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The Application of Particle Swarm Optimization in Sewer Budget Allocation

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Abstract

Sewer assets require regular inspection and maintenance plans to avoid any disruption due to structural and operational defects. Therefore, decision-makers are required to allocate budgets to enhance the performance of sewer manholes and pipelines. However, several municipalities confront major constraints when planning for rehabilitation due to restricted funds to repair all defected assets. Current practices focus on sewer pipelines disregarding the systematic improvement of sewer manholes. The objective of this research is to provide a framework to implement the Particle Swarm Optimization (PSO) method to reach a near optimum solution that maximizes the overall network performance (ONP), considering pipelines and manholes, and minimizes the total life cycle costing. The constrained problem can be solved by examining four different decision variables. The application of PSO in sewer infrastructure shall enhance current practices to systematically plan for renewals. As a result, defective assets are lessened, and the risk of sewage exfiltration is significantly reduced.

Keywords: Particle Swarm Optimization, Budget Allocation, Pipelines, Manholes

1. Introduction

Assessing the condition of infrastructure assets is essential due to its backbone need for any urban city (Kaddoura 2015). Sewer systems, forming one of the most capital-intensive infrastructure systems (Wirahadikusumah et al. 1998), transfer sewage medium from private/public outlets (i.e., buildings, houses, hospitals, schools, etc.) to laterals, which are connected to main pipelines that end at sewage treatment plants or disposal areas. They are the ultimate low-profile infrastructure assets in spite of their health and environmental benefits (Kirkham et al. 2000). These systems are buried in the subsurface and are distributed in a maze of a complex infrastructure. Their low visibility stands a reason for their frequent low rehabilitation and/or maintenance (Wirahadikusumah et al. 1998). Sewers are prone to collapse and failure, imposing severe consequences on the surroundings (Kirkham et al. 2000) and resulting in costly and difficult rehabilitation (Wirahadikusumah et al. 1998). Therefore, it is paramount to enhance the existing sewer systems by performing renewal interventions. These interventions, in the form of rehabilitation or replacement, will reduce any disruptions to the environment, economy, and society.

Municipalities have limited allocated budgets to improve existing conditions of their infrastructure. With the different infrastructure components, decision-makers should wisely allocate the required budgets. Optimization methods are commonly used to solve budget allocation problems in infrastructure asset management. Hence, this paper will establish a framework for the implementation of the Particle Swarm Optimization (PSO) method that will maximize sewer network performance.

1.1 Optimization Models in Infrastructure Assets

There are four main types of optimization algorithms that are commonly used in infrastructure: linear, non-linear, integer, and dynamic programming (Nunoo 2001). In the construction management domain, the budget allocation problem could be in the form of one or more objective functions that shall be minimized or maximized. However, because of limited resources and diverse requirements, the objective functions are subject to constraints related to money, time, manpower, etc. As a result, defining all possible solutions while restraining the problem could be very complex (Al-Tabtabai et al. 1999). Typical mathematical programming tools are used for unconstrained problems and as a result are not applicable to constrained objective functions and very large complex problems (Wang 2013). However, evolutionary algorithms (EAs) have emerged as alternative methods to solve large-scale and complex optimization problems (Veldhuizen and Lamont 1998).

For example, in sewer infrastructure, Lin et al. (2016) designed a sewerage rehabilitation multiobjective management model to prioritize sewer pipeline rehabilitation decisions. The authors used the non-dominated sorting genetic algorithm (GA)-II to design a number of Pareto surfaces considering desirable rehabilitation methods and the substituted material. Three conflicting objectives were determined: minimizing rehabilitation costs, maximizing pipe service and minimizing traffic disruption. The model was conducted on a real case study and the authors claimed that it saved almost 20% of the rehabilitation costs determined by the experts.

Marzouk and Omar (2013) presented a model for life-cycle maintenance planning for sewer network. Prior to developing a prioritization model, the authors developed a Markov chain model to predict the future deterioration of sewer pipelines. Next, they used a multi-objective GA model to build the prioritization model. Three objective functions were considered: improving the overall network, improving the intended network service life and reducing the present value of the life-cycle maintenance cost. Six different variables with different relevant states and benefits were considered: do nothing, routine cleaning, shotcrete, CIPP, reinforced fiberglass sliplining, and dig and replace with concrete pipeline.

On the other hand, Halfawy et al. (2008) proposed an integrated approach for systemizing the sewer renewal planning procedure after utilizing a multi-objective GA model. The authors relied on three main objectives: to minimize the average condition index, minimize the average risk measure of the network and minimize the total life-cycle cost. The proposed model was claimed to support short- and long-term planning situations as well as network-level and project-level planning.

Furthermore, Yang and Su (2007) established a GA-based optimization model to supply an optimal rehabilitation plan for sewer assets. The authors considered the three most popular rehabilitation methods: renewal, renovation and excavation, and trenchless replacement. The cost associated for each method was determined by an equation that is dependent on the pipeline diameter. In addition, the authors considered the substitution materials in the decision making process. After applying the methodology on a case study, they stated that the approach could reduce the rehabilitation costs by 20% of the actual rehabilitation expense.

DeMonsabert et al. (1999) utilized the integer programming method to optimize and prioritize a sewer rehabilitation schedule. The model was developed to choose the repair method that yielded the minimum present value-cost solution over a 20-year planning period with maintenance at 5-year intervals. The objective of the approach was to select the optimal repair strategy to minimize the total cost, subject to budget constraints.

Wirahadikusumah and Abraham (2003) suggested a decision-making framework to select the appropriate M&R plan, based on dynamic programming in conjunction with a Markov chain model. Before commencing the decision-making approach, the authors designed a Markov chain-based deterioration curve to predict the future condition of the sewer pipelines. The decision making approach considered five different states from 1 to 5 for the assets, and six different alternatives corresponding to a specific state: no maintenance/rehabilitation, routine cleaning, shotcrete, CIPP, reinforced fiberglass sliplining and dig and replace with concrete pipe.

Despite the multiple researches conducted in sewer assets, many of the models did not consider the overall network performance (ONP), which includes pipelines and manholes. Most of the models relied on optimizing the budget allocated on pipelines only. In addition, this paper will pioneer the application of PSO in buried infrastructure budget allocation.

1.2 Particle Swarm Optimization

Among the many EAs, the PSO method is easier to implement and has more competitive exploration and detection capabilities (Kennedy and Eberhart 2001); Parsopoulos and Vrahatis 2002). The PSO also has a faster convergence when compared to other EA methods. Several researchers have evaluated the performance of multiple optimization methods. For example, Koay and Srinivasan (2003) optimized a power plant maintenance scheduling problem using GA, Evolutionary Strategy (ES) and the PSO, and stated that the PSO method supplied better results and performance than GA and ES. Coello et al. (2004) and Baltar and Fontane (2006) utilized four distinct optimization tools to evaluate five multi-objective problems and concluded that the PSO attained faster convergence; they concluded that it is well-suited to the multi-objective optimization problem. El-Ghandour and Elbeltagi (2017) compared five different optimization techniques, the GA, PSO, Ant Colony (AC), Memetic Algorithm (MA) and Shuffled Frog Leaping (SFL) methods, on two benchmark water networks to determine the least cost for one and the least rehabilitation cost for the other. They concluded that the PSO surpassed the other algorithms in both test situations.

Comparing the application of the GA and PSO methods in solving single objective problems, Jung and Karney (2006) evaluated the performance of GA and PSO in optimizing the sizing and the selection of hydraulic devices for protection, and found that both methods provided similar results. However, they concluded that the PSO outperformed the GA method when the same number of iterations and population sizes were used.

PSO was inspired by the flocking patterns of birds and fish that move in swarms to search for food. As illustrated in Figure 1, this method commences with an initial random pool of solutions represented by a swarm. Each swarm encompasses a number of solutions that are known as the size of the population. The swarm determines the number of solutions, with each exemplified as a particle. Following an iterative approach, the best solution is found by considering the problem at hand.

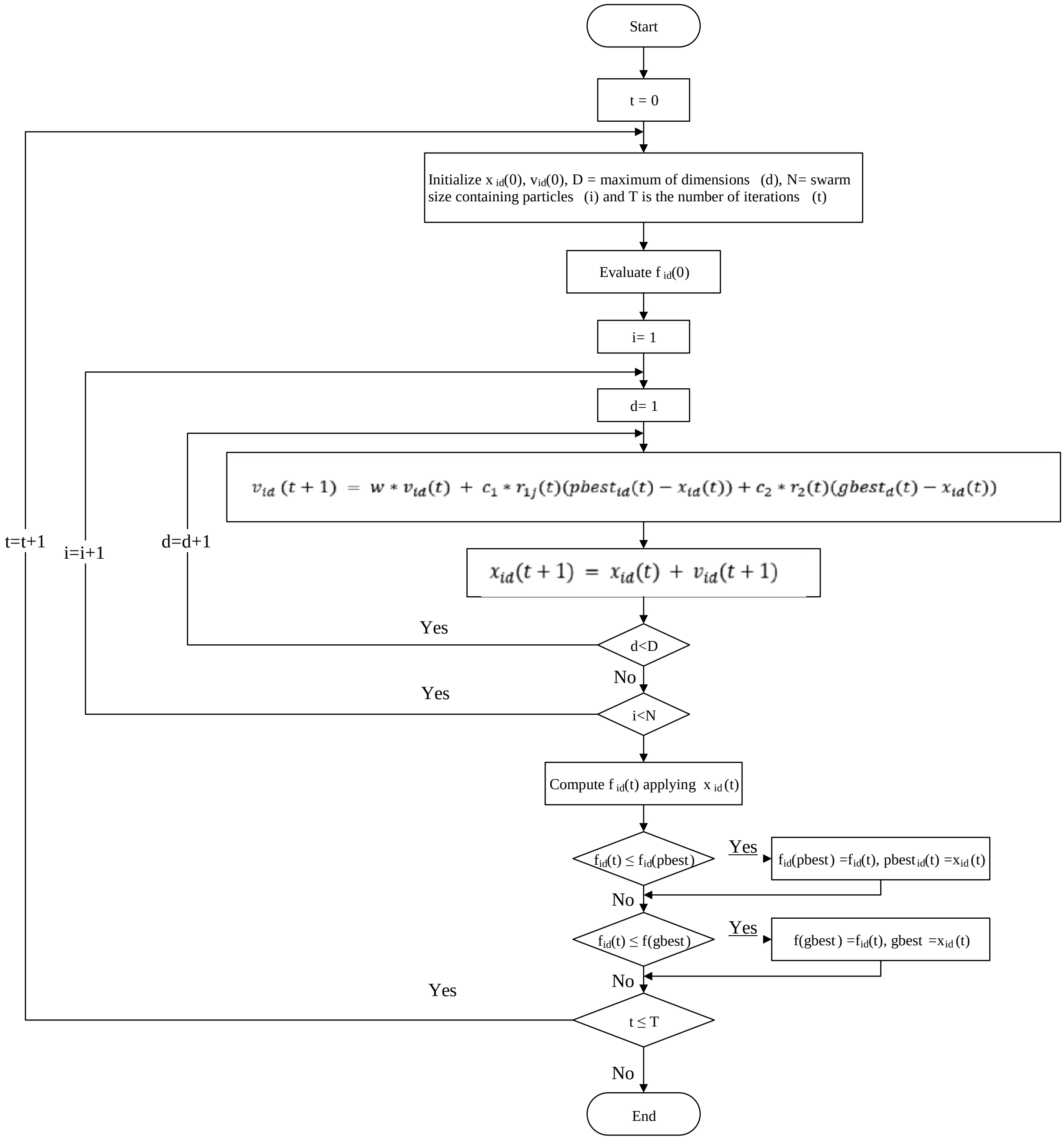

Figure 1: PSO Flowchart

Each particle in the swarm has a specific position. The fitness of the current position of any particle is evaluated according to a defined fitness function. Subsequently, the best fitness solution of each particle is denoted as *pbest* (particle best) and is archived and automatically updated once a better solution (position) is found. Considered as a minimization problem, the personal best of particle *i* in the subsequent step can be represented as

$$pbest_i\,(t+1) = \begin{cases} pbest_i\,(t) & if\ f\big(x_i(t+1)\big) > \ pbest_i\,(t) \\ x_i(t+1) & if\ f\big(x_i(t+1)\big) \le pbest_i\,(t) \end{cases} \qquad [1]$$

Among the *pbest* found in each iteration, the best position among all the positions is also stored for subsequent iterations and is described as the *gbest*. The $gbest\ (t) = min\,\{pbest_i(t)\}$ is always updated whenever new better overall position is reached.

The particles in the swarm are always updated by a better position in every iteration by considering randomized values toward some directions. These changes are calculated by using the velocity. The velocity of the particle relies on three mean factors: *pbest*, *gbest* and the random function. The evaluation scheme and the modifications repeat until the termination criteria is reached. The modifications are always completed through the velocity function. Considering D elements of array A = (z_{i1}, z_{i2}, $z_{i3,\ldots,}$ z_{iD}) as the search space, the *gbest* describes the global best particle of a swarm and $pbest_i$ denotes the archived best position of the i^{th} particle in the swarm population. Therefore, the velocity of the particle can be calculated according to equation 2 (Shi and Eberhart 1998). Considering the velocity values, the particle's updated position is computed using equation 3 (Shi and Eberhart 1998).

$$v_{id}\ (t+1) = w * v_{id}(t) + c_1 * r_{1}(t)(pbest_{id}(t) - x_{id}(t)) + c_2 * r_2(t)(gbest_d(t) - x_{id}(t)) \qquad [2]$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad [3]$$

where

t	is the iteration;
t+1	is the subsequent iteration;
d	is a value from the D space ranging from 1 to *D;*
N	is the total number of particles in a swarm (population size);
i	is the particle number that ranges between 1 to *N*
w	is the inertia weight that is taken as a parameter;
$x_{id}(t)$	is the current position of the *i*th particle in the d dimension;
$x_{id}(t+1)$	is the new position of the ith particle in d dimension
$v_{id}(t)$	is the current position of the *i*th particle in the d dimension;
$v_{id}(t+1)$	is the new velocity of the *i*th particle in the d dimension;
$pbest_i$	is the best position of the *i*th particle stored;
$gbest_d$	is the global best position of a swarm from among all the particles;
r_1	is a uniform random number [0,1];
r_2	is a uniform random number [0,1]; and
c_1 and c_2	are acceleration coefficients.

The parameter v_{id} restrains the particle to consider its previous direction and speed, thereby allowing the particle to discover new areas in the search space. The cognitive learning rate c_1 controls the velocity of the particle's movement towards the *pbest*, while the social learning rate c_2 controls the velocity towards the *gbest*. Large numbers of c_1 and c_2 can lead to expedited particle movements toward the current *gbest* or *pbest*; a situation which could lead to premature convergence.

Particles with larger v_{id} tend to move rapidly towards the global area; but, if they are close enough to the global area, the global position may be ignored and they can move to alternative areas. Since the value of the v_{id} impacts the converging criteria to a global optimum, the global and local searches shall be restrained such that the search space is limited to $x_{id} \in [-x_{max}, x_{max}]$, $v_{max} = k*x_{max}$, $0.1 \leq k \leq 1$. Nevertheless, the inertia factor w was introduced by Shi and Eberhart (1998) in order to limit the particle movement to new search areas. Keeping a value of $w = 1$ will maintain the standard form of PSO. In general, a large value of the weight expands the range towards new areas, while lower values encourage the particles to search in closer range areas.

2. Research Methodology

The overall optimization model is represented in Figure 2. The main two objectives for this problem are ensuring that the overall sewer performance is performing above a certain threshold and that the costs of enhancements are minimized. Therefore, the main two objectives are:

- Maximizing the overall sewer network performance; and
- Minimizing the total costs.

This research adopts the PSO algorithm because it outperformed multiple optimization methods, as mentioned in the literature. Building a budget allocation problem utilizing the PSO requires a process to represent each particle in the swarm, setting parameters to balance the exploration in the defined search space and accommodate the PSO algorithm in the budget allocation problem.

In designing a rehabilitation plan, assets in the network are subject to any type of intervention action. Therefore, each pipeline and manhole can be considered as a project. Each project can hold different types of rehabilitation actions (decision variables) throughout the considered life cycle and could have multiple combinations over the studied number of years. In addition, each asset shall interact with the other assets in order to measure the fitness of each particle in the swarm.

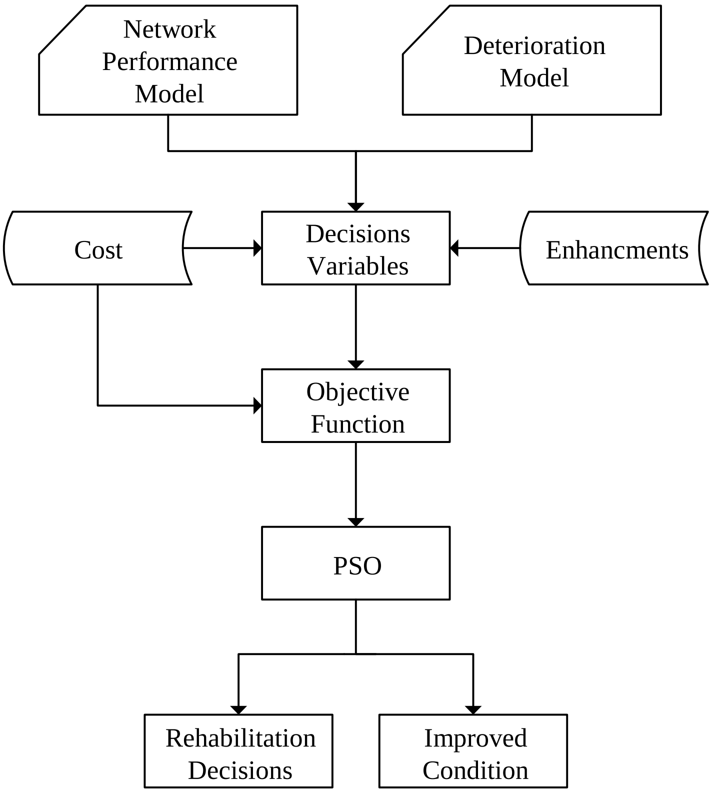

Figure 2: Optimized Rehabilitation Plan Model

2.1 Objective Functions

Each particle in a swarm is evaluated based on a fitness function. In this research, the fitness function is a combination of the total cost and the ONP. The aggregation of these two parameters is based on weights that are user-defined. An equal importance for the two parameters will establish 50% weights for each. To accomplish the optimization tool, the ONP shall be maximized and the total cost shall be minimized, given several constraints.

$$Maximize\ ONP = W_P\left(\frac{\sum_{i=1}^{k} CI\_P_i * CR_i}{\sum_{i=1}^{k} CR_i}\right) + W_M\left(\frac{\sum_{j=1}^{n} CI\_M_j * CR_j}{\sum_{j=1}^{n} CR_j}\right) \quad [4]$$

$$Minimize\ Total\ Life\ Cycle\ Costing\ (TLCC) = \frac{1}{(1+r)^t}\sum_{t=1}^{z}\sum_{i=1}^{k} C_{ti} + \frac{1}{(1+r)^t}\sum_{t=1}^{z}\sum_{j=1}^{n} C_{tj} \quad [5]$$

$$r = \frac{1+interest\ rate}{1+inflation\ rate} - 1 \quad [6]$$

where

r is the real interest rate;

z is the period from one inspection to another (in this study it is 5 years); and

C is the cost of the intervention plan of pipeline *i* and manhole *j* at any time *t*.

These two functions are aggregated into a single function as follows

$$Minimize\ Fitness\ Function\ =\ W_{ONP}(\frac{ONP}{Max\ Performance})\ +\ W_{TLCC}(\frac{TLCC}{Budget}) \qquad [7]$$

where

W_{ONP} is the importance weight of the ONP parameter; and

W_{TLCC} is the importance weight of the $TLCC$ parameter. These weights are user defined. The most significant parameter will have the higher weight.

subject to:

One decision variable to be rehabilitated per asset in the study period, such that

$ONP_{!} \leq Max\ Performance$ and [8]

$TLCC \leq Total\ Budget$ [9]

2.2 Particle Coding

Particle coding is key to facilitate solving the budget allocation problem as it impacts the initialization of the particle, fitness computation, movement and the archiving process. In this paper, a particle is represented as a 2D array (n x m) to propose a solution considering pre-defined objective functions. It is composed of rows and columns; the rows represent the number of the assets (s) in the network, and the columns represent the number of years considered in the study, which is five years. Each element in the array is considered as a potential decision variable (q) for each asset. The decision variables considered in this research are listed in Table 1.

Table 1: Decision Variables

Decision #	Interpretation	Example	Improvement	Cost for the Pipelines (Adjusted)	Cost for Manholes Average (Adjusted)
0	Do nothing	Do nothing	-	-	-
1	Minor Rehabilitation	Chemical Grouting and sealing	Max of 1 state	$40/m	$40/m
2	Major Rehabilitation	Structural Liner (Cured-in-place)	Max of 3 states (Marzouk and Omar 2013)	$1.77 (/mm/m)	$55,31.149 (Hughes 2009)
3	Replacement	Replace	Return state to 1 (Halfawy et al. 2008)	$1943.4/m (Marzouk and Omar 2013)	$11,434 (Hughes 2009)

As a result, the 2D array of each particle will be represented as shown in Figure 3:

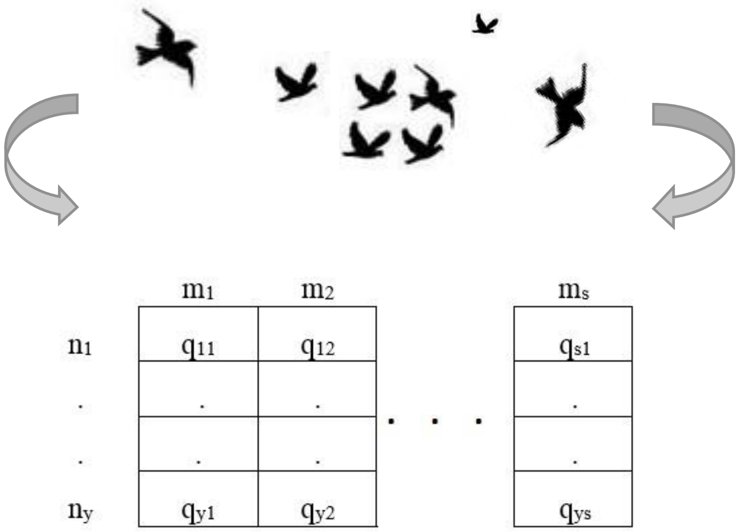

Figure 3: Particle Encoding

3. Conclusions

Infrastructure is an integral part of any urban city. Sewer, as a critical infrastructure, plays a major role in ensuring a safe environment. Hence, municipalities are required to preserve these assets by conducting regular renewal interventions. Due to the large number of pipelines and manholes, municipalities confront major obstacle in renewing them all. Therefore, a propoer budget allocation is needed to enhance current network performance. This research provided an initial step toward implementing the PSO method in sewers networks. This method was utilized as it surpassed many of the other evolutionary algorithms that were used in the same domain. This research shall be further implemented on an actual case study to conclude the numeral outcomes.

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