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EVALUATION OF THE FLOOD ROUTING FOR THE LOWER ZAB RIVER USING GENETIC EXPRESSION PROGRAMMING

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ABSTRACT

Flood routing is an analytical method for determining a flood hydrograph in a river section by analyzing flood flow data from one or more upstream sections. Flood routing is used in hydrological analyses for major issues such as flood forecasting, flood protection, reservoir design, and spillway design. Two basic types of routing can be distinguished, which are reservoir routing and channel routing, the change in the hydrographic shape of the channel as it moves down the channel. A Lower Zab river in the north of the country was chosen as a case study. The Genetic expression programming (GEP) method was used in the modeling of the Lower Zab river event. The need to use a few hydrological parameters, such as inflow and outflow and time, was the most prominent positive feature of this application. The results showed the high suitability of the proposed predictive model for flood routing based on the simulation results and the possibility of using the GEP model as a suitable alternative to traditional methods such as the Muskingum model.

Keywords: Lower Zab River, River Routing, Muskingum Method, GEP

I. INTRODUCTION

The importance of studying floods and their effects on human life and the infrastructures of the environment in which it resides comes from the serious damage they cause to lives, property, and the economic system. Flood peak values are required for the design of bridges, culvert waterways, dam spillways, and scour estimation of hydraulic structures, [1,2]. Flood routing has become one of the main criteria in designing flood protection measures, as it allows responsible departments to take appropriate measures to address the behavior of flood waves in rivers and to find adequate protection and cost-effective solutions, [3, 4, 5].

Gene Expression Program (GEP) is a new technology for creating computer programs and a powerful evolutionary method derived from Genetically Modified Programming (GP), as it reflects the knowledge acquired through the learned models, which was presented by Candida Ferreira, [6,7].

GEP is described in the form of linear string letters of a specific length (called chromosomes), and is expressed as trees (ETs) of various sizes and shapes during the subsequent fitness assessment. The GEP method has greater flexibility and the ability to explore the field of research compared to the traditional GP method by separating the genotype and phenotype. The GEP procedures yield positive results for a wide range of solutions including symbolic regression, optimization, time series analysis, identification, logic, automatic synthesis, etc., [8,9,10].

Many researchers have used AI methods in various technical fields, including civil, geotechnical, and environmental engineering. As a new adaptive algorithm for solving technical problems, some researchers have recommended the use of genomic programming [6], and others have used a genetic programming approach in flood routing, [11,12,13]. A Neuro-fuzzy approach has been used to predict the Muskingum model, [8,14]. Some research studies have indicated the use of gene expression programming in the development of a staged discharge

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curve for the Pahang River and other rivers, [15,16].While other researchers predicted Muskingum flood orientation parameters using databases, and developed a new nonlinear Muskingum model for lateral flow guidance, [17]. The researcher[13] predicted penetration depth for diving, water jetting using soft computing methods, and expected cleanliness in a curved channel using GEP around the side weir.

The aim of this study is to develop a model to predict the flooding routing of the Lower Zab river using the GEP method. Two qualities, appropriateness measures, namely, square root error (RMSE) and coefficient of determination (R^2), were used to evaluate the performance of the models and compare them with the observed results.

II. AN OVERVIEW OF GEP

Figure 1 shows a flowchart of the Genetic Expression Algorithm (GEA). The process begins with the random production of primary random chromosomes, and then they describe the chromosomes and evaluate their individual suitability. Individuals are selected for reproducing with modification according to fitness, leaving the progeny with new qualitative characteristics, [9,18,19]. In contrast, members of this new generation undergo the same developmental process: gene expression, selection, and reproduction with change. For several generations, the process is repeated until a solution is found. Noting that the outcome is not only regeneration, but the genetic procedures capable of creating genetic diversity also include replication. The genome is duplicated and transferred to the next generation during replication. Replication alone cannot introduce variation: genetic variation is introduced into the community only through the actions of the remaining operators. These operators select the chromosomes to be altered randomly, knowing that the chromosome in GEP is modified or not modified by one or more operators simultaneously, [17].

III. OPENING FRAMES AND GENES FOR READING

Chromosomes and expressive trees (ETs) are the main components of GEP. The chromosome is usually (one or more) of the genes that give a mathematical expression. The mathematical code for a gene is presented in two languages, the Karva language (such as the language of genes) and the language of expression trees (ET), [17]. GEP genes consist of two parts, the head, and the tail. Some math operators are used to notate mathematical expressions, encoding, variables, and constants. The tail includes terminal symbols which are variables and constants. If the mathematical expression is not explained by the terminal symbols in the header, then other symbols are used. With GEP technology, selection, transport, and crosscutting are the primary (recombination) operators. Through these operators, the chromosomes are modified to achieve better fitness for the next generation. The operator modifiers identified at the beginning of model construction show a certain probability of the chromosomes. The usually recommended mutation rate is 0.001 to 0.1. Additionally, 0.1 and 0.4 are recommended, respectively, for transport and crossover operators, Fig. 1, [9,18].

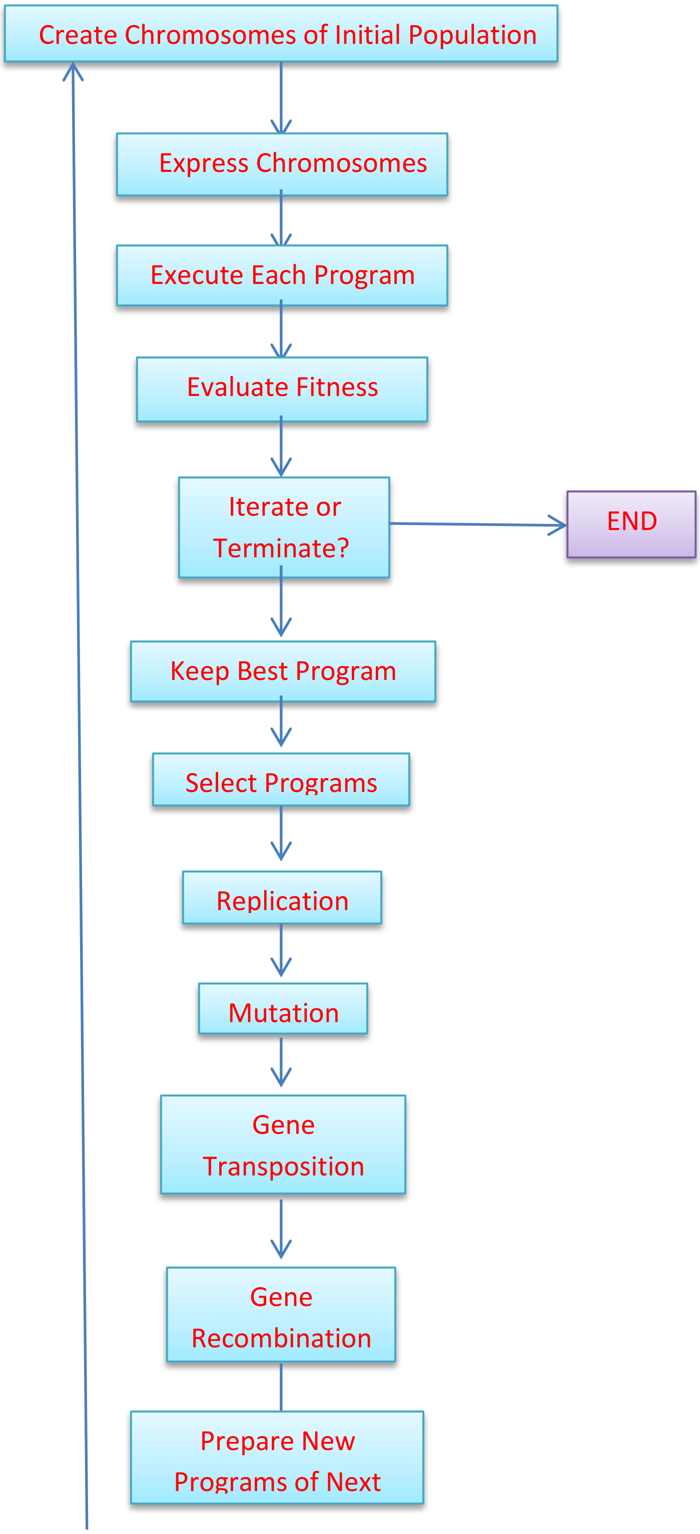

Fig. 1: Flowchart of Genetic Expression Algorithm (GEA).

The main purpose of developing GEP models is to establish the mathematical function of flood prediction. The variables used in implementing the GEP model are the flow and time values. It applies five main steps in operating the model, and the first step is choosing a fitness function. The fitness of an individual program is measured by the following, [13]:

$$F_i = \sum (M - |C_{i,j} - T_i|) \quad (1)$$

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Where M=specific selection range; C (i, j) =specific chromosome value i returned on j (out of Ct fitness cases); and Tj=specific value for fitness case J. When |C (i, j) − Tj| (precision) is lower or equal 0.01, then precision is zero, and fi = f_{max} = CiM. The precision is equal to zero. Used M=100 and thus f_{max} =1,000 in the case study.

The most prominent feature of fitness is the ability of the system to find the best solution for itself.

The second step involves identifying the set of T and F terminals to generate the chromosomes. As the terminal group includes the independent variable in this problem, i.e. Q = f (I, T). The third step is choosing the chromosomal structure such as head length and gene numbers while choosing the link function is the fourth step, [13,20,21].

Finally, the fifth step is selecting the set of transmitters that cause the variations and modifiers. All genetic operators (mutant, transposition, and recombination) are combined with the enhanced GEP parameters. This key step is choosing the chromosome structure, that is, head length and a number of genes.

The best results from GEP models after several tests are: head length, h = 10, and 3 genes per chromosome. Multiplication associated with sub-ETs (genes) of GMS, [13,19]. Finally, as a set of genetic operators, all genetic operators have been incorporated. GEP model training parameters are shown in Table 1.

Table 1: GEP Optimization Parameters.

Parameters	Description of Parameters	Setting of Parameters
P_1	chromosomes	30
P_2	Fitness function error type	R^2
P_3	Number of the genes	3
P_4	Head size	10
P_5	Linking function	*
P_6	Function set	+, -, *, /, 1/X, $X^{0.5}$, $X^{0.3}$,X^2,X^3
P_7	Mutation rate	0.045
P_8	One- point recombination rate	0.32
P_9	Two - point recombination rate	0.32
P_{10}	Inversion rate	0.15
P_{11}	Transposition rate	0.15

The performance efficiency of the GEP model is validated by statistical measurement factor (R2) and square root error (RMSE), [3,16].

$$R^2 = [\sum Qx\, Qy/(\sum Qx^2 \sum Qy^2)^{0.5}]^2 \qquad (2)$$

$$RMSE = [\sum(Qo - Q_p)^2/n]^{0.5} \qquad (3)$$

Where Qx=(Qo-Qom); Qy=(Qp- Qpm); Qo=observed values; Qom=mean of Qo; Qp=predicted value; Qpm=mean of Qp; and n=number of samples.

IV. STUDY AREA

The Lower Zab watershed, which includes the massive Dukan Dam, is one of the most significant catchment areas in Iraq's northern region. The Greater Zab (Upper Zab), Diyala, Khabur, and Al-Adhaim are four other catchment areas. The northern area of Iraq, like other parts of the world, has seen a lot of changes in the last few decades climate change, long-term droughts, water scarcity and sporadic flood events have had a major impact. Climate change has had a negative impact on a variety of regions across the region and remains a source of concern, while the impact of floods sometimes appears during the winter due to heavy rains and a lack of specific management of water resources in that area. The layout and boundaries of the river as shown in Fig.2 and Table 2, [22].

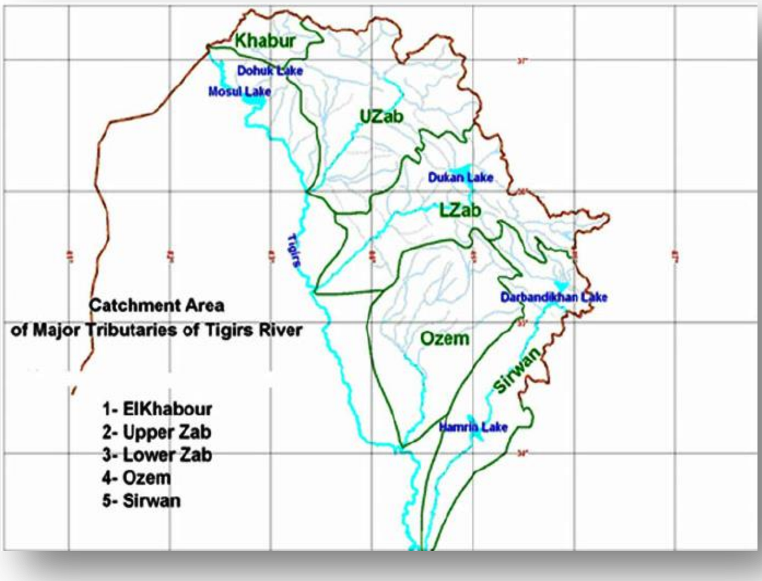

Fig. 2: Layout and Catchment Boundaries of Lower Zab River.

Table 2: Geomorphologic Parameters for the Lower Zab River.

Geomorphologic parameters	DEM value	GTM value	Geomorphologic parameters	DEM value	GTM value
Watershed area A_W	20030 km^2	19 km^2	**Watershed shape factors S_b**	3.52	3.72
Watershed perimeter L_p	1537 km	1198 km	**Watershed slope % L_s**	0.000202	0.000166
Basin length L_b	265.6 km	271.5 km	**Main canal slope C_S**	11.597	5.95
River length L_r	527.1 km	470.4 km	**Elongation of watershed L_l**	20.265 km	20.22
Tributary length L_t	1642 km	1053 km	**Elongation ratio R_r**	0.60	0.584
Form factors R_{ff}	0.248	0.268	**Relative ratio R_r**	0.00224	0.00233
Stream frequency C_f	0.0819	0.0532	**Relief ratio R_h**	0.0129	0.0103

V. RESULTS ANALYSIS AND DISCUSSION

Hydrological and hydraulic methods are commonly used for flood routing. During the flood period, hydrological methods depend on the principle of continuity and the relationship between discharge and temporary storage of excess water volumes, [4, 23,24,25]. Whereas numerical solutions of thermal diffusion equations or one-dimensional Saint-Venant equations for unstable flow increasingly diverse in open conduits are used in hydraulic routing methods. When comparing hydrological and hydraulic methods, hydraulic methods usually better explain the shape of the flood wave. On the other hand, hydraulic methods are limited in their practical application due to their high requirements for computing technology, as well as the quantity and quality of the input data, [5,26,27].

In this study, the gene expression programming (GEP) technique is compared to the Muskingum model as an alternative approach.

Applications of the GEP model are characterized by the use of fewer hydrological parameters (inflow, outflow, and time) compared to Muskingum's model. The Lower Zab river was chosen as a suitable site for constructing the GEP model, as the inflow and outflow hydrographs show different peak drainage characteristics, Fig. 3[22].

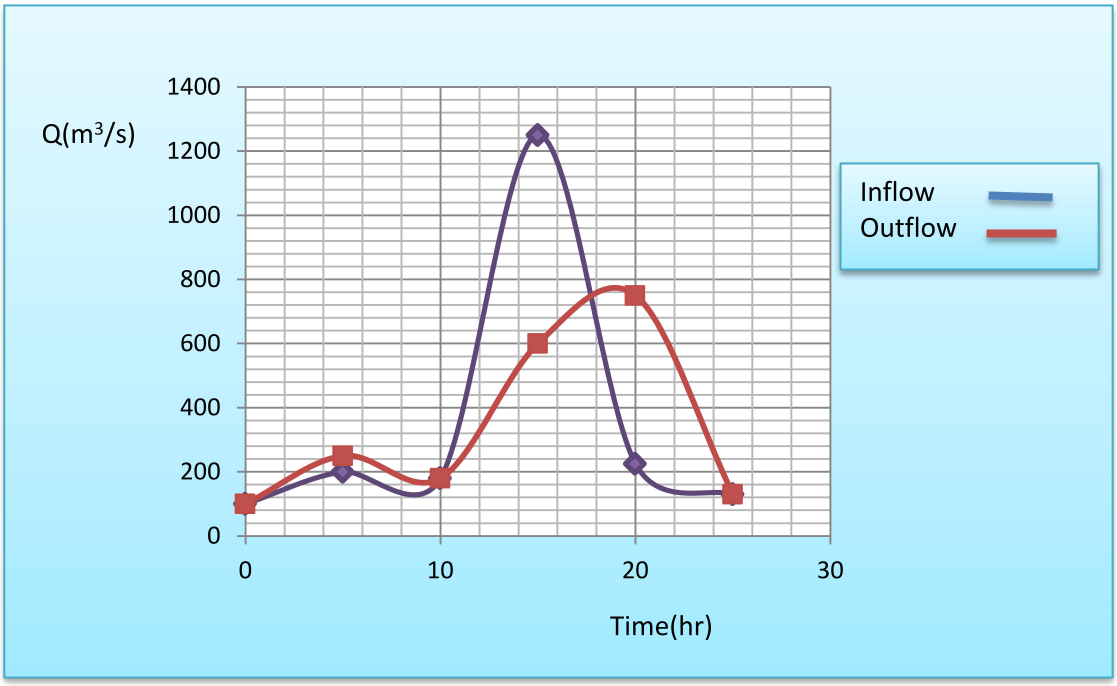

Fig. 3: Flood Hydrograph for Lower Zab Watershed.

Initially, the program was unable to obtain a sufficient predictive model for the multiple peaked hydrograph of the case study. As a result, the hydrograph was divided into two single peaked hydrographs. Effective models for hydrographs were obtained using three brackets. For the first and second single peaked outflow hydrographs of case studies, the simplified analytical form of the proposed GEP model is expressed as follows:

$$Q = [\{1/(I^{0.5}-T) - T- 6.59\}][I - 2I/(761\ T - I - 9.41)][(2I + T - M9.98)^{0.5} + (10.46/(T - 9.98)] \quad (4)$$

$$Q = [0.74 - 1/0.74\ I\ (T - 5.0.1)][126.1 + 0.15I^{3} - I][4.11 - I^{0.3} + 16.89/(I+2.90)]^{0.3} \quad (5)$$

Where (I) and (Q), are the amount of inflow and outflow respectively at the time interval (T).

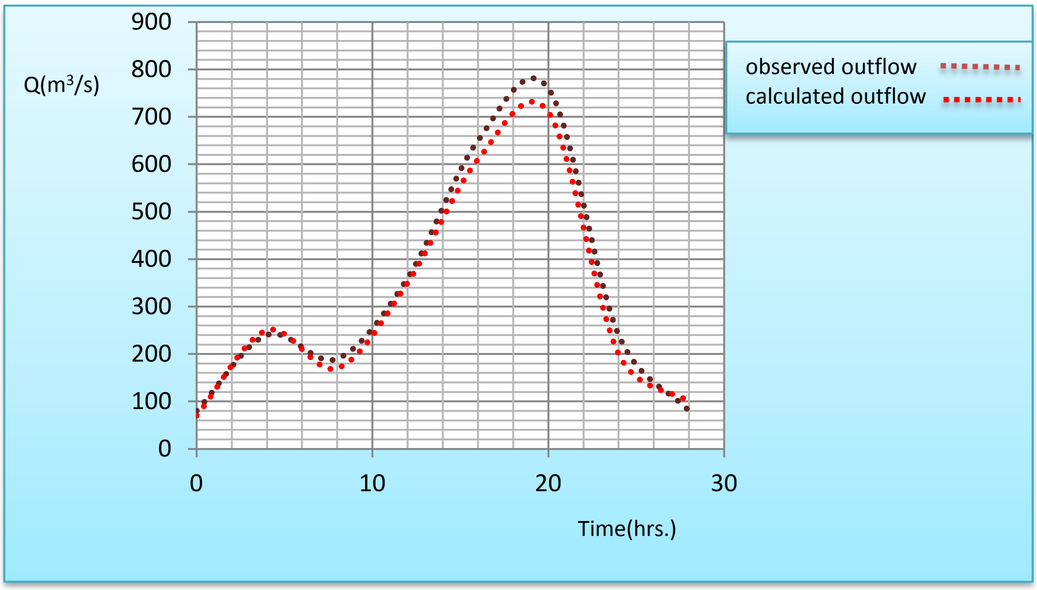

Fig. 4: Observed and Predicted Outflow.

As shown in Fig.4, the GEP model will do an excellent job of routing the multi-peak hydrograph of this study. When compared to the current case study prediction, the proposed GEP approach yields good results (R^2 = 0.9684 and RMSE = 6.21), Fig.5. Without using the Muskingum model, the peak is predicted with high accuracy.

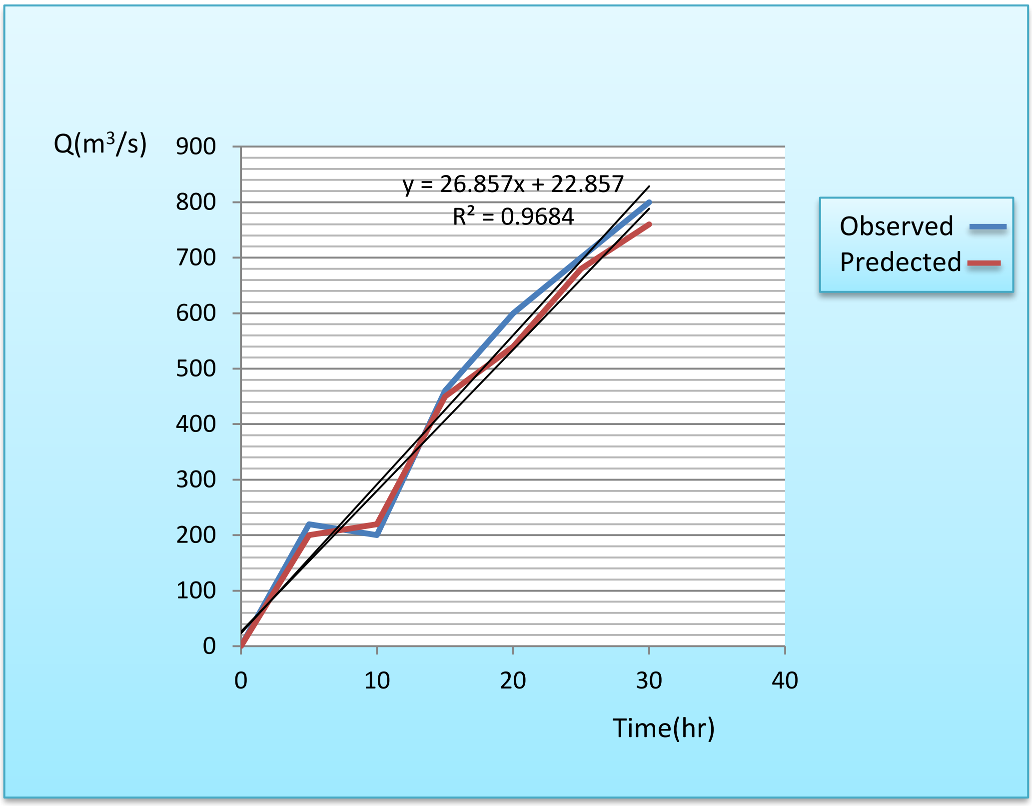

Fig. 5: Comparison of Observed Outflow and Predicted Outflow.

The results show that hydrological routing can be adopted because it is relatively easy to implement and reliably, in addition to the sobriety of constructing a GEP model without the need for parameters or a Muskingum flood routing model.

VI. CONCLUSIONS

This study demonstrates the utility of the GEP model for flood routing in natural channels (Lower Zab river). A new model can be used to predict flooding in natural rivers with a GEP approach. The proposed GEP model was tested, and the model results were found to agree well with the observed values. According to the comparison, the model has the lowest mean root error and highest determination. The GEP model provides predictions of outflow for a case study with R^2 = 0.9684 and RMSE = 6.21. According to the results, GEP techniques can be used to model flood routing more efficiently and reliably than traditional methods using available data.

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