	(m/s)		(m)	N ₀	(10^{-3} m)	(m/s)		(m)	
1	112	1.9570	1	7.3100	1	161.4	3.1682	1	9.8689	
$\overline{2}$	112	0.0100	$\overline{2}$	7.5000	$\overline{2}$	251.4	0.0125	$\overline{2}$	10.1259	
$\overline{3}$	112	0.0400	3	11.6600	3	161.4	0.0502	3	15.7464	
$\overline{4}$	251.4	0.5900	$\overline{4}$	12.5900	$\overline{4}$	251.4	0.7407	$\overline{4}$	17.0080	
5	251.4	0.3300	5	7.6500	5	251.4	0.4144	5	10.3395	
6	251.4	0.4500	6	7.1400	6	251.4	0.5655	6	9.6526	
$\overline{7}$	161.4	0.2100	$\overline{7}$	7.4800	$\overline{7}$	251.4	0.2640	$\overline{7}$	10.1156	
8	251.4	0.2300	8	7.0750	8	251.4	0.2892	8	9.5512	
9	112	0.1100	9	13.6200	9	251.4	0.1383	9	18.4551	
10	112	0.0800	10	18.4900	10	161.4	0.1006	10	25.0623	
11	112	0.0500	11	18.8300	11	161.4	0.0629	11	25.5232	
12	161.4	0.1500	12	8.9900	12	161.4	0.1889	12	12.1922	
13	112	0.1600	13	7.1500	13	161.4	0.2016	13	9.7014	
14	161.4	0.0200	14	7.1520	14	161.4	0.0252	14	9.7052	
15	112	0.0200	15	9.7600	15	161.4	0.0252	15	13.2451	
16	161.4	0.4500	16	10.1700	16	161.4	0.5674	16	13.8114	
17	112	0.0200	17	16.0200	17	161.4	0.0252	17	21.7601	
18	112	0.2900	18	13.0300	18	251.4	0.3666	18	17.6997	
19	251.4	0.3500	19	15.0800	19	251.4	0.4426	19	20.4902	
20	161.4	0.1300	20	16.5100	20	251.4	0.1644	20	22.4631	
21	112	0.3300	21	17.1000	21	251.4	0.4176	21	23.2684	
22	161.4	0.1900	22	9.6000	22	251.4	0.2405	22	13.0663	
23	112	0.0600	23	11.3600	23	161.4	0.0760	23	15.4649	
24	161.4	0.6900	24	7.1200	24	161.4	0.8743	24	9.6975	
25	161.4	0.1000	25	10.1600	25	161.4	0.1267	25	13.8400	
26	161.4	0.1500	26	22.5100	26	161.4	0.1901	26	30.7101	
27	161.4	0.1200	27	12.9900	27	251.4	0.1523	27	17.7235	
28	112	0.1800	28	11.2400	28	251.4	0.2285	28	15.3528	
29	112	0.0800	29	14.5200	29	251.4	0.1016	29	19.8441	
30	251.4	0.0800	30	12.1600	30	251.4	0.1016	30	16.6305	
31	251.4	0.0500	31	8.2200	31	251.4	0.0636	31	11.2475	
32	251.4	0.4500	32	9.0100	32	251.4	0.5724	32	12.3302	
33	161.4	0.0600	33	15.1200	33	251.4	0.0764	33	20.6965	
34	251.4	0.0300	34	26.3200	34	251.4	0.0382	34	36.0540	
35	251.4	0.3400	35	7.1570	35	251.4	0.4334	35	9.8094	
36	161.4	0.1200	36	26.6800	36	251.4	0.1531	36	36.5848	
37	251.4	0.1000	37	27.3800	37	251.4	0.1276	37	37.5550	

Table A.5 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Leftmost Extreme Point for Vanasthalipuram WDN in CWS and IWS

Rightmost Extreme Point-CWS					Rightmost Extreme Point-IWS					
(Network Cost=5.7930 million rupees and					(Network Cost=5.7930 million rupees and					
Network Resilience=0.4913)					Network Resilience=0.5443)					
Pipe	Diameter	Velocity	Node	Pressure	Pipe	Diameter	Velocity	Node	Pressure	
N ₀	(10^{-3} m)	(m/s)		(m)	N ₀	(10^{-3} m)	(m/s)		(m)	
1	251.4	1.8967	1	10.7494	1	251.4	2.3738	1	14.5429	
\overline{c}	251.4	0.0075	\overline{c}	8.8901	$\overline{2}$	251.4	0.0094	\overline{c}	14.9216	
$\overline{3}$	251.4	0.0299	3	13.9633	3	251.4	0.0374	3	23.2040	
$\overline{4}$	251.4	0.4413	$\overline{4}$	18.2607	$\overline{4}$	251.4	0.5518	$\overline{4}$	25.0631	
5	251.4	0.2461	5	8.8474	5	251.4	0.3080	5	15.2365	
6	251.4	0.3354	6	10.0311	6	251.4	0.4197	6	14.2242	
7	251.4	0.1561	$\overline{7}$	10.7400	$\overline{7}$	251.4	0.1958	$\overline{7}$	14.9064	
8	251.4	0.1707	8	8.1789	8	251.4	0.2143	8	13.9808	
9	251.4	0.0816	9	17.9919	9	251.4	0.1024	9	27.1956	
10	251.4	0.0593	10	23.5120	10	251.4	0.0744	10	36.9320	
11	251.4	0.0370	11	26.7548	11	251.4	0.0465	11	37.6113	
12	251.4	0.1110	12	11.2362	12	251.4	0.1396	12	17.9666	
13	251.4	0.1182	13	10.2856	13	251.4	0.1489	13	14.2961	
14	251.4	0.0147	14	8.6580	14	251.4	0.0186	14	14.3016	
15	251.4	0.0147	15	14.1742	15	251.4	0.0186	15	19.5181	
16	251.4	0.3317	16	14.9918	16	251.4	0.4180	16	20.3526	
17	251.4	0.0147	17	19.4945	17	251.4	0.0186	17	32.0659	
18	251.4	0.2133	18	15.2141	18	251.4	0.2695	18	26.0824	
19	251.4	0.2574	19	20.2367	19	251.4	0.3253	19	30.1946	
20	251.4	0.0955	20	19.0415	20	251.4	0.1207	20	33.1019	
21	251.4	0.2424	21	24.6228	21	251.4	0.3059	21	34.2886	
22	251.4	0.1395	22	14.0927	22	251.4	0.1757	22	19.2547	
23	251.4	0.0440	23	15.8683	23	251.4	0.0555	23	22.7892	
24	251.4	0.5046	24	8.7944	24	251.4	0.6362	24	14.2904	
25	251.4	0.0731	25	13.7793	25	251.4	0.0921	25	20.3948	
26	251.4	0.1097	26	33.2836	26	251.4	0.1379	26	45.2548	
27	251.4	0.0876	27	19.0099	27	251.4	0.1104	27	26.1175	
28	251.4	0.1314	28	15.3109	28	251.4	0.1656	28	22.6240	
29	251.4	0.0582	29	20.7249	29	251.4	0.0736	29	29.2424	
30	251.4	0.0581	30	17.5427	30	251.4	0.0736	30	24.5069	
31	251.4	0.0363	31	11.0645	31	251.4	0.0460	31	16.5745	
32	251.4	0.3264	32	10.3637	32	251.4	0.4137	32	18.1699	
33	251.4	0.0435	33	18.7177	33	251.4	0.0549	33	30.4985	
34	251.4	0.0218	34	34.2471	34	251.4	0.0274	34	53.1296	
35	251.4	0.2464	35	9.3093	35	251.4	0.3110	35	14.4552	
36	251.4	0.0869	36	38.8549	36	251.4	0.1097	36	53.9117	
37	251.4	0.0722	37	32.1352	37	251.4	0.0910	37	55.3414	

Table A.6 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Rightmost Extreme Point for Vanasthalipuram WDN in CWS and IWS

Leftmost Extreme Point						Rightmost Extreme Point					
(Network Cost=1.3201 million rupees,					(Network Cost=3.4126 million rupees,						
					Network Resilience=0.8829 and						
Network Resilience=0.4551 and Network Equity=0.7591)						Network Equity=0.9799)					
Pipe	Diameter Velocity			Pressure	Pipe	Diameter Velocity			Pressure		
N ₀	(10^{-3} m)	(m/s)	Node	(m)	N ₀	(10^{-3} m)	(m/s)	Node	(m)		
1	98.6	0.1315	1	10.9280	1	251.4	0.1185	1	11.8830		
$\mathfrak{2}$	125.4	0.6571	$\overline{2}$	11.7914	$\overline{2}$	251.4	0.5895	$\overline{2}$	12.5744		
$\overline{3}$	125.4	0.4900	3	14.7439	3	251.4	0.4401	3	15.6046		
$\overline{4}$	125.4	0.9451	$\overline{4}$	10.9232	$\overline{4}$	251.4	0.8432	$\overline{4}$	11.8702		
$\overline{5}$	125.4	0.7788	$\overline{5}$	13.4650	$\overline{5}$	251.4	0.6945	$\overline{5}$	14.2667		
6	98.6	0.3947	6	16.1062	6	251.4	0.3538	6	17.3076		
$\overline{7}$	80.4	0.5158	τ	17.5606	τ	251.4	0.4608	τ	18.6684		
8	80.4	0.0118	$\,8\,$	16.1196	$\,8\,$	251.4	0.0105	8	17.3729		
9	98.6	0.1080	9	14.4344	9	251.4	0.0964	9	15.5066		
10	98.6	1.5453	10	13.5537	10	251.4	1.3635	10	14.7893		
11	98.6	0.1081	11	12.9866	11	251.4	0.0962	11	14.1223		
12	125.4	0.6227	12	15.6075	12	251.4	0.5530	12	16.8439		
13	80.4	1.1403	13	17.4459	13	251.4	1.0023	13	19.0153		
14	80.4	0.5763	14	13.2896	14	251.4	0.5074	14	14.2179		
15	98.6	0.1800	15	16.3363	15	251.4	0.1591	15	17.4956		
16	98.6	0.7193	16	15.9356	16	251.4	0.6324	16	17.1154		
17	98.6	0.0120	17	17.2872	17	251.4	0.0106	17	18.6234		
18	98.6	1.0069	18	18.6212	18	251.4	0.8833	18	20.3904		
19	98.6	0.0962	19	13.4332	19	251.4	0.0847	19	14.5810		
20	98.6	0.3603	20	15.6894	20	251.4	0.3169	20	16.6517		
21	98.6	0.2042	21	11.4201	21	251.4	0.1798	21	12.4848		
22	98.6	0.4569	22	12.7296	22	251.4	0.4006	22	13.8998		
23	80.4	0.0843	23	10.5692	23	251.4	0.0740	23	11.4084		
24	80.4	0.3848	24	19.0257	24	251.4	0.3366	24	21.8196		
25	80.4	0.0843	25	15.2095	25	251.4	0.0738	25	16.1788		
26	80.4	0.0722	26	15.6390	26	251.4	0.0631	26	17.0643		
27	112	0.8794	27	14.6086	27	251.4	0.7633	27	15.9240		
28	98.6	0.0722	28	13.6788	$28\,$	251.4	0.0632	28	15.0609		
29	98.6	0.0842	29	16.6189	29	251.4	0.0737	29	18.2240		
30	98.6	0.0722	30	13.5330	30	251.4	0.0629	30	14.7555		
31	66.8	0.1084	31	15.2504	31	251.4	0.0941	31	16.5258		
32	98.6	0.8802	32	13.7648	32	251.4	0.7576	32	15.1617		
33	66.8	0.8801	33	14.0328	33	251.4	0.7581	33	15.4227		
34	98.6	0.0604	34	15.4558	34	251.4	0.0521	34	16.8103		
35	98.6	0.3380	35	14.7074	35	251.4	0.2909	35	15.9940		
36	98.6	0.2535	36	15.9228	36	251.4	0.2180	36	17.1877		
37	98.6	0.0604	37	17.1446	37	251.4	0.0520	37	18.5878		
38	98.6	0.3990	38	11.2905	38	251.4	0.3416	38	12.0664		
39	125.4	1.3667	39	10.1311	39	251.4	1.1587	39	11.1580		
40	112	1.1956	40	10.7020	40	251.4	1.0161	40	11.6524		

Table A.7 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Leftmost Extreme Point and Rightmost Extreme Point for Pamapur WDN (IWS)

Leftmost Extreme Point (Network Cost=3.2025 million rupees, Network Resilience=0.3680 and Network Equity $=0.7946$)					Rightmost Extreme Point (Network Cost=4.7747 million rupees, Network Resilience=0.4810 and Network Equity = 0.9833)					
Pipe	Diameter	Velocity		Pressure	Pipe	Diameter	Velocity		Pressure	
N ₀	(10^{-3} m)	(m/s)	Node	(m)	N ₀	(10^{-3} m)	(m/s)	Node	(m)	
1	251.4	2.9915	$\mathbf{1}$	10.7035	1	251.4	2.2083	$\mathbf{1}$	15.7727	
$\sqrt{2}$	251.4	0.0119	$\overline{2}$	10.9446	\overline{c}	251.4	0.0087	$\overline{2}$	16.1281	
3	161.4	0.0470	3	17.0472	3	251.4	0.0355	3	25.1210	
$\overline{4}$	251.4	0.7019	$\overline{4}$	18.2901	$\overline{4}$	251.4	0.5201	$\overline{4}$	26.9524	
5	251.4	0.3876	5	11.1857	5	251.4	0.2878	5	16.4834	
6	251.4	0.5272	6	10.4955	6	251.4	0.3970	6	15.4663	
$\overline{7}$	251.4	0.2484	τ	11.0109	$\overline{7}$	251.4	0.1846	$\overline{7}$	16.2258	
$\,8\,$	251.4	0.2724	$8\,$	10.4015	$8\,$	251.4	0.2026	8	15.2254	
9	251.4	0.1303	9	19.7715	9	251.4	0.0973	9	29.1355	
10	251.4	0.0938	10	27.2909	10	251.4	0.0704	10	40.2161	
11	251.4	0.0591	11	27.5634	11	251.4	0.0438	11	40.6177	
12	251.4	0.1789	12	13.0623	12	251.4	0.1307	12	19.2487	
13	251.4	0.1907	13	10.4103	13	251.4	0.1401	13	15.3407	
14	251.4	0.0239	14	10.4420	14	251.4	0.0176	14	15.3874	
15	251.4	0.0238	15	14.2169	15	251.4	0.0174	15	20.9502	
16	161.4	0.5349	16	14.9813	16	251.4	0.3964	16	22.0766	
17	161.4	0.0237	17	23.6662	17	251.4	0.0176	17	34.8747	
18	251.4	0.3473	18	19.2400	18	251.4	0.2513	18	28.3523	
19	251.4	0.4142	19	22.1999	19	251.4	0.3046	19	32.7140	
20	251.4	0.1550	20	24.3943	20	251.4	0.1134	20	35.9477	
21	251.4	0.3913	21	24.9440	21	251.4	0.2868	21	36.7577	
22	251.4	0.2265	22	14.1176	22	251.4	0.1640	22	20.8038	
23	251.4	0.0711	23	16.5656	23	251.4	0.0527	23	24.4112	
24	251.4	0.8263	24	10.5341	24	251.4	0.5977	24	15.5232	
25	251.4	0.1199	25	14.9045	25	251.4	0.0868	25	21.9635	
26	161.4	0.1800	26	33.3690	26	251.4	0.1309	26	49.1729	
27	251.4	0.1417	27	19.2211	27	251.4	0.1033	27	28.3244	
$28\,$	251.4	0.2126	$28\,$	16.5310	28	251.4	0.1547	$28\,$	24.3603	
29	251.4	0.0946	29	21.3171	29	251.4	0.0689	29	31.4131	
30	251.4	0.0956	30	17.9077	30	251.4	0.0698	30	26.3890	
31	251.4	0.0602	31	12.1382	31	251.4	0.0434	31	17.8869	
32	251.4	0.5395	32	13.3237	32	251.4	0.3858	32	19.6339	
33	251.4	0.0714	33	22.3113	33	251.4	0.0514	33	32.8781	
34	251.4	0.0356	34	39.1200	34	251.4	0.0259	34	57.6476	
35	251.4	0.4042	35	10.5013	35	251.4	0.2953	35	15.4748	
36	251.4	0.1425	36	39.4198	36	251.4	0.1037	36	58.0895	
37	251.4	0.1208	37	40.3240	37	251.4	0.0851	37	59.4219	
38	251.4	0.1331	38	18.2727	38	251.4	0.0942	38	26.9269	
39	161.4	0.0848	39	16.8541	39	251.4	0.0594	39	24.8364	

Table A.8 Comparison of Optimal Pipe Diameter, Velocity and Node Pressure representing Leftmost Extreme Point and Rightmost Extreme Point for Vanasthalipuram WDN (IWS)

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- 1. Mahesh B. Patil, Maddukuri Naveen Naidu, A Vasan, Murari R R Varma. "Water distribution system design using Multi-objective Particle Swarm Optimization", *Sadhana*, 45:21, 2020.
- 2. Pankaj, B.S., Naidu, M.N., Vasan, A., Murari RR Varma, Self-Adaptive Cuckoo Search Algorithm for Optimal Design of Water Distribution Systems. *Water Resources Management*, 34, 3129–3146, 2020.
- 3. Srinivasa Raju, K, A. Vasan and M Naveen Naidu, Fuzzy cluster analysis and decisionmaking algorithms for optimal water distribution network design, *ISH Journal of Hydraulic Engineering*, Taylor & Francis, 29:3, 341-350, 2022.
- 4. M Naveen Naidu, A Vasan, Murari RR Varma and Mahesh B. Patil, Multiobjective Design of Water Distribution Networks using Modified NSGA-II Algorithm, *Water Supply*, 23(3), 1220–1233, 2023.

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- 1. M Naveen Naidu, A Vasan, Murari RR Varma, *"Water Distribution Network Optimization – A Review"*, 50th IWWA Annual Convention 2018, Kala Academy, Panaji, Goa, February 19- 21, 2018.
- 2. M Naveen Naidu, Sriman Pankaj, A Vasan, Murari RR Varma, *"Optimization of Water Distribution Networks Using Cuckoo Search Algorithm"*, International Conference on Advanced Engineering Optimization Through Intelligent Techniques (AEOTIT), S.V. National Institute of Technology, Surat, Gujarat, India, August 03-05, 2018.
- 3. M Naveen Naidu, A Vasan, Murari RR Varma, *"Nature Inspired Multiobjective Optimization of Water Distribution Network Design"*, International Conference on Sustainable Practices and Innovations in Civil Engineering (SPICE 2019), Department of Civil Engineering, S.S.N. College of Engineering, Chennai, India, March 26-27, 2019.
- 4. M Naveen Naidu, A Vasan, Murari RR Varma, *"Many objective optimization of water distribution networks using NSGA-II"*, Water Future Conference 2019 – Towards a Sustainable Water Future, Divecha Centre for Climate Change, IISc Bengaluru, India, September 24-27, 2019.
- 5. M Naveen Naidu, Sriman Pankaj, A Vasan, Murari RR Varma, *"Improved NSGA-II Multiobjective Genetic Algorithm for Optimization of Water Distribution Network Design"*, 17th International Computing & Control for the Water Industry Conference, University of Exeter, UK, September 1-4, 2019.
- 6. Vasan A, M. Naveen Naidu and Murari RR Varma, "*Enhancing Equitable Distribution and Network Resilience in Intermittent Water Supply Systems*", 20th Annual Meeting of the Asia Oceania Geosciences Society (AOGS 2023), 30 July to 04 August, 2023, Singapore.
- 7. Naveen Naidu M, A Vasan and Murari RR Varma, "*Optimal Design of District Metered Areas for Water Distribution Networks*", 3rd International Conference on Environment sustainability: New Paradigms and Developments (ICES 2023), November 27-29, 2023, BITS Pilani Dubai Campus, Dubai, UAE.

BIOGRAPHY

Biography of Candidate

M. Naveen Naidu's academic journey in civil engineering showcases a strong commitment to excellence and a profound interest in water resources management. After obtaining his Bachelor of Technology in Civil Engineering from Sri Venkateswara University, Tirupati in 2013, where he demonstrated exceptional dedication, M. Naveen Naidu achieved an impressive 99.00 percentile in the Graduate Aptitude Test in Engineering (GATE). He then pursued a Master's degree in Water Resources Engineering at the esteemed National Institute of Technology (NIT) Nagpur, graduating in 2015 with continued academic success. Transitioning into academia, Naidu served as an Assistant Professor for nine months, contributing to the institution's academic and research endeavors. Naidu's dedication and passion underscore his significant contributions to civil engineering. Following this, he has been pursuing his PhD at BITS Pilani Hyderabad Campus, while concurrently serving as a Senior Research Fellow (SRF) in a Council of Scientific and Industrial Research (CSIR) Project from 2017 to 2020. In his PhD journey, he has been awarded a travel grant by CSIR for presenting a paper in a prestigious conference "Computing and Control for Water Industry (CCWI)" conducted by University of Exeter, United Kingdom in 2019. He has published four journal papers and seven conference papers from this research work.

Biography of Supervisor

Prof. A Vasan is a Professor in the Department of Civil Engineering at BITS Pilani, Hyderabad Campus. He has been actively involved in teaching, research and academic administration for nearly twenty-four years. He holds a PhD in Water Resources Engineering and did his Post-Doctoral studies at Western University, Canada. His research interests include Optimization of Reservoir Operation using Nature Inspired Algorithms, Water Distribution Network design optimization, Leak Detection in Water Distribution Networks using Machine Learning and IoTs. He is a recipient of awards for various research papers and has also received sponsored research funding from various agencies. He has published more than 100 research papers and has been serving as a reviewer for numerous reputed international journals.

Biography of Co-Supervisor

Prof. Murari R R Varma is an Associate Professor in the Department of Civil Engineering at Birla Institute of Technology and Science, Pilani, Hyderabad Campus, India and currently is the Head of the Department. He received his PhD from the Department of Civil Engineering, Indian Institute of Science, Bangalore. His research interests are in experimental and field hydrology, and water quality of natural water systems. He is actively publishing research articles in reputed journals and conferences. He also has completed or ongoing sponsored and consultancy projects under CSIR as well as the Government of Telangana State.