Life Cycle Cost-based Pipe Replacement Model and Application in Depopulation Scenario

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ABSTRACT

This paper examines the feasibility of pipe diameter reduction in a pumped water distribution system (WDS) during depopulation from the viewpoint of life cycle cost (LCC). A pipe replacement planning model using a genetic algorithm (GA) was developed and applied to a pumped and branched WDS under depopulation. Moreover, a local search algorithm (LSA) using normal distribution was proposed to improve GA in terms of solution convergence. The result showed that diameter reduction may increase LCC because of increased pump operational cost, while pipe diameters can be reduced without increasing LCC if immediate nodes have a surplus pressure at the time of pipe replacement. In addition, it was found that the proposed LSA significantly improves reliability of optimization.

Keywords: water distribution system, genetic algorithm, life cycle cost

1 Background

In Japan, a half century has passed since the high economic growth period of the late 1950s to 1970s; water supply pipes intensively buried during this period have deteriorated throughout the nation. In addition, successive depopulation has led to a decrease in user revenue unlike most other countries [1]. Operators must tackle how to sustainably replace their own stock within a framework of asset management given this dilemma: increasingly aged pipes and decreasing revenue. Countries with growing populations can use diameter enlargement, duplication etc.; however, diameter reduction is increasingly common among operators in Japan.

To efficiently execute asset management, it is crucial to minimize life cycle cost (LCC): pipe installation / replacement, pump operation, disaster risk and pipe removal. In Japan, the importance of LCC is mentioned in the national design criteria revised in 2012 [2]. To plan pipe replacement that minimizes LCC, an appropriate model is needed to best answer both optimal timing and diameter of pipe replacement. In particular, diameter reduction, which may lead to increased pump operational costs, must be validated from the viewpoint of LCC even in a situation of long-term depopulation.

In this paper, a genetic algorithm (GA) model that minimizes LCC has been developed. Next, a local search algorithm is proposed to improve the GA’s convergence. Finally, the resulting model is applied to a pumped and branched water distribution system (WDS) under depopulation, and an optimized replacement plan is discussed.
2 Previous research

Many researchers have found that by minimizing the sum of pipe replacement costs and age-associated pipe break risk, optimal pipe replacement timing can be obtained (e.g., [3]). A number of models have been developed using pipe break risk to determine replacement timing (e.g., [3]–[5]). Those models assume the same diameter both before and after replacement; thus low computational costs is expected, but hydraulic reliability is not secured over the planning period. Furthermore, diameter reduction prevents excessively low pipe velocity, which can cause deteriorating water quality because of decreased demand, and also reduces initial costs [6]. Phased design models optimize both timing and diameter; hence those models can optimize pipe replacement to minimize LCC while meeting hydraulic constraints (e.g., [7], [8]). However, none of these models consider pump operational cost; thus, how much diameter can be reduced in pumped WDSs under depopulation has yet to be researched from the perspective of LCC.

Roshani and Filion (2013) [9] developed a WDS-asset management model called OptiNET, which can optimize both timing and diameter to minimize LCC including pump operational cost and they used it to verify water conservation programs in a Canadian WDS [10]. Nevertheless, they did not validate WDS rebuilding in which long-term demand reduction is expected. Since a high-class cluster machine is required to use OptiNET, computational costs may also become problematic.

3 Life cycle cost

The objective of the pipe replacement model proposed in this paper is to minimize LCC in Eq. (1)

\[
\text{Minimize} \quad LCC = \sum_{t=0}^{T} DF_t (C_t + B_t + O_t) - R_T
\]

where \( t \) is time in years, \( DF_t \) is discount factor, \( C_t \) is pipe replacement cost, \( B_t \) is pipe break risk, \( O_t \) is pump operational cost and \( R_T \) is residual value.

3.1 Pipe replacement cost

Pipe replacement cost is calculated based on the unit cost functions [11] in Eq. (2)

\[
C_t = \sum_{i=1}^{I} f_{\text{pipe}}(D_{t,i})L_i
\]

where \( C_t \) is pipe replacement cost, \( i \) is pipe number \((i = 1, 2 \ldots I)\), \( f_{\text{pipe}}(D_{t,i}) \) is unit cost functions for pipe replacement (JPY/m), \( D_{t,i} \) is pipe diameter (mm) and \( L_i \) is pipe length (m).

3.2 Pipe break risk

To more exactly calculate pipe failure risk, pipe break models should reflect not only age, diameter, pipe type (e.g., ductile, cast iron or steel) etc., but also soil causticity and outer sleeve protection. The pipe break model developed by JWRC (2011) [12] was used as in Eq. (3)

\[
N_{t,i} = c_1 c_2 c_3 f_{\text{failure}}(a_{t,i})L_i
\]
where $N_{t,i}$ is future break rate (breaks/year), $c_1$ is outer surface coefficient, $c_2$ is diameter coefficient, $c_3$ is soil causticity coefficient, $f_{\text{failure}}(a_{t,i})$ is break growth function (breaks/km/year), $a_{t,i}$ is pipe age and $L_i$ is pipe length (km).

This model assumes that pipe breaks potentially result in water outage loss as well as pipe repair cost as in Eq. (4)

$$B_t = \sum_{l=1}^{l} N_{t,i} \left( g_{t,i} + \alpha_{t,i} \beta_{t,i} \gamma_{t,i} \right)$$  \hspace{1cm} (4)$$

where $B_t$ is pipe break risk, $N_{t,i}$ is future break rate (breaks/year), $g_{t,i}$ is unit repair cost (JPY/break), $\alpha_{t,i}$ is unit outage possibility (%/break), $\beta_{t,i}$ is unit restoration period (days/break) and $\gamma_{t,i}$ is unit outage loss (JPY/day). Because all parameters employed in Eq. (4) except for $\gamma_{t,i}$ are diameter-dependent, those values were set by JWRC (2011) [13]; $\alpha_{t,i}$ is 12% ($D_{t,i} \geq 450$) and 35% ($D_{t,i} < 450$), $\beta_{t,i}$ is four days ($D_{t,i} \geq 500$), two days ($300 \geq D_{t,i} \leq 450$) and one and a half days ($D_{t,i} \leq 250$). $\gamma_{t,i}$ is estimated at 12,367 (JPY/day) as calculated by MHLW (2012) [14].

### 3.3 Pump operational cost

Pump power is calculated in Eq. (5)

$$G_{t,m} = \frac{0.163 Q_{t,m}^{\text{pump}} H_{t,m}^{\text{max}}}{\eta} (1 + \delta)$$  \hspace{1cm} (5)$$

where $m$ is pump number ($m = 1, 2, \ldots, M$), $G_{t,m}$ is pump output (kW), $Q_{t,m}^{\text{pump}}$ is delivered water by pump (m$^3$/min), $H_{t,m}^{\text{max}}$ is maximum total head (m), $\eta$ is pump efficiency, $\delta$ is ratio of allowance (i.e., surplus). $\eta$ and $\delta$ are assumed to be 0.8 and 0.125, respectively [2].

With cast iron pipes (CIP), roughness growth associated with aging is well-known because CIP is not lined in their inner surface. This model, therefore, applied the Sharp-Walski roughness growth model for CIPs [15]. Roughness coefficients of other pipe types were set at 110 in this model.

Resulting pump operational cost is calculated from Eq. (6), which assumes 80% of annual pump working rate and 17.53 (JPY/kWh) electricity tariff as levied by TEPCO [16].

$$O_t = 24 \times 365 \times 0.8 \times 17.53 \sum_{m=1}^{M} G_{t,m}$$  \hspace{1cm} (6)$$

where $O_t$ is pump operational cost and $G_{t,m}$ is pump output (kW)

### 3.4 Residual value

Because residual asset values of pipes were not considered, the optimized pipe replacement strategies obtained by the models reviewed in chapter 2, were excessively biased towards continued use of existing aged pipes after the planning period. Therefore, this model includes residual value in Eq. (7)
where $R_T$ is residual value, $DF_T$ is discount factor, $T$ is the final year of time horizon, $U$ is institutionalized amortization year and $a_{T,i}$ is pipe age. $U$ is assumed to be 40 years in this model.

### 3.5 Constraints

As pipe replacement constraints, this model assumed a velocity requirement between 0.3 m/s to 3.0 m/s, and 3.0 m of minimum pressure requirement at the inflow of each tank.

### 4 GA optimization

#### 4.1 Gene coding

To optimize pipe replacement, a great number of combinations (e.g., timing, diameter etc.) must be efficiently searched. GA was mostly employed as the optimization method by the papers reviewed in chapter 2. In the proposed model, GA is applied based on integer-coding as used in Dandy and Engelhardt (2001) [7] and Roshani and Filion (2013) [9] as in Figure 1. In this gene coding method, decision variables of timings and diameters are given for each pipe. Diameter changes are represented as variables from current diameter based on the nominal diameter standardized by JSA [17]. Replacement timings are generated according to a range $[0, T+1)$. $T+1$ expresses no pipe replacement over the planning period, so that newer pipes would not be replaced erroneously.

In this model, Python™, an object-oriented programming language, was used to program in the proposed model [18]. As for GA design, simple GA (roulette selection, two-point crossover, mutation, elitism) were used; parameters were 4000 generations, 50 populations, 0.8 crossover rate, 0.35 mutation rate and two elite populations.

![Figure 1. Integer-coded genes in a chromosome](image-url)

#### 4.2 Local search algorithm

In any model for deciding replacement timing and diameters for minimizing LCC, the closer the decision variables are to optimal values, the greater the reduction of LCC. A simple GA, however, even if it can search efficiently for a global optimum solution by a relatively early generation, has only a limited search capability for local solutions, e.g., ±1 as a variable. To improve performance, a local search algorithm (LSA) using normal distribution was proposed. The pseudo-code of LSA is shown in Algorithm 1. In this model, it was assumed that LSA starts after generation 2500, $K=4$ and $N(0,1)$, respectively.
Algorithm 1: Local search algorithm in the integer-coded GA

1. if Current generation > Starting generation
2. Pick $Y_p = \{y_{p,1}, y_{p,2}, \ldots, y_{p,I}\}$ from the best population $p$ in current generation.
3. for $k$ in $K$
4. for $i$ in $I$
5. Generate $W_k = \{w_{p,1}, w_{p,2}, \ldots, w_{p,I}\}$ according to $N(\mu, \sigma^2)$.
6. $Z_k = Y_p + W_k$
7. if $LCC(Z_k) < LCC(Y_p)$
8. Replace $Y_p$ to $Z_k$ and $LCC(Y_p)$ to $CC(Z_k)$.
9. end
10. end
11. end
12. Return $Y_p$ and $LCC(Y_p)$ as the best population $p$.
13. end

where, $Y_p$ is an integer vector that contains decision variables, $p$ is population number, $i$ is pipe number ($i = 1, 2, \ldots, I$), $k$ is trial number ($k = 1, 2, \ldots, K$), $W_k$ is an integer vector generated from normal distribution, $N(\mu, \sigma^2)$ is normal distribution, $Z_k$ is candidate vector.

5 Model application

The proposed model was applied to a pumped and branched WDS as in Figure 2 and Table 1. In this case study, the following assumptions were made; the planning period is 50 years; each pipe can be replaced once or no replacement is allowed; all replaced pipes are ductile iron pipe (DIP); fixed-speed pumps were used and output is reviewed every 20 years ($t = 0, 20, 40$); population allocated to each tank evenly declines based on the projection made by IPSS (2017) [1] and in Figure 2(b); annual maximum peak demand coefficient of each node is 500 (L/person/d); the discount rate used to calculate discount factor is 4% [14].

Figure 2. (a) pumped and branched water distribution system, (b) population trend in the system
Table 1. Elements of pipes in the system

<table>
<thead>
<tr>
<th>Pipe</th>
<th>Type</th>
<th>Age</th>
<th>Diameter (mm)</th>
<th>Length (km)</th>
<th>Causticity</th>
<th>Outer sleeve</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DIP</td>
<td>5</td>
<td>900</td>
<td>1.8</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>2</td>
<td>CIP</td>
<td>48</td>
<td>450</td>
<td>2.2</td>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>3</td>
<td>DIP</td>
<td>10</td>
<td>800</td>
<td>3.0</td>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>4</td>
<td>DIP</td>
<td>10</td>
<td>450</td>
<td>0.8</td>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>5</td>
<td>CIP</td>
<td>55</td>
<td>700</td>
<td>2.1</td>
<td>High</td>
<td>No</td>
</tr>
<tr>
<td>6</td>
<td>DIP</td>
<td>20</td>
<td>500</td>
<td>1.0</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>7</td>
<td>DIP</td>
<td>25</td>
<td>400</td>
<td>3.0</td>
<td>High</td>
<td>No</td>
</tr>
<tr>
<td>8</td>
<td>DIP</td>
<td>35</td>
<td>250</td>
<td>2.2</td>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>9</td>
<td>DIP</td>
<td>5</td>
<td>300</td>
<td>3.5</td>
<td>High</td>
<td>Yes</td>
</tr>
</tbody>
</table>

5.1 The effectiveness of the local search algorithm

To confirm the effect of the LSA, convergences of GA with and without LSA were obtained through 100 different random seeds (i.e., 100 GA trials). The result is presented in Figure 3.

In the GA without LSA (i.e., simple GA), a clear improvement of LCC cannot be seen even after 2000 generations, and 95% confidential interval: which expresses the variation, still continues to the end. This means that simple GA keeps searching global search spaces and generates discrete suboptimal solutions at the final generation. In contrast, GA with LSA substantially improves LCC after LSA implementation and eventually generates solutions that are by far better than without LSA. In addition, solutions were completely converged only 500 generations after LSA implementation; thus, GA with LSA can optimize pipe replacement planning more reliably than without LSA.

5.2 Diameter reduction in situations of depopulation

The optimization result of the proposed model is indicated in Table 2. As shown in the table, pipe 2 and pipe 5, CIPs which deteriorate rapidly, are swiftly replaced. Subsequently, pipe 7 and pipe 8, which are the oldest DIPs and are not protected by outer sleeves, are replaced. As for diameter, pipe...
2 is significantly downsized in an early period of strong water demand while pipe 7 and pipe 8 are not downsized even in the mid-term and its decreased water demand. To discuss the inconsistency between water demand and diameter selection, total head of pump1 (Tank A, Tank B, Tank C and pump 2) and velocity in each pipe over the planning period are represented in Figure 4.

Table 2. Phase and diameter in the optimization result

<table>
<thead>
<tr>
<th>Decisions</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase</td>
<td>–</td>
<td>3</td>
<td>–</td>
<td>–</td>
<td>0</td>
<td>–</td>
<td>34</td>
<td>23</td>
<td>–</td>
</tr>
<tr>
<td>Diameter</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Before)</td>
<td></td>
<td></td>
<td>–</td>
<td>–</td>
<td>700</td>
<td>–</td>
<td>400</td>
<td>250</td>
<td>–</td>
</tr>
<tr>
<td>Diameter</td>
<td></td>
<td></td>
<td>–</td>
<td>–</td>
<td>600</td>
<td>–</td>
<td>400</td>
<td>250</td>
<td>–</td>
</tr>
<tr>
<td>(After)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4. Hydraulic change of the optimization result

As in Eq. (5), pump output is determined by water demand and total head of the target nodes $H_{t,m}^{max}$ that each pump has to service (e.g., pump 1 has to deliver water to Tank A, Tank B, Tank C and pump 2). Figure 4 (a) shows that total head required to deliver water to pump 2 (booster) is the highest over the planning period; it is referred to as $H_{t,1}^{max}$. If the group of pipes on the way to pump 2, (i.e., pipe 1, pipe 3, pipe 5 and pipe 7) is downsized but demand decline is insufficient, pressure constraint may be violated. On the other hand, if pipe 2, located just before Tank A, has a large pressure surplus, its diameter can be reduced without increasing pump output. It should be noted that pipe 2 cannot be further downsized because velocity in pipe 2 exceeds upper limit even with the decreasing demand.

In summary, operators should carefully determine diameter reduction even in depopulation situations because diameters reduction may result in higher LCC due to increased pump output. However, if pipes are located just before nodes that have large pressure surpluses at the time of replacement, diameters can be reduced without increasing LCC. It is hard to similarly reduce pipe diameters (even if there is large pressure surplus) in a population growth period, because of increasing peak water demand in the future, however such diameter reduction is possible in the situation of depopulation.

6 Conclusions

This paper examines the feasibility of pipe diameter reduction in pumped water distribution system (WDS) during depopulation in terms of life cycle cost (LCC). A pipe replacement planning model
using genetic algorithm (GA) was developed and applied to a pumped and branched WDS under depopulation. Moreover, a local search algorithm (LSA) using normal distribution was proposed to improve GA’s convergence. The result showed that diameter reduction may increase LCC because of increased pump operational cost, while pipe diameters can be reduced without increasing LCC if immediate nodes have a large surplus pressure at the time of pipe replacement. In addition, it was found that the proposed LSA significantly improves the reliability of resulting solutions.

7 References


