Sewer Network Multi-objective Optimization using Genetic Algorithms

Iulian Vasiliev
Department of Automation and Electrical Engineering
Dunărea de Jos University of Galati
Galati, Romania
iulian.vasiliev@ugal.ro

Laurentiu Luca
Department of Automation and Electrical Engineering
Dunărea de Jos University of Galati
Galati, Romania
laurentiu.luca@ugal.ro

Marian Barbu
Department of Automation and Electrical Engineering
Dunărea de Jos University of Galati
Galati, Romania
marian.barbu@ugal.ro

Ramon Vilanova
Department of Automation Systems and Advanced Control Research,
Autonomous University of Barcelona
Barcelona, Spain
ramon.vilanova@uab.cat

Sergiu Caraman
Department of Automation and Electrical Engineering
Dunărea de Jos University of Galati
Galati, Romania
sergiu.caraman@ugal.ro

***Abstract*—This paper focuses on the multi-objective optimization of a sewer network that serves a medium-sized Romanian city, with a population of 250,000 residents. The sewer network is modeled using BSMSewer software package. The obtained results are based on numerical simulations with the optimization algorithm considering two performance criteria: the volume of overflow and the quality of the overflowed wastewater. For optimization, two approaches that use a controlled elitist genetic algorithm were employed: a multi-objective optimization and a two-steps multi-objective optimization. Results analysis involved comparing them with a scenario where each performance criterion was separately minimized. Additionally, a comparison was made to the situation where the sewer network operated without a control system, meaning the valves were fully open and the pumps were running maximum capacity.**

Keywords—wastewater, sewer network, multi-objective optimization, controlled elitist genetic algorithm

I. INTRODUCTION

The issue of wastewater treatment has become crucial at the moment, being directly related to environmental protection. The main objectives are to avoid discharges to prevent floods and improve the quality of water discharged into natural receptors (rivers, lakes, groundwater etc.), which means increasing the efficiency of the operating of sewer networks, SN, and wastewater treatment plants, WWTP, (discharged water quality parameters must be in accordance with the legislation specific to this field). This problem can be treated separately (increasing the efficiency of the sewer networks and, separately, of the wastewater treatment plants), but also in an integrated way considering both entities.

The literature reports numerous approaches regarding the modeling and control of the sewer networks. Thus, regarding the sewer network modeling, various approaches can be found, from simplified discrete models [1] that are not requiring a lot of computational effort, to more complex models that are able to model the wastewater flow with its loads: particulate and soluble chemical oxygen demand, ammonia and phosphate and phenomena that are taking place in the pipes and in the soil [2]. Beside deterministic models of the sewer networks, stochastic quality models, that are data-driven, can be found. In [3] a stochastic model implemented in InfoWorks that is able to predict flow and quality profiles is proposed. A similar approach [4], being able to predict flow, nutrient and temperature changes is used to quantify the impact of water saving strategies.

The sewer network control strategies are important because they assure low-cost and safe operating of the sewer network. Usually, the main goal of the sewer network control systems is to reduce the pollution caused by overflows by reducing the quantity of discharged water or the quantity of pollutants discharged during overflow events. In [5] a generic methodology for optimal control of the sewer networks is proposed, a methodology that can be applied when a state-space model of the system is available. Other approaches based on simplified models consider only binary commands on the sewer network tanks outlet and use Binary Hybrid Topology Particle Swarm Optimization in an optimal control structure [6] or in a predictive control structure [7].

Fuzzy logic based control structure has been used in [8] to reduce the sewer network overflows effects. For each of the storage tanks, the fuzzy logic controller uses the levels in the storage tanks, the inflow and the downstream tank level to compute the outflow rate, aiming at improving the overflow in terms of pollution loads. The paper [9] took a step forward, by adjusting the membership functions of the fuzzy logic controller by using a genetic algorithm in order to provide the best results, leading to a 25% overflow volume decrease, compared to membership functions provided by human experts.

In [10] a multi-objective optimization algorithm based on NSGA II aims at minimizing the overflow pollution load and the operating cost of sewer network pumps.

In the present paper, the authors aim to optimize the operating of a sewer network considering two performance criteria (multi-objective optimization) consisting of the volume of overflows (V_{ovf}) and the quality of overflowed water (OQI). The sewer network considered in the paper serves a medium-sized city in Romania with a population of 250,000 inhabitants. It was modeled in the BSMSewer simulation environment. The analysis of the obtained results

Cite as: I. Vasiliev, L. Luca, M. Barbu, R. Vilanova, and S. Caraman, "Sewer Network Multi-objective Optimization using Genetic Algorithms", *Syst. Theor. Control Comput. J.*, vol. 3, no. 1, pp. 45–50, Jun. 2023.
DOI: 10.52846/stccj.2023.3.1.49

was made by comparison with the situation in which the optimization aimed at separately minimizing each performance criteria, by reporting at the case when the sewer network operates without control system (the valves were fully open, and the pumps were running at 100% capacity).

The paper is structured on 4 sections as follows: the second section presents the structure and the characteristics of the sewer network, the third section deals with the multi-objective optimization methods and the results analysis and the last section is dedicated to the conclusions.

II. Structure and Characteristics of the Sewer Network

In Fig. 1 the structure of the sewer network is presented. The sewer network includes seven tanks that collect polluted water from 5 collecting areas. The tanks no. 1 - 4 collect domestic polluted water and rainwater from urban areas, while the tank no. 5 collects wastewater from an industrial area (specifically from the brewery industry). The tanks no. 6 and 7 are storage tanks, the last one being connected to the wastewater treatment plant. A detailed description of the sewer network can be found in [11].

It is considered that the connection between the tanks is made both gravitationally (between tanks 1 and 7, 2 and 7, 3 and 6, 5 and 6), and by using pumping stations (the communication between tanks 4 and 6 and tanks 6 and 7).

The notations from Fig. 1 are the following:

- TK_i, $i = \overline{1 \ldots 7}$, the tank i;
- d_i, $i = \overline{1 \ldots 5}$, the inflow of the tank i from the corresponding collecting area;
- u_i, $i = \overline{1 \ldots 7}$, is the outflow of the tank i;
- $q_{over,i}$, $i = \overline{1 \ldots 7}$, represents the overflows of the tank i.

For each tank it was also considered:

- $V_i = 0.05 \cdot pe_i$ – The volume of the tank i (0.05 m^3 for each inhabitant of the collecting area served by the tank i), pe_i – the number of inhabitants of the collecting area i).
- $U_{max,i} = 3 \cdot Q_{pe} \cdot (pe_i + \sum_{j=1,u_j \subset d_i}^{n} pe_j)$ – Maximum flow at the output of the tank i – 3 times higher than the average wastewater production of the population served by the tank i and the tanks whose outflow is part of the influent of tank i ($Q_{pe} = 0.15\, m^3/day$ - the average domestic water (production/inhabitant/day).

The surface and the number of inhabitants corresponding to each collecting area are given in TABLE I. The volume values and maximum possible outflows can be found in TABLE II. The influent comes from the 5 collecting areas and contains the 3 components mentioned above (domestic polluted water, rainwater and industrial water). TABLE III presents the average flows and loads corresponding to the five collecting areas.

TABLE I. Collecting Areas characteristics

Collecting area no.	Surface of the collecting area [ha]	The population served [number of inhabitants]
1	2500	75000
2	5000	50000
3	6000	40000
4	7500	60000
5	3500	25000

TABLE II. Tank characteristics

Tank no.	Volume [m³]	Maximum outflow [m³/day]
1	3750	33750
2	2500	22500
3	2000	18000
4	3000	15000
5	3750	18750
6	2083	25000
7	2500	112500

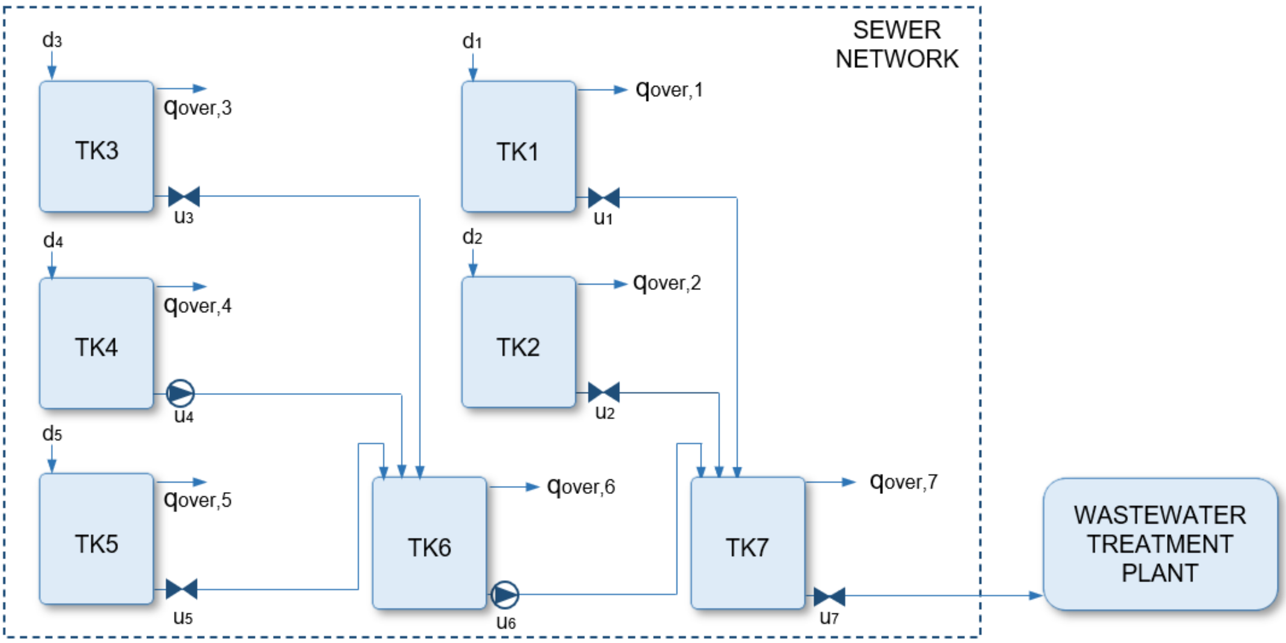

Fig. 1. The general scheme of the sewer network

TABLE III. MEDIUM LOADS AND FLOW FOR EACH COLLECTING AREA

Collecting area no.	*COD*sol [kg/day]	*COD*part [kg/day]	*NH*₄+ [kg/day]	PO_4^{3-} [kg/day]	Flow [m³/day]
1	720.71	4607.6	220.84	57.05	7786.2
2	487.97	3104.7	143.80	38.26	5283.0
3	421.18	2693.0	121.91	30.95	4400.5
4	589.17	3789.9	182.30	44.36	6369.4
5	2742.60	2051.3	132.67	61.22	4771.9

III. THE SEWER NETWORK OPTIMIZATION

A. Results obtained in "no control" operating regime

As mentioned in section I, the first simulations results have been obtained without using any control system. All valves at the tank outputs have been considered fully opened, while all the pumps were running at 100% as long as the wastewater level in the tank was over 0.5 meters. The results from TABLE IV have been obtained.

TABLE IV. "NO CONTROL" RESULTS

Tank no.	V_{ovf} [m³/year]	OQI
1	0	0
2	22729	192
3	50202	743
4	55134	1365
5	0	0
6	241600	3830
7	0	0
global	369665	6131

B. Results obtained in "V_{ovf} optimization" and "OQI optimization" operating regimes

In this case, the optimization was done in relation to each performance criteria. In [12] 5 options for choosing the form of the controls for optimization are presented. It should be noted that only the controls corresponding to the tanks 3, 4 and 5 outputs are considered for the optimization. The best results were obtained for the control presented in Fig. 2.

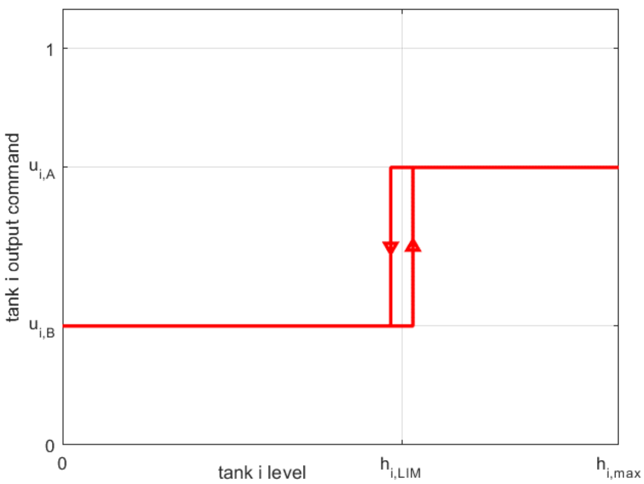

Fig. 2. The considered control form

As it can be seen the controls vary in time, depending on the liquid level in the tank as follows: if the liquid level in the tank is below a certain level $h_{i,LIM}$, the valve/pump control will be $u_{i,B}$, and if the level is above $h_{i,LIM}$ then the control will be considered $u_{i,A}$. No inequality constraints for $u_{i,A}$ and $u_{i,B}$ has been considered. This way, when the liquid level is getting over the limit, the new control value can be higher than the old one in order to make the overflow of the current tank smaller or it can be lower in order to help the tank whose inflow is the outflow of the current tank to overflow less. To prevent the control quickly changing when the tank level is around $h_{i,LIM}$, a hysteresis has been considered around this level.

The parameters of the control have been determined through the optimization procedure (genetic algorithm), the structure of the chromosome being the one presented in Fig. 3.

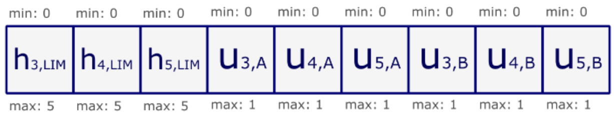

Fig. 3. The structure of the chromozome

Optimizing the volume of overflow resulted in the following optimal solution:

$$\begin{bmatrix} h_{3,LIM}^* = 3.507 & h_{4,LIM}^* = 4.3294 & h_{4,LIM}^* = 2.0954 \\ u_{3,A}^* = 0.6997 & u_{4,A}^* = 0.6910 & u_{5,A}^* = 0.51 \\ u_{3,B}^* = 0.8423 & u_{4,B}^* = 0.8927 & u_{5,B}^* = 0.9836 \end{bmatrix} \quad (1)$$

while optimizing the overflow quality index resulted in the following optimal solution:

$$\begin{bmatrix} h_{3,LIM}^* = 3.393 & h_{4,LIM}^* = 0.8911 & h_{5,LIM}^* = 3.9285 \\ u_{3,A}^* = 0.5510 & u_{4,A}^* = 0.8598 & u_{5,A}^* = 0.6190 \\ u_{3,B}^* = 0.9157 & u_{4,B}^* = 0.8414 & u_{5,B}^* = 0.9961 \end{bmatrix} \quad (2)$$

The performance criteria values resulted by optimization are presented in TABLE V (when minimizing V_{ovf}) and in TABLE VI (when minimizing OQI).

TABLE V. "MIN(V_{ovf})" RESULTS

Tank no.	V_{ovf} [m³/year]	OQI
1	0	0
2	22759	193
3	90614	1197
4	85118	1819
5	21207	727
6	24667	318
7	0	0
global	244365	4254

TABLE VI. "MIN(OQI)" RESULTS

Tank no.	V_{ovf} [m³/year]	OQI
1	0	0
2	22772	193
3	156472	1982
4	69088	1526
5	9111	299
6	17609	280
7	0	0
global	275052	4280

C. *Results obtained in "multi-objective optimization" operating regimes*

In this section a multi-objective optimization of the sewer network has been done by minimizing two of the performance criteria: V_{ovf} and OQI. For optimization two methods were approached, both based on a controlled elitist genetic algorithm [13], as follows:

1. Multi-objective optimization;
2. Multi-objective optimization in two steps;

1) Multi-objective optimization

It has been used to compute a set of points on the Pareto Front. The algorithm has the following characteristics:

- it will stop if the maximum number of generations (100) is reached or if it senses that no improvements of the population has been made in the last 30 generations;
- the chromosome structure number of genes and structure is given in Fig. 3;
- the number of chromosomes of the population has been chosen to be 20;
- the initial population is generated randomly using uniform distributions that are in the range of each gene;
- single point crossover operator;
- uniform mutation operator with a mutation probability equal to 0.05;
- the parent chromosomes are chosen using a tournament mechanism: from the entire population, a 4 individuals set is randomly chosen. The best individual from that set becomes a parent;
- the values of the two objective functions are linearly normalized:

$$\overline{V_{ovf}^{*}} = \frac{V_{ovf}^{*}}{V_{ovf,NC}} \quad (3)$$

and

$$\overline{OQI^{*}} = \frac{OQI^{*}}{OQI_{NC}} \quad (4)$$

where $V_{ovf,NC} = 369665$ and $OQI_{NC} = 6131$ are the values of the objective functions when "no control" regime is considered.

At each generation, the algorithm follows these steps:

1. Select parents from the current population by using the tournament mechanism;
2. Create 16 offspring by using the crossover and mutation operators;
3. Calculate the fitness of the offspring;
4. Combine the offspring with the current population in an extended population;
5. For each of the chromosomes in the extended population, calculate the rank and the crowding distance [13]
6. Use the extended population as the next generation population by trimming it to 20 individuals.

By running the optimization algorithm, the points on the Pareto Front graphically represented in Fig. 4 have been obtained.

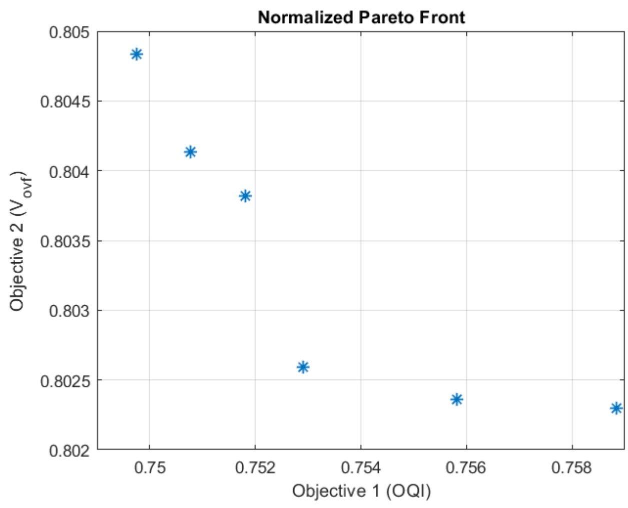

Fig. 4. Normalized points on Pareto Front

It can be noticed that the normalized values of *OQI* of the pareto-optimal solutions found by the algorithm varies between 0.7498 and 0.7588, while the normalized values of the V_{ovf} varies between 0.7588 and 0.8048.

There are multiple methods for choosing the best compromise from the Pareto Front, depending on the problem [14]: *Laplace's criterion*, *Wald's criterion*, *Hurwicz's criterion* etc. For this problem, selecting the solution to be used will be made by using *Nash Bargaining Solution* [15]. The advantage of this method is that it satisfies the monotonicity requirement, a principle of fair division and it is Pareto efficient. The chosen solution is the one that maximized the area of the rectangle defined by the solution point in the objective space and the point of disagreement, *D* (Fig. 5).

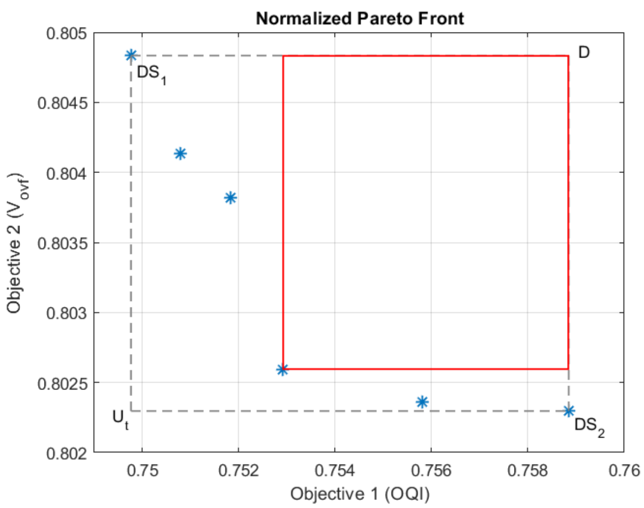

Fig. 5. Choosing the optimal solution by method *Nash Bargaining Solution*

Therefore, the optimal solution obtained with this method is:

$$\begin{bmatrix} h_{3,LIM}^* = 2.6064 & h_{4,LIM}^* = 1.6835 & h_{5,LIM}^* = 4.1865 \\ u_{3,A}^* = 0.6889 & u_{4,A}^* = 0.7109 & u_{5,A}^* = 0.9011 \\ u_{3,B}^* = 0.9927 & u_{4,B}^* = 0.7684 & u_{5,B}^* = 0.7793 \end{bmatrix} \quad (5)$$

with the following values of the objective functions: $V_{ovf}^* = 296689$ representing a decrease of 19.74% and $OQI^* = 4616$ representing a decrease of 24.71% compared to the "no control regime" values.

The genetic algorithm has been run 5 times obtaining the solutions from TABLE VII.

TABLE VII. 5 RUN RESULTS

Run no.	V_{ovf}^*	OQI^*
1	296689	4616
2	281674	4971
3	297676	4798
4	281674	4971
5	297569	4768

From TABLE VII, mean values of each of the objectives can be calculated: $mean(V_{ovf}^*) = 291056$ and $mean(OQI^*) = 4824$.

Comparing the obtained results with the ones obtained in [12] when the optimization has been made separately for each of the performance criteria, it can be seen that the solution found by using the multi-objective optimization is worse than the solutions found when only one of the performance criteria was minimized. This is because the multi-objective optimization algorithm tends to get trapped in local minimums and because it provides only a small portion of the Pareto Front, due to the fact that the initial population is randomly chosen and because the algorithm is an elitist one.

2) Multi-objective optimization in two steps

In [16] the following optimization method has been proposed. Firstly, single-objective optimization will be used to separately minimize both performance criteria, then the obtained solutions will be included in the initial population of the multi-objective optimization algorithm (Fig. 6).

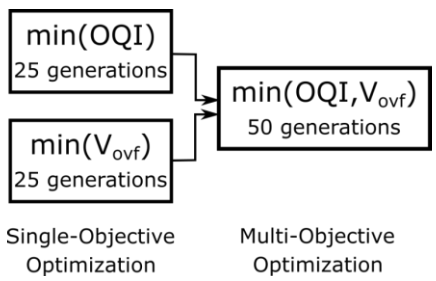

Fig. 6. The optimization method

To have the same number of fitness function evaluations, the maximum number of generations for each of the optimizations have been considered according to TABLE VIII.

TABLE VIII. MAXIMUM NUMBER OF GENERATIONS

Type	Criteria	Maximum number of generations
Single-Objective	*min(OQI)*	25
Single-Objective	min(V_{ovf})	25
Multi-Objective	*min(OQI, V_{ovf})*	50

Firstly, OQI indicator has been minimized. The normalized optimal value found by the algorithm was $\overline{OQI^*} = 0.7438$ ($OQI^* = 4560$). Secondly, V_{ovf} indicator has been minimized. The normalized optimal value found was $\overline{V_{ovf}^*} = 0.7037$ ($V_{ovf}^* = 260123$). The evolution of the best normalized fitness for both objective functions can be seen in Fig. 7.

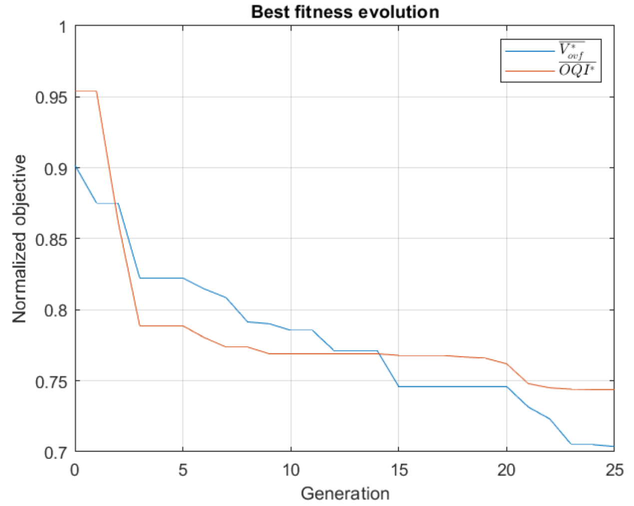

Fig. 7. Fitness function evolutions

Finally, the multi-objective optimization algorithm has been run for 50 generations, with the solutions of the two single-objective optimizations included in the initial population. The rest of the individuals in the initial population were randomly generated.

By running the optimization algorithm, seven points on the Pareto Front graphically represented in Fig. 8 have been obtained. It's interesting that all seven points have the same coordinates.

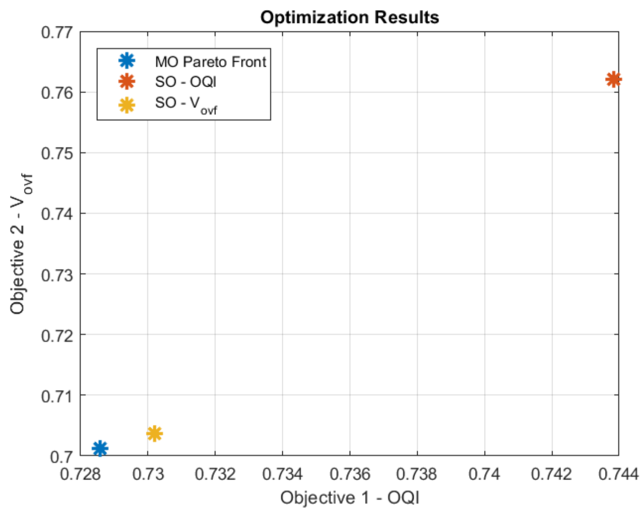

Fig. 8. The points of the Pareto Front

The following optimal solution has been obtained:

$$\begin{bmatrix} h_{3,LIM}^* = 1.3735 & h_{4,LIM}^* = 3.7458 & h_{5,LIM}^* = 1.9283 \\ u_{3,A}^* = 0.7775 & u_{4,A}^* = 0.5634 & u_{5,A}^* = 0.6545 \\ u_{3,B}^* = 0.9264 & u_{4,B}^* = 0.9993 & u_{5,B}^* = 0.9807 \end{bmatrix} \quad (6)$$

The values of the objective functions are: $V_{ovf}^{*} = 259206$ representing a decrease of 29.88% and $OQI^{*} = 4467$ representing a decrease of 27.14% compared to the "no control regime" values.

An explanation for the overlap of the seven points would be that the two criteria are correlated and minimizing one leads to minimizing the other.

IV. Conclusions

In conclusion, this paper deals with multi-objective optimization of a sewer network in terms of volume of overflow and overflow quality index. The multi-objective algorithm has been implemented by using a genetic algorithm and computes the Pareto Front. The best compromise form the Pareto Front is chosen by using Nash Bargaining Solution. The multi-objective algorithm, because it is an elitist algorithm and the initial population is randomly generated, tends to get trapped in local minimums and provides only a small portion of the Pareto Front. Therefore it provides worse results than when performing single-objective optimization with respect to the volume of overflow. To overcome this, a combination of single-objective and multi-objective optimization has been performed, keeping the same number of evaluations of the fitness functions, obtaining better results in terms of both objective functions than when using only multi-objective optimization or only single-objective optimization. However, this algorithm also provides a small portion of the Pareto Front.

Analyzing the results of the hybrid single-objective/multi-objective algorithm, another conclusion is that there is a strong connection between the volume of overflow and overflow quality index. Minimizing one of them lead to the minimization of the other one, this leading to a narrow Pareto Front. However, due to the geometry of the objective-space, single-objective optimization of the volume of overflow provides better results in terms of both objective functions than when performing single objective optimization of the quality.

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