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AI-based design of urban stormwater detention facilities accounting for carryover storage

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ABSTRACT

Rapid urbanization in metropolitan areas easily triggers flashy floods. Urban drainage systems conveying stormwater out of cities are key infrastructure elements for flood mitigation. This study develops an intelligent urban flood drainage system accounting for carryover storage through optimizing the multi-objective operation rules of pumping stations for effectual flood management in Taipei City. The Yu-Cheng pumping station constitutes the study case, and a large number of datasets collected from 17 typhoon/storm events are adopted for model construction and validation. Three objective functions are designed to minimize: (1) the sum of water level fluctuations in the flood storage pond (FSP); (2) the sum of peak FSP water levels; and (3) the mean absolute difference of pump switches between two consecutive times along operation sequence. The non-dominated sorting genetic algorithm II (NSGA-II) is applied to searching the Pareto-optimal solutions that optimize the trade-off between the objectives. We next formulate the optimal operation rules through a two-tier sorting process based on a compromised Pareto-optimal solution. The comparison of the simulated results obtained from both the optimal operation rules and current operation rules indicate that the optimal operation rules outperform current operation rules for all three objectives, with improvement rates reaching 43% (OBJ1), 3% (OBJ2) and 71% (OBJ3), respectively. We demonstrate that the derived intelligent urban flood drainage system can serve as reliable and efficient operational strategies for urban flood management and flood risk mitigation.

1. Introduction

The fast-growing urban population in the world is an inevitable fact. The rapid urbanization in metropolitan areas causes less water infiltration but flashy floods, which invariably increases flood risks. Large-scale floods are ravaging the globe and often leave fatal consequences in their wake. Global attention nowadays has been intensively drawn to flood prevention for the protection of life and property. Cohesive development and adaptation of new knowledge should be made not only to reduce flood risks but to increase the flood preparedness of residents and professionals (Becker et al., 2014; Chang et al., 2014; Girons Lopez et al., 2017; Hsu et al., 2013; Kundzewicz et al., 2014). Methodologies for the design of a sewer system control hierarchy using temporal decomposition were explored (Mollerup et al., 2016). Developing the optimal management of weirs, pumping stations, reservoirs and inlets at floodwater retention areas can significantly control the consequences brought by floods. Implementing advanced technologies and operational strategies for the combined sewer systems would be an important means to address challenges encountered in urban drainage. Lund et al. (2018) provided an overview of methods and tools for performing model predictive control (MPC) within the field of urban drainage, and they pointed out the concept of smart cities might lead to new operational goals such that MPC could be useful to migrate urban drainage systems from passive traditional infrastructure systems to proactive adaptive systems based on a high level of intelligent measures.

Intelligent urban flood control systems explored by artificial intelligence (AI) could promote the efficiency and reliability of drainage infrastructures (Chen et al., 2017; Liu and Cheng, 2014; Mollerup et al., 2016). It is desirable and beneficial to have a collaborative development and applications of new knowledge and advanced technologies to improve decision-making, increase community and flood resilience, and reduce flood-related damages. This will increase the potential in finding solutions to coping with highly complex problems such as multiple objectives pump operation.

In response to the rapid rise of flood flow during extreme events, the

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traditional urban flood control strategy is to build embankments along river banks to prevent cities from flooding. Besides pumping stations are set up around the drainage outlets behind embankments to pump flood water out of cities because gravity draining may fail during extreme events. Undoubtedly, pumping stations play a decisive role in urban flood control systems. Pumping stations unable to perform drainage functions properly would bring flood disasters, which usually cause property losses and residents' resentment. Accordingly, there is an urgent need for the optimal utilization of available means to flood prevention. Nevertheless, current pump operation guidelines were set up a long time ago and no pump operation rule was established particularly to cope with urbanization and climate change. Such phenomena occur in many developed cities in Asia. For instance, Hiramitsu and Abe (2001) stated that no well-defined concept of pump operation control was built in Japan. Several approaches were explored to improve such conditions. Chiang et al. (2011) proposed rule-based fuzzy neural networks to on-line predict the number of open and closed pumps of a pumping station in Taipei City, up to a lead time of 20 min. Yazdi and Kim (2015) developed a real-time optimization approach to searching the optimal policies for collaborative operation of drainage facilities in a portion of an urban drainage system in Seoul. The operation and maintenance cost of a pump station depends on a number of factors including climatic conditions, hydrological conditions, the type and age of pumps, quality of operation, and operator experience (Makaremi et al., 2017). Conventional pump operation guidelines are often vague and difficult to follow, and therefore skilled and experienced operators are required. To overcome such disadvantages, there is an imperative need to create new multi-objective operation rules for governing real-time pump operation based on careful consideration of current hydrological conditions and various pump operation objectives through systematical analyses and optimization mechanisms.

To protect cities from the ravages of floods, countermeasures to flooding should make a close collaboration with sewerage systems and river management. The optimal control of urban drainage networks would aim at tackling the problem and generating intelligent control strategies ahead of flood occurrence based on the monitoring data transmitted from telemetry systems for minimizing flooding and sewer overflows. This becomes a great challenge on account of the high complexity and uncertainty of the flood control system as well as the societal pressure on the efficient generation of solutions. In this study, we implement a state-of-the-art technology to propose efficient multi-objective pump operation rules for real-time urban flood control management. Previous studies facilitated AI techniques, such as genetic algorithms (GAs), artificial neural networks (ANNs) and fuzzy inference, to construct humanlike operation strategies regarding urban drainage systems (Chang et al., 2008; Yazdi and Kim, 2015), optimal pumping control (Cembrano, 2004; Zhuan and Xia, 2013), urban flood forecast (Chiang et al., 2010; Hsu et al., 2013; Noymanee et al., 2017), and flood deference (Tamotoet et al., 2008; Wang et al., 2013) for securing cities of interest. Nevertheless, there were few studies addressing the development of the optimal pump operation rules in urban drainage systems using multi-objective optimization methods (Yazdi et al., 2016). Among them, a global optimal control system was implemented in a sewer network of Quebec to real-time manage flows and water levels for reducing the frequency and volumes of combined sewer overflows discharged into rivers (Pleau et al., 2005). Fiorelli et al. (2013) proposed a control approach for a combined sewer network in Luxembourg, which considered three optimization goals for sewer systems and relied on a simple hydraulic model of the sewer system.

Plenty of real-world optimization problems are non-linear in nature and have multiple conflicting objectives, subject to various constraints (Deb, 2005). Conventionally, such problems could be solved by being artificially converted into a single-objective problem. With development in advanced technologies, multi-objective optimization can be achieved nowadays, which has a tremendous practical importance. Yet difficulties arise because such problems introduce a set of trade-off optimal solutions (i.e. Pareto-optimal solutions), instead of a single optimum solution. It then becomes critical to find as many of Pareto-optimal solutions as possible because any two optimal solutions form a trade-off between the objectives such that users will be in a better position to make an adequate choice from compromised (trade-off) solutions.

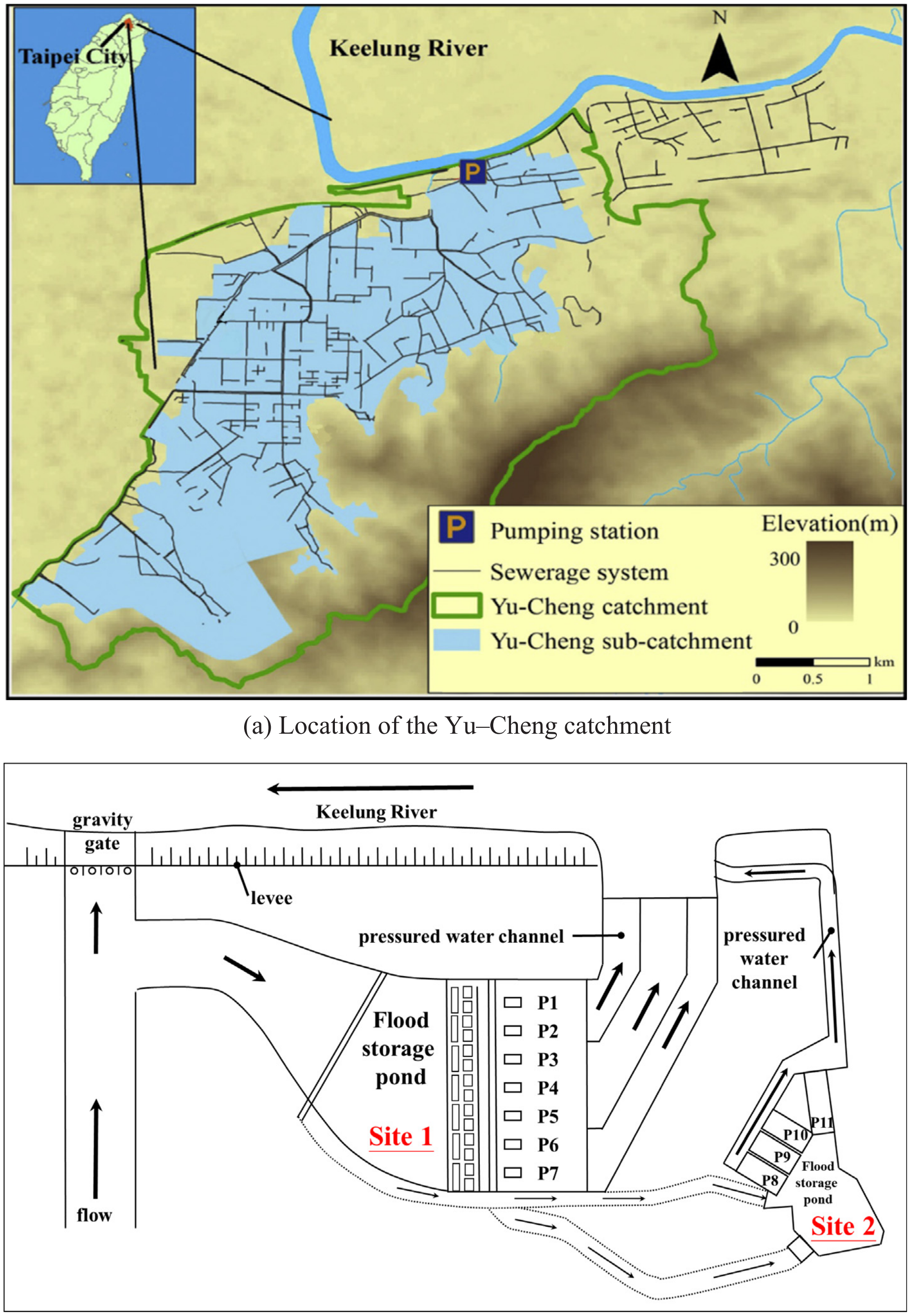
The evolutionary algorithm (EA) inspired by biological evolution is a generic population-based metaheuristic optimization algorithm. The EA can identify a diverse set of Pareto-optimal solutions to provides a spread of solutions that well converge to the non-dominated set for the problem investigated (Coello et al., 2006; Goldberg and Kuo, 1987). The compromised solutions produced from EAs usually perform better than traditional optimization solutions, and their tradeoffs are very useful when making a sound decision from alternative options. The non-dominated sorting genetic algorithm (NSGA-II) proposed by Deb et al. (2002) belongs to contemporary multi-objective EAs. The NSGA-II contains few tuning parameters but exhibits high performance, which makes itself very applicable to various kinds of optimization problems (Nicklow et al., 2010). There is noticeably increasing interest in the development and applicability of biologically-based EAs for solving multi-objective optimization problems in diversified water resources management issues, such as reservoir management (Chang and Chang, 2009; Davidsen et al., 2015; Ehteram et al., 2017; Lerma et al., 2015; Srinivasan and Kumar, 2018; Tsai et al., 2015, 2016), water utilization (Davijani et al., 2016; Li et al., 2018; Matrosov et al, 2015; Ormsbee and Lansey, 2015; Zheng et al., 2015), urban drainage system (Barreto et al., 2009; Li et al, 2015; Rathnayake, 2016; Yazdi et al., 2016), energy management and conversion (Feng et al., 2018; Karami et al, 2018; Peralta et al., 2014; Yang et al., 2015), sustainable groundwater modeling (Sadeghi-Tabas et al.,2017; Sreekanth et al., 2016; Yeh, 2015), and flood forecasting (Chang et al., 2016; Taormina et al., 2015; Zheng et al., 2015). These studies showed that EAs were flexible and powerful tools in solving an array of complex water resources problems.

Although the optimal control in urban drainage networks has recently caught the attention of numerous policy-making and regulatory agencies, it has been rarely addressed regarding the integrated engineering system for its planning, regulation, and management in an interdisciplinary way. This work specifically fills this gap by addressing the integrated multi-site flood control system. In particular, this study intends to develop a methodology that determines the optimal multi-objective pump operation rules using EAs so that the pump operation system can be more intelligent in optimizing its efficiency, effectiveness, and flexibility for flood control management. The requirements and basic components of the optimal pump operation rules accounting for carryover storage are presented and discussed. The Yu–Cheng pumping station and its drainage area in Taipei, Taiwan, forms the study case. The applicability and reliability of the proposed methodology is examined in light of the limitations on the existing pump operation and operator acceptance.

2. Study area and datasets

Taiwan is located in the subtropical jet stream monsoon zone of the North Pacific Ocean. Taipei City is the political, economic and cultural center of Taiwan, and the Taipei metropolitan area has a population over 7 million. Taipei City is surrounded by three confluent rivers flowing to the ocean through a narrow estuary. It is difficult for the city to effectively discharge massive flood water such that flood hazards may take place easily during typhoon/storm periods. Consequently, high levees were built along the river for preventing the city from flooding. Typhoons are usually coupled with intensive rainfalls, and thus urban flooding could occur within a few hours in Taipei City. Because of high levees, floodwater inside the levee system has become the main threat to the city nowadays. Therefore, pumping stations are facilitated to manage internal storm water for flood mitigation.

The Yu–Cheng catchment located in southeastern Taipei is the study



(a) Location of the Yu–Cheng catchment

(b) Hydrological/hydraulic connections between Site 1 and Site 2 of the Yu-Cheng pumping station

Fig. 1. Study area. (a) location of the Yu–Cheng catchment, and (b) hydrological/hydraulic connections between Site 1 and Site 2 of the Yu-Cheng pumping station.

area (Fig. 1(a)). This catchment occupying an area of about 1627 ha constitutes the biggest drainage system in Taipei City. The Yu–Cheng pumping station, with two operational sites, is the largest pumping station in the city. The original pumping capacity is 184.1 cms, which can deal with rainfall intensity up to 42.5 mm/hr. A near-by station expansion with a pumping capacity of 50.0 cms was built later on to join pump operation for coping with rainfall intensity of 56 mm/hr. Consequently, the total pumping capacity reaches 234.1 cms. The joint operation of the two connected sites did achieve expected performance during typhoon/storm events. However, due to climate change in recent years, it is imperative to make some adjustments on pump operation based on the accumulated experience in managing water levels to ensure the safety of residents in the future.

The station is equipped with a total of 11 pumps. Site 1 installs 7 pumps (#1 − #7) with an overall pumping capacity reaching 184.1 cms (26.3 cms/pump) while Site 2 installs 4 pumps (#8 − #11) with an overall pumping capacity reaching 50.0 cms (12.5 cms/pump). Fig. 1(b) shows the hydrological/hydraulic connections between Site 1 and Site 2, where Sites 1 and 2 are connected by a water diversion box culvert of size 5.0 m × 3.2 m and a back-up box culvert of size 4.1 m × 3.5 m. It is noted that pumps (26.3 cms/pump) in Site 1 have the same performance curve, which means all pumps have equal pumping capacity (similarly for discharge rate) under the same water level and water head. Pumps (12.5 cms/pump) in Site 2 also have the

Table 1
Typhoon and storm events used for model training and testing.

Event number	Year	Duration (MM/DD)	Event name	Total rainfall (mm)
Training phase (number of data[a]: 2,473)				
1	2004	09/11–09/13	HAIMA	381
2	2004	10/25–10/26	NOCK-TEN	117
3	2004	12/03–12/04	NANMADOL	130
4	2005	07/18–07/19	HAITANG	73
5	2005	08/31–09/01	TALIM	108
6	2006	09/10–09/11	910 Storm	114
7	2008	09/13–09/15	SINLAKU	458
8	2008	09/28–09/29	JANGMI	172
9	2009	10/04–10/06	PARMA	115
10	2010	10/21–10/23	MEGI	146
11	2012	06/12–06/13	612 Storm	225
12	2012	08/01–08/03	SAOLA	208
13	2014	05/20–05/21	520 Storm	257
Testing phase (number of data[a]: 316)				
14	2013	05/11–05/11	511 Storm	47
15	2013	07/13–07/13	SOULIK	49
16	2013	08/21–08/22	TRAMI	78
17	2013	08/31–09/02	KONG-REY	117

[a] Time step size: 10 min

same performance curve. However, the performance curves of Site 1 and Site 2 are different.

Pump operation highly depends on the water level of the flood storage pond (FSP), i.e. carryover storage. For Site 1, pumps are activated with a 3-minute warm up if the FSP water level reaches the warning level (1.8 m). Then inner water will be pumped out to the surrounding river (i.e. the Keelung River) of the station as soon as the FSP water level reaches the start level (2.2 m). Similar actions will be taken for Site 2, whose warning and start levels are 2.4 m and 2.6 m, respectively. Pump operation begins with Site 1, and Site 2 will join the operation as soon as all the 7 pumps in Site 1 are activated.

In this study, the investigative data were collected from 17 typhoon/storm events at a temporal resolution of 10 min during 2004 and 2014, including FSP water levels, river water levels, historical pumping records and pump performance curves. A total of 2,789 datasets are adopted to construct the optimal pump operation model, in which the numbers of datasets allocated into training and testing phases are 2,473 (13 storm events) and 316 (4 storm events), respectively (Table 1).

3. Methodology

The optimization model of an urban drainage system involves a set of equations that give an evaluation of the system's variables and their responses to control actions at the gates. The main objective of this study is to develop an intelligent flood drainage system accounting for carryover storage that optimizes multi-objective pump operation rules for minimizing the urban flood risk for the largest pumping station in Taipei City during storm events. We propose a two-tier sorting process based on Pareto-optimal solutions of the NSGA-II to formulate the optimal multi-objective pump operation rules. The proposed methodology first adopts 13 storm events to construct the optimal pump operation rules and then uses 4 storm events to evaluate the reliability and practicability of the constructed rules through an operational comparison between the optimal operation rules and the current ones. The research framework is presented in Fig. 2, and a detailed description of the methodology is introduced as follows.

3.1. Nsga-II

The goal of an optimization model is to recognize the best control trajectory for each actuator during the upcoming control horizon. The best set of control trajectories is the one that optimizes the objectives under the given constraints (Lund et al., 2018). In this study, the

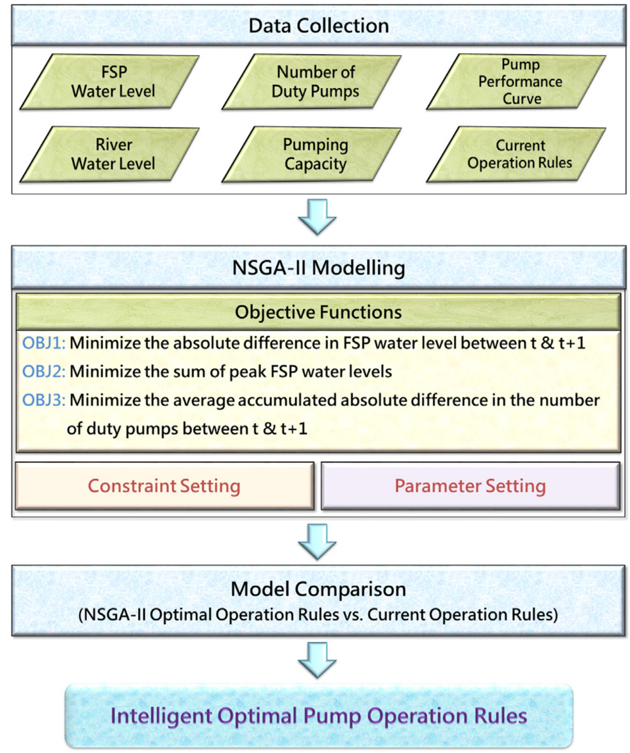


Fig. 2. Research framework.

optimal pump operation is conducted by the NSGA-II for mitigating unban flood risk as well as reducing energy consumption. The NSGA-II has the merit of coping better with computational complexity, non-elitism approach, and the need for specifying a sharing parameter. It can obtain a much better spread of Pareto-optimal solutions and better convergence, compared to other multi-objective optimization algorithms (e.g. Pareto-archived evolution strategy and strength-Pareto EA, two other elitist multi-objective EAs) (Deb, 2002). The implementation procedure of the NSGA-II is briefly summarized as follows.

Step 1: Randomly initialize a population P_0 of size N, apply the fast non-dominated sorting, and compute the crowding distances of the population.

Step 2: Implement reproduction, crossover and mutation to generate an offspring population Q_t.

Step 3: Evaluate the fitness values. Calculate the fast non-dominated sorting and crowding distances of P_t and Q_t to generate an offspring population P_{t+1} of size N.

Step 4. Repeat Steps 3 and 4 until reaching the stop criterion.

P_0 denotes the N sets of operation rules that are randomly generated. In this study, each set of operation rules contains 22 points (11 FSP water levels (X-axis), and 11 water heads (Y-axis)), which support the NSGA-II to conduct the optimal search.

Model optimization involves both decision variables and constraints. We adapt a simple constraint-handling strategy to the NSGA-II. The strategy assigns each infeasible solution with an overall constraint violation value while assigns a feasible solution with a zero value of constraint violation. Each feasible solution receives a better non-domination rank than all infeasible solutions. Correspondingly, an infeasible solution would receive a better non-domination rank if it has a smaller overall constraint violation value than the others. The parameter setting of the NSGA-II model is listed in Table 2.

Multi-objective optimization commonly has two goals: converging to the Pareto Front, and maintaining the diversity of the Pareto-optimal solutions. The diversity metric Δ is defined as Eq. (1).

Table 2
NSGA-II parameter setting.

Parameter	Attribute
Encoding	Real code
Number of chromosomes	22[a]
Population size	1000
Generation	500
Reproduction method	Tournament
Crossover method	Simulated Binary Crossover, SBX, Probability: 80%
Mutation method	Polynomial Mutation; Probability: 5%
Number of objective functions	3
Number of constrains	5 ($NP_{k,t}$[b] + 11 + 11)

[a] A total of 11 pumps, and each requires the determination of two values (the start level to pump water and the water head).
[b] $NP_{k,t}$: the number of duty pumps in the k^{th} event at time step t

$$\Delta = \frac{d_f + d_1 + \sum_{i=1}^{N-1} |d_i - \bar{d}|}{d_f + d_l + (N-1)\bar{d}} \tag{1}$$

where d_i is the Euclidean distance between consecutive solutions in the Pareto-optimal set of solutions; d_f and d_l are the distances between the extreme solutions and the boundary solutions, respectively ($d_f = d_l = 0$ in this case); and $\bar{d}$ is the average distance of all distances d_i.

3.2. Objectives

The purpose of applying the optimal control is to compute feasible strategies for the actuators in the network, which produces the best admissible states of the network. The goals of urban drainage systems are generally concerned with flood prevention and minimization of the combined sewer overflow to the environment. In this study case, flood prevention gains the top priority. Flood damages can be greatly mitigated through careful scheduling of pump operation, which is highly sensitive to the FSP water level. According to pump performance curves, the water head (i.e. the water level difference between the FSP and the river) significantly influences pumping capacity. The larger the water head is, the lesser the water a pump discharges. This study aims at developing the optimal multi-objective pump operation rules using the NSGA-II, with a close assessment on the collaborative impacts of FSP water level and water head on pump operation. We consider three objectives, which are: (1) OBJ1 that minimizes the sum of FSP water level fluctuation to make smooth pump operation; (2) OBJ2 that minimizes the sum of peak FSP water levels to reduce urban flood hazards; and (3) OBJ3 that minimizes the accumulated absolute difference of pump switches between two consecutive times along the operation sequence to avoid frequent switch on/off of a pump within a short time.

OBJ1 minimizes the sum of FSP water level fluctuations for typhoon events, as shown in Eq. (2).

$$MinOBJ1(\mathrm{m}) = \sum_{k=1}^{K} \sum_{t=2}^{T} |WL_{k,\mathrm{t}} - WL_{k,t-1}| \tag{2}$$

where $WL_{k,\mathrm{t}}$ is the FSP water level; K is the number of training events (13 in this study case); k is the training event; T is the number of time steps in the kth event; and t is the time step in the kth event. The time interval is 10 min in our case.

One way to reduce the risk of urban flood hazard is to minimize the peak FSP water level, which can be achieved through rapidly starting up pumps to discharge the inner storm water into the surrounding river. Therefore, OBJ2 minimizes the sum of the peak FSP water levels for typhoon events, which is formulated in Eq. (3).

$$MinOBJ2(\mathrm{m}) = \sum_{k=1}^{K} \max(WL_k) \tag{3}$$

where $\max(WL_k)$ is the peak of the FSP water level in the kth event.

Pump operation should avoid frequent switch on/off of a pump within a short time, otherwise it would increase energy consumption and damage the pump and therefore raise its maintenance cost. We notice that considering the number of pump switches instead of real maintenance cost is a means to simplifying the problem for formulating it mathematically (Makaremi et al., 2017). The third objective function proposed in this study aims at tackling this issue by minimizing the number of pump switches to provide operators with optimal scheduling programs. The formulation of the third objective function, OBJ3, is to minimize the mean absolute difference in the numbers of duty pumps between t and t + 1 along operation sequences, as shown in Eq. (4).

$$MinOBJ3(pumps/\mathrm{timestep}) = \frac{\sum_{k=1}^{K} \sum_{t=1}^{T} |NP_{k,t} - NP_{k,t-1}|}{\sum_{k=1}^{K} TS_k} \tag{4}$$

where $NP_{k,t}$ is the number of duty pumps in the kth event at time step t, and TS_k is the total number of time steps in the kth event.

3.3. Constraints

Constraint setting usually confines the search space and avoids the occurrence of abnormal conditions, for instance when the FSP water level is higher than the maximum FSP water level, or the number of duty pumps exceeds the maximum number of available pumps. In this study, constraints involve the number of pumps, FSP water level, and water head.

The number of duty pumps should fall between 0 and the number of available pumps (Eq. (5)).

$$0 \le \mathrm{NP}_{k,t} \le NP_{max} \tag{5}$$

where $NP_{k,t}$ is the number of duty pumps in the kth event at time step t, and NP_{max} is the maximum number of available pumps.

Due to urbanization and climate change, flash floods usually cause a very quick increase in the FSP water level. In practice, operators may activate pumps to discharge water even though the FSP water level is lower than the start level (2.2 m) of current operation rules. Therefore, the start level is re-designed as 1.8 m for adapting to practical operation when searching for the optimal operation rules in this study. These constraints are formulated as follows.

$$1.8m \le WL_p \le 2.7m \; p = \#1 - \#7(Site1) \tag{6}$$

$$2.7m \le WL_p \le 5.0m \; p = \#8 - \#11(Site2) \tag{7}$$

where WL_p is the FSP water level for the p_{th} pump.

$$0 \le WH_p \le 5.20m \; p = \#1 - \#7(Site1) \tag{8}$$

$$0 \le WH_p \le 7.25m \; p = \#8 - \#11(Site2) \tag{9}$$

where WH_p is the water head (the water level difference between the FSP and the river) for the p_{th} pump.

$$WL_{k,\mathrm{t}+1} = WL_{k,\mathrm{t}} + WL(Inflow_{k,t}) - WL(Outflow_{k,t}) \tag{10}$$

where k is the training event; t is the time step in the kth event; $WL(Inflow_{k,t})$ and $WL(Outflow_{k,t})$ are the FSP water levels converted from inflow and outflow in the kth event at time step t, respectively.

Consequently, the performance of the obtained optimal pump operation rules is compared with that of current pump operation rules to evaluate the reliability and practicability of the proposed model. The NSGA-II algorithm implemented in this study was re-written using Microsoft Visual Studio C# programming language based on the NSGA-II algorithm (written in C-language) released in Deb (2002).

4. Results and discussion

This study proposes an optimization framework determining a set of pump operating rules that are optimal with respect to multiple objectives for an integrated urban drainage/river system accounting for

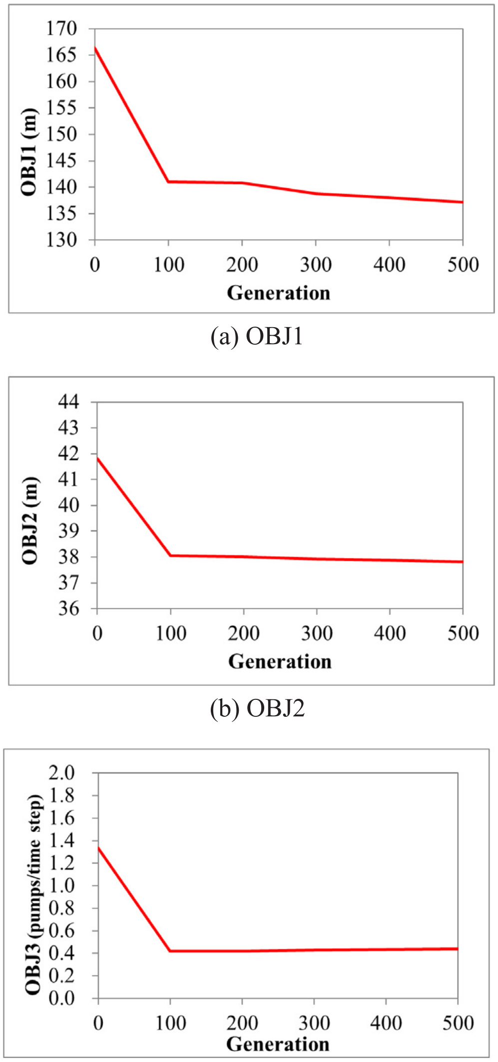


Fig. 3. Optimal values of three objective functions obtained from the search procedure of the NSGA-II.

carryover storage across a variety of typhoon/storm events.

4.1. Optimization of multi-objective pump operation

For a nontrivial multi-objective optimization problem, objective functions may conflict with each other while there are a set of Pareto compromised solutions that are considered equally good. Our mission is to find a set of Pareto-optimal solutions that satisfy the diverse preferences of decision makers. The search for the Pareto Front of the optimal operation rules subject to objectives and constraints is conducted by the NSGA-II based on 2,473 datasets of 13 storm events. Fig. 3 indicates that the NSGA-II search procedure can well converge before 100 generations for all the three objectives, i.e. the three objective functions converge into relatively small ranges after a certain number of search generations.

Fig. 4 presents the Pareto Front of 1,000 converged solutions in a three dimensional view corresponding to the three objectives. Fig. 4(a) shows that the solutions to OBJ1 fall within 137 m − 145 m, the solutions to OBJ2 fall within 37.6 m − 38.4 m, and the solutions to OBJ3 fall within 0.37 pumps/time step − 0.45 pumps/time step. Fig. 4(b) − (d) show the results of OBJ1 vs. OBJ2, OBJ1 vs. OBJ3 and OBJ2 vs. OBJ3, respectively. In sum, OBJ2 has negative correlations with OBJ1 and OBJ3 (Fig. 4(b) and (d)) while OBJ1 and OBJ3 are positively correlated (Fig. 4(c)). It appears that there exist several short horizontal lines that aggregate many solutions in Fig. 4(b) and (d), which suggest the sum of peak FSP water levels (OBJ2) remains the same while the other two objectives would fluctuate widely. It is noted that Solutions I-5 and I-632 produce the highest values for OBJ2 but the lowest values for OBJ1 and OBJ3, while Solutions I-209 and I-267 produce the lowest values for OBJ2 but the highest values for OBJ1 and OBJ3 (Fig. 4(d)).

4.2. Assessment of the optimal pump operation

Fig. 5 illustrates the simulated results (number of duty pumps and FSP water level) along the time sequence of Typhoon SAOLA (2012) concerning four selected optimal solutions obtained from the NSGA-II. Fig. 5(a) and (b) show that the number of duty pumps and the FSP water level associated with Solutions I-5 and I-632 do not make much difference over time, except for only a few time points (time steps). Fig. 5(c) and (d) show similar results for Solution I-5 and I-632. That is to say, the number of duty pumps and the FSP water level associated with these two solutions are almost the same along the time sequence, except for only a few time points (after the 121th time step).

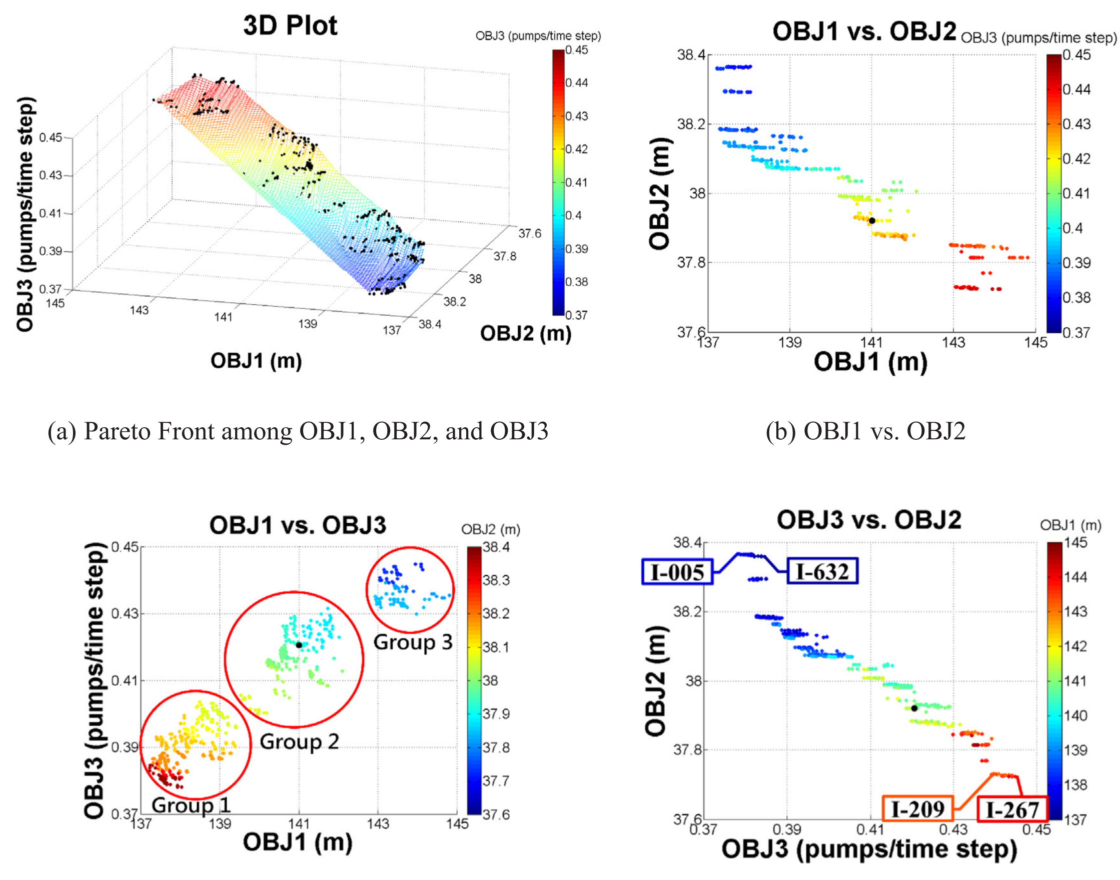
4.3. Features of the optimal pump operation

The 1000 optimal solutions displayed in Fig. 4(c) can be clearly distinguished into three groups (i.e. Groups 1–3). We further explore the specific features of Groups 1–3 using 3D representation, as shown in Fig. 6(a)–(c), respectively. Fig. 6(a) displays the optimal solutions representative of larger peak FSP water levels (OBJ2, red or yellow) but smaller FSP water level fluctuations (OBJ1) and smaller differences in the number of duty pumps (OBJ3). In contrast, Fig. 6(c) displays the optimal solutions representative of smaller peak FSP water levels (OBJ2, from light blue to blue) but larger FSP water level fluctuations (OBJ1) and larger differences in the number of duty pumps (OBJ3). Alternatively, Fig. 6(b) displays the optimal solutions representative of medium-sized peak FSP water levels (OBJ2, green or light blue).

4.4. Comparison between the optimal operation rules and current operation rules

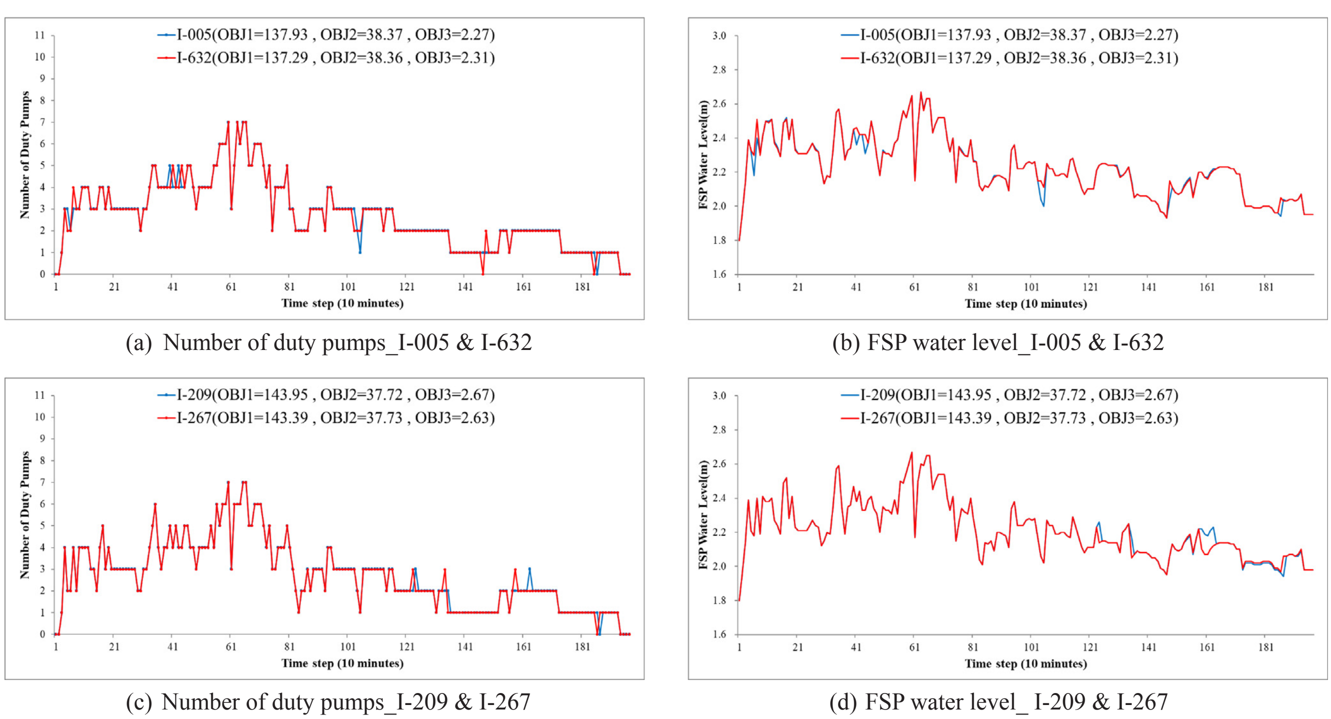
Table 3 shows the comparison of the pump operational results between the optimal rules obtained from the NSGA-II and the current rules. For OBJ1, the minimal value of the optimal operation rules occurs at 137.22 m, which is approximately half of the value (247.98 m) of current operation rules. It means current operation rules would produce more fluctuations in the FSP water levels and therefore cause operators to switch on/off pumps more frequently, which suggests the optimal operation rules are much more effective than current operation rules. For OBJ2, the minimal value (37.72 m) of the optimal operation rules is less than that (39.01 m) of the current operation values, which suggests the optimal operation rules produce a better result (effectively decrease the peak FSP water level as well as reduce the flood risk). For OBJ3, the minimal value (0.38 pumps/time step) of the optimal operation rules is only about 1/4 of the value (1.46 pumps/time step) of current operation rules, which shows the efficiency (switch on/off pumps less frequently) of the optimal operation rules. In brief, the optimal operation rules deliver superior results than current operation rules in the perspectives of all the three objectives. Table 3 also shows the objective values of a compromised solution (the black dot shown in Fig. 4) randomly selected from the 1000 Pareto-optimal solutions. It appears that the compromised solution performs much better than the current pump operation rules in terms of all three objective functions (OBJ1-OBJ3), which evidently explains the true meaning (benefit & effectiveness) of the Pareto Front in a trade-off sense.

As a result, the optimal operation rules obtained from the NSGA-II not only could significantly decrease the frequency of switching on/off pumps but could effectively mitigate the fluctuations of the FSP water



(a) Pareto Front among OBJ1, OBJ2, and OBJ3
(b) OBJ1 vs. OBJ2
(c) OBJ1 vs. OBJ3
(d) OBJ3 vs. OBJ2

Fig. 4. Pareto Front of 1000 converged solutions obtained the NSGA-II. The black dot shown in (b)-(d) is a comprised solution randomly selected from the Pareto Front. I-5, I-632, I-209 and I-267 are the optimal solutions selected from the Pareto Front for further investigation.



(a) Number of duty pumps_I-005 & I-632
(b) FSP water level_I-005 & I-632
(c) Number of duty pumps_I-209 & I-267
(d) FSP water level_ I-209 & I-267

Fig. 5. Simulated operation results along the time sequence of Typhoon SAOLA (2012) based on four optimal solutions obtained from the NSGA-II (Solutions I-5 & I-632 and I- Solutions 209 & I267, as shown in Fig. 4(d)).

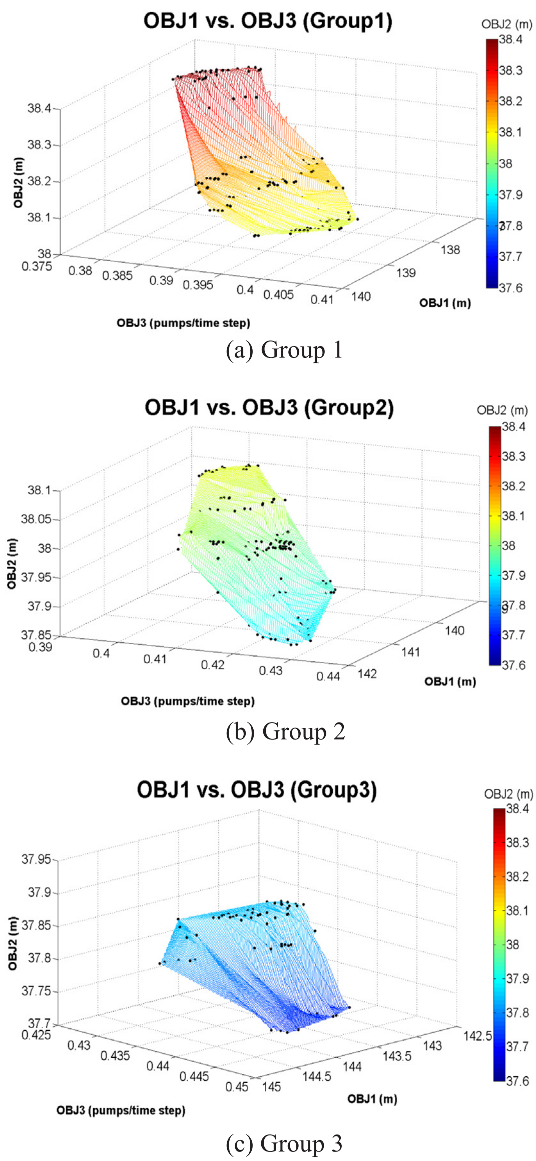


Fig. 6. 3D representations with respect to Groups 1, 2 and 3 shown in Fig. 4(c). The black dots in each subfigure denote the Pareto Front solutions that spread over the relevant search space.

Table 3
Operational results of the 13 events (the training set) based on the optimal pump operation rules and current pump operation rules, respectively.

Pump operation rules	Objective value		
	OBJ1 (m)	OBJ2 (m)	OBJ3 (pumps/ time step)
Optimal operation rules obtained from the NAGA-II			
Minimum value of OBJ1	**137.223**[c]	38.361	0.384
Minimum value of OBJ2	144.134	**37.724**	0.443
Minimum value of OBJ3	138.034	38.366	**0.378**
Selected compromised solution[a]	141.010	37.920	0.421
Current operation rules	247.982	39.013	1.462
Improvement rate[b]	43.1%	2.8%	71.2%

[a] Selected compromised solution: the black dot shown in Fig. 4.
[b] Comparison between the optimal operation rules and current operation rules (benchmark) with respect to the selected compromised solution. For instance, 43.1% = (247.98–141.01)/247.98*100
[c] a value in bold denotes the minimum in its own category.

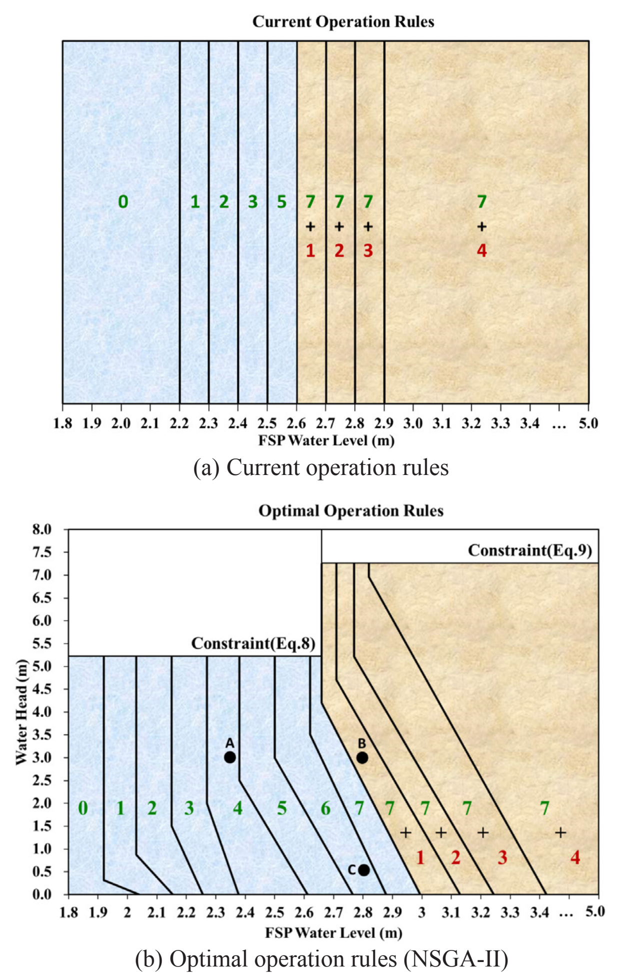
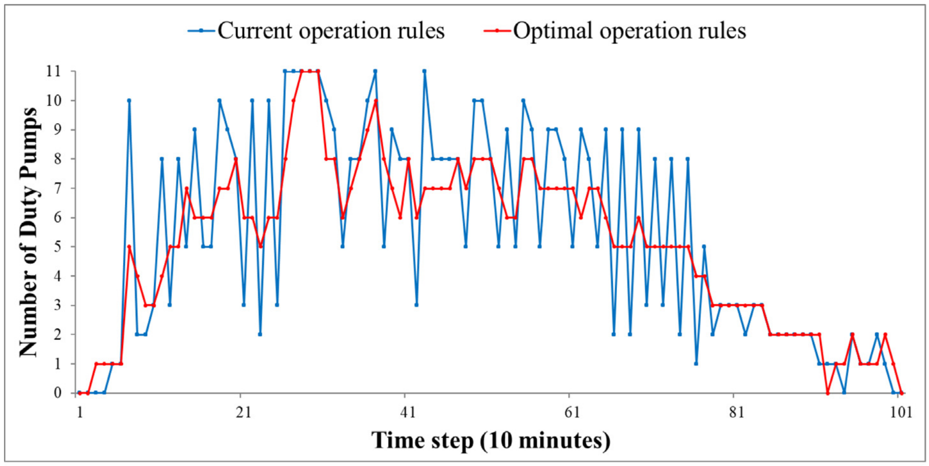


Fig. 7. Pump operation rules. (a) current operation rules; and (b) the optimal operation rules associated with the selected compromised solution (the black dot shown in Fig. 4) obtained from the NSGA-II. The blue zone represents the operation of Site 1 only. The brown zone represents the joint operation of Site 1 and Site 2. The number shown in each sub-zone (stripe) denotes the number of duty pumps between two operation rules (i.e. the laddered FSP water level). Numbers in green denote duty pumps of Site 1 while numbers in red denote duty pumps of Site 2.

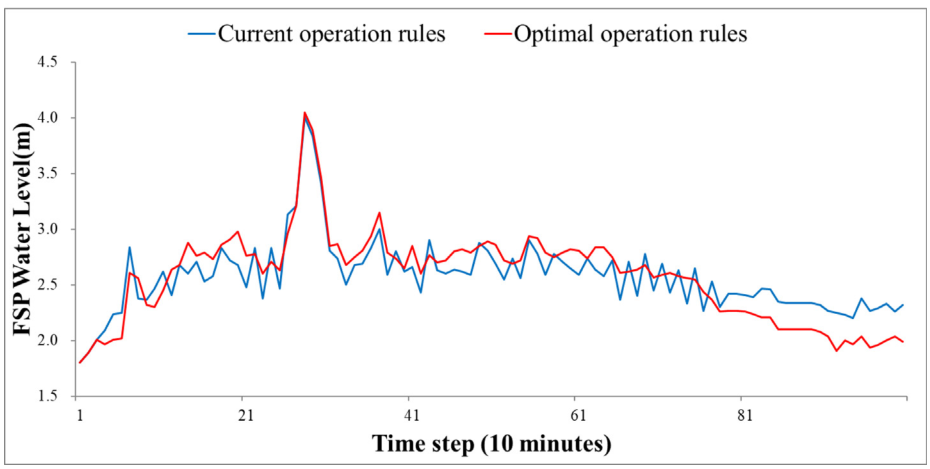
level. Besides, the optimal operation rules could effectively reduce the peak FSP water levels during typhoon events and therefore significantly decrease the risk of overflow from the FSP into the city. The Pareto-optimal solutions suggest practical management options for decision makers and operators to manage the pump operational system. When comparing the existing and alternative pump operational schemes, the NSGA-II results (alternative schemes) would significantly improve the performance of the three objective functions (OBJ1-OBJ3) for the pump operational system, where the number of duty pumps could be reduced and the peak FSP water level could be decreased during flood events. We conclude that the optimal pump operation rules obtained from the NSGA-II could significantly mitigate the flood risk of Taipei City.

4.5. Optimal operation rules and performance evaluation

Fig. 7 presents the optimal pump operation rules associated with the selected compromised solution (the black dot shown in Fig. 4) and the current pump operation rules. It is noted that the Yu-Cheng pumping station has eleven pumps (seven in Site 1 and four in Site 2), which are jointly operated (Site 1 gains higher priority in operation than Site 2).



(a) Number of duty pumps



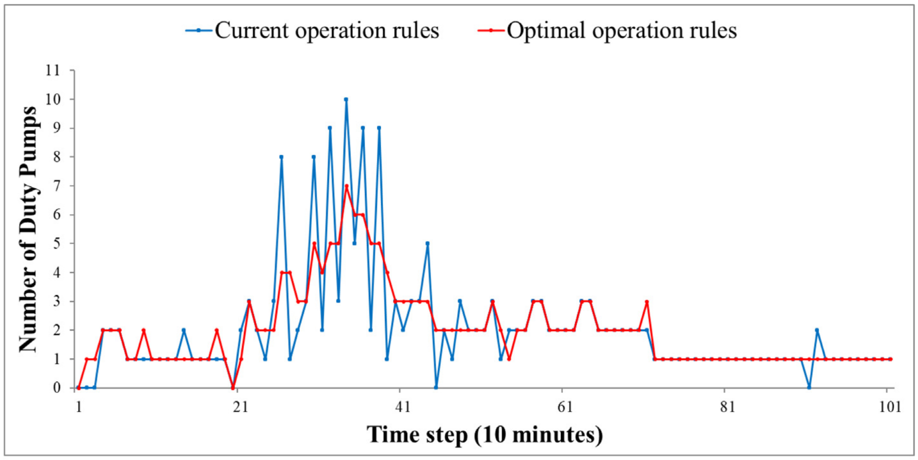
(b) FSP water level

Fig. 8. Comparision of the simulated results based on the optimal operation rules obtained from the NSGA-II and current opertion rules for a training case (612 Storm Event, 2012). (a) the number of duty pumps; and (b) FSP water level.

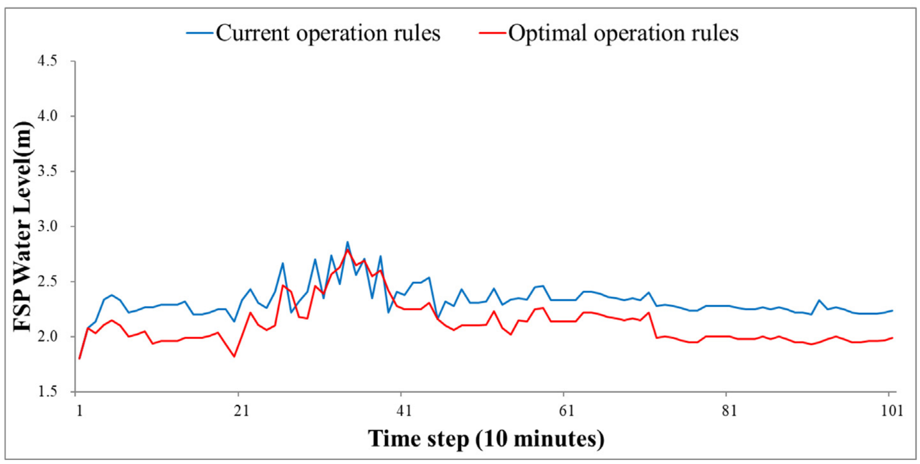
To better depict the joint operation, each subfigure of Fig. 7 is divided into two zones: the blue zone represents the operation of Site 1 only, and the brown zone represents the joint operation of Site 1 and Site 2. The number shown in each sub-zone (stripe) denotes the number of duty pumps between two operation rules (i.e. the laddered FSP water level). Numbers in green denote duty pumps of Site 1 while numbers in red denote duty pumps of Site 2.

Fig. 7(a) reveals that the activation of pumping activity under current operation rules depends solely on the FSP water level, which inevitably causes operators to frequently switch on/off pumps in response to the dynamic fluctuations of the FSP water level, especially when flash floods occur. Such a phenomenon can be observed in Figs. 8 and 9 (operation hydrographs of a training case and a test case, respectively). In contrast, the optimal operation rules configured by the NSGA-II consider the FSP water level and the water head simultaneously. Fig. 7(b) shows the optimal operation rules of the selected compromised solution. The pump operation in Site 1 follows Eqs. (6) and (8), i.e. the FSP water level ∈【1.8 m, 2.7 m】 and the water head ∈【0 m, 5.2 m】, while the pump operation in Site 2 follows Eqs. (7) and (9), i.e. the FSP water level ∈【2.7 m, 5.0 m】 and the water head ∈【0 m, 7.25 m】. The optimal operation rules of each compromised solution in the Pareto Front could be derived from a two-tier sorting process, introduced as follows. The number of duty pumps associated with FSP water level and water head can be drawn by sorting the 22 chromosomes (Table 2). The two-tier sorting process begins with the sorting of the 22 chromosomes in an increasing order along the Y-axis (water head), followed by the sorting along the X-axis (FSP water level). The sorted pairs are denoted as 【(X_1, Y_1),…, (X_2, Y_2), (X_3, Y_3),…, (X_{11}, Y_{11})】, where $X_i \le X_{i+1}$, i = 1,…, 11; and $Y_j \le Y_{j+1}$, j = 1,…, 11. The sorted pairs can be used to construct the optimal operation rules by linking these pairs in the following way: 1) linking coordinates $(X_i, 5.2)$, i = 1,…, 7 (Eq. (8)); and 2) linking coordinates $(X_i, 7.25)$, i = 8,…, 11 (Eq. (9)). According to the optimal operation rules shown in Fig. 7(b), Point A (2.35 m FSP water level and 3 m water head) requires 4 duty pumps; Point B (2.8 m FSP water level and 3 m water head) requires 8 duty pumps; and Point C (2.8 m FSP water level and 0.5 m water head) requires 6 duty pumps.

Fig. 7(b) further demonstrates that the number of duty pumps can be determined collaboratively by FSP water level and water head. It is noted that the optimal operation rules require fewer duty pumps than current operation rules under the same FSP water level when the FSP water level exceeds 2.6 m. For instance, the optimal operation rules associated with Point C require only 6 pumps but current operation rules require 10 pumps. When the FSP water level is less than 2.6 m, the optimal operation rules require more duty pumps than current operation rules at the same FSP water level. The reason is that for lower FSP water levels (less than2.6 m), it is advised to reserve more flood storage capacity by discharging water from the FSP at the early stage such that the possible serious fluctuation of the FSP water level can be reduced in future pump operation. Such advantages can be observed from Fig. 5,



(a) Number of duty pumps



(b) FSP water level

Fig. 9. Comparision of the simulated results based on the ptimal operation rules obtained from the NSGA-II and current opertion rules for a test case (Typhoon KONG-REY, 2013). (a) the number of duty pumps; and (b) FSP water level.

which shows the hydrographs of the optimal and current operation rules, respectively. For flood risk mitigation, decisions often have to be made based on complex information. We have noticed that researchers have endeavored to develop mathematical decision-making models in consideration of flood risks. The optimal pump operation rules proposed in this study provide more flexibility, stability, and reliability in pump operation than current operation rules by collaboratively incorporating the water head into pump operation.

This study further evaluates the performance of the proposed methodology based on one training case and four test cases. Table 4 presents the individual performance of the optimal operation rules and current operation rules for these five events, respectively. The results demonstrate that the optimal operation rules make significant improvement (improvements rates: 19.8%–72.4% for OBJ1; 1.0%–6.3% for OBJ2; and 53.9%–86.4% for OBJ3), taking current operation rules as the benchmark.

We noticed that the total number of pump switches along the operation sequence differed event by event because storm durations were different from each other. Therefore, OBJ3 is defined as the total pump switches divided by the total time steps (pumps/time step). This is the reason why a decimal point may occur in the optimal results of OBJ3. When applying the OBJ3 results to actual operation, the number of activated pumps during control horizon could simply be identified based on the corresponding FSP water level and water head according to the optimal operation rules of Fig. 7(b). Examples are shown in Figs. 8 and 9.

Fig. 8 shows the comparative results of the optimal operation rules and current operation rules for the 612 Storm Event (a training case), respectively. We notice from Fig. 8(a) that the number of duty pumps derived from the optimal operation rules generally increases over time in the rising stage of the FSP water level, then keeps nearly flat in the peak stage, and decreases over time in the descending stage. Nevertheless, current operation rules make frequent jumps/drops on the number of duty pumps throughout the whole operational sequence. Fig. 8(b) reveals that the curve of the FSP water level associated with the optimal operation rules is much more stable and smoother than that of current operation rules. This also indicates that the optimal operation rules can avoid switching pumps on and off frequently. These results also disclose the advantages of the optimal operation rules.

Fig. 9 shows the comparative results of the optimal operation rules and current operation rules for the event of Typhoon KONG-REY (a test case), respectively. Fig. 9(a) reveals that the number of duty pumps suggested by the optimal operation rules fluctuates at each time step less than that for current operation rules, especially during the 21th and the 60th time steps (the peak stage of the FSP water level). Besides, the maximum numbers of duty pumps are 7 and 10 for the optimal operation rules and current operation rules, respectively. Fig. 9(b) reveals that the FSP water level of the optimal operation rules is more stable and smoother than that of the current rules. This again demonstrates that the optimal operation rules can avoid frequent switch on/off of pumps. The results also give the evidence on the advantages of the optimal operation rules.

Table 4
Operation results of one training event and four test events (optimal operation rules obtained from the NSGA-II vs. current operation rules).

Events	Operation Rules	Objective value		
		OBJ1 (m)	OBJ2 (m)	OBJ3 (pumps/time step)
Training case				
612 storm (2012)	Optimal operation rules[a]	10.14	4.01	0.65
	Current operation rules	17.69	4.05	2.72
	Improvement rate[b]	42.7%	1.0%	76.1%
Test cases				
511 Storm (2013)	Optimal operation rules	1.67	2.53	0.28
	Current operation rules	6.06	2.66	2.05
	Improvement rate	72.4%	4.9%	86.4%
KONG-REY (2013)	Optimal operation rules	7.96	2.79	0.31
	Current operation rules	11.20	2.86	0.77
	Improvement rate	28.9%	2.4%	60.3%
TRAMI (2013)	Optimal operation rules	2.74	2.57	0.39
	Current operation rules	6.03	2.74	1.80
	Improvement rate	54.6%	6.2%	78.3%
SOULIK (2013)	Optimal operation rules	1.82	2.37	0.38
	Current operation rules	2.27	2.53	0.81
	Improvement rate	19.8%	6.3%	53.9%

[a] Optimal operation rules obtained from the NSGA-II
[b] Comparison between the optimal operation rules and current operation rules

5. Conclusion

Intelligent management of urban drainage systems is an efficient way to take full advantage on the capacity of a drainage system to reduce flood risks. This study proposes an AI-based design of urban stormwater detention facilities accounting for carryover storage to enhance the efficiency and reliability of the drainage infrastructure. The proposed model transforms pump operation into three main objectives for increasing the efficiency of pump operation and reducing flood risks, with a close assessment on the collaborative impacts of FSP water level and water head on pump operation. The results of four test cases demonstrate the superiority of the optimal operation rules to current operation rules in the perspectives of all the three objectives, with improvement rates reaching 43% (OBJ1), 3% (OBJ2) and 71% (OBJ3), respectively. The optimal operation rules could diminish flood risk, decrease the total number of duty pumps significantly, and avoid switching on and off pumps frequently, which largely reduce energy consumption as well as wear and tear of pumping facilities. Moreover, the obtained optimal results favorably fulfill the expectation of experienced operators. In other words, the optimal operation rules are reliable and applicable, and they can satisfactorily benefit and assist operators in practice.

Furthermore, the urban drainage system is a complex task and requires a number of mutually interdependent choices. Therefore, the formulation of an optimization model is a crux choice from the beginning, which would involve trade-offs between the number of optimization variables and the degree of details lying in the internal systems (Lund et al., 2018). The multi-objective optimization approach proposed in this study demonstrates to well fit these key considerations within the wider urban drainage control literature. We conclude that the optimal operation rules proposed by our methodology could mitigate the fluctuation of the FSP water level and minimize the total number of duty pumps during the whole operation period so as to reduce the flood risk in Taipei City. Consequently, the socio-economic welfare of the society can be maximized. Future study can incorporate predictions of the future system state and climatic forecasts to enhance the multi-objective pump operation several steps ahead while reducing the uncertainty of the drainage system.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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