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Applying micro-genetic algorithm in the one-dimensional unsteady hydraulic model for parameter optimization

Tsun-Hua Yang, Yu-Chi Wang, Shun-Chung Tsung and Wen-Dar Guo

ABSTRACT

Selection of an appropriate value for Manning's roughness coefficient could significantly impact the accuracy of a hydraulic model. However, it is highly variable and depends on flow circumstances, such as water stage and flow quantity; a stream's geomorphology, such as the fluvial process and river meandering; and physical conditions, such as the channel surface roughness and irregularities. Nevertheless, choosing proper roughness coefficients is not easy, especially with limited information and time in a practical application. Even it is done for a specific event it may not apply to another event due to its time- and site-dependency. This study proposes a Visual Basic (VB)-based system, which integrates the HEC-RAS modeling tool and the μGA to efficiently search for Manning's roughness coefficients. The matching coefficients will thereafter improve the accuracy of hydraulic modeling. Two events in the Yilan River Basin were applied to test the feasibility of the system and four evaluation criteria were used to evaluate the system performance. The results showed that μGA efficiently converged and the hydraulic model showed good agreement in comparison with the measured data. The system can be used as a good tool for finding onsite Manning's roughness coefficients in hydraulic modeling when detailed information is not available.

Key words | HEC-RAS, Manning's roughness coefficient, micro-genetic algorithm, parameter optimization

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INTRODUCTION

Manning's roughness coefficient, mostly denoted as '*n*', is a common factor used by hydraulic engineers to describe a river's surface roughness and sinuosity in hydraulic modeling. Three approaches include (1) measurements, (2) parameter values estimation, and (3) parameter values fitting mentioned by Vidal *et al.* (2007). The parameter is usually empirically and often uncertain. To determine an empirical parameter is tedious and time-consuming. A confident selection of the Manning's roughness coefficient will help engineers and modelers to better estimate the stream condition and to minimize overall discrepancies between simulations and observations; however, it will require considerable experience and investigation of the site. To help select an appropriate roughness coefficients, many people, such as Chow (1959) and Barnes (1967), have proposed referencing a Manning's roughness coefficient with detailed descriptions and color photographs; but, another problem then occurs – one cannot directly apply the referenced value by just looking at descriptions and photographs due to the lack of complete similarity in channel conditions and geometry. Even for the same stream, the Manning's roughness coefficients would change. For example, resistance decreases with an increasing water level as the effective relative roughness diminishes; it then increases again as the flow reaches a floodplain or spills over the bank (Chow 1959). Topography or geomorphology, which is known to change over time, would alter the Manning's roughness coefficient in the hydraulic models as well. To increase the efficiency for engineers applying the hydraulic modeling tool, the third approach, parameter values fitting, mentioned by Vidal *et al.* (2007), was applied in the study. It includes two approaches: the first one which is the

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traditional approach 'trial-and-error' was not applied as it was considered to be too time-consuming, and the second one, the optimization search technique, was implemented in the study. A system was developed to integrate the one-dimensional (1D) river hydraulic modeling tool, HEC-RAS, and a search heuristic, micro-genetic algorithm (μGA), to efficiently define the Manning's roughness coefficient even with limited information. The accuracy of hydraulic modeling would therefore be improved. For flood operators, it will help decision making in real-time operations and prevent possible disasters or floods. When available information is limited, the study provides a tool which helps hydraulic modelers to identify parameters in the hydraulic simulations and run the simulations smoothly and correctly. In the study, the parameter to be identified is Manning's roughness coefficient. The proposed integration can be applied to identify other parameters if necessary.

HEC-RAS is a 1D hydraulic modeling tool capable of simulating unsteady- and steady-flow movements along a channel. To simulate flow and stage, HEC-RAS uses the Saint-Venant equations (de Saint-Venant 1871) that can be solved with the Preissmann's implicit finite difference scheme (Cunge et al. 1980) by using a modified Newton–Raphson iteration technique (USACE 2010). It is a widely used river hydraulic modeling tool throughout the world because of its prediction accuracy and user-friendly interface. Many researchers and engineers have applied HEC-RAS to study river hydraulics for their own topics or practical applications. For practical applications, Hicks & Peacock (2005) discussed the viability of the HEC-RAS unsteady flow routine for flood forecasting through an application to the Peace River in Alberta, Canada. The HEC-RAS is a standard tool for floodplain delineation studies and is broadly used in Canada. In the United States, the Federal Emergency Management Agency (2001) issued a memorandum to encourage the use of HEC-RAS for the National Flood Insurance Program. Malekmohammadi et al. (2010) applied the HEC-RAS modeling tool real-time flood management in the river-reservoir systems in Iran. Using the optimization mode, this model can be effectively used for flood management and real-time operation of cascade river-reservoir systems. In combining with other modules or models, HEC-RAS can be applied to different research topics, such as the sedimentation process (Gibson et al. 2010) and water quality simulation (Fan et al. 2009). This study applies HEC-RAS as a component of river hydraulic modeling due to its popular and extensible advantages.

The genetic algorithm (GA) is an artificial intelligent technique commonly used to optimize search problems. Solomatine (1998) compared GA with other global optimization algorithms in the hydrologic and hydrodynamic applications. The study showed that GA is normally quite close to the global minimum for the applications of three variables. For two variables, GA is also the least efficient among applied algorithms. However, Hongesombut et al. (2002) mentioned that there is a possibility for GA to converge to a suboptimal solution. In addition, the search process for GAs is usually time consuming. Thus, other search algorithms have been developed as an efficient and globally optimal answer. The term μGA refers to a small-population GA with re-initialization. The idea was suggested by theoretical results obtained by Goldberg (1989). Starting from a randomly generated population, μGA applies the small population to the genetic operators until reaching nominal convergence, which means all the individuals in the population have either identical or very similar genotypes.

A new population would be generated by transferring the best individuals out of the converged population to the next generation (elitist strategy). The remaining individuals in the new generation would be randomly generated (re-initialization). Krishnakumar (1990) first implemented the μGA using a population size of five, a crossover rate of one, and a mutation rate of zero. Krishnakumar (1990) and Senecal (2000) both reported faster and better results with their μGAs on their applications. μGA has the advantage of generating a small population base for each generation. Conventional GAs usually deal with population sizes ranging from 100 to 10,000, while μGA typically works with a population with between five and 50. It also reaches near-optimal regions quicker than the conventional GAs. In his application, Chakravarty et al. (2002) showed that using the μGA can decrease the computational run time by 50%, even for the 'worst-case' problems for the conventional GAs. In the study, the μGA is applied and Krishnakumar's (1990) assumptions for the μGA are implemented in the proposed system.

To improve the accuracy of hydraulic modeling, the optimization of Manning's roughness coefficients is

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attracting interest from researchers. The back calculation from measured flow and stage is a trial and error process. It is time consuming and may not be applicable for real time operations due to its complexity and variability. Many auto calibration approaches thus have been proposed. Fread & Smith (1978) adopted an automated method to minimize the error of calibrated parameters between rivers. Tang et al. (2010) used a GA for parameter identification and applied it in the Xijiang River network. Ayvaz & Genc (2012) applied the Harmony Search (HS) for roughness estimation. The HS searching process is analogous to musicians who play some notes from memory. Selecting parameters would affect the convergence of HS. For example, if a low harmony memory considering rate (HMCR) is selected, one of many parameters in HS, only few elite harmonies would be selected. It results in slow convergence. Azamathulla et al. (2012) applied the gene expression programming (GEP) to predict Manning's roughness coefficients in open channels. Comparing with five chromosomes in μGA, the GEP consists of 50 chromosomes. Comparing with previous studies mentioned above, μGA has the advantage of a small population and it reaches the convergence in a faster way.

A few studies worked on the identification of Manning's roughness coefficients. Among them, Yeh (1986) has found out that the problem is hard to obtain unique solution for unknown parameters. Ding et al. (2004) mentioned that none of them can automatically guarantee stability and uniqueness in the parameter identification. Thus, this study proposes a Visual Basic (VB)-based system that integrates HEC-RAS and μGA to automatically search for the optimal Manning's roughness coefficient in the applied waterway. The μGA has advantages of stability and consistency for reaching a globally optimal answer. The found coefficients lead to increased accuracy of hydraulic modeling. To validate the proposed system, it was applied in the Yilan River Basin in Yilan County, Taiwan. An experimental watershed in the Yilan River Basin with detailed measured data, including flow quantity and water stage, has been developed by the Water Resources Agency, Ministry of Economic Affairs, Taiwan (WRA), and Taiwan Typhoon and Flood Research Institute (TTFRI) since 2012. Even though μGA has advantages of efficiency and accuracy in searching for the best result, good quality measured data are necessary for the optimization process. Thus, the experimental watershed in the Yilan River Basin is a perfect location in which the proposed system can be applied and validated. To the authors' knowledge, no studies have focused on the Yilan River Basin in terms of hydraulic modeling. Some studies were focused on the Lan-Yang River, which is another main river at the south of Yilan River. For example, Yu (2010) applied the GA on parameter calibration in Lan-Yang River. Two different events, one with high-flow conditions and another with low-flow conditions, were applied. The measured stages at two bridges, the Zhuangwei Bridge and Leawoo Bridge, were used to find the best-fit Manning's roughness coefficient. Meanwhile, for the purposes of evaluation, the simulated stages modeled by HEC-RAS with the best-fit roughness coefficients are compared with measured data at the same locations with the four evaluation criteria.

METHOD

HEC-RAS

A 1D river hydraulic modeling tool, HEC-RAS, was applied to simulate the Yilan River's flow and stage. In the model, the Saint-Venant equations listed below were solved (USACE 2010):

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q \tag{1}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (Q^2/A)}{\partial x} + gA\frac{\partial h}{\partial x} = gA(S_0 - S_f) \tag{2}$$

where A = cross-sectional area perpendicular to the flow (m^2); Q = discharge (m^3/s); q = lateral inflow per unit length ($m^3/s/m$); g = acceleration due to gravity (9.81 m/s^2); h = water height (m); S_0 = river bed slope (m/m); S_f = friction slope (m/m); t = temporal coordinate (sec); x = longitudinal coordinate (m).

The Saint-Venant equations are nonlinear. To obtain analytical solutions, it is necessary to make restrictive assumptions which are not always unrealistic. Thus, these equations are approximated using implicit finite differences,

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and solved numerically using the Newton–Raphson iteration with a technique that was developed by Preissmann as reported by Liggett & Cunge (1975) and Chen (1978) to avoid possible convergence problems at discontinuities in the river geometry. The implicit technique, Preissmann scheme, is widely used to solve the Saint-Venant equations for applications in routing water in river systems despite its disability to solve transcritical flows (Sart *et al*. 2010).

Micro-genetic algorithm (μGA)

Krishnakumar's assumptions (1990) for μGA were applied in this study. These assumptions are a population size of five, a crossover rate of one, and a mutation rate of zero. The flow chart (Figure 1) displays the working process of the

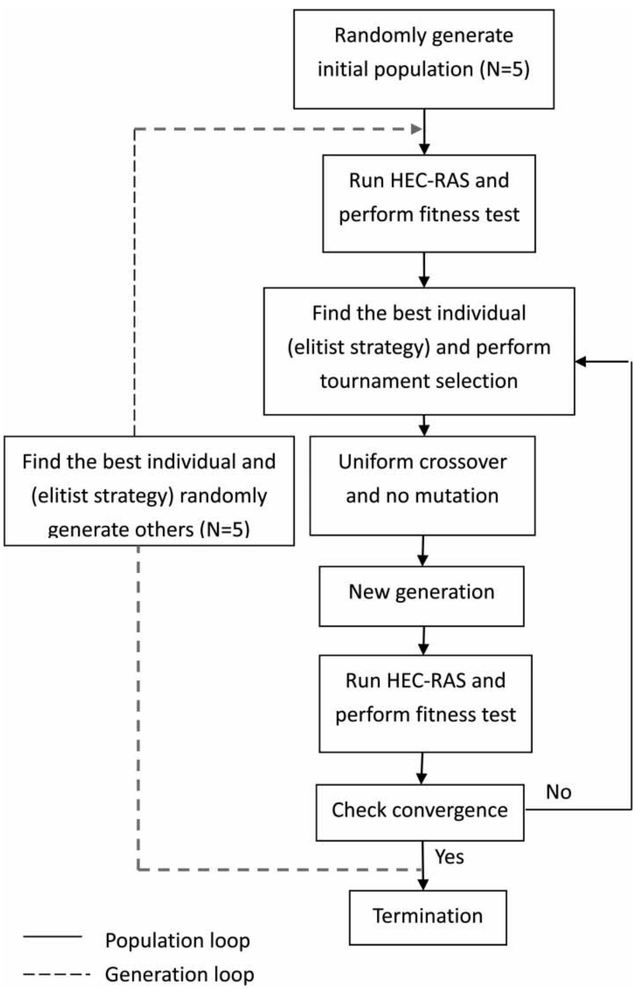

Figure 1 | Flow chart of the integrated system.

proposed integration of HEC-RAS and μGA. For most of the time, there is a lack of information regarding the onsite situation so the roughness coefficients are hard to define along the waterway. The most common approach assumes a uniform Manning's roughness coefficient and users will assume a value by reference (for example, Chow (1959) and Barnes (1967)). Thus, a set of Manning's roughness coefficients includes the left bank, main channel, and the right bank, and are assigned to all cross sections along the waterway. It is identical to the most common way to input Manning's roughness coefficients in the HEC-RAS. The following steps are listed to describe how HEC-RAS and μGA work together.

1. A group of five chromosomes ($N=5$) are randomly generated. Each chromosome can be decoded to three Manning's roughness coefficients, which represent the left bank, main channel, and right bank. The binary string is used to code the three Manning's roughness coefficients into a chromosome.
2. HEC-RAS is run with the generated Manning's roughness coefficients and the fitness value is obtained. The fitness value minimum is the objective function. The fitness value is calculated as follows:

$$f=\frac{1}{N}\frac{1}{T}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(1-\frac{h_{i,t}}{h_{i,t}^{0}}\right)^{2} \tag{3}$$

   where $h_{i,t}$ and $h_{i,t}^0$ = modeled and measured stages at the given station; i = the ith station; t = time in hour; T in hours = the total time in comparison; N = the total number of stations to be compared and there are two stations used to evaluate the performance.
3. Keep the most fit chromosome for the next generation and perform the tournament selection for the remaining four chromosomes with a crossover rate of one and a mutation rate of zero until the new generation ($N=5$) is achieved.
4. Run the HEC-RAS and calculate the fitness value. Thereafter, the nominal convergence, which means all the individuals in the population have either identical or very similar genotypes, is checked.
5. In the population loop (solid line in Figure 1), the nominal convergence in the study is when more than 29 out

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of 30 genes in each chromosome in the entire population share the same value. To complete the search process, 40 generation loops are executed.

The proposed system is controlled by a VB-based graphical user interface (GUI), shown in Figure 2, to integrate the HEC-RAS and μGA. The automation for matching the best-fit Manning's roughness coefficients runs after typing the event's information and the number of data to be evaluated into the GUI.

Performance evaluation criteria

At present, the hydrological or hydraulic models lack a consistent way to evaluate the model performance. Different measures have been proposed or discussed by many studies. Hall (2001) listed 10 goodness-of-fit measures for a typical daily rainfall-runoff model. Dawson *et al.* (2007) and Napolitano *et al.* (2010) proposed four performance measures that are applied in the study to evaluate the performance in terms of comparing simulated and measured data. The four performance measures are listed as below:

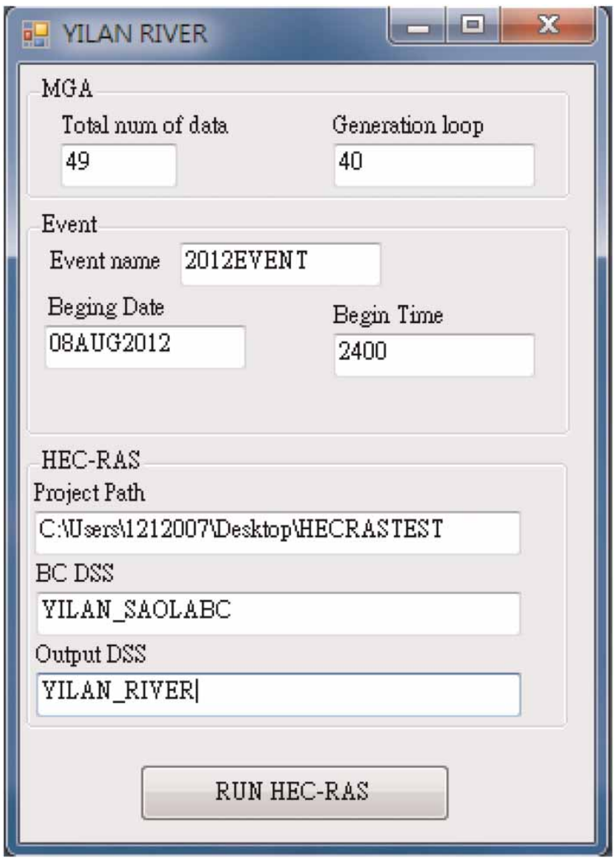

Figure 2 | The GUI for the integration of HEC-RAS and MGA.

1. The mean absolute error (MAE).
2. Coefficient of efficiency (CE).
3. Percent error in peak stage (PE).
4. Coefficient of determination (R^2).

The mean absolute error (MAE)

The MAE was suggested by Willmott & Matsuura (2005) to replace the root mean square error since it is a more natural definition of an average error and is unambiguous. It is because the difference between measured and modeled stage is instinctively defined by the subtraction and the average would describe the overall performance. The MAE is defined as follows:

$$\mathrm{MAE} = \frac{1}{T}\sum_{i=1}^{T}|P_i - O_i| \tag{4}$$

where O_i = the measured stage (m); P_i = the modeled stage (m); i = time (hour); T = the entire evaluation time period (hour).

Coefficient of efficiency (CE)

The CE has been widely used to evaluate the performance of hydrologic models (Legates & McCabe 1999). It ranges from minus infinity to 1.0, and higher values indicate better agreement. The equation to obtain the CE is shown below:

$$\mathrm{CE} = 1.0 - \frac{\sum_{i=1}^{T}(O_i - P_i)^2}{\sum_{i=1}^{T}(O_i - \bar{O})^2} \tag{5}$$

where O_i = the measured stage (m); P_i = the modeled stage (m); i = time (hour); T = the entire evaluation time period (hour); $\bar{O}$ = the mean of the observed stage which is $1/T\sum_{i=1}^{T} O_i$.

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Percent error in peak stage (PE)

The peak stage usually indicates the decision-making moment for the operators. The peak value itself is also an important value for the evaluation of possible disaster threats, such as overtop flooding. The accuracy of a simulated peak stage is thus an important factor, and the PE is calculated as below:

$$PE = \frac{P_{\mathrm{Peak}} - O_{\mathrm{peak}}}{P_{\mathrm{peak}}} \times 100 \tag{6}$$

where O_{peak} and P_{peak} = the measured and simulated peak stage (m), respectively.

Coefficient of determination (R^2)

R^2, known as the product moment correlation coefficient, is also called the 'Pearson product moment correlation coefficient' (Pearson 1895), which describes the squared ratio of the combined dispersion of two series to the total dispersion of the observed and modeled series. It is a common measure used in statistics to compare the similarity of two sets of data. The equation to obtain R^2 is described below:

$$R^2 = \left[\frac{\sum_{i=1}^{T} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{T} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{T} (P_i - \bar{P})^2}} \right]^2 \tag{7}$$

where O_i = the measured stage (m); P_i = the modeled stage (m); i = time (hour); T = the entire evaluation time period (hour).

$\bar{P}$ = the mean of the modeled stage which is $\frac{1}{T}\sum_{i=1}^{T} P_i$

$\bar{O}$ = the mean of the observed stage which is $\frac{1}{T}\sum_{i=1}^{T} O_i$

APPLICATION

The Yilan River Basin is in Yilan County in northeastern Taiwan (see Figure 3 for the location). The main stream of the Yilan River is approximately 24.4 km long and covers area of about 149.06 km^2. The main stream flows through a major city in the county, Yilan City. The major commercial activity along the river is agriculture. Precipitation, river stage, flow velocity, and inundation depth due to flooding have been carefully measured by the WRA and TTFRI for the Yilan River experimental watershed since 2012. The proposed system applied here takes advantage of detailed data that have been carefully collected and processed. The integration of HEC-RAS and μGA covers part of the Yilan River, from the ChungSan Bridge to the Kamalan Bridge, a total of 12 km out of 24.4 km. Two events were applied: Event 1 is the Saola typhoon, a high-flow event that happened from August 1 to August 5, 2012; Event 2 is a regular rain event, a low-flow event that happened from August 9 to August 11, 2012. This document discusses the performance of the proposed system associated with different flow conditions. The measured data at ChungSan Bridge and Kamalan Bridge are the upstream and downstream boundary conditions, respectively. The geometry was surveyed at ChungSan Bridge and pertinent water surface velocity was measured by radar surface velocimeters. The surface velocity multiplied by an experimental factor gives the mean velocity. The experimental factor was estimated according to Acoustic Doppler Current Profiler (ADCP) measurement. From the mean velocity and

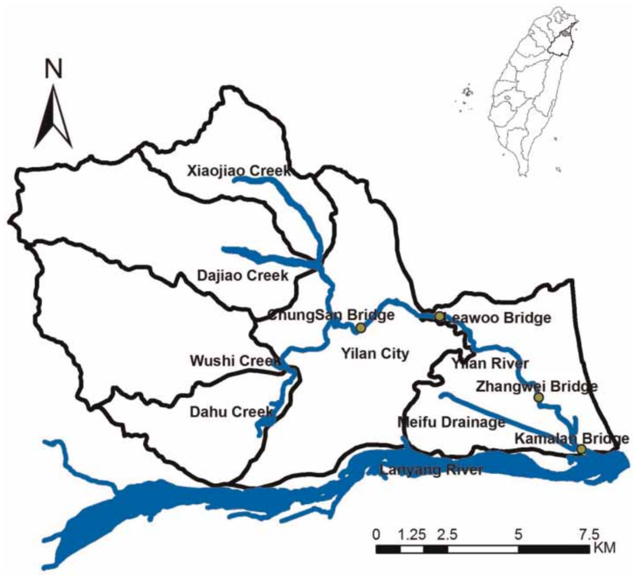

Figure 3 | Location map of the Yilan River Basin.

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cross-section area, the upstream inflow boundary condition was calculated. The real time measured stage at Kamalan Bridge is the downstream boundary condition. The stage at Leawoo Bridge (approximately 4 km downstream from ChungSan Bridge) and Zhangwei Bridge (approximately 3 km upstream from Kamalan Bridge) are the reference locations to evaluate the performance.

RESULTS AND DISCUSSION

Two events were used to test the proposed system. Event 1 is a high-flow event that occurred from August 1 to August 5, 2012, for about 72 hours. Event 2 is a low-flow event which happened from August 9 to August 11, 2012, for about 48 hours. The upstream boundaries for Events 1 and 2 are shown in Figures 4(a) and 6(a). The maximum inflows at ChungSan Bridge for Events 1 and 2 are approximately 400 and 40 cubic meters per second (m^3/s), respectively. The flow is calculated by post-processing the measured river stage and velocity at ChungSan Bridge. The downstream boundaries for Events 1 and 2 are also shown in Figures 4(a) and 6(a). The maximum stages at the downstream boundary, Kamalan Bridge, are 2.5 and 0.8 m, respectively. Because the location is near the Pacific Ocean, the stage variation of Kamalan Bridge is strongly impacted by the tidal effect.

For Event 1, Figures 4(b) and 4(c) show the stage hydrograph obtained for the proposed system as compared to the observed stage at the Zhangwei and Leawoo bridges. For reference, the stages at the observed locations for the first 2 hours were not included in the process because the model was warming up. The μGA reached the nominal convergence at the 21st iteration and the fitness value is 0.00857 (see Figure 5). The recommended best-fit Manning's roughness coefficients are 0.0343 for the left bank, 0.0325 for

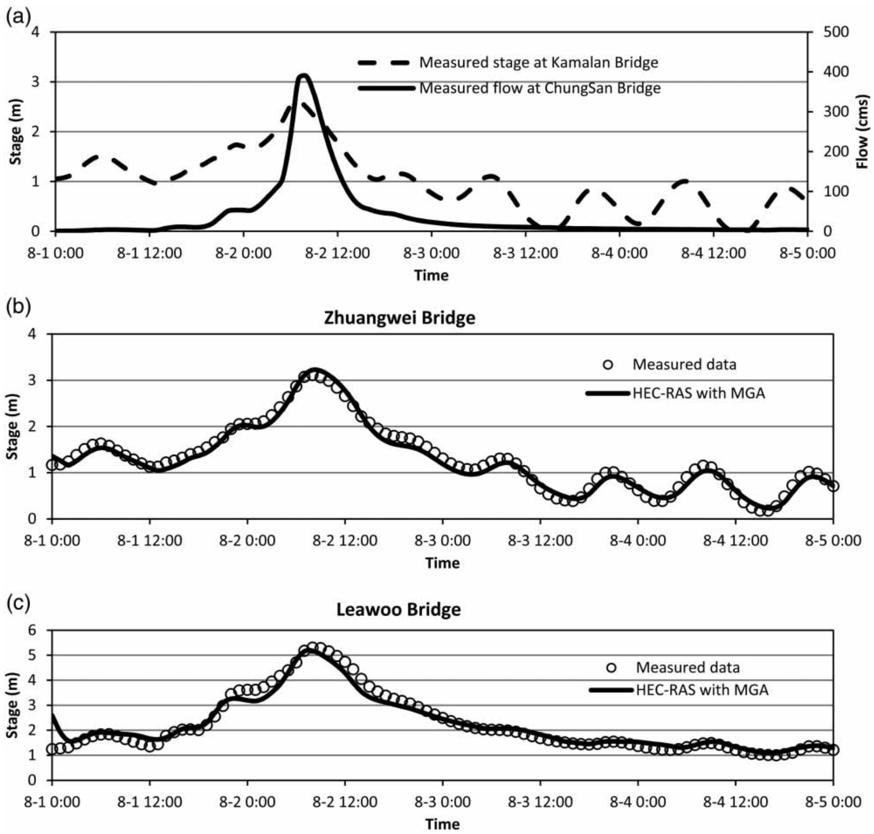

Figure 4 | Comparison of modeled stage with observed data for Event 1: (a) upstream and downstream boundary conditions; (b) comparison of stage at Zhuangwei Bridge; (c) comparison of stage at Leawoo Bridge.

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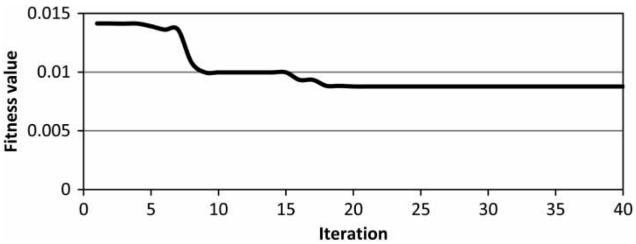

Figure 5 | Iteration vs. objective function value for Event 1.

the main channel, and 0.044 for the right bank. In terms of the four measurement criteria, the results are shown in Table 1. The MAEs are below 0.13 m. The PEs are less than 5%, which are 0.23 m for Leawoo Bridge and 0.05 m

Table 1 | Comparison criteria for Event 1

Location/Measure	MAE (m)	CE	PE (%)	R^2
Leawoo Bridge	0.133	0.971	–4.899	0.987
Zhuangwei Bridge	0.098	0.974	1.067	0.988

for Zhuangwei Bridge. For the other two statistics-related measures, the CEs and R^2 are approximately 0.97 and 0.99, respectively. Theoretically, if the CE and R^2 are closer to 1, the simulated stages fit better with the measured data. For Event 1, the computed water levels are in fairly good agreement with the observed data. The recommended Manning's roughness coefficients are also within the realistic range proposed by Chow (1959). In that regard, the proposed integration can provide hydraulic modelers information in terms of setting up the Manning's roughness coefficients in the hydraulic models. In this tested event 1, the converged Manning's roughness coefficients represent clean, straight full stage in the main channel and high grass in the floodplain, respectively (Chow 1959). It matched in-situ high-flow condition in the Yilan River.

Figures 6(b) and 6(c) show the stage hydrograph obtained for the proposed system as compared with the observed stage at the same locations for Event 2. The μGA coincidentally reached the nominal convergence at the

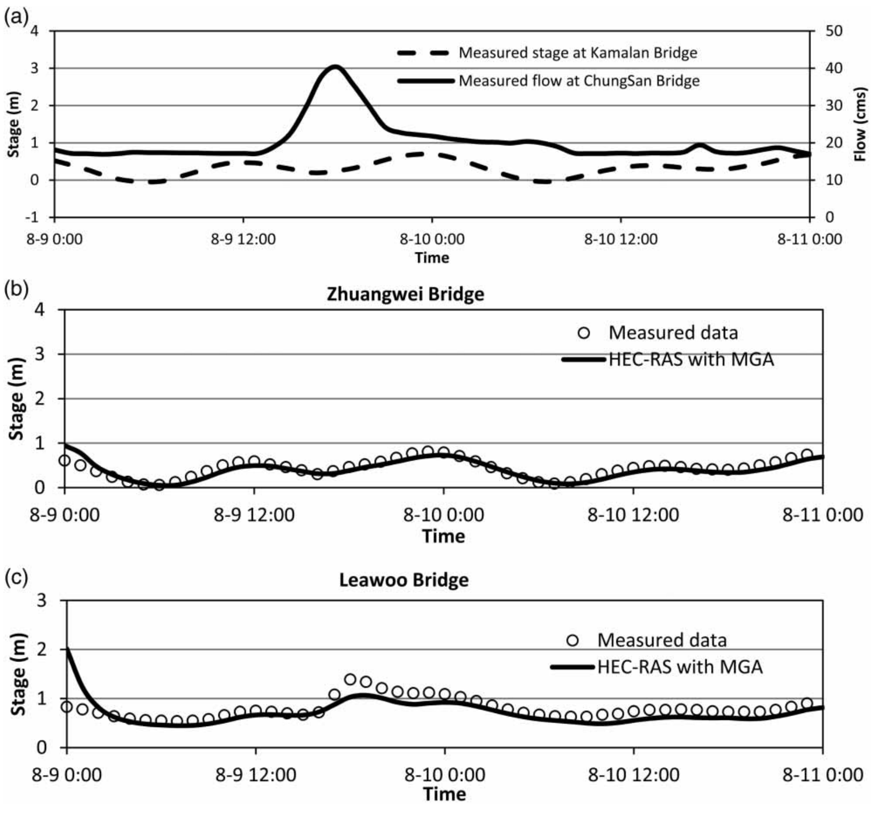

Figure 6 | Comparison of modeled stage with observed data for Event 2: (a) upstream and downstream boundary conditions; (b) comparison of stage at Zhuangwei Bridge; (c) comparison of stage at Leawoo Bridge.

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24th iteration, the same as the previous event. The fitness value is 0.0272 (see Figure 7). The recommended best-fit Manning's roughness coefficients are 0.0719 for the left bank, 0.0277 for the main channel, and 0.0739 for the right bank. In terms of the four measurement criteria, the results are shown in Table 2. For the Zhuangwei Bridge, the MAE is below 0.07 m and the PE is approximately 12%, which in terms of absolute value is 0.09 m. For the Leawoo Bridge, the MAE is below 0.05 m. The PE is approximately 15% and 0.19 m in terms of absolute value. For the statistics-related measures, the CEs for Zhangwei and Leawoo bridges are 0.853 and 0.885 and the R^2 are 0.942 and 0.895, respectively. In terms of the four performance measures, the proposed system for Event 2 did not perform as well as it did for Event 1. The recommended Manning's roughness coefficients for banks within the realistic range proposed by Chow (1959) are higher, compared to the previous event. The CE and R^2 are close to 0.9, meaning the simulated data well-fitted to the observed data. In this tested event 2, the converged Manning's roughness coefficients represent clean, straight full stage in the main channel and scattered brush, heavy weeds in the floodplain, respectively. It makes senses that the roughness or resistance for banks was high since only a little water existed and flew slowly for the low-flow event.

All the optimized Manning's roughness coefficients fell in the realistic range according to the references proposed

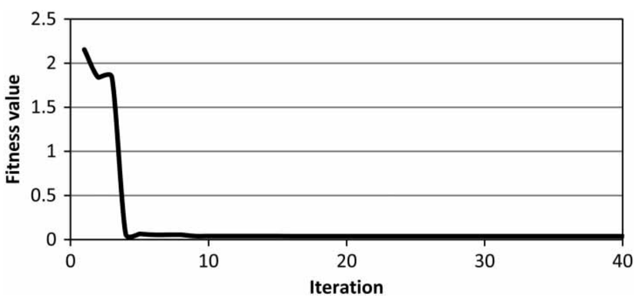

Figure 7 | Iteration vs. objective function value for Event 2.

Table 2 | Comparison criteria for Event 2

Location/Measure	MAE (m)	CE	PE (%)	R^2
Leawoo Bridge	0.050	0.885	−15.393	0.895
Zhuangwei Bridge	0.068	0.853	−11.730	0.942

by Chow (1959). The variation of roughness coefficients to different flow conditions is also consistent with the theory that for a free-flowing river, roughness decreases with increased stage and flow (USACE 2010). However, there would be a risk that the converged Manning's roughness coefficients achieve the minimal fitness value but fall beyond the realistic physical condition. By looking at the four evaluation criteria, the proposed system in the low-flow event seemed to not work as well as it worked in the high-flow event. Taking Leawoo Bridge as an example, the CE of 0.971 in the high-flow event decreased to 0.885 in the low-flow event, while the PE increased from 5 to 15%. Two major uncertainties could possibly impact the accuracy of the modeling results and the associated optimizing process. One is the upstream inflow measurement at the boundary condition; the other is a detailed surveying of cross sections. The upstream inflow condition affects the results at Leawoo Bridge, which is close to the upstream end. Compared with the high-flow event, the low-flow event has the disadvantages of a shallow water depth and low-flow velocity. Both of these increase the challenges for taking measurements in the field to calculate the average velocity and its related estimation of flow. The detailed surveying of waterway cross sections is necessary to improve the accuracy of modeling. HEC-RAS assigns the Manning's roughness coefficients and calculates the governing equations according to the left-bank, main channel, and right-bank locations. A clear definition of those locations in the model has a positive impact on the accuracy of the calculation; so do the optimized Manning's roughness coefficients. Nevertheless, applying the μGA is still very efficient in the hydraulic modeling to identify the proper Manning's roughness coefficients when detailed information is not available. It yields results of very acceptable accuracy in terms of comparison with measured data.

The cross section and peak simulated stage at the upstream of Leawoo Bridge for Event 1 are shown in Figure 8. This is an example to show that the bank may be filled with no water for most of the simulation time during low-flow conditions (ex. Event 2). The converged Manning's roughness coefficients for Event 2 for both banks are almost twice as much as for Event 1 (Table 3). It is explained that the water in the banks was too low and flow velocity was very slow. As a consequence, the Manning's roughness

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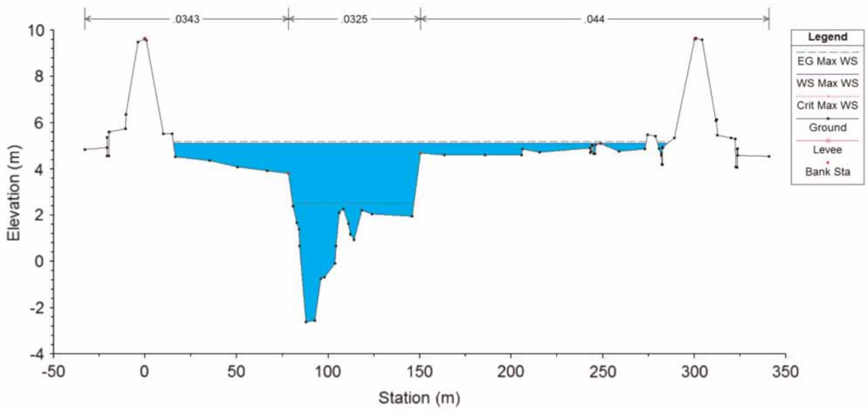

Figure 8 | The cross section and simulated stage at the upstream of Leawoo Bridge for Event 1.

Table 3 | Optimized Manning's roughness coefficient for Events 1 and 2

Name	Time	Total duration (hour)	Left bank	Main channel	Right bank
Event 1	8/1/12–8/5/12	96	0.0343	0.0325	0.0440
Event 2	8/9/12–8/11/12	48	0.0719	0.0277	0.0739

coefficients were high in the 1D hydraulic model to reflect the flow condition in the banks. This leads to another issue to be discussed: the μGA converges to certain Manning's roughness coefficients based on the measured data. However, the empirical parameters, such as Manning's roughness coefficients, are actually not the main factors to influence the simulated results, ex. the river stage. Figure 9 shows a comparison of the sensitivity of simulated stages with respect to different Manning's roughness coefficients. The event 1's boundary conditions were applied. The black line shows the simulated stages from the model with original converged Manning's roughness coefficients (0.0343, 0.0325, and 0.0440). The gray dash line means the simulated stages from the model with another converged Manning's roughness coefficients from Event 2 (0.0719,

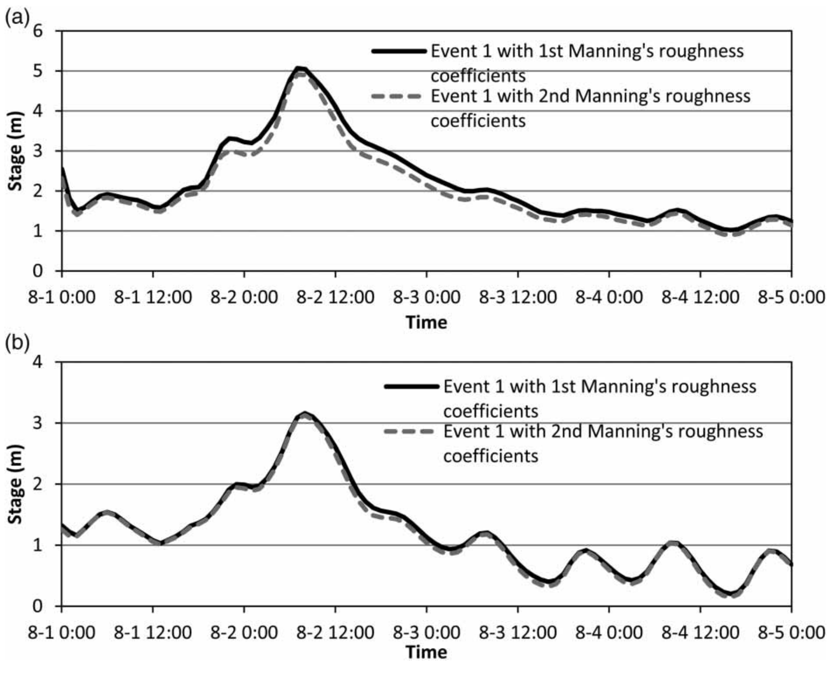

Figure 9 | Comparison of modeled stages with different Manning's roughness coefficients for Event 1: (a) upstream of Leawoo Bridge; (b) Zhuangwei Bridge.

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0.0277, and 0.0739). The results show the Manning's roughness coefficients plays a not very significant role at Zhuangwei Bridge which is very close to the downstream end. The tidal effect or the inertia force has a bigger impact on the stage. However, the difference is significant for the simulated results of Leawoo Bridge. The tidal effect has less influence on the bridge since it is far away from the downstream end. In conclusion, applying μGA to retrieve the optimized Manning's roughness coefficients is beneficial to increase the accuracy of hydraulic models. However, the users may need to survey the applied condition and see if the parameters are solely dependent on a specific condition. For example, if the μGA is applied to obtain the Manning's roughness coefficients only based on the Zhuangwei Bridge, the converged results may be less meaningful due to the significance of downstream tidal impact for the stage at the bridge. Despite the insignificant issue, the μGA is still a good tool which is used by the hydraulic modelers to obtain optimized parameters.

CONCLUSION

In this study, a VB-based automated system that integrates a 1D river hydraulic modeling tool, HEC-RAS, and a search heuristic, μGA, was proposed to find the optimized Manning's roughness coefficients in the waterway for a given event. The system was tested in the Yilan River Basin, an experimental watershed which has been developed by WRA and TTFRI since 2012. Using two events, one high flow and the other low flow, the measured river stages at two locations in the stream were used to evaluate system performance. Applying μGA and measured stages, the Manning's roughness coefficients could be identified in the HEC-RAS model and the simulated stages showed a good agreement with the measured data for the two events. Comparatively, the results of low-flow conditions are not as good for the high-flow conditions in terms of four measures' results. The 1D HEC-RAS modeling tool has the advantages of efficiency and accuracy. The optimization algorithm, μGA, can efficiently converge to the optimal solution to meet the objective function requirement. The proposed system, which integrates HEC-RAS and μGA, can provide engineers with a good way to identify the optimized Manning's roughness coefficients and run the hydraulic model with the concurrent events while the onsite information is limited. For further applications, the operators can use the system to efficiently and accurately forecast the downstream stage and respond to the flood in time.

Ding *et al*. (2004) mentioned that the best estimation of the parameters not only are dependent on the objective function but also are determined by the uniqueness and stability of the minimization process. The application of μGA is proved to satisfy the requirements. However, using the technique to identify the parameters in the model takes precautions. For example, the objective function is a key for the performance of μGA. The goal of the objective function is to minimize the difference between measured and simulated stages at selected locations. The selected location is not recommended close to the downstream end since it is highly influenced by the tidal effect. Thus the searching process of optimized Manning's roughness coefficients may not be significant. The major driven force to the variation of stage is the downstream boundary condition or the inertia force. The impact of Manning's roughness coefficients is less significant with respect to the objective function. Regarding the application of μGA or other techniques in parameter optimization in hydraulic models, the users must pay attention to the significance of parameters in the objective function. The further explanation of optimized parameters in terms of the meaning in the process may need to be addressed in the future studies.

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