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Developing an Optimal Model for Water Distribution System Design

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ABSTRACT

Future difficulties related to water utilization in sustainable cities will be influenced by factors such as urban development, climate change, and resource scarcity. Distribution accounts for 80–85% of the entire cost of a water supply system, making it a crucial part of all urban water systems. To increase system reliability, water distribution systems (WDS) are typically designed with the "worst scenario" or "robustness" in mind. Because deterministic assumptions are historically incorrect, a new design methodology that acknowledges uncertainty and provides greater flexibility is needed. To design WDS that are more adaptive, a Genetic Algorithm Flexibility Optimization (GAFO) model is created in Visual C++ and connected to EPANET. In contrast to classical GA optimization, GAFO uses a dynamic decision-making method to maximize a WDS's versatility at the lowest possible cost while taking into account a variety of potential future scenarios. The result is a WDS that may develop a staged implementation strategy that enables a gradual evolution of the WDS over time and follows various future trajectories (changing conditions). The convergence and flexibility of the GAFO model were determined to be good after it was tested on several fictitious scenarios. In comparison to traditional, non-flexible designs, cost reductions of 35% to 72% were achieved.

Keywords: *Flexibility Optimization, Water Distribution Systems, Smart Cities, Uncertainties, Genetic Algorithm*

INTRODUCTION

Water is essential to sustainable growth and is required for human life, socioeconomic progress, and ecological health. Aiming to optimize the design of urban water distribution systems and other infrastructure, sustainable city development aims to adapt to future change requirements (1). The operation of water distribution systems (WDS) will be hampered in the future by factors such population expansion, urban sprawl, climate change, and socioeconomic changes,

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making this goal difficult to achieve. The majority of the time, these distribution systems are made to last for several decades. Growing demands have a significant impact on WDS's relative cost and efficiency, with implications for the entire community (2). Cities will face challenges in effectively managing increasingly scarce and unreliable water resources due to a combination of factors including climate change and inherent risks associated with traditional urban water management practices. It is primarily anticipated that the distribution and safe yield of water to consumers will be impacted by global demands. Making realistic and accurate projections for long-term repercussions is challenging since distributional uncertainty are case-by-case (3).
Deterministic presumptions have served as the foundation for traditional WDS design planning. Conventional designs, for instance, often operate under the premise that all model input variables—such as the need for water volume and the characteristics of pipe friction—are precisely understood (4). Predictions, however, may show a significant departure from actual conditions because of uncertainty related to global issues that appear locally. Generally speaking, the conventional deterministic design method may result in WDS that are undersized and perform badly (or vice versa) (5). Deteriorating performance may lead to higher maintenance and operating expenses. Unplanned adaption actions are necessary to bring underperforming WDS up to the expected performance, which may result in significant additional expenses (6). Because it ignores variations in the costs and performance of the WDS, researchers and practitioners are increasingly of the opinion that the conventional deterministic design approach is no longer appropriate (7).

Deteriorating performance may lead to higher maintenance and operating expenses. Unplanned adaption actions are necessary to bring underperforming WDS up to the expected performance, which may result in significant additional expenses (8). Because it ignores variations in the costs and performance of the WDS, researchers and practitioners are increasingly of the opinion that the conventional deterministic design approach is no longer appropriate (9).

However, powerful designs come with a number of disadvantages. For instance, these systems lack the flexibility to adjust or adjust to changes in the external environment that were not anticipated during the planning and design stages (10). Staggered growth systems should not be designed using a robust method. In order to accommodate the spatially growing emergent area, these robust projects frequently overdesign, which drives up initial prices (11). Since their designs are modified, they are unable to shrink in response to lower expectations or adjustments to projections for the future (12). Moreover, a lot of robust design techniques only account for small-scale uncertainties (like modeling anomalies) and ignore larger-scale uncertainties related to future pressures and system changes, like lowering system losses, removing corroded pipe that has a higher friction loss, and increasing pressure at pumping stations to move larger volumes of water (13).

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The ability to make modifications to the fundamental architecture long after the system has been put into place in order to adapt to new trajectories has been suggested as a solution to sustainable growth (14). The capability of urban drainage systems to employ their active capacity to act and respond to pertinent adjustments during operation in a rapid, economical, and performance-efficient manner is known as flexibility. Pressurized WDS follows the same idea (16). The decision-making process in flexible design is centered on multiple subsequent checkpoints in time rather than a single, finite goal. According to the theory put forth by, a system's increased flexibility offers the ability to adapt to external uncertainties, which is necessary for the system to change and advance to new phases (17).

Scholtes (2007) acknowledged flexibility as a means of converting uncertainty-related risks into opportunities (18). The flexibility philosophy asserts that future uncertainties should be taken into account while designing WDS in order to achieve the desired performance with the least amount of initial investment. We are just beginning to talk about flexibility in WDS (19). There are no techniques or resources available in the technical literature for designing flexible WDS optimally. The idea of flexible design for WDS is difficult to operationalize, necessitating the development of fresh strategies and techniques (20).

This research discusses a novel modeling tool known as Genetic Algorithm based Flexibility Optimization (GAFO) and presents a novel strategy for the flexibility-based optimization of WDS based on a Genetic Algorithm (GA) optimization technique. GAFO maximizes a WDS's flexibility while keeping costs to a minimum by adhering to a special target function (21). It focuses on minimizing the costs of adaptation and investment related to adapting to a changing environment. Throughout the whole design process, the objective function is optimized and subject to limitations to guarantee system performance (22). Because of a GAFO's special feature, flexibility may be incorporated into a WDS design while optimization is being done against all potential future scenarios. The optimization process results in a WDS that can adapt to unforeseen changes in water use patterns. This allows for the gradual evolution of the WDS over time through a staged implementation strategy. When flexibility is incorporated into the planning, designing, and building of new water systems or the extension of current ones, cities become more resilient and sustainable (23).

METHODOLOGY

2.1 Basic optimization for WDS

Constraints, objective functions, and design variables are used in the formulation of problems in WDS design. In an optimization issue, any number or option that the designer has direct control over is referred to as a design variable. The choice of pipe diameters, pump types, tank capacity, valve pressure settings, and valve positions are examples of design variations.

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Objective functions are parameters that must be simultaneously maximized, including the characteristics of the payoff between overall cost, dependability, and water quality (24). A restriction is a prerequisite that needs to be met for the design to be workable. Restrictions may be related to user needs, resource limits, or limitations on the analytical model's validity. Energy and continuity equations are used to represent the general restrictions in a WDS's hydraulic analysis. It is possible to specify minimum and maximum permissible pressures at every demand point, minimal and maximum velocity limits for each pipe, and water quality standards as bound constraint variables in a WDS optimization problem. There may be other material restrictions, such as the resources needed for various rehabilitation options (cleaning, relining, etc.).

As stated by Mays (2000), providing the required water demand at the withdrawal nodes with a sufficient pressure head is the primary constraint in a WDS optimization problem. A WDS's ideal design is frequently thought of as the lowest-cost optimization problem—one in which the importance of cost should be kept to a minimum. It has, nevertheless, also been used to achieve various goals in the creation and functioning of a WDS. Whole-life costs, network dependability, redundancy, water quality, pump upkeep, WDS model calibration, valve placement, etc. are some of these (25).

Equations 1 through demonstrate how the total optimization problem for determining the least expensive combination of pipe size may be mathematically represented while taking capital cost into account. Here, C(v) represents the cost of the pipes; D is the design dynamic pipe diameter; N is the number of pipes (26). The cost of the component with diameter Dj and length Lj is denoted by $C(Dj, Lj)$; Pipe head-loss is represented by hf; external flow or demand at each node is represented by Q; flow into and out of a junction is represented by Qin; Pump energy is denoted by $\mathbf{D}P$, commercially available size is indicated by A, and the lower and upper bounds of the nodal pressure head are represented by $Hmin$ and $Hmax$.

$$Minimizing\ f_{cost}(D) = \sum_{j=1}^{N} C(D_j, L_j)$$

$$S.t, \quad \sum Q_{in} - \sum Q_{out} = Q$$

$$\sum h_f - \sum E_p = 0$$

$$H_{min} < H < H_{max}$$

$$D \in \{A\}$$

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It is presumed that the capital cost of a pipe fluctuates nonlinearly with its diameter and may be described using one expression for all diameters when discussing pipe cost. Regression coefficients K and n are dependent on the regional pipe cost function, and $C(Dj, Lj) = K\ Lj\ Dn$. The general optimization formula used in equations 1 through 5 follows a predetermined set of system objective requirements throughout time. The changing system needs that take into account potential scenario routes should be taken into account while creating flexible WDS.

2.2 Unique objective function for flexibility optimization

The main goal of flexibility-based optimisation is to increase the system's capacity to adjust to novel, varied, or evolving requirements. A system must be adaptable enough to change or respond in a way that maximizes both performance and economy in order to be able to handle an environment that is always changing. Therefore, the creation of an objective function for flexibility needs to concentrate on minimizing the costs of adaptation and investment related to the changing environment while maintaining the minimal performance necessary for all potential future circumstances (the so-called "range of uncertainties").

"To address future change and unpredictability, this study creates an objective function for flexibility that is based on two distinct features: (i) the objective function should take into account a wide range of challenges for which the system must adapt, and (ii) the objective function ought to include a staged function that allows adaptation from one stage to the next." There are currently two main classifications used for quantifying uncertainties: the scenario approach, which defines several conceptually distinct models expressing the uncertainty, and the probabilistic approach, which describes a stochastic model for capturing all uncertainty. There are also some hybrid variations of these strategies. To represent the uncertainty inside a scenario, one can use a stochastic model. Although none of the strategies produce exact answers, the information available determines which strategy is chosen.

A decision tree is used in the scenario method to describe a range of uncertainty throughout time. The decision tree's nodes offer distinct endpoints for examining system trajectories and looking for spots where flexibility might be added or changed to better accommodate novel or shifting demand scenarios. Among the scenario approach's other advantages are:

- *Simplicity*— discreet, uncomplicated families with a variety of options
- *Checkpoints*— snapshots of decision trees that continuously evaluate adaptability
- *Flexibility*— Systems are adaptable to particular requirements and changing circumstances.
- *Prevalence*— enhances communication when dealing with strategic growth by using a single, shared language

The input scenarios, such as projected water demand, serve as the foundation for the suggested flexibility optimization. The objective of its formulation is to reduce the Net Present Value (NPV) linked to any future adaptation checkpoint. Due to the nature of the issue of optimization, a nested-loop method involving the following elements is necessary:

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- Examining a variety of potential future conditions and related expenses. Equation 6 illustrates how the cost function incorporates the sum of the cost values of all states at each stage, where C(y) is the cost of the pipes at each stage; The parameters that make up the pipe cost function are as follows: $\boldsymbol{Xj}$ is the length of the jth pipe; N is the total number of piping; D is the design variable that defines the dimension of components (i.e., pipe diameter); t is the development stage; Δt is the period for each stage; r is the rate of discount; m is the greatest number of future states (s); and **N** and n are the regression coefficients for each pipe.
- The total cost values. The cost variables from step (i) above are added together to form the cost function. This indicates that the goal function is minimized across the complete range of stages when the total cost values of all the stages are added together. With $fcost(D)$ representing the overall cost of the original investment and adaptation, t denoting the design stage {0, 1, 2, …, St}, and St the highest number of staging in the design horizon, the Equation below is used to ascertain the cumulative cost values.

$$f_{cost}(D) = \sum_{t=0}^{St} f_t$$

The objective function is a complicated procedure that involves evaluating every possible state at each step and then adding up all of the stages. Equation 8 provides a mathematical expression for the combined equation for the lowest-cost flexibility optimization problem. Here, fcost (D), D, K, L, N, Δt, K, $\boldsymbol{U}$, and n are as previously mentioned; t represents the design stages {0, 1, 2, …, St}; St is the maximum number of stages in the design horizon. Cost values for all potential states of all stages that the system must adjust to are combined in this calculation.

2.3 Optimization model for flexible WDS design using genetic algorithms

It has been proposed by numerous scholars that a Genetic Algorithm (GA) provides almost ideal answers in a manageable amount of iterations. Huang (2012) claims that GA works better when creating adaptable WDS in the face of uncertainty (27). When designing for flexibility, a broad range of future uncertainties must be optimized over, encompassing a sizable design area. Similarly, several stages and future uncertainty states need to be taken into account when calculating the optimization objective function as defined in Equation 8. Discrete decision stages are used to indicate the future conditions and their respective times, in addition to a scenario tree. Better optimization techniques for discrete choice variables are needed for these. Consequently, here we discuss a Genetic Algorithm Flexibility Optimization (GAFO) to enable the progressive evolution of WDS over time (28).

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The C++ programming language was used to create the code for the GAFO model. The creation of an early population, hydraulic research, uncertainty-based quality assessment, creation of a new population (using genetic operators for mutation, selection, and cross-over), and termination are the main processes in GAFO. Two main differences between the GAFO method presented here (Fig. 2) and those described in earlier publications are as follows:

i. This method of optimization is carried out for a variety of future circumstances. This implies that a system's adaptability to future changes is taken into consideration while evaluating it. Additionally, the system performance is assessed across a broad range of future uncertainty using a modified penalty function.
ii. This method of optimization likewise relies on phased decision-making, enabling the WDS to evolve gradually over time.

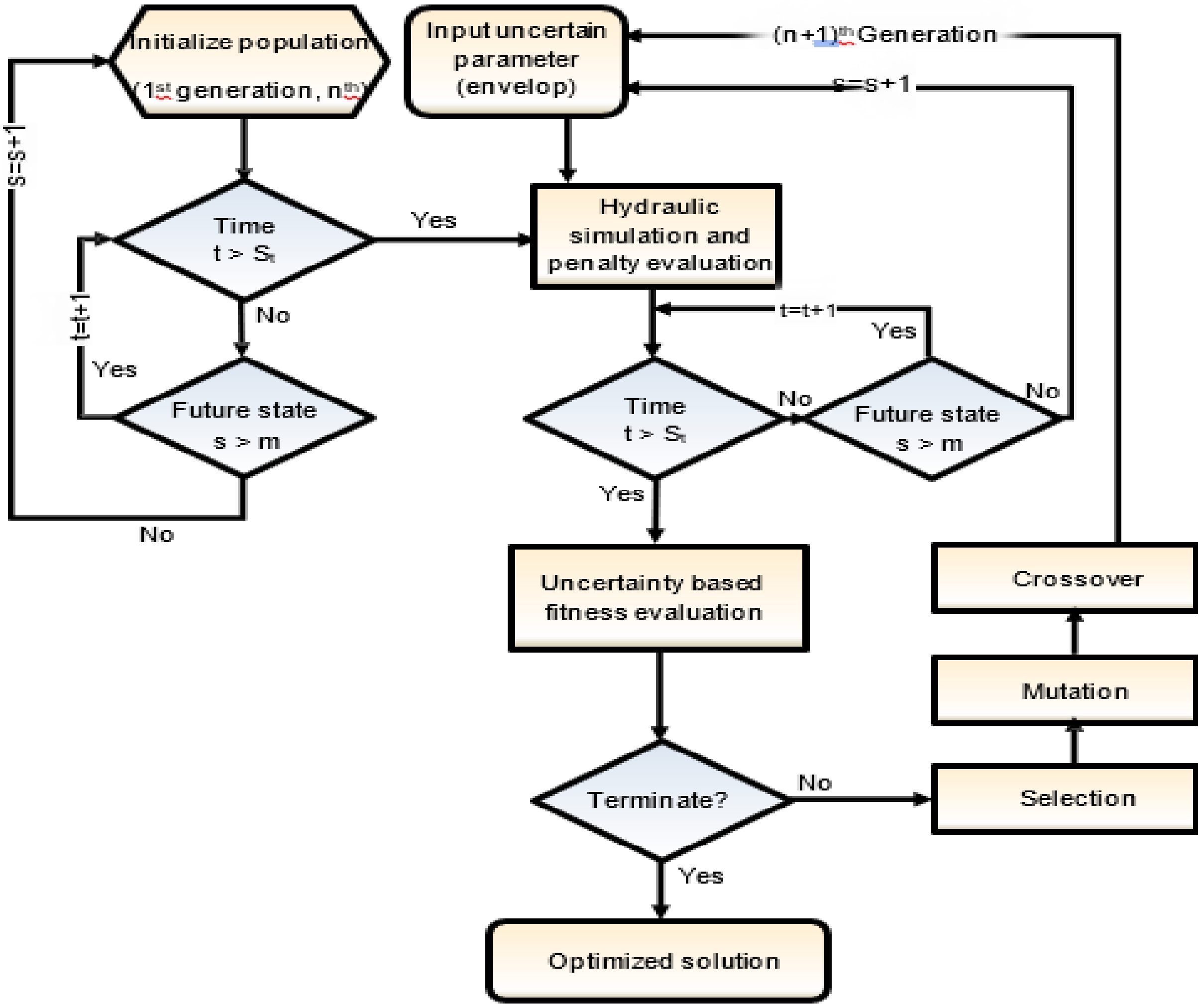

Fig. 2. GAFO model algorithm.

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In the GAFO model, a population at random is initialized for every scenario that could arise in the future (all future states, s, and time stages, t) (Fig. 2). A complex loop process that calls for a variety of ambiguous input parameters that are represented by the future state and design stage (t) is also involved in the hydraulic simulation and penalties calculations. Similar to this, a wide range of future conditions are covered by the fitness function that uses the minimization objective function. The fittest population that permits a stage-by-stage evolution of the WDS under various future situations was investigated using the GAFO optimizer

2.4 GAFO initial population generation

Using a random generator, GAFO creates an initial population of "n" number of chromosomes, or potential solutions. This is an example of a potential first pipe network solution (string) in a WDS design. This optimization is special because it starts with a population of potential pipe network solutions (strings) for every state (s) at every design stage (t). This facilitates the GA optimizer's search for optimal solutions that function well across a variety of uncertainties (29). Although real or binary coding can be applied, binary coding produces duplicate states, and the suggested solutions frequently cause the GA to perform poorly. This article's distinct design variable, pipe diameters, is subjected to a genuine coding algorithm by the GAFO. There are no duplicate states and every gene is linked to a diameter thanks to real coding. Actual coding integers 1 to 14 can be utilized to denote a pipe with a diameter of 14 units, for instance, if there are 14 units of commercially available diameters.

2.5 **Fitness evaluation for flexibility and a penalty function based on GAFO uncertainty**

The GA finds the pipes that are feeding the nodes that don't have the minimum pressure needed and charges a penalty to them. One of the difficulties in solving an optimization problem, though, is determining an appropriate penalty function. In order to highlight the subpar performance of the pipes providing low-pressure nodes, Dijk et al. (2008) proposed using large fines. According to the severity of the infraction (30), Vairavamoorthy and Ali (2000) propose a variable penalty coefficient. Pc represents the penalty cost and Pk is the penalty factor for the Kt℗ level of violation and the it℗ pressure constraint, illustrates how the variable penalty coefficient is derived heuristically and depends on the amount of violation (31).

The value per meter assigned to the pressure head under the permitted minimum pressure head is expressed as the penalty coefficient. Under various levels of uncertainty, the degree of violation at every node is measured using the penalty function. When determining a punishment function for GAFO, the following three distinctive characteristics are taken into account:

i. The GAFO is designed for staged design, in which the range of uncertainties is taken into account while evaluating the WDS performance at various design periods.
ii. All potential ranges of uncertainty established by the state of nature (i.e., water

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demand values) should be taken into account when determining the degree of violation of the WDS from the minimum amount that is required.

iii. Based on the idea that those pipes that carry more water are more significant than the ones that deliver less water, GAFO uses a weighted penalty. The percentage of the supply pipe significance distribution depending on flow rate (V/V) is taken into account by the weighted penalties. The distinctive penalty function for adaptability, where a is the design stage $\{0, 1, 2, \ldots, St\}$; $\boldsymbol{U}$ is the discount rate; m is the greatest number of scenarios (s) that indicate future uncertainty; and Pc is the penalty cost term.

The pressure-bound restriction mechanism's penalty function was created for this debate. If more than one constraint is present, a similar method might be used to find the penalty function for those additional requirements (velocity = change in position/time, for example). The adjusted total expense for each string is computed by adding the network costs and penalty costs after the penalty term for the pipelines is established (producing the nodal pressure deficit) (Equation below).

$$T_c = f_{cost}(D) + P_c(D)$$

The suitability of the solution is then ascertained using the adjusted total cost (Tc). The GAFO search determines the optimal solution to the optimization issue through a fitness calculation. The degree to which the provided design solution approaches accomplishing the goal function is indicated by the fitness function (32).

The special feature of the GAFO searching mechanism assesses fitness over the entire spectrum of uncertainty, in contrast to classical GA optimization. This indicates that under a broad variety of future scenarios, the most optimal solution will function better. Typically, the string's fitness is interpreted as a function of the goal function. Equation 12 illustrates one way to define the fitness function (based on the minimal cost objective function): using the inverse total cost (network + penalty cost), where fi denotes the fitness of the it™ string solution.

2.6 GAFO Model Recommendations

In contrast to other conventional GA optimization methods, GAFO optimizes over a larger range of potential future states step-by-step. Ten steps have been identified as the summary of the optimization process to help direct GAFO-based designs:

1. Examine the population size, the maximum number of generations, needed minimal pressure, likelihood of mutation, design horizon, design stages, quantity of decision points (scenario nodes), penalty aspect, and network expense data.
2. Examine the scenario data to find the ambiguous parameters. Various future water demand scenarios are presented below, broken down by future state (s) and time stage (t).
3. Using a random generator, create an initial population for each potential future state

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(s) and time interval (t). This is one potential pipe network solution that could be used in the WDN design at first.

4. Counter 1 (iteration 1).

5. For all populations, perform the following:

   a) To find the flow and nodal pressure values, dial in to the WDS design program (EPANET – WDS modeling software) and do a hydraulic study. This is carried out in every case imaginable (step 2).
   b) Analyze the solution networks' price. The Net Present Value (NPV) for each scenario scenario (s) along with the time stage (t) solution is shown here.
   c) Determine the penalty cost for each node whose pressure falls short of the minimum if the solution fails to satisfy the minimum needed pressure head. For every scenario state (s) and time step (t), this is carried out.
   d) Determine the overall expense by adding the network cost and the penalty cost for each and every state and stage of the design process (including all potential outcomes).
   e) Determine each future state's fitness.

6. Increment counter 1.

7. The GA converges if the counter exceeds the maximum generation or if the fitness function does not improve for a set number of specified generations. If so, move on to step 10 and set aside the best answer. If not, move on to step 8.
8. Generate a new population
   a) Apply a selection method to find the best-fitting answer.
   b) Apply the crossover depending on the likelihood of crossover to the chosen population. To create two offspring, choose two at a time. Don't allow crossover; instead, preserve the best solution from the prior population (offspring will be a copy of fathers).
   c) Change the progeny according to varying rates of mutation.
   d) Put the new population in storage.

9. Repeat steps 5 using 7.
10. 10. Keep track of the information for the WDS solution that works best in unpredictable situations.

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The Supplementary Materials include the C++ program GAFO combined with EPANET, which is available for download on the internet (33).

RESULTS AND DISCUSSION

GAFO parameters and input pipe data

A fictitious case study is offered to illustrate how the proposed GAFO model can be used. The model can be used with any water distribution network, but it was important to employ a basic pipe network for the type of research done here in order to show the usefulness of the GAFO and its decision metrics. To accurately depict potential demand situations, the subsequent presumptions were established:

- Demand fluctuation in both space and time was seen as an unknown parameter.
- Over the course of the design period, demand may rise or fall within the same spatial bounds. The network's spatial extent may vary over time and may be correlated with temporal spikes or drops in demand.
- Organized (stepwise) expansion is used to capture the spatial expansion of demand. Analysis is done with a 40-year design timeframe and a three-stage deployment. A smaller or bigger developmental stage, though, might be taken into consideration.
- A variety of scenarios are employed to account for demand uncertainty. For examination, a unique instance involving developing nations' growing communities was selected. An growing demand pattern is employed in this particular scenario, with an initial stage of 20 L/s (the known current demand) and subsequent stages of 20 L/s to 60 L/s, with an uncertainty range changing between 20 L/s and 40 L/s during the first stage.

Fig. 3 depicts the configuration of the water distribution network under the critical spatial development scenario; Table 1 lists all other possibilities. All pipes in Fig. 3 have a length of 1000 m and a roughness of 130. This case study takes into account a three-stage deployment plan with a 40-year design horizon. The least expensive WDS solution that can adapt to changes in demand and uncertainty was found by using the established GA optimization model (34).

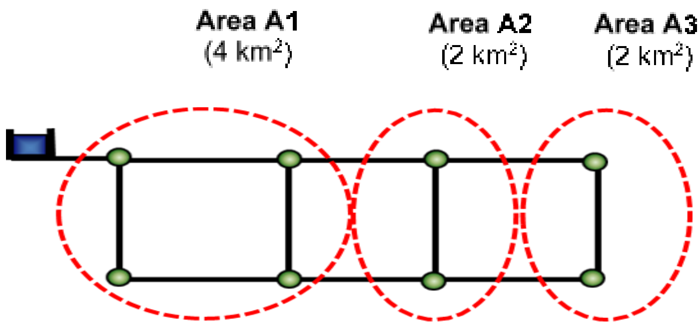

Fig. 3. Typology of the hypothetical WDS.

t=0 t=20 t=40 years

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Numerous unpredictable spatial and temporal requirements were the focus of the optimization. Three distinct design stages—0, 20th, and 40th year—were used to investigate nodal demand uncertainty. Table 1 displays the quantity of options and demand at each design stage (35).

Table 1. Design stages and future growth

Simulation time step (i)	Period of Design(years)	decision points of numbers (d)	Nodal demand in L/s (Q)	Spatial growth	Total decision points
T0	0	1	[20]	A1 ($4km^2$)	6
T1	20	2	[20, 40]	A2 ($2km^2$)	
T2	40	3	[20, 40, 60]	A3 ($2km^2$)	

In 2, the future demand growth possibilities for every design stage are depicted. In this research, the worst-case scenario takes 40–60 L/s nodal demand into account. This spectrum reflects actual instances in numerous tiny, developing cities in developing nations. In fewer than 30 years, the water demand in Africa might rise by 283%, according to Jacobsen et al. (2012) (36). Rapid population expansion is causing water usage to rise in many parts of the world. High birth rates and migration from rural to urban areas are the main causes of certain African regions. Arua, a tiny town by Uganda with 80,000 residents, is predicted to have a 200% growth in population over the next 20 years (37). Due to rising socioeconomic conditions making it more affordable to connect to the mainline water system, the town's water demand will rise even faster than its population. Similar effects on water distribution systems have also been noted in the United States, namely in the City of Cape Coral, Florida. Demand vectors were used to model the uncertainty corresponding to the given range of demand and spatial breadth. These demand vectors function as input variables (38).

Table 2. Uncertain demand scenarios

Scenarios	Spatial extent Year 0-20^{th}-40^{th}	Nodal demand (L/s) Year 0-20^{th}-40^{th}
1	A1T0-A1T1-A1T2	20-20-30

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2	A1T0-A1T1-A2T2	20-30-40
3	A1T0-A2T1-A2T2	20-40-40
4	A1T0-A2T1-A3T2	20-40-60

In order to expand and renovate the current WDS, parallel pipe is typically laid alongside the network or old pipes are replaced with ones of the same or greater diameter. Choosing such a combination optimally is a difficult task. A WDS needed either both expansion and capacity increase in this case study. A parallel pipe system is used by the adaptive WDS to incorporate flexibility for a variety of future demands (Table 2). As seen in Fig. 4, flexibility was produced in addition to adaptability by staging the system deployment so that the WDS might alter in response to various future modification requirements.

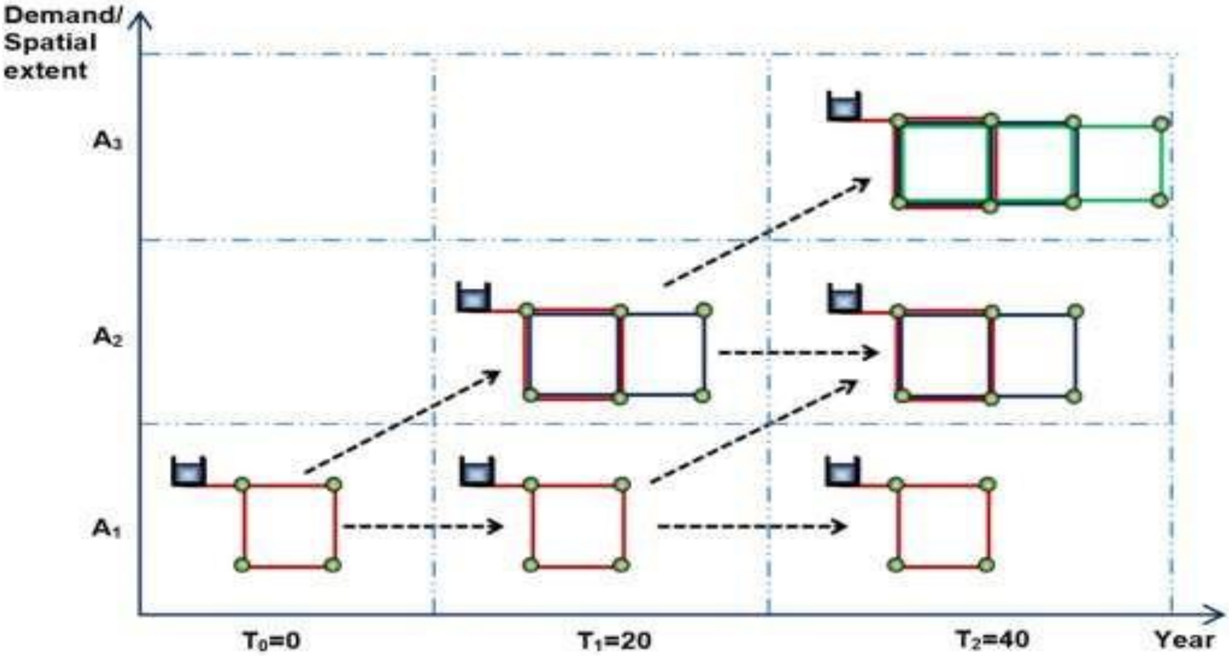

Fig. 4. WDS spanning over the range of scenario.

A WDS that tracks the rise in demand over 40 years, from A1 to A3, is shown in Fig. 4. Its arrangement is predicated on centralized designs. This illustration demonstrates a flexible strategy that uses tiny, gradual pipe modifications to boost the WDS's capacity to handle a range of potential future changes (39).

In this instance, the maximum number of future states at each period ranged from $s = \{1\}$ to $s = \{1, 2, 3\}$. The discount rate was r = 3%. The design stages were $t = \{T0, T1, T2\}$, where

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each stage is Δt = 20 years. The cost optimization was supplied with an amount of pipe links N = {4, 6, 8} that follow the spatial expansion, as illustrated in Fig. 4.

In this case study, the diameter of the pipe was the only design parameter taken into account. About the continuous design variable (pipe diameters), GAFO employs a real coding approach. Each gene corresponds to a diameter, and redundant states are prevented by using real coding. Fourteen commercially available diameters were utilized. The pipes' diameters range from 25.4 mm at the least to 609.6 mm at the largest. The 14 diameters can be represented by the integers 0 to 13. The sole design variable taken into account during the design process is pipe diameter. Using a random number generator that yields a pseudo-random value between zero and Rand max, the GAFO creates an initial population for each decision point (13).

Considering a population of fifty people with 500 generations, GAFO was used. Consequently, a sample of 250,000 people (50 chromosomes in 500 generations) was included in the analysis. With all 11 pipes and 14 distinct commercially accessible pipe sizes for the typology depicted in Fig. 4, the solution space at each design step has a total of 1411=4.05X1012 different feasible solutions. As a result, approximately 0.000006% of the solution space is represented by a GAFO sample. Below are the outcomes of the GAFO model's step-by-step application. Furthermore, the model is also tested with various mutation rate values—that is, a penalty factor with various crossover and selection strategies (40).

GAFO process and result analysis

In order to calculate a pressure head, nodal supply, and pipe output under the given input parameters, GAFO was integrated with the already-in-use WDS modeling program EPANET. The GAFO creates an initial population input for the EPANET hydraulic simulation for each decision point. The performance violation resulting from altering input settings was calculated using GAFO. Every demand situation that can arise was examined in relation to each population's performance (41). For nodes that do not meet the minimum needed pressure of 20 m, an ongoing penalty factor of 10,000 was applied. The performance variance in GAFO was calculated with the special penalty functions created here. The formula takes into account the performance variability for each of the six decision points, which are made up of the various design stages (t={0,1,2}) and potential future states (s={1,2,3}).

The community's fitness under a wide variety of uncertainty was determined by adding up the penalty values. GAFO's performance was evaluated for both "roulette-wheel" and ranking selection techniques. Different probability one- and two-cut crossover techniques were used. Additionally, the GAFO simulation was conducted with various mutation rates. Similar processes were used to make successive generations. Two termination conditions were applied in order to achieve the goal: either the GA ends after 500 generations or, if the fitness value of

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the best chromosome is improved by less than 0.01% for 10% of the generation (50 generations) (42).

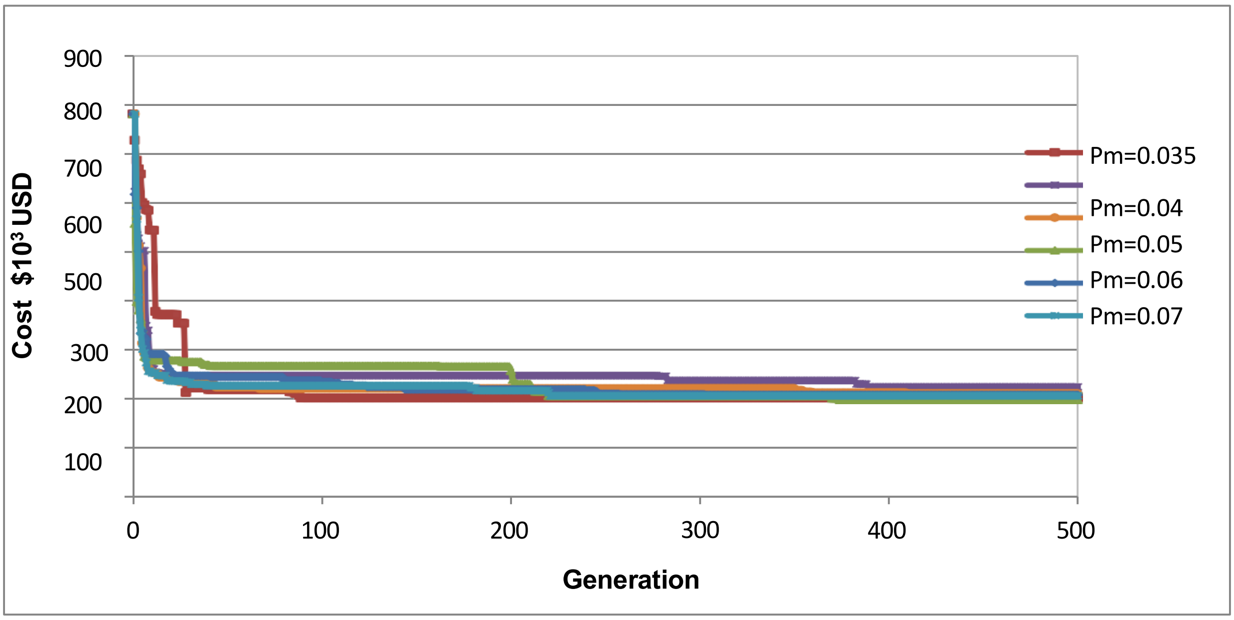

Fig. 5. GAFO progression (roulette-wheel with one-point crossover)

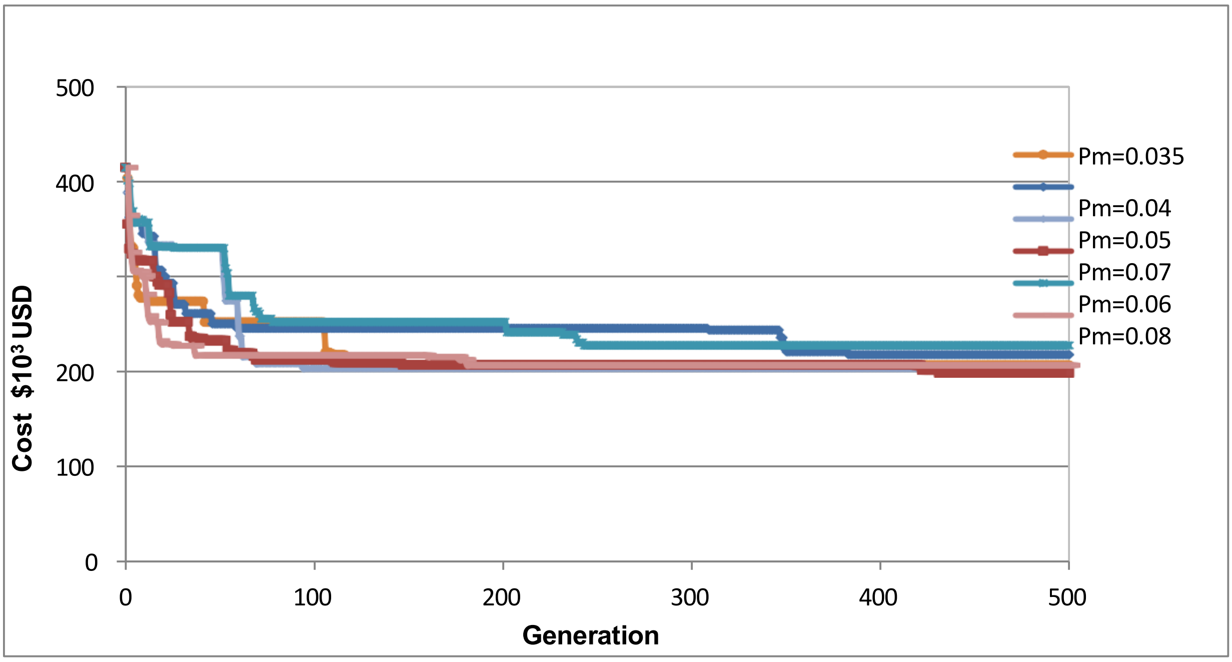

Fig. 6. GAFO progression (roulette-wheel with two-point crossover)

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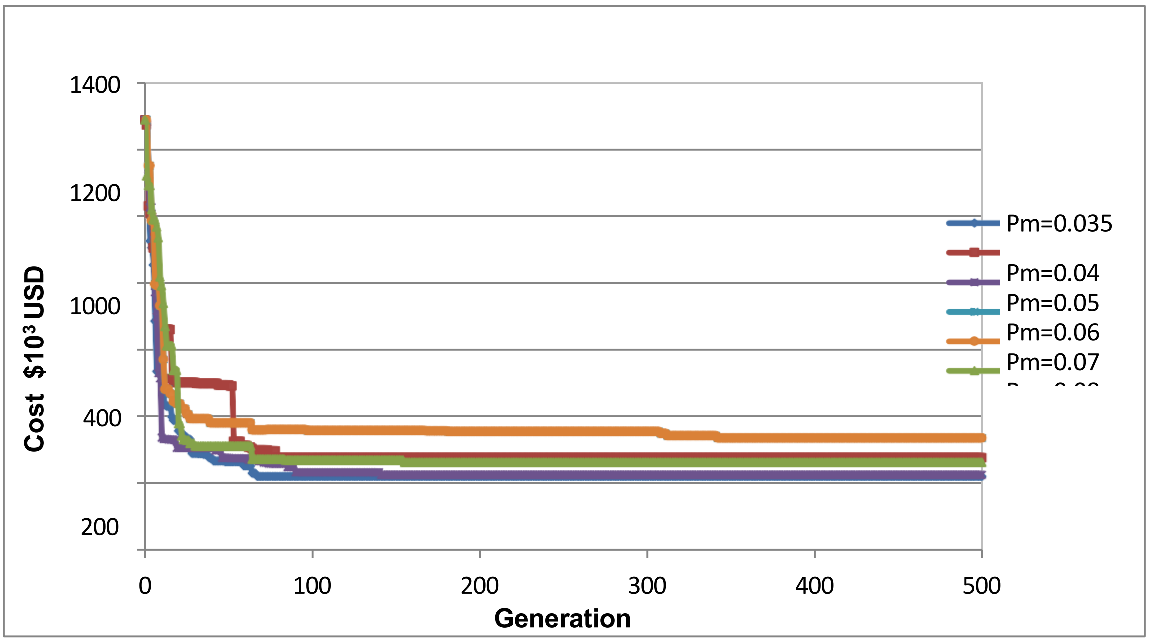

Fig. 7. GAFO progression (ranking selection with one-point crossover)

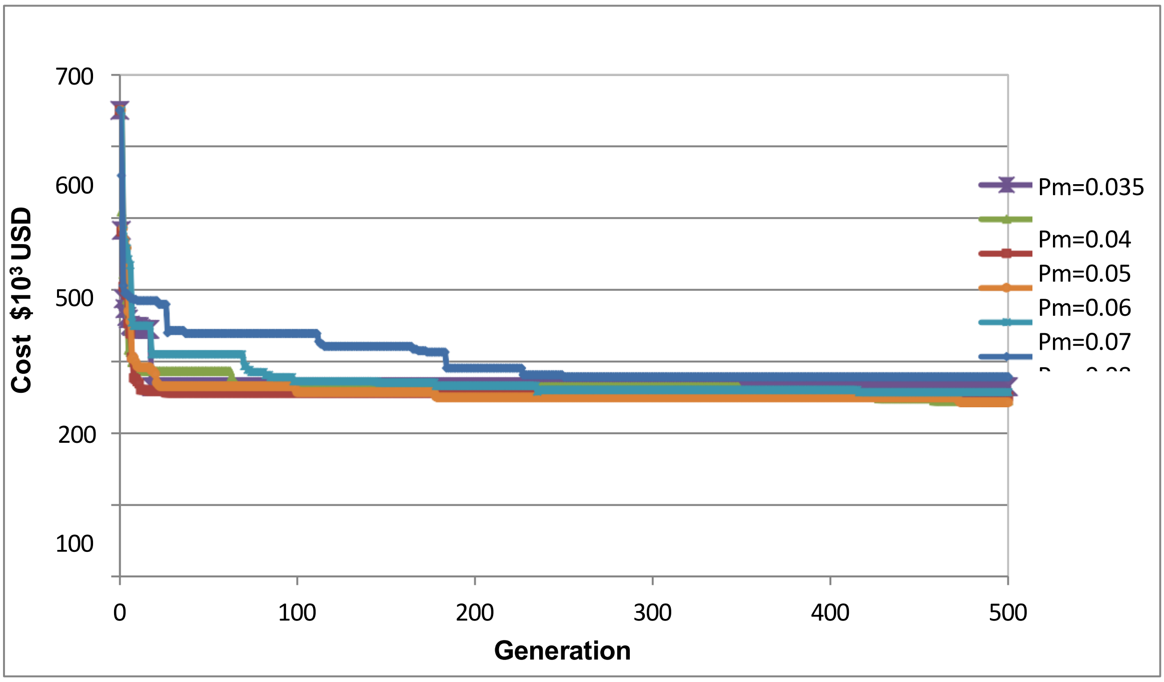

Fig. 8. GAFO progression (ranking selection with two-point crossover)

The findings shown in Figures 5-8 demonstrate that the GAFO converges more slowly as it approaches the ideal solution (lowest cost WDS) than it does in the early generations. GA

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optimization approaches generally exhibit this asymptotic characteristic. However, different selection strategies and mutation probabilities will have distinct convergence characteristics. Table 3 presents the population that was deemed to be the "best fit" for every mutation rate (43).

Table 3. Least cost for different selection scheme and crossover operator

Selection scheme	Crossover	Best fitness population for different mutation probability (cost in US dollars)					
		0.035	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**
Roulette-wheel	One-point	201037	224430	211213	197828	207652	205052
	Two-point	204761	216832	203321	227695	198627	205761
Ranking	One-point	212180	375419	224714	334406	334516	262424
	Two-point	264981	244378	251233	244109	257658	276788

Table 3 illustrates that, in contrast to the ranking selection method, the GAFO findings using the roulette-wheel selection technique yield the lowest cost value. The findings for the one-point crossover simulation under the roulette-wheel selection were a better fit than the two-point crossover, as can be shown by comparing the various crossover processes.

The GAFO flexible design's outcome (Net Present Value) was compared to a standard, non-flexible WDS baseline scenario. A staged development was chosen for both the classic (baseline) and flexible WDS in order to allow for a fair comparison. While GAFO employs a distinct nested loop optimization for each scenario, a stepwise comparison with the baseline is made (node to node along scenario path). The baseline WDS was created for a single scenario combination, but it expanded spatially in the same manner as the flexible WDS. It has a single design horizon and is intended to last for three stages—0, 20, and 40 years. There is only one state at each stage (the decision node for the matching demand) (44).

If the anticipated rise in demand is not realized, this node offers investment deferral. In contrast to the baseline scenario, a single stage 40-year design will have higher upfront investment expenses (with no possibility for investment deferral). Tables 4 and 5 display the GAFO and conventional (staged) design solutions.

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Table 4. Optimized pipe solution for scenario A1T0-A2T1-A3T2

	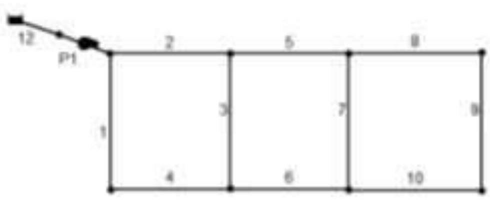					
	Optimized Pipe Diameters (mm)					
	GAFO (Flexible) Design			**Traditional (Stage) Design**		
Link	**t=0**	**t=20**	**t=40**	**t=0**	**t=20**	**t=40**
1	102.6	203.3	51.8	355.6		
2	202.2	253	345.6	406.4		
3	76.3	50.7	162.4	304.8		
4	151.4	50.6	51.8	50.8		
5		253	314.8		405.4	
6		50.7	51.8		253	
7		202.2	50.6		50.6	
8			304.7			345.6
9			50.7			51.8
10			253			244
Cost ($)	57000	124000	232000	204000	126000	96000
Cost $ NPV	57000	69309	71438	204000	70327	29735
Total Cost ($)	198636			304054		

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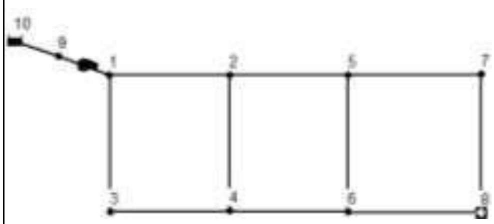
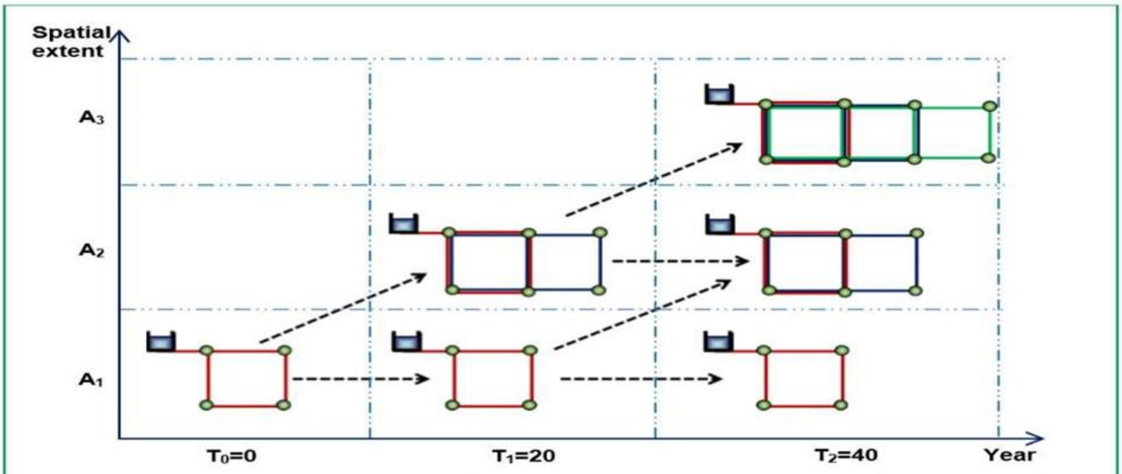
Table 5. Pressure heads for the worst scenario A1T0-A2T1-A3T2



Node	Pressure head, H (m) (Infeasible solution, H < 30 m)	
	GAFO (Flexible) Design	**Traditional (Stage) Design**
1	70.27	69.95
2	46.30	56.13
3	58.47	56.41
4	35.89	42.05
5	45.59	48.73
6	30.31	32.63
7	36.40	41.53
8	30.22	31.73



Scenarios	Scenario path	Optimal cost in US$ T_0	T_1	T_2	Total cost (US$)
1	A_1T_0-A_1T_1-A_1T_2	58000	0	0	58000
2	A_1T_0-A_1T_1-A_2T_2	58000	0	38320	96320
3	A_1T_0-A_2T_1-A_2T_2	58000	69209	0	127209
4	A_1T_0-A_2T_1-A_3T_2	58000	69209	71428	198637

Figure 9. GAFO model results for the flexible WDS.

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Table 5 lists the cost numbers for each path in the baseline scenario. Several scenario paths could be taken by using the same decision node (cost) in the scenario tree (45). For instance, in scenario A1T0-A1T1-A1T2, the four pipes will be chosen initially. Subsequent decision nodes will only be added at an extra expense, and this just reflects one of the three stages of development. Table 5 provides an example of this, as do Scenarios 2, 3, and 4. Figure 10 presents a cost comparison between the standard technique and the flexible WDS built using GAFO, modeled under various situations (46).

Table 5. Least cost for each scenario path of a baseline design

Scenarios	Scenario path	Optimal cost in USD			Total cost (USD)
		T0	T1	T2	
1	A1T0-A1T1-A1T2	205000	0	0	205000
2	A1T0-A1T1-A2T2	205000	0	38933	243933
3	A1T0-A2T1-A2T2	205000	70317	0	275317
4	A1T0-A2T1-A3T2	205000	70317	29736	305053

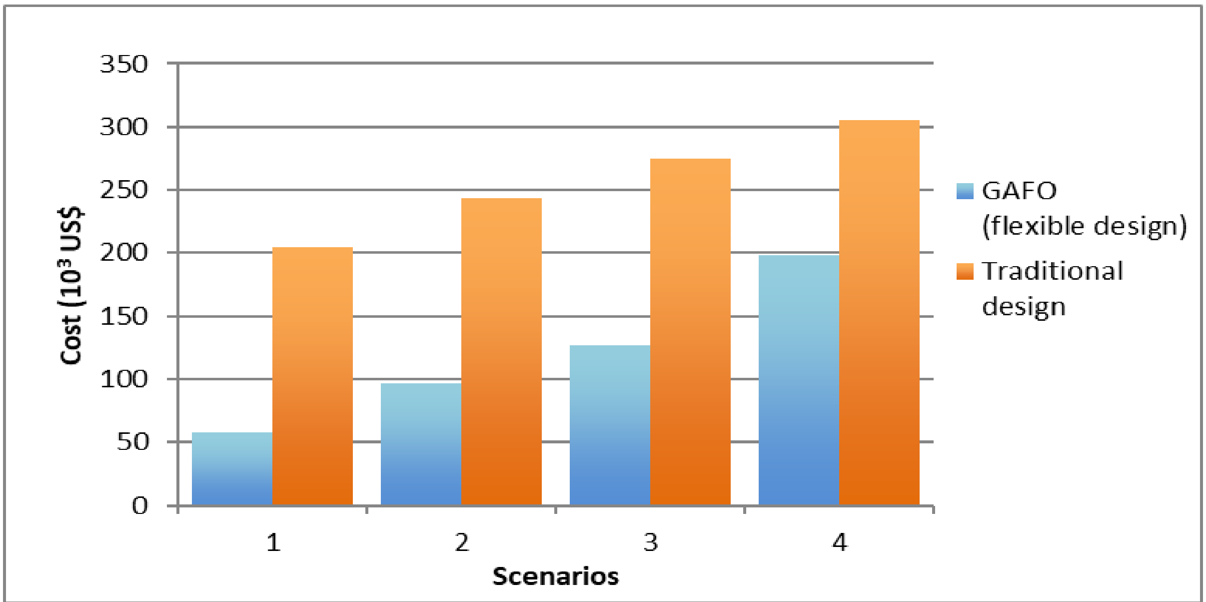

Fig. 10. Baseline (traditional) vs GAFO model result

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Figure 10 presents the enhanced cost of the flexible design values that proved to be less expensive in each of the four cases. Therefore, in all potential future scenarios, the WDS flexibility integrated utilizing the GAFO model delivered significant cost reductions. Adaptive WDS are able to deal with a changing environment. These systems give towns and cities more sustainability and resilience to deal with the growing number of global challenges and the unavoidable climate change (47,48).

CONCLUSION

In order to create flexible WDS for sustainable cities and societies, a novel optimization technique known as Genetic Algorithm Flexibility Optimization (GAFO) was created. The GAFO paradigm incorporates adaptability into the design phase, enabling a progressive evolution of WDS over time. The GAFO model provides municipal water system designers with a streamlined method for integrating flexibility into WDS in an economical way. It also makes it easier to create flexible WDS that adapts over time to future change pressures and related uncertainties. The fundamental processes of the suggested GAFO model include population initialization, hydraulic simulation, fitness evaluation based on uncertainty, and formation of new populations through the use of a model impacted by reproductive biology (comparative description). Every GA optimization technique follows these four main steps. However, there are two key differences in the suggested GAFO model. Initially, by maximizing the objective function over a broad range of future uncertainty represented by a scenario tree, the GAFO model maximizes flexibility. The optimization process makes decisions dynamically, with each step's decision influencing the next, while adhering to the scenario path. This indicates that in order for the WDS solution to function in every case, the goal functions are minimized and fitness is assessed. Second, a WDS's adaptability is improved by the GAFO model. By seamlessly integrating adaptability from one state to another, the optimization function maximizes the system's capacity to handle uncertainty. This improves a tiered architecture that permits WDS to gradually evolve.

To test various crossover operators, mutation probabilities, and selection strategies, a hypothetical case study was subjected to a GAFO model. For every scenario, the GAFO model exhibited good convergence performance. Using a "roulette-wheel" selection strategy with a one-point operator, the GAFO model performed best, according to a comparison of the findings for the best and average fitness values. Furthermore, a study comparing the flexible WDS built by GAFO with a traditional, rigid WDS model revealed cost savings ranging from 35% to 72% for four distinct GAFO situations.

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