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Examination of the storage function of intercepting sewers using long-term flow monitoring data

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ABSTRACT

This study proposes a method for examining storage function of intercepting sewers, following sewerage rehabilitation works to convert combined-type to separate-type systems. The selected case study sewage treatment area recently completed a large-scale rehabilitation work; the area incorporates six sub-areas (SAs) and one wastewater treatment plant (WWTP), the latter having treatment capacity of 11,000 m^3/d. Sewage flow generated in dry weather was domestic sewage flow only. Wet weather wastewaters consist of the dry weather sewage flow, in addition to rainfall-derived infiltration/inflow. In order to calculate wet weather wastewater flows of the six SAs, an advanced regression model was used. This was calibrated and verified using long-term monitoring flow data of 816 and 204 h, respectively; the model was then used to predict wastewater flows for 168 h. Hydraulic simulations of intercepting sewers were conducted using a conventional pipe hydrodynamic model (i.e. Saint-Venant equations). By assuming different inflow conditions to the WWTP (multiples of daily peak flows, Q_d), storage function tests were conducted, based on water balance calculations between sewage flows generated from the six SAs and inflow measured at the WWTP. The existing intercepting sewer of the case study area appears to have 70, 11, and 3 h flow storage functions, for inflow controls of 1.5Q_d, 2Q_d, and 2.5Q_d, respectively. Under 3Q_d inflow conditions, almost all wastewater flowed to the WWTP. The storage function is thus expected to be effective for wet weather operation of the WWTP. Such storage function would also be achievable in other areas conducting large-scale rehabilitation works. The method proposed in this study will be useful for decision-making concerning the removal of existing intercepting sewers.

Keywords: Intercepting sewers; Sewer storage; Sewer flow calculation; Rainfall derived infiltration/inflow; Advanced regression model

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1. Introduction

Traditionally, the most common type of sewerage system was a combined system, which carries both the wastewater and stormwater. Total sewer lengths in Korea in 2003 were of 78,605 km; of these, combined and separate sewers comprised 46,167 km (58.7%) and 32,438 km (41.3%), respectively. The proportion of separate sewers has increased continuously; in 2012, 70,820 km (59.8%) of sewers were comprised of separate systems [1]. While new construction of separate-type sewers has increased the proportion of separate-type systems in Korea, sewerage rehabilitation works have also introduced separate instead of combined-type systems. In separate systems, wastewater and stormwater are carried in separate pipes. In this system, the wastewater pipes operate all day and carry wastewaters to wastewater treatment plants (WWTPs), while stormwater that is not mixed with wastewater discharges directly to receiving water bodies. This system has an obvious advantage, in that it does not lead to combined sewer overflows (CSOs), and hence does not cause additional pollutant problems for receiving water bodies [2].

In case of most sewerage rehabilitation works that seek to convert combined systems to separate-type ones, existing combined sewers are being used as stormwater pipes, and only additional wastewater pipes are newly constructed. The separate system therefore is operated by storm sewers (existed combined sewers) and newly installed sanitary sewers. This implies intercepting sewers, which were used to direct large-scale flows to the WWTPs in the combined system, are also still present even after completion of the rehabilitation works. That means both the storm sewers and sanitary sewers are finally connected to the existing intercepting sewers that direct flows to the WWTPs. Intercepting sewers of the combined system were initially designed to carry both stormwater and wastewater in the same pipes, up to the level below CSO occurrence. Normally, the intercepting sewers are designed to carry flows up to several times the daily treatment capacity of the WWTP. As they are still exist even after the rehabilitation work, considerable amounts of water could be stored within existing intercepting sewers of separate-type systems.

This work aims to develop a methodology for examining the storage function of existing intercepting sewers, following sewerage rehabilitation works to convert combined-type to separate-type sewers. The existed intercepting sewers are likely to carry only wastewater during dry weather, but could have mixture of stormwater and wastewater up to the capacity of intercepting sewers during wet weather as it did before the rehabilitation work (system conversion of combined to separate type). The methodology consists of two main parts. First, quantities of wastewaters are predicted using a regression model; the generated wastewater flows are then simulated using a conventional hydrodynamic model.

Typical residential dry weather flow in a catchment has a characteristic diurnal pattern and can be calculated based on population, population density, water consumption, and land uses. However, wet weather flows, which have additional rainfall-derived infiltration and inflow (RDII) from foul sewers and which occur as a result of storm events, also need to be estimated. RDII quantification methods investigated by the Water Environment Research Foundation [3] include constant unit rate methods, percentage of rainfall volume (R-value) methods, percentage of stream-flow methods, synthetic unit hydrograph (SUH) methods, probabilistic methods, predictive equations based on rainfall/flow regression, predictive equations based on synthetic stream flow and basin character, and RDII as a component of hydraulic software.

Among these, the use of regression models has a long history and is widespread in the literature [3–6]. Regression analysis is a traditional statistical technique modeling relationships between an outcome or response variable, and one or more predictor or regressor variables. The simpler form of regression model includes a predictor variable for unknown parameters with an error term [7]. The more advanced forms, the advanced regression models, enhance the model performance of conventional regression model [8].

Advanced regression models are rather general term having advanced forms than simple regression models. For example, polynomial regression model can also be called an advanced type regression than simple linear regression, since it accounts for curvature in a data-set [8]. Several time series regression models often used include auto regressive (AR), auto-regressive moving average (ARMA), and auto-regressive moving average model with exogeneous inputs (ARMAX) models. ARMA model is an advanced type of auto-regressive model that included moving average to use additive seasonal time series consists of a mixture of trend cycle, seasonal, and irregular components, and ARMAX additionally applied influences of exogenous input data [9]. Our case model is a modified form of ARMAX model suggested by Tan et al. [10]. The detailed model description is given in later section. These models widely applied in wastewater studies. For example, multiple linear models are first used to derive a relationship between rainfall and RDII; subsequently, the AR models are adjusted by manipulating model coefficients to deliver the best fit between predicted and actual flows in [11]. Zhang [12,13] applied the AR method to estimate RDII using measured sewer flow and rainfall data series. The ARMA model in [14,15] was used to predict inflows of WWTP. In order to optimize treatment plant operation, [16] applied ARMA and multivariate ARMA process to model wastewater influent variables. Tan et al. [10] applied an ARMAX model for forecasting wastewater flow. Measured rainfalls were used to predict rainfall-related flows, and dry weather flows were superimposed.

The use of computer models, such as storm water management model (SWMM) [17], and of methods embedded in hydraulic software, is also described in the literature. In the SWMM model, the RDII calculation model equation is based on the SUH method of RDII calculation, which assumes that RDII generation is similar to rainfall-runoff calculations of a catchment. It calculates RDII as a specified unit hydrograph that relates RDII to unit precipitation volume, specific duration, and watershed characteristics. The sanitary sewer overflow analysis and planning toolbox, introduced by the [5,6], integrates the SWMM interface of flow routing and the RTK method (based on SHU hydrographs) of RDII generation.

Artificial intelligence appears to have been more recently applied to wastewater calculation. El-Din and Smith [18] applied artificial neural network (ANN) models for short-term prediction of wastewater inflow rate to a WWTP, using observed rainfall data. The integrated model of sewer flow introduced by [19] applied a neural network model for describing sewer flow forecasting, with the ANN applied for set weather flow forecasting through a case study of the Milwaukee Metropolitan Sewerage District [20]. Fernandez et al. [21] used fuzzy logic to describe wastewater flow. The model was fitted using actual flow data and used for long-term forecasting; it produced an error less than 10%. Other applications of artificial intelligence models include estimation of the relationship between rainfall and runoff on a catchment scale [22–26].

This study applied the ARMAX model for wastewater calculation, including RDII, during rainfall events. An ARMAX model was selected because of its general strengths, in generating high accuracy outputs and relatively easier application in the RDII calculation [3]. For purposes of the selected case study, the ARMAX model application was developed for wastewater flow data generation of several sub-areas (SAs). Models were built for six SAs, using long-term monitored flow data, and then used to predict wastewater flows. The XP SWMM model was then used to simulate wastewater flows in intercepting sewers. By considering different inflow conditions to the WWTP, which is connected in the final link intercepting sewers, the storage function of the latter was tested.

2. Study area and methodology development

2.1. Study area description

The case study network selected was the Hongcheon sewage treatment area, located in Gangwon province, South Korea. Fig. 1 shows a schematic representation of the case study area; details of each SA, including area, population, number of properties, and characteristics of sewers, are described in Table 1. The Hongcheon area has a population of 39,000. Six SAs (SA1–SA6) direct their wastewater to the Hongcheon WWTP, which has a daily treatment capacity of 11,000 m^3. The area is served by 84.13 km of sewers,

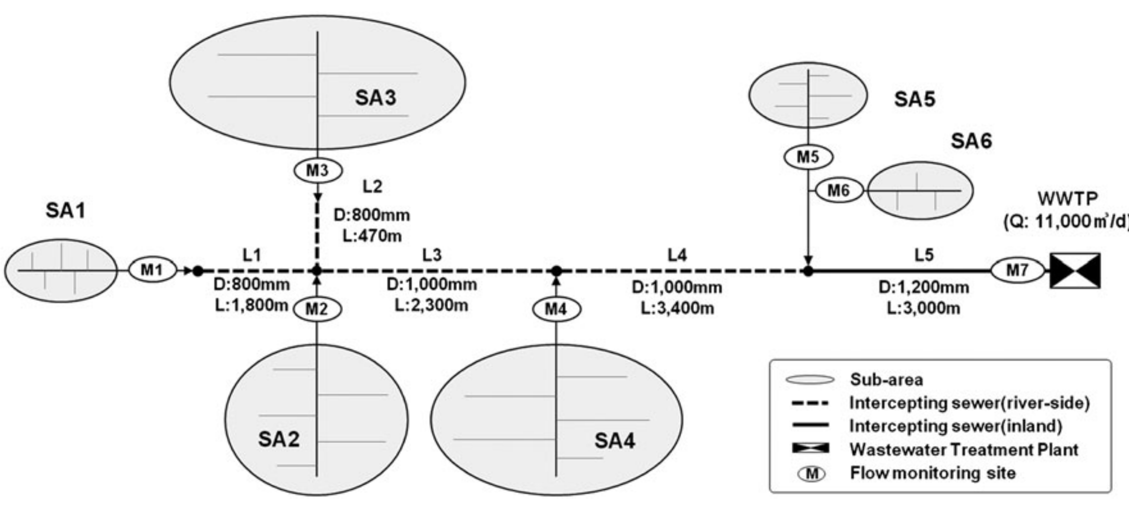

Fig. 1. Schematic representation of case study area.

Table 1
Characteristics of case study area

Sub-area	Area (km^2)	Population	No. of properties	Avg. sewer dia. (mm)	Total sewer length (m)
SA1	0.42	340	154	320	3,844
SA2	1.25	8,467	3,637	270	13,352
SA3	1.44	14,571	4,945	250	25,491
SA4	1.36	15,294	4,023	270	28,240
SA5	1.08	777	336	260	9,000
SA6	0.31	504	221	200	4,200
Sum	5.86	39,953	13,316	–	84,127

and 10.77 km of intercepting sewers (L1–L5) are connected to the WWTP. SA2, SA3, and SA4 support relatively larger numbers of properties than the other three SAs. Sewerage rehabilitation across the entire area was completed in 2010, with conversion from combined to separate-type sewers.

Fig. 2 describes rainfall and wastewater flows in the case study area, as measured in 2011. The black solid and dotted lines represent inflow to the WWTP monitored at flow monitoring site (M7), and the sum of wastewaters measured at the flow monitoring site (M1–M6) of the six SAs between January and December 2011. The WWTP was designed to cope with daily peak flow (Q_d) generated from the Hongcheon area of 11,000 m^3. The WWTP inflow graph shows that inflow exceeded treatment capacity during the 2011 wet season (June–September). The normal procedure used in the design of intercepting sewers in combined systems in Korea is to triple the values of daily peak flows generated from the serviced area [27]. The inflow graph shows that WWTP inflow has not exceeded the calculated $3Q_d$, of 33,000 m^3/d, even during wet seasons, indicating that intercepting sewers could play an

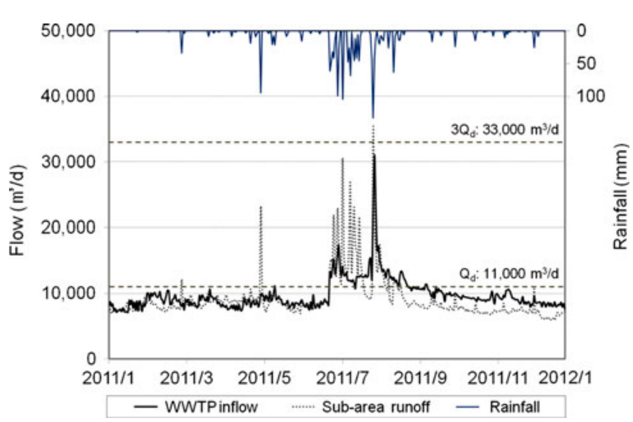

Fig. 2. Description of wastewater flows.

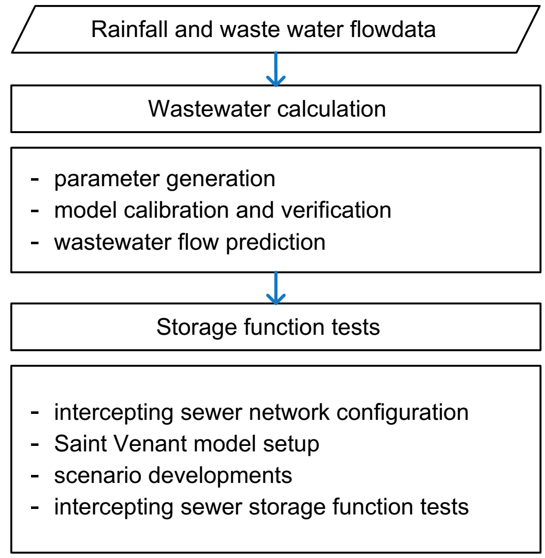

Fig. 3. Framework for testing of storage function of intercepting sewers.

important role in controlling excess flow, relative to the WWTP treatment capacity.

2.2. Framework of storage function test

The flowchart in Fig. 3 shows the framework adopted for storage function tests in this study. The developed model was first used to predict wastewater flows of SAs. Long-term measured rainfall and wastewater flow data for the outlet of each SA were used to calibrate and verify the model. During dry weather conditions, wastewaters consist of domestic sewage flow only, but wet weather wastewaters include additional wastewater derived from rainfall events. Therefore, models were calibrated and verified for both dry and wet weather conditions. The fitted models were used to predict wastewaters generated following a selected rainfall event. Once the intercepting sewer network structure connecting the SAs was configured, scenarios for storage function tests were developed. The main purpose of the storage function tests was to explore the role of intercepting sewers during rainfall events. Four different inflow conditions to the WWTP were considered. The hydraulic simulations were designed to accommodate flows of $1.5Q_d$, $2Q_d$, $2.5Q_d$, and $3Q_d$ to the WWTP, and to test the storage function of intercepting sewers. Hydraulic simulations of intercepting sewers describing flows from SAs to the WWTP were conducted using a conventional pipe hydrodynamic model (i.e. Saint-Venant equations) in the use of XP SWMM model. In order to represent the steady inflow for different conditions ($1.5Q_d$, $2Q_d$, 2.5Q$_d$, and 3Q$_d$), we assumed a virtual pump which controled the inflow. As the design capacity of the WWTP was 11,000 m^3/d, the inflows only up to 16,500, 22,000, 27,500, and 33,000 m^3/d for 1.5Q$_d$, 2Q$_d$, 2.5Q$_d$, and 3Q$_d$, respectively, are directed to the WWTP and the excess flows are stored in the intercepting sewers. The stored water flows reduce after the peak flow, as inflows to the WWTP diminish.

3. Wastewater calculation

3.1. Advanced regression model descriptions

The wastewater prediction model applied here is multivariate regression model, additionally considered dry weather wastewater flow pattern and wastewater flow generated by rainfall event. The model developed was modified forms of the ARMAX model described in [10] and can be represented by Eq. (1), where P_t, S_t and e_t are trend cycle, seasonal, and error term respectively. $P_t = \alpha_0 + \sum_{i=1}^{m}\alpha_i U_{it}$; $S_t = \sum_{j=1}^{k}\beta_j V_{jt}$ and the U_{it} and V_{it} are the trend and seasonal variables.

$$Z_t = P_t + S_t + e_t$$

$$= \alpha_0 + \sum_{i=1}^{m}\alpha_i U_{it} + \sum_{j=1}^{k}\beta_j V_{jt} + e_t \quad (1)$$

Factors relevant to wastewater flow generation include time, rainfall, and presence of dry and wet periods. Dry weather wastewater flows have a specific daily pattern, and hence wastewater flows can differ substantially, depending on time of occurrence. In order to represent the trend cycle of dry weather wastewater over a day, a linear trend cycle component P_t in Eq. (1) can be written as an m th-order polynomial in time as $P_t = \alpha_0 + \sum_{i=1}^{m}\alpha_{it}$, where α_0 is the baseline value. The seasonal component S_t can be simplified as, $S_t = \beta_0 V_t$ where the seasonal variable, V_t = 0 for dry

Table 2
Calculated parameters of the wastewater prediction model

Sub areas	SA1		SA2		SA3		SA4		SA5		SA6	
	α	p	α	p	α	p	α	p	v	p	α	p
α_1	−11.2	0.02	−250.6	0.00	−475.6	0.10	−554.4	0.12	−25.5	0.02	−16.4	0.02
α_2	−21.0	0.00	−434.2	0.00	−901.0	0.00	−1,101.8	0.00	−48.0	0.00	−30.9	0.00
α_3	−20.8	0.00	−417.7	0.00	−558.4	0.05	−1,107.6	0.00	−47.5	0.00	−30.8	0.00
α_4	−19.5	0.00	−431.1	0.00	−599.4	0.04	−1,016.1	0.00	−44.6	0.00	−28.9	0.00
α_5	−10.8	0.02	−389.5	0.00	−356.9	0.21	−371.9	0.29	−24.6	0.02	−15.5	0.03
α_6	−3.0	0.53	−244.7	0.00	17.2	0.95	20.3	0.95	−6.8	0.53	−4.0	0.57
α_7	27.6	0.00	430.8	0.00	1,196.8	0.00	1,691.0	0.00	63.1	0.00	41.4	0.00
α_8	52.8	0.00	1,004.4	0.00	2,226.9	0.00	3,067.3	0.00	120.8	0.00	78.8	0.00
α_9	46.2	0.00	957.8	0.00	1,981.2	0.00	2,421.1	0.00	105.5	0.00	68.9	0.00
α_{10}	43.8	0.00	956.6	0.00	1,901.9	0.00	2,191.7	0.00	100.2	0.00	65.4	0.00
α_{11}	36.6	0.00	838.1	0.00	1,642.9	0.00	1,706.9	0.00	83.7	0.00	54.8	0.00
α_{12}	37.0	0.00	736.6	0.00	1,721.6	0.00	1,849.3	0.00	84.4	0.00	55.2	0.00
α_{13}	32.8	0.00	647.1	0.00	1,712.8	0.00	1,460.4	0.00	74.9	0.00	49.1	0.00
α_{14}	29.9	0.00	613.2	0.00	1,538.9	0.00	1,313.4	0.00	68.3	0.00	44.1	0.00
α_{15}	18.5	0.00	441.7	0.00	985.6	0.00	659.8	0.06	42.2	0.00	27.1	0.00
α_{16}	24.1	0.00	397.2	0.00	1,226.8	0.00	1,242.7	0.00	55.0	0.00	36.1	0.00
α_{17}	32.4	0.00	498.5	0.00	1,596.6	0.00	1,803.1	0.00	74.2	0.00	48.5	0.00
α_{18}	38.9	0.00	675.8	0.00	1,756.6	0.00	2,187.5	0.00	88.9	0.00	58.1	0.00
α_{19}	41.3	0.00	791.4	0.00	1,816.1	0.00	2,241.0	0.00	94.4	0.00	61.7	0.00
α_{20}	38.5	0.00	821.5	0.00	1,520.4	0.00	2,122.2	0.00	88.1	0.00	57.6	0.00
α_{21}	36.4	0.00	750.0	0.00	1,431.0	0.00	2,058.2	0.00	83.2	0.00	54.4	0.00
α_{22}	33.8	0.00	666.9	0.00	1,343.9	0.00	1,939.7	0.00	77.1	0.00	50.5	0.00
α_{23}	18.0	0.00	349.6	0.00	736.7	0.01	1,027.9	0.00	41.2	0.00	27.2	0.00
α_0	98.9	0.00	1,218.6	0.00	6,013.6	0.00	4,919.3	0.00	226.0	0.00	146.1	0.00
β_0	−49.2	0.00	−273.3	0.00	−3,259.0	0.00	−2,834.1	0.00	−112.4	0.00	−72.8	0.00
γ_0	11.4	0.00	35.0	0.00	579.2	0.00	858.4	0.00	26.0	0.00	16.9	0.00
R^2	0.630		0.716		0.585		0.554		0.630		0.630	

weather periods and is otherwise 1, since wastewater flows can only have additional components with rainfall events. The variable β_0 represents changes in wastewater occurring as a result of rainfall influences, such as ground water infiltration and inflow. The irregular components represent changes which relate to the rainfall amount variable, D_{jt} (rainfall depth, mm), with the variable representing different catchment characteristics, γ_0. An advanced regression model of wastewater estimation with an error term e_t can therefore be represented as Eq. (2). The model first finds suitable parameters for, α_0, β_0, γ_0, and α_i is estimated using the variance of wastewaters.

$$Z_t = P_t + S_t + e_t$$

$$= \alpha_0 + \sum_{i=1}^{m} \alpha_{it} + \beta_0 V_t + \gamma_0 \sum_{j=1}^{n} D_{jt} + e_t \tag{2}$$

3.2. Wastewater flow prediction

Table 2 lists parameters of the model in Eq. (2) for estimated wastewater calculation and significance probability of parameters (p) and determination coefficient (R^2). The probability of significance for α_0, β_0, and γ_0 estimated for every SA was below 0.05. While some p values calculated for the $\alpha_{1\text{–}23}$ were relatively higher than 0.05, overall R^2 (0.55–0.72) indicated that model parameters fit wastewater flow characteristics with large variability relatively well. The AR models were calibrated, and verified monitored wastewater flow data in each SA for 816 h (34 d, measured 23 June 2011–23 July 2011) and 240 h (10 d, measured 15–24 August 2012), respectively. Errors in total flow were largest in SA4, with values of 9% and 12% for model calibration and verification, respectively. Figs. 4a and 4b compare measured wastewater flows, and flows generated in model calibration, and verification. Total flows calculated are summarized in

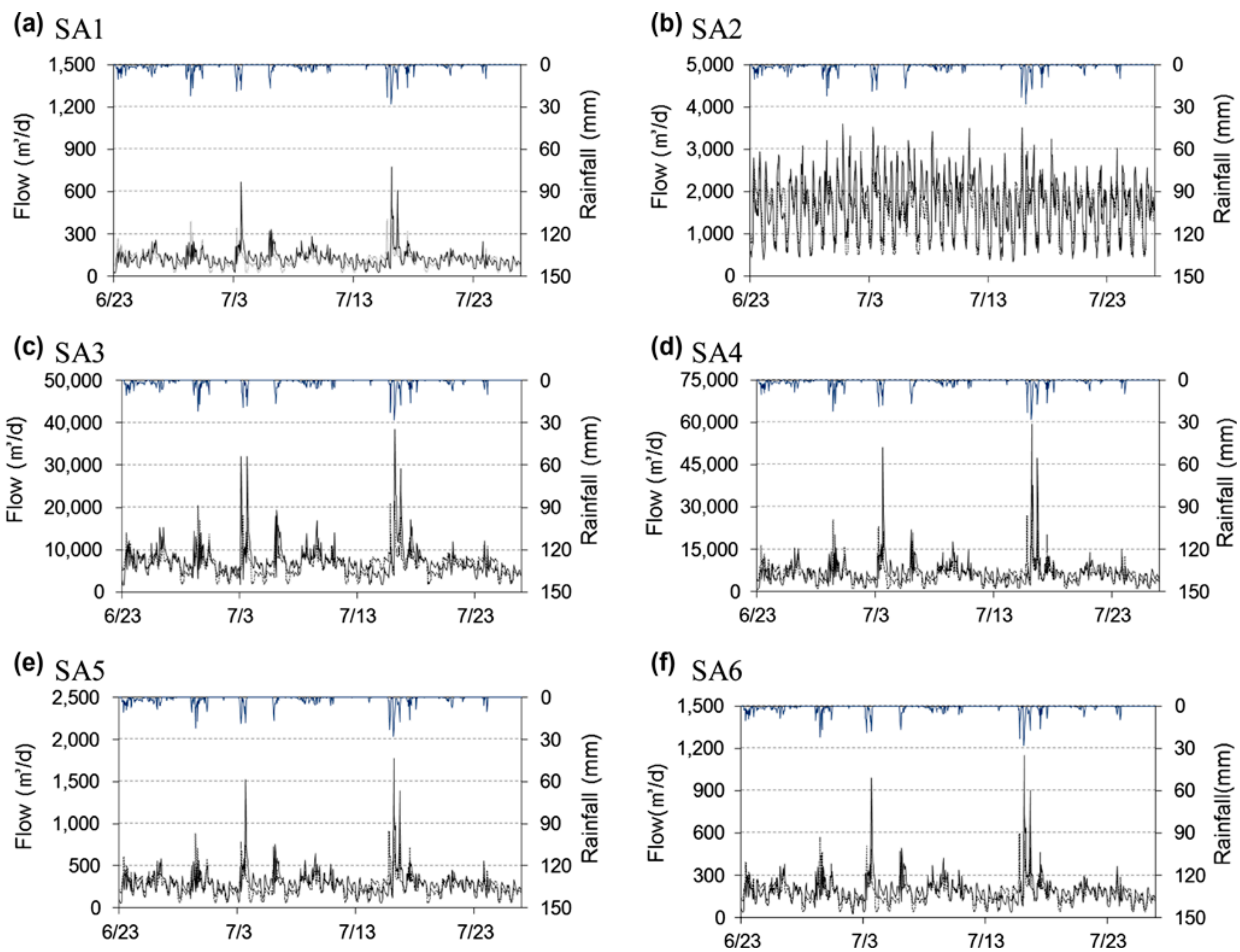

Fig. 4a. Results of model calibration (23 June–23 July 2011, 816 h) (simple line: measured flow, dotted line: modeled flow).

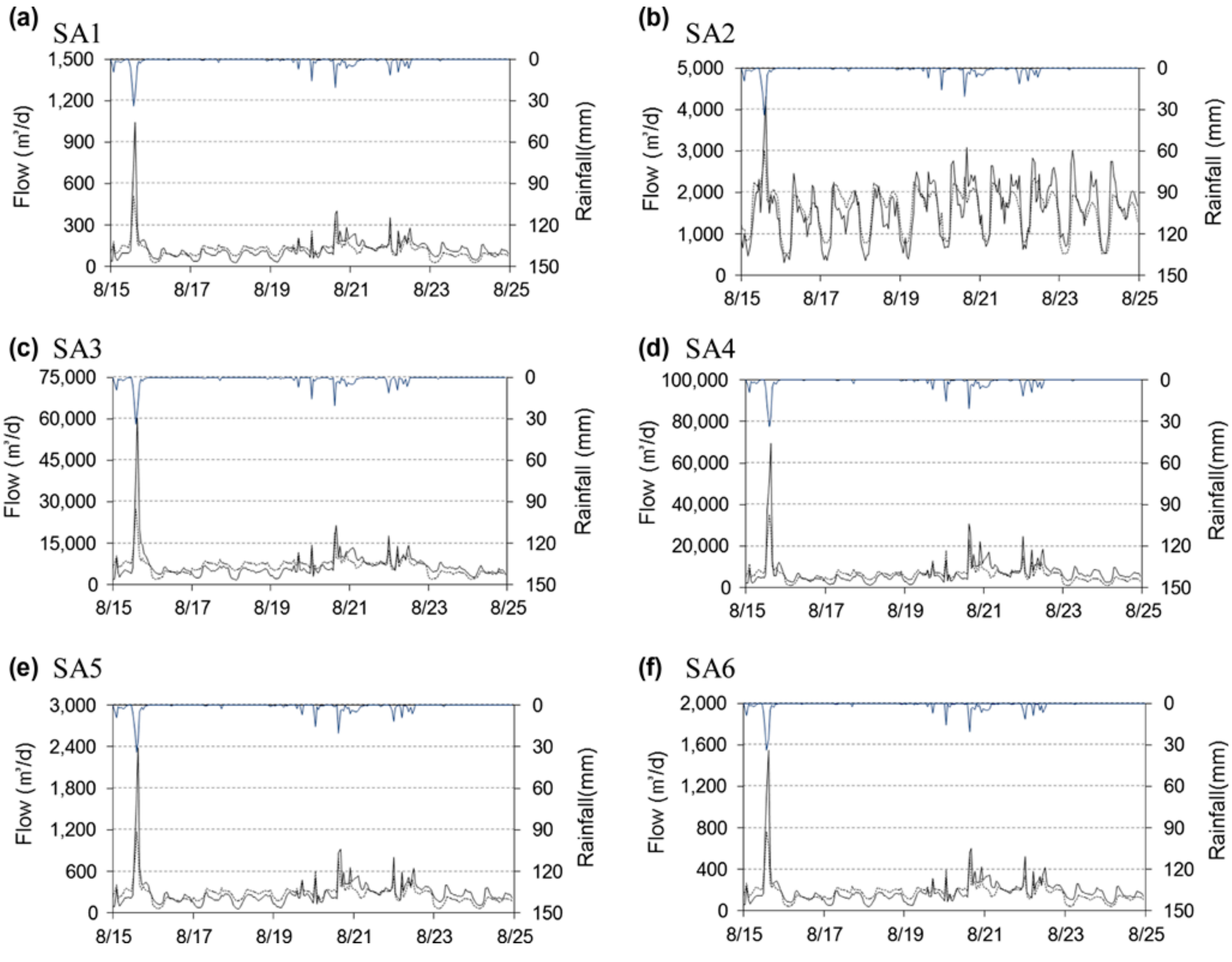

Fig. 4b. Results of model verification (15–24 August 2012, 240 h) (simple line: measured flow, dotted line: modeled flow).

Table 3. Wastewater flows using the fitted AR models were then calculated for 168 h of wastewater flows for 3–9 July 2012. Flow data over the 7 d was not measured, and relatively large rainfall depths were recorded. A total of 95 mm rainfall depth was recorded during 168 h. A depth of 82 mm was recorded on 6 July, with 13 mm/h peak intensity. The rainfall event was expected to generate more than $1.0Q_d$ of WWTP capacity. The storage function tests therefore opted to use predicted wastewater flow data of 168 h. Total wastewater flows estimated using the developed models, for the 7-d period, were 109,212, 1,669,162, 6,004,174, 5,470,109, 161,729, and 249,583 m^3 for SA1–SA6, respectively.

4. Storage function tests

In order to test storage function of intercepting sewers (L1–L5), different inflow conditions ($1.5Q_d$, $2Q_d$, $2.5Q_d$, and $3Q_d$) to the WWTP were considered. Under $1.5Q_d$ inflow assumption conditions, the WWTP has a steady inflow of $1.5Q_d$ (16,500 m^3/d), and hence, flow remains in the intercepting sewers.

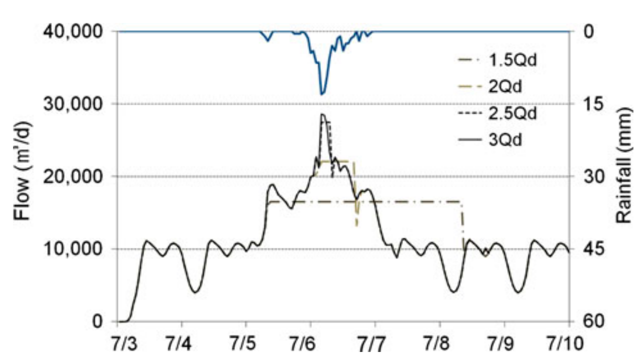

Fig. 5. Hydrographs of inflow to the WWTP under different inflow conditions.

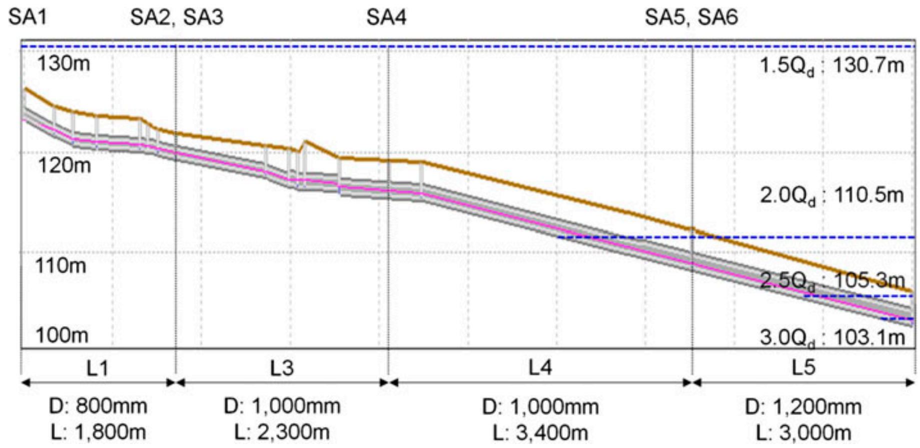

Fig. 6. HGL of intercepting sewers.

Table 3
Results of wastewater prediction model calibration and verification

SA	Measured flow (m^3)	Calibration modeled flow (m^3)	Error (%)	RMSE	Measured flow (m^3)	Verification modeled flow (m^3)	Error (%)	RMSE
SA1	3,513,856	3,230,178	−8	50	301,403	283,741	−6	61
SA2	45,992,342	43,299,526	−6	407	3,796,444	3,765,796	−1	392
SA3	198,016,191	182,387,460	−8	3,025	16,148,182	16,039,867	−1	3,574
SA4	185,291,162	168,277,857	−9	3,758	16,866,514	14,833,086	−12	4,254
SA5	5,198,666	4,784,137	−8	115	446,786	420,246	−6	139
SA6	8,030,281	7,382,010	−8	75	688,795	648,440	−6	90

Once rainfall ends, the wastewater flow stored in the intercepting sewers gradually directs to the WWTP. Under conditions of $2Q_d$, $2.5Q_d$, and $3Q_d$, the steady inflow amounts to the WWTP are 22,000, 27,500, and 33,000 m^3/d, respectively. Hydrodynamic simulations for the different inflow conditions were conducted using XP SWMM model. Using wastewater inputs from the six SAs, as generated from the ARMAX model, the hydrodynamic simulations tested the storage function of intercepting sewers for different inflow conditions to the WWTP, by assuming inflow pump operation conditions in the inlet of the WWTP.

Figs. 5 and 6 show pipe flow hydrographs and hydraulic gradient lines (HGL) in L1–L5, comprising the main stream of intercepting sewers to the WWTP. In the case of $1.5Q_d$ inflow conditions, up to 16,500 m^3/d flow is continuously directed to the WWTP, with flows exceeding the amount remaining in interception sewers between 50 and 180 h from the start of simulation. The HGL shown in Fig. 6 reached 130.7 m, and all four links (L1, L3, L4, and L5) were used for wastewater storage. Under $2Q_d$ inflow conditions, over 22,000 m^3/d of wastewater was stored in intercepting sewers between 89 and 100 h after the start of simulation, and only L4 and L5 were used for flow storage. When the WWTP is assumed to have $2.5Q_d$ and $3Q_d$ inflow control conditions, only the final link served as a storage, with maximum HGL of 105.3 and 103.1 m during the simulation periods, respectively.

Existing intercepting sewers stored wastewaters for 70, 11, and 3 h, under WWTP inflow control conditions of $1.5Q_d$, $2Q_d$, and $2.5Q_d$, respectively. Almost all the wastewater flowed to the WWTP under $3Q_d$ inflow conditions. The sewer storage function is thus expected to be effective for wet weather operation of the WWTP, up to the $3Q_d$ inflow condition; as previously noted, this threshold represents the conventional design criterion for intercepting sewers within combined sewer areas.

5. Conclusions

This study proposes a method for examining the storage function of intercepting sewers, following sewerage rehabilitation works for conversion of sewers from combined to separate-type systems. In order to evaluate in detail the storage function of intercepting sewers, a simple mathematical model, utilizing runoff generated from a statistical model, was used in this study. A conventional advanced regression model, which represented a type of random process of time-varying inputs, was used to generate runoff hydrographs for each SA. A rainfall event was then selected as an input to the advanced regression model, and wastewater flows were generated for 168 h for storage function testing. Different inflow conditions to the WWTP were considered, and the intercepting sewer hydraulics were solved using Saint-Venant Equations. Based on results obtained, the sewer storage function is expected to be effectively used for wet weather operation; this function could also work in other areas where similar large-scale rehabilitation works are also being conducted. The method suggested, utilizing simplified calculation of runoff generation and hydraulic simulation, will be useful for decision-making concerning the removal of existing intercepting sewers in various areas.

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