RESEARCH ARTICLE Indian Journal of Agricultural Research, Volume 60 Issue 1: 46-54 (January 2026)

A New Approach for Flood Routing Modelling using a Neuro-fuzzy System 'For a Contribution to the Protection of Agricultural Land and Crops'

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10.18805/IJARe.AF-983

ABSTRACT

Background: Monitoring the phenomenon of flood routing is of great techno-economic interest and a preventive factor for agricultural land and crops protection. Particularly, modelling the phenomenon constitute an essential component. This work presents the development and evaluation of a numerical model for simulating flood routing by optimising the temporal variation of downstream flow in river reaches. The proposed approach employs an Adaptive Neuro-fuzzy Inference System (ANFIS) as a stochastic, data-driven tool.

Methods: Two model structures were tested; A three-input version ANFIS (3 Var) based on inflow, outflow and the discharge derivative ($\partial Q/\partial t$) at time t. And an extended four-input version ANFIS (4 Var) that additionally incorporates the derivative at $t+\Delta t$. The models were applied to two real-world cases. The first case involved a non-smooth hydrograph from the river wye in the United Kingdom and the second case concerned the Karun River hydrograph in Iran.

Result: In the first case, the four-input model reduced maximum and mean outflow errors at 7.7% and 1.6%, outperforming both the three-input version and the Grey Wolf Optimizer (GWO) benchmark. For the second case, the four-input model achieved mean outflow error of 3%, again exhibiting a distinct and consistent error-reduction pattern. In both cases, simulated and observed hydrographs were nearly superimposed with an average deviation less than 1.8%, confirming the model's accuracy and robustness. These findings demonstrate that ANFIS (4var) can offers strong predictive capability, high reliability and practical applicability for forecasting and decision-making even for other rivers.

Key words: Agricultural land protection, ANFIS, Crops protection, Flood routing, Neuro-fuzzy models, Outflow hydrograph modelling.

INTRODUCTION

Floods are one of the most catastrophic natural disasters causing hugely negative socioeconomic, urban and agricultural impacts and taking thousands of humans lives every year all around the globe (Borah and Buragohain, 2025; Nandi and Reddy, 2022; Grimaldi *et al*., 2019). Particularly in semi-arid regions, where the occurrence of seasonal thunderstorms and the expansion of agricultural land along riverbanks, the accurate prediction of flood hydrograph and flood inundation extent presents significant challenges (Bougherra and Mansour, 2023).

The floods caused by river overflows have demonstrated their harmful effects in several regions, damaging crops and reducing sugar-cane yield (Berning *et al*., 2000). The flood risk management projects are usually require accurate hydraulic models to evaluate hydraulic consequences in terms of the depth, duration and velocity of the water and, on the other hand, accurate damage models able to quantify the vulnerability of the different land uses affected in order to estimate the socio-economic consequences of flooding (Brémond *et al*., 2013).

The flood-routing studies aim to predict downstream discharge and channel storage based on known upstream flow conditions, by other words is to optimize the outflow hydrograph using inflow hydrograph (Yoon and Padmanabhan, 1993; Perumala *et al*., 2017; Reggiani and Todini, 2018).

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How to cite this article: Mustapha, S.A. and Ahmed, H. (2026). A New Approach for Flood Routing Modelling using a Neuro-fuzzy System 'For a Contribution to the Protection of Agricultural Land and Crops'. *Indian Journal of Agricultural Research*. **60(1):** 46-54. doi: 10.18805/IJARe.AF-983.

Submitted: 03-10-2025 **Accepted:** 01-12-2025 **Online:** 11-12-2025

Many effective methods have been used for flood routing in the world, we cite, Viviroli *et al*. (2009); Liang (2010); Seyoum *et al*. (2012); Fenton (2019); Alhumoud (2022) and Khalifeh *et al*. (2020). These studies employed either the analytical approach, which relies on hydrodynamic equations primarily the Saint-venant where we cannot include all the details and the full set of parameters governing the problem and requires the use of complicated numerical techniques such as the finite difference method, finite element method or the finite volume method (Dottori and Todini, 2011; Fenton, 2019). Or a simplified approach that considers the temporal evolution of storage within the

studied reach. The latter is based on a volume balance within the system, with the Muskingum model serving as a well-known example of this method. including the flow rate, water depth and location, the drawback of this method is the neglect of the river's morphology and physical characteristics which leads to uncertain parameters.

In the last years, the new algorithms and numerical techniques, have shown considerable effectiveness in solving hydrological problems. Mohan (1997) and Kim *et al*. (2001) implemented the genetic algorithm (GA) and the harmony search (HS) algorithm. In order to estimate the parameters of their Muskingum model, Niazkar and Afzali (2015) adopted the honey-bee mating optimization (HBMO) algorithm and compared the outputs to the results of 17 other algorithms. Noteworthy in this algorithm is the fast convergence to the optimum value within a broad range of values. Benefiting from the Grey Wolf Optimizer (GWO) algorithm (Akbari and Hessami-Kermani, 2021) optimized the parameters of the Muskingum model. Cai *et al*. (2014) use the dynamic simulation property of a cellular automaton was used to make further progress in flood routing for define submerged area.

The main idea of this work is to develop a numerical model suitable for simulating flood routing by optimising the temporal variation of flood discharge downstream or outflow hydrograph in a river reach. The connectionist models, such as artificial neural networks and fuzzy logic, have demonstrated their performance and efficiency in addressing hydrological and agricultural problems (Anandakumar *et al*., 2019; Hadj-Miloud and Djili, 2022; Han *et al*., 2010; Sidi, 2024). Among these models is the hybrid model, adaptive neuro-fuzzy inference system ANFIS employed in this study. The ANFIS approach is based on a stochastic method that utilises only the impact of the system's main apparent parameters, along with comparing the results obtained to those of another method applied in flood routing. Here, we incorporated the time derivative of discharge because it reflects the rate of change and trend of the discharge function. The outflow discharge can differ for the same discharge value depending on whether the flow is increasing or decreasing. The aforementioned model has thus been employed in two case studies, in each of which the outflow hydrograph was developed after the calibration of the ANFIS model. It has been indicated that this model provides relatively more accurate results. It should be noted that although it has significative result the ANFIS system in other works (Jianhua, 2015; Han, 2010; Talei, 2010).

MATERIALS AND METHODS

Model perspective

In hydrodynamics field, flood propagation is governed by the Saint-Venant equations, which are represented by the continuity equation and the momentum conservation equation simplified and formulated in one dimension (1D) as:

$$\begin{cases} \dfrac{\partial Q}{\partial t} + \dfrac{\partial (Q^2/A)}{\partial x} + gA\left(\dfrac{\partial h}{\partial x} + S_f - S_o\right) \\ \dfrac{\partial Q}{\partial x} + \dfrac{\partial A}{\partial t} - q = 0 \end{cases} \quad ...(1)$$

Where,

Q= Flow in time t.

A= Cross section of river.

h= Flow hight.

S_f and S_0= Slops of the free water surface and river bed respectivly.

q= The lateral flow.

The model is simplified through the Muskingum linear simplified model, as shown below:

$$Q_{out}^{t+\Delta t} = C_0 Q_{int}^{t+\Delta t} + C_1 Q_{int}^{t} + C_2 Q_{out}^{t} \quad ...(2)$$

It should be noted that a nonlinear model also exists.

Where,

Q_{int}^{t} and Q_{out}^{t} = A discharge of inflow and outflow at time (t).

The coefficients C_0, C_1 and C_2 are functions of the parameters K, X and Δt.

While, K represents the travel time of water through a river reach and know as storage time constant and X is a dimensionless parameter that controls the relative influence of inflow and outflow on the storage within the river reach known as the weighing factor (Alhumoud, 2022; Akbari and Hessami-Kermani, 2021).

The majority of researchers in this context work either on the discretization of the hydrodynamic model or on the determination of the parameters of the Muskingum model.

At present, stochastic models demonstrate strong performance and efficiency in the field of hydrology, particularly connectionist models associated with artificial intelligence. These models generally rely on learning from the historical data of the studied system (Sidi *et al*., 2024). Their effectiveness mainly depends on two factors: The choice of the applied method characteristics and the selection of the system's explanatory variables (inputs).

In this study, we present an alternative perspective inspired by the previously presented models, seeing that the variation of the outflow, $Q_{out}^{t+\Delta t}$, at the section's outlet at time t+Δt depends on the inflow and outflow at time t noted Q_{int}^{t} Q_{out}^{t} as well as the variation in the inflow expressed by the derivative $(\partial Q/\partial t)_{int}^{t}$, this parameter has a significant influence on the rate of decrease or increase of the outflow at the downstream section under study (Fig 1).

Innovation and modelling tool

Given the complexity of the problem and in order to define and characterize the model, we will rely on a neuro-fuzzy system known as the Adaptive Neuro-Fuzzy Inference System (ANFIS).

Which takes Q_{int}^{t}, Q_{out}^{t} and $(\partial Q/\partial t)_{int}^{t}$ as explanatory variables of the model (Inputs) and $Q_{out}^{t+\Delta t}$ as the endogenous variable (Output).

In the initial phase, we focused a network, noted ANFIS (3Var) with three input variables, Q_{int}^{t}, Q_{out}^{t} and (Fig 1).
Where,

$$\left(\frac{\partial Q}{\partial t}\right)_{int}^{t} = \frac{Q_{int}^{t} - Q_{int}^{t+\Delta t}}{\Delta t} \quad ...(3)$$

In a second step, we made use of the two states of the derivative at t and $t+\Delta t$ denoted by $(\partial Q/\partial t)_{int}^{t}$ and $(\partial Q/\partial t)_{int}^{t+\Delta t}$ (Fig 1). In this case, the network used consists of four input variables, ANFIS (4Var).
Where,

$$\left(\frac{\partial Q}{\partial t}\right)_{int}^{t+\Delta t} = \frac{Q_{int}^{t} - Q_{int}^{t+\Delta t}}{\Delta t} \quad ...(4)$$

Adaptive neuro-fuzzy inference system (ANFIS)

The Adaptive Neuro-fuzzy Inference System (ANFIS) utilizes a multilayer neural network consisting of five (5) layers (Fig 2). Each layer of the network corresponds to the execution of a specific step in a Takagi-Sugeno type fuzzy inference system (Jang, 1993).

The first layer of an ANFIS architecture comprises a number of neurons equal to the number of input variables n multiplied by the number of fuzzy subsets *p* present in the inference system. The number (n) of subsets typically ranges from 2 to 5. To avoid model complexity and the proliferation of fuzzy rules, we selected n=3, which facilitates the learning process of the ANFIS system.

In our cases we have *n.p=3.3=9* for three input variables and n.p=4.3.=12 for four input variables.

This configuration enables the system to transform crisp input values into degrees of membership across different fuzzy sets, facilitating the fuzzification process essential for subsequent inference operations.

We incorporated the derivative of discharge in time because it reflects the rate of change and trend of the discharge function. The outflow discharge can differ for the same discharge value depending on whether the flow is increasing or decreasing. This derivative parameter is incorporated in two possible forms, either in form $(\partial Q/\partial t)_{int}^{t}$ or form $(\partial Q/\partial t)_{int}^{t+\Delta t}$.

The second hidden layer is designed to compute the activation level of the premises. Each of its neurons represents the premise of a fuzzy inference rule. The activation functions of these neurons depend on the operators present in the rules (And or Or).

In our cases we obtain 3^3 as 27 rules for the network of three input variables and 3^4 as 81 for the network of four input variables.

The third hidden layer aims to normalize the degree of rule activation by computing the ratio between the i^{th} rule weight and the total sum of all rule weights. This operation is known as normalization step.

The fourth hidden layer is used to determine the parameters of the consequent part of the rules a, b, c, d, e. The function of each neuron in this layer is as follows:

- For our ANFIS model with three input variables we have;

$$f_k^4 = \overline{W}_k (a_k Q_{int}^{t} + b_k Q_{out}^{t} + c_k \frac{\partial Q}{\partial t} + e_k) \quad ...(6)$$

- For our ANFIS model with four input variables we have;

$$f_k^4 = \overline{W}_k (a_k Q_{int}^{t} + b_k Q_{out}^{t} + c_k \left(\frac{\partial Q}{\partial t}\right)_{int}^{t} + d_k \left(\frac{\partial Q}{\partial t}\right)_{int}^{t+\Delta t} + e_k) \quad ...(7)$$

f_k^4 is the output of k^{th} neuron in the fourth hidden layer.
Where,
$\overline{W}_k$= The output of the third layer.
a, b, c,e= The consequent parameters.

The fifth output layer contains a single neuron in this layer, which computes the overall output as the sum of all incoming signals, that is:

$$Q_{out}^{t+\Delta t} = \sum_k \overline{W}_k f_k^4 \quad ...(8)$$

The study was conducted at Ahmed Zabana University of Relizane in Algeria, during the year 2025.

RESULTS AND DISCUSSION

The models were applied to two real-world cases. The first case involved a non-smooth hydrograph from the River Wye in the United Kingdom. The second case concerned a single-peak hydrograph from the Karun River in Iran. The optimized outflows are computed by both model variants as ANFIS(3var) and ANFIS(4Var) for the characteristics presented in Table 1, in order to compare them with the results obtained by the GWO algorithm.

Case study 1

This is a non-smooth flood hydrograph belonging to the River Wye in the United Kingdom, which has been studied in many researchers works (Akbari and Hessami-Kermani, 2021).

In this case, the system data are presented in the form of inflows and outflows. The total number of data points is 33 observations, with a time step of 6 hours (Table 2).

$$\begin{cases} \text{If } (Q_{int}^{t})_1 \text{ is low and } (Q_{out}^{t})_1 \text{ is low and } \left(\frac{\partial Q}{\partial t}\right)_1^{t} \text{ is low then } Q_{out}^{t+\Delta t} \text{ is } f_1. \\ \text{If } (Q_{int}^{t})_i \text{ is medium and } (Q^{t}{}_{out})_i \text{ is low and } \left(\frac{\partial Q}{\partial t}\right)_i^{t} \text{ is high then } Q_{out}^{t+\Delta t} \text{ is } f_i. \\ \text{If } (Q_{int}^{t})_m \text{ is high and } (Q_{out}^{t})_n \text{ is high and } \left(\frac{\partial Q}{\partial t}\right)_n^{\partial t} \text{ is high then } Q_{out}^{t+\Delta t} \text{ is } f_m. \end{cases} \quad ...(5)$$

It should be noted that, the performance of the GWO method is evaluated by comparing its results with those obtained in various relevant research studies (Akbari and Hessami-Kermani, 2021).

The ANFIS(3Var) model with three input parameters Q^t_{int} ,Q^t_{out} and $(\partial Q/\partial t)_{int}$ showed discharge errors of up to 10.4%, with an average error of 3.1%. This error was reduced by adding at system a fourth explanatory parameter $(\partial Q/\partial t)^{t+\Delta t}_{int}$ resulting in a maximum error of 7.7% with an average error of 1.6% (Table 1), which is lower than that obtained by the GWO model as 9.7%. Moreover, a clear opposite trend in the error variation is observed in Fig 3.

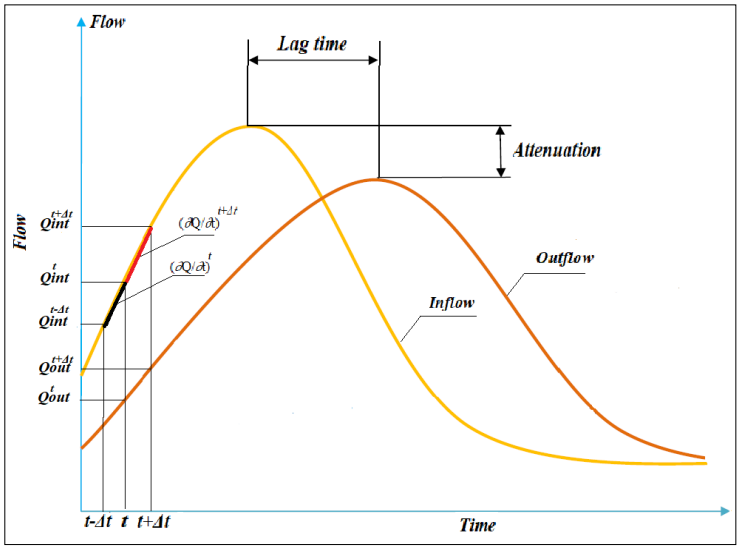


Fig 1: Hydrographs of Inflow and outflow in a river reach.

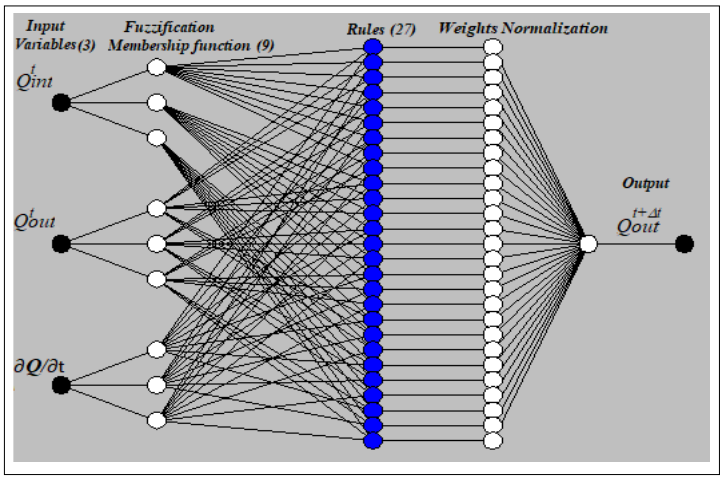


Fig 2: The ANFIS model structure with three input variables [ANFIS (3Var)].

Table 1: Characteristic of the ANFIS (3Var) and ANFIS (3Var) models at case study 1.

Characteristic	ANFIS (3 Var)	ANFIS (4 Var)
Input parameters	3	4
fuzzy subsets N^{br}	3	3
Rules N^{br}	27	81
Testing/training (Data<1000)	20/80 as 25%	25%
Mean of observed outflow values	268.48	788
Mean absolute percentage error (MAPE)	3.1%	1.6%
Root mean square error (RMSE)	6.89 m^3/s	4.20 m^3/s
Nash-sutcliffe efficiency (NSE)	0.95	0.98
Max error	10.4%	7.7%

Table 2: Comparison of observed outflows and obtained from ANFIS (3Var), ANFIS (4Var) and GWA (case study 1).

Step	Time (h)	Observed data		Computed outflow (Present study)		Computed outflow (GWO algorithm) (Akbari and Hessami-Kermani, 2021)
		Inflow (m^3/s)	Outflow (m^3/s)	With 3 Vars	With 4 Vars	
1	0	150.00	140.00	137.32	141.27	143.80
2	6	219.00	169.00	151.39	166.17	149.20
3	12	182.00	190.00	190.92	191.16	182.70
4	18	182.00	209.00	213.85	211.10	191.40
5	24	192.00	218.00	204.06	216.85	185.10
6	30	165.00	210.00	211.30	206.66	187.30
7	36	150.00	194.00	204.70	195.23	178.40
8	42	128.00	172.00	178.84	174.04	161.10
9	48	168.00	149.00	157.49	152.95	139.20
10	54	260.00	136.00	147.70	136.20	154.60
11	60	471.00	228.00	226.88	228.30	200.80
12	66	717.00	303.00	303.32	302.94	267.30
13	72	1092.00	366.00	365.84	366.01	347.80
14	78	1145.00	456.00	456.02	456.00	419.10
15	84	600.00	615.00	615.01	615.00	602.30
16	90	365.00	830.00	830.00	830.00	879.10
17	96	277.00	969.00	968.99	968.99	839.00
18	102	277.00	665.00	665.01	664.98	689.00
19	108	187.00	519.00	518.98	519.06	530.70
20	114	161.00	444.00	444.01	444.00	414.30
21	120	143.00	321.00	311.86	315.22	289.90
22	126	126.00	208.00	225.63	224.03	202.80
23	132	115.00	176.00	165.29	162.85	149.80
24	138	102.00	148.00	142.16	145.80	122.50
25	144	93.00	125.00	125.36	126.11	104.90
26	150	88.00	114.00	109.64	110.10	93.50
27	156	82.00	106.00	99.81	104.16	87.80
28	162	76.00	97.00	94.61	97.89	81.40
29	168	73.00	89.00	88.46	86.29	74.90
30	174	70.00	81.00	81.38	80.48	72.40
31	180	67.00	76.00	77.55	75.63	69.20
32	186	63.00	71.00	74.52	74.09	66.10
33	192	59.00	66.00	72.11	70.42	61.50

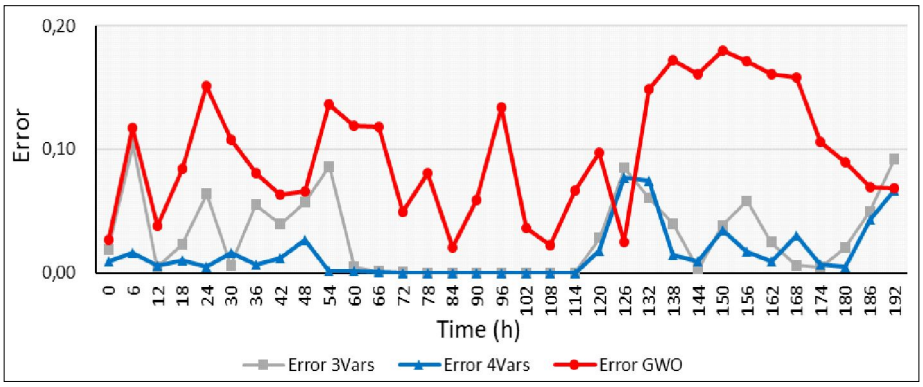


Fig 3: Error variation obtained by the three models, ANFIS (3Var) ANFIS (4Var) and GWO for case study 1.

This observation has led us to conclude that the ANFIS(4Var) model, demonstrates considerable performance in this case.

The ANFIS models were implemented in MATLAB on Windows 10 64-bit. The datasets, obtained from previous studies (Akbari and Hessami-Kermani, 2021), were fully pre-processed and serve as a reliable basis for model validation.

The effectiveness of the ANFIS (4 Var) model is observed in the output hydrograph as show in Fig 4, where the calculated discharges are almost superimposed on the observed discharges with Nash–Sutcliffe Efficiency (NSE) of 0.95.

Case study 2

After successfully demonstrating its effectiveness in the previous example, the ANFIS (4Var) model was applied to another real-world case on a river in Iran. The Karun River, the longest in southwestern Iran, receives inflow from the Dez River-another key component of the region's ecosystem. Target discharges were measured at two gauging stations, Godar and Gotvand, with inflows ranging from 380 to 1.300 m³/s. In this hydrograph, the time step used was two hours (Akbari and Hessami-Kermani, 2021; Moghaddam *et al*., 2016). The optimized outflows presented in Table 3 were computed by the ANFIS (4Var) model in order to compare them with the results obtained by the GWO algorithm appliqued also in this case by (Akbari and Hessami-Kermani, 2021).

In this stage, the calculation of outflows by the ANFIS(4Var) model recorded a Root Mean Square Error (RMSE) as 25.14m^3/s a maximum error of 19.7% with an average error MAPE of 3%, compared to the maximum and average errors obtained by the GWO model of 18.9% and 3.4%, respectively. This observation allows us to conclude that the ANFIS(4Var) model demonstrates a high level of performance and reliability in this case study.

Fig 5 reveals a distinctly opposite trend in the variation of errors, which provides further insight into the model's behavior. This contrasting pattern underscores the consistency and robustness of the ANFIS(4Var) model when applied to this case study. Based on these findings, we can confidently conclude that the ANFIS(4Var) model demonstrates not only considerable performance but also strong predictive capability and reliability, making it a suitable tool for accurately simulating and forecasting.

The ANFIS(4var) effectiveness is also clearly reflected by the output hydrograph in Fig 6, where the simulated discharges are nearly indistinguishable from the observed values superimposed, with an average deviation equal 1.8% and a NSE of 0.98. This close alignment between calculated and measured flows highlights the model's ability to accurately reproduce the hydrological behavior of the system, thereby reinforcing its suitability for forecasting and decision-making in similar rivers.

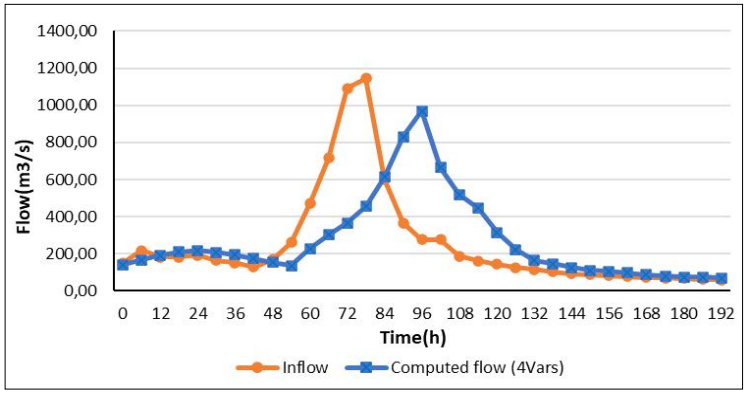


Fig 4: The inflow and simulated outflow by ANFIS (4Var) for case study 1.

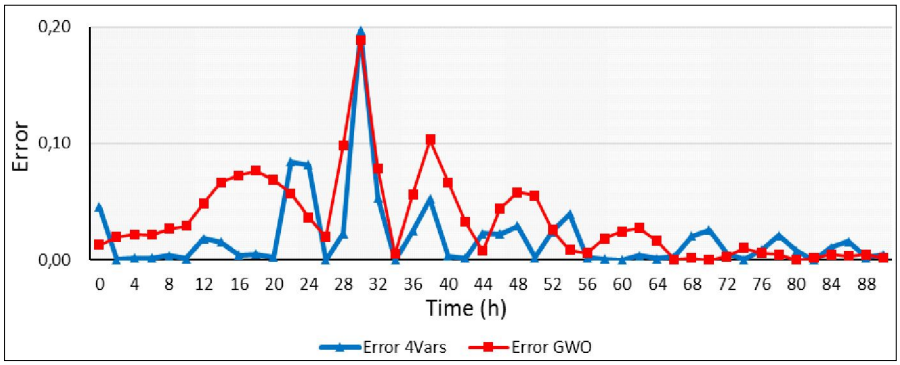


Fig 5: Error variation of obtained results by the models, ANFIS(4Var) and GWO for case study 2.

Table 3: Comparison of observed outflows and obtained from ANFIS (4Var) and GWA for case study 2.

Step	Time (h)	Observed data		Computed outflow (Present study) with 3 Vars	Computed outflow (GWO algorithm) (Akbari and Hessami-Kermani, 2021)
		Inflow (m^3/s)	Outflow (m^3/s)		
1	0	430	383.5	401.0	378.6
2	2	445	387.0	386.9	379.4
3	4	460	393.0	392.4	384.4
4	6	475	399.0	399.7	390.5
5	8	490	408.5	407.0	397.7
6	10	505	418.0	417.5	405.8
7	12	520	436.0	427.9	414.9
8	14	540	455.0	448.0	424.8
9	16	560	470.0	467.9	435.8
10	18	595	485.0	487.6	447.9
11	20	630	496.0	497.2	462.0
12	22	770	507.0	464.2	478.1
13	24	910	523.5	480.8	504.3
14	26	995	540.0	540.0	550.7
15	28	1080	558.0	570.6	612.8
16	30	1095	576.0	689.2	684.7
17	32	1110	702.5	740.3	757.8
18	34	1125	829.0	829.0	824.9
19	36	1140	938.5	915.2	885.5
20	38	1170	1048.0	993.0	940.1
21	40	1200	1061.5	1057.7	990.8
22	42	1250	1075.0	1073.0	1040.0
23	44	1300	1082.0	1106.6	1090.4
24	46	1255	1089.0	1064.9	1137.0
25	48	1210	1103.0	1135.3	1167.2
26	50	1180	1117.0	1119.4	1179.1
27	52	1150	1149.5	1121.3	1179.2
28	54	1125	1182.0	1135.3	1172.0
29	56	1100	1153.0	1150.4	1160.0
30	58	1070	1124.0	1124.9	1144.6
31	60	1040	1099.5	1099.4	1126.2
32	62	995	1075.0	1079.2	1104.5
33	64	950	1061.5	1062.6	1078.8
34	66	885	1048.0	1044.8	1048.4
35	68	820	1011.0	1031.7	1012.7
36	70	800	974.0	999.2	974.1
37	72	780	935.0	940.2	937.9
38	74	760	897.0	897.5	906.2
39	76	740	872.5	865.2	877.8
40	78	730	848.0	830.0	852.1
41	80	720	829.5	822.6	829.4
42	82	720	811.0	811.0	809.7
43	84	720	797.0	805.5	793.3
44	86	730	783.0	795.3	780.3
45	88	740	774.5	776.0	770.8
46	90	750	766.0	769.8	764.8

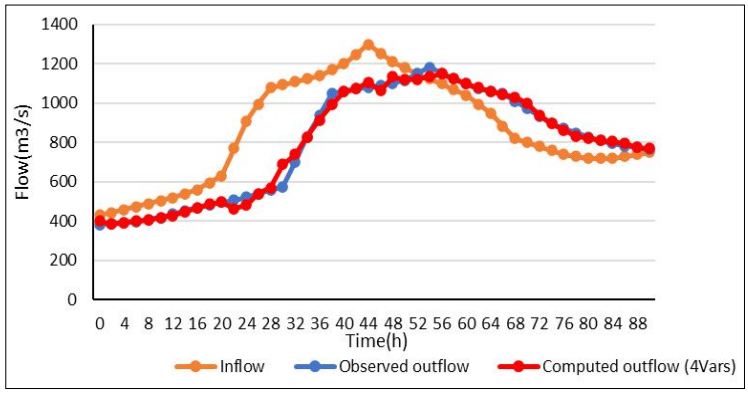


Fig 6: The inflow with observed and simulated outflow by ANFIS (4Var) for case study 2.

CONCLUSION

This work aimed to develop and evaluate a numerical model capable of simulating flood routing by optimizing the temporal variability of downstream discharge. By employing the Adaptive Neuro-fuzzy Inference System (ANFIS), The study demonstrated that a stochastic, data-driven methodology is capable of representing the flow dynamic in river reach with only a minimum of explanatory parameters. Two configurations were explored: A three-input version and an extended four-input version that incorporates an additional derivative term to better represent temporal flow changes. Application to the River Wye showed that the four-input ANFIS significantly lowered average errors at 1.6% compared with the three-input model with 3.1% and even outperformed the benchmark GWO algorithm with 9.7%. The performance of the GWO method results is evaluated and compared with those obtained using other methods applied in various relevant research studies. The convergence between simulated and observed hydrographs confirmed the accuracy of the proposed approach. A second application to the Karun River under different flow conditions further validated these findings, with the four-input ANFIS again producing lower average errors as 3% than the GWO model with 3,4% where a simulated and observed hydrographs were nearly superimposed with an average deviation varies between 0.8% and 1.8%.

Across both case studies, the ANFIS model demonstrated not only improved predictive performance but also robustness and consistency. Ultimately, it depends on the appropriate selection of input parameters, with particular emphasis on the derivative parameter ("*Q*/"t). These results highlight its suitability for operational flood forecasting and decision-making, especially where detailed hydraulic data are limited. Overall, the research confirms that the ANFIS (4Var) model is a powerful and reliable tool for simulating and forecasting flood routing in diverse hydrological settings.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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