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An indirect approach for discharge estimation: A combination among micro-genetic algorithm, hydraulic model, and in situ measurement

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ABSTRACT

To develop a flood forecasting system, estimating the discharge hydrograph is essential. In general, discharges at gauged river sites are calculated by applying simple methods such using the relationship of measured stages to discharges, namely rating curves, or multiplying mean velocity with flow cross-sectional area. The flow cross-sectional area can be determined using measured stages from river geometry surveys. The mean velocity is considered to be the measured surface velocity multiplied by a conversion factor. The conversion factor can be estimated by using the regression approach given a known discharge. However, to obtain discharge for extreme events is difficult. Extrapolation was necessarily made among known discharges to “guess” the discharge hydrograph during floods. Therefore, a novel approach which combines micro-genetic algorithm (μGA), a one-dimensional (1-D) flood routing model, and onsite instrumentation is being proposed to obtain the optimal conversion factor, and therefore the discharge hydrograph. This approach was validated using two events: one synthetic test and one recorded event at Yilan River. The results showed that μGA efficiently converged to an optimal conversion factor which showed a less than five percent difference when comparing with synthetic versus observed values. A sensitivity analysis was also conducted to assess the impact of the quantity of selected gauged stations on the value of optimal factor in the optimization process.

1. Introduction

Discharge estimation is essential for engineering applications, such as water resources management and the flood forecasting system. For flood disaster prevention, an effective and accurate approach to estimate incoming discharge will help those downstream respond to possible threats. The approaches to estimate discharge are categorized into contact and noncontact approaches. The contact approach means that the measurement devices touch the water directly. Contact approaches most commonly use the current meter to sample velocity along different verticals. The sampled values of velocity can be used to calculate discharge by multiplying velocity with the cross-sectional area or controlled area. Advanced techniques such as ultrasonic techniques are also applied to measure the velocity. For example, Acoustic Doppler Current Profilers (ADCP), a technique using ultrasonic technique, is used to estimate discharge and acquire detailed bathymetry [13]. He also applied ADCP to assess longitudinal dispersion coefficients in the river. However, the contact approach is usually time-consuming and always poses a concern with regard to the safety of the instrument and operators during extreme events. As a result, the noncontact approach was developed to avoid direct contact with the water. The most common noncontact approach is to measure water stage with a mounted device. The mounted device is used to measure the river stages. Discharge is then obtained by using a stage – discharge rating curve. However, there are many uncertainties in the rating curve, such as hysteresis during flood-wave propagation [18]. Thus, other technologies have also been developed to measure discharge. Tsubaki et al. [28] used Large-Scale PIV (LSPIV) and Space-Time Image Velocimetry (STIV) to measure flood discharge in a small-sized river. Bjerklie et al. [2] estimated the discharge using remotely sensed hydraulic information which included water surface and channel widths. These, coupled with channel slope data was used to estimate discharge. Negrel et al. [32] applied earth observation (EO) measurements of river surface hydraulic variables to estimate river discharge based on limiting assumptions about river flow. The assumptions were

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used to simplify the Saint-Venant equations to two expressions for the discharge and the discharge expressions which are a function of the surface variables and hydraulic parameters. In addition, radar sensors have been developed to measure surface velocity [6,9]. The measured surface velocity is converted to mean velocity to estimate discharge by multiplying velocity and cross-sectional area, or through used of an entropic model.

Other than physical devices using for discharge measurements, nonphysical numerical models also have been applied to estimate continuous discharge. Moramarco et al. [19] developed a physics-based rating curve model (RCM) to estimate discharge. Tayfur et al. [27] mentioned that the RCM model requires that the stage hydrograph be observed at least until peak stage occurs, thus inhibiting the model to be applied to real-time operation. Developed from the RCM model, a genetic-algorithm (GA) based approach called GA-RCM was developed to estimate discharge. None of them considered on-site physical conditions such as topography and channel geometry conditions. As far as the authors are aware, only a few studies have applied physically-based flood routing models that use measured water levels or flow velocity to estimate real-time discharge. Aricò et al. [1] developed a one-dimensional (1-D) flood routing model to estimate discharge by means of a water level hydrograph analysis. The upstream discharge was estimated using instrument data, and was tested using a sensitivity analysis. The modeling results were validated with laboratory experiments. Corato et al. [5] applied a 1-D flood routing model and measured water levels and flow velocity to estimate the discharge hydrograph. The flood routing model was applied to route recorded stages while a velocity distribution model was used to assess the instantaneous discharge. The studies above applied a water level hydrograph or a velocity distribution model to assess the discharge which could not validate in real time operations.

This study integrates a flood routing model, machines learning technique, and in situ measurements to identify the factor that converts the measured surface velocity to mean velocity which is then used to estimate the discharge hydrograph. The integration can be applied to real time operations. The factor could be verified by using the measured stages versus modeled results during the extreme events. Furthermore, the flood forecasting system can apply the approach to improve its accuracy during floods. It is a novel approach and, to the authors' knowledge, no similar studies have been developed.

This paper is organized as follows: Section 1 describes the methods applied in the study, which includes the theoretical background of the hydraulic model applied for flood routing, the approach to estimate discharge using measured surface velocity and measured stages, instrumentation, the assumption of μGA and its application in the study. Section 2 provides a short description of the study area. Section 3 describes the measured criteria used to evaluate performance and shows the results from two events and a sensitivity analysis of μGA's results with a number of gauged stations' data. Conclusions are drawn in the Section 4.

2. Methods

2.1. Micro-genetic algorithm (μGA)

The GA is an artificial intelligent technique commonly used to optimize search problems. Park et al. [21] integrated a flood routing model, UNET, and multi-objective GA (MOGA) to develop a washland optimization model. The term μGA refers to a small-population GA with re-initialization. The idea was suggested by theoretical results obtained by Goldberg [11] and Krishnakumar [14] first implemented the μGA using a population size of five, a crossover rate of one, and a mutation rate of zero. Krishnakumar [14] and Senecal [26] both reported faster and better results with their μGAs. [3] showed that using the μGA can decrease the computational run time by 50 percent, even for the "worst-case" problems for the conventional GAs. Tayfur et al. [27] applied traditional GA to estimate discharge using 100 chromosomes and 10,000 iterations. Using the μGA method, the number of chromosomes and number of iterations can be significantly decreased and the efficiency of calculation can be improved. In this study, the μGA was implemented in the optimization process. In ths study, Krishnakumar's assumptions (1990) for μGA were applied in this study. These assumptions include a population size of five, a crossover rate of one, and a mutation rate of zero. The flowchart (Fig. 1) displays the working process of the proposed integration of 1-D flood routing model, HEC-RAS, and μGA. The following steps are listed to describe how HEC-RAS and μGA work together.

Step 1: A group of five chromosomes ($N=5$) are randomly generated. Each chromosome can be decoded to a factor α which converts measured surface velocity to mean velocity. Here the range of α is defined within 0 to 1 due to assume that the mean velocity is always less than the surface velocity. The binary string is used to code the factor into a chromosome. Since the factor is generated, the mean velocity is calculated by multiplying α with the measured velocity. The discharge hydrograph used for the upstream boundary condition is estimated by the area velocity method in Section 2.3. using a known cross-sectional area.

Step 2: A 1-D flood routing model runs with the estimated upstream discharge hydrograph to obtain the fitness value. The minimum fitness value is the objective function and is calculated

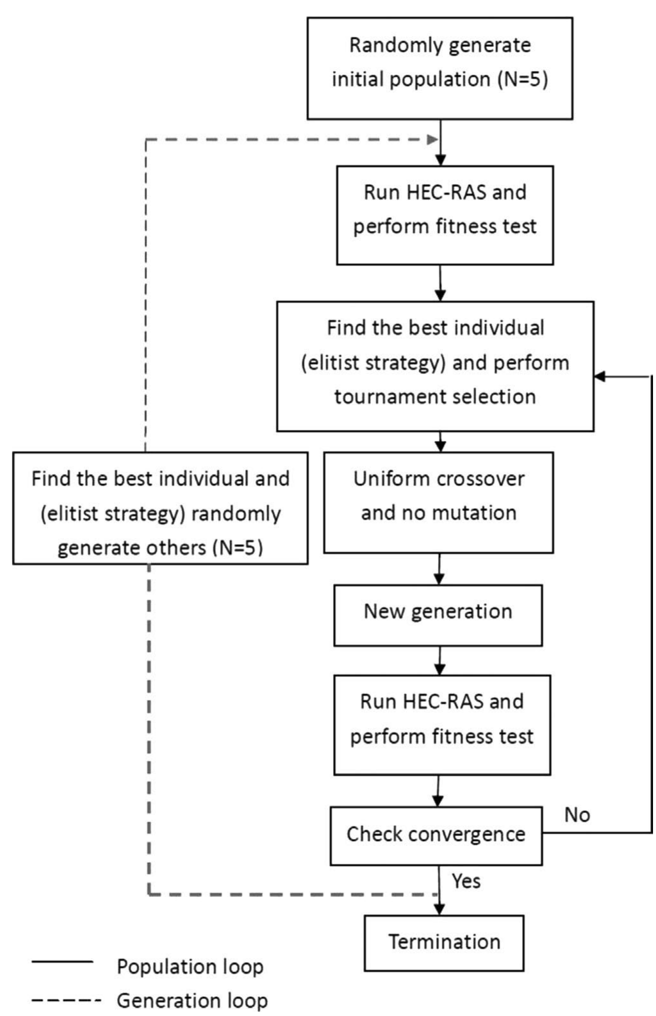

Fig. 1. Flow chart of the optimization progress.