An Integrated Decision-Making Framework Based on Many-Objective Brain Storming Optimization for Urban Drainage System Design

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ABSTRACT Many cities around the world face the flooding management problems as extreme rainfall events have become more frequent. It’s of great practical significance to design an effective urban drainage system (UDS) to improve the stormwater runoff quality. An integrated decision-making analysis framework based on many-objective brain storm optimization is proposed to make the optimal design of UDS. Firstly, a generic mathematical model is presented considering five objectives simultaneously. Secondly, an effective many-objective brain storm optimization based on local region dominance is designed as the solver of the model and a set of Pareto-optimal solutions are obtained. Thirdly, two kinds of multi-attribute decision analysis methods are introduced to rank the Pareto-optimal solutions. Fourthly, the comparison experiments of a case study with three multi-objective swarm intelligence algorithms show the promising performance of the integrated decision-making framework and the corresponding optimization algorithm.

INDEX TERMS Urban drainage system, many-objective optimization, brain storm optimization, multi-attribute decision, decision maker.

I. INTRODUCTION
Global climate change, rapid expansion of cities, and the aging of existing urban drainage infrastructure raise new challenges for urban flood management. The inefficient drainage systems can lead to a series of problems such as sewer overflow and urban flooding, which are likely to cause environmental pollution, urban roads and buildings damage, and even threaten the safety of people’s lives and properties [1], [2]. Therefore, urban drainage system (UDS) design has drawn more and more attention [3], and it’s urgent to build an economical and effective UDS to cope with the extreme rainfall events.

The design of UDS is a daunting task due to its inherent characteristics such as hydraulic complexity together with the conflicting objectives. This leads to an increasing number of studies regarding the design of UDS as a multi-objective optimization problem (MOP). Most traditional optimization methods (e.g., linear or nonlinear programming and dynamic programming) can’t handle it well for its nonlinearity, multimodal and multidimensional [4]. Swarm intelligence (SI) algorithms, such as particle swarm optimization (PSO), brain storm optimization (BSO) [5] and Evolutionary algorithm (EA), have been proved effective and efficient in many complex multi-objective engineering optimization [6], [7]. Accordingly, multi-objective SI algorithms are applied as the solver of the optimal design of UDS. Muleta et al. presented the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to solve the optimal pipe size of drainage system with two objectives including both the overflow volume and the cost of pipes [8]. Duan et al. analyzed the uncertainty and sensitivity of UDS based on the improved PSO [9]. Ngamalieu-Nengo et al. linked the Storm Water Management Model (SWMM) and the designed multi-objective EA to carry out
the hydraulic simulation and multi-objective optimization respectively. The objectives are to minimize both the investment cost and the flood damage cost [10]. Ghodsi et al. adopted the NSGA-II algorithm to solve three objectives of minimizing overall implement cost, flood volume and flood pollution for obtaining a set of reasonable low impact development areas and locations [11]. Wang et al. proposed a two-stage optimization model to get the efficient distribution of storage tanks by minimizing drainage system cost, overflow volume and total suspended solids [12]. Wang et al. linked the Borg multi-objective optimization algorithm [13] and SWMM to optimize the pipe size considering minimizing the pipes cost and the flood volume of the designed drainage system [14]. Lin et al. introduced an engineering-based method into multi-objective EAs to optimize the diameter and slope of the pipes efficiently with two optimization objectives which is minimizing cost and the peak water depth in pipes [15]. Ghodsi et al. took the runoff volume and the cost of the low influence development as the optimization objectives to get the optimal design of the sustainable drainage system [16]. The above studies have shown the promising performance of the multi-objective SI algorithms in UDS design problem.

Although the existing studies have made some achievements, most of the proposed optimization models consider two or three optimization objectives, which are insufficient to evaluate the overall benefit of the designed UDS comprehensively. On the other hand, some factors that are difficult to express by mathematical equations are often not considered in the design process of UDS. Secondly, when using multi-objective SI algorithms to deal with the UDS design problem, a set of Pareto-optimal solutions are obtained as the final output. How to select a most suitable solution for decision makers from the output is rarely mentioned in previous research. Furthermore, some multi-objective SI optimization algorithms have shown good performance when two or three optimization objectives are considered. But for the case of more than three objectives, which is called many-objective optimization problem (MaOP), these traditional algorithms can’t work well because of the dominant resistance (DR) [17]. Therefore, this article focused on tackling the above several challenges. The main contributions are summarized as follows:

- An integrated framework including system modelling, many-objective optimization and multi-attributes decision-making analysis is proposed to solve the UDS design problem.
- The UDS optimization model considering five objectives is proposed to comprehensively assess the benefits of designed UDS. And a novel LRD dominance principle is proposed to improve the selection pressure in the many-objective BSO algorithm.
- Two kinds of multi-attribute decision analysis methods are introduced to help decision makers select an appropriate option among the Pareto-optimal solutions, which is rarely mentioned in other related works. Specially, the factors that are difficult to establish the mathematical expression are also considered in this process.

The article is organized as follows: The design of urban drainage system and the proposed framework are introduced in Section II, which contains system modelling, optimization and decision-making. The model formulation of the UDS problem is described in detail in Section III. And the many-objective BSO algorithm named LRD-BSO is presented in Section IV. Two kinds of multi-attribute decision analysis methods are discussed in Section V. A study case of the proposed framework and the experimental study of LRD-BSO are shown in Section VI. The conclusion is followed in Section VII.

II. THE PROPOSED FRAMEWORK OF URBAN DRAINAGE SYSTEM DESIGN

Many factors should be considered by engineers in the process of UDS design. It has been widely taken as a MOP, in which the points that need to be considered are regarded as the optimization objectives. Most of the existing multi-objective UDS optimization models only consider two or three objectives. But in fact, there are a range of criteria can be used to assess the performance of the designed UDS from different angles, including the flood volume, flood damage, the peak runoff, the flood duration, the cost of storage tanks, the pipe material cost, and the costs of land use, construction as well as the maintenance of the UDS. These models with limited objective number may not be enough to design the UDS with commendable overall performance. Trade-off among more optimization objectives can better reflect the planning objectives of the engineers in real-word UDS design. Therefore, a many-objective UDS optimization model considered five optimization objectives is presented in this article.

With the increase of the number of objectives, the traditional multi-objective SI algorithms can’t solve the corresponding UDS optimization problem well. Therefore, it is necessary to design an effective many-objective optimization algorithm to find the Pareto-optimal solution set with good distribution and great convergent performance. The solutions in the set are also called noninferior solution, which means the solutions are equally well. It’s complicated for the decision makers to select the most suitable solution from the Pareto-optimal solution set. Furthermore, apart from the optimization objectives considered in the optimization model, there are also some aspects that are difficult to be mathematically represented, such as the construction safety and citizen satisfaction, which also should be involved in the decision-making process. As a result of this problem, the multi-attribute decision-making methods are introduced to consider not only the optimization objectives but also these necessary aspects in the final decision-making.

The proposed framework of the UDS design, includes three components, as shown in Fig. 1. The first component is model formulation. The main aim is to assess the overall benefits of the designed UDS more comprehensively. The second
component is many-objective optimization algorithm design. The aim is to get the Pareto-optimal solution set with excellent performance in terms of convergence and diversity. The last component is the final decision-making. The aim of this part is to provide methods for decision makers to get the final decision result. The sequential connection of these three components is also displayed in Fig. 1. The detailed description of each component is given in the following sections.

III. MODEL FORMULATION

In this article, we assume first that each subbasin of a specific watershed is hydrologically independent and has its own treatment station, drainage network, tributary to a receiving water body, and onsite detention storage device. Then, a many-objective UDS optimization model with five objectives is proposed. The decision variables are storage capacity, rainwater treatment capacity, and maximum permissible overflow. And the five objectives include the cost of drainage network, the cost of storage tank, the cost of treatment device, the flood damage loss, and the intended economic loss caused by flood, which are listed in detail as follows. The drainage network cost mainly comprises of the pipe cost and other implement cost. It can be calculated as the following formula:

\[
F_{D\text{cost}} = \sum_{i=1}^{N_P} C_P(D_i)L_i + C_O
\]

where \(D_i\) is the diameter of \(i\)th pipe, \(C_P(D_i)\) represents the \(i\)th pipe cost per unit length, and \(L_i\) is the length of \(i\)th pipe, \(N_P\) indicates the total number of pipes in the designed UDS, \(C_O\) is other implement cost. The total storage tanks cost is defined as:

\[
F_{S\text{cost}} = \sum_{i=1}^{N_T} C_T(V_i)
\]

where \(V_i\) is the volume of \(i\)th storage tank, \(C_T(V_i)\) indicates the cost of the \(i\)th storage tank, \(N_T\) is the total number of storage tanks in the designed UDS. The cost of treatment device is measured by:

\[
F_{T\text{cost}} = \sum_{i=1}^{N_M} DF_i
\]

where \(DF_i\) represents the cost of \(i\)th treatment device, \(N_M\) is the total number of the treatment device. There are two types of flood damage, tangible and intangible damages, and only tangible cost is taken into account in this article. The following equation is used to calculate the flood damage loss [18]:

\[
F_{\text{FloodDam}} = w_0 + w_1 \times \text{DEP} + w_2 \times \text{DUR}
\]

where \(w_0\), \(w_1\) and \(w_2\) are the coefficients about the local land, \(\text{DEP}\) indicates the water depth and \(\text{DUR}\) is the flood duration. Finally, the intended economic loss caused by flood is defined as:

\[
F_{\text{FloodEco}} = \eta_0 \times \text{VOL} + \eta_1
\]

where \(\eta_0\) and \(\eta_1\) are the parameters of local economic and \(\text{VOL}\) indicates the flood volume. Overall, the necessary inputs of the UDS optimization model are presented in Table 1.

IV. MANY-OBJECTIVE BSO OPTIMIZATION ALGORITHM

The typical multi-objective SI optimization algorithms, such as NSGA-II [19], have widely used as the optimization solver of UDS design problem, and make great performance in the case of two or three optimization objectives [20]. But, due to the existence of dominance resistance, they can’t work well when handling the many-objective UDS optimization model discussed in this article. BSO is a new SI algorithm proposed in recent years, and it uses all possible individuals to update the population, so as to good diversity, which is especially beneficial to solve multi-objective optimization problems. Some multi-objective BSO algorithms have been proposed [21], [22], [23], [24], and perform well on a wide range of MOP. A novel many-objective BSO algorithm based on BSO was proposed to deal with the many-objective UDS optimization model.

A. BSO ALGORITHM

Inspired by the human brainstorming conference, BSO is guided by the cluster centers and other individuals according to a certain probability, which can balance convergence and diversity greatly. The main process of the BSO includes three important operations [25]: clustering, disruption, and creation, which is shown in Fig. 2. Clustering is a kind of techniques that divides individuals into several groups (clusters), and the individuals being similar (or related) in the same cluster, which could refine a search area. Without losing generality, these solutions are clustered by the \(k\)-means algorithm, and the solution with best fitness in each cluster is regarded as its cluster center. A probability value is used to replacing a cluster center by a randomly generated solution in the disruption operation. This could avoid the premature convergence and the local optima. A new individual can be generated by one or two cluster(s). One cluster could refine a

| TABLE 1. The input of the optimization model. |
|---------------------------------------------|
| Model input                                |
| drainage network                           |
| pipe implement cost                        |
| land coefficients                          |
| local economic parameters                  |
|                                             |
|                                             |

| PIPE | D, L, Np | C0 | \(w_0\), \(w_1\), \(w_2\) | \(\eta_0\), \(\eta_1\) |
|------|----------|----|-----------------|-----------------|
|      |          |    |                 |                 |

FIGURE 1. Three components of the proposed framework.
search region and improve the exploitation ability. Two clusters could improve the diversity of population. The creation process is described as the following formula:

\[ X_{\text{new}} = X_{\text{selected}} + \xi \times N(0, 1) \]  

(6)

where \( X_{\text{new}} \) is the new generated solution, \( N(0, 1) \) denotes a random value following the standard normal distribution, \( X_{\text{selected}} \) denotes the selected solution in current iteration as shown in Formula (7),

\[
X_{\text{selected}} = \begin{cases} 
X_i, & \text{one cluster} \\
\text{rand} \times X_{i1} + (1 - \text{rand}) \times X_{i2}, & \text{two clusters}
\end{cases}
\]

(7)

In Formula (7), \( X_{i1} \) and \( X_{i2} \) represent two selected solutions, \( \text{rand} \) is a random value obeying uniform distribution within 0 to 1, \( \xi \) represents the current step length as shown in Formula (8),

\[
\xi = \log \sin\left(\frac{0.5 \times T - C}{k} \right) \times \text{rand}
\]

(8)

In Formula (8), \( T \) is the maximum number of iterations, \( C \) indicates the current iteration, \( \log \sin() \) is the transfer function, and \( k \) denotes the change rate of \( \log \sin() \) function which is usually a constant.

B. MANY-OBJECTIVE ALGORITHM BASED ON BSO

The phenomenon of the proportion of nondominated solution in MaOP increasing exponentially is called DR, which leads to the decrease of selection pressure of the multi-objective optimization algorithms [26]. Hence, a new dominance relation is proposed to improve the selection pressure, and it contributes to balance the convergence and diversity. In addition, two offspring generation manners, i.e., inter-cluster and intra-cluster, are designed to carry out the exploration and exploitation in evolution, respectively.

Algorithm 1 Main Framework of the Proposed LRD-BSO

1: **Input:** the maximal number of iterations \( t_{\text{max}} \), the probability \( P_{\text{one}} \) of selecting one individual to generate new individual, the probability \( P_{\text{Center}} \) of selecting the cluster center to generate new individual;

2: **Output:** final population \( P_t \);

3: /* Initialization */

4: Initialize the population \( P_0 \); Generate reference point set \( V \); Cluster the reference point set \( V \); \( t \leftarrow 0 \);

5: /* Main Loop */

6: while \( t < t_{\text{max}} \) do

7: \( Q_t \leftarrow \text{Offspring-Generation}(V, P_t, P_{\text{one}}, P_{\text{Center}}) \);

8: \( R_t = P_t \cup Q_t \);

9: \( P_{t+1} \leftarrow \text{Environment-Selection}(R_t) \);

10: \( t = t + 1 \);

11: end while

As shown in Algorithm 1, the framework of the LRD-BSO includes three main parts: initialization, offspring generation and environment selection. Note that the proposed new dominance relation and two offspring generation manners are applied to the environment selection as well as offspring generation operations, respectively. The details of above three operations are as follows.

1) **INITIALIZATION**

The initialization procedure of LRD-BSO contains two main aspects. One is the initialization of parent population \( P_0 \), the other is the generation of reference points. To be specific, the initial parent population \( P_0 \) is randomly sampled via a uniform distribution. The reference points are generated by the Normal-Boundary Intersection (NBI) method proposed by Das and Dennis [27].

2) **OFFSPRING GENERATION**

The generation of offspring population \( Q_t \) includes two steps. First is the reference-point-guided clustering: The reference point set \( V \) are grouped by k-means algorithm. And the \( N \times N \) angle matrix between solution vectors (from origin to solutions in \( P_1 \)) and reference vectors (from origin to reference points in \( V \)) are calculated. Each solution is allocated to the reference points based on the angle value. Specifically, \( v_1, v_2, v_3 \) and \( v_4 \) in Fig.3 are vectors from origin point to reference point and \( F \) is the vector from origin point to a certain solution. Obviously, the \( \theta_1 \) is minimum among \( \theta_1, \theta_2, \theta_3, \) and \( \theta_4 \) for the solution vector \( F \), so this solution is allocated to the reference point corresponding to \( v_3 \).

Afterward, the clustering result of each solution in \( P_t \) is the same as the reference point it belongs. This clustering method makes the clusters have better spatial distribution.

Second is offspring generation: Two ways, that is, inter-cluster and intra-cluster generation, are designed for this purpose according to the probability \( P_{\text{m}} \) as displayed in Fig. 4. The inter-cluster generation is adopted to improve the exploitation of the LRD-BSO algorithm. The new solutions
which is determined by the probability \( p \) are generated by one or two solution(s) in current cluster. The details of the above processes are shown in Algorithm 2.

FIGURE 3. The solution allocation based on angle value.

Algorithm 2 Offspring Generation

1: \textbf{Input:} Population \( P_t \), Cluster results \( \text{Cluster}_i \), Probability \( p_{\text{one}} \), Probability \( p_m \);
2: \textbf{Output:} Population \( Q_t \);
3: // Generation offspring process
4: for \( i = 1 \) to \( N \)
5: if random < \( p_{\text{one}} \) then
6: if random < \( p_m \) then
7: \( \text{pselect} \leftarrow \text{a solution is randomly selected from the } \text{Cluster}_i \);\n8: else
9: \( \text{pselect} \leftarrow \text{two solutions are randomly selected from the } \text{Cluster}_i \) and made the weighted sum;
10: end if
11: else
12: \( \text{pselect} \leftarrow \text{two solutions are randomly selected from the } \text{Cluster}_i \) and another random cluster respectively, and made the weighted sum;
13: end if
14: \( Q_t[i] \leftarrow \text{perform mutation operation on the } \text{pselect} \);
15: end for

FIGURE 4. The procedure of selecting parent individuals.

are generated by one or two solution(s) in current cluster which is determined by the probability \( p_{\text{one}} \). The intra-cluster generation is designed to improve the exploration of the LRD-BSO algorithm. The new solutions are generated by two solutions from two clusters. It should be emphasized that two parent solutions carry out the weighted sum and polynomial mutation operation to generate new solutions, while one parent solution only needs polynomial mutation operation. The details of the above processes are shown in Algorithm 2.

Algorithm 3 Environment Selection

1: \textbf{Input:} Combined population \( R_t \);
2: \textbf{Output:} Population \( P_{t+1} \);
3: // Environment selection process
4: \( S_t \leftarrow \text{Pareto-Nondominated-Sorting}(R_t) \);
5: \( I(S_t) \leftarrow \text{Objective-Space-division}(R_t) \);
6: \( C(S_t) \leftarrow \text{Convergence-Degree}(R_t) \);
7: \( \{F_{LRD,1}, F_{LRD,2}, \ldots \} \leftarrow \text{LRD-Nondominated-Sorting}(S_t) \);
8: \( P_{t+1} \leftarrow \emptyset \); \( i \leftarrow 1 \);
9: while \( |P_{t+1}| + |F_{LRD,i}| < N \)
10: \( P_{t+1} \leftarrow P_{t+1} \cup F_{LRD,i} \);
11: \( i \leftarrow i + 1 \);
12: end while
13: \( P_{t+1} \leftarrow P_{t+1} \cup \text{Truncation-Selection}(F_{LRD,i}, N - |P_{t+1}|) \);

3) ENVIRONMENT SELECTION OBJECTIVE SPACE DIVISION BASED DOMINANCE RELATION

In this section, next generation population \( P_{t+1} \) with \( N \) elite solutions is obtained from the combined population \( R_t \) with \( 2N \) solutions \( (P_t \) and \( Q_t \). The specific environment selection process includes three parts, and the details are displayed in Algorithm 3.

\( a: \text{PARETO NON-DOMINATE SORTING} \)

The Pareto dominance level of solutions in combined population \( R_t \) are calculated by the Pareto non-dominated sorting [19]. For the population \( S_t = \bigcup_{i=1}^{T} F_i \), \( F_i \) is the Pareto-dominated level and \( \tau \) holds \( \sum_{i=1}^{\tau-1} |F_i| \leq N \) and \( \sum_{i=1}^{\tau} |F_i| \geq N \). For the problems with high number of objectives, \( |F_i| \) is almost always greater than \( N \), which means that \( S_t = F_1 \) [28]. So, the solutions in \( F_1 \) should make a further distinction through the LRD relation proposed by us.

\( b: \text{LRD NON-DOMINATE SORTING} \)

For a \( M \)-objective problem, if a point (solution) can minimize \( k(k < M) \) objectives simultaneously in current population, it is a corner point [29]. Take the corner point as the center, each solution of current population is assigned to the corner point with the smallest Euclidean distance with it, as follows:

\[
I(X) = \arg \min_{i \in \{1, \ldots, M\}} \|f(X) - f(X_{\text{corner},i})\|_2 (9)
\]

where \( X \) is a solution, \( X_{\text{corner},i} \) denotes \( i \)-th corner point and the number of corner points is equal to the number of objectives. So that the objective space is divided into several subspaces. Then, the convergence degree of solution \( X \) is defined as follows [30]

\[
C(X) = \sum_{i=1}^{M} f_i(X) (10)
\]
The new dominance relation takes the dominance comparison among local region solutions, named local region dominance (LRD). The definition of the LRD is as follows:

**Definition 1 (LRD):** Suppose that there are two solutions $X_1$ and $X_2$; $I(X_1)$ is the subspace index which $X_1$ belongs, obtained from above (9); and $X_1$ is LPD-dominance $X_2$ (denoted by $X_1 \lessdot_{\text{LRD}} X_2$), if the following two conditions hold true:

$$I(X_1) = I(X_2) \& C(X_1) < C(X_2) \quad (11)$$

It’s noted that, only the solutions are assigned to the same subspace can make the LRD relation comparison.

The LRD-dominated levels of solutions in $S_t$ are obtained by the LRD non-dominated sorting, after calculating the $I$ and $C$ values of each solution. For the population $S' = \bigcup_{i=1}^{N'} F_{\text{LRD},i}$, $F_{\text{LRD},i}$ is the LRD-dominated level and $\tau$ holds $\sum_{i=1}^{\tau} |F_{\text{LRD},i}| \leq N$ and $\sum_{i=1}^{\tau+1} |F_{\text{LRD},i}| \geq N$. The solutions from $F_{\text{LRD},1}$ to $F_{\text{LRD},\tau+1}$ are reserved in the $P_{t+1}$, and $N-|P_{t+1}|$ solutions are selected from the $F_{\text{LRD},\tau}$ based the angle crowded distance to fill the slots of population $P_{t+1}$.

### C: TRUNCATION BASED ON ANGLE CROWDING DISTANCE

In the final selection from the $F_{\text{LRD},\tau}$, we are inclined to delete the solutions located in the denser distribution area. For the MaOP, the Euclidean distance has been proved to be unable to measure the similarity of solutions well [31]. So, angle crowded distance is introduced in LRD-BSO to make it. The difference between the Euclidean crowded distance and the angle crowded distance is shown in Fig. 5. The solid dot 8 should be deleted based on the Euclidean distance, which is shown in Fig. 5(a). And the solid dot 11 should be deleted according to the angle crowded distance shown in Fig. 5(b). Obviously, the solid dot 11 locates at a denser area than the solid dot 8.

Accordingly, the angle crowded distance may provide a more promising way to describe the solution distribution. $N-|P_{t+1}|$ solutions with larger angle crowded distance are preserved in the final selection to improve the diversity of the LRD-BSO.

### V. DECISION-MAKING PROCESS

Two decision-making methods are provided in this article to help decision makers make the suitable option. One is Simple additive weighting method (SAWM), and the other method is technique for order preference by similarity to ideal solution (TOPSIS). SAWM is for the decision makers who have certain prior knowledge about the UDS design problem. MTOPSIS is for the decision makers who know so little about the problem that they can’t give the relatively important degree of different objectives. The details of two methods are introduced as follows.

#### A. SIMPLE ADDITIVE WEIGHTING METHOD(SAWM)

The core idea of the SAWM is that setting a weight for each attribute so as to evaluate the quality of alternatives according to the weight sum of its attributes [32], [33]. The algorithm contains three main operations, that is, normalization, weight setting and calculation of weight sum [34]. The details are summarized as follows:

1) Normalize the decision matrix to make different attributes comparable. As the most frequent normalization way [33], [34], the Max method is adopted in this article. The formula for the normalization is shown as follows.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{x_{ij}^+}, & j \in \Omega_{\text{max}} \\ \frac{x_{ij}^-}{x_{ij}}, & j \in \Omega_{\text{min}} \end{cases} \quad (12)$$

where $X$ is the decision matrix, $x_{ij}$ is the $j$th attribute value of the $i$th alternative, $x_{ij}^+$ represents the maximum value of the $j$th benefit attribute as well as $x_{ij}^-$ denotes the minimum value of the $j$th cost attribute. $\Omega_{\text{max}}$ and $\Omega_{\text{min}}$ indicate both the benefit and cost attribute set and $r_{ij}$ denotes the normalized value.

2) Set weight for each attribute according to the Formula (13),

$$W = (w_1, w_2, \ldots, w_n) \quad (13)$$

3) Calculate the attribute weight sum of each alternative according to the Formula (14),

$$A_i = \sum_{j=1}^{n} r_{ij}w_j \quad (14)$$

where $A_i$ is the attributes weight sum of the $i$th alternative. In the SAWM, the weight sum $A_i$ denotes the quality of the $i$th alternative. The higher the better.

#### B. MODIFIED TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SOLUTION(MTOPSIS)

Technique for order preference by similarity to Ideal solution (TOPSIS) was proposed by Hwang and Yoonin [35]. The further study is given in [36]. The essential idea of the TOPSIS is to identify positive ideal point and negative ideal point respectively. The solution closest to the positive ideal point while furthest from the negative ideal point is thought to be best one. The procedures are listed as follows.
1) Normalize the decision matrix according to Formula (15) and compute the weight sum of normalized decision matrix according to Formula (16).

\[ r_{ij} = \frac{x_{ij}}{\sum_{k=1}^{m} x_{kj}^2}, \quad i = 1, \ldots, m; \quad j = 1, \ldots, n \]  
\[ u_{ij} = r_{ij}w_j \]  

where \( w_j \) is the weight of the \( j \)th attribute.

2) Determine the positive/negative ideal point as the Formulas (17) and (18):

\[ A^+ = \{u_{ij}^+, \ldots, u_{ni}^+\} \]  
\[ A^- = \{u_{ij}^-, \ldots, u_{ni}^-\} \]

where \( A^+ \) and \( A^- \) indicate both positive and negative ideal point. For the beneficial attributes, the positive and negative ideal point are maximum and minimum attribute value among all alternatives, respectively. While the positive ideal point is maximum attribute value as well as maximum attribute value denotes negative ideal point for the cost attributes.

3) Calculate the distances between each alternative and two types ideal solution according to the Formula (19) and (20):

\[ B_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad i = 1, \ldots, m \]  
\[ B_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \quad i = 1, \ldots, m \]  

4) Compute the relative distance between the ideal solution and each alternative according to the Formula (21). And the alternatives with highest relative distance \( C_i \) is thought to be best.

\[ C_i = \frac{B_i^-}{B_i^+ + B_i^-} \]  

VI. CASE STUDY RESULT AND DISCUSSION
In this section, a classical urban drainage system proposed by Mulsselman and Talavage [37], is used as a case study to verify the effectiveness of the proposed framework. The details of the UDS case are described as follows.

A. CASE STUDY DESCRIPTION
The conceptualization of UDS case is shown in Fig.6. The runoff from rainfall and snowfall is guided to treatment facility before being released into the receiving body of water. It is usually transferred to a temporary storage facility to wait for treatment firstly as it could not be immediately treated. Once the storage facility is filled, any new runoff either overflows into the receiving body of water or it backs up.

For the optimization of this UDS case, the decision variables of subbasin’s optimization model are \( x_1, x_2, \) and \( x_3 \), where \( x_1 \) is storage capacity in local detention(basin\textbullet inches), \( x_2 \) denotes the highest rate of treatment (basin\textbullet inches/hour), and \( x_3 \) represents maximum permissible overflow rate (basin\textbullet inches/hour). The five initial objectives of the proposed many-objective optimization objective model are all considered. Besides, seven different kinds of constraints are also considered and the description of each constraint is as follows:

- Mean number of floods per year \( y_1 \).
- Mean annual floods \( y_2 \).
- Mean weight of suspended solids per year \( y_3 \).
- Mean weight of sediment solids per year \( y_4 \).
- Mean weight of biochemical oxygen demand per year \( y_5 \).
- Mean annual total nitrogen weight \( y_6 \).
- Mean weight of positive phosphoric acid per year \( y_7 \).

The hydrologic performance of the subbasin is simulated by an urban hydrologic simulation program named LANDSTORM [37], and twenty-three years of recorded rainfall data from the studied area as well as the land characteristics are used as the simulation input. Due to the model outputs is obtained from the simulation software, it is necessary to approximate the simulation outputs by regression models. To this end, numerous models are attempted for each of the output, and the model with respectable fit performance is chosen. The objective function and constraint function expressions are displayed in Table 2 and Table 3, respectively.

B. RESULT AND DISCUSSION
1) COMPARISON OF LRD-BSO WITH OTHER ALGORITHMS
To verify the effectiveness of the proposed LRD-BSO in solving many-objective problems, three multi-objective SI optimization algorithms, NSGA-III [38], NSGA-II [19], and MOPSO [39], are selected for comparative experiments. The experiments are conducted on the many-objective UDS optimization model of above study case. The parameter setting of three compared algorithms is the same as the original papers and the parameters of LRD-BSO are listed in Table 4.

The indicator HV [40] is utilized to evaluate the convergence and diversity performance of these four algorithms. The HV values (the higher the better) of the four algorithms are shown in Table 5 and Fig. 7. It can be seen that the
proposed LRD-BSO performs significantly better than the three compared algorithms (i.e., NSGA-III, NSGA-II, and MOPSO). Even with the worst case of the HV value 0.5206, it still has best performance among the four algorithms.

Compared with NSGA-III algorithm, the performance of LRD-BSO is better. As we all knows, the searching process of NSGA-III performs well when the optimization problem with regular Pareto front. as it is guided by a set of uniformly distributed reference vector. But it is highly probability that the study case owns an irregular Pareto front, which may lead to the poor performance.

2) PARETO-OPTIMAL SOLUTION SET

As for the NSGA-II and MOPSO, crowd distance and grid method can’t work well in the high-dimensional objective space to maintain the diversity of solutions. While the novel offspring generation process in LRD-BSO ensures both exploration and exploitation, which will promote the production of the high-quality new solutions. Moreover, the angle-based selection strategy is beneficial to improve the selection pressure and maintain the diversity of solutions. Therefore, it’s reasonable that the proposed LRD-BSO possesses remarkable performance compared with other three multi-objective EAs.

To make the decision makers easily understand and study, the parallel axis plot is used to display the distribution of Pareto-optimal solution set. Two design examples of the UDS

| TABLE 2. The objective function expression. |
|---------------------------------------------|
| Name                                    | Function Expression          |
| Minimize five Objectives                  | 0.00139 / x_i x_j + 4.94x_j - 0.08 ≤ 1 |
| Cost of drainage network                  | 0.0000306 / x_i x_j + 0.1082x_j - 0.00986 ≤ 0.10 |
| Cost of storage device                    | 12.307 / x_i x_j + 49408.24x_j - 4051.02 ≤ 500000 |
| Cost of treatment device                  | 2.098 / x_i x_j + 8046.33x_j - 696.71 ≤ 160000 |
| Intended flood damage loss                | 2.138 / x_i x_j + 7883.39x_j - 705.04 ≤ 100000 |
| Intended economic loss caused by flooding | 0.417 / x_i x_j + 1721.36x_j - 136.54 ≤ 2000 |
| (5) Intended economic loss caused by flooding | 0.164 / x_i x_j + 631.13x_j - 54.48 ≤ 550 |

| TABLE 3. The constraint function expression. |
|-----------------------------------------------|
| Function expression                           |                                        |
| \( y_1(x) = 0.00139 / x_i x_j + 4.94x_j - 0.08 \leq 1 \) |
| \( y_2(x) = 0.0000306 / x_i x_j + 0.1082x_j - 0.00986 \leq 0.10 \) |
| \( y_3(x) = 12.307 / x_i x_j + 49408.24x_j - 4051.02 \leq 500000 \) |
| \( y_4(x) = 2.098 / x_i x_j + 8046.33x_j - 696.71 \leq 160000 \) |
| \( y_5(x) = 2.138 / x_i x_j + 7883.39x_j - 705.04 \leq 100000 \) |
| \( y_6(x) = 0.417 / x_i x_j + 1721.36x_j - 136.54 \leq 2000 \) |
| \( y_7(x) = 0.164 / x_i x_j + 631.13x_j - 54.48 \leq 550 \) |

| TABLE 4. The parameter settings for LRD-BSO algorithm. |
|--------------------------------------------------------|
| Population size | Iteration number | \( P_m \) | \( P_{max} \) |
| 100             | 100000           | 0.8        | 0.2           |

| FIGURE 7. The comparison of four algorithms on HV value. |

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FIGURE 8. The parallel axis plot presents the trade-off among five optimization objectives in UDS optimal design, in which each axis represents an optimization objective and each line passing through the five coordinate axes denotes a Pareto-optimal solution. a) the Pareto-optimal solutions that the drainage network cost lies between 65000$ and 70000$ are marked in red, b) the Pareto-optimal solutions that the storage cost lies between 300$ and 800$ are marked in red. problem are provide to explain the meaning of the parallel axis plot here.

The first example shows the feasible solutions (marked in red) when the budget of drainage network cost is from 65000$ to 70000$, which is shown in Fig. 8 (a). From Fig. 8, the decision makers can select the solution that satisfies their need from the feasible solutions further. The second example gives the solutions, marked as red in Fig. 8(b), when the storage cost is given priority, from 300$ to 800$. The decision makers can also choose the proper solution from the marked solutions.

3) THE FINAL DECISION-MAKING

As mentioned above, it is very important to help UDS decision makers select an appropriate solution from the obtained Pareto-optimal solution set. The multi-attribute decision-making methods are adopted to make the final decision by considering not only the optimization objectives but also the aspects difficult to express mathematically for practical reasons.

TABLE 6. The final scheme of decision-making process.

| Objective value | $f_1$(S) | $f_2$(S) | $f_3$(S) | $f_4$(S) | $f_5$(S) |
|----------------|---------|---------|---------|---------|---------|
| 60805.8        | 300.0   | 83892.0 | 3710500.0 | 13530.0 |

| Decision variable value | $x_1$ (basin-inches) | $x_2$ (basin-inches/hour) | $x_3$ (basin-inches/hour) |
|-------------------------|----------------------|--------------------------|--------------------------|
| 0.1000                  | 0.0294               | 0.0301                   |

TABLE 7. The final scheme of decision-making process.

| Objective value | $f_1$(S) | $f_2$(S) | $f_3$(S) | $f_4$(S) | $f_5$(S) |
|----------------|---------|---------|---------|---------|---------|
| 63872.0        | 78.0    | 39351.0 | 6497400.0 | 128990.0 |

| Decision variable value | $x_1$ (basin-inches) | $x_2$ (basin-inches/hour) | $x_3$ (basin-inches/hour) |
|-------------------------|----------------------|--------------------------|--------------------------|
| 0.0260                  | 0.0103               | 0.0100                   |

In this study case, the citizen satisfaction is also considered in the decision-making process besides the five objectives described in the optimization model. Assumed that the citizen satisfaction is measured by scoring between 0 and 1. The goal of the decision maker is to minimize the five optimization objectives and improve citizen satisfaction. So, the former are five cost attributes and the latter is benefit attribute.

When the decision makers have certain prior knowledge for the USDS design problem, SAWM can make the suitable decision. They can provide the weight of each attribute. For example, the weight vector is randomly set as $M$. According to the procedures of SAWM, the weighted sum value $A_i$ of each solution is obtained and the solution with highest value shown in Table 6. The final output depends on the weight vector, and different weight vector means the different design requirements.

For the decision makers who can’t give the relatively weight of different objectives, TOPSIS can help them make decisions. According to the step of TOPSIS mentioned in section 5, set all attributes to equal weight, the relative distance $C_i$ to the ideal solution of each alternative is obtained and the solution with maximum $C_i$ is the optimal scheme in this decision-making process, which is shown in the Table 7.

The above multi-attribute decision-making process not only consider the five objectives of UDS optimization model, but also the citizen satisfaction that can’t be expressed mathematically. For the SAWM method, the decision makers can participate in the design of the UDS by determine the weight vector, which might reduce the bad procedural results, resistance and conflicts when decision-makers feel undervalued and neglected. On the other hand, TOPSIS can help decision-making when the decision-makers do not give weight vector, and the result can provide reference for the final UDS design.
It must be noted that the decision-making results are based on a specific case study and no general conclusion can therefore be made. However, the proposed framework can be applied to different case studies with different situation.

VII. CONCLUSION
With the improvement of urbanization level, the effective UDS is more and more necessary. An integrated decision-making framework based on many-objective optimization is proposed to make the optimal design of UDS. It consists of three parts: model formulation, many-objective optimization and final decision-making. Firstly, a generic many-objective mathematical model of UDS is presented considering five objectives simultaneously. Then as the solver of the model mentioned above, the effective LRD-BSO based on the LRD-dominance is designed to get the Pareto-optimal solution set. Lastly, a case study is applied to verify the effectiveness of the proposed framework. The comparison experiments with three multi-objective SI algorithms also shows the promising performance of the proposed LRD-BSO. The further research may focus on the improvement of the computational performance as the efforts of the SI algorithms may increase exponentially when the scale of UDS design problem expands. Besides, there are many uncertainties in the actual UDS design process. The current optimization model does not explicitly take the uncertainty (e.g., randomness of rainfall events) into account. Hence, our future work will extend the proposed optimization model to the uncertainty of UDS.

CONFLICT OF INTEREST
The authors declare that they have no conflict of interest.

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