Optimal Design of Regional Wastewater Pipelines and Treatment Plant Systems

Noam Brand, Avi Ostfeld*

ABSTRACT: This manuscript describes the application of a genetic algorithm model for the optimal design of regional wastewater systems comprised of transmission gravitational and pumping sewer pipelines, decentralized treatment plants, and end users of reclaimed wastewater. The algorithm seeks the diameter size of the designed pipelines and their flow distribution simultaneously, the number of treatment plants and their size and location, the pump power, and the required excavation work. The model capabilities are demonstrated through a simplified example application using base runs and sensitivity analyses. Scaling of the proposed methodology to real life wastewater collection and treatment plants design problems needs further testing and developments. The model is coded in MATLAB using the GATOOL toolbox and is available from the authors. Water Environ. Res., 83, 53 (2011).

KEYWORDS: optimization, wastewater, system.

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Introduction

The subject of wastewater pipelines and treatment plants systems optimization is an emerging discipline. Most of the modeling optimization efforts, to date, concentrated on either the transmission/sewer pipeline system or the treatment plant.

When designing a regional wastewater pipeline and treatment plant system that connects cities to treatment plants, engineers are facing the problem of wastewater links design and operation and how the treated wastewater from the treatment plants will be transported to a main concentration point for centralized transmission. An example of such a system is shown in Figure 1. The central collection point in Figure 1 represents a regional mutual disposal/central transmission site. Treatment plants 1 to 3 are characterized through their cost as a function of their required treated flow. Water quality explicit considerations are not incorporated in this study. Only flow that needs to be transmitted and treated is accounted for.

Searching for the best pipeline diameter links and pumping power for such systems through enumeration is an exhaustive process. On the other hand, exploring only a limited number of alternatives substantially reduces the likelihood of finding an optimal solution. Thus, an efficient search technique is required.

There are almost no optimization models that incorporate the wastewater sources, pipeline/transportation network, treatment plants, and end disposals/users, in a single framework. The objective of this study is to develop and demonstrate a model of this type.

The developed model in this work addresses a single objective of minimizing the capital and operational costs of a wastewater treatment plant (WWTP) system by using a genetic algorithm (GA) framework. Through a simplified example application, the potential of the proposed model for solving the design problem of sizing wastewater collection and treatment plants systems is demonstrated.

Literature Review

A literature review on wastewater optimization models divided into optimization models for sewer networks, treatment plants, and the entire system, is presented herein.

Sewer Networks Optimization. Early studies on sewer networks optimization used dynamic programming for the least cost design of sewer systems (Dajani et al., 1977; Nzewi et al., 1985; Walters, 1985). Dajani et al. (1977) used separable convex, dynamic, and geometric programming for optimizing the layout and capacity of a sewer system. Nzewi et al. (1985) developed a heuristic search methodology coupled with discrete dynamic programming for the least cost design of sewer networks. Walters (1985) used dynamic programming for the least cost design of sewer networks considering the sewers diameters, nodes layout, diameters, and slopes as decision variables. Abraham et al. (1998) used deterministic dynamic programming for identifying suitable sewer rehabilitation techniques during the planning horizon of a sewer system. deMonsabert et al. (1999) used integer programming to optimize sewer rehabilitation schedules for minimizing the costs of repairs and the inflow and infiltration associated with sewer pipeline and manhole defects. Diogo and Graveto (2006) extended previous studies by presenting a multi-level dynamic programming model for the optimal deterministic selection of sewer pumping stations, intermediate manholes, pipe sections, and pipeline installation depth. The deterministic model was extended further to incorporate uncertainty through the implementation of a simulated annealing scheme. Weng and Liaw (2007) used mixed integer programming coupled with a screening bounded implicit enumeration algorithm for sewer network optimization, demonstrating a saving of approximately 12% compared with using traditional sewer design approaches. Breyssie et al. (2007) developed a technical and economic performance index for asset aging and maintenance of sewer systems. The index was demonstrated for optimal inspection, maintenance, and rehabilitation strategies of sewer networks. Chang and Hernandez (2008) outlined several schemes for sewer system optimal expansion under uncertainty. The methodology included deterministic least-cost optimization modeling algorithms, which further incorporat-
Numerous wastewater management studies related to optimizing the design, calibration, operation, and control of treatment plants were published in the research literature in the last 3 decades. A review of selected recent modeling efforts, mostly relevant for extending the capabilities of the current study, is provided below.

Chang et al. (2001) developed a methodology for industrial WWTP control by linking a genetic algorithm with a neural network model for addressing the uncertainty involved in the operation of WWTP operation. The developed methodology uses a genetic hybrid methodology, which can be adapted to other WWTP problems. Chen et al. (2001, 2003) used a similar framework as that of Chang et al. (2001), yet with adding a fuzzy logic layer for assessing the control of the treatment plants. Chen and Chang (2007) proposed a special rule-based extraction analysis for optimal design of an integrated neural-fuzzy process controller and rules for screening out inappropriate fuzzy operators. The rule was demonstrated using an aerated submerged biofilm wastewater treatment process. Chen et al. (2007) developed a hybrid artificial neural network model coupled with a genetic algorithm for predicting the effluent water quality data of a treatment plant. Zeng et al. (2007) developed a model for the selection of wastewater treatment alternatives based on the application of an analytic hierarchy process coupled with grey relational analysis. Beraud et al. (2007) constructed a multi-objective genetic algorithm optimization model using the Benchmark Simulation Model 1 (Copp, 2002) for trading off effluent quality versus energy consumption of a treatment plant. Holenda et al. (2007) applied a genetic algorithm to optimize the aerobic and anoxic conditions required for nitrogen removal of a treatment plant. Pollution loads and energy consumptions were minimized, showing a substantial improvement over previous applied control methodologies. Gupta and Shrivastava (2008) developed a treatment plant reliability-constrained optimal design model by linking a genetic algorithm with Monte Carlo simulations. The objective function minimized the cost subject to design- and reliability-based performance constraints. Saveyna et al. (2008) used a quadratic model for the assessment of the relative importance of different sludge and polyelectrolyte variables with regard to sludge pressure dewatering.

System Optimization. Optimization of complete wastewater systems started to receive attention only recently. This is both because of the understanding that optimizing the sewer network and the treatment plant separately can result in sub-optimal solutions, and as the use of generic heuristic optimization search techniques such as genetic algorithms (Goldberg, 1989; Holland, 1975) are becoming more common in engineering practices, allowing a holistic representation of the system for optimizing its performance.

Vollertsen et al. (2002) linked a model for in-sewer microbial process simulations with treatment plant design. The model was implemented for optimizing the layout of a sewer system for meeting the requirements of various treatment plant treatment scenarios. Butler and Schütze (2005) developed a coupled simulation and control methodology for integrated real-time control strategies of urban wastewater systems. Leitao et al. (2005) suggested a decision support tool based on geographic information systems and two greedy algorithms for optimal planning of regional wastewater systems. Joksimovic et al. (2008) presented an integrated decision support framework for optimization of treatment and distribution aspects of water reuse and end-users selection. Lim et al. (2008) minimized the capital and operational costs associated with a total wastewater treatment network system, including distributed and terminal water treatment plants, using life-cycle assessment and life-cycle costing.

The models cited in the literature review deal with optimizing portions of a wastewater and treatment plant system. None of them address the problem of optimizing the entire system, with an explicit description of the system hydraulics, sewer flows as decision variables, excavation costs, and pipelines and pumping system costs, as this study is proposing.

Model Formulation

In this section, the objective function components, constraints, and decision variables are outlined. The selected model coefficients herein are empirical, based on Dekel (2006) and Friedler and Pisanty (2006). Friedler and Pisanty (2006) derived cost functions expressing the effects of design flow and treatment level on construction costs, through the analysis of 55 municipal WWTs in Israel (secondary, advanced secondary, and advanced treatment). Dekel (2006) is an Israeli price list database specialized in civilian engineering and construction. Its data set is established according to results of tenders of governmental offices, authorities, and private bodies. The database includes prices of sections in the fields of civil engineering, construction works, concrete, installations, electricity, and various construction costs, as this study is proposing.

Figure 1—Schematic layout of a regional wastewater pipeline and treatment plant system.
The objective function is the total cost of construction (eqs 1 to 4) and operation (eq 5), comprised of the following parts:

1. **Pumping pipeline construction cost:**
   \[ C_{pp} = C_1 / \text{FRC}_{pp}(\text{int, npp}) = 382.5 \, D_g^{1.455} \, L \]
   \[ (1) \]
   Where
   - \( C_{pp} \) (\$) = pipeline construction cost;
   - \( C_1 \) (\$/year) = annual pumping pipeline construction cost;
   - \( \text{FRC}_{pp} \) (int, npp) = annual pipe cost return coefficient, which is equal to \((1 + \text{int})^{\text{npp}} / [(1 + \text{int})^{\text{npp}} - 1]\), where int = annual interest, npp (years) = life span of the pipeline; \( D_g \) (cm) = pipeline (steel) diameter for pumping line; and \( L \) (km) = pipeline length.

2. **Gravitational pipeline construction cost (see Figure 2):**
   - **Shallow excavation:**
     \[ C_2 / \text{FRC}_{pg}(\text{int, npg}) = 21.6 \, D_g^{2.26} \, L + 7 \, \frac{H_1^2 - C_{\min}^2}{2(J - J_s)} L_w \]
     \[ \text{for } H_1 \leq 4 \, \text{m} \]
     \[ (2) \]
   - **Deep excavation:**
     \[ C_2 / \text{FRC}_{pg}(\text{int, npg}) = 21.6 \, D_g^{2.26} \, L + 7 \, \frac{H_1^2 - C_{\min}^2}{2(J - J_s)} L_w + 10 \left[ L_{\min} + \frac{L^2}{2} (J - J_s) - \frac{H_1^2 - C_{\min}^2}{2(J - J_s)} \right] L_w \]
     \[ \text{for } H_1 > 4 \, \text{m} \]
     \[ (3) \]
   Where
   - \( C_2 \) (\$/year) = annual gravitational pipeline construction cost;
   - \( \text{FRC}_{pg} \) (int, npg) = annual pipe cost return coefficient;
   - \( \text{npg} \) (years) = life span of the pipeline;
   - \( D_g \) (cm) = pipeline (highly density Poly-Ethelene) diameter for gravitational pipelines;
   - \( H_1 \) (m) = least excavation cost depth (i.e., \( H_1 \) is a user-defined parameter for the least excavation depth, above which, the cost of excavation increases. It is assumed, in this study, that \( H_1 \) is equal to 4 m);
   - \( C_{\min} \) (m) = minimum pipeline depth;
   - \( L_w \) (m) = pipe excavation width; and
   - \( J_s, J \) = soil slope and gravitational required pipeline slope, respectively.

3. **Pump construction cost:**
   \[ C_3 / \text{FRC}_{pu}(\text{int, npu}) = 64920 \, P^{0.33} \]
   \[ = 64920 \left[ 3.454 \, \Delta h \, Q + 6409 \left( Q^{2.852} \, D_p^{-4.87} \, L \right) \right]^{0.33} \]
   \[ (4) \]
   Where
   - \( C_3 \) (\$/year) = annual pump construction cost;
   - \( \text{FRC}_{pu} \) (int, npu) = annual pump cost return coefficient;
   - \( \text{npu} \) (years) = life span of a pump;
   - \( P \) (W) = pump power;
   - \( \Delta h \) (m) = total head difference along the line (e.g., elevations difference of two tanks at the two pipeline ends); and
   - \( Q \) (m³/h) = flow through pipeline.

The pump power \( P \) as a function of \( Q, D_p, \) and \( L \) is derived using basic hydraulics computations with the assumption that the pump is operating at an efficiency of 0.8 and that the Hazen-Williams formula is used for headloss computation with a headloss coefficient of 130.

4. **Pump energy cost:**
   \[ C_4 = \frac{\text{EC} \, HR}{1000} \left[ 3.454 \, \Delta h \, Q + 6409 \left( Q^{2.852} \, D_p^{-4.87} \, L \right) \right] \]
   \[ (5) \]
   Where
   - \( C_4 \) (\$/year) = pump annual energy cost,
   - \( \text{EC} \) (\$/kWh) = energy cost, and
   - \( HR \) (hr/year) = number of annual pumping operational hours.

5. **Treatment plant construction cost:**
   \[ C_5 / \text{FRC}_T(\text{int, nT}) = 85825 \, Q_T^{0.71} + 1000 \, Q_T \]
   \[ (6) \]
   Where
   - \( C_5 \) (\$/year) = annual treatment plant construction cost,
   - \( \text{FRC}_T \) (int, nT) = annual treatment plant cost return coefficient,
   - \( \text{nT} \) (years) = life span of the treatment plant, and
   - \( Q_T \) (m³/h) = treated flow at treatment plant.

The first component in eq 6 is related to the plant design cost, where the second linear term is associated with the treatment area purchase cost. Note that the nonlinear power of the treatment plant design flow \( Q_T \) in eq 6 is less than unity. This expresses the feature that the incremental increase in the treatment plant construction cost declines as the incoming design flow increases. This poses an advantage for constructing a central treatment plant instead of several small facilities.

**Constraints.** The model constraints are given below (eqs 7 to 9).

1. **Cities mass balance (see Figure 1):**
   The total wastewater production from each of the cities should be distributed among the treatment plants:
   \[ \sum_{j=1}^{NT} Q_{ij} = \text{NS}_i \quad \forall i \in \text{NC} \]
   \[ (7) \]
   Where
   - \( Q_{ij} \) (m³/h) = flow from the \( i \)-th city to the \( j \)-th treatment plant,
Plan view

Cross section A - A

Legend

$L_w$ = pipe excavation width: pipe diameter D + 30 centimeter space between the pipeline and the excavation on both of its sides

$L$ = pipeline length

$C_{min}$ = minimum pipeline depth

$H_1$ = least excavation cost to a depth of $H_1$

$A1$, $A2$ = excavation areas to and above a depth of $H_1$, respectively:

$A1 = \frac{H_1^2 - C_{min}^2}{2(J - J_1)}$

$A2 = L C_{min} + \frac{1}{2} (J - J_1) - \frac{H_1^2 - C_{min}^2}{2(J - J_1)}$

Figure 2—Schematic of a gravitational pipeline layout.

NS$_i$ (m$^3$/h) = total wastewater production of the i-th city,

NC = number of cities, and

NT = number of treatment plants.

(2) Treatment plant mass balance:

The total incoming wastewater to a treatment plant should be equal to the total treated flow effluents, as follows:

$$\sum_{i=1}^{NC} Q_{ij} = TS_j \quad \forall j \in NT$$

Where

$TS_j$ (m$^3$/h) = total effluents outlet from the j-th treatment plant.

(3) Gravitational min-max flow:

The Manning’s equation for flow in a non-full cross-section of 80% of the pipeline diameter is used for gravitational pipelines. This leads to an average cross-section velocity, $V_g$ (m/s), as in eq 9, using a Manning’s headloss coefficient of 0.013.

$$V_g = 1.615 D_0^{0.667} J_0^{0.5}$$

Minimum and maximum velocity requirements of 0.6 (m/s) and 2.5 (m/s), respectively, are imposed to avoid particles accumulation and to protect the pipeline.

**Decision Variables.** The decision variables are the vectors of flows ($Q$), diameters ($D$), and required gravitational pipeline slopes ($J$). The flows ($Q$) and the required gravitational pipeline slopes ($J$) are continuous decision variables. The vector of diameter $D$ is discrete in reality, but, in this study, is treated as continuous. This is a model simplification justified by the assumption that the influence on the objective function value, resulting from choosing the nearest appropriate commercial pipe diameter, or two pipelines in series, which generate the same hydraulic headloss as the model diameter selection, is small. Such a simplification was used previously (e.g., Fujiwara and Khang, 1990) for distribution system optimization and is made to ease the model solution scheme. However, it is not a necessity, as a genetic algorithm is used. No constraints are imposed on the required pump capacities.

**Complete Model.** The complete mathematical formulation of the model is as follows:

Minimize $\sum_{k=1}^{5} C_k(Q, D, J)$

Which is subject to the following:

$$\sum_{j=1}^{NT} Q_{ij} = NS_i \quad \forall i \in NC$$

$$\sum_{j=1}^{NT} Q_{ij} = TS_j \quad \forall j \in NT$$

$$0.6 \leq V_g \leq 2.5 \quad \forall g \in G$$

Where

$C_k = k$-th component of the objective function total annual cost (e.g., $C_1$ = vector of all pumping pipeline construction costs); and

$G =$ set of all gravitational pipelines.

**Solution Scheme**

A MATLAB code using the genetic algorithm toolbox GATOOL based on Chipperfield et al. (1994) was implemented.
for solving the model outlined in eqs 10 to 13. Although other genetic algorithm tools could have been selected (e.g., optiGA, 2002), the MATLAB environment was chosen, as it provides convenient access to additional modeling and built-in simulation software especially suited for control problems. It should be noted that other evolutionary computational schemes, such as Ant Colony (Dorigo et al., 1996), likely could be implemented.

Genetic algorithms (Goldberg, 1989; Holland, 1975) are heuristic combinatorial search techniques that imitate the mechanics of natural selection and natural genetics of Darwin’s evolution principle. The basic idea is to simulate the natural evolution mechanisms of chromosomes (represented by string structures), involving selection, crossover, and mutation. This is accomplished by creating a random search technique, which combines survival of the fittest among string structures with a randomized information exchange. As genetic algorithms are already very well-known schemes for heuristic optimization, the reader is referred to any genetic algorithm textbook (e.g., Goldberg, 1989) for further technical information.

Example Application

The layout of an example application is shown in Figure 3. The system is comprised of two cities connected through four optional gravitational and pumping pipelines to three possible treatment plants, which are further linked using three gravitational pipelines to a central collection point. The problem base run parameters are provided in Table 1.

The example application incorporates the following subsections:

(1) Genetic algorithm base run and genetic algorithm parameters statistics sensitivity runs.
(2) Results for the best base-run-obtained solution, and
(3) Problem-oriented sensitivity runs.

Genetic Algorithm Base Run and Parameters Statistics Sensitivity Runs. Figures 4 and 5 summarize the data and results of statistics of 100 model runs for each of 10 cases—1 base run and 9 genetic algorithm additional parameter sensitivities (i.e., a total of 1000 model repetition trials) using the MATLAB genetic algorithm toolbox GATOOL on a Dual Core 2.26 GHz, 4GB RAM PC.

The following genetic algorithm base run parameters were used:

- Population size of 100—100 individuals in each generation;
- Fitness scaling of type rank—scales the population individuals according to their rank within the population sorted scores;
- Selection method of type stochastic uniform—selects parents for reproduction using a line in which each parent corresponds to a section of a line of a length proportional to its expectation;
- Elite count of 2—specifies the number of best individuals in each generation that move unchanged to the next generation;
- Crossover fraction of 0.8—defines the next generation fraction produced by crossover;
- Crossover of type scattered—uses a random binary vector for gene combinations of individual parents for reproduction;
- Mutation of type Gaussian, with a scale of 2 and a shrink of 1—generates a random number for mutation for each individual string using a Gaussian distribution centered on zero. The scale of 2 specifics a standard deviation of 2 for the first generation, which shrinks linearly to zero at the last generation with a shrink parameter of 1; and
- Stopping criteria—the foremost to occur among the use of a maximum of 2000 generations or a computational time exceeding 20 seconds with no model improvement.

In GA-SA1 (genetic algorithm sensitivity analysis 1), the selection method was altered to tournament of size 2 (i.e., a tournament between two randomly selected individuals, from which the better is chosen as a parent); in GA-SA2, a roulette wheel was applied for selection (i.e., using a roulette wheel for parents selection, with the roulette area partitioned into segments, where each segment is proportional to an individual expectation according to its fitness); in GA-SA3, the elite count was modified to 5; in GA-SA4, the crossover fraction was altered to 0.9; in GA-SA5 and GA-SA6, a 1-point crossover (i.e., a single crossover location on each individual string) and 2-points crossover (i.e., 2-points crossover locations on each individual string) were used, respectively; in GA-SA7, the Gaussian mutation scale was altered to 4; in GA-SA8, the population size was increased to 200; and, in GA-SA9, the population size was modified to 200 and the stopping criteria to a maximum of 4000 generations and a maximum computational time of 60 seconds with no results improvement.

The top and bottom of Figure 4 describe the genetic algorithm data and results, respectively. Figure 4 shows that the best result was attained for the base run for all cases in which the population size remained unchanged (i.e., GA-SA1 to SA7). As the population size increased, a better solution was received (i.e., GA-SA8, SA9). Increasing the population size and relaxing the stopping criteria in GA-SA9 resulted in the best solution, although...
Table 1—Example application base run data.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value (Units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{min}}$</td>
<td>Minimum pipeline depth</td>
<td>Assumed very close to the surface (i.e., approximately zero)</td>
</tr>
<tr>
<td>EC</td>
<td>Energy cost</td>
<td>0.1 ($/kWh$)</td>
</tr>
<tr>
<td>$\text{FRC}<em>{\text{pp}}$ (int, np); $\text{FRC}</em>{\text{pg}}$ (int, np)</td>
<td>Annual cost return coefficient for pipeline construction</td>
<td>0.075 (−)</td>
</tr>
<tr>
<td>$\text{FRC}_{\text{pu}}$ (int, npu)</td>
<td>Annual cost return coefficient for pump construction</td>
<td>0.110 (−)</td>
</tr>
<tr>
<td>$\text{FRC}_{\text{T}}$ (int, nT)</td>
<td>Annual cost return coefficient for treatment plant construction</td>
<td>0.072 (−)</td>
</tr>
<tr>
<td>$H_1$</td>
<td>Least excavation cost depth</td>
<td>4 (m)</td>
</tr>
<tr>
<td>$\text{HR}$</td>
<td>Number of annual pumping operation hours</td>
<td>8760 (h/year)</td>
</tr>
<tr>
<td>int</td>
<td>Annual interest</td>
<td>7 (%)</td>
</tr>
<tr>
<td>$J_s$</td>
<td>Soil slope</td>
<td>assumed zero or very close to zero</td>
</tr>
<tr>
<td>$L_w$</td>
<td>Pipe excavation width</td>
<td>pipe diameter + 0.6 (m)</td>
</tr>
<tr>
<td>$L_1, \ldots, L_7$</td>
<td>Link length</td>
<td>1 (km)</td>
</tr>
<tr>
<td>$\text{NS}_1, \text{NS}_2$</td>
<td>Total wastewater production for city 1 and city 2, respectively</td>
<td>8000 (m$^3$/h)</td>
</tr>
<tr>
<td>$\text{npp}, \text{npg}$</td>
<td>Life span of pipeline</td>
<td>40 (years)</td>
</tr>
<tr>
<td>$\text{npu}$</td>
<td>Life span of pump</td>
<td>15 (years)</td>
</tr>
<tr>
<td>nT</td>
<td>Life span of treatment plant</td>
<td>50 (years)</td>
</tr>
<tr>
<td>$V_{g, \text{min}} ; V_{g, \text{max}}$</td>
<td>Minimum and maximum gravitational pipeline velocities, respectively</td>
<td>0.6, 2.5 (m/s)</td>
</tr>
<tr>
<td>$\Delta h$</td>
<td>Total head difference along a line</td>
<td>10 (m)</td>
</tr>
</tbody>
</table>

A: Genetic algorithm DATA

<table>
<thead>
<tr>
<th>Case</th>
<th>Population size</th>
<th>Fitness scaling</th>
<th>Selection method</th>
<th>Elite count</th>
<th>Crossover</th>
<th>Mutation</th>
<th>Stopping criteria</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Fraction</td>
<td>Type</td>
<td>Type</td>
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<tr>
<td>Base run</td>
<td>100</td>
<td>RA</td>
<td>SU</td>
<td>2</td>
<td>0.8</td>
<td>S</td>
<td>G</td>
</tr>
<tr>
<td>GA-SA1</td>
<td>100</td>
<td>RA</td>
<td>T2</td>
<td>2</td>
<td>0.8</td>
<td>S</td>
<td>G</td>
</tr>
<tr>
<td>GA-SA2</td>
<td>100</td>
<td>RA</td>
<td>R</td>
<td>2</td>
<td>0.8</td>
<td>S</td>
<td>G</td>
</tr>
<tr>
<td>GA-SA3</td>
<td>100</td>
<td>RA</td>
<td>SU</td>
<td>5</td>
<td>0.8</td>
<td>S</td>
<td>G</td>
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<tr>
<td>GA-SA4</td>
<td>100</td>
<td>RA</td>
<td>SU</td>
<td>2</td>
<td>0.9</td>
<td>S</td>
<td>G</td>
</tr>
<tr>
<td>GA-SA5</td>
<td>100</td>
<td>RA</td>
<td>SU</td>
<td>2</td>
<td>0.8</td>
<td>OP</td>
<td>G</td>
</tr>
<tr>
<td>GA-SA6</td>
<td>100</td>
<td>RA</td>
<td>SU</td>
<td>2</td>
<td>0.8</td>
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<td>G</td>
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<td>RA</td>
<td>SU</td>
<td>2</td>
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<td>G</td>
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<td>S</td>
<td>G</td>
</tr>
<tr>
<td>GA-SA9</td>
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<td>RA</td>
<td>SU</td>
<td>2</td>
<td>0.8</td>
<td>S</td>
<td>G</td>
</tr>
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</table>

B: Genetic algorithm RESULTS

<table>
<thead>
<tr>
<th>Case</th>
<th>Minimum Solution</th>
<th>Maximum Solution</th>
<th>Average Solution</th>
<th>Standard deviation</th>
<th>Minimum Number of function fitness evaluations to convergence</th>
<th>Maximum Number of function fitness evaluations to convergence</th>
<th>Average Number of function fitness evaluations to convergence</th>
<th>Standard deviation</th>
<th>Ratio of average number of function fitness evaluations to convergence to average solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base run</td>
<td>1821248</td>
<td>2338925</td>
<td>1999269</td>
<td>146134</td>
<td>62700</td>
<td>200000</td>
<td>185536</td>
<td>30131</td>
<td>0.093</td>
</tr>
<tr>
<td>GA-SA1</td>
<td>1838803</td>
<td>2419030</td>
<td>2050428</td>
<td>160555</td>
<td>72100</td>
<td>200000</td>
<td>174134</td>
<td>38509</td>
<td>0.085</td>
</tr>
<tr>
<td>GA-SA2</td>
<td>1825239</td>
<td>2315412</td>
<td>2006158</td>
<td>162338</td>
<td>76800</td>
<td>200000</td>
<td>176539</td>
<td>36474</td>
<td>0.088</td>
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<td>GA-SA3</td>
<td>1823521</td>
<td>2343141</td>
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Legend: GA-SA1 = genetic algorithm sensitivity analysis 1; RA = rank; SU = stochastic uniform; S = scattered; G = Gaussian; T2 = tournament selection of size 2; R = roulette selection; and OP, TP = one point and two points crossover, respectively.

Figure 4—Genetic algorithm sensitivity analysis.
with minor improvement (i.e., 1,818,468 $/year in GA-SA8 compared with 1,816,130 $/year in GA-SA9). The best solution obtained in GA-SA9 used the maximum number of function fitness evaluations and the highest computational price of 0.308 (i.e., ratio of average number of function fitness evaluations to convergence to average solution).

Figure 5 scales the best solution acquired in GA-SA9 to all other cases and the corresponding computational price. Figure 5 shows that the worst result among all cases (i.e., SA-GA5) has the lowest computational price of 0.059. It is relatively distant from the best solution (i.e., GA-SA9) by approximately 3.6%.

Figure 6 shows a typical progression of the genetic algorithm; the first feasible solution is obtained at generation 66 at an annual cost of approximately $1.9 \times 10^6$/year; the algorithm then progresses in a “stair-like” manner, with the best attained solution of approximately $1.86 \times 10^6$ ($/year) received after 500 generations.

**Detailed Base Run Results.** Figure 7 presents the best base-run-obtained results, and Table 2 presents detailed results for the best base run and three problem-oriented sensitivity analyses runs. Figure 7 shows that gravitational pipeline 1 and pumping pipeline 3 were selected to transmit the cities’ wastewater production to treatment plant 1, and gravitational pipeline 5 was selected to
transmit the cities’ wastewater production to the central collection point. To guarantee a minimum pipeline diameter, links were excluded during the solution process (i.e., assigned a zero flow) if their capacity was less than 10% of the entire cities’ wastewater production. Using this heuristics links 2, 4, 6, and 7, and, as a result, treatment plants 2 and 3 were excluded from the final solution. It should be noted that the 10% figure for pipes elimination is heuristic for simplification purposes (i.e., similar to treating pipe diameters as continuous instead of discrete variables). Incorporating a decision of “elimination” is binary (i.e., 0 or 1) and can be used in principle as a genetic algorithm is used.

The best base run solution obtained was a total cost of 1 821 248 ($/year), with most of its portion (83.3%) devoted to the treatment plant construction cost, 15.1% for the pumping pipeline, and only 1.6% for the gravitational transmission. As the treatment plant construction cost dominates the solution costs, only one treatment plant was selected. The velocity (2.3 m/s) at gravitational pipeline 5 is close to the maximum allowable gravitational pipeline velocity of 2.5 m/s.

Problem-Oriented Sensitivity Analysis Runs. Four sensitivity analysis runs aimed at testing the model solution behavior to modifications made in the problem data or the constraints, as compared with the base run results, are explored herein.

In sensitivity analysis 1 (SA1), each city’s wastewater production was doubled (i.e., 2000 m$^3$/h compared with 1000 m$^3$/h at the base run). As a result (Table 2), the total system cost was increased to 2 964 332 ($/year) (85.5% for the treatment plant cost, 12.6% for the pumping pipeline, and 1.9% for the gravitational transmission). The results of SA1 show that the entire system capacity was increased, and the system layout (i.e., the selection of pipelines 1, 3, and 5, and treatment plant 1) remained unchanged; the gravitational pipelines 1 and 3 diameters were increased to 60 and 82 cm, respectively (compared with 43 and 58 cm, respectively, at the base run); the pumping pipeline diameter was increased to 90 cm (75 cm at the base run), and the pumping power was increased to 74 kW (36 kW at the base run). The SA1 results demonstrate, as in the base run, the dominance of the treatment plant cost; thus, the model selects to increase capacity, yet not to alter the base run model layout.

In sensitivity analysis 2 (SA2), pumping pipeline 3 is excluded (i.e., only pipelines 1, 2, 4, 5, 6, and 7 are considered). The model selects four gravitational pipelines—1, 4, 5, and 7, all with the same diameter of 43 cm at a slope of 0.013, and two treatment plants (1 and 3). The total system cost is 1 871 536 ($/year), out of which, 97.4% is for the treatment plants cost and 2.6% is for the pipelines. Note that the obtained cost of 1 871 536 ($/year) is an increase over the base run solution of 1 821 248 ($/year). This is the result of the removal of pipeline 3, which imposes an additional constraint to the model, thus reducing the feasible domain, which results in an increase in cost.

In sensitivity analysis 3 (SA3), the length of links 1, 3, and 5 are increased to 20 km (1 km at the base run; i.e., the distance of treatment plant 1 to the cities and to the central collection point is increased substantially). As a result, pumping pipeline 2 is selected (with the same properties as pipeline 3 in the base run), with gravitational pipelines 4, 6, and 7, and treatment plants 2 and 3. The total system cost is increased to 2 133 444 ($/year), out of which, 85.4% is for the treatment plants construction, 12.9% is for the pumping pipeline, and 1.7% is for the gravitational pipelines.

In sensitivity analysis 4 (SA4), the model was run with different annual interest rates—5 to 10% (7% at the base run). Figure 8 shows the tradeoff (i.e., the exchange) between the system’s cost results and the annual interest rate (best solutions out of 100 trials for each explored interest rate). Figure 8 shows that the system’s cost increased approximately linearly as the interest rate increased.

Figure 9 is a graphical summary of the best base run and SA1-SA3 sensitivity runs, as described above, showing the relative percentage in all runs of the objective function components C1, …C5. For example, the gravitational pipeline construction relative cost (C2) is 17% (29 181 $/year) for the base run, 33% (56 305 $/year) for SA1, 29% (48 812 $/year) for SA2, and 21% (35 852 $/year) for SA3.

Conclusions

A genetic algorithm model for optimizing regional wastewater treatment systems comprised of transmission gravitational and pumping sewer pipelines, decentralized treatment plants, and end-users of reclaimed wastewater was developed and demonstrated. The model was coded in MATLAB using the GATOOL toolbox, which provides a convenient environment for genetic algorithm analysis and further access to control simulation tools.

The model contribution to wastewater pipelines and treatment plants systems optimization is in providing an integrated model for optimizing a total regional wastewater treatment network system, considering the following:

1. An explicit formulation of the system’s hydraulics for both the sewers and pumping pipelines;
2. Pipeline flows as decision variables, where previous studies optimized the system for a given flow distribution, which
substantially narrowed the feasibility domain and thus the ability to obtain good solutions; and

(3) Possible modifications in the system’s layout, by initially suggesting a “rich” layout setup and allowing the model to select and size the most appropriate pipelines, pumps, and treatment plants.

A simplified example application was explored for 1 base run and 13 sensitivity analysis cases—9 for the influence of modifying genetic algorithm parameters and 4 for altering problem-dependent data. The genetic algorithm sensitivity results showed the following:

(1) Convergence in all cases to the vicinity of the best obtained solution, with a maximum relative difference of 3.6%, and

(2) That the most significant genetic algorithm parameter was the population size.

The problem-oriented sensitivity runs produced explanatory outcomes, showing a close-to-linear tradeoff between the system cost and the annual interest rate. However, it should be emphasized that the example application is a simplified representation of reality and was meant to demonstrate a “proof of concept”. Extension of the proposed methodology to real-world problems with a network of pipes and geographical constraints will need to address issues such as the following:

(1) Different pipe materials, routes, and cross-sections;
(2) Locations of pumping stations with diverse characteristics;
(3) Storage facilities and their effects;
(4) Pipes network layout complexities;
(5) Multiple loadings;
(6) An improved representation of the cost functions and, in particular, the treatment plant construction and operation costs, as related to the treated wastewater quality and geographical location; and
(7) Multi-objective optimization frameworks (e.g., reliability/risk versus cost).

In reality, the system will be highly complex; it is anticipated that the parameters that will be the most dominant in determining

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**Table 2—Best base run and sensitivity analysis detailed results.**

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<th>Component</th>
<th>Feature</th>
<th>Component Feature</th>
<th>Component Feature</th>
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<td>Pipeline 2 (P)</td>
<td>Q (m³/h); D (cm); P (kW)</td>
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<td>Pipeline 3 (P)</td>
<td>Q (m³/h); D (cm); P (kW)</td>
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* Legend:

BR = base run; SA1 = sensitivity analysis 1; Pipeline 1 (G), Pipeline 2 (P) = optional gravitational pipeline 1 and pumping pipeline 2, respectively; TP1 = treatment plant 1; PICC, EXC, TC ($/year) = annual pipeline construction, excavation, and total cost, respectively; J (°) = pipeline slope; D (cm) = pipeline diameter; Q (m³/h) = pipeline flow; V (m/s) = pipeline velocity; P (kW) = pump power; PUCC, EC ($/year) = annual pump construction, and energy cost, respectively; NS = not selected; and RC = removed connection.
the total cost will differ as a function of the particular system layout, components, cost functions, and imposed loadings. As genetic algorithms prove to be robust and reliable schemes, we believe that such extensions are doable, yet with an anticipated increase in computational costs.

**Nomenclature**

- \( C_1 \) ($/year) = annual pumping pipeline construction cost,
- \( C_2 \) ($/year) = annual gravitational pipeline construction cost,
- \( C_3 \) ($/year) = annual pump construction cost,
- \( C_4 \) ($/year) = pump annual energy cost,
- \( C_5 \) ($/year) = annual treatment plant construction cost,
- \( C_i \) = vector of the i-th component of the objective function,
- \( C_{\text{min}} \) (m) = minimum pipeline depth,
- \( C_{\text{pp}} \) ($) = pipeline construction cost,
- \( D_g \) (cm) = pipeline (highly density Poli-Ethilean) diameter for gravitational pipelines,
- \( D_p \) (cm) = pipeline (steel) diameter for pumping line,
- \( D \) (cm) = vector of pipeline diameters,
- \( EC \) ($/kWh) = energy cost,
- \( FRC_{pu} \) (int, npu) = annual pump cost return coefficient,
- \( FRC_{pg} \) (int, npg), \( FRC_{pp} \) (int, npp) = annual pipe cost return coefficient,
- \( FRC_T \) (int, nT) = annual treatment plant cost return coefficient,
- \( H_1 \) (m) = least excavation cost depth (assuming 4 m),

**Figure 8**—Tradeoff between the system cost and annual interest rate.

**Figure 9**—Best base run and sensitivity analysis summary results.
HR (h/year) = number of annual pumping operation hours, 
int = annual interest,

\( J_s, J \) = soil slope and gravitational required pipeline slope, respectively,

\( J \) = vector of required gravitational pipeline slopes,
\( L \) (km) = pipeline length,
\( L_{eq} \) (m) = pipe excavation width,
\( NC \) = number of cities,
\( NS_i \) (m³/h) = total wastewater production of the i-th city,
\( NT \) = number of treatment plants, 
\( npp \) (years) = life span of the pipeline, 
\( npp \) (years) = life span of the pipeline, 
\( nT \) (years) = life span of the treatment plant, 
\( npu \) (years) = life span of a pump, 
\( O \) (k) = k-th generated population, 
\( P \) (W) = pump power, 
\( Q \) (m³/h) = flow throughput, 
\( Q \) (m³/h) = vector of flows through pipeline, 
\( QT \) (m³/h) = treated flow at treatment plant, 
\( TS_j \) (m³/h) = total outlet effluents of the j-th treatment plant, 
\( V_c \) (m/s) = average cross-section velocity, and
\( \Delta h \) (m) = total head difference along the line (e.g., elevations difference of two tanks at the two pipeline ends).

**Credits**

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**References**


