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Optimization of Drinking Water and Sewer Hydraulic Management: Coupling of a Genetic Algorithm and Two Network Hydraulic Tools

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Abstract

Veolia has developed an optimization platform for the operation of sewer networks (POSTEVENT) and drinking water networks (OPTIM'HYDRO). This platform couples a genetic algorithm NSGA-II with hydraulic network simulation tools (INFOWORKS CS and EPANET). The challenge is to optimize the design and operation of networks according to given objectives and constraints, by changing asset control parameters. This article deals with optimization challenges raised and developed off-line support tools. It ends with a case study on a French drinking water network consisting in upscale set points for pumping stations to optimize the procurement management of water and reduce the energy costs.

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*Keywords:*Optimization; Hydraulic modeling; Genetic algorithms; Drinking water system; Sewer system.

1. Introduction

Drinking water and sewer network managers are, nowadays, faced with relatively complex optimization problems, such as the minimization of system management costs and ensuring the required level of service. This optimization must be carried out with existing infrastructures, despite the evolution of the requirements that they face in an increasingly complex regulatory and environmental context [1]. The modeling of urban networks has become widespread. Coupling modeling with methods of optimization could greatly increase their added value for network

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operation diagnosis [2]. This article details how Veolia Water and Veolia Environment Research and Innovation intend to render optimization available for system managers, with the development of a platform coupling a genetic algorithm NSGA-II and hydraulic network simulation tools (INFOWORKS CS for sewer and EPANET for drinking water). First, optimization issues concerning drinking water and sewer network operation are dealt with and translated in objectives, constraints and variables into the offline optimization tools POSTEVENT and OPTIM'HYDRO. Then a case study of a French drinking water network is presented which objective was to find optimal pumping schedule in order to optimize the procurement management of water and reduce the energy costs.

2. Multi-objective optimization using genetic algorithm

2.1. Optimization problems

Optimization problems can be expressed as follows; given a function, as

$$f : A \rightarrow \mathbb{R}^m, \begin{cases} min_{x \in A} f(x) \\ subject\ to\ g(x) \leq 0 \end{cases} \quad (1)$$

- x is called *decision variable*. It can be a scalar or a vector. In the latter case, the components of the decision variable, called in the following *decision variables*, may be continuous or discrete;
- n is the number of decision variables;
- A is called *search space*. It is a subset of $\mathbb{R}^n$ if all decision variables are continuous; it is $\{0,1\}^n$ if all variables are binary or a combination of continuous and discrete subspaces;
- g is the function specifying constraints. The simplest constraints are the lower and upper bounds of the decision variables;
- f is called *objective function*. It expresses the performance of the decision variables and can be a scalar or a vector in case of multi-objective optimization (m> 1);
- m is the number of objectives.

In this study, the objective function could not be calculated analytically with the values of the decision variables. Instead, the decision variables values are used to specify operating conditions in external models simulating water or wastewater networks operation; the simulation is then run and the objective function is eventually calculated with the simulation outputs. As a consequence, the difficulty of the optimization problem did not only depend on the characteristics of the optimization problem (e.g., n, m, A…), but also from that of the model.

2.2. Multi-Objective Optimization

Multi-objective optimization problems arise when conflicting objectives have to be optimized simultaneously. Comparing solutions with multiple objectives is not trivial if no hierarchy among objectives is set, and one has often to compare compromises rather than a simple performance indicator. In order to classify solutions in a multi-objective context, Pareto introduced the dominance context:

Let *X* and *Y*be two solutions. X is said to **dominate** *Y* if, for all objectives *j*, the following holds:
$Obj^j(X) \leq Obj^j(Y)$, with at least one strict inequality. Obj^j is the value of the j^{th}objective (2)

Dominance relationships can easily be represented in the objective space as depicted in Fig.1, for a 2-objective problem. Dominance domains (i.e. for all objectives) or partial dominance domains can be defined (Fig.1 a)). In the case of partial dominance, X and Y solutions are comparable. The set of non-dominated points represents the best compromises between the two objectives, it is called Pareto front (Fig.1 b)). One of the solutions from that front may be eventually selected by the decision-maker as the optimal one.

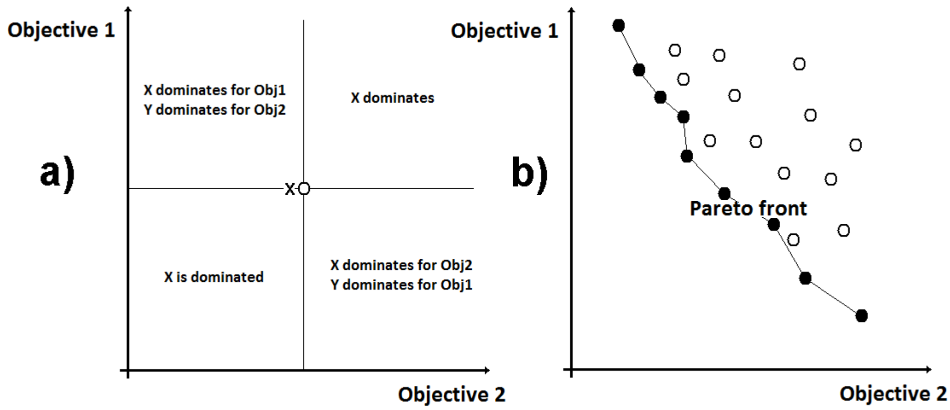

Fig.1. a) Graphical representation of the dominance concept: X is set and Y can be located in one of the four subdomains of the graph; b) Set of potential solutions (empty circles) and set of non-dominated solutions (full circles).

2.3. Genetic algorithms

Given the characteristics of the optimization problems, a genetic algorithm was selected as optimization algorithm. Genetic Algorithms (GA) are often preferred with highly non-linear multi-objective functions, despite their high computational cost. Moreover, GA have the ability to take into account easily mixed sets of decision variables (that is, continuous and discrete variables simultaneously).GAs are based on the evolution of a population of candidates for the solution of an optimization problem. The algorithm proposes successive generations of candidates that progressively converge to a solution, thus iteratively improving. The principles leading to the formulation of GAs were derived from considerations on natural species evolution [3].Three key principles are used for the generation of new candidate solutions: selection, mutation and recombination (also called crossover). Selection consists in selecting from a set of solutions the best ones; typically this is done on the solutions of the same generation. Mutation consists in altering the current solution to see what could be achieved in its neighborhood [4]. It is a pretty old technique and can be seen as a simple modification of traditional hill-climbing techniques [5]. Recombination consists in taking two good solutions and exchanging some of their characteristics. This strategy was directly inspired by considerations on the evolution of species, and on the genetic interbreeding techniques aiming at producing the best fitted individuals. The recombination is assumed to provide fast convergence to the optimum (compared to mutation) and to avoid the entrapment in local extrema by early convergence. Early convergence is encountered when a very fit member of the population appears early. Due to its high fitness, it is more likely to reproduce and propagate its characteristics through the generations, eliminating the options that may have eventually led a global optimum. Practically, early convergence can be prevented by high mutation rates, but this strategy remains case-dependent [6]. The main drawback is that only near optimal solutions are found with GAs [5]. The algorithm used in this study is called NSGA-II (Non-Sorted Genetic Algorithm). It was originally proposed by [7].

3. OPTIMIZATION PLATFORM AND TOOLS: POSTEVENT AND OPTIM'HYDRO

3.1. Context and major issues

Hydraulic modeling has for a long time allowed sewer and drinking water network operators for a diagnosis of the operation of their networks or for the validation of new solutions. But in recent years, its added-value has also been considered for optimization. Sewer networks have grown in size and in facilities. Their structure has become more complex, evolved from spinal to gridded, storage tanks have been built and a growing proportion of their infrastructures have been equipped with real time control devices such as moveable weirs, moveable valves, variable speed pumps which settings have usually been adjusted locally, sometimes through modeling, some other times through experience. Within this growing complexity, the objectives of the sewer network operators have remained the same: maximize the volume of sewerage treated, minimize the overflow volumes, minimize the flood volumes while, if they can, minimizing the energy consumptions during their operation. With regard to drinking water networks operation, the optimization problems generally consist in minimizing expenditures. These could be future capital expenditures (resizing of pipes, replacement of a group of pumps, positioning of new infrastructures) or minimizing operating expenditures (adjusting the control rules of the pumping stations or valves).

3.2. Common optimization platform for networks

To render optimization available for system managers, Veolia has developed an optimization platform for the operation of networks by coupling the genetic algorithm NSGA-II, with hydraulic network simulation tools InfoWorks CS and EPANET. Two off-line decision or design support tool are available: POSTEVENT for sewer networks modeling in InfoWorks CS and OPTIM'HYDRO for drinking water networks modeling in EPANET.

A schematic representation of an optimization resulting from the combination of a hydraulic network model and a genetic algorithm is presented below in Fig.2.

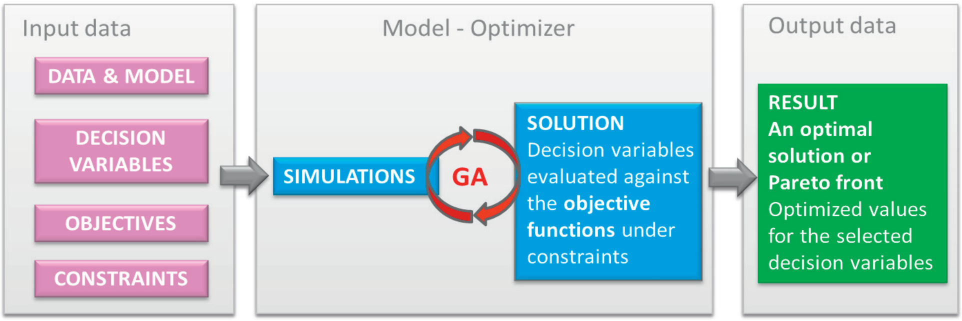

Fig.2. Schematic representation of an optimization resulting from the combination of a hydraulic network model and a genetic algorithm

For both optimization tools, the minimum input data required is a robust i.e., well calibrated and validated network model, a consistent selection of decision variables, objectives and constraints for the optimization and for OPTIM'HYDRO a set of added data such as electricity prices or pipe renewal costs per diameter. Once this is completed, the GA will randomly generate initial solutions which will be simulated and evaluated against the objectives and constraints of the optimization. Following the principles described in chapter 2.3, the best solutions will be kept to generate new solutions until an optimal solution (for single objective optimizations) or a Pareto front (for multi-objective optimizations) is found. The optimization platform allows for a distribution of the calculations on a computer network, in order to reduce the processing time. The Table 1 illustrates for each tool (POSTEVENT or OPTIM'HYDRO) what the decision variables, objectives and constraints can be.

Table 1. Summary of the optimization's criteria for POSTEVENT and OPTIM'HYDRO

	POSTEVENT	OPTIM'HYDRO
MODELING TOOL	InfoWorks CS	EPANET
DECISION VARIABLES	Control devices (pumps, valves, weirs) parameters in control rules: - level to be maintained in a node - discharge flow rate - pump start/stop levels - type of controller and its characteristics	Pipe parameters: - diameters Pump parameters: - pump characteristics (Total dynamic head, Flow capacity) - pump state (on/off) and speed

	POSTEVENT	OPTIM'HYDRO
		- settings in control rules (state, level in a tank, pressure in a node, operation schedule) Other control devices (valves, flow controllers) parameters: - state, setpoint - settings in control rules (state, setpoint or operation schedule)
OPTIMIZATION OBJECTIVES	Overflow volume (m^3) Overflow pollutant load (kg) Maximum wastewater level (m) Energy consumption (J)	Pipe renewal or pipe extension costs (€) Energy consumption (kW) and/or energy cost (€) Water production cost or water acquisition cost (€) Water residence time in tank (s)
OPTIMIZATION CONSTRAINTS	Overflow volume (m^3) Overflow pollutant load (kg) Maximum wastewater level (m) Energy consumption (J)	Pressure (mCE) in a demand node Level (m) or volume (m^3) in a tank Age of the water (s) in a demand node Pump on/off frequency (number/h or number/d) or minimum operating time between start and stop (min) Water production or water acquisition capacity (m^3/hr or m^3/d) Maximum velocity in a pipe (m/s)

In POSTEVENT, the decision variables are to be chosen from the regulators of the hydraulic network model: variable speed pumps, groups of fixed pumps, variable crest or width weirs, or variable valves. It is their control rule, for instance: a level to be maintained in a critical point of the network. Objectives and constraints for an optimization can be chosen from the same list of possible treatments and each treatment can be applied to a group of pipes or manhole to be chosen by the user. The definition of the overflow volumes and overflow pollutant loads treatments in the case of wastewater quality model are intuitive and will not be explained. The maximum wastewater level treatment is the difference between the wastewater level in a manhole and its ground level and is mainly used as a constraint in order to minimize flood volumes during a simulation. Finally, the energy consumption is an indicator of the energy consumption of all the pumps of the sewer network during a simulation.

In OPTIM'HYDRO, there are four different objectives for an optimization. Depending on the chosen objective, different decision variables, other input data and constraints will be relevant or not. For instance, for an optimization of a future pipe design, the decision variables will be the selected pipes' diameter, the other input data will be the possible pipe diameters and their costs of renewal depending on the renewal techniques, and the constraints will have to be chosen between maximum velocities in pipes, pressure requirements in selected demand nodes. Because there are a number of possible combinations between objectives and constraints for an optimization in OPTIM'HYDRO, a case study is developed in the next chapter.

4. A CASE STUDY ON DRINKING WATER NETWORK

4.1. Context

OPTIM'HYDRO has been used on several drinking water networks in France and in China. The following case study is about the drinking water network of a municipality in the North of France, delivering water to 250,000 inhabitants. 33,000 m^3/d are supplied by 11 boreholes and two water purchase points. Two main constraints for the network have been identified. First, the quality of the groundwater resources is variable. Some denitrification treatment plants have been temporarily implemented in the network to decrease the nitrate level pumped from the wells. Second, even though the network of this municipality is equipped with 18 tanks, they offer a very low storage capacity. The challenge was to optimize the energy cost without increasing the cost of water purchase and denitrification treatment. The first phase of this study consisted in an optimization without investments, finding the optimal operating set points for the existing pumping stations. The strategic network (1315 km) is modelled in EPANET, with: 15,839 demand nodes, 18 tanks and 21 pumping stations. Additional data required for this case study was:

- measured pump curves and efficiency pump curves
- unit cost of purchased water (in €/purchased m^3)
- unit cost for the denitrification water treatment plants (€/treated m^3)
- unit cost of electricity for each pumping stations (€/m^3)
- operational data: average consumption of water, peak consumption of water.

The current control rules of the pumping stations and water purchase points are implemented in order to compare the results of the optimization with the initial situation.

4.2. Optimization settings

The settings for the optimization are illustrated in Fig.3 below. It summarizes the decision variables, objectives and constraints chosen for the optimization.

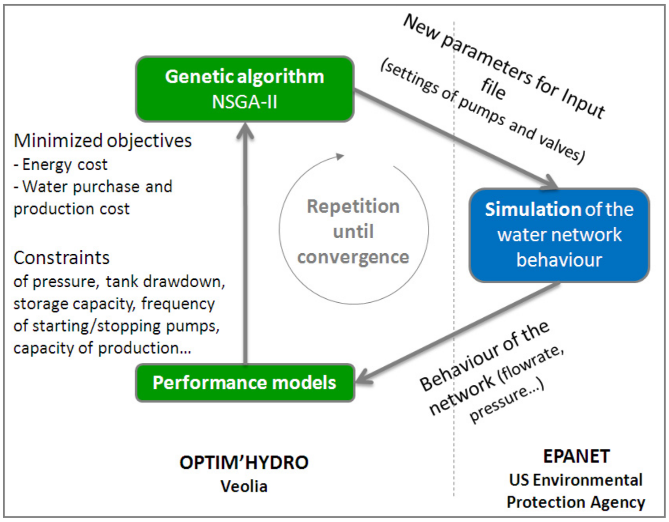

Fig.3. Optimization settings for the case study of a municipality in the North of France

4.2.1. Optimization objectives

The objectives of the optimization are to reduce the energy cost and optimize the usage of purchased water. The pumping stations operation is essentially responsible for the energy consumption of the network. The contract with the electricity supplier is structured with a fixed monthly subscription and a variable subscription proportional to the consumption. According to the seasons and the type of tariff, there are two or three electricity tariff bands per day.

The cost of purchased water is regulated by two different contracts with two neighboring municipalities. Depending on the boreholes, the production cost of water includes (or not) the cost of denitrification. The chemical agent volume is proportional to the volume of treated water.

4.2.2. Decision variables

The optimization will serve to upscale set points for 18 pumping stations. To reduce the electricity cost, the possible triggers could be to minimize the consumption and/or minimize the pumping during peak and high hours of electricity tariff band. The pumping stations are started for a minimum level of water in a tank and stopped for a maximum level of water in a tank. Pumps are fixed speed. Thus, for each pump variables are a set of set points by electricity tariff band with a low starting set point and a high stopping set point according to level in tanks.

4.2.3. Constraints

The constraints have been set in order to restrict solutions to those respecting the network operating conditions:

- Stable tank drawdown over 24 hours. The hydraulic simulations are done over 48 hours. The first 24 hours correspond to the initialization of the system. Therefore, the objectives and constraints are calculated over the last 24 hours. The tanks must have the same level at the beginning of the day (t=24h) and at the end of the day (t=48h). This constraint allows for a comparison of solutions with equal pumping volume, no additional storage or retrieval in the system during the day.
- Minimum storage capacity in tanks set to 50% of the tank's total volume. This constraint makes sure that the tanks conserve a security volume.
- Frequency of pump start/stop and minimum time between pump start/stop. These constraints allow for preventing the overheating of pumps. The values are adapted to each pump depending on their power.
- Minimum capacity of purchased water for each neighbouring municipality in m^3/d.

Another operating constraint is the minimum pressure of 20 mCE and maximum pressure of 80 mCE at demand nodes, in order to ensure correct supply service. Although it has not been considered as a constraint in this optimization, node pressures in the optimized and initial solutions have been compared making sure the situation would not be degraded in the optimized solutions.

4.2.4. Scenario

Optim'Hydro is not a Real-Time Control tool. The optimization is performed on typical days according to different scenarios of water consumption (average/peak consumption day) and electricity tariff band (summer, winter or peak winter electricity tariff). Only one scenario is presented in this article: average water consumption day and summer electricity tariff. The objectives and constraints of the initial situation have been evaluated (Table 2). These values will represent the reference against which the optimized solutions will be compared.

Table 2 Initial situation (average water consumption and summer electricity tariff) in the municipality

Objectives	Energy cost (€/d)	382
	Water purchase and production cost (€/d)	2,794
Constraints	Maximum water purchase capacity - purchase 1 (m^3/d)	216
	Time of exceeding of minimum volume of storage in tanks (s)	12,600
	Number of tanks without conservation of level on 24 hours (number of tanks)	0
	Number of pumps over maximum frequency of starting/stopping pumps (number of pumps)	2

The initial situation does not respect the constraints of water purchase capacity, minimum volume of storage and maximum frequency of pump start/stop. An objective of the optimization is also to improve operational conditions and levels of delivered service.

4.3. Results: Pareto front for scenario

The solutions of the optimization scenario average water consumption and summer electricity tariff are shown on the Pareto front in Fig. 4. This Pareto front represents all the solutions respecting the constraints described earlier, against the two objectives of the optimization: « Energy cost » and « Water purchase and production cost ».Each solution improves the operation of the network. For example, the maximum water savings with constant energy is 4%

and the maximum energy savings with constant water cost is 8%, without investment. Each solution corresponds to a schedule of operating setpoints for pumps. The drawdown zone of the tanks and the pumps can be displayed in EPANET. After the optimization, the tank drawdown is increased in the night and decreased during the day. The pumping is decreased during high hours electricity band and therefore the electricity costs decreased.

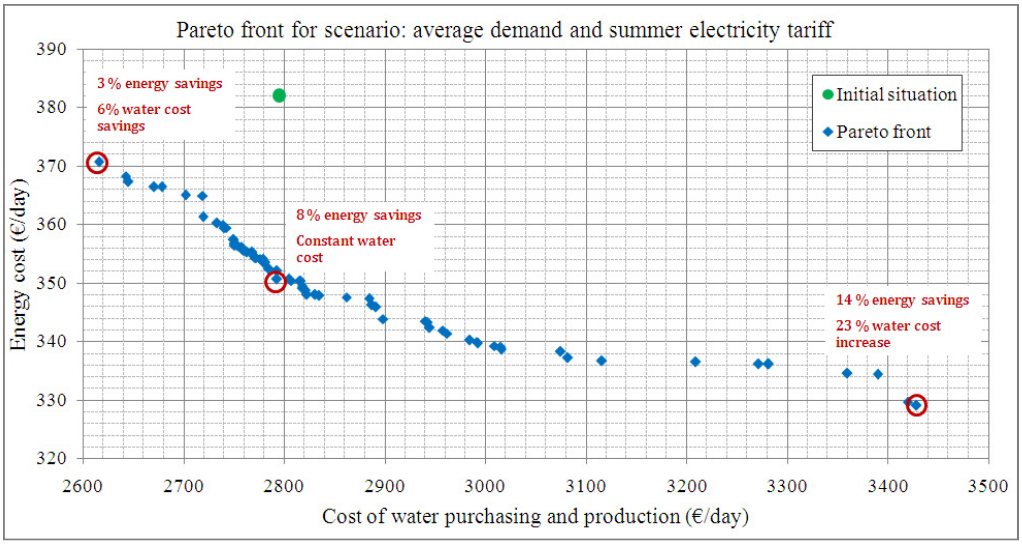

Fig.4. Pareto front of scenario average water consumption and summer electricity tariff

Savings are dependent on the daily demand volume. A solution that provides savings for an average water consumption day will not necessarily present savings during a peak consumption day. A specific study on the sensitivity of the results with regard to the demand has also been done in order to define which scenario should be chosen to optimize and modify the operating settings. The next step of this case study is the implementation of the optimized settings on site. Distributed volume, flows through pumping stations and energy cost and consumption will be monitored before and after the modifications of the settings, in order to quantify the operational savings in comparison with the theoretical ones.

5. CONCLUSION

Optimization tools are becoming available for decision-makers to better operate their assets providing that they have well calibrated and validated modeling tools, sufficient knowledge on how the network/assets operate and sufficient monitoring and additional data to feed these powerful tools. The example of this municipality in the North of France demonstrates the possible positive outcomes of such optimization studies but has also highlighted the importance of undertaking sensitivity analyses, never forgetting uncertainties related to modeling or input data in general. Monitoring the implementation of the new set points and comparing the operational savings with the theoretical ones will play its part into the valorization of such tools.

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