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

Kourosh Behzadian[1*], Zoran Kapelan[2], Seyed Jamshid Mousavi[3], Amir Alani[4]

[1]Senior Lecturer, School of Computing and Engineering, University of West London, London, UK, St Mary's Rd, London, W5 5RF

[2]Professor, Centre for Water Systems, College of Engineering, Mathematics and Physical Sciences, University of Exeter, UK, North Park Road, Exeter, EX4 4QF

[3]Professor, Department of Civil and Environmental Engineering, Amirkabir University of Technology (Tehran Polytechnic), Iran, Hafez Street, Tehran

[4]Professor, School of Computing and Engineering, University of West London, UK, St Mary's Rd, London, W5 5RF

[*] Corresponding author. Tel.: +44 (0) 20 8231 2466
E-mail address: kourosh.behzadian@uwl.ac.uk

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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

44 result in both potable water saving in water supply systems and reduction of stormwater runoff discharge

45 into the wastewater systems.

46

47 Performance assessment of different RWH schemes has been frequently carried out in the literature. The

48 focus of those studies has been either on water supply only (Rozos et al. 2010) or on more integrated

49 aspects (Behzadian et al. 2014a). Some studies analysed RWH schemes for non-potable water use only

50 and hence water supply reliability (e.g. Eroksuz and Rahman 2010; Khastagir and Jayasuriya 2010;

51 Imteaz et al. 2011; Ward et al. 2012) and resilience in the context of distribution systems (Basupi et al.

52 2014) were mainly investigated. As a result of these analyses, a wide range of potable water saving

53 efficiencies have been reported in the literature ranging from 21.6% by Chiu et al. (2009) in Taipei and

54 59% by Zaizen et al. (1999) in Japan to 70% by Nodle (2007) in Germany. However, other studies applied

55 multi-purpose RWH analysis in which non-potable domestic water use and stormwater control were

56 considered simultaneously (e.g. Partzsch 2009; and Jones and Hunt 2010). In the UK context, the British

57 Standard for RWH (BS8515:2013) gives recommendations primarily for non-potable water use but also

58 recommends the integrated sizing approach for multi-purpose RWH in situations where the potential of

59 the average runoff for harvesting is greater than the average non-potable demand supplied by harvested

60 rainwater (BSI 2013).

61

62 A RWH scheme is typically implemented as a tank that harvests rainwater from impermeable surfaces

63 (e.g. building roof) and supply for non-potable water consumptions (e.g. toilet flushing) which are

64 complemented with a mains water top-up (Ward et al. 2012). The performance of RWH schemes under

65 different climates (e.g. dry and wet) has also been investigated in the literature to either evaluate the

66 system reliability (Rozos et al. 2010) or to determine the tank size (Imteaza et al. 2011). More recently,

67 Bouziotas et al. (2015) investigated the flood attenuation performance of RWH schemes under different

68 urban densities.

69

70 The most common (i.e. conventional) type of RWH schemes is characterised as a passive or reactive

71 system where filling, empting and spilling a tank is a function of rainfall, demand and storage capacity,

72 respectively (BSI 2013). More specifically, the general functionality of a conventional RWH scheme is

73 described as follows: it harvests rainwater during rainfall events typically from impermeable surfaces

74   (e.g. roofs, roads and pavements) and fills the tank as long as there is enough room in the storage capacity

75   (Fig. 1a). This process continues irrespective of any subsequent rainfall events. Once the tank is full

76   specifically during extreme or frequent rainfall events, the tank overflows runoff into the wastewater

77   system. The conventional approach has been used to investigate the operation of RWH schemes by many

78   researches (e.g. Rozos et al. 2010, Eroksuz and Rahman 2010, Imteaz et al. 2011 and Ward et al. 2012).

79   However, the conventional approach can be a major disadvantage for RWH schemes especially when

80   stormwater management is crucial. This drawback has also been reported in the literature by Jones and

81   Hunt (2010) that logged frequent overflows in their monitored RWH tank during most rainfall events.

82   One general solution to diminish this negative impact is to simply enlarge the storage capacity of the

83   tank to provide more spare storage for stormwater management during large storms (Jones and Hunt

84   2010). However, an over-sized tank is unlikely to be a cost-effective and desirable option (Ward et al.

85   2012).

86

87   Unlike the above passive configuration, an active RWH (called smart RWH henceforth) scheme can be

88   envisaged in which the storage volume is proactively managed to ensure spare storage is maintained

89   especially during large storm events to effectively store runoff at all times (BSI 2013). More specifically,

90   the smart RWH scheme can be designed that provides adequate spare storage in a timely manner. This

91   is achieved through pre-empting the storage volume and standby for collecting stormwater runoff hence

92   efficiently attenuating potential urban flooding while harvested water is supplied based on available

93   storage. On the other hand, provision of spare storage in this way is in conflict with the efficiency of

94   potable water saving. More specifically, this implies that some available harvested runoff needs to be

95   discharged without being used by any water demand and therefore a compromise exists. Despite a

96   plethora of investigations exploring various aspects of the RWH performance, to the best of the authors'

97   knowledge, none of the previous works has examined the performance of smart RWH schemes (as

98   outlined above) in the context of integrated UWS. Hence, the primary aim of this paper is to explore

99   whether and how the smart RWH can be beneficial for integrated UWS and explore how efficient a smart

100 RWH scheme can be in integrated UWS for reducing excess stormwater while supplying to non-potable

101 domestic water use. This paper is also aimed at identifying the optimal range of design parameters that

102 the smart RWH can achieve the best performance of stormwater control in integrated UWS and then

103 compare it with corresponding conventional RWH schemes.

104

Methodology

105

106 This paper presents a new approach for smart RWH schemes that assist the integrated UWS in mitigating

107 urban flood and hence improve performance of UWS with smart RWH. All this is examined through a

108 conceptual WaterMet[2] model. The optimal performance of the smart RWH schemes with different

109 *operational* and *design* parameters is also identified and compared with conventional RWH for an

110 integrated UWS over a specified planning horizon. The suggested smart RWH is briefly described below

111 followed by formulation of the optimisation model and description of the UWS model used in the paper.

112

Smart RWH

113

114 The concept of the smart RWH scheme defined here is inspired by the active RWH introduced by the

115 British Standard for RWH in BS8515 (BSI 2013). More specifically, the British standard recommends

116 two storage management approaches for actively control stormwater runoff using RWH: 1) approach

117 based on rainfall forecasting and 2) approach based on water level control. The smart RWH suggested

118 here is following the second approach, i.e. it proactively manages/controls the water volume/level in the

119 tank to ensure spare capacity is maintained at all times to collect the runoff during rainfall events. Such

120 a smart system can perform this function by using sensors to measure rainfall depth and water volume in

121 the tank. These data can be used by the smart system in order to trigger actuators (i.e. valves/pumps)

122 releasing specific amount of storage volume based on a pre-specified timetable across the year. The

123 released water needs to be discharged into permeable surfaces in a time of no rain such that it has no

124 contribution to exacerbating flooding in the sewer networks downstream (BSI 2013). Such a scheme for

125 pre-emptying specific volume of the tank as shown in Fig. 1b is the basis for the smart RWH used in this

126 paper.

127

128 **Fig. 1** Structure of the conventional and smart RWH
129

130 The operational policy of the RWH tank requires to specify water release of the tank for each time step

131 according to water availability in the tank and water demands (Rozos and Makropoulos 2013). One of

132 the commonly used types of operational policy is regression formula which was used in water resources

133 systems (Karamouz et al. 2003) and urban water supply systems (Rozos and Makropoulos 2013). A

5

134   general form of non-linear regression formula based on the total available water storage (i.e. volume plus

135   inflow) is suggested in this paper. In other words, the suggested smart RWH scheme considers improving

136   the operational policy of the RWH tank based on the measurement of tank inflow and volume by using

137   related sensors. Actuators then release a specific water volume (R_t) from the tank at time step t as a

138   function of water volume (V_t) at time step (*instance*) t and inflow volume into the tank (I_t) at time *interval*

139   t (i.e. between time steps t and t-1), i.e. as follows:

140

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

142

143   where a_i and b_i are two *operational* parameters of RWH tank that are assumed to be constant for each

144   calendar month. The released water (R_t), which is assumed to be discharged into permeable surfaces,

145   allows the tank to keep some space free and on standby for extreme rainfall and therefore mitigate

146   potential local flooding. It should be noted that the RWH simulation is based on daily time step for the

147   duration of a specified planning horizon (at least one year to include seasonal variations). However, the

148   operational parameters in Eq. (1) need to be specified for each calendar month such that the long-term

149   performance of the smart RWH tank in the integrated UWS can lead to both maximising local flood

150   attenuation and minimising water usage from the mains over a specified planning horizon. This can be

151   obtained from a multi-objective optimisation model which is described below.

152

153   *Multi-objective optimisation model*

154   A two-objective optimisation model is developed here to identify the optimal values of *operational*

155   parameters in Eq. (1) that will lead to optimal operation of the smart RWH scheme in an integrated UWS.

156   The total number of decision variables is equal to 24 (the number of calendar months, i.e. 12, multiplied

157   by the number of operational parameters in each month, i.e. 2). The two objectives are to minimise total

158   water demand supplied from the potable water mains (i.e. conventional distribution pipes) and to

159   minimise the total urban flooding (i.e. total volume of stormwater and sanitary sewage exceeding the

160   storage capacity of a combined sewer network). The objective functions can be written as the following

161   normalised quantities:

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

6

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

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

165

166   where V_i^{SP} and V_i^{NSP} are volume of water demands supplied from the mains at time step t if smart RWH

167   and no RWH exist, respectively; V_t^{SEx} and V_t^{NSEx} are excess volume of stormwater (i.e. flood) at time

168   step t if smart RWH and no RWH exist, respectively; V_t^{SW} is volume of stormwater runoff discharged

169   into the combined sewer networks at time step t; V_t^{TO} is volume of the smart RWH tank overflow

170   discharged into the combined sewer networks at time step t; V_t^{SS} is volume of sanitary sewage at time

171   step t; Cap_{WS} is storage capacity of the combined sewer networks; T is number of analysed time steps. In

172   other words, the first objective states the proportion of the water demands supplied from the potable

173   water of the mains when smart RWH exists relative to the conditions that the potable water of the mains

174   supplies the entire water demands without smart RWH. Thus, the ratio between potable water demands

175   in these two conditions is expressed as a percentage in the first objective. The same relation is in place

176   for the second objective which is expressed as a percentage of the ratio between local floods in the same

177   two conditions. It should also be noted that Eq. (4) states that excess volume of stormwater happens in a

178   time step when the total discharge of that time step exceeds the capacity of the combined sewer network

179   (Fig. 2).

180

181   The multi-objective evolutionary algorithm of NSGA-II is used to solve the above optimisation problem

182   (Deb et al. 2002). NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a multi-objective

183   evolutionary algorithm (MOEA) optimisation model that could alleviate the difficulties of previous

184   MOEAs such as non-elitism approach and considerable computational effort (Behzadian et al. 2009).

185   Comparison of several popular MOEAs in the problems of water distribution systems shows that NSGA-

186   II with minimum parameters tuning remains a good choice that can achieve the best spread of optimal

187   solutions (Wang et al. 2014).

188

189   The values of two objective functions shown in Eq. (2) and (3) are calculated using the simulation model

190   of the integrated UWS. The model used here is the WaterMet[2] model (Behzadian and Kapelan 2015b)

191   which is described in more detail in the next section.

192

193   *WaterMet² simulation model*

194   WaterMet² is a mass-balanced-based simulation model which assesses the performance of integrated

195   UWS over a specified planning horizon (Behzadian and Kapelan 2015a). The WaterMet² model with

196   daily time step tracks down different flows and fluxes (e.g. water, energy, greenhouse gas emissions and

197   materials) within an integrated UWS. WaterMet² adopts a simplified but distributed approach for

198   conceptual modelling of the main physical UWS components in the main infrastructures of water supply

199   and wastewater including separate/combined sewer networks. WaterMet² inherited the mass-balanced

200   and distributed modelling approach from some tools such as *UVQ* (Mitchell and Diaper, 2010) and

201   *UWOT* (Makropoulos et al., 2008) and combined it with industrial ecology based modelling approach

202   from *DMM* (Venkatesh et al. 2015). All this has led WaterMet² to be made up of an arbitrary number of

203   conveyance and storage components which are connected to each other through the sub-catchments (Fig.

204   2).

205

206   The main consecutive components of the water supply infrastructure modelled in WaterMet² are water

207   resources, water supply conduits, Water Treatment Works (WTW), trunk mains, service reservoirs and

208   distribution mains. Sewer networks and Wastewater Treatment Works (WWTW) are also two

209   components which constitute the wastewater infrastructure. All these components are also connected

210   with water sources (i.e. water inflows and rainfalls) and sinks (i.e. receiving water bodies) that form the

211   water boundaries. The clean water, transported by the water supply infrastructure, is converted into

212   sanitary sewage by water demand profiles in the WaterMet² sub-catchments and then collected by the

213   wastewater infrastructure. The water demand profiles cover six types of indoor (household) appliances

214   and fittings (i.e. kitchen sink, hand basin, washing machine, shower, toilet and dish washer) plus

215   commercial and other outdoor demands including frost tapping and household irrigation (e.g. garden

216   watering). WaterMet² also simulates rainfall-runoff modelling and the overland runoff collected by the

217   wastewater infrastructure. All this enables WaterMet² to simulate rainwater harvesting potential which

218   is used for water demand profiles in sub-catchments. Each WaterMet² sub-catchment comprises a group

219   of neighbouring local areas which cover water demands profiles and total surface area for rainfall-runoff

220   modelling. As a result of the daily simulation of all UWS components, WaterMet² is able to calculate

221   daily water supplied from different sources (e.g. water mains and RWH tanks) as well as excess

222 stormwater overflowed (i.e. flood) in wastewater infrastructures as defined in Eq. (4) over a specified

223 time horizon. Further details of WaterMet^2 modelling processes and assumptions can be found in

224 Behzadian and Kapelan (2015a).

225

226 **Fig. 2** Main UWS components of WaterMet^2 including RWH tank
227

228 **Case Study**

229 The suggested methodology is validated and demonstrated on a real-world UWS of a northern European

230 city which was taken from Venkatesh et al. (2015) and Behzadian and Kapelan (2015a, 2015b). Based

231 on the world map of The Köppen Climate Classification (Peel et al. 2007), the case study is located under

232 "Dfb" climate (warm summer humid continental climate). The WaterMet^2 model is calibrated by using

233 a manual, trial and error approach for historical daily measurements in both water and wastewater

234 production. This approach is used here as it can lead to reasonably good prediction accuracy and has

235 been successfully employed in similar models such as UVQ (Mitchell and Diaper 2010). The calibrated

236 WaterMet^2 model of the real-world UWS is used here to examine the capabilities of the smart RWH. The

237 real-world case study is an integrated UWS which contains both subsystems of water supply and

238 wastewater including combined sewer networks. More specifically, the water supply subsystem

239 comprises two existing water resources, each connected to one WTW and then the distribution mains.

240 The wastewater subsystem is characterised by a largely combined sewer network feeding two WWTWs.

241 A single WaterMet^2 subcatchment with two associated local areas, one with RWH and the other without

242 RWH, is used to define water consumption and rainfall-runoff modelling. The main input data for

243 modelling runoff and water demands at local area and household scales are given in Table 1. All water

244 demand categories except household irrigation and frost tapping are necessary during the whole year.

245 Household irrigation (i.e. garden) is carried out between mid-May and the end of August (4.5 months)

246 while frost tapping (water flowing through the main pipelines to prevent freezing) is required from

247 November until the end of March (5 months). The rainfall-runoff modelling and evaporation are

248 calculated in WaterMet^2 based on the Rational Method and the Preferred method, respectively (Maidment

249 1992). The above integrated UWS is simulated in WaterMet^2 with a daily time step over one year to

250 identify the optimal operational parameters of the smart RWH. Based on the recommendations of

251 conventional designs, the storage capacity of each household RWH tank is assumed to be predefined at

252 3 m^3 (Behzadian and Kapelan 2015b). This tank size is calculated based on the specifications of

9

253   households and climate in the case study given in Table 1 and recommendations made by BSI (2013)

254   and Ward et al. (2012). A single RWH scheme is used to represent many small domestic RWH units

255   across the city. The key characteristics of the UWS and the model calibration procedure can be found in

256   Behzadian and Kapelan (2015b).

257

258   **Table 1** Input data related to water demands and runoff modelling
259

260   **Results and discussion**

261   The above methodology is first applied and discussed on the case study for four constant tank capacities

262   (i.e. sizes) in proportion to the full-size of the RWH storage capacity, i.e. 3m^3 for each household (see

263   the above section), separately. Thus, the total sum of the tank capacities analysed here for all households

264   with RWH are: 1) 12.5% of full capacity, i.e. 0.06 million cubic metres (MCM) (equal to

265   0.125×3m^3×160,000 households); 2) 25% of full capacity, i.e. 0.12 MCM; 3) 50% of full capacity i.e.

266   0.24 MCM and 4) full (100%) capacity i.e. 0.48 MCM. The objective here is to analyse the long-term

267   performance of the smart RWH for different tank capacities and levels of tank releases and then compare

268   all this with conventional RWH. It is assumed that the RWH tank collects runoff from impermeable

269   surfaces (i.e. roofs, roads and pavements) and supplies to flushing toilet and household (i.e. garden)

270   irrigation only.

271

272   The NSGA-II parameters, used for all multi-objective optimisation models, are obtained after a limited

273   number of trial runs and are as follows: population size of 84, tournament selection, random-by-gene

274   mutation with the probability of 0.0417 (equal to the inverse of the number of genes, i.e. 1/24), single

275   point crossover with the probability of 0.9. The stopping criterion of the algorithm is mainly dominated

276   by the number of generations which is set to 1,000 for each optimisation run.

277

278   Fig. 3 illustrates the Pareto fronts (PFs) obtained by the two-objective optimisation models for the

279   analysed tank capacities. Each PF, representing one specific tank size, shows the trade-off between the

280   two conflicting objectives of the RWH tank (i.e. reduction of potable water use versus attenuation of

281   urban flood). Each PF provides decision makers with a set of non-dominated optimal solutions (i.e. there

282   is no solution in which both objectives are better than other solutions). The following can be noted from

283   the figure: (1) The optimal solution with the minimum local flood attenuation and maximum reduction

10

284 of potable water supply from the mains on each PF, i.e. the most left hand side point (e.g. point A),

285 represents the performance of the UWS with conventional RWH. This performance is due to the fact that

286 the harvested rainwater is not released from the tank according to Eq. (1), i.e. operational parameter a is

287 zero for all months (not shown here); (2) On the other hands, the optimal solution with the maximum

288 local flood attenuation on each PF (e.g. point C) shows the performance of the UWS with smart RWH;

289 (3) This trend (i.e. from conventional to smart RWH) can also show the impact of smart technologies on

290 the improved flood attenuation while compromising potable water supply in the four different tank sizes.

291 For instance, flood attenuation for the smallest storage capacity (i.e. 0.06 MCM) is only 2.3% (i.e. from

292 91.3% to 89.0%) whereas volumetric flood attenuation for larger RWH capacities (i.e. 0.24 and 0.48

293 MCM) is considerably larger, approximately 7%. This can be attributed to the increased flexibility of

294 larger capacities which cover both a higher number of floods and larger flood events; (4) Each PF shows

295 that the larger the release of water from the smart RWH tank, further local flood mitigation can be

296 expected although the less potential of the harvested rainwater can also occur. The generated PFs can be

297 useful for stakeholders in a case study and help them make more informed decisions based on their

298 preferences to the objectives of RWH; (5) Finally note that the improved RWH performance with

299 increased tank size (for both objectives) which is demonstrated by the fact that PF for larger tanks are

300 closer to the ideal point (0,0). This will be analysed and discussed further in the next section.

301

302 **Fig. 3** Pareto optimal solutions for different tank sizes of the smart RWH
303

304 The performance of the UWS with smart RWH can be further explored in the time analysis of the RWH

305 tank over the analysed period. Hence, the monthly average performance of the RWH tank for the three

306 solutions of A, B and C in the PF associated with the total storage capacity of 0.24 MCM (Fig. 3) are

307 analysed here as shown in Fig. 4(b)-(d). Fig. 4(a) also shows the stormwater runoff after deducing

308 evaporation, infiltration and depressions of permeable and impermeable surfaces for each local area.

309 These solutions represent the performance of three types of RWH including a maximum water supply

310 from RWH (i.e. solution A as conventional RWH), smart RWH with maximum flood reduction (solution

311 C) and finally solution B which compromises the above two objectives. When comparing the overall

312 performance of conventional and smart RWH in Fig. 4, three time periods (months 3-4, 5-7 and 9-11)

313 can be distinguished based on the stormwater runoff in Fig. 4a and water demand from RWH (i.e. toilet

314 flushing and household irrigation). Note that the daily water demand of toilet flushing, which is required

11

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

346 replacement is due to the fact that the objectives in Eqs. (2) and (3) are indirectly correlated and only the

347 second objective (i.e. percent of total excess stormwater) can implicitly consider the other one.

348

349 In the first two-objective optimisation model, the new first objective is to minimise the storage capacity

350 of the RWH tank. The model also assumes the collection surface for harvesting rainwater include all

351 impermeable surfaces (i.e. roof, pavement and road). The first two-objective optimisation model results

352 in the PF of the optimal solutions for the smart RWH as shown in Fig. 5. The performance of local flood

353 mitigation in the conventional RWH for the corresponding tank capacities is also simulated in the UWS

354 and shown in the same figure. As it can be seen from the figure, the best conventional RWH solution that

355 leads to the maximum flood mitigation (i.e. approximately 85% of total excess stormwater) needs to have

356 at least 0.22 MCM storage capacity (around 46% of full-size tank capacity of conventional design) while

357 a smart RWH scheme with 0.09 MCM storage capacity (19% of full-size tank capacity of conventional

358 design) can provide the similar level of flood mitigation. This corroborates the advantage of the active

359 (i.e. smart) RWH scheme that design storage capacities of smart RWH are generally smaller than those

360 of passive (i.e. conventional) one (BSI 2013). In addition, the similar performance of flood reduction for

361 both smart and conventional RWH for the tank sizes smaller than 0.05 MCM (equivalent to around 10%

362 of full-size tank capacity of conventional design) indicates that there is no sensible point to develop the

363 suggested smart method for small tank RWH capacities. This can be likely attributed to the very low

364 ratio of runoff yield (due to the small storage capacity) to the water demand, which empties the storage

365 volume very quickly. On the other hand, for the tank sizes greater than 0.05 MCM, there is an increasing

366 trend for the improvement of the flood reduction performance with the smart RWH relative to the

367 conventional RWH. This improvement gradually becomes significant with a maximum of 7.4% for the

368 storage capacity of about 0.24 MCM from which point the difference of the two approaches for larger-

369 sized tanks is slightly similar. This can be indicative of the full potential of flood reduction when using

370 smart approach in RWH and also provides the best tank size which leads to the maximum local flood

371 mitigation.

372

373 **Fig. 5** Impact of the storage capacity of the RWH tank on flood mitigation in the UWS
374

375 In the second two-objective optimisation model, the first objective is defined as to minimise percentage

376 of the collection surface for harvesting rainwater in the second optimisation model. It assumes that both

13

377   permeable and impermeable surfaces are considered for harvesting rainwater in the second optimisation

378   model. Collection of rainwater from permeable surfaces assumes that they are converted to impermeable

379   surfaces and hence the infiltration rate, i.e. 30%, would reduce to only 5% to account water detention

380   related to the runoff coefficient of impermeable surfaces according to the surface properties in Table 1.

381   The storage capacity of the RWH tank in the second model is constant and equal to 0.24 MCM.

382

383   Fig. 6 shows the PF of the optimal solutions in the smart RWH as a result of the second two-objective

384   optimisation model to address the influence of the collection surface area. Similarly, the performance of

385   the local flood mitigation with the conventional RWH for the corresponding surface areas of harvesting

386   rainwater is also shown in the figure. Similar to the sensitivity analysis of the storage capacity, there is

387   no benefit of applying smart RWH for small surface areas for harvesting rainwater (i.e. about 10% of the

388   total surface areas). This can also be due to the fact that small surface areas for harvesting rainwater

389   would result in the small ratio of the small average runoff yield to the large non-potable water demand

390   from the harvested rainwater. This also corroborates the BSI (2013) that recommends for the small above

391   ratio, the pre-emptying process happens relatively rare which is in fact the opposite to the basic function

392   of the smart RWH. In addition, as it can be seen from Fig. 6, enlarging the area for harvesting rainwater

393   in the smart RWH can have a substantial impact on local flood mitigation as the RWH tank can affect

394   larger surface areas and hence more floods can be prevented or mitigated. As the percentage of the total

395   impermeable surface areas in the case study is 16% (see Table 1), those percentages greater than this in

396   the figure need the inclusion of permeable surface area for harvesting rainwater. As this assumes that

397   those included permeable surface areas are converted to impermeable surface areas, this results in the

398   increase of runoff as it reduces the water loss due to the infiltration rate of smaller permeable surface

399   area. The resultant impact of combining this conversion with larger surface areas for harvesting rainwater

400   is negative for the conventional RWH (i.e. increasing flood) while the performance of flood reduction

401   with the smart RWH have been improved even more for those percentages of surface areas.

402

403   **Fig. 6** Impact of percentage of the total surface area for harvesting rainwater on local flood mitigation
404

405   A combination of the design parameters analysed above can be envisaged in a three-objective

406   optimisation model (i.e. objectives of flood reduction, storage capacity and surface area for harvesting

407   rainwater) which is analysed here. Fig. 7 shows the result of this three-objective optimisation model as a

408 PF of the optimal solutions for smart RWH and the concurrent impact of both design parameters (storage

409 capacity and percentage of the total surface area for RWH) on flood mitigation. Similarly, the

410 performance of conventional RWH for the corresponding design parameters is also shown in the figure.

411 As can be seen, the larger tank capacities and the surface area for harvesting rainwater would result in

412 substantial mitigation of local floods in the smart RWH (maximum to the level of about 32%) whereas

413 the conventional RWH can only decline the UWS flood to about 77% among all values defined for these

414 parameters. Provision of such a three-objective PF can be very useful specifically for long-term planning

415 of both smart and conventional RWH. Apart from these two design parameters, other parameters such as

416 precipitation and various water demands (Rozos et al. 2010, Imteaz et al. 2011) may have a substantially

417 influence on the main performance indicators (e.g. water supply reliability and flood peak attenuation)

418 of the UWS.

419

420 **Fig. 7** Three-objective PF for the impact of both design parameters of storage capacity and percentage
421 of the total surface area for harvesting rainwater
422

423 The smart RWH analysed here is mainly based on the second approach suggested by BS8515 (BSI 2013)

424 i.e. the control of water level using the operational policy as defined in Eq. (1). According to this policy,

425 the amount of water released from the tank is specified based on what is currently stored and current

426 inflow in different months. However, it should also be based on what is likely to arrive soon (i.e. future

427 rainfall/inflow) as suggested in the first approach of the British Standard (BSI 2013). The impact of the

428 rainfall forecasting on operation of smart RWH can be quite significant in cases that there is no rainfall

429 forecasted in the near future and even though the tank is fairly full, the water can supply non-potable

430 water demands only, i.e. not release any extra water. On the other hand, if weather forecast shows a lot

431 of rainfall will happen soon, the policy orders to release all of the stored water even though the tank is

432 fairly full. The analysed smart RWH here strive to highlight the primary advantages of water level control

433 but this cannot overcome the need to forecast rainfall. Therefore, integration of the suggested operational

434 policy with a rainfall forecast module in smart RWH schemes needs to be further investigated in the

435 future researches.

436

437 Furthermore, climatic conditions can be a determining factor to identify the effectiveness of key

438 performance indicators (KPI) in smart RWH schemes. The impact of this factor on KPIs has been

15

439   analysed for conventional RWH schemes in previous research works (e.g. design robustness of RWH

440   schemes by Rozos et al. 2010). The climatic conditions analysed in this paper is humid continental

441   climate with an annual average rainfall of 803 mm. Hence, all the findings obtained in the results can

442   only be considered for similar climatic conditions. For climates with more annual rainfall (e.g. equatorial

443   regions), the smart RWH can be even more effective than the analysis conducted in here due to larger

444   potential for flood peak attenuation. On the other hand, this effectiveness may decline for regions with

445   less annual rainfall (e.g. semi-arid regions) due mainly to the reasons explained for small tank capacities

446   in Fig. 5 and small surface areas of harvesting rainwater in Fig. 6. However, further investigation may

447   be required to analyse different climatic conditions for smart RWH and obtain compelling evidence for

448   this statement.

449

450   **Conclusions**

451   The new methodology for smart RWH schemes was developed and analysed here and their impact on

452   the performance of an integrated UWS was explored. The smart RWH considered the optimal operational

453   policy of the tank to proactively control water tank level based on the current storage volume and inflow

454   in the analysed case study. The integrated UWS performance was evaluated by using the WaterMet^2

455   model. Optimal design parameters of smart RWH (i.e. tank size and the surface area for rainwater

456   harvesting) were also identified and its performance in the integrated UWS was compared with

457   conventional RWH. As a result of the application of the proposed approach in the real-world UWS, the

458   following key findings can be concluded:

459   1. The proposed smart RWH methodology can provide optimal operation of the tank throughout

460   the year for variable rainfall and water consumption conditions. This is due to the fact that the

461   smart RWH tank operation can maximise the efficiency of storage usage during rainfall events

462   (resulting in improved local flood attenuation) whilst, at the same time, efficiently harvesting

463   rainwater to complement water supply from the mains.

464   2. Choosing optimal operational and design parameters for multi-purpose RWH is important for

465   both smart and conventional RWH schemes in order to achieve optimal performance of the

466   integrated UWS. The results obtained in the paper suggest that there is no meaningful difference

467   in the UWS performance between smart and conventional RWH schemes for small-sized tanks

468   (i.e. less than about 10% of full-size tank capacity of conventional design) and small surface

469   harvesting areas (i.e. less than about 10% of the total surface areas). Opposite of this, as the

470   RWH tanks and surface harvesting areas increase in size, substantial improvement in the UWS

471   performance with smart RWH schemes can be seen when compared to the conventional

472   alternative. This further emphasises the importance of choosing optimal operational/control and

473   design parameters of smart RWH schemes.

474   3.   The Pareto fronts obtained for smart RWH schemes provide essential information regarding key

475   trade-offs involved between given competing objectives. These fronts could and should be used

476   by decision makers for the improved planning of UWS and ultimately assessing the potential of

477   RWH schemes against other water demand management (i.e. water saving) technologies and

478   other flood attenuation options (e.g. other types of sustainable drainage systems).

479

480   The analyses and subsequent results presented here represent only a first step in using smart RWH

481   schemes. Although there seems to be considerable potential for their application in integrated UWS,

482   further investigations are required to validate the effectiveness of smart technologies in RWH under

483   different climates and uncertain rainfall. Moreover, other parameters (e.g. prediction of precipitation and

484   various water demands) and technologies/modules (e.g. smart household irrigation and rainfall forecast)

485   should be included in future analyses of smart RWH.

486

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