



Optimal Design of Spatially Constrained Interplant Water Networks with Direct Recycling Techniques using Genetic Algorithms

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In this work, an industrial city spatial representation that accounts for different plant layouts and arrangements is utilized for interplant water network synthesis. The problem has been previously tackled using deterministic optimization methods. This work employs a stochastic optimization approach, using genetic algorithms, for the design of spatially constrained interplant water networks using direct recycling techniques. The approach identifies well-performing solutions in an evolutionary manner, by generating populations of candidate solutions, then sampling regions that are associated with the highest performance probabilities. This ensures that only the fittest designs survive, when evaluating the network performance. A fitness objective that accounts for both freshwater and piping costs was utilized in the design evaluation stage. When compared to the results that have been obtained using deterministic optimization, trade-off trends between the optimum cost of the network and fresh/waste targets were manifested by means of stochastic optimization. Enhanced network performance was attained for a reduced total cost, at the expense of a certain deviation from fresh/waste targets.

1. Introduction

The continuous industrial reliance on water has instigated ample interest in the development of effective water management strategies for industrial cities. Many countries across the world have set water targets for major water-consuming industrial sectors. Inefficient practices for wastewater disposal are currently being minimized as a step towards easing the pressure on freshwater resources, as well as complying with imposed environmental regulations. The concept of industrial water integration and reuse has gained considerable attention as a means of reducing the volume and cost of industrial freshwater consumption, and wastewater discharge.

Many water integration techniques have been developed and successfully applied on various problems to effectively design water allocation networks within a single plant. For instance, Wang and Smith (1994) introduced an approach for maximizing water reuse (MWR) in process industries. Their methodology involves a targeting stage that determines minimized levels for freshwater use and wastewater discharge in the system through the construction of composite curves to show limiting water profiles for each operation. The concept behind the construction of composite curves was similar to that introduced by El-Halwagi and Manousiouthakis (1989). Moreover, the work by Wang and Smith (1994) was applied to both single and multiple contaminant scenarios, and was later extended to accommodate flowrate constraints, as well as multiple sources of fresh water (Wang and Smith, 1995). Other water integration contributions such as Savelski and Bagajewicz (2000), investigated the necessary conditions of optimality for a single-contaminant Water Allocation Problem (WAP), as it has been posed by Wang and Smith (1994), for which the objective was to minimize the total water intake.

Later on, theories and principles behind industrial ecology (Côté and Cohen-Rosenthal, 1998) have inspired a number of studies beyond the boundaries of a single plant, thus introducing interplant water

integration (IPWI) problems. Chew et al. (2008) formulated both MINLP and MILP models to obtain global solutions for various problems involving Interplant Water Integration. Lovelady and El-Halwagi (2009) investigated water allocation optimization opportunities amongst multiple plants using a source-interception-sink structural representation, for a common Eco-Industrial park (EIP). More recently, Boix et al (2012) tackled industrial water network design problems using a multi-objective optimization strategy, in which fresh water, regenerated water, and the number of connections in the network were minimized. The problem was also formulated as a MILP, and the linearization of their model was based on the necessary conditions of optimality introduced by Savelski and Bagajewicz (2000).

However, to date, not much attention has been given towards accounting for spatially constrained water transport amongst an existing cluster of processing facilities. Effective synthesis and design of interplant water networks greatly depends on the geographical locations of water-using and water-producing operations that could lie across the different plants operated by different entities. Moreover, industrial city infrastructure in terms of assigned water transport sites, more commonly known as service corridors, inevitably affects the determination of optimum piping routes for water transport in a given plot. Handling spatial constraints in water optimization problems within industrial cities has been previously tackled using deterministic optimization methods (Alnouri et al., 2014). The representation that has been introduced also benefits macroscopic energy integration studies for heat reuse (Stijepovic and Linke, 2011) and combined heat and power generation (Stijepovic et al, 2012). In this work a stochastic optimization approach, using genetic algorithms has been employed for the design of spatially constrained interplant water networks, using direct recycling techniques. stating that the representation

2. Genetic Algorithms for Network Design

Based on the survival-of-the-fittest principle, Genetic Algorithms (GAs) are rigorous stochastic optimization techniques that utilize a selection process derived from biological evolution concepts (Beasley et al, 1993). Genetic Algorithms are executed by first creating a random set of solutions, then generating new solutions, referred to as populations, from already existing ones. Each solution is characterized using a string of symbols called 'chromosomes' (Mitchell, 1996). For each generation of solutions created, fitness values are calculated accordingly, thus allowing the solutions to be ranked in an increasing order of fitness according, using a rank selection procedure as described by Eq(1) below (Mitchell, 1996).

$$ExpVal(i,t) = Min + (Max - Min) \frac{rank(i,t) - 1}{N - 1} \quad (1)$$

where $ExpVal(i,t)$ corresponds to the expected value of solution i in a population at time t , $rank(i,t)$ corresponds to the rank of solution i in a population at time t , Min is the expected value of the solution with rank 1, where Max is the expected value of the solution with rank N .

The highest fitness individuals are accordingly selected to be parents for the next generation, and new populations of solutions are created using crossover and mutation principles, hence ensuring that only the finest characteristics in the population are retained. Crossover involves the relocation of genes from the parents' chromosomes, so as to produce potentially more superior chromosome combinations when generating a new population of solutions, without introducing any new genetic material into the population (Mitchell, 1996). Therefore, it extracts the best genes from the parents and recombines them to produce potentially more superior solutions for the next generation. On the other mutation involves applying random changes to some of the parents' genetic material in order to ensure that the generated populations are supplied with new genetic information (Mitchell, 1996). This can possibly entail substituting two or more genes from the parents' chromosome, so as to produce different traits in the generated population of solutions. Hence, selection, crossover and mutation steps keep hold of the finest hereditary information from generation to generation.

3. Problem Formulation and Implementation

The objective function utilized for fitness assessment of all generated solutions incorporates a minimization function of freshwater and piping costs associated with the water network design. Piping costs were computed according to suitable relations involving the pipe lengths and respective diameters, which in turn were calculated according the amount of water flow in the pipe. Process constraints involved the total mass balances for all process water sources and water sinks, as well as total component balances on all water sinks were the process constraints in the problem. Moreover, additional constraints describing

bounds on the respective contaminants for each sink were included utilized. All calculated pipe diameters were rounded up to an appropriate value, so as to accommodate standard size availability. Initially, all shortest routes that achieve feasible water transport are extracted by executing Dijkstra's Algorithm (Dijkstra, 1959), utilizing a given industrial city arrangements for the various plants involved. Subsequently, the nonlinear optimization for the water network design problem employs the built-in GA MATLAB function. The problem was implemented in MATLAB, on a desktop PC with a 64-bit Operating System (2.7 GHz, 8.00 GB RAM), and an Intel® Core™ i7-2620M.

4. Case Study Illustration

The following case study has been carried out as an illustration, using the layouts provided in Figure 1, assuming a total area of 36 km², spread over 1,600 equally-spaced regions. Two different constraints for pipe structuring were employed, in order to investigate their influence on the solutions extracted. Figure 1 illustrates the case of only allowing right angled connectivity amongst the various piping arrangement options, and will be referred to as Type 1. Figure 2 on the other hand involves both crosswise and right angled arrangements for interplant piping connectivity, and will be referred to as Type 2. It is evident that Type 2 connectivity has twice as much connectivity options as Type 1 from node to node. Appropriate directional constraints, as well as weight assignments for each type of connection have been utilized when extracting all optimum source-to-sink paths. Table 1 summarizes flowrate and contaminant composition data used in this case study. Additionally, Tables 2 and 3 provide all distance information, which correspond to the shortest distance routes that have been obtained by means of Dijkstra's algorithm, provided the given arrangement for both types of piping connectivity, respectively. Although a single contaminant was assumed for this case study, the methodology can be applied for multiple contaminants as well.

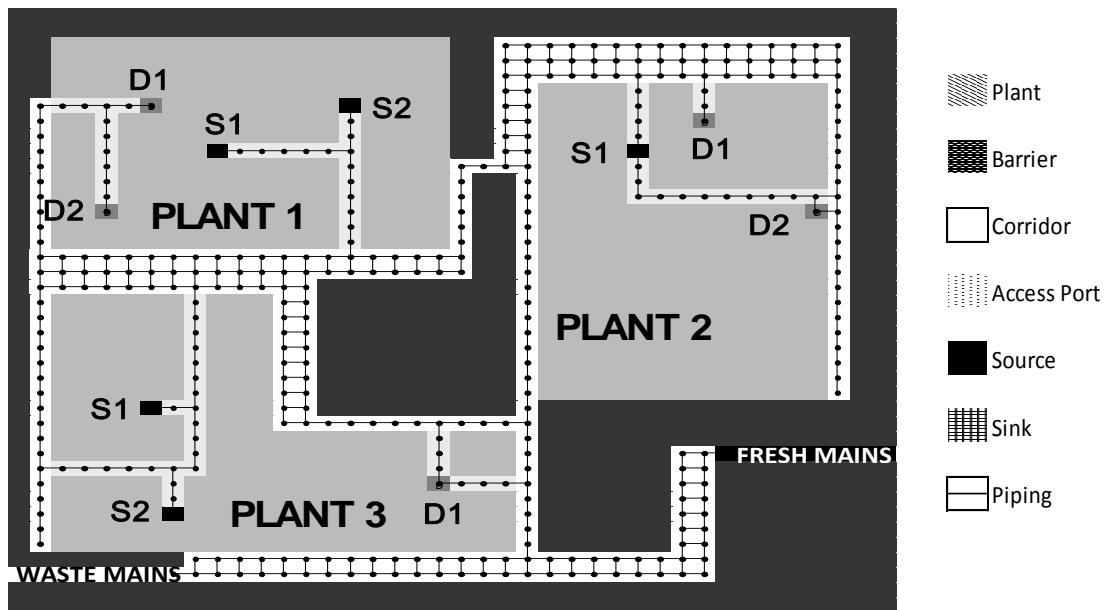


Figure 1: Industrial city layout illustrated using Type 1 piping connectivity

Table 1: Case Study flowrate and composition data

Sinks	Flow (t/h)	Conc. (ppm)	Sources	Flow (t/h)	Conc. (ppm)
P1D1	210	140	P1S1	160	200
P1D2	160	180	P1S2	180	350
P2D1	200	90	P2S1	70	470
P2D2	150	150	P3S1	105	320
P3D1	150	120	P3S2	230	280

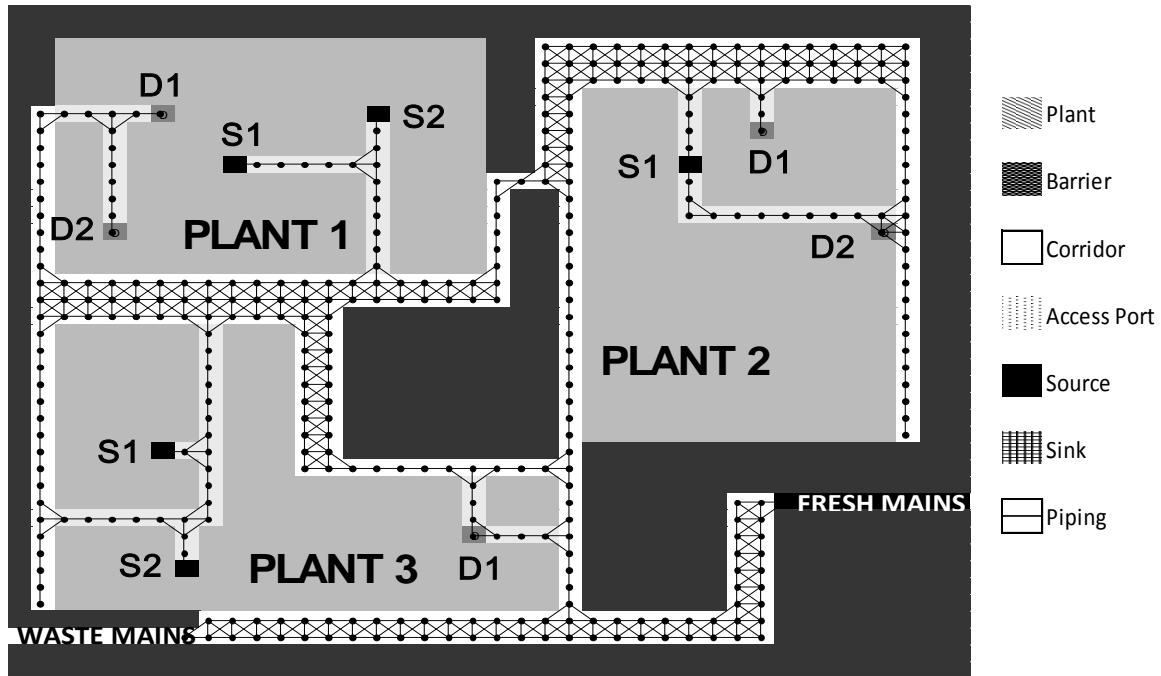


Figure 2: Industrial city layout illustrated using Type 2 piping connectivity

Table 2: Source-to sink distances extracted using Type 1 piping connectivity constraints

Distance (km)	P1D1	P1D2	P2D1	P2D2	P3D1	Waste
P1S1	6.30	7.05	6.60	8.25	5.40	9.30
P1S2	5.85	6.60	6.15	7.80	4.95	8.85
P2S1	8.85	9.60	1.65	1.80	6.15	8.85
P3S1	5.1	5.85	7.50	9.15	5.10	9.00
P3S2	5.7	6.45	8.40	10.05	6.00	9.90
Fresh	10.95	11.70	8.85	10.50	3.75	4.95

Table 3: Source-to sink distances extracted using Type 2 piping connectivity constraints

Distance (km)	P1D1	P1D2	P2D1	P2D2	P3D1	Waste
P1S1	5.94	6.60	5.88	7.35	4.95	8.49
P1S2	5.58	6.24	5.52	6.99	4.59	8.13
P2S1	8.13	8.79	1.47	1.62	5.79	8.49
P3S1	4.56	5.22	6.60	8.07	4.56	8.10
P3S2	5.43	6.09	7.50	8.97	5.46	9.00
Fresh	9.69	10.35	8.31	9.78	3.30	4.59

Table 4: Water Allocation Strategy (Network Design 1)

Flowrate (t/h)	P1D1	P1D2	P2D1	P2D2	P3D1	Waste
P1S1	0	0	0	70.0	90.0	0
P1S2	0	0	0	0	0	180.0
P2S1	0	0	0	0	0	70.0
P3S1	63.43	0	0	0	0	41.56
P3S2	32.5	102.8	64.28	30.35	0	0
Fresh	114.06	57.14	135.7	49.64	60.0	0

Table 5: Water Allocation Strategy (Network Design 2)

Flowrate (t/h)	P1D1	P1D2	P2D1	P2D2	P3D1	Waste
P1S1	0	0	90.0	70.0	0	0
P1S2	0	0	0	0	0	180.0
P2S1	0	0	0	18.1	0	51.9
P3S1	0	0	0	0	36.9	68.1
P3S2	105.0	102.9	0	0	22.1	0
Fresh	105.0	57.1	110.0	61.9	91.0	0

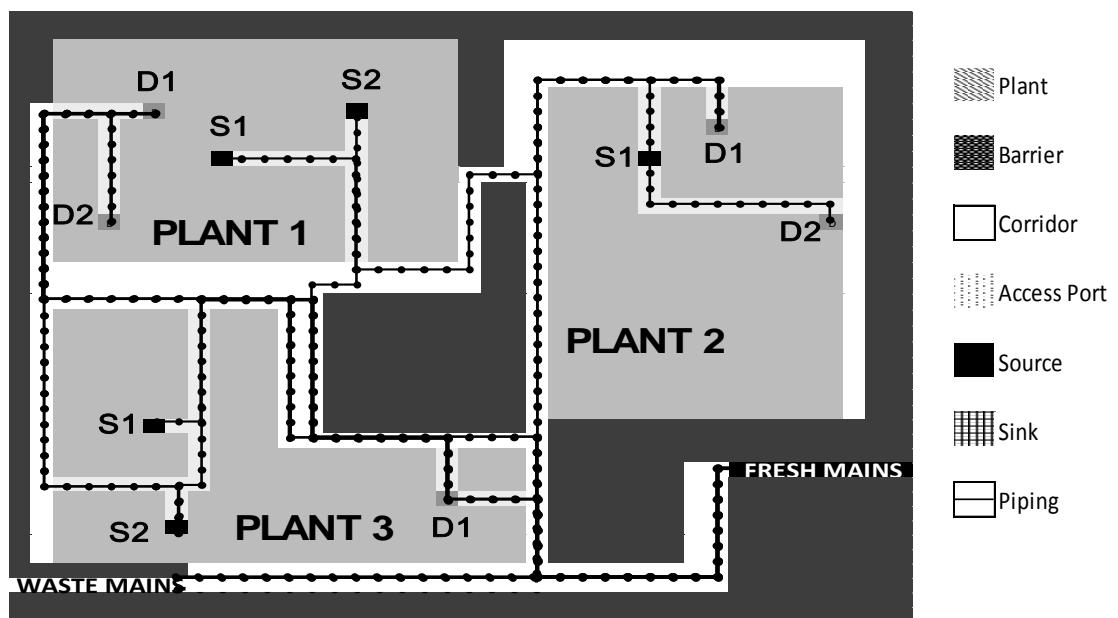


Figure 3: Optimal Water allocation Strategy using Type 1 piping connectivity (Network Design 2)

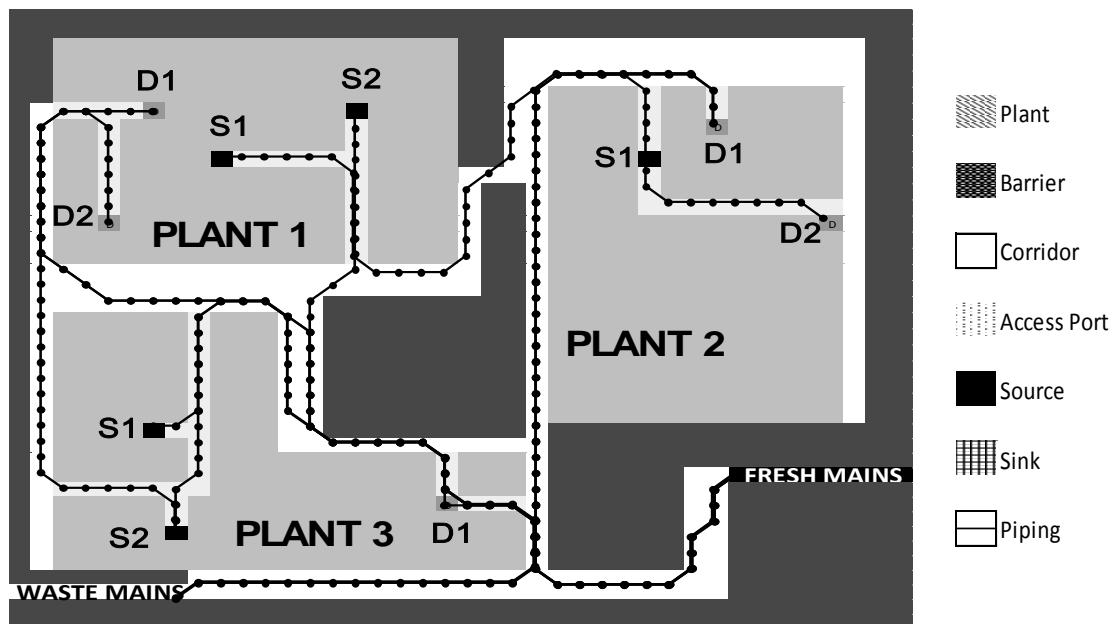


Figure 4: Optimal Water allocation Strategy using Type 2 piping connectivity (Network Design 2)

Multiple solutions of similar performance are identified for the problem. Tables 4 and 5 summarize two distinct network designs. Network Design 1 (Table 4) follows a strategy where fresh water flows are minimized at the expense of capital investment (Alnouri et al., 2014b). The total cost of this network is 1.129×10^6 \$/y for the case involving Type 1 connectivity, and 1.073×10^6 \$/y for the case of Type 2 piping connectivity. Network Design 2 (Table 5) follows a strategy that uses more fresh water, but requires less capital investment. The total cost of the network is 1.043×10^6 \$/y for the case involving Type 1 connectivity, and 0.995×10^6 \$/y for the case of Type 2 piping connectivity. Such trade-offs between the optimum cost of the network and fresh/waste targets can be easily explored using the stochastic search method and the GA solver is able to provide alternative solutions with comparable network performance. Significant solution diversity is observed for source-sink implementations that can benefit decision making for direct water reuse.

5. Conclusions

This paper discusses interplant water network design using stochastic optimization, by means of genetic algorithms. The case study presented in this paper illustrates that attractive interplant water network designs indeed can be achieved in terms of total costs, as well as freshwater and wastewater requirements.

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