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Optimal Operation of Urban Storm Detention Ponds for Flood Management

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Abstract

Operation of existing flood control facilities is one the efficient method for urban stormwater management. In order to quantitatively manage urban floods, operational policies of facilities should be adapted, before need to the enlargement of hydro-infrastructures with high expenditure. A new optimization based methodology is proposed in this paper for urban detention pond operation. The approach integrates an evolutionary algorithm known as Differential Evolution (DE) with EPA-SWMM simulation model to effectively manage detention storage capacities during flood periods. The proposed method is applied to in-line detention ponds at central part of Tehran Stormwater Drainage System (TSDS) to attain optimal rule curves of detention pond operation. Optimal rule curves are compared with the current method of operation and show that the proposed method can decrease network flooding of the smallest and largest extreme rainfall events more than75% and 30% respectively, and in average 55% considering all extreme rainfalls during 1979 to 2013. Therefore, the approach is recommended to replace with the current method of pond operating.

Keywords Optimization · Simulation · Flood · Operation · Urban storm · DE

1 Introduction

A need to collect excess rainwaters in urban surfaces has led to the construction of flood control systems. Urban flood control systems including stromwater collecting network, storage tanks and pumping stations are important municipal facilities that require more development. In other words, investing in the development of effective flood management activities is necessary in order to overcome the negative impacts of increasing surface runoff caused by urbanization and climate change (Yazdi et al. 2016a). However, before any system expansion, it is economically beneficial to use the maximum flood control capacity of the existing system. During floods, the performance of pumps, gates and storage tanks is of great importance for

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reducing flood damages. Nevertheless, usually there is no suitable guideline to determine the best performance of system operation or if there is, it is based on the trial and error procedure. Efficiency of these methods are directly related to the skills, knowledge and experience of engineers and technicians who work as the system operator. Therefore, the possibility of failure or lower performance in these methods is relatively high. Since there are no certain policies to get the best performance, operation of these systems requires qualified personnel at the time of flooding to regulate the facilities according to rainfall intensity, surface runoff volume and water level changes (Chang et al., 2008). Traditional guidelines of system operation are not only vague and difficult to use in practice, but also need qualified people with high experience and skills which should constantly monitor the changes during heavy rains and flooding and adjust the system's function. Beside the difficulty and being time consuming, these traditional approaches do not guarantee a reliable performance (Chiang et al. 2011).

To overcome the problems mentioned above, the use of systematic methods such as using simulation and optimization tools is necessary at the time of floods (Jafari et al., 2018). Optimal control of urban drainage systems (UDS) components, however, is a complicate problem due to physical and hydraulic characteristics of the system, uncertainty of rainfalls as well as complexity and nonlinearity of relations among the system components (Jafari et al. 2018). Instead, applying optimal rules of system operation results in an improved performance during heavy rainfall and flooding. Development of such intelligent tools to achieve the best performance of controllable elements in UDS has been increased in recent decades. Many researchers have developed and applied different models to improve the operation of UDS facilities (e.g. see Yagi and Shiba, 1999; Duchesne et al. 2004; Pleau et al., 2005; Darsono and Labadie 2007; Chang et al., 2008; Wei et al., 2014; Bogardi and Balogh 2013; Yazdi and Kim 2015; Yazdi et al. 2016b; Jafari et al. 2018).

Yagi and Shiba (1999) applied fuzzy logic control and genetic algorithms to improve pump operation in a combined sewer network. Pumping rates were determined by a fuzzy inference system and genetic algorithm was used to improve fuzzy control rules, automatically. Pleau et al. (2005) studied the real-time control (RTC) of the Quebec urban drainage system and stated that RTC could decreased combined sewer overflow (CSO) volumes at four overflow sites by more than 85% for seven rainfall events. Darsono and Labadie (2007) presented a neural-optimal control algorithm that incorporates the complexities of dynamic, unsteady hydraulic modeling of combined sewer system flows and optimal coordinated, system-wide regulation of in-line storage. Wei et al. (2014) proposed a two-stage intelligence-based pumping control (TWOPC) model for real-time pumping operations using a multilayer perceptron (MLP), and tree-derived rules obtained from relevant classifiers. They found that the TWOPC model had better performance than the traditional method. Gaborit et al. (2013) developed several RTC scenarios of a dry detention pond located at the outlet of a small urban catchment near Quebec City, Canada. Their results showed that RTC strategies provide a substantial improvement of the pond's performance in which the TSS removal efficiency increases from 46% (current state) to about 90%. Bogardi and Balogh (2013) proposed a model in order to minimize expected flood losses along all river reaches by optimal operation of floodway system consisting of several levee reaches. Results indicated the benefit of using optimal control policy versus other possible schemes. Hsu et al. (2013) developed two artificial-intelligence techniques, historical ANFIS and optimized ANFIS, based on historical operation records and best operation series, respectively. They reported that optimized ANFIS has better performance than the historical ANFIS and traditional operation methods according to the results obtained by models from two flood events. Yazdi and Kim (2015) used Harmony

Search (HS) for the optimal operation of pumps in UDSs. They introduced an active control approach for gate and pump manouver based on hydrological/hydraulic modeling and updated rainfalls in real time. Yazdi (2016) derived optimal operating rule of pump startions in UDSs by coupling a mathematical model and a multi-objective evolutionary algorithm considering the stochastic nature of rainfall events. The approach showed a high efficiency in terms of flood mitigation and performance of pumps compared to the traditional approach so that averagely a 40% decrease of peak water levels was obtained without increasing the number of pump switches. Using a gossip-based algorithm, Garofalo et al. (2017) studied real time operation capabilities in an urban drainage network equipped by sensors and a series of electronically movable gates. Their results showed that optimal operation can significantly reduce flooding and combined sewer overflow (CSO) by effective use of the storage capacities. Jafari et al. (2018) compared the performance of multi-period and single-period simulation-optimization to derive the real-time control policies of pumping stations in UDSs. Based on their results, multi-period optimization showed a high efficiency while the policies derived by single-period optimization were not reliable, and in some cases, they even performed worse than ad-hoc policies applied by system operators.

A major disadvantage of the real time control is the computational time of system modeling and optimization required to obtain the operating policy where the available lead time to update the policy is short. This limitation is more highlighted when there is a computationally expensive simulation model to get system response under different rainfall loads. Considering this important concern, the aim of this research is presenting a novel optimization-based methodology for effective operation of urban detention ponds during the heavy rainfalls. The proposed approach aims at finding optimal robust operating rules for controllable elements of UDS considering the occurrence of severe rainfalls. When using the real time operation is not possible or efficient because of time limitations, the proposed approach in this research can lead to more reliable and efficient operating method. Therefore, this approach is recommended as a guideline for system regulator operation. The approach is examined for the south part of the main drainage network of Tehran, capital city of Iran and the effectiveness of the approach is justified.

2 Methods and Materials

2.1 Simulation Model

Simulation tool is used here to model rainfall-runoff process and predict the response of urban drainage network under different external (rainfalls) loads and control actions. EPA's Storm Water Management Model (EPA-SWMM) model is selected here for rainfall-runoff modeling and flood routing. EPA-SWMM is known as one of the most comprehensive models available for analyzing urban floods in both combined and separate drainage systems. Zoppou (2001) reviewed 12 different models for simulating stormwater quantity and quality in an urban environment and showed that EPA-SWMM model is a suitable model for designing and analyzing urban drainage systems and sewage systems. This model is a free-domain and very popular software generally used for planning, analysis and design related to stormwater runoff, combined and sanitary sewers, and other drainage systems in urban areas. It is a dynamic hydrologic-hydraulic water quality simulation model, used for single event or continuous simulation of runoff quantity and quality from primarily urban areas. The routing portion transports this runoff through a system of pipes, channels, storage/treatment devices, pumps, and regulators. It has recently been extended to model hydrologic performance of specific types of low impact development (LID) controls (EPA, 2015).

2.2 Optimization Model

Design, construction, operation and maintenance of urban flood control systems need large resources of investments. Therefore, one of the goals of the system management is to provide maximum protection with minimum costs. Various studies show that optimization techniques can noticeably help to find optimal policies of the system operation. Optimization tool is used here to determine optimal operation of the gates in detention ponds under different storage states for effective flood management. Here, minimizing the flood volumes surcharging from the nodes (manholes) in drainage network under extreme rainfall events is considered as the objective function. The mathematical formulation of the optimization problem can be expressed as:

$$Min\ V_{fT} = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{m} V_{f,j,i}\right) \tag{1}$$

$$Subject \qquad to:$$

$$0 \le H_t \le H_{\max} \tag{2}$$

$$GO_k \begin{cases} = 0 \ \ if \ \ H_t \le B_{L,k} \\ \in \{0, 0.1, 0.2, ..., 1\} \ \ otherwise \end{cases} \tag{3}$$

$$H_t = f\left(GO_k, Q_{in,t-1}, H_{t-1}\right) \tag{4}$$

$$h_i \in \{h_1, h_2, ..., h_d = H_{\max}\} \tag{5}$$

$$V_{f,j,i} = f(R, H_t, ...) \tag{6}$$

where V_{fT} is total flooding exceeded from the network capacity considered as the objective functions; $V_{f,j,i}$ is flooding in j^{th} node of the network under i^{th} extreme rainfall event. n and m are the number of considered extreme events and nodes in the network, respectively; h_i is the discretized water depth of detention pond. H_t is the water depth of pond in time t; $H_{\max}$ is the maximum permissible water depth in the pond; GO_k is the opening of k^{th} gate which can take a value between zero and one when the water elevation in the pond exceeds the gate bottom elevation, $B_{L,k}$; The values of gate opening in each of discretized depth consist the vector of decision variables as illustrated in Fig. 1, assuming there is N control gates on the intake of detention pond. In this figure, upper script "*d*" stands for the number of pond depth discretization. To satisfy Eq. (2), a penalty value, *BigM* was used in the objective function when the constraint is violated:

$$BigM = \begin{cases} 0 & ; if \ \ H_t \le H_{\max} \\ 10000 & ; otherwise \end{cases} \tag{7}$$

The constraint presented in Eq. (6) shows that to calculate flooding, $V_{f,\, j,\, i}$ in drainage system, rainfall-runoff modeling should be conducted and this output variable is implicitly a function of rainfall characteristics R, water depth of the pond H_t, and other model parameters.

2.2.1 Solver Algorithm

Objective function in this study do not have an explicit mathematical form of decision variables and thus, for objective function evaluation, running of rainfall-runoff model is needed. On the other hand, decision variables can take only discrete values in the problem studied. For these categories of optimization problems, evolutionary algorithms are best-suited. Therefore, to solve the above optimization problem, a widely used evolutionary algorithm known as Differential Evolution (DE) is used. DE is an improved version of Genetic Algorithm (GA), originally proposed by Storn and Price (1995) for solving global optimization problems. This algorithm has the same operators as GA, but its performance substantially relies on its effective mutation operator than crossover. Many researches show that DE outperforms GA across various benchmark test functions and engineering optimization problems. Some studies are typically reviewed in the following.

Considering the advantages of DE, Reddy and Kumar (2007) presented a multiobjective version of DE algorithm, called multiobjective differential evolution (MODE), with an application to a case study in reservoir system optimization. Results showed that MODE outperforms the nondominated sorting genetic algorithm-II (NSGA-II). Vasan and Simonovic (2010) applied DE for the least cost design problem of water distribution systems and recommended it as a potential alternative tool for economical and reliable water distribution network planning and management. Xu et al. (2012) applied DE for estimation of Muskingum model parameter. The experimental results showed an excellent performance in its optimization result and performance analysis and demonstrated that DE is an alternative technique to estimate the parameters of the Muskingum model. Elci and Ayvaz (2014) coupled a hybrid DE algorithm with a regional-scale groundwater flow model to find best locations of groundwater production wells considering the restriction of seawater intrusion. Yazdi (2016) casted DE in a decomposition-based evolutionary search algorithm and showed that it gives better results relative to genetic algorithm (GA) and harmony search (HS) for water distribution network design. Yazdi et al. (2017) developed a multiobjective version of DE and after validation, they applied it for the hydraulic rehabilitation of UDSs. Moosavian and Lence (2017) verified DE for multiobjective design of water distribution systems and obtained better results than NSGA-II benchmark optimization algorithm. There are many other research works in the literature that show DE is a strong EA for solving different engineering optimization problems. Accordingly, it was selected in this research for deriving the optimal operating rules of gate opening in detention ponds of UDSs. More information about this algorithm and its operators can be found in the work of Sedki and Ouazar (2012).

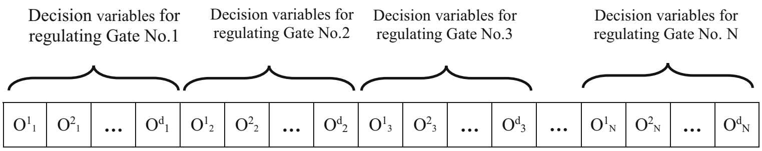


Fig. 1 Decision variables vector defined in optimization model

2.3 Case Study

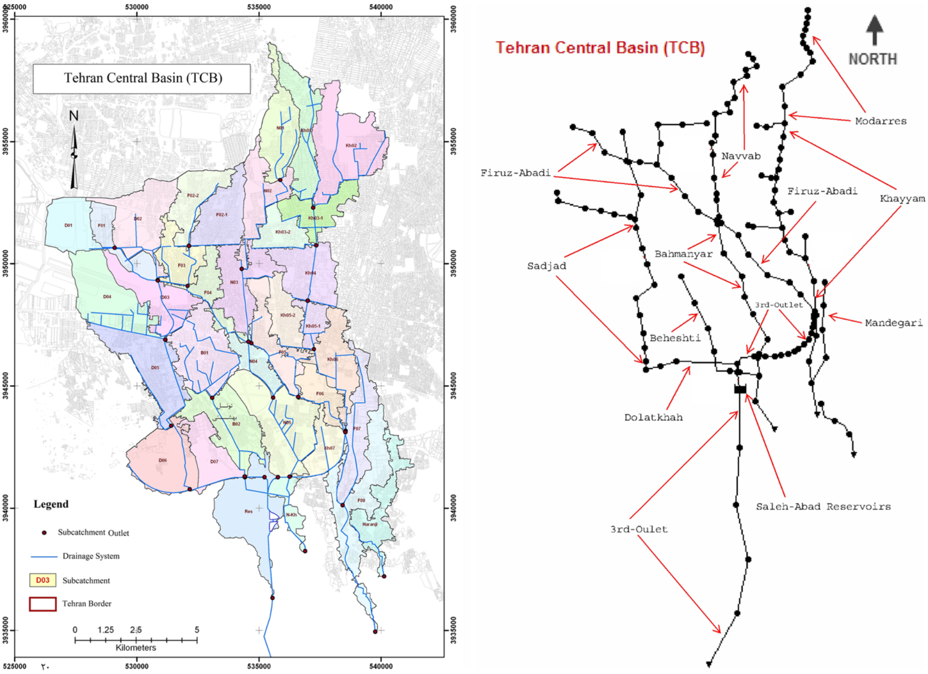
The south part of main drainage network of the capital city, Tehran, Iran is selected as the case study. Mean annual rainfall in Tehran is about 320 mm, but annual rainfall varies between 200 mm in southern parts of the city and 500 mm in the north. The studied drainage system mostly includes underground tunnels with 116 km length in which 15.6 km of the conduits does not have enough hydraulic capacity to safely convey stromwater runoff related to the design rainfall (with 50-yr return period). This network drains 156 km^2 area and includes 42 sub-catchments and 132 conduits (Fig. 2a). Conduits (tunnels) at the downstream part do not have enough hydraulic capacity. Thus, two detention ponds, called Saleh_Abad, have been constructed to mitigate urban flooding on this part of the network. Saleh_Abad ponds consist of northern and southern parts, which are connected together by a central Culvert (Fig. 3). The area of the northern part is approximately 85,000 square meters and that of the southern part is about 75,000 square meters. Figure 3a shows the longitudinal profile of the ponds in the direction of the base flow and Fig. 3b illustrates different parts of the ponds. Since these two ponds are interconnected and act hydraulically as a single pond, hereafter it is considered as one detention pond. Outlet intake structure is built of concrete and has an octagon shape. Three steel gates with 1.6×1.6 m^2 sizes are installed on three faces of the intake at different levels (Fig. 4). At the upper part, eight rectangular openings with 0.6×0.9 m^2 sizes are located which act as spillway in the case of filling the pond or improper functioning of the gates to discharge collected runoff. On the roof, an octagonal opening with a diameter of about 3 m is also built that can serve as another spillway.

2.4 Model Set up

Model setup and calibration for the central zone of TSDS has been already carried out by Mahab Ghods Consultant Engineers (MGCE, 2011) and here the same modeling approach and parameters have been used for the model preparation. The NRCS curve number method, introduced by U.S. Natural Resources and Conservation Service (NRCS), was set up for estimating the precipitation losses based on the local land use and soil type properties (USACE, 2010). According to the land uses and soil types, totally 35 sub-catchments were considered in hydrological modeling. Calculated surface runoff of sub-catchments are routed in the tunnels and conduits of the network (including Saleh_Abad pond) through solving dynamic wave by EPA-SWMM. Figure 2b depicts the hydraulic network of study area in SWMM. As mentioned, the parameters of SWMM were set as those of calibrated model reported by MGCE, (2011). The parameters of DE were set: crossover probability = 0.7, scaling factor = 0.5 as those widely used in the literature (e.g. Yazdi 2016). According to the number of decision variables, population size and number of iterations were set both equal to 100.

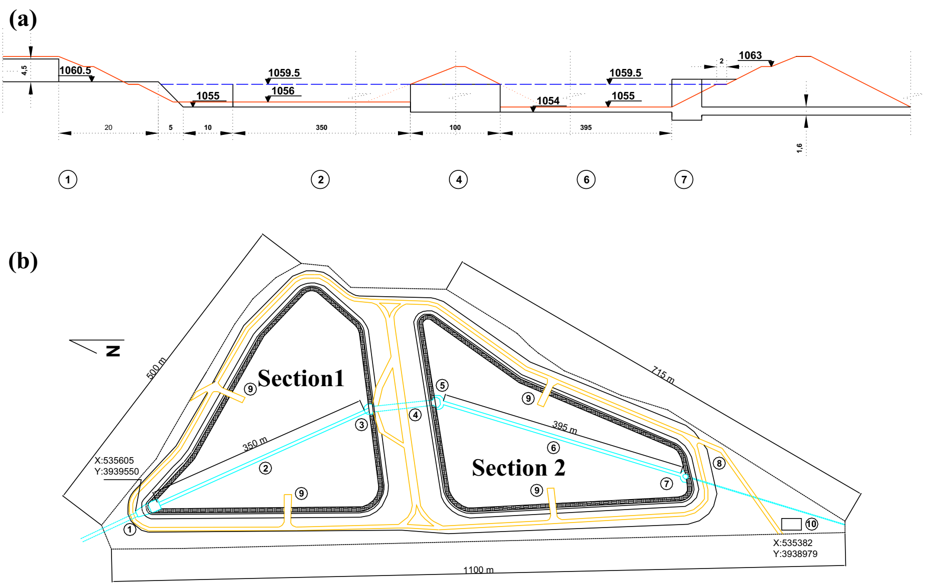
3 Results and Discussion

At the present, there is no control policy for the gate opening of Saleh_Abad pond. As soon as the water level reaches the gate level, it is completely opened and thus, it seems that gate opening increases linearly as the water level rises in the pond. When it reaches at the top level of the gate, the opening is constant and equal to 100%. Figure 5 indicates this fact for all gates



(a) Central sub-watershed of Tehran main drainage system, (b) The studied drainage network in SWMM environment

Fig. 2 **a**) Central sub-watershed of Tehran main drainage system, **b**) The studied drainage network in SWMM environment



(a) Section view, (b) Plan of Saleh_Abad ponds

Fig. 3 **a**) Section view, **b**) Plan of Saleh_Abad ponds

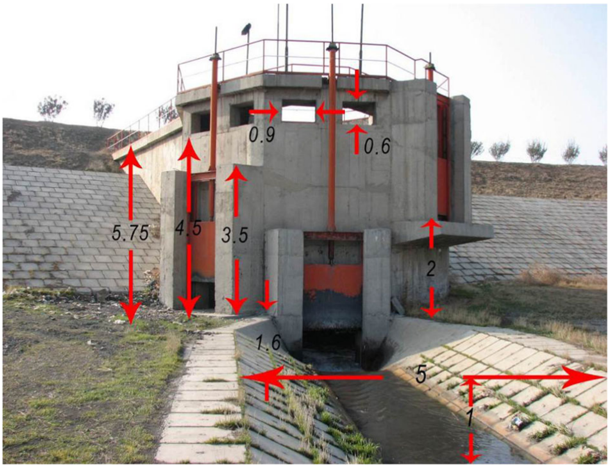


Fig. 4 Dimensions of the outlet gates (m) in intake structure of Saleh_Abad pond

of Sale_Abad pond. The starting point of opening for each of the gates is when the water level reaches to the bottom elevation of that gate. Such approach of gate maneuver is called in this study as "uncontrolled rule curve" of pond operation. As demonstrated in the following, uncontrolled rule is not necessarily a good approach of pond operation, especially when there is a limited flood control capacity. To find optimal rule curves of the pond gates, DE code was linked to SWMM model and executed for the extreme events on the study area. It is noticeable that DE and EPA-SWMM was coupled in Matlab environment. The policy of gate operation was generated by DE externally, and then was defined in SWMM simulation engine through writing the policy in the input text files of SWMM model. According to the computational efforts required for optimization task, the running time was nearly 236 h on a computer Pentium® Dual-Core CPU 3.00 GHz with 4.00 GB RAM.

The extreme events considered in the modeling were included 35 largest annual rainfall events occurred between 1978 and 2013 ($n = 35$ in Eq. (1)). Maximum permissible water depth of the pond is 6.7 m which was divided to 67 discrete values with 10 cm increments. The bottom elevation of the gate no. 1 is on the pond floor. Therefore, 67 decision variables can be defined for the operation of this gate so that in each 10 cm increment, optimization model should be decided that how much the optimum gate opening is. Gate no. 2 is located in upper

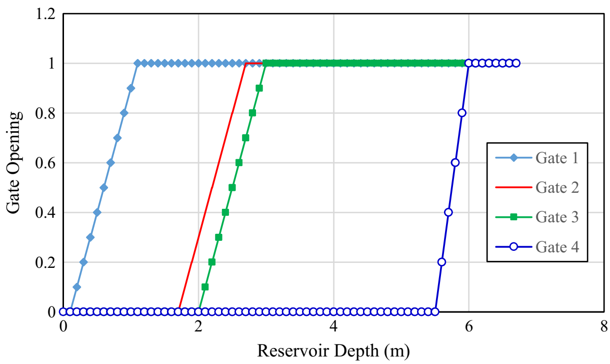


Fig. 5 Current rule of gate opening (uncontrolled rule) for the intake of Saleh_Abad pond

elevation relative to the gate no. 1 and therefore, smaller number of decision variables is needed for its operation. This is also the case for two other top gates. Total number of decision variables in this study is 176 including 67 variables for the gate no. 1, 50 variables for the gate no. 2, 47 variables for the gate no. 3 and 12 variables for the gate no.4.

After running the DE-SWMM model and converging the search algorithm to the (near) optimal solution, optimal operating rules of the intake gates were obtained as the graphs shown in Fig. 6. This figure indicates that the percentage of gate opening per each 10 cm increase across the water depth. To assess the performance of proposed optimization method, optimal operating rules are compared with uncontrolled rule in terms of network flooding in Fig. 7. Figure 7a compares the mean of network flooding in two operation methods under all 35 annual extreme events. As illustrated, optimal operating rules of the gate opening could decrease flooding in all considered 35 extreme rainfalls relative to the current uncontrolled operation. The obtained results also revealed that the procedure of pond operation have a very small effects on the nodal flooding of upstream network, but it considerably decreases the flooding occurred at downstream of the pond. Figure 7b indicates the mean of flood volumes of extreme events in a part of the network located at downstream of Saleh_Abad pond. It is obvious that optimum gate opening noticeably outperforms the traditional method. It could yield a 30% reduction on flooding of the largest extreme rainfall during 1979 to 2013 and 55% decrease on the mean of flooding raised by all extreme rainfalls.

To evaluate the optimal operation with more details, six extreme rainfalls are selected among the annual extreme rainfalls recorded in 1979 to 2013 including two smallest, two moderate and two largest extreme rainfalls.

These events with their rainfall depth and duration are presented in Table 1. The optimal and uncontrolled rules are compared in terms of flood hydrograph released by the pond corresponding to the events in Table 1. In two small extreme events, although the peak discharge of hydrographs in optimal case is slightly higher than the uncontrolled method for

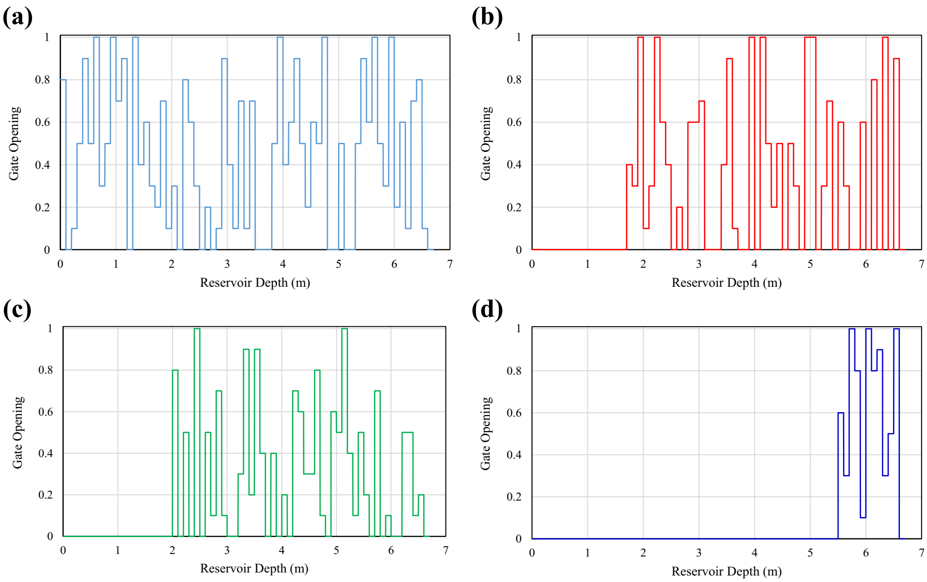


Fig. 6 Optimal rule curves of the gate opening determined by proposed model for the intake of Saleh_Abad pond, **a**) gate no.1, **b**) gate no. 2, **c**) gate no. 3 and **d**) gate no. 4

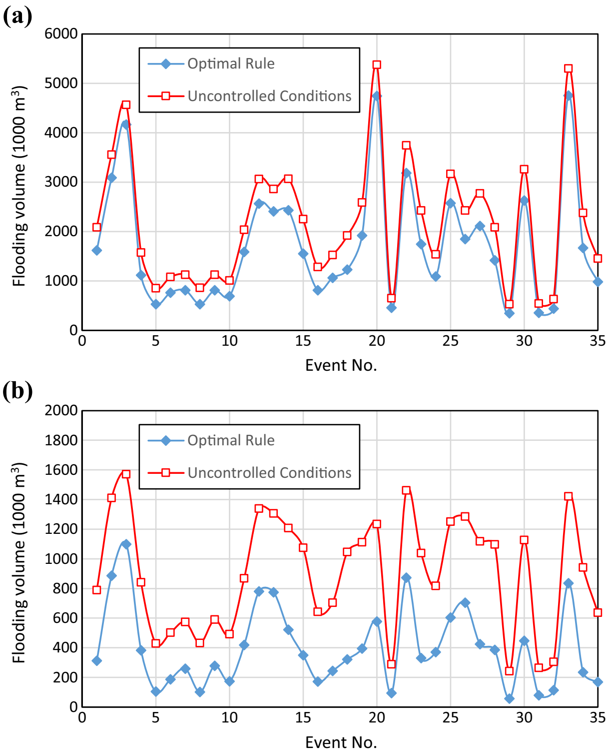


Fig. 7 Comparing the optimal rule curve and uncontrolled conditions of the pond in terms of **a**) total flood volume of the network, **b**) total flood volume of the network downstream of the Saleh_Abad pond

a very short time, discharges released by optimal rule is noticeably lower than those of traditional method. Optimal rule decreases respectively 59% and 65% stormwater releases in the events no 1 and 2, compared to the uncontrolled rule.

The same trend can be seen for two moderate extreme events in Fig. 8 (c and d). Totally, 53% and 61% flood volume reduction was achieved in the released discharge of extreme events no. 3 and 4 (with moderate severity), respectively through applying optimal operation. As illustrated in Fig. 8 (e and f), in the case of two largest extreme events no. 5 and 6, there is a fixed release rate at a portion of simulation time period. During this period of simulation time, pond release exceeds the maximum hydraulic capacity of downstream conduit and therefore, excess water beyond the downstream conduit capacity surcharges from the network. In fact,

Table 1 The selected extreme events in the study area considered for model evaluation

Event No.	Start Date	Start time	End Date	End Time	Duration (min)	Depth (mm)
1	5/5/2004	1:00	5/5/2004	7:45	405	8.75
2	3/28/2002	15:15	3/28/2002	18:25	190	9.14
3	12/7/1984	10:20	12/7/1984	14:10	230	25.71
4	2/13/2002	18:10	2/13/2002	8:50	880	27.29
5	1/31/1994	22:50	2/31/1994	15:05	975	60.69
6	10/28/2011	17:30	11/28/2011	15:35	1325	61.5

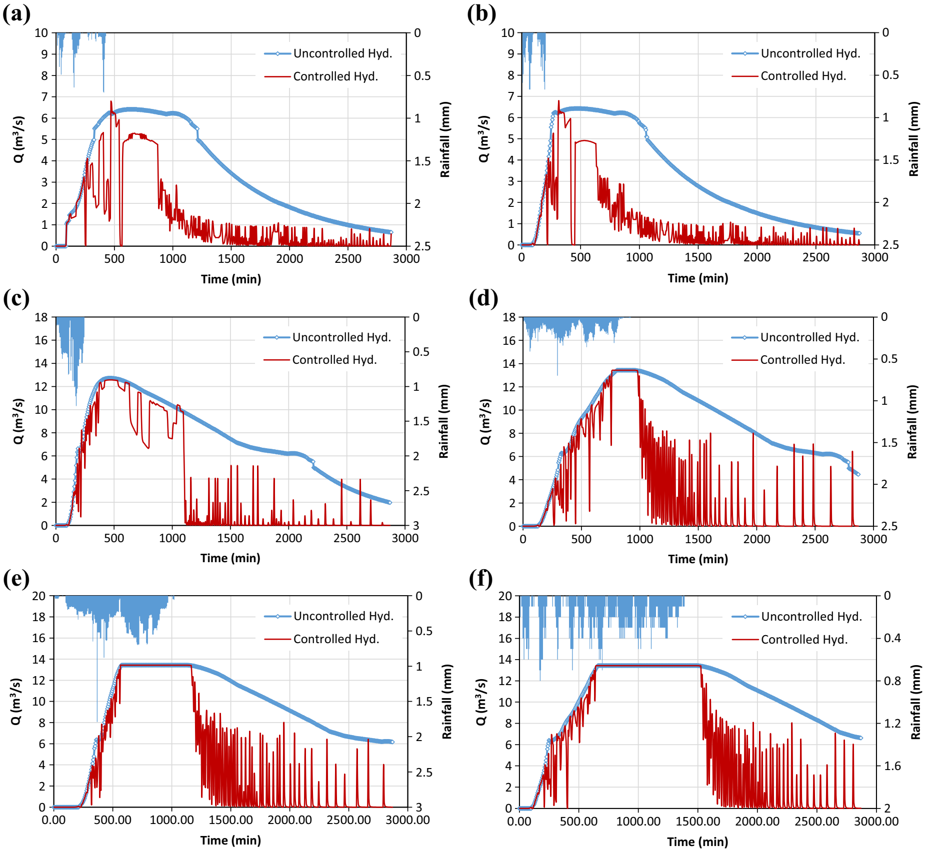


Fig. 8 Flood hydrographs released from the Saleh_Abad pond corresponding to the selected extreme rainfall events: **a**) 5/5/2004 **b**) 3/28/2002 **c**) 12/7/1984 **d**) 2/13/2002 **e**) 1/31/1994 **f**) 10/28/2011

for these large-size events, the manner of operation cannot control all stromwater due to lack of hydraulic capacity in existing conduits. Nevertheless, relative to the conventional operating method, optimal operation could also decrease nodal flooding up to 51% and 39% in the largest events no. 5 and 6, respectively. These results justify the high performance of proposed optimization approach for advanced operation of urban detention ponds across a wide variety of floods with different sizes and severities.

4 Conclusion

In this paper, an optimization model was proposed for adaptive operation of urban detention ponds during heavy rainfalls. This model gave the optimum rules of gate maneuver underlying a significant flood load scenarios entering detention pond, simulated by SWMM rainfall-runoff model. Comparative results of the optimal and traditional operations revealed that proposed method noticeably outperforms the traditional pond operation in terms of flood mitigation. Optimal rule provided more than 55% decrease in nodal flooding of the drainage network, downstream of the pond. This valuable outcome was achieved only by gate operation without any structural increase in system components. Results also showed that the manner of pond operation does not have a sensible effect on flooding of the network upstream of detention pond and it only acts positively on downstream parts.

According to the results, the approach is recommended to extend for system operation when there are several detention ponds and other controllable elements to investigate their interaction and achieve more flexible operation strategies for urban flood risk management.

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