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An Integrated Simulation-Optimization Approach for Dynamic Design of the Urban Wastewater Collection Systems

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ABSTRACT

In this study, a simulation-optimization approach is proposed for dynamic design of the urban wastewater collection systems. The proposed approach consists of the mutual integration of the Storm Water Management Model (SWMM), developed by the U.S. Environmental Protection Agency (US-EPA) and the heuristic Harmony Search (HS) optimization approach. Unlike the previous approaches developed to solve wastewater collection system design problems, the proposed approach simulates the hydraulic flow process by considering unsteady state flow conditions based on the dynamic wave model. The objective of the HS-based optimization model is to determine the pipe slopes so that the total system cost is minimized. After determining the pipe slopes, the corresponding pipe diameters were determined by developing an internal solution approach. All the physical and managerial constraints that should be considered during the search process have been considered by means of the penalty function approach. The applicability of the proposed approach was evaluated by solving two example problems. Identified results indicated that the proposed approach can effectively solve the dynamic design problems of the wastewater collection systems.

Keywords: Wastewater collection system, SWMM, harmony search, dynamic design.

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1. INTRODUCTION

One of the most important tasks of civil and environmental engineering is to dispose the used water from residential or industrial areas by means of the wastewater collection systems. These systems include high number of equipment, such as pipes, manholes, pumping facilities, and require significant excavation works. Therefore, costs of these systems are usually high and a small amount of reduction in their installation costs corresponds to significant savings [1]. Depending on these facts, the concept of optimum design by using the integrated simulation-optimization approaches is crucial nowadays to find a solution with minimum cost.

In practice, the problem of optimum wastewater collection system design can be solved by considering both combined and separated sewer systems depending on the project requirements. Note that both systems consider the same solution procedure such that commercial pipe diameters and/or pipe slopes are selected as the decision variables of the optimization model [1]. For the first case, the commercial pipe diameters are determined by the optimization model and the corresponding pipe slopes are calculated by means of the Manning's equation. Since diameters of the pipes are selected from the set of commercial pipes, it is required to solve a discrete optimization problem. In the second case, the optimization model considers pipe slopes as decision variables and the corresponding pipe diameters are calculated again by using the Manning's equation. However, it is required to convert the calculated pipe diameters into the commercial sizes and this process also makes the problem discrete although the associated decision variables of the problem are continuous. The last case consists of the more general case where both pipe diameters and their slopes are considered as the decision variables. However, this kind of use increases the number of decision variables twofold. Therefore, mathematical search space of the problem becomes more complex and finding an optimum solution becomes difficult especially for the systems with excessive number of pipes [2]. Note that there is a strong interaction between diameters and slopes of the pipes for three cases mentioned above. For instance, although increasing the pipe slopes allows to transmit the same flow with the smaller pipe diameters, it increases the excavation cost due to the increased pipe slopes. On the contrary, reducing the pipe slopes decreases the excavation cost, but it is required to use larger pipe diameters to transmit the same flow, and this increases the pipe costs [1-2]. Therefore, finding a trade-off between pipe diameters and their corresponding slopes by using the optimization approaches is important.

The current literature includes various solution approaches to solve both storm and urban sewer system design optimization problems. Depending on the branched nature of the sewer systems, the problem was previously solved by using the dynamic programming (DP) based approaches [3-6]. Furthermore, linear and nonlinear programming approaches were also employed to the solution of the optimum sewer system design problems [7-10]. Although these optimization approaches are well effective on solving the problem, there may be possibilities of stucking to local optimum solutions especially for the problems with non-convex and/or discontinuous search spaces [1, 11]. Therefore, nowadays, heuristic optimization approaches became the popular tools to solve the sewer system design problems. Note that the main idea of the heuristic optimization approaches is to mimic the processes in nature, mathematically. Unlike the traditional approaches, heuristic optimization approaches can easily find the global optimum or near global optimum solutions even if the search space of the problem is non-convex and/or discontinuous. Furthermore, they do not require special initial points to find an optimum solution since the search process is conducted by using multiple solutions [12]. By using heuristic optimization approaches, the optimum sewer system design problem was previously solved by many researchers. Although these conducted studies have some similarities in terms of their computational structures, their main differences are due to the considered optimization approaches. For example, genetic algorithm (GA), which applies the genetic evolution processes in nature to the optimization problems, was previously applied in some studies [2, 13-15]. Similarly, particle swarm optimization (PSO), which is developed based on the social behavior of animals, such as bird flocking or fish schooling, was also used to solve the associated problem in different studies [16-20]. In addition to these studies, different heuristic optimization approaches have also been applied to the solution of optimum sewer system design problems, and the details of these studies can be found in [1, 20-29].

It should be noted that, in all the studies mentioned above, design process of sewer systems was conducted by considering the peak value of the flow hydrograph as design discharge. In other words, the optimum system is designed by considering the steady-state flow conditions. This design strategy requires the assumption that the shape of the flow hydrograph remains unchanged as the water moves from upstream to downstream through the pipes. However, this assumption is not satisfied in real life and the shape of the flow hydrograph changes during operation of the system. This change results with a time lag and the attenuated peak value of the downstream flow hydrograph [30]. Although these attenuations are usually negligible in small systems, they may be significant for the big sewer systems such that the shape of the upstream flow hydrographs significantly change when it comes to the downstream locations. If this fact is not considered during design, larger design discharges are calculated at downstream locations than they should actually be. This situation results with a calculation of the larger pipe diameters at downstream locations, and consequently, increases the cost of the system. Therefore, it would be better to consider the unsteady flow conditions during design of the sewer systems to fully address the flow routing process in real life.

There are limited studies in literature that consider unsteady flow simulations in designing the sewer network systems. Afshar et al. [31] developed a GA based optimization approach for hydrograph-based design of the storm sewer systems. In their model, unsteady flow simulations through pipes have been conducted by means of the transport module of the United States Environmental Protection Agency (US-EPA) Storm Water Management Model (SWMM). Shao et al. [32] proposed a SWMM based approach to solve the storm sewer network design problems. In the proposed approach, an automated algorithm is proposed by considering two computational steps where the pipe diameters and their corresponding slopes are determined sequentially without using an optimization approach. Note that these two studies given above focused on designing the storm sewer collection systems by considering the transient flow conditions. Regarding the household wastewater collection system design, Zaheri et al. [33] developed a solution approach where a cellular automata (CA) is used as the optimization tool and SWMM is used as the simulation tool. Their approach considers the diameters and nodal elevations of the pipes as decision variables and solves the problem in two phases. However, they applied a constant flow hydrograph from upstream manhole locations of the pipes and not considered the diurnal wastewater discharge patterns of the residential buildings and/or industrial facilities during design process.

In this study, a simulation-optimization approach is proposed for dynamic design of the urban wastewater collection system design problems. In the proposed approach, SWMM is used as the simulation model for performing the dynamic simulations of the network. This simulation model is then integrated to an optimization model where heuristic harmony search (HS) optimization approach is used. Note that HS based optimization approach was previously used to solve a similar problem in a conference proceeding [27] and this study is an extension of the related study. The key difference of the proposed approach from the one given in [27] is that the problem has been solved by considering unsteady diurnal wastewater discharge patterns of the residential buildings and/or industrial facilities whereas the classical steady-state solution was conducted in [27]. According to the authors' knowledge, this is the first application of HS and SWMM for designing the urban wastewater collection networks by considering the unsteady flow conditions. Applicability of the proposed simulation-optimization approach is evaluated by solving two example networks. Identified results indicated that the proposed approach not only finds similar or better results than those obtained in literature, but also effectively solve the problem by considering the time dependent wastewater discharges during the optimum design process.

2. MODEL DEVELOPMENT

The problem of optimum urban wastewater collection system design is dynamically solved by using the proposed simulation-optimization approach. In the following sections, first, the problem of optimum sewer system design is formulated. After that, the main computational structures of the simulation and optimization models are described. Finally, how to integrate them in an optimization framework is defined.

2.1. Optimum Sewer System Design Problem

As stated in the previous section, the problem of optimum sewer systems design can be formulated as an optimization problem. In this formulation, the objective is to minimize the total system cost by adjusting the diameters and/or nodal elevations of the pipes. During the search process, it is required to satisfy some physical and managerial constraints. Depending on these definitions, the optimum design problem by considering the unsteady state flow conditions can be mathematically stated as follows:

Let n_p and n_m be the number of pipes and manholes; D_i and L_i be the diameter and length of the i^{th} pipe $\left(i = 1,2,3,\cdots,n_p\right)$; $\bar{Z}_i$ be the mean excavation depth of the i^{th} pipe; and H_k be the depth of the k^{th} manhole $(k = 1,2,3,\cdots,n_m)$ in the system. Using these definitions, the following objective function and constraints can be defined for the problem [2, 33]:

$$\Phi = \min\left\{\sum_{i=1}^{n_p} L_i \cdot \mathcal{C}_1(D_i,\bar{Z}_i) + \sum_{k=1}^{n_m} \mathcal{C}_2(H_k)\right\} \tag{1}$$

subject to

$$g_{i1}:\ \max\{q_i(t)\} \geq \max\{Q_i(t)\} \tag{2}$$

$$g_{i2}:\ \max\{V_i(t)\} \le V_{\max} \tag{3}$$

$$g_{i3}:\ \min\{V_i(t)\} \ge V_{\min} \tag{4}$$

$$g_{i4}:\ \frac{\max\{y_i(t)\}}{D_i} \le \alpha \tag{5}$$

$$g_{i5}:\ S_i \ge S_{\min} \tag{6}$$

$$g_{i6}:\ E_i^u \le E_{\max} \tag{7}$$

$$g_{i7}:\ E_i^u \ge E_{\min} \tag{8}$$

$$g_{i8}:\ E_i^d \le E_{\max} \tag{9}$$

$$g_{i9}:\ E_i^d \ge E_{\min} \tag{10}$$

where Φ is the objective function to be minimized; $C_1(\bullet,\bullet)$ and $C_2(\bullet)$ are the cost functions for the pipes and manholes, respectively; $q_i(t)$ is the flow discharge of the i^{th} pipe at t^{th} time period; $Q_i(t)$ is the design discharge hydrograph of the i^{th} pipe at t^{th} time period; $V_i(t)$ is the flow velocity of the i^{th} pipe at t^{th} time period; $V_{\min}$ and $V_{\max}$ are the minimum and maximum allowable velocity values, respectively; $y_i(t)$ is the flow depth in the i^{th} pipe at t^{th} time period; α is the maximum allowable ratio of flow depth to pipe diameter; S_i is the slope of the i^{th} pipe; $S_{\min}$ is the minimum pipe slope; E_i^u and E_i^d are the cover depths at upstream and downstream ends of the i^{th} pipe, respectively; $E_{\min}$ and $E_{\max}$ are the minimum and maximum allowable values of the cover depths, respectively. These variables can be seen on the schematic profile in Figure 1.

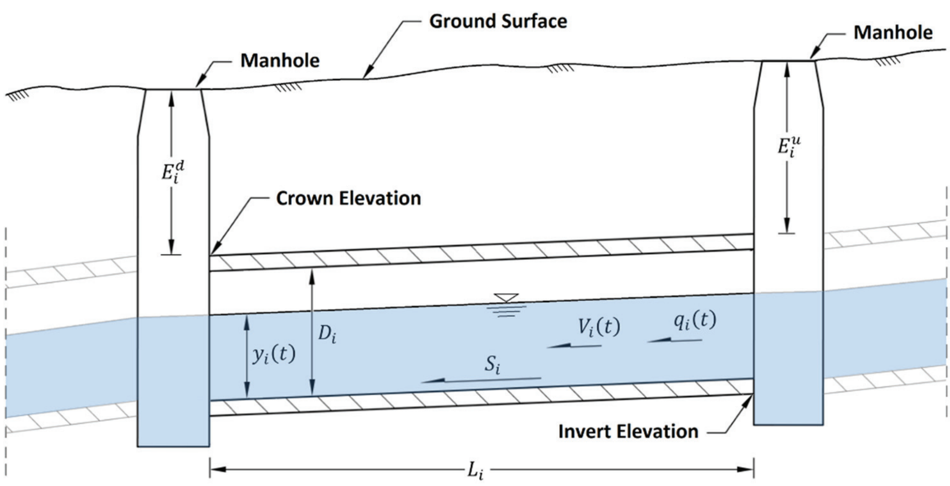

Figure 1 - Illustration of the variables used in the optimization process (adapted from [1])

The formulation given above states that the optimum sewer system design problem is a constrained optimization problem. Therefore, during minimization of Equation (1), all the constraints between Equations (2) to (10) need to be satisfied to obtain a feasible solution. Among these constraints, Equation (2) is used to control if flow discharge of the pipes is equal or greater than the design flow hydrograph. This constraint is very important since diameters of the pipes are determined based on these flow values during design process. Equations (3) and (4) are used to maintain the flow velocities between specified minimum and maximum values. This is also important since these constraints are used to prevent sediment accumulation and internal erosion of the pipe materials, respectively. Equation (5) is used to guarantee the free surface flow conditions through pipes of the system. Equation (6) is used to satisfy the minimum pipe slope value, and Equations (7) to (10) are used to satisfy the minimum and maximum allowable cover depths on upstream and downstream ends of the pipes, respectively. Note that the problem given above is stated by considering unsteady flow conditions through pipes. Thus, value of the design discharge hydrograph should be routed hydraulically as water moves from upstream to downstream locations of the system and this process is conducted by modeling the hydraulic flow process on SWMM.

2.2. Simulation Model: SWMM

SWMM, developed by US-EPA, is a widely used mathematical simulation model and used for simulating the flow and pollution transport processes in sewer and drainage networks [34]. SWMM considers the drainage system as a set of interrelated elements called objects which are placed in a series of layers. These objects can be visual elements (e.g., junctions, conduits, reservoirs, pumps, etc.) or non-visual elements (e.g. general specifications of the system) and all of them can be used to conduct hydrological, hydraulic or pollution transport analyses [35]. Note that hydraulic routing process on SWMM is simulated by sequentially solving the continuity and momentum equations by considering the unsteady free surface flow process through pipes. Mathematical definition of the continuity and momentum equations which are called as the St. Venant equations can be expressed as follows:

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = 0 \tag{11}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (Q^2/A)}{\partial x} + gA\frac{\partial y}{\partial x} - gA\left(S - S_f\right) = 0 \tag{12}$$

where x is the distance; t is the time; Q is the flow rate; A is the cross-sectional flow area; g is acceleration of gravity; S is the pipe bed slope; and S_f is the friction slope. The value of friction slope S_f is expressed by using the Manning's equation as follows:

$$S_f = \frac{n^2 Q|Q|P^{4/3}}{A^{10/3}} \tag{13}$$

where n is the Manning's surface friction and P is the wetted perimeter. Note that this equation system is mostly solved by means of the numerical solution approaches and these solutions are conducted by considering kinematic wave, diffusion wave, and dynamic wave approaches. In kinematic wave approach, the solution is conducted by just taking the last term of Equation (12) into account. For diffusion wave, approach the last two terms of Equation (12) are considered. Compared to kinematic wave approach, diffusion wave approach provides more information about the flow process since more data is used. Lastly, in dynamic wave approach, all the terms of Equation (12) are considered, and this solution provides most accurate results compared to the others [34]. Note that SWMM can numerically solve this equation system by using both diffusion and dynamic wave approaches. During this solution, SWMM uses an implicit backwards Euler method which solves the equation system by means of the Picard's iteration approach [34].

2.2. Optimization Model: Harmony Search (HS) Optimization Approach

HS is a musical-based heuristic optimization approach which is inspired by the observation that the aim of the music is to seek for a perfect state of harmony [36]. This process in music is analogous to the optimization process since the main objective of the optimization is to seek for a globally optimum solution. This analogy between musical improvisation and optimization processes was first established by Geem et al. [37]. In this adaptation, the musicians, for example in a jazz trio, correspond to decision variables of the optimization problem, and the notes in the musicians' memories correspond to the potential values of the decision variables. Note that the musicians can produce a new harmony by considering three musical operations: (i) by playing a series of pitches in their memory; (ii) by playing slightly adjusted pitches from previously played ones in their memory; (iii) by playing a series of pitches randomly without considering their memory. These three musical operations have

Step 1

Generate random solution vectors $(\boldsymbol{x}^1, \boldsymbol{x}^2, \boldsymbol{x}^3, \cdots, \boldsymbol{x}^{HMS})$ as many as harmony memory size (HMS), then, store them in harmony memory (HM).

Step 2

Generate a new solution vector $(\boldsymbol{x}')$. For each element (x_i'):

- with probability of $HMCR$, (harmony memory considering rate), pick the stored value from HM such that $x_i' \leftarrow x_i^{\text{int}[r(0,1)\times HMS]+1}$ where $r(0,1)$ is the uniform random number.

  Step 3

  - with probability of PAR (pitch adjusting rate), change the value of x_i' by a small amount such that $x_i' \leftarrow x_i + bw \times (r(0,1) - 0.5)$ where bw is the bandwidth which can be defined as the amount of the maximum change in pitch adjusting process.
  - with probability of $1 - PAR$, do nothing.
- with probability of $1 - HMCR$, pick a random value within the allowed range.

Step 4

If $\boldsymbol{x}'$ is better than the worst vector $\boldsymbol{x}^{\text{worst}}$ in HM, replace $\boldsymbol{x}^{\text{worst}}$ with $\boldsymbol{x}'$

Step 5

Repeat from Step 2 to Step 4 until termination.

Figure 2 - Computational sequence of HS optimization algorithm.

been mathematically formulated by Geem et al. [37] and they proposed three operational processes of HS: (i) memory consideration; (ii) pitch adjusting; (iii) random selection. Note that combination of these three operations is used to generate a new solution vector. If this new generated solution vector provides better objective function value than the worst one in harmony memory, the vector with the worst function value in harmony memory is replaced with the new generated solution vector and this process is repeated until termination. This computational sequence can be summarized in Figure 2.

To solve an optimization problem based on the solution sequence given in Figure 2, it is required to provide the solution parameters of HS which are: harmony memory size (HMS), harmony memory considering rate $(HMCR)$, pitch adjusting rate (PAR), and bandwidth (bw). HM is a matrix where the decision variables and the corresponding objective function values are stored, $HMCR$ and PAR are the probabilities which are used to explore the search space globally and locally, and bw is used for the pitch adjusting process. Detailed explanation of this computational procedure is summarized in Figure 3.

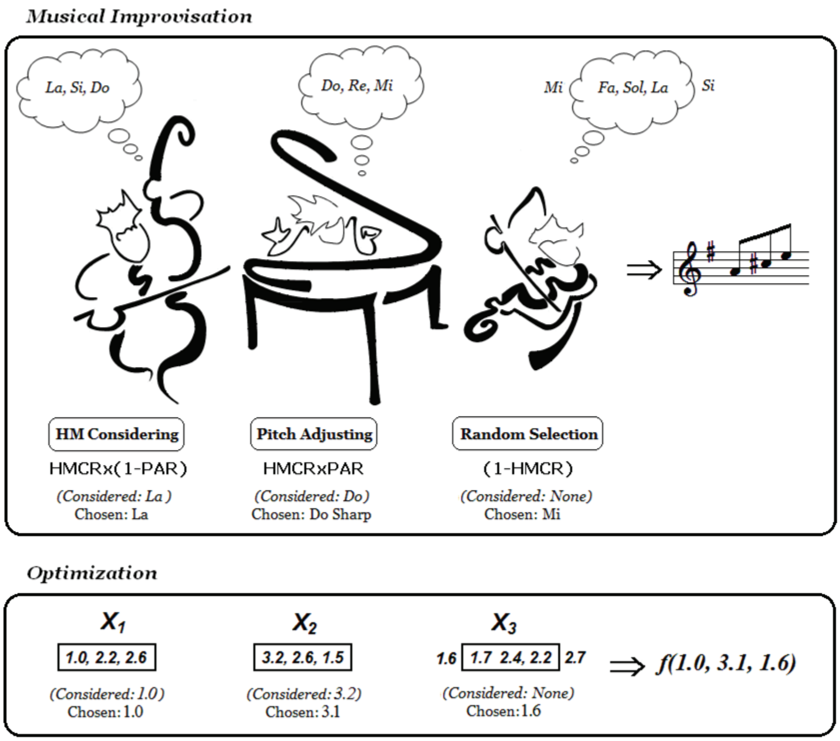

Figure 3 - Analogy between musical improvisation and optimization (adapted from [38]).

It can be seen from Figure 2 that the musicians have different notes in their HM. As indicated previously, their aim is to find a musically pleasing or fantastic harmony by making some improvisations. Depending on the computational structure of HS, this process is conducted as follows [27]:

i) The first musician in Figure 3 has three notes in HM. With probability $HMCR \times (1 - PAR)$, he considers and plays La. Since La, Si, Do in HM corresponds to the values of 1.0, 2.2, 2.6 in the optimization process, choosing and playing La corresponds choosing and using 1.0 as the potential value of the first decision variable. Therefore, the first decision variable value is determined based on the memory consideration rule of HS. *ii)* The second musician in Figure 3 also has three notes in HM. Unlike the first musician, with probability $HMCR \times PAR$, he selects Do and plays its neighbor Do#. Since Do corresponds to 3.2 in the optimization process, its neighbor note Do# corresponds to 3.1 which is a slightly adjusted value of 3.2. Therefore, the second decision variable value is determined based on the pitch adjusting rule of HS. *iii)* The third musician in Figure 3 also has three notes, Fa, Sol, La in HM. Although his HM was previously used, for the current improvisation, he decides to select and play a random note, Mi for this case. Unlike the first and second variables, this note corresponds to a random value (1.6) in the search space. Depending on this result, the value of the third decision variable is determined based on the random selection rule of HS.

Depending on the memory consideration, pitch adjusting, random selection processes, the new harmony is composed as (La, Do#, Mi) and these notes correspond to the decision variable values of (1.0, 3.1, 1.6). After this process, these values are used as input of the objective function. If this newly calculated objective function value is better than the worst one in HM, the solution with the worst objective function value is excluded from HM and the newly generated one is included, and this solution sequence is repeated until termination.

2.3. Problem Formulation

As indicated in Section 2.1, the problem of optimum sewer system design is a constrained optimization problem. Therefore, minimization of Equation (1) should be conducted by considering the constraint set given between Equations (2) and (10). At this point, there is an important issue that requires further analysis. Just as the other heuristics, HS is an unconstrained optimization approach and cannot directly consider the constraint set during minimization or maximization of an objective function. Since the optimization problem here is a constrained one, it is required to convert this problem to an unconstrained optimization problem by means of the penalty function approach. For the problem considered here, this process is conducted as follows:

$$\Phi' = \min\{\Phi + \boldsymbol{\lambda} \cdot \mathcal{P}(\boldsymbol{g})\} \tag{14}$$

where Φ' is the penalized objective function value; $\boldsymbol{g} = [g_{ij}]$ is a constraint matrix ($i = 1,2,3,\cdots,n_p$; $j = 1,2,3,\cdots,9$) which stores the problem constraints given between Equations (2) and (10); $\mathcal{P}(\bullet)$ is the penalty function which is used to prevent constraint violation; and $\boldsymbol{\lambda} = \{\lambda_j\}$ is a vector ($j = 1,2,3,\cdots,9$) including the penalty coefficients which are used to adjust the magnitude of the penalty terms. Note that selection of the values of penalty coefficients is very important to prevent constraint violations. Since there is not any mathematical approach to determine their exact values, their magnitudes are usually adjusted by means of the trial-and-error approaches. A general procedure is that use of the larger values for λ_j means greater effort to satisfy the constraint sets [38]. In literature, there are various penalty function approaches proposed to solve the constrained optimization problems. Among them, the following structure is used:

$$\mathcal{P}(g_{ij}) = \begin{cases} 0 & ; \quad \hat{g}_{ij} \leq 0 \\ (\hat{g}_{ij})^2 & ; \quad \text{otherwise} \end{cases} \tag{15}$$

where $\hat{g}_{ij}$ is the normalized constraint function which is modified as to be equal to or lower than zero. Depending on this definition, the optimum sewer system design problem can be stated mathematically as follows:

$$\Phi' = \min\left\{\sum_{i=1}^{n_p} L_i \cdot \mathcal{C}_1(D_i, \bar{Z}_i) + \sum_{k=1}^{n_m} \mathcal{C}_2(H_k) + \sum_{j=1}^{9} \lambda_j \sum_{i=1}^{n_p} \mathcal{P}(g_{ij})\right\} \tag{16}$$

subject to

$$\hat{g}_{i1}: \left(1 - \frac{\max\{q_i(t)\}}{\max\{Q_i(t)\}}\right) \leq 0 \tag{17}$$

$$\hat{g}_{i2}: \left(\frac{\max\{V_i(t)\}}{V_{\max}} - 1\right) \leq 0 \tag{18}$$

$$\hat{g}_{i3}: \left(1 - \frac{\min\{V_i(t)\}}{V_{\min}}\right) \leq 0 \tag{19}$$

$$\hat{g}_{i4}: \left(\frac{\max\{y_i(t)\}}{\alpha \cdot D_i} - 1\right) \leq 0 \tag{20}$$

$$\hat{g}_{i5}: \left(1 - \frac{S_i}{S_{\min}}\right) \leq 0 \tag{21}$$

$$\hat{g}_{i6}: \left(\frac{E_i^u}{E_{\max}} - 1\right) \leq 0 \tag{22}$$

$$\hat{g}_{i7}: \left(1 - \frac{E_i^u}{E_{\min}}\right) \leq 0 \tag{23}$$

$$\hat{g}_{i8}: \left(\frac{E_i^d}{E_{\max}} - 1\right) \leq 0 \tag{24}$$

$$\hat{g}_{i9}: \left(1 - \frac{E_i^d}{E_{\min}}\right) \leq 0 \tag{25}$$

By using the penalty function definition in Equation (15) and the problem formulation between Equations (16) and (25), the problem of optimum sewer system design can be solved for unsteady flow conditions by using the proposed simulation-optimization approach. The decision variables of the HS based optimization model is the bed slope S_i for each pipe $(i = 1,2,3, \cdots, n_p)$.

2.4. Integration of Simulation and Optimization Models

As stated previously, the proposed simulation-optimization approach consists of the mutual integration of SWMM and HS. For this purpose, a code in Visual Basic for Applications (VBA) platform has been developed. The structure of this code is given in Figure 4.

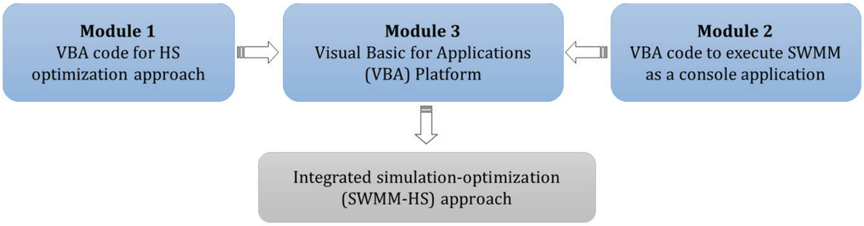

Figure 4 - Integration of HS-SWMM on VBA platform.

As can be seen from Figure 4, the developed VBA code has three modules. The first module includes the VBA code of the HS optimization approach which is an independent code and can be used to solve any optimization problem. The second module is developed for executing the SWMM as a console application. This process can be conducted from the command line within a DOS window. Therefore, the second module aims to write the input data of the problem to INP file of the SWMM, to execute SWMM from the DOS platform for the generated INP file, and to read the generated RPT file to get the results of the unsteady model simulation for the provided INP file. Finally, the last module aims to integrate these two modules in an optimization framework. Note that Module 3 also includes an implicit solution procedure for determining the pipe diameters for the generated pipe slopes by HS optimization approach. This solution procedure is based on the solution sequence given in Figure 5.

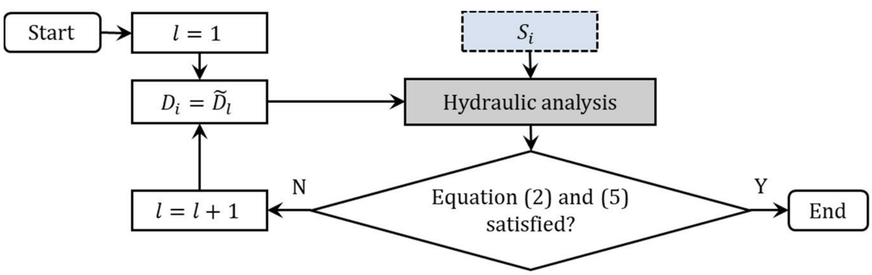

Figure 5 - Implicit pipe diameter selection procedure.

where $\widetilde{\boldsymbol{D}} = \{\widetilde{D}_1, \widetilde{D}_2, \widetilde{D}_3, \cdots, \widetilde{D}_l\}$ is a vector which includes commercial pipe diameters in the market. As can be seen from Figure 5, the hydraulic analysis is started by using the smallest pipe diameter. After execution of SWMM model for that diameter, the flow in the pipe is evaluated in terms of the constraints given in Equations (2) and (5). If both constraints are satisfied, the selected pipe diameter is used for the other analyses. Otherwise, its value is increased to the next one and the same procedure is repeated until satisfying Equations (2) and (5). Note that evaluation of Equations (3) and (4) is not considered here since their values are forced to control by using the penalty functions.

3. NUMERICAL APPLICATIONS

The applicability of the proposed simulation-optimization approach is evaluated by solving two example design problems. The first problem is used to verify the HS based optimization model by solving a well-known benchmark example system given in literature. The second example is used to evaluate the applicability of the proposed dynamic design approach considering diurnal wastewater discharge patterns for residential and industrial areas. These two examples have been solved by considering the optimization formulation between Equations (16) and (25) based on the integration scheme given in Figure 4. In this integration, the values of the penalty coefficients are assumed to be $\lambda_{1-9} = 10^9$ depending on some previous model executions. Although HS is an efficient optimization approach on solving various optimization problems, its efficiency should be evaluated for different solution parameters. As indicated previously, there are 4 solution parameters of HS which are the HMS, $HMCR$, PAR, and bw. Among them, the value of bw is usually adjusted based on the lower ($\boldsymbol{x}_{\min}$) and upper ($\boldsymbol{x}_{\max}$) bounds of the decision variables. Therefore, its value is taken as $bw = (\boldsymbol{x}_{\max} - \boldsymbol{x}_{\min})/100$ for all the decision variables. For the other solution parameters, a detailed sensitivity analysis has been conducted to evaluate the algorithm's performance for different parameter combinations. Note that two different scenarios have been considered in this analysis. In Scenario A, it is assumed that each HS solution parameter gets the following discrete values: $HMS \in [10, 20, 30, 40]$, $HMCR \in [0.80, 0.85, 0.90, 0.95]$ and $PAR \in [0.20, 0.30, 0.40, 0.50]$. Using these parameter values, the proposed approach is

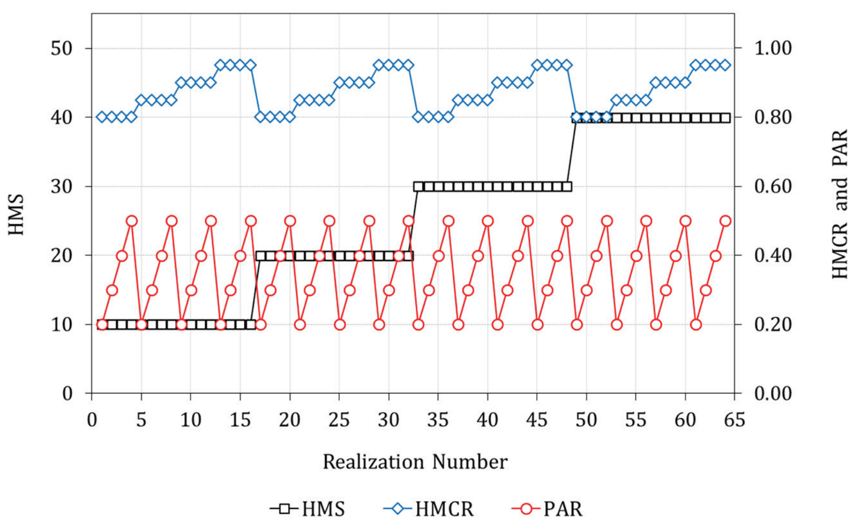

Figure 6 - HS optimization parameter combinations used in Scenario A

executed for $4^3 = 64$ different parameter combinations where the variation of these parameters relative to each other is considered. The value of the parameter sets for each model realization can be seen in Figure 6. After obtaining the best parameter combination providing the minimum objective function value, these parameter values are fixed, and the problem is solved 10 times again in Scenario B by considering different random number seeds. Therefore, the model performance is also evaluated for different random numbers in the optimization model.

3.1. Example Problem 1

The first example consists of a well-known storm sewer system which was first solved by Mays and Wenzel [3] by means of the discrete differential dynamic programing approach. After that study, the problem has been investigated by many researchers by using different solution approaches for steady and unsteady flow conditions [1-4, 8, 20, 31-33, 39]. The schematic view of this network is given in Figure 7. The network consists of 21 manholes which are connected through 20 pipes with the total length of 2.6 km. Characteristics of the system including ground elevations at manhole locations, pipe lengths, and design discharges are given in Table 1. As given in Afshar et al. [31], design discharges of the system are given as the constant flow hydrographs in which the values in Table 1 correspond to their maximum. The network should be designed by satisfying the minimum and maximum velocity values of 0.60 m/s and 3.60 m/s, respectively. Similarly, the cover depths over the pipes should be minimum 2.40 m and maximum 6.00 m. Note that all the previous studies given above used the sum of the functions given in Equations (26) and (27) as the cost function [40]. Therefore, the same cost function is also considered in this study to obtain comparable results.

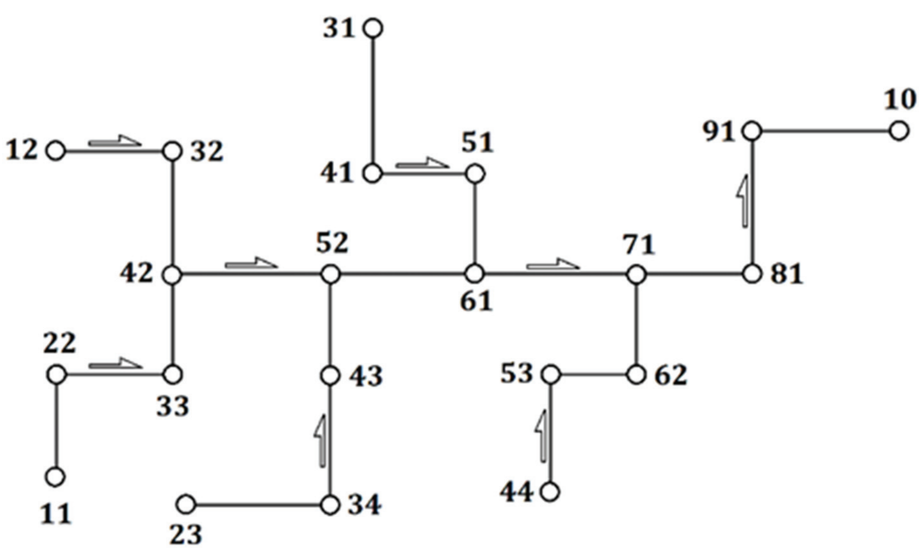

Figure 7 - Schematic view of the storm sewer system in Example 1

$$\mathcal{C}_1(D_i, \bar{Z}_i) = \begin{cases} 10.98D_i + 0.80\bar{Z}_i - 5.98 & ; \quad D_i \leq 3, \bar{Z}_i < 10 \\ 5.94D_i + 1.166\bar{Z}_i + 0.504\bar{Z}_i D_i - 9.64 & ; \quad D_i \leq 3, \bar{Z}_i \geq 10 \\ 30.00D_i + 4.90\bar{Z}_i - 105.90 & ; \quad D_i > 3 \end{cases} \tag{26}$$

$$\mathcal{C}_2(H_k) = 250 + (H_k)^2 \tag{27}$$

Table 1 - Characteristics of the sewer network for Example 1.

Pipe	Ground Elevations (m)		L_i	$\max\{Q_i(t)\}$
	Upstream	Downstream	(m)	(m^3/s)
11-22	152.40	150.88	106.68	0.1132
22-33	150.88	148.49	121.92	0.1982
33-42	148.49	146.30	106.68	0.2548
12-32	149.35	147.83	121.92	0.1132
32-42	147.83	146.30	131.08	0.2265
42-52	146.30	143.26	167.68	0.6229
23-34	149.35	147.83	147.64	0.2265
34-43	147.83	144.78	137.16	0.3398
43-52	144.78	143.26	106.68	0.4530
52-61	143.26	141.73	152.40	1.2459
31-41	147.83	144.78	152.40	0.2548
41-51	144.78	143.26	106.68	0.4530
51-61	143.26	141.73	106.68	0.5663
61-71	141.73	138.65	172.21	2.0104
44-53	142.65	141.43	121.92	0.1132
53-62	141.43	140.21	91.44	0.1699
62-71	140.21	138.65	105.23	0.2548
71-81	138.65	137.46	121.92	2.4635
81-91	137.46	136.55	152.40	2.5201
91-10	136.55	135.64	186.54	2.6617

where $\mathcal{C}_1(D_i, \bar{Z}_i)$ and $\mathcal{C}_2(H_k)$, previously defined in Equation (1), represent the pipe ($/ft) and manhole ($) cost terms, respectively. By using these definitions, the objective of the proposed approach is to determine the optimum system design by minimizing the total cost. This design process is conducted by adjusting the pipe slopes $(S_i\,;\; i = 1,2,3,\cdots,20)$ as decision variables of the optimization model. After determination of these slopes by the optimization model, the corresponding pipe diameters are determined based on the implicit approach given in Figure 5. Note that the pipe diameters for this example are selected from the following commercial diameter set: $D_i \in$ {304.8 mm (12 in), 381.0 mm (15 in), 457.2 mm (18 in), 533.4 mm (21 in), 762 mm (30 in), 914.4 mm (36 in), 1066.8 mm (42 in), and

1219.2 mm (48 in)}. During the search process, Manning's surface roughness and maximum allowable ratio of flow depth to pipe diameter values are used as $n = 0.013$ and $\alpha = 0.82$, respectively. As indicated previously, the performance of the proposed approach has been evaluated by considering two scenarios (A and B) and the maximum number of HS improvisations for these scenarios are used as 100,000 and 500,000, respectively. After these definitions, the proposed simulation-optimization approach is executed for Scenario A. Figure 8 shows the convergence profiles for these model executions which are obtained by using different optimization parameter combinations. As can be seen from Figure 5, all the solutions start the search process from different initial solutions and converge roughly to the same solutions. Regarding the solution profiles, it is observed that each model execution starts with penalties due to constraint violations at early solutions and values of these penalties significantly reduce as the solution proceed. Statistical evaluation of these 64 model executions for Scenario A is given Table 2.

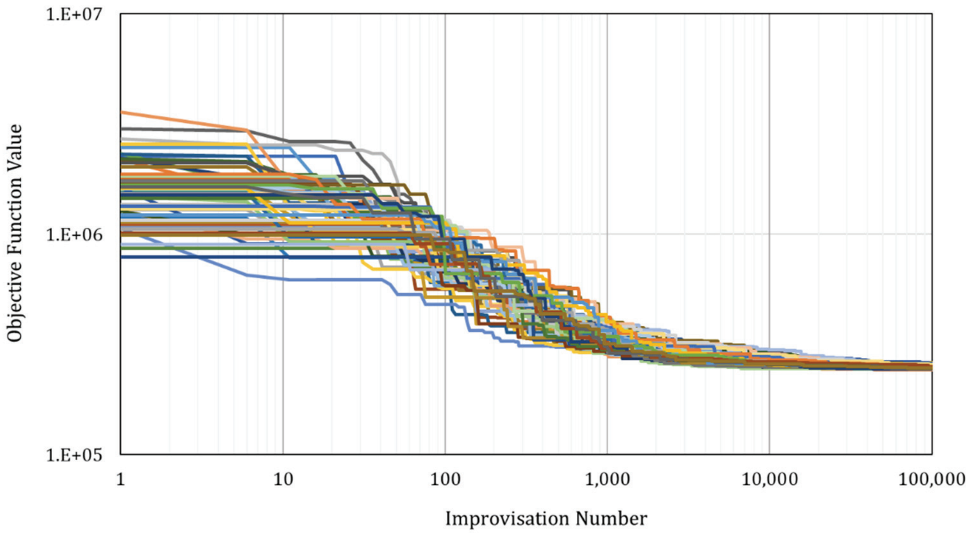

Figure 8 - Convergence profiles for 64 different model executions by using different optimization parameter combinations (Scenario A).

Table 2 - Statistical evaluation of the final objective function values obtained from Scenario A and B for Example 1

	Total System Cost (US $)	
	Scenario A	Scenario B
Number of Solutions	64	10
Minimum	241,797	240,068
Maximum	254,058	241,033
Mean	244,343	240,579
Standard Deviation	2,388	352

It can be seen from Table 2 that, in Scenario A, the proposed approach resulted with the minimum and maximum system costs of 241,797 \$ and 254,058 \$, respectively. For 64 model executions, the mean system cost has been obtained as 244,343 \$. All the solutions are scattered around the mean solution with a standard deviation of 2,388 \$. Note that the minimum system cost has been obtained for 14th parameter combination which has the parameter values of $HMS = 10$, $HMCR = 0.95$, and $PAR = 0.30$. After determining the best parameter combination in Scenario A, these parameter values are fixed and the problem is solved 10 times again to evaluate the model performance for different random number seeds in Scenario B. As stated previously, this is an important analysis for the heuristic optimization approaches since the computational structures of these approaches require the use of the uniformly distributed random numbers. The convergence profiles for 10 different model executions in Scenario B can be seen in Figure 9.

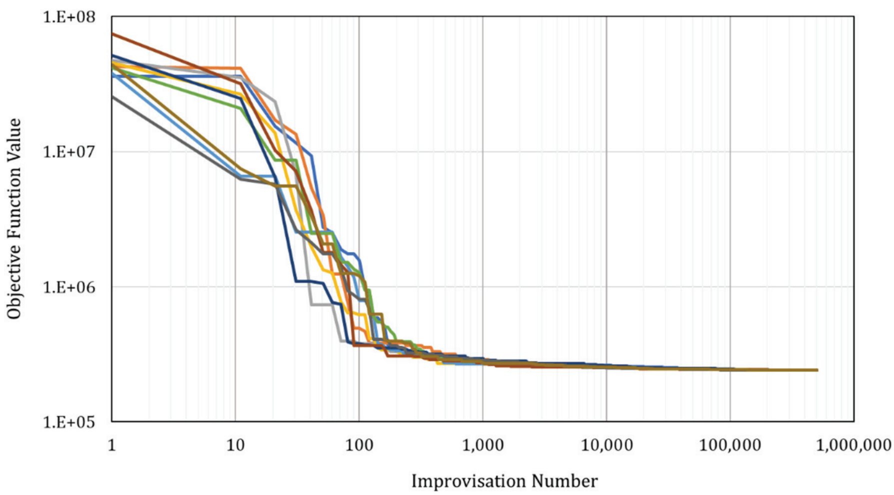

Figure 9 - Convergence profiles for 10 different model executions by using different random number seeds (Scenario B).

As can be seen from Figure 9, all the solutions start the search process with different initial solutions and converge to the approximately the same final solutions no matter where the solution starts. Table 2 also includes the statistical evaluation of the identified solutions in Scenario B. As can be seen, the minimum and maximum system costs have been obtained as 240,068 \$ and 241,033 \$, respectively. For these solutions, the mean system cost is 240,579 \$ with the standard deviation of 352 \$. This evaluation states that the convergence behavior of the proposed approach does not influence from both initial solutions and random number seeds. For the best solution in Scenario B, the identified decision variable values (e.g. slope of each pipe), pipe diameters, and manhole depths are schematized in Figure 10. The other identified system characteristics can be seen in Table 3.

As can be seen from Table 3, diameters of the pipes have been selected from the provided diameter set by means of the proposed implicit procedure given in Figure 5. As indicated previously, pipe design discharges for this example have been given to SWMM model as constant flow hydrographs. Therefore, flow characteristics, such as the flow velocity and water depths in the pipes, are also obtained in a constant hydrograph format. Table 3 includes only the maximum values of the velocity and relative water depth hydrographs observed in the pipes. Since output hydrographs are also of constant format, the minimum values of the velocity and relative water depth are the same as the respective maximum values; that is why they have not been included in Table 3. As can be seen, all the constraints of the problem are satisfied without any violation. Note that this example was previously investigated by many researchers by using steady and unsteady state model simulations. The final results obtained for some of the studies are compared in Table 4. As can be seen from Table 4, the final objective function value (240,068 US $) of the proposed approach is better than the previously conducted studies except for Tan et al. [1] (239,961 US $) where the problem was solved by using differential evolution (DE) optimization approach. It is worth reminding that most of the previous studies considered steady-state hydraulic simulations and there are very limited studies that solve the problem for unsteady-state flow simulations. When the identified results are compared with them given in Table 4, it can be concluded that the proposed approach again provides similar or better results in terms of the final objective function values.

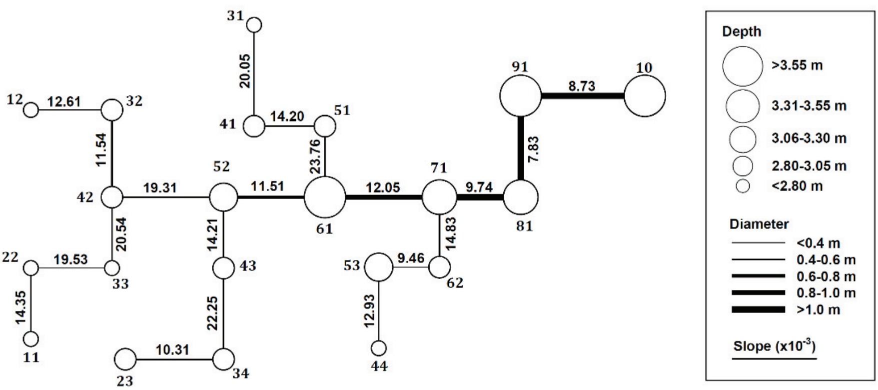

Figure 10 - Schematic representation of the identification results for Example 1.

Table 3 - Identified pipe slopes and the other characteristics of the network for Example 1.

Pipe	Diameter	Maximum Velocity	Relative Water Depth	Cover Depths	
	D_i (mm)	max $\{V_i(t)\}$ (m/s)	max $\{y_i(t)\}/D_i$ (m/m)	E_i^u (m)	E_i^d (m)
11-22	304.80	1.89	0.77	2.40	2.41
22-33	381.00	2.47	0.67	2.41	2.40
33-42	381.00	2.62	0.80	2.40	2.40
12-32	304.80	1.77	0.82	2.40	2.42
32-42	457.20	2.10	0.63	2.42	2.40

Table 3 - Identified pipe slopes and the other characteristics of the network for Example 1. (continue)

Pipe	Diameter	Maximum Velocity	Relative Water Depth	Cover Depths	
	D_i (mm)	$\max\{V_i(t)\}$ (m/s)	$\max\{y_i(t)\}/D_i$ (m/m)	E_i^u (m)	E_i^d (m)
42-52	533.40	3.18	0.82	2.40	2.60
23-34	457.20	2.02	0.65	2.40	2.40
34-43	457.20	2.97	0.66	2.40	2.40
43-52	533.40	2.68	0.71	2.40	2.40
52-61	762.00	3.11	0.82	2.40	2.62
31-41	381.00	2.59	0.80	2.40	2.40
41-51	533.40	2.68	0.71	2.40	2.40
51-61	533.40	3.44	0.69	2.40	3.40
61-71	914.40	3.60	0.80	3.40	2.40
44-53	304.80	1.79	0.81	2.40	2.76
53-62	381.00	1.78	0.79	2.76	2.40
62-71	457.20	2.38	0.62	2.40	2.40
71-81	1066.80	3.54	0.73	2.40	2.40
81-91	1066.80	3.21	0.82	2.40	2.68
91-10	1066.80	3.40	0.82	2.68	3.40

Table 4 - Comparison of the obtained system costs for different solution approaches.

	Solution Type	Solution Approach	Total System Cost (US $)
Mays and Wenzel [3]	SS	DP	265,775
Robinson and Labadie [4]	SS	DP	275,218
Afshar [20]	SS	ACO	241,496
Afshar [2]	SS	GA	241,896
Tan et al. [1]	SS	DE	239,961
Tan et al. [27]	SS	HS	240,981
Afshar [19]	SS	PSO	242,889
Afshar et al. [41]	SS	CA	253,484
Afshar et al. [31]	USS	GA	244,747
Zaheri et al. [33]	USS	CA	240,084
Proposed Approach	USS	HS	240,068

SS: Steady-State, USS: Unsteady-State, DP: Dynamic Programming, ACO: Ant Colony Optimization; GA: Genetic Algorithm, DE: Differential Evolution; HS: Harmony Search, PSO: Particle Swarm Optimization, CA: Cellular Automata

3.1. Example Problem 2

This example aims to evaluate the applicability of the proposed approach including the diurnal discharge patterns of the residential or industrial areas during the dynamic design process. As indicated previously, inclusion of diurnal discharge patterns may be an important improvement especially for analysis of big systems since the shape of the upstream discharge hydrographs can change when they arrive to downstream locations. For this case, the considered example system is given in Figure 11. As can be seen, the example network includes 42 manholes which are connected through 41 pipes with the total length about 2.4 km. Characteristics of the system including ground elevations at manhole locations, pipe lengths, and design discharges are given in Table 5.

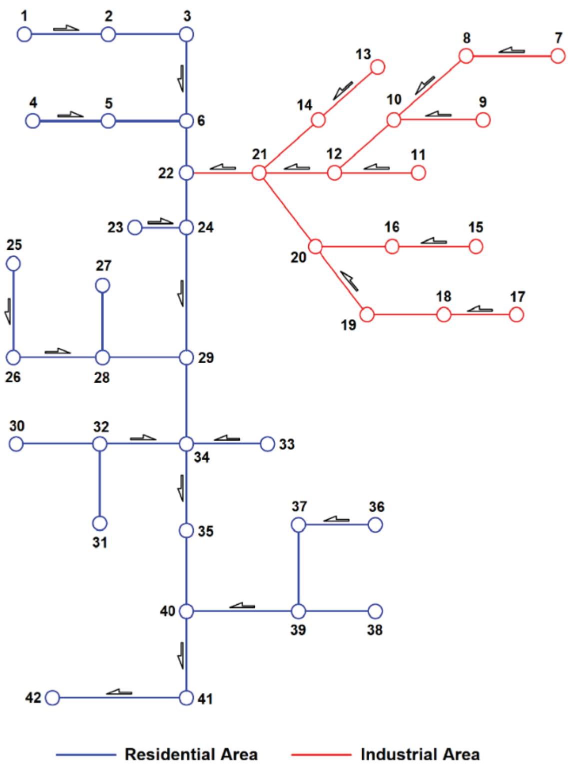

Figure 11 - Schematic view of the household sewer system in Example 2

The example network system in Figure 11 includes two areas where residential buildings (blue lines) and industrial facilities (red lines) are located. Note that these areas have different wastewater discharge characteristics due to the change of their hourly water consumption patterns. There are different diurnal patterns in literature which are used for obtaining the hourly variation of wastewater discharges. These patterns consist of some multiplication factors which are used to convert a peak flow into the hourly wastewater discharges. Among them, the diurnal patterns given in Qasim [42] have been used. Figure 12 shows these patterns for residential and industrial areas, respectively. As can be seen, there are two peaks in the diurnal pattern of the residential areas which are observed at early noon and evening times. For the industrial areas, it is assumed that wastewater discharge process starts at morning and ends at the late afternoon. By using these patterns, the discharge hydrographs of each pipe are obtained by multiplying the max $\{Q_i(t)\}$ values in Table 5 with the multiplication factors given in Figure 12 (a) and (b) for the residential and industrial areas.

After obtaining the design discharge hydrographs for each pipe, the dynamic design process is conducted by considering the maximum velocity value of 3 m/s. Note that minimum velocity constraint is not considered for this example since the industrial facilities (red lines in Figure 11) have some periods without any discharge according to their diurnal patterns. However, this situation is only valid for this example, and it is not a general case where both residential and industrial areas release the wastewater to the same manhole locations. For such cases, the minimum velocity constraints can also be defined just as given in Example 1. Similar to Example 1, the network should be designed with the minimum and maximum cover depths of 2.40 m and 6.00 m, respectively. Manning's surface roughness and maximum allowable ratio of flow depth to pipe diameter values are taken as $n = 0.013$ and $\alpha = 0.82$, respectively. Note that the following cost function given in Afshar et al. [41] is used in calculation of the objective function.

$$\mathcal{C}_1(D_i, \bar{Z}_i) = 1.93e^{3.43D_i} + 0.812\bar{Z}_i^{1.53} + 0.437D_i\bar{Z}_i^{1.47} \tag{28}$$

$$\mathcal{C}_2(H_k) = 41.46H_k \tag{29}$$

Table 5 - Characteristics of the sewer network for Example 2.

Pipe	Ground Elevations (m)		L_i (m)	max $\{Q_i(t)\}$ (m^3/s)
	Upstream	Downstream		
1-2	495.00	494.37	60	2.33
2-3	494.37	493.67	56	2.18
3-6	493.67	493.00	60	2.33
4-5	494.27	493.70	54	2.10
5-6	493.70	493.00	56	2.18
6-22	493.00	492.17	36	1.40
7-8	492.93	492.76	66	4.51
8-10	492.76	492.63	68	4.64
9-10	492.80	492.63	64	4.37
10-12	492.63	492.43	56	3.82
11-12	492.51	492.43	60	4.10
12-21	492.43	492.33	54	3.69
13-14	492.55	492.47	56	3.82
14-21	492.47	492.33	56	3.82

Table 5 - Characteristics of the sewer network for Example 2. (continue)

Pipe	Ground Elevations (m)		L_i (m)	$\max\{Q_i(t)\}$ (m^3/s)
	Upstream	Downstream		
15-16	492.78	492.64	60	4.10
16-20	492.64	492.53	55	3.75
17-18	493.13	492.93	52	3.55
18-19	492.93	492.70	55	3.75
19-20	492.70	492.53	60	4.10
20-21	492.53	492.33	65	4.44
21-22	492.33	492.17	52	3.55
22-24	492.17	491.71	38	1.48
23-24	492.13	491.71	37	1.44
24-29	491.71	490.60	90	3.50
25-26	492.81	492.19	65	2.53
26-28	492.19	491.60	64	2.49
27-28	492.04	491.60	50	1.94
28-29	491.60	490.60	60	2.33
29-34	490.60	489.87	60	2.33
30-32	491.19	490.56	60	2.33
31-32	491.25	490.56	55	2.14
32-34	490.56	489.87	62	2.41
33-34	490.48	489.87	58	2.26
34-35	489.87	489.12	60	2.33
35-40	489.12	487.83	56	2.18
36-37	490.52	489.84	55	2.14
37-39	489.84	489.27	60	2.33
38-39	489.99	489.27	55	2.14
39-40	489.27	487.83	80	3.11
40-41	487.83	487.43	60	2.33
41-42	487.43	486.54	96	3.73

where $\mathcal{C}_1(D_i, \bar{Z}_i)$ and $\mathcal{C}_2(H_k)$ represent the pipe (\$/m) and manhole (\$) cost terms, respectively. By using these cost function definitions, the objective of the proposed approach is to determine the pipe slopes (S_i ; $i = 1,2,3,\cdots,41$) by minimizing the total system cost. Just as in Example 1, the pipe diameters are determined by means of the proposed implicit procedure given in Figure 5. Pipe diameters have been selected from the following commercial diameter set: $D_i \in \{$150 mm, 200 mm, 250 mm, 300 mm, 400 mm, 500 mm, 600 mm, and 700 mm$\}$. Like Example 1, the performance of this example is also evaluated for two scenarios. Previous trials on this example indicates that the HS based optimization model converges faster than those in Example 1, and therefore, maximum numbers of HS improvisations for Scenario A and B are set to 20,000 and 100,000, respectively. After these definitions, the proposed approach is executed for Scenario A for different HS parameter combinations. Figure 13 shows convergence profiles for each model executions.

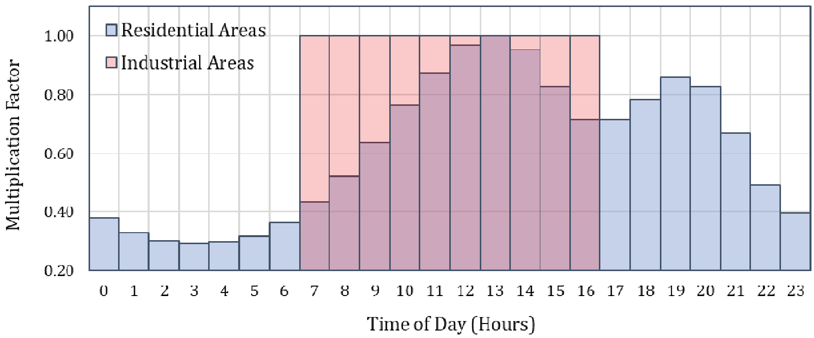

Figure 12 - Diurnal wastewater discharge patterns [42].

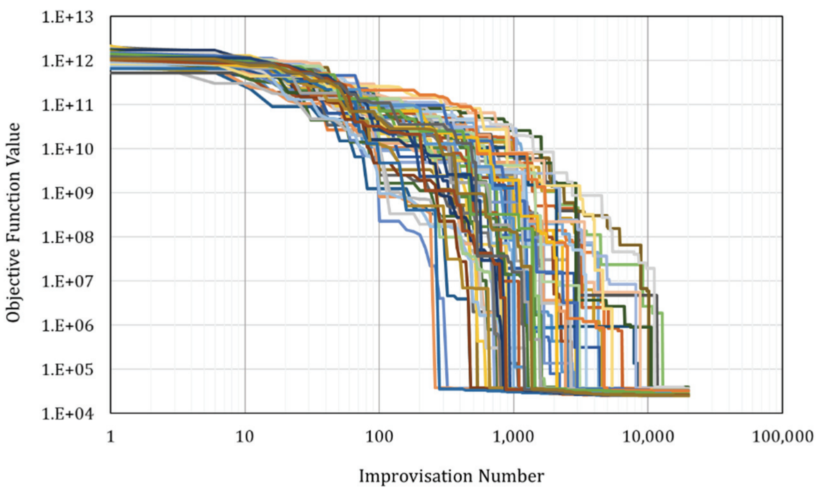

Figure 13 - Convergence profiles for 64 different model executions by using different optimization parameter combinations (Scenario A).

As can be seen from Figure 13, all the solutions start the optimization process with very high penalty values due to violation of constraints in early solutions. As the search process proceed, the solutions evolve and generate results without any penalties due to constraint violation. The profiles indicate that there is no significant change in the objective function values after 13,000th improvisation. For the final solutions at 20,000th improvisation, statistical evaluation of 64 different model executions can be seen in Table 6. As can be seen, the minimum and maximum objective function values have been obtained as 24,925 \$ and 38,958 \$, respectively. For 64 different executions, the mean system cost is obtained as 29,664 \$ and all the solutions are scattered around this mean value with a standard deviation of 3,815 \$. According to the final objective function values, the best solution is obtained for 15[th] model execution which has the optimization parameters of $HMS = 10$, $HMCR = 0.95$, and $PAR = 0.40$. After this process, these parameter values are fixed and the proposed approach is executed 10 more times to evaluate model performance for different random number seeds in Scenario B. Figure 14 shows convergence profiles for these model executions. Like Scenario A, all the solutions in Figure 14 starts the optimization process with large penalty values and these penalties significantly reduce as the solutions proceed. After about 5,000[th] improvisation, the system cost does not change significantly.

Table 6 - Statistical evaluation of the final objective function values obtained from Scenario A and B for Example 2

	Total System Cost (US \$)	
	Scenario A	Scenario B
Number of Solutions	64	10
Minimum	24,925	24,407
Maximum	38,958	24,964
Mean	29,664	24,598
Standard Deviation	3,815	169

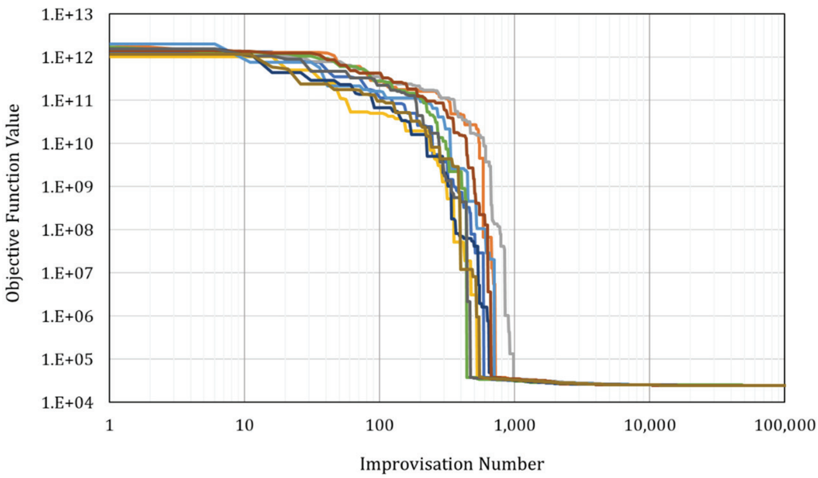

Figure 14 - Convergence profiles for 10 different model executions by using different random number seeds (Scenario B).

For the final values, the performance of 10 different model executions is compared statistically in Table 6. As can be seen, the minimum and maximum systems costs are obtained as 24,407 $ and 24,964 $, respectively. The mean and standard deviation values are 24,598 $ and 169 $, respectively. These results indicate that the proposed approach is not significantly influenced from the random number seeds in the optimization process. For the best solution of Scenario B, the final pipe slopes, diameters, and manhole depths are schematized in Figure 15. The other identified system characteristics are summarized in Table 7.

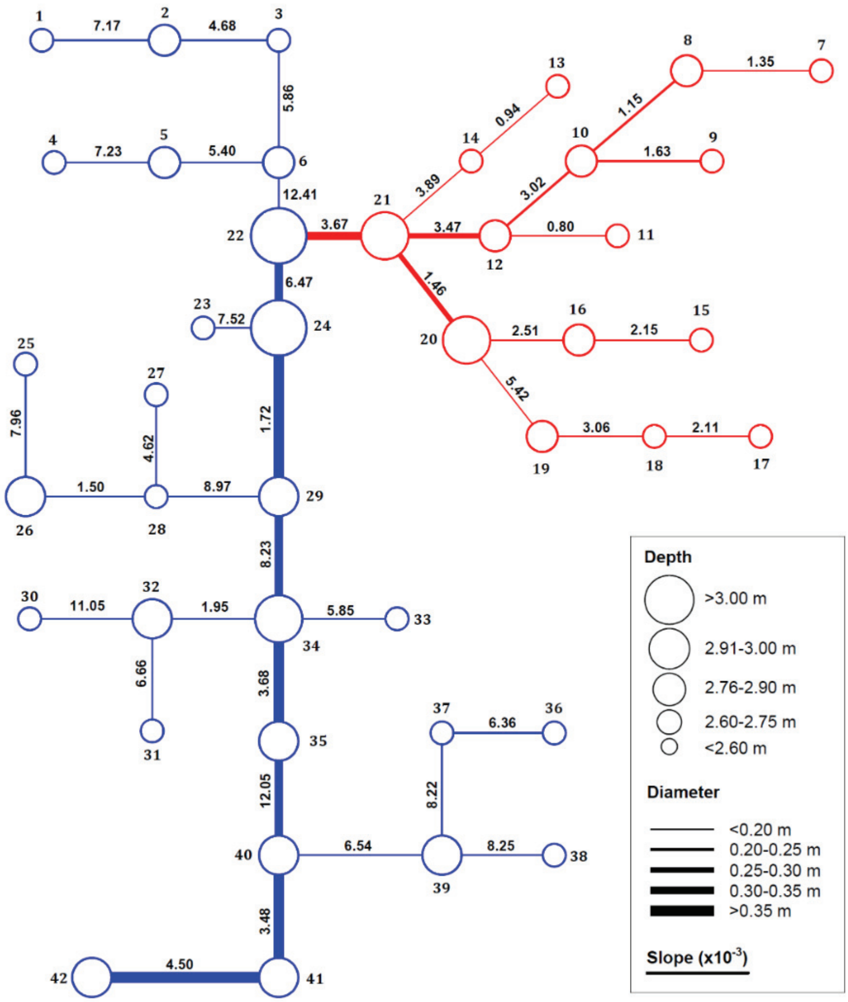

Figure 15 - Schematic representation of the identification results for Example 2.

Table 7 - Identified pipe slopes and the other characteristics of the network for Example 2.

Pipe	Diameter	Maximum Velocity	Relative Water Depth	Cover Depths	
	D_i (mm)	$\max\{V_i(t)\}$ (m/s)	$\max\{y_i(t)\}/D_i$ (m/m)	E_i^u (m)	E_i^d (m)
1-2	150	0.39	0.37	2.40	2.52
2-3	150	0.50	0.51	2.52	2.43
3-6	150	0.69	0.55	2.43	2.45
4-5	150	0.38	0.35	2.40	2.51
5-6	150	0.45	0.53	2.51	2.46
6-22	150	1.05	0.64	2.46	2.49
7-8	150	0.39	0.66	2.40	2.41
8-10	200	0.37	0.78	2.41	2.42
9-10	150	0.40	0.70	2.40	2.42
10-12	200	0.74	0.70	2.42	2.49
11-12	150	0.37	0.59	2.40	2.41
12-21	250	0.85	0.58	2.49	2.63
13-14	150	0.32	0.71	2.40	2.41
14-21	150	0.65	0.63	2.41	2.56
15-16	150	0.40	0.74	2.40	2.46
16-20	150	0.56	0.73	2.46	2.54
17-18	150	0.33	0.61	2.40	2.41
18-19	150	0.53	0.80	2.41	2.46
19-20	150	0.77	0.81	2.46	2.70
20-21	250	0.57	0.82	2.70	2.70
21-22	300	1.02	0.81	2.70	2.81
22-24	300	1.23	0.80	2.81	2.83
23-24	150	0.49	0.22	2.40	2.47
24-29	400	0.78	0.76	2.83	2.42
25-26	150	0.36	0.52	2.40	2.61
26-28	150	0.41	0.65	2.61	2.41
27-28	150	0.34	0.44	2.40	2.41
28-29	150	0.84	0.65	2.41	2.45
29-34	300	1.46	0.82	2.45	2.58
30-32	150	0.40	0.59	2.40	2.75
31-32	150	0.53	0.28	2.40	2.42
32-34	150	0.51	0.72	2.75	2.52
33-34	150	0.52	0.29	2.40	2.43
34-35	400	1.06	0.71	2.58	2.43
35-40	300	1.71	0.80	2.43	2.45
36-37	150	0.41	0.34	2.40	2.41
37-39	150	0.46	0.54	2.41	2.61
38-39	150	0.88	0.27	2.40	2.49
39-40	150	0.80	0.65	2.61	2.42
40-41	400	1.15	0.75	2.45	2.46
41-42	400	1.33	0.67	2.46	2.45

As can be seen from Table 7, the identified results satisfy all the constraints of the problem. Similar to Example 1, the pipe design discharges are specified to the system as flow hydrographs. Unlike the Example 1, the given hydrographs have not constant flow values against time due to the diurnal patterns given in Figure 12. Since input of the model consists of the time varied flow values, their corresponding outflows have also the same structures considering the routing process of flow through the pipes. Therefore, only maximum values of the routed velocity and relative water depth hydrographs are given in Table 7.

4. DISCUSSION AND CONCLUSIONS

In this study, a new simulation-optimization approach is proposed for solving the dynamic urban wastewater collection system design problems by considering unsteady flow conditions. The proposed approach consists of the mutual integration of US-EPA SWMM with heuristic HS optimization approach. In this integration, SWMM aims to solve the governing equations by means of the dynamic wave flow routing approach and HS aims to determine the pipe slopes by minimizing the total cost of the system including pipe, excavation, and manhole costs. The applicability of the proposed approach is evaluated by solving two examples. The first example is a well-known benchmark example given in literature and solution of this example aims to evaluate the performance of the HS based optimization model. After demonstrating the efficiency of HS on this example, the performance of the proposed approach is evaluated on the second example which is developed by considering the diurnal wastewater discharge patterns for residential and industrial areas. Regarding the outcomes of the proposed approach, the following discussions and conclusions can be drawn:

The concept of optimum design is crucial on solving the sewer system design problems. In practice, design process of the sewer system is conducted by manually adjusting the bed slope of the pipes and determining the pipe diameters by including the associated slope values and the other design criteria to the Manning's equation. Although this process looks useful, it cannot be easy especially for the big systems since there is a strong conflicting relation between the slopes and diameters of the pipes. For example, increasing the pipe slopes lead to use the smaller pipe diameters. However, use of large slopes increases the excavation costs. On the contrary, increasing the pipe diameters results with the requirement of less pipe slope. However, there is an increase of the pipe costs compared to excavation works. Therefore, use of the optimization-based solution approaches makes solution of the problem easy due to their efficiencies on handling these conflicting relations.

In practice, design process of the sewer systems is conducted by considering the peak values of the discharge hydrographs as the design flows of the pipes. In another words, the design process is conducted by considering steady state flow conditions in the system. Although this is a useful approach for many cases, it does not represent the true flow process in real life. Normally, the design flow discharges of the pipes are not constant in a day due to diurnal discharge patterns. Since the shape of the discharge hydrograph changes as the water flows through pipes, the peak values of them are attenuated together with a time lag. Although these attenuations are not significant in small systems, they might be important for the big systems such that larger design discharges can be obtained at downstream locations if routing process through pipes are not considered. This outcome results with the determination of larger pipe diameters at those locations which increases the cost of the system. Therefore, use of the proposed approach can be a good alternative to prevent these problems.

Although the proposed approach is effective on solving the optimum design problem by considering unsteady flow conditions, its main difficulty is the requirement of the high computational times for the big systems. This is due to the association of the approach with the hydraulic simulation process by SWMM model which is based on the numerical solution of the St. Venant equations. Since HS based optimization approach requires the execution of the SWMM model for each generated decision variable values, obtaining the optimum system design may require long computational times on the classical personal computers. For such cases, the problem can be solved on supercomputers or cloud computing platforms which are the beyond of the scope of this study.

In the proposed approach, it is considered the bed slope of the pipes as decision variables of the optimization model. As indicated previously, the corresponding pipe diameters are determined by using the proposed implicit diameter selection procedure in Figure 5. Although this procedure can effectively determine the pipe diameters for the generated slope values, it also increases the computation time since additional SWMM model executions are required during determination of the appropriate pipe diameters. To overcome this difficulty, the pipe diameters can also be considered as additional decision variables of the optimization model. However, this kind of use increases the number of variables twofold, and thus increases the complexity of the mathematical search space. Therefore, this approach is not considered in this study.

For all the solutions in this study, the optimum system design is determined by considering the open channel flow conditions in the pipes. However, in some cases, pressurized flow conditions together with the pumping facilities can also be considered. These issues are not considered in this study and may be investigated as a future work.

Software Availability

The open-source form of the developed VBA code can be accessible by requesting from the corresponding author.

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