Fuzzy Optimization Framework for Facilitating Best Management Practices in the Context of Urban Floods

Rohit Dwivedula, Rampalli Madhuri, K. Srinivasa Raju, and A. Vasan

Abstract Placement of best management practices (BMPs) is a constructive approach to control surface runoff. However, deciding where these BMPs need to be placed in practice remains a complex question, often requiring practitioners in the field to analyze trade-offs between the financial capital available and physical goals such as runoff reduction and pollutant reduction. This work describes a multiobjective optimization framework applied to Greater Hyderabad Municipal Corporation (GHMC), India, for the 2016 flooding event. The fuzzy approach converts a multi-objective optimization problem to a single objective problem through a membership function. Three membership functions, namely, nonlinear, exponential, and hyperbolic, were employed. Single Objective Genetic Algorithm (SOGA) is used for performing the optimization. Performing the optimization procedure with hyperbolic membership function yielded a degree of satisfaction, $\lambda = 0.8796$, corresponding to a BMP configuration spanning 61.98 km^2 of the urban case study area. This configuration would have reduced surface runoff by 1.02×10^7 m^3 while removing 73.87 tons of pollutants during this historic extreme rainfall event and arrived at a monetary cost of Rs. 1.16×10^{10}. Using the exponential membership function with 125 different sets of parameters yielded solutions with λ ranging from 0.5479 to 0.6432, and the average value of λ is 0.5950. Similar experiments with a nonlinear membership function yielded λ varying from 0.1307 to 0.9601 with an average λ of 0.5454.

Keywords Best management practices (BMPs) · Fuzzy optimization · SOGA

R. Dwivedula
Department of Computer Science & Information Systems, BITS Pilani, Hyderabad Campus, Hyderabad 500078, India
e-mail: f20170029h@alumni.bits-pilani.ac.in

R. Madhuri (✉) · K. Srinivasa Raju · A. Vasan
Department of Civil Engineering, BITS Pilani, Hyderabad Campus, Hyderabad 500078, India
e-mail: p20140406@hyderabad.bits-pilani.ac.in

K. Srinivasa Raju
e-mail: ksraju@hyderabad.bits-pilani.ac.in

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1 Introduction

Best management practices (BMPs) have been widely used for over two decades globally to manage flood risks, remove pollutants, or reduce sediment in water bodies [1–3]. To optimize the placement of BMPs, the present approaches use a range of mathematical optimization techniques such as integer programming, nonlinear programming, and evolutionary algorithms [4]. Behroozi et al. [5] used multiobjective particle swarm optimization (PSO) in District 10, Tehran, Iran, to minimize peak water flow rate and pollutant concentration. Singh et al. [6] describe a case study from Heredia, Costa Rica, where bioretention areas, green roofs, and infiltration trenches are placed in an urban setting to control flood risks. They use a nonlinear programming technique to optimize and formulate the trade-offs between land use and cost. Foomani and Malekmohammadi [7] proposed fuzzy logic and analytic hierarchy process for identifying optimum locations of BMPs in the northern region of Tehran, Iran. Li [8] developed SWMM_FLC, a combination of SWMM, fuzzy logic control, and GA, to reduce downstream flooding volume. Zhang et al. [9] applied Storm Water Management Model (SWMM) and System for Urban Stormwater Treatment and Analysis Integration (SUSTAIN) to conduct watershed-level optimization for Sponge City, China. Annual average runoff volume and total pollutants reduced workout to 87.61% and 85%. Dwivedula et al. [10] employed an ensemble of (1) nondominated sorting genetic algorithm-III and (2) constrained two-archive evolutionary algorithm for optimizing zone-wise BMP placement in GHMC. Studies presented here, including that of [10] and elsewhere, have not reported any applications of fuzzy optimization in the placement of BMPs.

2 Study Area and Data Source

2.1 Greater Hyderabad Municipal Corporation

In this study, a fuzzy multiobjective approach is used to optimize the placement of BMPs for GHMC as a whole (not zone-wise). This section briefly describes the following:

- Case study and process(es) used to identify potential BMP sites.
- Multiobjective optimization problem, i.e., the decision variables, objectives, and constraints.
- Fuzzy optimization framework and membership functions used.
- Single Objective Genetic Algorithm (SOGA).

The fuzzy optimization process allows converting a multiobjective problem to a single objective problem, enabling us to use a Single Objective Genetic Algorithm (SOGA). Figure 1 presents the study area.

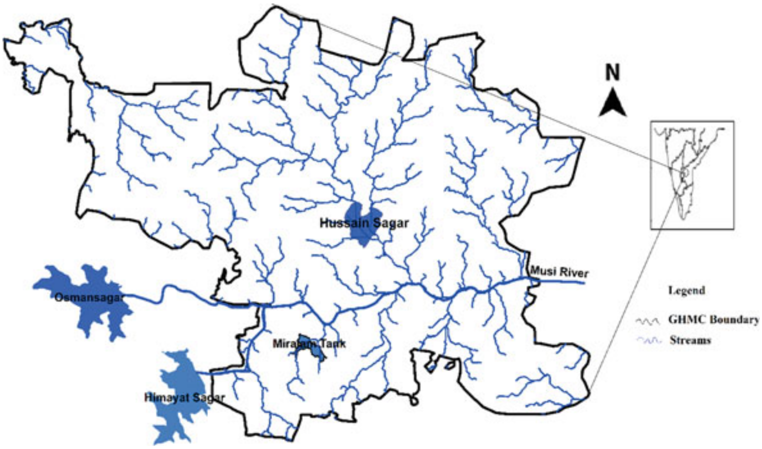

Fig. 1 Study area of GHMC

2.2 *Data Used*

The present study examines a historic extreme rainfall event of 237.5 mm during September 20–28, 2016. We attempt to analyze the impact of BMP placement if a similar extreme event was to happen again. Hydrologic Engineering Centre's-Hydrologic Modeling System (HEC-HMS) was employed to simulate surface runoff [11] and SUSTAIN [12] was used for identifying the potential BMP sites. EPA-SUSTAIN siting tool identified a total of 5,45,895 possible sites. Nine types of BMPs are being considered for placement in the GHMC.

2.2.1 Multiobjective Optimization Problem

The three objectives we wish to optimize are maximizing runoff reduction volume Z_1 (in m^3) and pollutant load reduction Z_2 (in tons) while minimizing the cost of construction Z_3 (in Indian Rupees). For an individual BMP for total area A_k, we can select (all the areas/a fractional part of an area/none of an area. This choice is encapsulated as a *decision variable*, denoted by X_k $(0 \leq X_k \leq 1)$. There is a total of K decision variables. The decision variables (X) are related to the objectives (Z) as:

$$\begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \end{bmatrix} = \sum_k \left\{ \begin{bmatrix} R_k * \rho_k \\ S_k * \eta_k \\ -1 * d_k * c_k \end{bmatrix} * A_k * X_k \right\} \forall k \in [0, k] \tag{1}$$

where R is the rainfall, S is the runoff, ρ is the runoff reduction efficiency of the BMP, η is the pollutant reduction efficiency, d is the depth of the BMP, and c is the construction cost of the BMP per unit volume. More details about case studies, modeling, and data requirements are available from [10].

2.2.2 Fuzzy Optimization and Membership Functions

Our problem in optimization is maximizing the objectives (Z). Lower Z_L and upper limits Z_U for goals are shown in Table 1.

Each objective Z can be represented as a function of the decision variables (X), i.e., $Z_i = f_i(X)$ (Eq. 1). In this work, we define a membership function denoted by $\mu_z(X)$ for each objective. We studied hyperbolic, exponential, and nonlinear membership functions (refer to Table 2).

For all three membership functions, $Z \leq Z_L$ is 0 and $Z \geq Z_U$ is 1.

We notice that the hyperbolic membership function does not have any parameters that the decision-maker must choose, unlike nonlinear or exponential membership functions. S is a non-zero parameter $0 < S \leq 1$ [13]. β determines the shape of the membership function.

The fuzzy optimization problem (with N objectives) is as follows:

Maximize λ, subject to constraints:

$\mu_z(X) \geq \lambda \ \forall i \in \{1, 2, \ldots N\}$
$0 \leq \lambda \leq 1$
$Z_1 \geq 3.5 \times 10^6\ \text{m}^3$ and $Z_2 \geq 25$ tons

along with other existing constraints and bounds.

Table 1 Lower and upper limits of the objective functions

Objective	Units	Z_L	Z_U
Runoff reduction (Z_1)	10^7 m^3	0	1.547
Pollutant load reduction (Z_2)	10^{11} mg	0	1.109
Monetary cost (Z_3)	10^{10} Rs	– 3.497	0

Table 2 Types of membership functions and corresponding equations for $Z_L < Z < Z_U$

Hyperbolic	$\frac{1}{2}\tanh\left[\left(Z - \frac{Z_U+Z_L}{2}\right)\frac{6}{Z_U-Z_L}\right] + \frac{1}{2}$
Exponential	$\left[\frac{e^{-S\left(\frac{Z_U-Z}{Z_U-Z_L}\right)} - e^{-S}}{1-e^{-S}}\right]$
Nonlinear	$\left[\frac{Z-Z_L}{Z_U-Z_L}\right]^{\beta}$

2.2.3 Single Objective Genetic Algorithms

SOGA with a population size of 1000, simulated binary cross-over probability of 0.9 [14], polynomial mutation probability of 0.1 [15], and tournament selection are used for optimization. The PyMoo library [16] is employed for implementing the optimization functions.

3 Results and Discussions

The results of optimization with three membership functions are as follows. All source codes used to run these experiments have been open sourced under the MIT license and are available online.[1]

3.1 Hyperbolic Membership Function

Performing the optimization procedure with hyperbolic membership function for all three objectives yielded a solution of satisfaction $\lambda = 0.8796$, corresponding to a real-world configuration of BMPs spanning 61.98 km^2 of area, which reduce surface runoff by $1.02 \times 10^7 m^3$, while removing 73.87 tons of pollutant at a monetary cost of Rs. 1.16×10^{10}. The progress of SOGA can be visualized by plotting the best-discovered value of λ against the number of function evaluations as depicted in Fig. 2.

3.2 Exponential Membership Function

Next, we present the results of the exponential membership function. Optimization procedure was run with 125 different configurations of the parameter s such that: s_1, s_2, $s_3 \in \{0.2, 0.4, 0.6, 0.8, 1\}$.

Here, s_1, s_2, s_3 are the parameters for runoff reduction, pollutant load reduction, and cost (Z_3). Use of exponential membership function with these 125 different sets of parameters yielded solutions with λ ranging from 0.5479 to 0.6432. The average value of λ is 0.5950. Optimization convergence of all these 125 different sets of parameters can be visualized in Fig. 3. Each line in Fig. 3 represents a different set of parameters. It is noticed that all the lines follow similar trends, suggesting that the optimization process is not very sensitive to changes in parameters s_1, s_2,

[1] Link to code repository: https://github.com/rohitdwivedula/bmp-multiobjective-optimisation (https://doi.org/10.5281/zenodo.6676306).

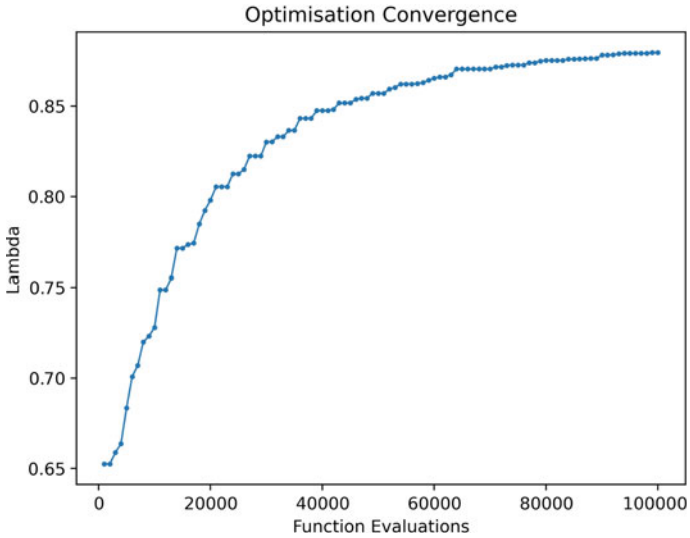

Fig. 2 Optimization process with hyperbolic membership function for all three objectives

s_3. We also notice that the value of λ begins to plateau for most lines after the 60th generation (or 60,000 function evaluations), indicating that the optimization approach has converged.

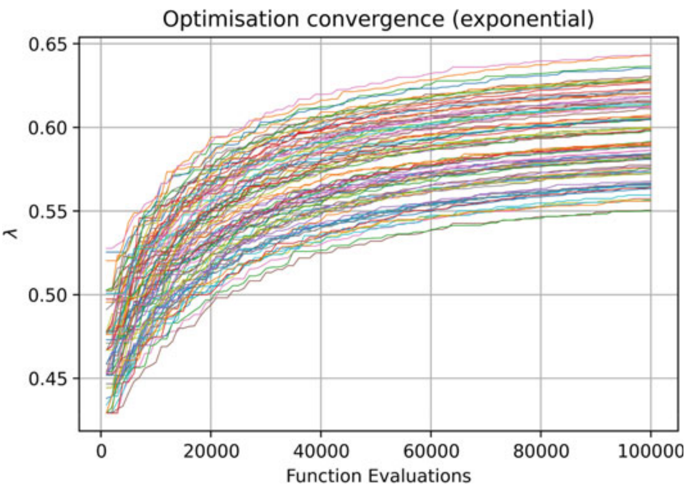

Fig. 3 Optimization process with exponential membership function for all three objectives and various values of the parameter

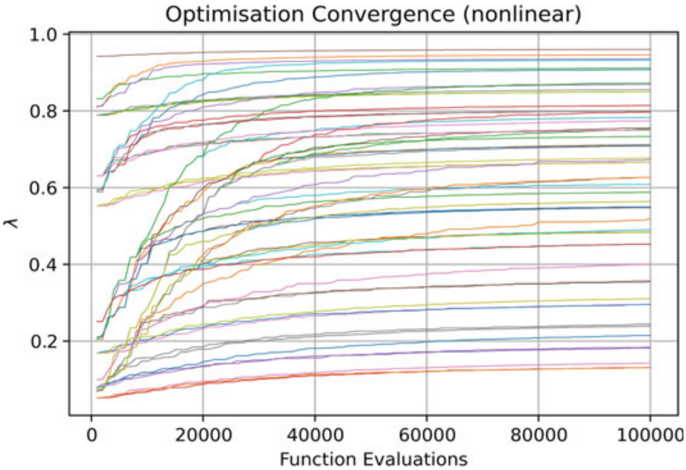

Fig. 4 Optimization process with nonlinear membership function with varying values of membership function parameter β

3.3 Nonlinear Membership Function

Use of nonlinear membership function with 125 different sets of parameters yielded solutions with λ ranging from 0.1307 to 0.9601 with a moderate satisfiability of $\lambda = 0.5454$. The parameters of β_i used were: $\beta_1, \beta_2, \beta_3 \in \{0.1, 0.4, 1.0, 3.0, 5.0\}$.

Here, β_1, β_2, and β_3 are the parameters for Z_1, Z_2, and Z_3, respectively. Optimization convergence for nonlinear membership functions is plotted in Fig. 4, similar to the plots in previous sections. One key difference noticed is that solution is susceptible to changes in the parameter β. For example, using $(\beta_1, \beta_2, \beta_3) = (5, 5, 5)$ yields the least value of $\lambda = 0.1307$, while $(\beta_1, \beta_2, \beta_3) = (0.1, 0.1, 0.1)$ yields the highest value of $\lambda = 0.9601$. Values of β_i will have to be decided based on the relative importance of each objective; that is, objectives that are relatively more important must have a larger β relative to others.

4 Conclusions

A fuzzy optimization approach was applied to optimize BMPs in the GHMC. Experimentation was done with a wide range of parameters to analyze the sensitivity of each membership function with its parameters. It is observed that the nonlinear membership function is relatively more sensitive to changes in parameters when compared to the exponential membership function. Future work could include experimentation with more optimization algorithms, extending the analysis for potential future rainfall events, and applying this framework to other case studies.

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