



# Drainage Systems Optimization Under Climate Change Scenarios

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## Abstract

The increasing frequency of extreme rainstorms due to climate changes calls for cost-effective methodologies to optimize drainage networks and flood risk mitigation practices. This paper presents an effective methodology that combines two well-known methods to optimize the drainage network design. The methodology uses the Harmony Search algorithm to identify the best solution for the drainage network and the simulations obtained through the Storm Water Management Model to verify the respect of the hydraulic constraints. The methodology is applied to the literature case study of Anytown, showing a significant reduction of 34.5% of the drainage network design cost compared with the common Rational Method. Moreover, the methodology is able to identify the optimum allocation and volumes of detention ponds for runoff control in case of variations in rainfall regime. The methodology allowed to prevent floods, by decreasing the channel filling degree.

**Keywords** Drainage networks · Detention ponds · Flood risk · Climate change

## 1 Introduction

In last decades the vulnerability to flood hazards of drainage networks increased worldwide due to the rapid urbanization and climate change–induced extreme events (Hammond et al. 2015). Regional impacts of climate change include changes in precipitation, temperature, snowpack accumulation and vegetation, and hence the increase in frequency and magnitude of floods (Şen 2020). Specifically, climate change largely impacts on water cycle and precipitation pattern, directly affecting the runoff (Mahmood et al. 2017; Zhou et al. 2019). Intense rainfall events are expected to increase due to greenhouse gases effects (Ngamaliu-Nengoue et al. 2019).

The urgent need to improve the capacity of existing drainage systems calls for the development of cost-effective methodologies to achieve a good trade-off between investment and flood control in drainage networks (Yu et al. 2017).

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The drainage system design optimization problem has been widely studied. The optimization models are usually coupled with physical drainage simulations to account for the rainfall process and the hydraulic constraints (Muleta and Boulos 2007). Different studies also have accounted for Low Impact Development (LID) storm water Best Management Practices (BMPs) (Gülbaz and Kazezyılmaz-Alhan 2018) to comply with the hydraulic constraints. Some of these have shown the limitations to the use of BMPs due to the lack of regulations (Kim et al. 2017). Other studies have tested the effectiveness of BMPs applying Simulated Annealing (SA) algorithm (Sebti et al. 2016) or web-based Decision Support System (DSS) (Ahmed et al. 2017).

Deterministic optimization methods, such as linear (Swamee and Sharma 2013) and dynamic programming (Mays and Wenzel 1976), have been often employed for the optimization of drainage networks, due to their effectiveness in solving serially connected systems. However, deterministic methods have shown poor performances in case of numerous hydraulic constraints and presence of both continuous and discrete decision variables (Tan et al. 2019). Furthermore, they struggle to include hydraulic simulations models (Eckart et al. 2018).

Therefore, in the last decade there has been a move towards the use of Evolutionary Algorithms (EAs) for the drainage network design. These models solve the optimization problems by the mathematical application of natural processes, such as the evolution process in Genetic Algorithm GA (Cozzolino et al. 2015), the swarm intelligence in the Particle Swarm Optimization algorithm (PSO) (Montalvo et al. 2008), the behaviour of ants in finding the shortest path in Ant Colony Optimization (ACO) (Afshar et al. 2015). Such algorithms can be easily coupled with simulation models and are able to handle high levels of multi-dimensional complexities (Maier et al. 2014), accounting for both discrete or continuous decision variables. However, in literature EA-based methods the constraints are usually defined in the solution space, thus not ensuring the feasibility of the solution in the decision phase (Walski 2001). As a result, the optimal solutions may not be adoptable for practical applications. In addition, the EAs are often characterized by a high computational burden that can easily overcome the computational resources of industries and companies (Yin et al. 2020).

Although heuristic approaches, such as EAs, have been widely used for designing drainage systems, there are few applications of the Harmony Search (HS) algorithm (Geem et al. 2001) to hydraulic networks. Even though the HS algorithm have shown very good performances (De Paola et al. 2018, 2017; Tan et al. 2019), no study investigated its application to identify cost-effective solutions that satisfy the hydraulic constraints under climate variability with a low computational burden.

In view of future climate changes, this paper aims at investigating the effectiveness of the HS in optimizing both drainage network and storage facilities to mitigate flood risks in case of variations in rainfall regime.

This paper contributes at improving both efficiency and solution practicality of drainage network design optimization, by presenting a HS-based methodology that can account for rainfall variability.

The proposed methodology enables the cost-effective design of both drainage network and storage facilities for runoff control, identifying solutions that comply with the hydraulic constraints even under climate variability. Specifically, the HS algorithm is used to identify the best solution for the drainage network, by interacting with the simulations of the Storm Water Management Model (SWMM) (James et al. 2010) to verify the respect of the hydraulic constraints.

In this work the methodology is successfully applied to the literature case study of Anytown (Cimorelli et al. 2016), carrying out two different applications. The methodology is first applied to identify the optimal design of the drainage network and then to optimize the detention ponds in case of variations in rainfall regime.

## 2 Methodology

This section presents an effective methodology for drainage networks design optimization, based on the combined application of an optimization algorithm, the HS, and the software SWMM (James et al. 2010). The HS algorithm is used to assess the most economically advantageous solutions for drainage systems. SWMM is used for the simulation of the hydraulic behaviour of drainage systems to verify that the solutions of the HS comply with the hydraulic constraints.

SWMM is one of the most powerful rainfall-runoff modelling software and performs hydraulic simulations through the numerical integration of the De Saint Venant equations (De Saint Venant 1871), defining flow rates and water depth throughout the networks.

Since SWMM needs rainfall data, in this work a constant rainfall intensity over a time span was considered. SWMM accounts for the water infiltration process, as well. In this work, the Curve Number method (Williams et al. 2012) was used to estimate the stormwater runoff. This method has been developed by the Soil Conservation Service (SCS) and assumes that the total soil infiltration capacity can be assessed from the tabulated Curve Number of the soil, based on the land use and the hydrological group. Then, during the rainfall the total infiltration capacity decreases as a function of the cumulative rainfall and the remaining capacity.

Furthermore, the kinematic wave approach for routing through the drainage network was used. According to this approach, the disturbances can propagate only in the downstream direction. Therefore, backwater effects are neglected, assuming that upstream computations are not affected by downstream conditions.

The SWMM input file, including both the water catchments characteristics and the first attempt hydraulic characterization of the drainage system (i.e. water depth and flow rate values throughout the network), is used as initial configuration of the network to start the HS calculations. Then, at each iteration the HS data interact with SWMM simulations, identifying the best solution based on the morphological and hydraulic constraints.

In order to verify the solution applicability, the following constraints were considered:

- maintaining a minimum velocity (set equal to 0.5 m/s) to ensure the self-cleaning capability of the pipes;
- not exceeding the maximum velocity (5 m/s) to prevent pipes scouring;
- limiting the water depth within the maximum value to not exceed the flow capacity of the drainage network; to this aim, the maximum degree of channel filling (i.e. the ratio between the water depth and the diameter of the channel) was set equal to 80%;
- ensuring that the diameter of each pipe is greater than or equal to those of the corresponding upstream pipes, to maintain flow continuity and avoid backwater effects.

In the following subsections, the HS algorithm and its application in case of two different optimization problems are presented.

## 2.1 Harmony Search

The HS is a heuristic algorithm developed by Geem et al. (2001) and simulates the improvisation of music players to solve optimization problems. In the framework of music harmony, the best state is determined by the sounds of joined instruments, that in turn can be improved through practice. Similarly, the best state in optimization problems is determined by the values of different variables that in turn can be improved through iterations.

Let us assume a constrained optimization problem with objective function  $f(\mathbf{x})$  subjected to:

$$h_i(\mathbf{x}) = 0, \quad i = 1, \dots, p \quad (1)$$

The HS identifies the optimum solution vector  $\mathbf{x} = (x_1, \dots, x_n)$  that optimizes (i.e. minimizes or maximizes)  $f(\mathbf{x})$  and can be used for both continuous and discrete decision variables.

The steps of the HS are as follows. First, the Harmony Memory (HM) is initialized by generating many random solution vectors as the Harmony Memory Size (HMS). Then, a new harmony vector  $\mathbf{x}' = (x_1', \dots, x_n')$  is generated. The value of each decision variable can be chosen among the values included in the HM or a totally random value can be selected. The probability of choosing one value from those stored in the HM is called Harmony Memory Considering Rate (HMCR). Then, the pitch adjustment mechanism is used to improve the solution and avoid local optima. The algorithm selects a neighbouring value within a range of possible values with a probability equal to the Pitch Adjusting Rate (PAR). Finally, if the new solution vector is better than the worst one in the HM, it is included into the HM while the worst solution vector is excluded from the HM. The algorithm stops when the stopping criterion is satisfied, i.e. when the Number of Iteration (NI) is reached.

The steps of the HS are summarized in Fig. 1a.

The HS combines different heuristic algorithms. Indeed, similarly to the Tabu Search (TS) algorithm (Da Conceição and Ribeiro 2004), the HS enables the preservation of the history of past vectors by using the HM. In addition, the HMCR allows to vary the adaptation rate during the resembling process as in the Simulated Annealing (SA) algorithm (Kirkpatrick et al. 1983), while managing many vectors at the same time as the GA (Goldberg 1989). However, compared to the GA that generates a new vector from only two parents vectors, the HS accounts for all vectors in the HM for making a new vector. Furthermore, the GA has to keep the gene structure and cannot independently select the component variables, while in the HS generation each variable is considered separately.

Concluding, in this work, the HS was used to solve two different optimization problems, as explained in details in the following sections.

## 2.2 Drainage Network Costs Optimization

The methodology is aimed at optimizing drainage networks and allows to choose the optimal diameter for each channel of the networks, accounting for hydraulic constraints. The optimization problem consists in minimizing a cost function  $C$ , assuming the diameters as decision variables:

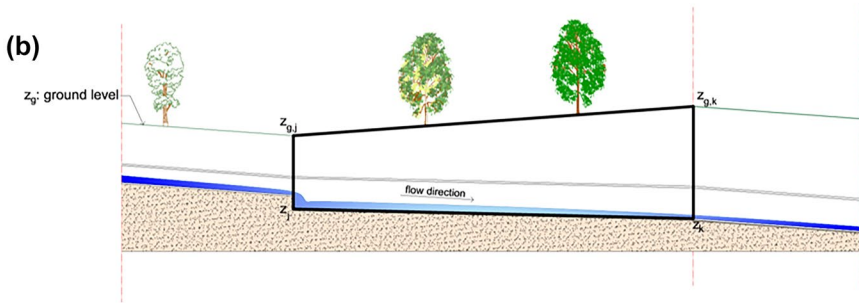
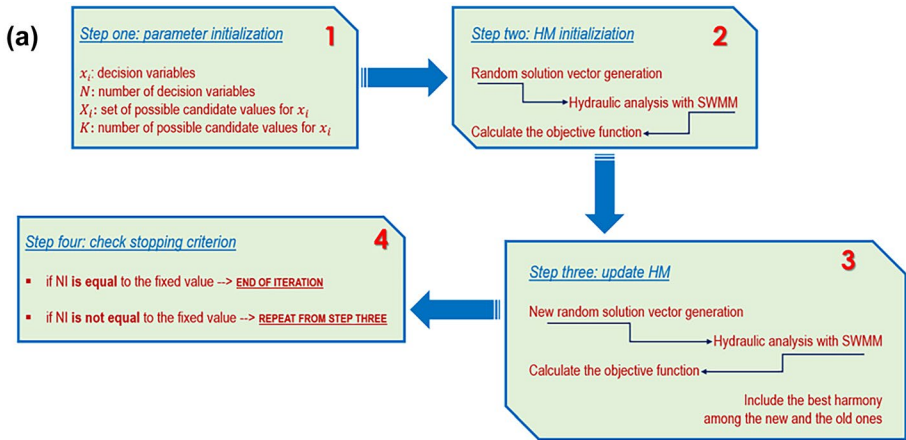


Fig. 1 Steps of the HS methodology (a) and schematization of the excavation volume for pipes allocation (b)

$$C = \sum_{i=1}^N f_1(D_i L_i) + \sum_{i=1}^N f_2(W_i) \tag{2}$$

where  $f_1(D_i L_i)$  is the cost of the pipes and  $f_2(W_i)$  is the excavation cost;  $D_i$ ,  $L_i$  and  $W_i$  are the diameter, the length and the excavation volume for the  $i$ -th channel of the drainage network, respectively;  $N$  is the total number of the channels in the network.

Since for each channel the cost is estimated by multiplying the pipe unit cost (€/m) to the channel, the HM includes different diameters sizes with the relative unit cost. For each channel, the excavation cost is estimated by multiplying the total excavation volume to the excavation cost per unit (€/m<sup>3</sup>). Referring to Fig. 1b, for the  $i$ -th channel the excavation volume  $W_i$  is calculated by using the following formula:

$$W_i = [(z_{g,j} - z_j) + (z_{g,k} - z_k)] \cdot \frac{L_i}{2} \cdot (D_{e,i} + 0.80) \tag{3}$$

where  $z_j$  and  $z_k$  are the invert elevations of the nodes  $j$  and  $k$  at the ends of the  $i$ -th channel;  $z_{g,j}$  and  $z_{g,k}$  are the ground elevations at the nodes  $j$  and  $k$ , respectively;  $D_{e,i}$  is the size of the external diameter of the  $i$ -th channel and is increased by 0.80 to account for the backfill material.

The HS determines the optimal diameter in terms of size and material for each channel, accounting for the information about the tributary channels. Once the diameter is determined for each channel of the drainage network, the HS is able to calculate the so called out-offset  $O_i$  of each  $i$ -th channel, namely the difference between the diameter of the downstream pipe and that of the corresponding upstream pipe ( $O_i = D_{e,i+1} - D_{e,i}$ ). In order to maintain flow continuity and avoid backwater effects, the value of  $O_i$  must always be greater than or equal to zero. At this stage, given that channels slopes, lengths, out-offsets and the elevation of the outfall of the drainage network are known, nodes elevation are assessed.

Concluding the HS algorithm provides the optimal diameters, the out-offsets, and the nodes elevations, as well as the minimum total cost of the drainage system.

In this application, a constant rainfall intensity over a time span equal to the maximum concentration time  $t_c$  of the drainage network was considered. To this aim, first the diameters for the entire drainage network were defined for a constant hyetograph with intensity and duration respectively equal to 50 mm/h and 15 min. Then, the concentration time for each catchment within the drainage network was assessed by applying the Rational Method (Kuichling 1889). Finally, in order to account for the contribution of all catchments to the stormwater runoff, the maximum value of  $t_c$  was used ( $t_c = 19.6 \text{ min}$ ). The intensity–duration–frequency (IDF) curve developed in the framework of the VAPI project (Ferrari and Versace 1994) was used. In the VAPI project a regional frequency analysis approach is applied to carry out the statistical analysis of rainfall in Italy, providing the parameters of the IDF curve for each Italian region. Thus, referring to the Campania region and assuming a return period  $T_R$  equal to 5 years (common value for urban drainage network design) the intensity  $i_c$  resulted in 63 mm/h.

### 2.3 Runoff Control Optimization

The methodology can be used to mitigate the effects of the variations in rainfall regime due to climate change. In case of rainfalls of short duration and high intensity, the methodology identifies the optimal locations and volumes of effective devices for runoff control, such as detention ponds.

In order to account for climate change effects, three different applications were carried out: the initial intensity was increased of 20%, 40% and 60% resulting in  $i_c = 75.6 \text{ mm/h}$  (*Application 1*),  $i_c = 80.2 \text{ mm/h}$  (*Application 2*) and  $i_c = 100.8 \text{ mm/h}$  (*Application 3*) respectively.

It is worth nothing that the applications were aimed at testing the methodology in case of need to improve the capacity of existing drainage systems due to climate change. In view of future climate change scenarios, the increase of rainfall intensity is the expected effect that can mostly affect drainage networks, exceeding their capacity. Thus, considering increasing rainfall intensities is suitable to investigate the effectiveness of the methodology in optimizing flood risk mitigation under different climate change scenarios.

Once the rainfall parameters are assessed, the optimal location of detention ponds can be identified through SWMM. In case of an extreme runoff event that exceeds the drainage system capacity, the hydraulic simulation obtained by SWMM shows the nodes where the saturation level is reached and hence where a storage volume is needed to prevent flooding. Then, the HS assesses the optimal volumes of the detention ponds.

In this case, the optimization problem is aimed at minimizing the total cost of the detention ponds as a function of their volumes. Indeed, when designing detention ponds, the

most important parameter is the volume that must enable the peak discharge reduction. For the calibration of the objective function a preliminary analysis about detention ponds costs was carried out. Specifically, different sizes of detention ponds on the market for both rectangular and circular types were considered to define through the regression the following relationship between cost ( $C_d$ , in €) and volume ( $W_d$ , in  $m^3$ ):

$$C_d = 284 \cdot W_d^{0.93} \quad (4)$$

In SWMM the detention pond is designed as a storage unit and modelled as a node. Its storage volume is described by a *Storage Curve*, that defines how the surface area of the unit varies with water depth. In this work, a constant value of the surface area to varying water depth was set. For simplicity, the evaporation process was neglected, by setting the *Evaporation Factor* to 0. Finally, the *Maximum Depth* of the storage unit was set equal to that of the downstream channel. It is worth noting that each node of the network was designed as a storage unit.

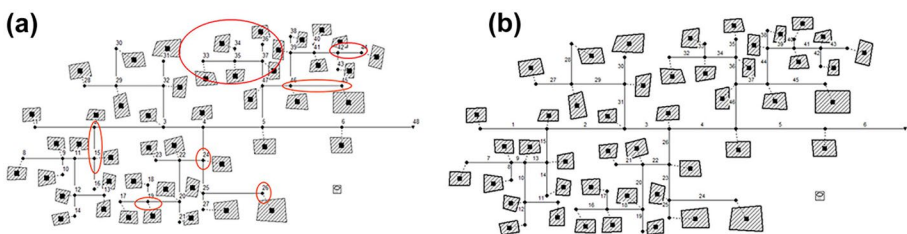
The HS results in the area of each detention pond, that in turn is multiplied to the relative maximum depth to determine the maximum volume to be used in Eq. (4). This is done within an iterative process where the HS data interact with SWMM simulations at each iteration, identifying the best solution based on the constraints set.

### 3 Application

The methodology was applied to the literature case study Anytown (Cimorelli et al. 2016) that consists of a water catchment of 36,5 ha and a drainage network including 46 branches. The layout of the drainage network is shown in Fig. 2. In order to reproduce the runoff conditions of a built-up area, the percentage of impermeable area of each subcatchment was set to 80%.

In addition, the following input data were used:

- four types of pipe material, namely CAST IRON, ECOPAL, PRFV and PVC;
- size of external ( $D_e$ ) and internal diameter ( $D_i$ ), i.e.  $D_e$  from 350 to 2400 mm corresponding to  $D_i$  from 300 to 2278 mm;
- pipe unit cost ( $C$ ), accounting for  $C$  from 37.18 €/m to 1670 €/m according to the pipe material and the diameter size;
- Manning roughness coefficient (equal to 0.01 for each type of pipe).



**Fig. 2** Layout of the drainage network of Anytown with nodes numbering (a) – the areas most vulnerable to flood in case of a rainfall intensity increment of 40% are highlighted in red – and branches numbering (b)



The number of tributary channels, slope, end nodes and length of each channel were used as input data (for further details about the data see Cimorelli et al. 2016).

Then, a sensitivity analysis was carried out to assess the values of the HS parameters, by using Eq. (2) as cost function. Referring to literature values (De Paola et al. 2018, 2017), two values of HMS (30, 40), four values of HMCR (0.80, 0.85, 0.90 and 0.95) and six values of PAR (0.01, 0.02, 0.03, 0.05, 0.07 and 0.09) were considered, while assuming NI equal to 7500. Since the minimum cost was obtained for HMS = 30, HMCR = 0.95 and PAR = 0.07, such values were chosen for the simulations.

## 4 Results and Discussion

The following sections discuss the results of the presented methodology. First, the results of the drainage network design optimization are presented. For a better understanding, these results are compared to those of the Rational method (Kuichling 1889), that is commonly used for drainage network design. Then, the results obtained in case of variations in rainfall regime are discussed.

### 4.1 Results—cost optimization

The results of the drainage network design optimization are discussed here. Table 1 shows the results for each branch of the drainage network in terms of upstream node elevation, out-offsets, diameters and pipe materials. As shown by the table, the methodology was able to analyse different solutions, combine different size and type of pipes and assess the best choice for each branch. Moreover, the optimal solution complies with the hydraulic constraints set. Unlike the current EA-based optimization models (Yin et al. 2020), the methodology resulted in a final solution that is in compliance with the common regulation of designing upstream pipe not larger than the immediately downstream pipe.

Concluding, the total minimum cost was 885568 €. It is worth noting that the iterations were completed in almost 2 h and 15 min, resulting in a higher computational efficiency compared to literature EAs (Afshar et al. 2015; Liu et al. 2016).

Then, in order to carry out a comparison, the Rational method was used. For simplicity, only a portion of the network of Anytown, including branches 1, 2 and those from 7 to 15, was considered. Table 2 shows the results in terms of external diameters ( $D_e$ ), degree of channel filling ( $h$ ), maximum velocity ( $V_{\max}$ ) and flow rates ( $Q_{\max}$ ) for each branch. The results were in compliance with the hydraulic constraints for both the methodologies. However, for all branches the proposed methodology resulted in higher  $h$  and  $V_{\max}$  compared to the Rational method due to the application of the De Saint Venant equations. This means that the proposed methodology led to more realistic results and accounted for more severe conditions to be on the safe side.

Moreover, for all branches the  $D_e$  obtained by the HS method were smaller than the Rational method ones (Table 2), allowing to reduce costs. Indeed, compared to the Rational method, the HS enabled a total cost reduction of 34.5%, equal to 54141 €. It is worth noting that only the cost of the pipes was considered in the comparison, since the Rational method does not account for the excavation volumes costs.

These results are in agreement with those obtained by Tan et al. (2019) for a similar drainage network layout (20 links with a total length of 2.62 km). The HS based optimization approach of Tan et al. (2019) resulted in lower costs compared to different literature



**Table 1** Results in terms of upstream node elevation ( $z$ ), out-offset ( $O_i$ ), internal ( $D_i$ ) and external ( $D_e$ ) diameters, and pipe material for each branch of the drainage network of the case study

Branch	$z(\text{m})$	$O_i(\text{m})$	$D_i(\text{mm})$	$D_e(\text{mm})$	Material
1	97.8	0.22	400	465	ECOPAL
2	94.8	0.20	616	650	PRFV
3	92.4	0.23	816	860	PRFV
4	91.4	0.28	1044	1100	PRFV
5	89.8	0.00	1328	1400	PRFV
6	88.8	0.00	1328	1400	PRFV
7	98.9	0.10	300	350	ECOPAL
8	97.0	0.10	300	350	ECOPAL
9	97.4	0.00	400	465	ECOPAL
10	96.3	0.10	300	350	ECOPAL
11	97.1	0.10	300	350	ECOPAL
12	98.0	0.00	400	465	ECOPAL
13	97.9	0.10	400	465	ECOPAL
14	95.3	0.20	300	350	ECOPAL
15	96.2	0.12	500	580	ECOPAL
16	95.2	0.10	300	350	ECOPAL
17	94.0	0.10	300	350	ECOPAL
18	93.8	0.13	400	465	ECOPAL
19	93.3	0.19	344	400	ECOPAL
20	93.8	0.00	533	630	ECOPAL
21	92.8	0.23	300	350	ECOPAL
22	93.7	0.23	533	630	ECOPAL
23	91.9	0.00	470.8	500	PVC
24	92.8	0.17	300	350	ECOPAL
25	92.9	0.29	470.8	500	PVC
26	93.0	0.29	758	800	PRFV
27	96.4	0.10	300	350	ECOPAL
28	94.6	0.10	300	350	ECOPAL
29	95.6	0.20	400	465	ECOPAL
30	93.8	0.20	400	465	ECOPAL
31	93.1	0.22	600	700	ECOPAL
32	92.7	0.08	300	350	ECOPAL
33	92.1	0.08	300	350	ECOPAL
34	92.0	0.09	376.6	400	PVC
35	91.6	0.20	300	350	ECOPAL
36	91.3	0.33	470.8	500	PVC
37	91.4	0.26	344	400	ECOPAL
38	91.0	0.02	376.6	400	PVC
39	91.5	0.06	344	400	ECOPAL
40	91.2	0.10	400	465	ECOPAL
41	91.4	0.20	300	350	ECOPAL
42	91.6	0.10	500	580	ECOPAL
43	91.6	0.00	600	700	ECOPAL
44	91.3	0.26	344	400	ECOPAL
45	90.9	0.20	600	700	ECOPAL
46	90.6	0.53	800	930	ECOPAL

**Table 2** Results in terms of external diameters ( $D_e$ ), degree of channel fillings ( $h$ ), maximum velocities ( $V_{max}$ ) and flow rates ( $Q_{max}$ ) for the Rational and HS methods

Branch	Rational Method					HS Method				
	$D_e$ (mm)	$h$	$V_{max}$ (m/s)	$Q_{max}$ (m <sup>3</sup> /s)	$C$ (€)	$D_e$ (mm)	$h$	$V_{max}$ (m/s)	$Q_{max}$ (m <sup>3</sup> /s)	$C$ (€)
1	800	0.45	2.83	0.46	30690	580	0.61	3.72	0.47	14355
2	1200	0.47	3.08	1.13	73727	930	0.72	4.32	1.68	48895
7	465	0.41	1.85	0.09	5830	350	0.57	2.42	0.09	3718
8	580	0.42	1.40	0.11	3828	350	0.56	1.68	0.11	1487
9	580	0.44	2.52	0.21	2871	400	0.67	3.16	0.21	1399
10	630	0.56	1.80	0.23	10711	465	0.59	2.13	0.17	5247
11	350	0.2	0.77	0.01	2788	350	0.31	1.00	0.07	2788
12	350	0.55	1.53	0.06	1859	350	0.73	2.13	0.18	1859
13	700	0.34	2.20	0.18	4785	580	0.57	3.33	0.39	4785
14	465	0.49	1.44	0.09	4372	350	0.67	1.78	0.09	2788
15	800	0.42	1.47	0.22	15,345	800	0.61	2.68	0.60	15345
$C_{tot}$ (€)	156808					102667				

methodologies. Specifically, for EAs, such as ACO and GA, the total system cost was 241496 – 241896 \$, corresponding to 218578 – 218940 € and 83427–83565 €/Km. However, the proposed methodology resulted in a lower cost per kilometre, i.e. 66667 €/Km, showing higher performances of HS compared to EAs and improving the previous results of Tan et al. (2019) (83249 €/Km).

Finally, the methodology allowed to significantly reduce the total cost of the drainage network, by identifying the optimal diameter for each branch of the network in compliance with the hydraulic constraints.

### 4.2 Results–runoff control optimization

The results of the proposed methodology for detention ponds optimization are presented here. In this case NI was set equal to 15000 to achieve more accurate results, while the values of the other HS parameters were the same as in the previous case.

Table 3 reports the areas and volumes of the detention ponds designed. For an increment of the rainfall intensity of 20% (*Application 1*), the HS identified 3 nodes where the detention ponds were needed to prevent floods, for a total cost of 67148 €. The absence of the detention ponds in the nodes identified by the HS or their underestimated sizing would cause flooding in the surrounding nodes. This is due to the kinematic wave approach: in case of absence of detention ponds or inadequate volumes, the peak runoff would reach more quickly the surrounding downstream nodes exceeding their flow capacity. Therefore, the HS resulted in the optimum values of the detention ponds areas.

Figure 3 shows the comparison between the results of the methodology and those in absence of detention ponds for the main sewer (i.e. from channel 1 to 6), in terms of max flow rates  $Q_{max}$  (a), max velocities  $V_{max}$  (b) and max channel filling degree  $h$  (c), for *Application 1*. As shown by Fig. 3a, the methodology enabled a slightly reduction of  $Q_{max}$ . The average percentage reduction of  $Q_{max}$  for the entire drainage network was of 1.8%. The

**Table 3** Detention ponds characteristics for each application

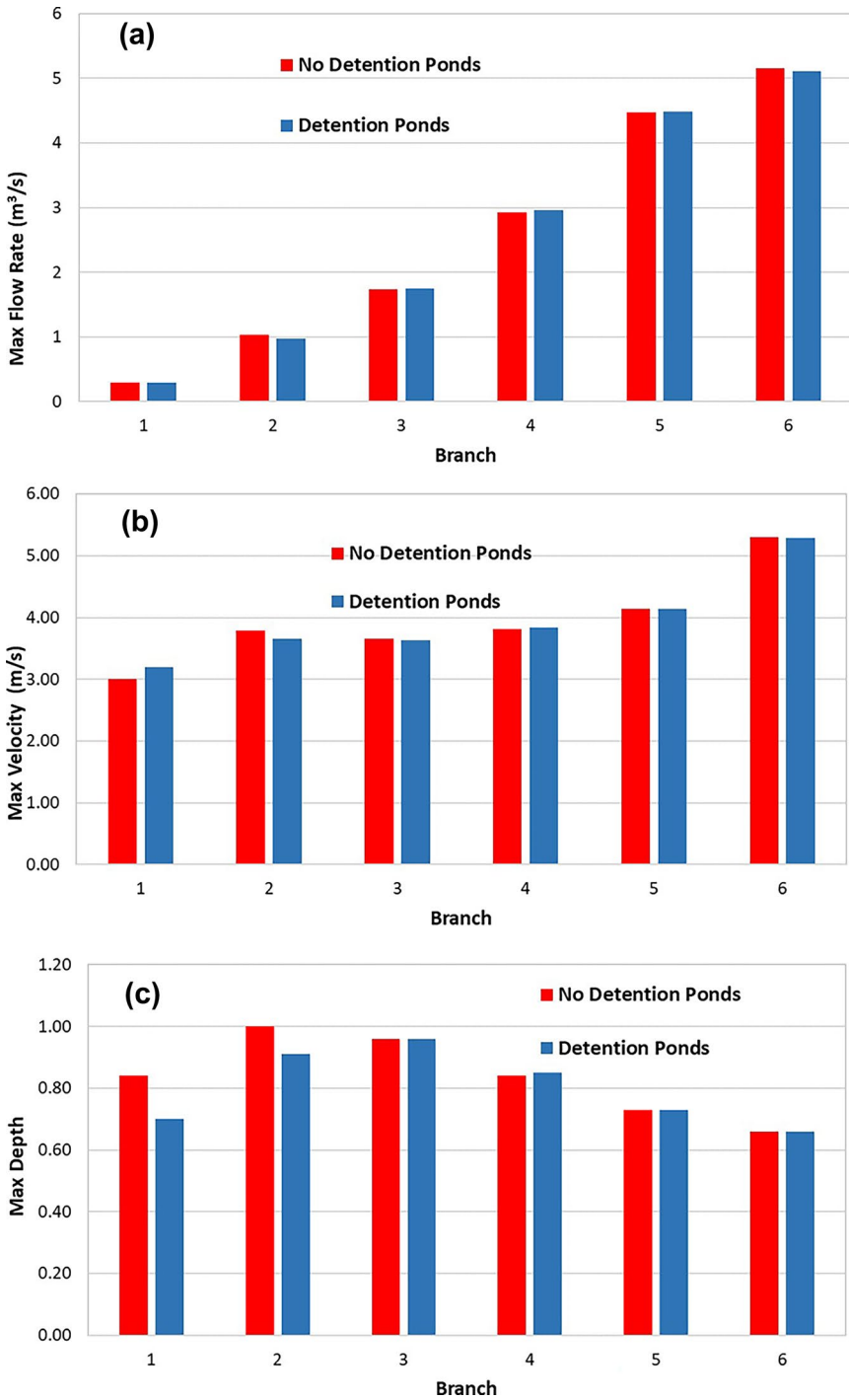
Application 1			Application 2			Application 3		
Node	Area (m <sup>2</sup> )	Volume (m <sup>3</sup> )	Node	Area (m <sup>2</sup> )	Volume (m <sup>3</sup> )	Node	Area (m <sup>2</sup> )	Volume (m <sup>3</sup> )
15	394	62	2	29	8	3	496	241
22	42	17	4	91	23	4	465	76
60	393	142	9	477	72	5	95	23
-	-	-	11	107	35	9	472	81
-	-	-	12	63	18	12	478	73
-	-	-	15	114	34	15	492	88
-	-	-	22	472	127	19	103	29
-	-	-	25	90	24	22	474	144
-	-	-	32	95	24	25	481	73
-	-	-	35	489	81	32	100	29
-	-	-	49	463	237	33	1039	214
-	-	-	59	121	67	35	482	92
-	-	-	60	487	190	39	471	188
-	-	-	62	65	29	50	114	92
-	-	-	63	76	58	55	59	35
-	-	-	-	-	-	60	491	225
-	-	-	-	-	-	62	102	48

$V_{max}$  was also slightly reduced (Fig. 3b), but the methodology did not appropriately reduce the velocity in branch 6, where the velocity value was slightly above the threshold. However, given that branch 6 was the only one with the velocity value above the threshold and its velocity only slightly exceeded the threshold (5.30 m/s), the velocity reduction can be considered a negligible aspect. The allocation and optimum sizing of the detention ponds also reduced  $h$  (Fig. 3c). This was critical, since without detention ponds several branches exceeded the maximum value (80%), reaching even values of 100% and hence leading to flooding. The methodology allowed to prevent the flood risk all over the drainage network, resulting in an average reduction of  $h$  of 4.5%. This was the exact necessary reduction to prevent flooding in the system. Given the unsteady flow conditions, decreasing the channel degree below the 100% can be considered a satisfactory and reliable result, even if the  $h$  is not below the threshold value set.

For a rainfall intensity increment of 40% (*Application 2*), the methodology resulted in 15 detention ponds (Table 3), for a total cost of 213552 €. Figure 4 shows the results of the methodology and those obtained without detention ponds for the main sewer, for *Application 2*. Even in this case, the optimum allocation of detention ponds reduced the peak flow rates (Fig. 4a). Compared to the *Application 1*, the average  $Q_{max}$  reduction for the entire drainage network was higher, equal to 6.6%. For  $V_{max}$  no reduction was needed (Fig. 4b), excluding branch 6 where the value was again slightly above the threshold.

Finally, even in this case, the methodology allowed to prevent floods, by decreasing  $h$  (Fig. 4c). In this application the average reduction of  $h$  was of 13%.

For *Application 3*, i.e. for a rainfall intensity increment of 60%, the HS identified 17 nodes for the allocation of detention ponds (Table 3), for a total cost of 357604 €. Thus, the number of detention ponds was almost the same of *Application 2*, even though the rainfall intensity increment was higher. This is because the volumes of the detention ponds were



**Fig. 3** Barplot of the values of max flow rate (a), max velocity (b) and max channel filling degree (c) for the branches from 1 to 6, with and without detention ponds, for *Application 1*

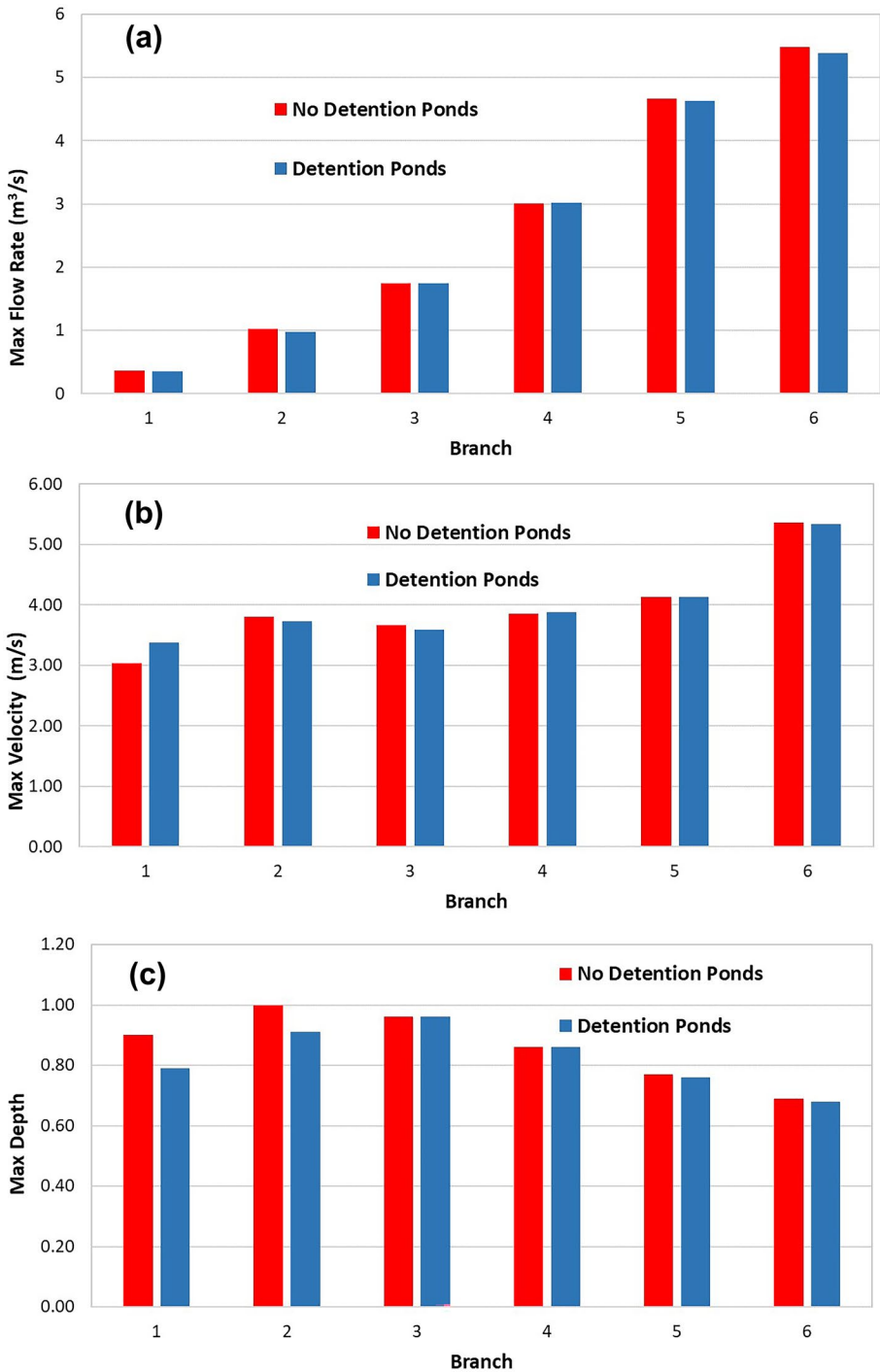
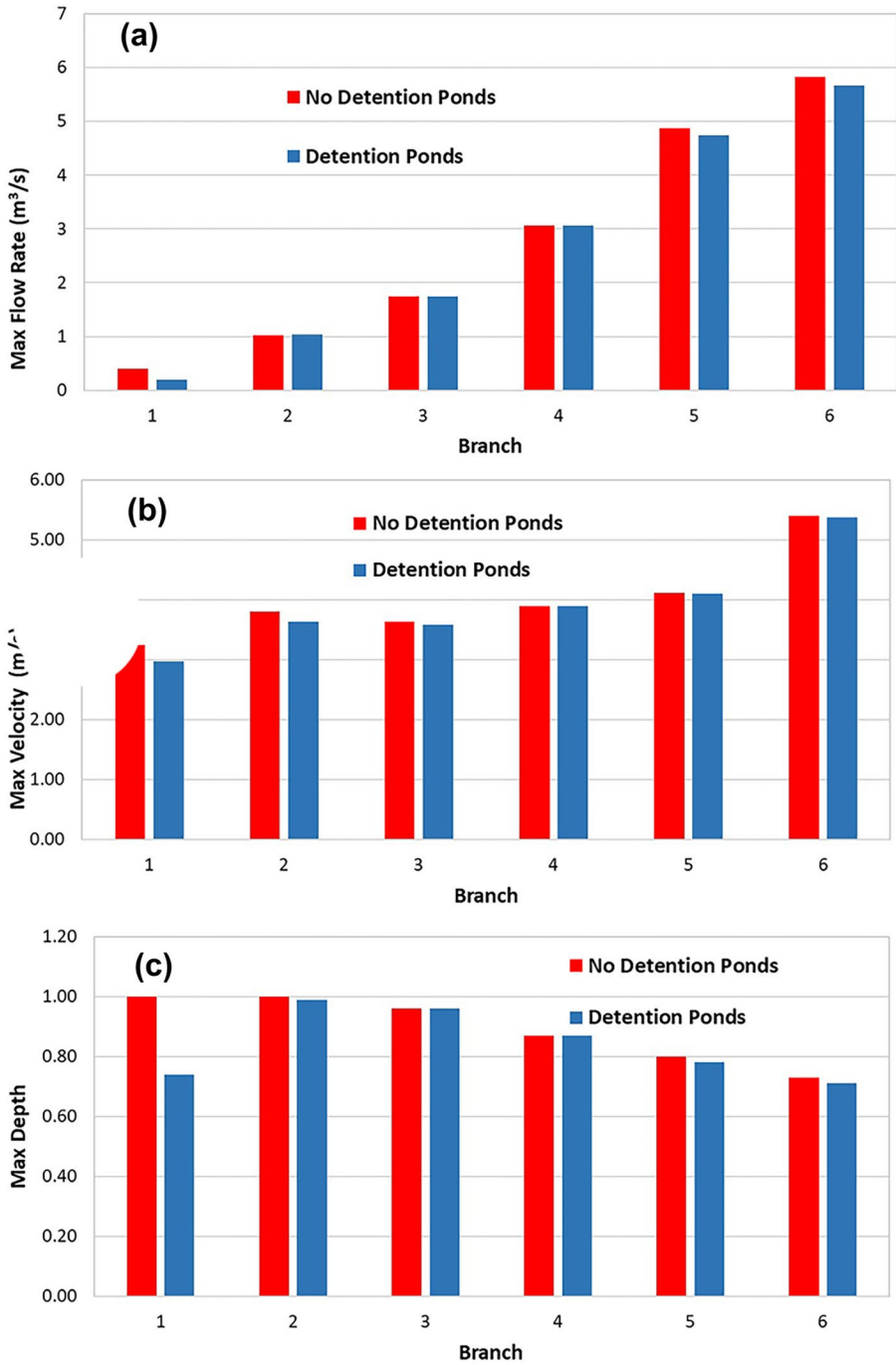


Fig. 4 Barplot of the values of max flow rate (a), max velocity (b) and max channel filling degree (c) for the branches from 1 to 6, with and without detention ponds, for *Application 2*



**Fig. 5** Barplot of the values of max flow rate (a), max velocity (b) and max channel filling degree (c) for the branches from 1 to 6, with and without detention ponds, for *Application 3*

on average bigger than those of *Application 2*. This means that the HS was able to identify for each application the best trade-off between number and volumes of detention ponds in terms of costs, accounting for the hydraulic constraints. Figure 5 reports the results for *Application 3*. Figure 5a shows that the detention ponds significantly decreased  $Q_{max}$ , being the average reduction equal to 12%. Concluding, the channel filling degrees were significantly decreased (Fig. 5c), proving the effectiveness of the methodology in flood prevention even in case of high variations in the rainfall regime. In this application the average reduction of  $h$  was equal to 15%.

As shown by Table 3 there are 3 nodes (i.e. 22, 60, 15) that were identified as the optimum ones for detention ponds allocation for all the applications performed. This means that in a drainage network there are crucial nodes for flood prevention that mainly affect the hydraulic behaviour of the network. However, the volumes of the detention ponds for such nodes changed depending on the application. Therefore, the cost-effective design of the detention ponds should account for the different variations in rainfall regime. This issue was successfully addressed by the proposed methodology that was able to identify cost-effective solutions in terms of number and volumes of detention ponds.

It is worth nothing that for the same case study lower performances have been obtained by using EAs for the optimization of detention ponds. Indeed, the GA-based methodology of Cimorelli et al. (2016), in case of a 23% increase of the runoff coefficient and hence under conditions similar to *Application 1* (20% rainfall intensity increment), resulted in a cost of 111756 €, that is higher than the one obtained by the presented methodology (67148 €). In addition, the GA-based methodology was not always able to complain with the hydraulic constraints, further proving the higher performances of the HS compared to other EAs.

Concluding, the methodology enabled flood risk prevention, identifying the most effective solutions for the minimum cost.

## 5 Conclusions

This paper presents a new methodology to optimize drainage networks accounting for future climate change scenarios. The methodology enables the optimization of both drainage network design and storage facilities to mitigate climate change-related flood risks. The methodology uses the HS algorithm to identify cost-effective solutions for the drainage system. The HS is combined with the hydraulic simulations of SWMM to verify the compliance of the solutions identified with the hydraulic constraints set.

The literature case study of Anytown showed the effectiveness of the methodology in optimizing the design of drainage networks and detention ponds.

Compared to the well-known Rational Method (Kuichling 1889), the presented methodology enabled a significant reduction of the drainage network design cost equal to 34.5%. Compared to common literature methods (Afshar et al. 2015; Liu et al. 2016; Yin et al. 2020), the methodology enabled compliance with all the hydraulic constraints and showed a higher computational efficiency.

Moreover, the methodology allowed to identify the optimum allocation and volumes of detention ponds in case of rainfall variability. The methodology was able to prevent flooding even in case of a high rainfall intensity increment (60%). For different rainfall intensity



increments, the methodology achieved reductions of flow rates and channel filling degrees ranging respectively between 1.8–12% and 4.5–15%.

The analysis also enabled the identification of the nodes and links most prone to be flooded (i.e. where the maximum volumes are reached) as showed in Fig. 2a. In this figure, the areas highlighted in red are the most vulnerable to flood in case of a rainfall intensity increment of 40%. This kind of information is very useful for implementing flood risk mitigation practices.

Given the good performance showed by the methodology in designing detention ponds, future works will investigate the effectiveness of the methodology in the optimization of different Best Management Practices (BMPs) for runoff control. Furthermore, in order to deeply investigate the capacity of the methodology to account for future climate change, future developments will include weather projections from Global Climate Models (GCMs) to deduce projected IDF curves.

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**Availability of Data and Material** All data used in this work are available from the corresponding author by request.

**Code Availability** The codes used in this work are available from the corresponding author by request.

## Declarations

**Ethical Approval** Not applicable.

**Consent to Participate** Not applicable.

**Consent for Publication** Not applicable.

**Conflicts of Interest/Competing Interests** The authors declare no conflicts of interest.

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