Can Smart Rainwater Harvesting Schemes result in the improved performance of Integrated Urban Water Systems?

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Abstract

Although rainwater harvesting (RWH) schemes have gradually gained more credibility and popularity in recent times, efficient utilisation and larger scale implementation of multi-purpose RWH is still a challenging task. This paper aims to explore the potential of using smart RWH schemes and their impact on the efficiency improvement in integrated urban water systems (UWS). The smart RWH scheme analysed here is capable of proactively controlling the tank water level to ensure sufficient spare storage is maintained at all times that accommodates the runoff from storm events. The multi-purpose RWH tank can mitigate local floods during rainfall events and supply harvested rainwater to non-potable residential water consumption. Optimal design parameters of the smart RWH scheme is also identified to achieve the best operational performance of the UWS. WaterMet^2 model is used to assess the performance of the UWS with smart RWH schemes. The efficiency of the proposed methodology is demonstrated through modelling a real case of integrated UWS. The results obtained indicate that utilisation of smart RWH with an optimally-sized tank, compared to the corresponding conventional RWH, is able to significantly improve the UWS efficiency in terms of mitigation of local flooding and reliability of water supply from harvested rainwater.

Keywords: Flood mitigation, rainwater harvesting, smart technologies, urban water systems.

Introduction

Strategic planning of integrated urban water systems (UWS) needs to evaluate a combination of potential intervention options to identify the most appropriate strategies which provide long-term sustainability of these systems. Previous assessment of sustainability-based performance of integrated UWS indicates that highly ranked intervention strategies are those supporting both (a) efficient water abstraction, supply and reduced consumption and (b) stormwater/wastewater collection and controlled release, i.e. strategies such as rainwater harvesting (RWH) and other water recycling options (Behzadian and Kapelan 2015a). In particular, the application of rainwater harvesting in urban water management has gained considerable attention in recent decades as a new alternative resource given increasingly severe droughts, increased water demands and limited potable water resources (Tchobanoglous et al. 2003). In particular, RWH can result in both potable water saving in water supply systems and reduction of stormwater runoff discharge into the wastewater systems.

Performance assessment of different RWH schemes has been frequently carried out in the literature. The focus of those studies has been either on water supply only (Rozos et al. 2010) or on more integrated aspects (Behzadian et al. 2014a). Some studies analysed RWH schemes for non-potable water use only and hence water supply reliability (e.g. Eroksuz and Rahman 2010; Khastagir and Jayasuriya 2010; Imteaz et al. 2011; Ward et al. 2012) and resilience in the context of distribution systems (Basupi et al. 2014) were mainly investigated. As a result of these analyses, a wide range of potable water saving efficiencies have been reported in the literature ranging from 21.6% by Chiu et al. (2009) in Taipei and 59% by Zaizen et al. (1999) in Japan to 70% by Nodle (2007) in Germany. However, other studies applied multi-purpose RWH analysis in which non-potable domestic water use and stormwater control were considered simultaneously (e.g. Partzsch 2009; and Jones and Hunt 2010). In the UK context, the British Standard for RWH (BS8515:2013) gives recommendations primarily for non-potable water use but also recommends the integrated sizing approach for multi-purpose RWH in situations where the potential of the average runoff for harvesting is greater than the average non-potable demand supplied by harvested rainwater (BSI 2013).

A RWH scheme is typically implemented as a tank that harvests rainwater from impermeable surfaces (e.g. building roof) and supply for non-potable water consumptions (e.g. toilet flushing) which are complemented with a mains water top-up (Ward et al. 2012). The performance of RWH schemes under different climates (e.g. dry and wet) has also been investigated in the literature to either evaluate the system reliability (Rozos et al. 2010) or to determine the tank size (Imteaza et al. 2011). More recently, Bouziotas et al. (2015) investigated the flood attenuation performance of RWH schemes under different urban densities.

The most common (i.e. conventional) type of RWH schemes is characterised as a passive or reactive system where filling, empting and spilling a tank is a function of rainfall, demand and storage capacity, respectively (BSI 2013). More specifically, the general functionality of a conventional RWH scheme is described as follows: it harvests rainwater during rainfall events typically from impermeable surfaces (e.g. roofs, roads and pavements) and fills the tank as long as there is enough room in the storage capacity (Fig. 1a). This process continues irrespective of any subsequent rainfall events. Once the tank is full specifically during extreme or frequent rainfall events, the tank overflows runoff into the wastewater system. The conventional approach has been used to investigate the operation of RWH schemes by many researches (e.g. Rozos et al. 2010, Eroksuz and Rahman 2010, Imteaz et al. 2011 and Ward et al. 2012). However, the conventional approach can be a major disadvantage for RWH schemes especially when stormwater management is crucial. This drawback has also been reported in the literature by Jones and Hunt (2010) that logged frequent overflows in their monitored RWH tank during most rainfall events. One general solution to diminish this negative impact is to simply enlarge the storage capacity of the tank to provide more spare storage for stormwater management during large storms (Jones and Hunt 2010). However, an over-sized tank is unlikely to be a cost-effective and desirable option (Ward et al. 2012).

Unlike the above passive configuration, an active RWH (called smart RWH henceforth) scheme can be envisaged in which the storage volume is proactively managed to ensure spare storage is maintained especially during large storm events to effectively store runoff at all times (BSI 2013). More specifically, the smart RWH scheme can be designed that provides adequate spare storage in a timely manner. This is achieved through pre-empting the storage volume and standby for collecting stormwater runoff hence efficiently attenuating potential urban flooding while harvested water is supplied based on available storage. On the other hand, provision of spare storage in this way is in conflict with the efficiency of potable water saving. More specifically, this implies that some available harvested runoff needs to be discharged without being used by any water demand and therefore a compromise exists. Despite a plethora of investigations exploring various aspects of the RWH performance, to the best of the authors' knowledge, none of the previous works has examined the performance of smart RWH schemes (as outlined above) in the context of integrated UWS. Hence, the primary aim of this paper is to explore whether and how the smart RWH can be beneficial for integrated UWS and explore how efficient a smart RWH scheme can be in integrated UWS for reducing excess stormwater while supplying to non-potable domestic water use. This paper is also aimed at identifying the optimal range of design parameters that the smart RWH can achieve the best performance of stormwater control in integrated UWS and then compare it with corresponding conventional RWH schemes.

Methodology

This paper presents a new approach for smart RWH schemes that assist the integrated UWS in mitigating urban flood and hence improve performance of UWS with smart RWH. All this is examined through a conceptual WaterMet^2 model. The optimal performance of the smart RWH schemes with different *operational* and *design* parameters is also identified and compared with conventional RWH for an integrated UWS over a specified planning horizon. The suggested smart RWH is briefly described below followed by formulation of the optimisation model and description of the UWS model used in the paper.

Smart RWH

The concept of the smart RWH scheme defined here is inspired by the active RWH introduced by the British Standard for RWH in BS8515 (BSI 2013). More specifically, the British standard recommends two storage management approaches for actively control stormwater runoff using RWH: 1) approach based on rainfall forecasting and 2) approach based on water level control. The smart RWH suggested here is following the second approach, i.e. it proactively manages/controls the water volume/level in the tank to ensure spare capacity is maintained at all times to collect the runoff during rainfall events. Such a smart system can perform this function by using sensors to measure rainfall depth and water volume in the tank. These data can be used by the smart system in order to trigger actuators (i.e. valves/pumps) releasing specific amount of storage volume based on a pre-specified timetable across the year. The released water needs to be discharged into permeable surfaces in a time of no rain such that it has no contribution to exacerbating flooding in the sewer networks downstream (BSI 2013). Such a scheme for pre-emptying specific volume of the tank as shown in Fig. 1b is the basis for the smart RWH used in this paper.

Fig. 1 Structure of the conventional and smart RWH

The operational policy of the RWH tank requires to specify water release of the tank for each time step according to water availability in the tank and water demands (Rozos and Makropoulos 2013). One of the commonly used types of operational policy is regression formula which was used in water resources systems (Karamouz et al. 2003) and urban water supply systems (Rozos and Makropoulos 2013). A general form of non-linear regression formula based on the total available water storage (i.e. volume plus inflow) is suggested in this paper. In other words, the suggested smart RWH scheme considers improving the operational policy of the RWH tank based on the measurement of tank inflow and volume by using related sensors. Actuators then release a specific water volume (R_t) from the tank at time step *t* as a function of water volume (V_t) at time step (*instance*) *t* and inflow volume into the tank (I_t) at time *interval* *t* (i.e. between time steps *t* and *t-1*), i.e. as follows:

$$R_t = a_i \times (V_t + I_t)^{b_i} \qquad i=1,\ldots,12 \qquad (1)$$

where a_i and b_i are two *operational* parameters of RWH tank that are assumed to be constant for each calendar month. The released water (R_t), which is assumed to be discharged into permeable surfaces, allows the tank to keep some space free and on standby for extreme rainfall and therefore mitigate potential local flooding. It should be noted that the RWH simulation is based on daily time step for the duration of a specified planning horizon (at least one year to include seasonal variations). However, the operational parameters in Eq. (1) need to be specified for each calendar month such that the long-term performance of the smart RWH tank in the integrated UWS can lead to both maximising local flood attenuation and minimising water usage from the mains over a specified planning horizon. This can be obtained from a multi-objective optimisation model which is described below.

Multi-objective optimisation model

A two-objective optimisation model is developed here to identify the optimal values of *operational* parameters in Eq. (1) that will lead to optimal operation of the smart RWH scheme in an integrated UWS. The total number of decision variables is equal to 24 (the number of calendar months, i.e. 12, multiplied by the number of operational parameters in each month, i.e. 2). The two objectives are to minimise total water demand supplied from the potable water mains (i.e. conventional distribution pipes) and to minimise the total urban flooding (i.e. total volume of stormwater and sanitary sewage exceeding the storage capacity of a combined sewer network). The objective functions can be written as the following normalised quantities:

$$Potable\ water\ supplied = \min \frac{\sum_{t=1}^{T} V_t^{SP}}{\sum_{t=1}^{T} V_t^{NSP}} \times 100 \qquad (2)$$

$$\text{Total Excess stormwater} = \min \frac{\sum_{t=1}^{T} V_t^{SEx}}{\sum_{t=1}^{T} V_t^{NSEx}} \times 100 \quad (3)$$

$$V_t^{(N)SEx} = \begin{cases} V_t^{SW} + V_t^{TO} + V_t^{SS} - Cap_{WS} & if\ (V_t^{SW} + V_t^{TO} + V_t^{SS}) > Cap_{WS} \\ 0 & if\ (V_t^{SW} + V_t^{TO} + V_t^{SS}) \le Cap_{WS} \end{cases} \quad (4)$$

where V_i^{SP} and V_i^{NSP} are volume of water demands supplied from the mains at time step *t* if smart RWH and no RWH exist, respectively; V_t^{SEx} and V_t^{NSEx} are excess volume of stormwater (i.e. flood) at time step *t* if smart RWH and no RWH exist, respectively; V_t^{SW} is volume of stormwater runoff discharged into the combined sewer networks at time step *t*; V_t^{TO} is volume of the smart RWH tank overflow discharged into the combined sewer networks at time step t; V_t^{SS} is volume of sanitary sewage at time step *t*; Cap_{WS} is storage capacity of the combined sewer networks; *T* is number of analysed time steps. In other words, the first objective states the proportion of the water demands supplied from the potable water of the mains when smart RWH exists relative to the conditions that the potable water of the mains supplies the entire water demands without smart RWH. Thus, the ratio between potable water demands in these two conditions is expressed as a percentage in the first objective. The same relation is in place for the second objective which is expressed as a percentage of the ratio between local floods in the same two conditions. It should also be noted that Eq. (4) states that excess volume of stormwater happens in a time step when the total discharge of that time step exceeds the capacity of the combined sewer network (Fig. 2).

The multi-objective evolutionary algorithm of NSGA-II is used to solve the above optimisation problem (Deb et al. 2002). NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a multi-objective evolutionary algorithm (MOEA) optimisation model that could alleviate the difficulties of previous MOEAs such as non-elitism approach and considerable computational effort (Behzadian et al. 2009). Comparison of several popular MOEAs in the problems of water distribution systems shows that NSGA-II with minimum parameters tuning remains a good choice that can achieve the best spread of optimal solutions (Wang et al. 2014).

The values of two objective functions shown in Eq. (2) and (3) are calculated using the simulation model of the integrated UWS. The model used here is the WaterMet² model (Behzadian and Kapelan 2015b) which is described in more detail in the next section.

WaterMet^2 simulation model

WaterMet^2 is a mass-balanced-based simulation model which assesses the performance of integrated UWS over a specified planning horizon (Behzadian and Kapelan 2015a). The WaterMet^2 model with daily time step tracks down different flows and fluxes (e.g. water, energy, greenhouse gas emissions and materials) within an integrated UWS. WaterMet^2 adopts a simplified but distributed approach for conceptual modelling of the main physical UWS components in the main infrastructures of water supply and wastewater including separate/combined sewer networks. WaterMet^2 inherited the mass-balanced and distributed modelling approach from some tools such as *UVQ* (Mitchell and Diaper, 2010) and *UWOT* (Makropoulos et al., 2008) and combined it with industrial ecology based modelling approach from *DMM* (Venkatesh et al. 2015). All this has led WaterMet^2 to be made up of an arbitrary number of conveyance and storage components which are connected to each other through the sub-catchments (Fig. 2).

The main consecutive components of the water supply infrastructure modelled in WaterMet^2 are water resources, water supply conduits, Water Treatment Works (WTW), trunk mains, service reservoirs and distribution mains. Sewer networks and Wastewater Treatment Works (WWTW) are also two components which constitute the wastewater infrastructure. All these components are also connected with water sources (i.e. water inflows and rainfalls) and sinks (i.e. receiving water bodies) that form the water boundaries. The clean water, transported by the water supply infrastructure, is converted into sanitary sewage by water demand profiles in the WaterMet^2 sub-catchments and then collected by the wastewater infrastructure. The water demand profiles cover six types of indoor (household) appliances and fittings (i.e. kitchen sink, hand basin, washing machine, shower, toilet and dish washer) plus commercial and other outdoor demands including frost tapping and household irrigation (e.g. garden watering). WaterMet^2 also simulates rainfall-runoff modelling and the overland runoff collected by the wastewater infrastructure. All this enables WaterMet^2 to simulate rainwater harvesting potential which is used for water demand profiles in sub-catchments. Each WaterMet^2 sub-catchment comprises a group of neighbouring local areas which cover water demands profiles and total surface area for rainfall-runoff modelling. As a result of the daily simulation of all UWS components, WaterMet^2 is able to calculate daily water supplied from different sources (e.g. water mains and RWH tanks) as well as excess stormwater overflowed (i.e. flood) in wastewater infrastructures as defined in Eq. (4) over a specified time horizon. Further details of WaterMet^2 modelling processes and assumptions can be found in Behzadian and Kapelan (2015a).

Fig. 2 Main UWS components of WaterMet^2 including RWH tank

Case Study

The suggested methodology is validated and demonstrated on a real-world UWS of a northern European city which was taken from Venkatesh et al. (2015) and Behzadian and Kapelan (2015a, 2015b). Based on the world map of The Köppen Climate Classification (Peel et al. 2007), the case study is located under "Dfb" climate (warm summer humid continental climate). The WaterMet^2 model is calibrated by using a manual, trial and error approach for historical daily measurements in both water and wastewater production. This approach is used here as it can lead to reasonably good prediction accuracy and has been successfully employed in similar models such as UVQ (Mitchell and Diaper 2010). The calibrated WaterMet^2 model of the real-world UWS is used here to examine the capabilities of the smart RWH. The real-world case study is an integrated UWS which contains both subsystems of water supply and wastewater including combined sewer networks. More specifically, the water supply subsystem comprises two existing water resources, each connected to one WTW and then the distribution mains. The wastewater subsystem is characterised by a largely combined sewer network feeding two WWTWs. A single WaterMet^2 subcatchment with two associated local areas, one with RWH and the other without RWH, is used to define water consumption and rainfall-runoff modelling. The main input data for modelling runoff and water demands at local area and household scales are given in Table 1. All water demand categories except household irrigation and frost tapping are necessary during the whole year. Household irrigation (i.e. garden) is carried out between mid-May and the end of August (4.5 months) while frost tapping (water flowing through the main pipelines to prevent freezing) is required from November until the end of March (5 months). The rainfall-runoff modelling and evaporation are calculated in WaterMet^2 based on the Rational Method and the Preferred method, respectively (Maidment 1992). The above integrated UWS is simulated in WaterMet^2 with a daily time step over one year to identify the optimal operational parameters of the smart RWH. Based on the recommendations of conventional designs, the storage capacity of each household RWH tank is assumed to be predefined at 3 m^3 (Behzadian and Kapelan 2015b). This tank size is calculated based on the specifications of households and climate in the case study given in Table 1 and recommendations made by BSI (2013) and Ward et al. (2012). A single RWH scheme is used to represent many small domestic RWH units across the city. The key characteristics of the UWS and the model calibration procedure can be found in Behzadian and Kapelan (2015b).

Table 1 Input data related to water demands and runoff modelling

Results and discussion

The above methodology is first applied and discussed on the case study for four constant tank capacities (i.e. sizes) in proportion to the full-size of the RWH storage capacity, i.e. $3m^3$ for each household (see the above section), separately. Thus, the total sum of the tank capacities analysed here for all households with RWH are: 1) 12.5% of full capacity, i.e. 0.06 million cubic metres (MCM) (equal to $0.125\times3m^3\times160{,}000$ households); 2) 25% of full capacity, i.e. 0.12 MCM; 3) 50% of full capacity i.e. 0.24 MCM and 4) full (100%) capacity i.e. 0.48 MCM. The objective here is to analyse the long-term performance of the smart RWH for different tank capacities and levels of tank releases and then compare all this with conventional RWH. It is assumed that the RWH tank collects runoff from impermeable surfaces (i.e. roofs, roads and pavements) and supplies to flushing toilet and household (i.e. garden) irrigation only.

The NSGA-II parameters, used for all multi-objective optimisation models, are obtained after a limited number of trial runs and are as follows: population size of 84, tournament selection, random-by-gene mutation with the probability of 0.0417 (equal to the inverse of the number of genes, i.e. 1/24), single point crossover with the probability of 0.9. The stopping criterion of the algorithm is mainly dominated by the number of generations which is set to 1,000 for each optimisation run.

Fig. 3 illustrates the Pareto fronts (PFs) obtained by the two-objective optimisation models for the analysed tank capacities. Each PF, representing one specific tank size, shows the trade-off between the two conflicting objectives of the RWH tank (i.e. reduction of potable water use versus attenuation of urban flood). Each PF provides decision makers with a set of non-dominated optimal solutions (i.e. there is no solution in which both objectives are better than other solutions). The following can be noted from the figure: (1) The optimal solution with the minimum local flood attenuation and maximum reduction of potable water supply from the mains on each PF, i.e. the most left hand side point (e.g. point A), represents the performance of the UWS with conventional RWH. This performance is due to the fact that the harvested rainwater is not released from the tank according to Eq. (1), i.e. operational parameter *a* is zero for all months (not shown here); (2) On the other hands, the optimal solution with the maximum local flood attenuation on each PF (e.g. point C) shows the performance of the UWS with smart RWH; (3) This trend (i.e. from conventional to smart RWH) can also show the impact of smart technologies on the improved flood attenuation while compromising potable water supply in the four different tank sizes. For instance, flood attenuation for the smallest storage capacity (i.e. 0.06 MCM) is only 2.3% (i.e. from 91.3% to 89.0%) whereas volumetric flood attenuation for larger RWH capacities (i.e. 0.24 and 0.48 MCM) is considerably larger, approximately 7%. This can be attributed to the increased flexibility of larger capacities which cover both a higher number of floods and larger flood events; (4) Each PF shows that the larger the release of water from the smart RWH tank, further local flood mitigation can be expected although the less potential of the harvested rainwater can also occur. The generated PFs can be useful for stakeholders in a case study and help them make more informed decisions based on their preferences to the objectives of RWH; (5) Finally note that the improved RWH performance with increased tank size (for both objectives) which is demonstrated by the fact that PF for larger tanks are closer to the ideal point (0,0). This will be analysed and discussed further in the next section.

Fig. 3 Pareto optimal solutions for different tank sizes of the smart RWH

The performance of the UWS with smart RWH can be further explored in the time analysis of the RWH tank over the analysed period. Hence, the monthly average performance of the RWH tank for the three solutions of A, B and C in the PF associated with the total storage capacity of 0.24 MCM (Fig. 3) are analysed here as shown in Fig. 4(b)-(d). Fig. 4(a) also shows the stormwater runoff after deducing evaporation, infiltration and depressions of permeable and impermeable surfaces for each local area. These solutions represent the performance of three types of RWH including a maximum water supply from RWH (i.e. solution A as conventional RWH), smart RWH with maximum flood reduction (solution C) and finally solution B which compromises the above two objectives. When comparing the overall performance of conventional and smart RWH in Fig. 4, three time periods (months 3-4, 5-7 and 9-11) can be distinguished based on the stormwater runoff in Fig. 4a and water demand from RWH (i.e. toilet flushing and household irrigation). Note that the daily water demand of toilet flushing, which is required all over the year, accounts for about 40% of the total water demand from the RWH tank while the remaining 60% is needed for household irrigation which is required only between months 4.5 and 8. In the first time period (months 3-4) with a relatively high rainfall (Fig. 4a) but a low water demand from the RWH tank (i.e. about 40% of the total demand), the tank volume and inflow into conventional RWH (i.e. solution A) are relatively high and thus the average overflow is high (due to the aforementioned low water demand). However, the smart RWH (e.g. solution C) keeps the most of the tank volume empty, i.e. an average 88% of storage capacity is free as shown in Fig. 4b, in order to attenuate more flood and therefore the average overflow in this solution is trivial. In the second period (months 5-7) which is characterised as being both high rainfall and high water demand, the performance of all RWH types are quite similar. However, in the third time period (months 9-11) characterised by high rainfall in Fig. 4a and low water demand (i.e. again about 40% of the total demand), the smart RWH keeps storing small water volumes to increase the spare storage for capturing larger inflows. As a result, the tank overflow in this scheme is considerably smaller compared to much larger overflows in the conventional RWH. Note that in all of the above time periods, the performance of solution B lies between solution A and C, i.e. represents a compromise of these two solutions.

Fig. 4 Monthly aggregated results of three solutions for (a) stormwater runoff in each local area; (b) average RWH volume; (c) average RWH overflow and (d) average RWH inflow

The above results discussed so far shows the performance of the suggested method only for specified values of design parameters in RWH such as tank storage size and fixed collection surface areas (see the case study section). Therefore, determination of the most efficient design parameters of RWH to achieve the best performance of the suggested smart technologies is explored below.

Optimal design parameters of smart RWH schemes

The above results only consider the optimal operational parameters of smart RWH. This section considers analysing the combined optimal operational and design parameters of smart RWH simultaneously for local flood mitigation in the integrated UWS. The design parameters analysed here are storage tank size and collection surface area which are explicitly considered as new objective functions. To that end, two new two-objective optimisation models similar to those presented above are first analysed with new first objectives instead of the objective in Eq. (2) (i.e. percent of potable water supplied from the mains). This replacement is due to the fact that the objectives in Eqs. (2) and (3) are indirectly correlated and only the second objective (i.e. percent of total excess stormwater) can implicitly consider the other one.

In the first two-objective optimisation model, the new first objective is to minimise the storage capacity of the RWH tank. The model also assumes the collection surface for harvesting rainwater include all impermeable surfaces (i.e. roof, pavement and road). The first two-objective optimisation model results in the PF of the optimal solutions for the smart RWH as shown in Fig. 5. The performance of local flood mitigation in the conventional RWH for the corresponding tank capacities is also simulated in the UWS and shown in the same figure. As it can be seen from the figure, the best conventional RWH solution that leads to the maximum flood mitigation (i.e. approximately 85% of total excess stormwater) needs to have at least 0.22 MCM storage capacity (around 46% of full-size tank capacity of conventional design) while a smart RWH scheme with 0.09 MCM storage capacity (19% of full-size tank capacity of conventional design) can provide the similar level of flood mitigation. This corroborates the advantage of the active (i.e. smart) RWH scheme that design storage capacities of smart RWH are generally smaller than those of passive (i.e. conventional) one (BSI 2013). In addition, the similar performance of flood reduction for both smart and conventional RWH for the tank sizes smaller than 0.05 MCM (equivalent to around 10% of full-size tank capacity of conventional design) indicates that there is no sensible point to develop the suggested smart method for small tank RWH capacities. This can be likely attributed to the very low ratio of runoff yield (due to the small storage capacity) to the water demand, which empties the storage volume very quickly. On the other hand, for the tank sizes greater than 0.05 MCM, there is an increasing trend for the improvement of the flood reduction performance with the smart RWH relative to the conventional RWH. This improvement gradually becomes significant with a maximum of 7.4% for the storage capacity of about 0.24 MCM from which point the difference of the two approaches for larger-sized tanks is slightly similar. This can be indicative of the full potential of flood reduction when using smart approach in RWH and also provides the best tank size which leads to the maximum local flood mitigation.

Fig. 5 Impact of the storage capacity of the RWH tank on flood mitigation in the UWS

In the second two-objective optimisation model, the first objective is defined as to minimise percentage of the collection surface for harvesting rainwater in the second optimisation model. It assumes that both permeable and impermeable surfaces are considered for harvesting rainwater in the second optimisation model. Collection of rainwater from permeable surfaces assumes that they are converted to impermeable surfaces and hence the infiltration rate, i.e. 30%, would reduce to only 5% to account water detention related to the runoff coefficient of impermeable surfaces according to the surface properties in Table 1. The storage capacity of the RWH tank in the second model is constant and equal to 0.24 MCM.

Fig. 6 shows the PF of the optimal solutions in the smart RWH as a result of the second two-objective optimisation model to address the influence of the collection surface area. Similarly, the performance of the local flood mitigation with the conventional RWH for the corresponding surface areas of harvesting rainwater is also shown in the figure. Similar to the sensitivity analysis of the storage capacity, there is no benefit of applying smart RWH for small surface areas for harvesting rainwater (i.e. about 10% of the total surface areas). This can also be due to the fact that small surface areas for harvesting rainwater would result in the small ratio of the small average runoff yield to the large non-potable water demand from the harvested rainwater. This also corroborates the BSI (2013) that recommends for the small above ratio, the pre-emptying process happens relatively rare which is in fact the opposite to the basic function of the smart RWH. In addition, as it can be seen from Fig. 6, enlarging the area for harvesting rainwater in the smart RWH can have a substantial impact on local flood mitigation as the RWH tank can affect larger surface areas and hence more floods can be prevented or mitigated. As the percentage of the total impermeable surface areas in the case study is 16% (see Table 1), those percentages greater than this in the figure need the inclusion of permeable surface area for harvesting rainwater. As this assumes that those included permeable surface areas are converted to impermeable surface areas, this results in the increase of runoff as it reduces the water loss due to the infiltration rate of smaller permeable surface area. The resultant impact of combining this conversion with larger surface areas for harvesting rainwater is negative for the conventional RWH (i.e. increasing flood) while the performance of flood reduction with the smart RWH have been improved even more for those percentages of surface areas.

Fig. 6 Impact of percentage of the total surface area for harvesting rainwater on local flood mitigation

A combination of the design parameters analysed above can be envisaged in a three-objective optimisation model (i.e. objectives of flood reduction, storage capacity and surface area for harvesting rainwater) which is analysed here. Fig. 7 shows the result of this three-objective optimisation model as a

PF of the optimal solutions for smart RWH and the concurrent impact of both design parameters (storage capacity and percentage of the total surface area for RWH) on flood mitigation. Similarly, the performance of conventional RWH for the corresponding design parameters is also shown in the figure. As can be seen, the larger tank capacities and the surface area for harvesting rainwater would result in substantial mitigation of local floods in the smart RWH (maximum to the level of about 32%) whereas the conventional RWH can only decline the UWS flood to about 77% among all values defined for these parameters. Provision of such a three-objective PF can be very useful specifically for long-term planning of both smart and conventional RWH. Apart from these two design parameters, other parameters such as precipitation and various water demands (Rozos et al. 2010, Imteaz et al. 2011) may have a substantially influence on the main performance indicators (e.g. water supply reliability and flood peak attenuation) of the UWS.

Fig. 7 Three-objective PF for the impact of both design parameters of storage capacity and percentage of the total surface area for harvesting rainwater

The smart RWH analysed here is mainly based on the second approach suggested by BS8515 (BSI 2013) i.e. the control of water level using the operational policy as defined in Eq. (1). According to this policy, the amount of water released from the tank is specified based on what is currently stored and current inflow in different months. However, it should also be based on what is likely to arrive soon (i.e. future rainfall/inflow) as suggested in the first approach of the British Standard (BSI 2013). The impact of the rainfall forecasting on operation of smart RWH can be quite significant in cases that there is no rainfall forecasted in the near future and even though the tank is fairly full, the water can supply non-potable water demands only, i.e. not release any extra water. On the other hand, if weather forecast shows a lot of rainfall will happen soon, the policy orders to release all of the stored water even though the tank is fairly full. The analysed smart RWH here strive to highlight the primary advantages of water level control but this cannot overcome the need to forecast rainfall. Therefore, integration of the suggested operational policy with a rainfall forecast module in smart RWH schemes needs to be further investigated in the future researches.

Furthermore, climatic conditions can be a determining factor to identify the effectiveness of key performance indicators (KPI) in smart RWH schemes. The impact of this factor on KPIs has been analysed for conventional RWH schemes in previous research works (e.g. design robustness of RWH schemes by Rozos et al. 2010). The climatic conditions analysed in this paper is humid continental climate with an annual average rainfall of 803 mm. Hence, all the findings obtained in the results can only be considered for similar climatic conditions. For climates with more annual rainfall (e.g. equatorial regions), the smart RWH can be even more effective than the analysis conducted in here due to larger potential for flood peak attenuation. On the other hand, this effectiveness may decline for regions with less annual rainfall (e.g. semi-arid regions) due mainly to the reasons explained for small tank capacities in Fig. 5 and small surface areas of harvesting rainwater in Fig. 6. However, further investigation may be required to analyse different climatic conditions for smart RWH and obtain compelling evidence for this statement.

Conclusions

The new methodology for smart RWH schemes was developed and analysed here and their impact on the performance of an integrated UWS was explored. The smart RWH considered the optimal operational policy of the tank to proactively control water tank level based on the current storage volume and inflow in the analysed case study. The integrated UWS performance was evaluated by using the WaterMet^2 model. Optimal design parameters of smart RWH (i.e. tank size and the surface area for rainwater harvesting) were also identified and its performance in the integrated UWS was compared with conventional RWH. As a result of the application of the proposed approach in the real-world UWS, the following key findings can be concluded:

1. The proposed smart RWH methodology can provide optimal operation of the tank throughout the year for variable rainfall and water consumption conditions. This is due to the fact that the smart RWH tank operation can maximise the efficiency of storage usage during rainfall events (resulting in improved local flood attenuation) whilst, at the same time, efficiently harvesting rainwater to complement water supply from the mains.
2. Choosing optimal operational and design parameters for multi-purpose RWH is important for both smart and conventional RWH schemes in order to achieve optimal performance of the integrated UWS. The results obtained in the paper suggest that there is no meaningful difference in the UWS performance between smart and conventional RWH schemes for small-sized tanks (i.e. less than about 10% of full-size tank capacity of conventional design) and small surface

harvesting areas (i.e. less than about 10% of the total surface areas). Opposite of this, as the RWH tanks and surface harvesting areas increase in size, substantial improvement in the UWS performance with smart RWH schemes can be seen when compared to the conventional alternative. This further emphasises the importance of choosing optimal operational/control and design parameters of smart RWH schemes.

3. The Pareto fronts obtained for smart RWH schemes provide essential information regarding key trade-offs involved between given competing objectives. These fronts could and should be used by decision makers for the improved planning of UWS and ultimately assessing the potential of RWH schemes against other water demand management (i.e. water saving) technologies and other flood attenuation options (e.g. other types of sustainable drainage systems).

The analyses and subsequent results presented here represent only a first step in using smart RWH schemes. Although there seems to be considerable potential for their application in integrated UWS, further investigations are required to validate the effectiveness of smart technologies in RWH under different climates and uncertain rainfall. Moreover, other parameters (e.g. prediction of precipitation and various water demands) and technologies/modules (e.g. smart household irrigation and rainfall forecast) should be included in future analyses of smart RWH.

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