Multiobjective Optimization of Low Impact Development Scenarios in an Urbanizing Watershed

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Abstract

Low Impact Development (LID) is a relatively new concept in urban stormwater control, and it emphasizes on using distributed on-site Integrated Management Practices (IMPs) to reach both water quantity and quality control goals. Previous studies were focused on using a single type of IMP, such as detention basins, and trying to reach an optimum control design. This research focuses on using both infiltration and the detention types of IMPs to reach the optimal control. A revised version of the Non-dominated Sorted Genetic Algorithm-II (NSGAII) alogrithm, the Epsilon Non-dominated Sorted Genetic Algorithm (ε-NSGAII) (Kollat and Reed, 2005), was used to optimize various LID designs on an urbanizing watershed. The optimization process results in a non-dominant Pareto front between total cost and the water quantity performances, and this tradeoff front is very valuable for informed and defendable stormwater decision-makings.

1 INTRODUCTION

Decision-making in stormwater control always involves maximizing the improvements in stormwater runoff quantity and quality while minimizing the total control cost. Thus a Pareto-front that depicts the trade-off between the total cost and the improvements in runoff conditions is crucial to defendable stormwater control decision-making. Previous studies either rely on traditional gradient-based methods to carry out the optimization (Elliot, 1998; Lee, et al., 2005) or focus on optimizing a single type of IMP, such as detention basins (Harrell and Ranjithan, 2003; Zhen, et al., 2004). There lacks a powerful tool that is capable of optimizing LID designs, which consists of both detention type of IMPs and infiltration type of IMPs such as green roof and porous pavement.

In this study we use the Epsilon-Dominance Non-Dominated Sorted Genetic Algorithm II (ε-NSGAII), which is a revised version of the NSGAII developed by Deb et al. (2002), to carry out the optimization of LID designs on an urbanizing watershed. Potential IMP types and sizes, as well as their costs and efficiencies in stormwater control are evaluated and optimized by ε-NSGAII. A total number of 38,000 LID scenarios are evaluated and 47 non-dominated solutions between total cost and performances in runoff volume and peak rate are identified. The USEPA Stormwater Management Model (SWMM version 5.0) is used for calculating the runoff in each LID design. Section 2 provides an overview of the background in stormwater control optimization. Section 3 introduces the optimization framework used in this study. A real application example is presented in Section 4 with initial results and discussions. Summary and conclusions are provided in Section 5.

2 LITERATURE REVIEW

2.1 URBAN STORMWATER CONTROL CONCEPTS

Urban sprawl always causes increase in surface runoff volume and peak rate, as well as the deterioration in downstream water quality. Traditional stormwater best management practices (BMPs) focus on fast drainage and temporally holding the stormwater at a centralized detention basin. However, this method reduces local groundwater recharge and at the same time causes downstream flooding and deterioration of water quality. The low impact development (LID) concept was first proposed by the Prince George's County, Maryland and is increasingly accepted across the country as a new method in stormwater control.

Different from the traditional stormwater control, which heavily depends on curbs, gutters, and pipe networks to reach fast drainage, the low impact development method emphasize more on controlling the stormwater at the source. The LID method uses small-scale integrated management practices (IMPs) such as green roof, porous pavement, detention basins, and bio-retention area across a watershed, and runoff is encouraged to infiltrate into the ground where it originates. Meanwhile the IMPs are also capable of treating stormwater runoff pollutants such as Phosphorus, Nitrite and Nitrate, Petroleum and oil & grease, Cu, Pb, and other common pollutants found in urban stormwater runoff. The overall goal of the LID method is to mimic the pre-development or natural hydrologic functionally landscape.

2.2 OPTIMIZATION IN STORMWATER CONTROL

In an effort to develop a model for determining the optimal location of stormwater quality controls and thus to reduce the sediment in receiving waters, Elliot (1998) used a gradient-based search procedure in a simplified mathematical model. The search process was repeatedly applied at various starting points and a global optimum was selected based on the results from multiple runs. Lee et al. (2005) used a linear programming solver to optimize the performance of stormwater storage-release systems and on-site wet-weather controls (WWCs).

Optimization of detention pond and land use planning was carried out by Harrell and Ranjithan (2003), who used a simple genetic algorithm (GA) to generate a cost-effective detention pond configuration within sub-catchments of a watershed in order to reach target water quality control. Zhen et al. (2005) investigated the optimization of location and sizing of stormwater basins at the watershed scale. The scatter search method was used to build the optimization model, and a trade-off curve between the total cost and the reduction in pollutants was identified in the study.

2.3 STORMWATER CONTROL COSTS

Life cycle costs of stormwater control usually involve initial construction cost, land opportunity cost, and operation and maintenance (O&M) cost. Since the land opportunity cost and O&M cost are highly site specific, usually the construction cost is used as capital stormwater control cost for analysis purposes (Sample et al., 2003).

The construction costs of different IMPs have been investigated in many studies. Table 1 is a generalization of the construction costs of several types of IMPs.

Table 1: Construction costs of IMPs

IMP TYPE	COST
Detention basins	$C=2.195*10^4V^{0.75}$
Green roof	$C=80000*A$
Sand filters	$C=50300*A$
Bio-retention area	$C=18.5*V^{0.7}$
Porous pavement	$C=65000A$

V is in cubic feet and A is in acres

2.4 NSGAII AND E-NSGAII

The Non-dominated Sorted Genetic Algorithm-II (NSGAII) developed by Deb et al. (2002) is a revision from the original Non-dominated Sorted Genetic Algorithm (NSGA) (Deb, 1995). Compared to the original version, NSGAII reduced the computational complexity, incorporated explicit elitism, and eliminated the need for specifying the sharing parameter of σ_{share} (Coello Coello et al., 2002). In NSGAII, a solution is ranked according to the number of solutions that dominate it. Two-step crowded binary tournament selection is then carried out based on the fitness value of each solution. During the process, the solution with a lower rank is always preferred. When two solutions have the same rank, the one with a larger crowding distance is selected. By doing this NSGAII ensures a more distributed set of solutions along the final Pareto front (Kollat and Reed, 2005).

As a further revision to NSGAII, ε-NSGAII (Kollat and Reed, 2005) adds ε-dominance archiving, adaptive population sizing, and automatic termination to the original NSGAII algorithm (Kollat and Reed, 2005). The ε-dominance is a user-specified factor that determines how precise solution to each objective will be. A large ε value means a coarser grid of the solution space (which means less ultimate solutions) and vice versa. After a user-specified number of generations within each run, the ε-NSGAII automatically adapts its population size according to the "archived" best solutions ever found (Figure 1). Using an injection scheme, the adapted population consists of 25% of the ε-non-dominated archive solutions and 75% of new randomly generated solutions. The search for the Pareto front can be automatically terminated by ε-NSGAII if the number and quality of the solutions have not increased above Δ% within two successive runs (Kollat and Reed, 2005).

When using the ε-NSGAII algorithm, the user needs to specify an initial population size for the algorithm to start with. Other required parameters include the maximum number of function evaluations (nfe) and the maximum generations per run.

The ε-NSGAII algorithm has been successfully applied to long-term groundwater monitoring problems to find the Pareto front between sampling cost and sampling errors (Kollat and Reed, 2005). Various tests also showed that the ε-NSGAII algorithm outperforms the NSGAII and other evolutionary algorithms (EAs) in aspects of distribution and diversity of solutions found, number of function evaluations, and robustness (Kollat and Reed, 2005).

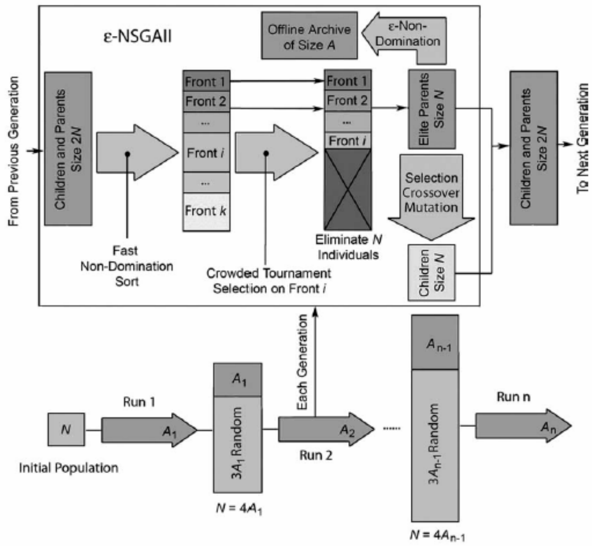

Figure 1: Schematic diagram of the ε-NSGAII algorithm (from Kollat and Reed, 2005)

2.5 THE EPA-SWMM MODEL

Developed by USEPA in 2005, the Stormwater Management Model (SWMM, version 5.0) is a distributed on-site model primarily developed for urban areas. The model is capable of making both water quantity and quality predictions. Typical urban settings such as manholes, underground pipes, storage units, dividers, orifices, weirs, and open channels can all be represented within SWMM. The model has been widely applied to design planning and long-term performance evaluations in urban stormwater control (Huber and Dickinson, 1988; Urbonas and Stahre, 1993; Tsihrintzis and Hamid, 1998; Huber et al., 2005).

3 OPTIMIZATION MODEL

3.1 THE GENERIC PROBLEM FORMULATION

Optimization of urban stormwater control is always the process of identifying the tradeoff curve between conflicting goals of maximizing stormwater control while minimizing the total cost. Given a watershed with m possible locations of applying IMPs, and n is the number of IMP types to select from for each potential location, the optimization of various LID scenarios can be stated as:

Objective:

$$\min \sum_{i=1}^{m}\sum_{j=1}^{n} C_i^j(s_i^j) * y_i^j \qquad (1)$$

$$\min\ t_{ps}\text{-}t_p \qquad (2)$$

$$\min\ q_{ps}\text{-}q_p \qquad (3)$$

$$\min\ V_s\text{-}V \qquad (4)$$

$$\min \sum_{i=1}^{m}\sum_{j=1}^{n}[1 - E_i^{j,P}(s_i^j) * y_i^j] * M_i^P - T^P \qquad (5)$$

subject to:

$$y_i^j = \{0,1\} \quad and \quad \sum_{j=1}^{n} y_i^j = \{0,1\} \quad \forall i, j \qquad (6)$$

$$s_i^j \in S_i \quad \forall i, j \qquad (7)$$

where

C_i^j =cost of IMP type j at location i,
s_i^j =the size of IMP type j at location i,
y_i^j =binary variable that indicates whether IMP type j will be selected or not at location i,
t_{ps}=simulated time to peak,
t_p=target time to peak,
q_{ps}=simulated peak flow rate,
q_p=target peak flow rate,
V_s=simulated total runoff volume,
V=target total runoff volume,
$E_i^{j,P}$ =efficiency of IMP type j at location i in removing pollutant P,
M_i^P =loading of pollutant P to location i,
T^P =target loading of pollutant P,
S_i =feasible range of IMP sizes at location i, m=total number of possible locations to apply IMP techniques, and
n=total number of available IMP techniques.

3.2 OPTIMIZTION ALGORITHM

The ε-NSGAII algorithm is well suited for solving the LID scenario optimization problem. Since both ε-NSGAII and SWMM are available in C code, it is possible to generate an initial population of various LID scenarios in ε-NSGAII and to pass onto SWMM. The SWMM simulated results can then be sent back to ε-NSGAII for evaluation against objectives of cost and water quantity/quality. Mutation and crossover operations can then be carried out afterwards and the process will be iterated until the true Pareto-front is approximated. A pseudo-code for the whole process is shown in Figure 2, and the detailed steps for carrying out the optimization are introduced in the next section.

```
Start
Read SWMM input
While run number<maximum nfe
    Initialize population of LID designs
      Generate random population-size M
    Update SWMM input with population
    Evaluate objective values based on SWMM results
    Assign rank based on Pareto dominance
     For i=1 to number of generations per run
        Combine parent and child population
        Fast non-dominated sorting
        Evaluation of new population in SWMM
        Crowded tournament selection
        Perform ε-non-dominant sorting and update
          archive
        Mutation and crossover
      End loop
      Run injection into population size with three times
        of archive size
End loop
End
```

Figure 2: Pseudo-code for LID Scenario Optimization Using the ε-NSGAII Algorithm

3.3 OPTIMIZATION FRAMEWORK

3.3.1 Initialization of ε-NSGAII

As an initialization of the ε-NSGAII algorithm, a population of LID scenarios is randomly generated. Each individual of the population is made up of a binary part and a real variable part. The binary part depicts which type of IMP to use at each potential site, and the real variable part represents the size of that IMP.

The length of an individual is jointly decided by the number of potential IMP locations, m, within a watershed and by the available IMP types, n. The length, L, can be expressed as:

$$L = m * n_b + m \qquad (8)$$

where n_b is the number of binary digits needed to represent the real numbers 0~n, with 0 represents no IMP is implemented at a certain location.

3.3.2 Evaluation of LID Scenario Population

At each generation of ε-NSGAII, a child generation (N) of LID scenarios is mixed with the parents (N) from previous generation. Each individual in the mixed population is sent to SWMM and evaluated. Objective values including total cost of a scenario, runoff quantity, and runoff quality are calculated. The LID scenarios ($2N$) are then ranked using ε-dominance according to their objective values. A crowded tournament selection is performed on each front and the best N scenarios are selected as the elitist new parent population, which is sent to an offline archive of best LID scenarios ever found. Crossover and mutation operations are also performed on the parent population to generate a new child population (N) of LID scenarios.

3.3.3 Population injection

At the end of each run, the ε-NSGAII automatically changes the population size for the next run through a 25% injection scheme. That is, given an archive size of S best LID scenarios at the end of the previous run, the ε-NSGAII will randomly generate $3S$ new LID scenarios and mix it with the archived S scenarios for the next run. The population size for the next run of ε-NSGAII will then be $4S$. The whole process will be iterated until the maximum number of function evaluations (nfe) is reached.

4 CASE STUDY

4.1 WATERSHED DESCRIPTION

The Fox Hollow Watershed (Figure 3) located at Centre County, Pennsylvania, is used to apply the optimization analysis in this study. The Fox Hollow Watershed is 186 hectares in area and consists of an intensively urbanized Penn State University campus portion and a less developed meadow/pasture land portion. Runoff from the Fox Hollow Watershed contributes to a major downstream groundwater recharge field, which serves as water resources to the University through several potable wells. As the University campus is continuously urbanized and the meadow/pasture land area is to be developed in the future, there is a grave concern about the future stormwater runoff quantity and quality.

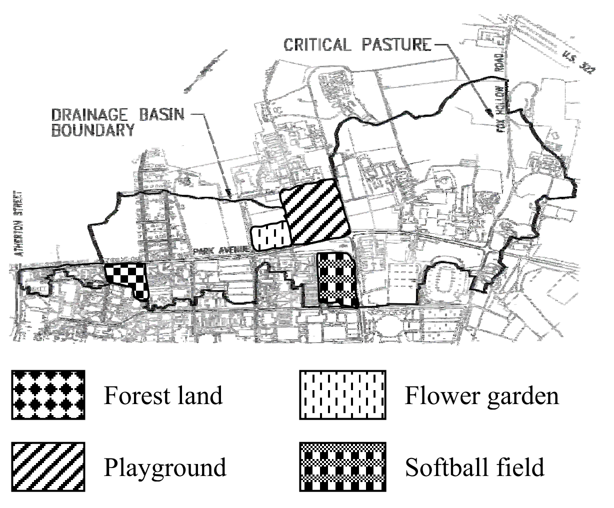

Figure 3: The Fox Hollow Watershed at Centre County, PA, and the Potential Locations for IMP Applications (adapted from Fennessey et al., 2005)

4.2 LID SCENARIO DESIGN

In this study four sub-catchments within the Fox Hollow Watershed are assumed to be developed, and they are the forest land area, the flower garden area, the playground area, and the softball field area (Figure 3). LID scenarios will be applied to the developed sub-catchments and an optimization analysis will be carried out on these LID scenarios. Three types of IMPs, including green roof, porous pavement, and bio-retention area will be available to choose for building the LID scenarios.

This study mainly focuses on optimizing the water quantity control of various LID scenarios. Two major concerns in stormwater control, which are peak runoff rate and the total volume, are optimized along with the total cost of various LID designs.

4.3 OPTIMIZATION MODEL FORMULATION

Given the four possible IMP locations and three potential IMP types at each location, the length of an individual can be calculated using Equation 8 as:

$L= m*n_b + m$ =4*2+4=12.

Here n_b =2, which is the number of binary digits needed to represent 0~3.

As an effort to avoid the mixed binary and real values in an individual and thus to simplify the mutation and crossover processes, a pseudo-binary representation of IMP types is created (Table 2).

Table 2: Pseudo-binary Representation of IMP types

REAL NUMBER		BINARY VALUES	LID TYPE	
0~0.5	0~0.5	0 0	(0)	No LID
0~0.5	0.5~1	1 0	(1)	Green roof
0.5~1	0~0.5	0 1	(2)	Porous pavement
0.5~1	0.5~1	1 1	(3)	Bio-retention area

Two real values, instead of binary values, are used to represent the four potential IMP types at a certain location within the watershed. In this way each individual is composed of 12 real values, with the first 8 values depicts the IMP chosen at the four locations and the following four values specifies the respective IMP sizes. Meanwhile, the four locations are arranged in the order of the forest land area, the flower garden area, the playground area, and the softball field area in an individual.

A further endeavor to simplify the IMP size representation is to normalize the IMP sizes to the sub-catchment areas. Thus a ratio value between 0 and 1 can be used to specify the IMP size used in a potential location. A typical individual that represents a LID scenario in the Fox Hollow Watershed is shown in Figure 4.

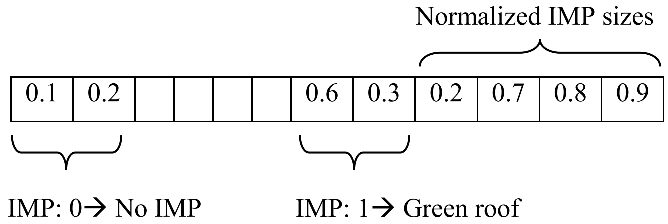

Figure 4: Sample Individual with Information of IMP Types and Sizes in an LID Scenario

As is shown in Figure 3, the forest land area, which is the first one in the four locations, chooses the IMP type 0. This means no IMP will be implemented at the forest land, and the 0.2 ratio thus has no real meaning. Whereas the softball field area, which is the last one in the four potential locations, chooses IMP type 1 with an area ratio of 0.9. This means that the green roof IMP will be implemented on 90% of the softball field area. IMP types for the flower garden area and the playground area (which are arranged as the second and third locations) are not shown in Figure 3 but follow the similar principle.

4.4 OPTIMIZATION RESULTS AND DISCUSSION

The ε-NSGAII algorithm is linked with the SWMM model in Visual C++ following the pseudo-code shown in Figure 2. After the optimization model is set up, various parameter configurations for the optimization process are used to fully explore the search space. A list of parameter configurations for these analyses can be found in Table 3. All the analyses in Table 3 use an initial population size of 12, and a population injection value of 0.25 is used.

Table 3: Non-dominated LID Scenarios for the Fox Hollow Watershed as Identified in Initial Runs

Index of analysis	Max gen. per run	# of random seeds	Max # of nfe	# of archived best solutions
1	100	1	5,000	12
2	40	1	3,000	7
3	120	1	4,000	6
4	90	2	6,000	14
5	60	1	20,000	9

In Table 3, the maximum generation per run represents the number of generations after which the ε-NSGAII algorithm self-terminates the current run and starts a new run if no improvement in the solution performance is found. While the number of random seeds and the maximum number of function evaluations (nfe) are self-explanatory, the number of archived best solutions is the non-dominated best solutions found at the end of maximum function evaluations.

As is shown in Table 3, a total number of 38,000 LID scenarios are evaluated and 48 non-dominated solutions are identified. A non-dominated sorting is then carried out to the 48 solutions, and a final 47 solutions are identified as the non-dominated solutions for the LID optimization problem. An excerpt of the 47 solutions can be found in Table 4.

Table 4: Non-dominated LID Scenarios for the Fox Hollow Watershed after 38,000 Evaluations

Total cost (Millions of $)	**Total volume (1000 ft^3)**	**Peak flow rate (cfs)**
6.955	42.195	6.5608
6.720	42.257	6.562
6.440	39.213	7.676
4.302	42.413	6.603
1.595	71.443	9.369
3.592	42.968	6.745
4.720	41.705	8.024

The conflicting relationship between total cost and the performances in total runoff volume and peak rate is well revealed by the solutions shown in Table 4. In general, a higher total cost, which means bigger IMP sizes at various locations, results in lower values of total volume and peak rate. The contrary situation is observed when a lower cost is reached at the expense of suffering worse runoff situations (higher total volume and peak rate). This is in accord to common situations that decision-makers are often faced with.

Table 4 also shows that the total runoff volume and peak rate do not necessarily increase or decrease jointly all the time for all LID scenarios, and this can be very useful in certain stormwater control situations. For example, scenario *A* may have a higher total volume than scenario *B* and the peak rate from scenario *A* is lower than that from scenario *B*, and meanwhile scenario *A* incurs a lower total cost as compared to scenario *B*. In this instance, scenario *A* will be a better choice when flooding is a major concern, since high peak rate is directly related to flooding occurrences.

The 47 non-dominated solutions are illustrated in Figure 5. As can be seen in the figure, more solutions are needed for building a continuous Pareto front. Future efforts will focus on applying a bigger initial population size, which is to explore the decision space more completely and thus identify more non-dominated solutions. With that, a more continuous Pareto front is expected to be identified. The continuous surface can help decision-makers to fully explore design possibilities with respect to specific control objectives.

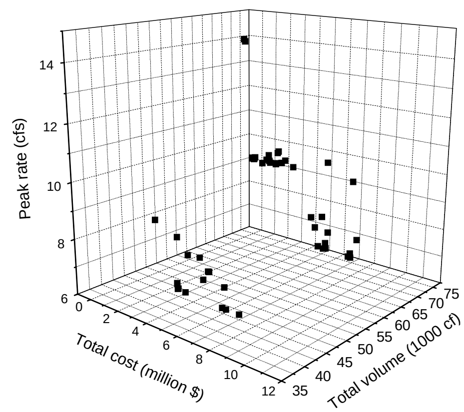

Figure 5: The Non-dominated Pareto-front Identified between LID Cost and Water Quantity Performances after 38,000 Evaluations

5 SUMMARY AND CONCLUSION

An optimization model is built to identify the Pareto front between the cost of LID scenarios and the corresponding peak runoff rates and the total runoff volume, which are confilicting objectives in urban stormwater control. The ε-NSGAII algorithm is linked to the USEPA SWMM model for carrying out the multi-objective optimization. Three possible types of IMPs are used to make up LID scenarios within an urbanizing watershed, and the optimization model evaluates the LID scenarios by changing the IMP types and sizes at four potential locations.

A total number of 38,000 LID scenarios are evaluated and 47 non-dominated solutions are found. On the final Pareto front between total cost and performances of water quantity, appropriate LID scenarios can be easily selected based on specific budget and water quantity control objectives. In general, the optimization model can be a very useful tool in urban stormwater related decision-makings, especially for optimizing LID scenarios.

Acknowledgments

This project is generously supported by the Office of Physical Plant (OPP) at the Penn State University. The author is very thankful to Dr. Patrick Reed at Civil Engineering Department of Penn State University for the insightful guidance and the permission to using the ε-NSGAII code. Great help from Yong Tang and Joshua

Kollat at Civil Engineering Department on building the optimization model is also highly appreciated here.

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