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Computation of Flow Coefficient *via* Non-deterministic Approach of Fuzzy Logic Called "SMRGT" Based on Meteorological Properties

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ABSTRACT

In light of the current global climate changes, floods have emerged as a significant hydraulic and hydrological challenge on a global scale. The primary contributors to the expansion of impermeable areas and the intensification of flood flow are extensive urbanization, the proliferation of concrete edifices and the construction of asphalt thoroughfares. Anticipating the flow beforehand will be conducive to the successful execution of the task at hand. The objective is to reduce the likelihood of harm to individuals and damage to assets. By accurately determining the flow coefficient, which is a significant factor in flood flow, it is possible to mitigate existing issues to a significant degree. Numerous methodologies for modeling flow coefficients can be found in the extant literature. However, most of these methodologies rely on black-box techniques and are not easily generalizable. Hence, the present investigation has opted for a novel methodology; namely, the fuzzy SMRGT method that takes into account the physical characteristics of the phenomenon and is designed to assist individuals who encounter difficulties in selecting the appropriate quantity, structure and rationale of membership functions and fuzzy rules within a given fuzzy set. The data comprising annual precipitation, temperature and relative humidity measurements was acquired from the Regional Directorate of Meteorology. The model outcomes were juxtaposed with the actual observations. Statistical parameters, such as the coefficient of determination (R^2), the root mean square error (RMSE), the Nash-Sutcliffe efficiency coefficient (NSE) and the mean absolute percentage error (MAPE), were used to evaluate the performance of the model. The statistical test results were: (RMSE: 0.096, NSE: 0.90, MAPE: 17.3, R^2:0.96). The findings suggest that the SMRGT model is highly effective in accurately forecasting the flow coefficient and represents a robust approach for constructing membership functions and fuzzy rules.

KEYWORDS: Fuzzy logic, Uncertainty modeling, SMRGT, Flow coefficient, Precipitation, Mamdani fuzzy inference system.

INTRODUCTION

The flow coefficient is a metric that expresses the proportion of precipitation volume superficially drained during a specific period, as defined by Bedient et al. (2013) and Júnior (2015). A runoff coefficient is an essential tool utilized in hydrological investigations of various engineering endeavours in both urban and rural settings (Sen and Atunkaynak, 2006). It serves as an indicator of the volume of water that emanates from specific precipitation events and also reflects the influence of natural geomorphological features on the flow (Ochsner, 2013). Furthermore, the employment of runoff coefficients facilitates comparisons between various watersheds, thereby enabling a comprehensive comprehension of how diverse landscapes alter precipitation into rainfall events (Blume et al., 2007; Che et al., 2018). The transformation process of rainfall into flow in a watershed is a complex hydrological phenomenon that is influenced by numerous climatic and physiographic factors. These factors exhibit

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temporal and spatial variability, thereby exerting control over the hydrologic behaviour of the watershed. The correlation between precipitation and consequent surface water flow is a multifaceted phenomenon that is impacted by various factors pertaining to the hydrological basin and atmospheric conditions. The demand for precise representation of the precipitation-flow phenomenon has experienced a significant surge in recent decades. Despite the intricate nature of the phenomenon, numerous models are being developed to characterize it, owing to its highly stochastic property accurately. In contemporary times, hydrologists have increasingly employed Artificial Intelligence (AI) methodologies, including the Artificial Neural Network (ANN) and fuzzy-logic methods (FL), for the purpose of precipitation-flow modeling and other hydrological applications. The utilization of ANN in hydrology has been observed in various applications, one of which is the modeling of the rainfall-flow process as demonstrated by Sajikumar et al. (1999) and Kumar et al. (2021). Casper et al. (2007) have devised a rainfall flow modeling system utilizing the Takagi-Sugeno-Kang methodology, which is based on fuzzy rules. The study of Tayfur and Singh (2006) focused on the creation and evaluation of artificial neural network (ANN) and fuzzy-logic (FL) models for the purpose of predicting event-based rainfall flow. The performance of these models is compared to that of the kinematics wave approximation (KWA).

The fuzzy set theory forms the basis for the methodology of fuzzy logic (FL). One of the field pioneers of fuzzy sets was Zadeh (1965). It was considered a pivotal moment in assessing the modern meaning of uncertainty. In his research, Zadeh developed the theory of fuzzy sets, which is applied to things with ill-defined boundaries. This work resonated not only as a departure from probability theory, but also as a possible departure from Aristotelian logic, the foundation of virtually all sciences up until that time. The theoretical basis of fuzzy logic lies in the linguistic representation of hydrological variables, which involves the allocation of consecutive fuzzy terms, such as 'low', 'medium' and 'high', to various sub-groups. The methodology involves the contemplation of the variable not as a comprehensive unit, but instead as fragmented sub-sets. This facilitates enhanced validation of sub-relationships among two or more variables grounded on imprecise terminology. Insufficient and inaccurate sub-groups can lead to forecast bias, whereas an excessive number of sub-groups can result in a high computational burden. Many fields have started to implement FL into their models of natural phenomena. For instance, in 1-, 2- and 3-dimensional modeling (Bardossy et al., 1995), infiltration (Bardossy et al., 1993), water structures (Toprak and Aytek, 2001) and irrigation (Toprak et al., 2002), many studies, such as solid matter transport (Dou et al., 1997), hydrology (Bardossy et al., 1997; Droesen, 1997), engineering systems (Bardossy and Duckstein, 1997) and electrical-electronics (Mamdani, 1977), can be given as examples. Numerous alternative applications can be observed within the domain of water sciences, as evidenced by various studies (Chau et al., 2005; Vernieuwe, 2005; Ozalkan and Duckstein, 2001; Xiong et al., 2001; Cheng et al., 2002).

One of the significant limitations of fuzzy systems, as pointed out by Jang (1993), is the lack of a definitive method for determining the optimal number of fuzzy rules and membership functions required for each rule. The principal objective of this research is to furnish a proof that the suggested fuzzy model possesses the capability to generate a precise estimation concerning the flow coefficient. A thorough understanding of river flow is imperative for proficiently managing water resources, devising and erecting water infrastructure and alleviating the consequences of natural calamities. The fuzzy SMRGT approach, first proposed by Toprak (2009), incorporates expert opinion to reflect the fundamental principles of physics within the model. Furthermore, the utilization of existing data enables the attainment of superior outcomes. It is possible to consider that the inclusion of the principles of physics as an authoritative viewpoint in fuzzy logic could introduce certain idealizations. However, these idealizations exhibit relatively diminutive proportions when compared with alternative approaches. The fuzzy logic approach was favoured based on the aforementioned justifications. The preference for a current approach was also influenced by the lack of a corresponding study in the existing literature. The SMRGT technique has been utilized in numerous research projects, as evidenced by various studies (Toprak et al., 2013; Coskun, 2014; Toprak et al., 2015; Altas et al., 2017; Toprak and Karakaya, 2018; Toprak, 2017a; Bayri, 2018; Unes et al., 2019; Sevgin, 2021; Toprak et al., 2017b). The study's authors arrived at the conclusion that the fuzzy SMRGT technique surpasses other methods documented in the literature due to its simplicity and reliability in execution. The fuzzy SMRGT approach is commonly classified as a non-deterministic technique due to its handling of imprecision and uncertainty. This is achieved by incorporating fuzzy variables or probabilistic methods within the methodological framework.

The annual datasets of precipitation, temperature and relative humidity have been collected from the Turkish State of Meteorological Service for thirty years (from 1990 to 2020) and used in this study. The amount and intensity of precipitation directly impact the flow coefficient. If precipitation is heavy and continuous, it can saturate the soil quickly, leading to higher flow coefficients. This is especially true if the soil has low permeability or is already saturated from previous rainfall. On the other hand, if precipitation is light or spread out over a longer period, the soil has more time to absorb the water, resulting in a lower flow coefficient. Temperature and relative humidity influence the flow coefficient indirectly through their effect on evaporation rates. Higher temperatures increase the rate of evaporation, which reduces the amount of water available for flow, while higher humidity means that the air is closer to saturation, which reduces the evaporation rate and, in turn, increases the potential for flow.

MATERIALS AND METHODS

Description of Study Area

Aksu river basin was selected as the study region, which is a sub-basin of the Antalya basin. The geographical location of the basin is delineated by the coordinates of 36-38 degrees north latitude and 30-32 degrees east longitude. The Aksu river originates from the Toros mountains. Based on extensive research conducted on the river's water flow over an extended period, it has been determined that the Aksu river basin exhibits an average annual discharge of 94.98 hm^3 (Tokgozlu and Ozkan, 2018). According to Geographic Information System GIS measurements, the basin has a drainage area of about 7505 km^2.

Collection of Meteorological Data

The present study sourced the data and locations of observation stations (POSs) from the Turkish State of Meteorological Service (TSMS). A dataset comprising 57 observation stations (POSs) has been utilized. The dataset includes 1793 records of monthly precipitation data, 2882 records of monthly mean temperature and 3466 records of monthly mean relative humidity, spanning over 20 years. The annual mean precipitation was 963.60 mm, the annual mean temperature was 16.03°C and the annual mean relative humidity was 63.3%.

SMRGT Model Development

Developing a membership function (MF) and setting a set of fuzzy rules (FR) are the two most crucial steps in building a fuzzy database model. Recently, various methods and algorithms have been proposed for building MFs and making FRs. These include genetic algorithms (Kissi et al., 2004), combining GAs and ANNs (Pal, 2003), ANNs (Rutkowska, 1998), Kalman filters (Jin and Sendhoff, 2003), probability measurements (Simon, 2002) and many more. Several authors presented strategies for adjusting or optimizing the MFs count, while others described methods for calculating the FRs. In addition, very little work has been done to optimize MFs and FRs simultaneously. Furthermore, estimating the size and shape of MFs, as well as the number and logic of FRs, has been proposed in a variety of ways in the literature. Thus, in this study, the flow coefficient was determined by employing Simple membership functions and the fuzzy-rules generation technique (SMRGT). Toprak (2009) developed a new approach to model open-canal flow that required only a handful of central values for all MFs of input and output variables. The defuzzification strategy and the membership-function geometry informed the selection of the corresponding key values (centroid, maximum membership degree, … etc.). There are no prerequisites for using the SMRGT model. The range of the model's input values is entirely flexible. This means a user-determinable range of values within which the model operates.

For effective results with the new method presented in this study, the following steps can be summarized:

1. The variables that influence the current event have been identified and categorized as either independent or dependent. The independent variables function as inputs to the fuzzy system, whereas the dependent

variables function as outputs. The present investigation was formulated to incorporate distinct variables; namely, precipitation, temperature and relative humidity. It is recommended to constrain these variables within a specific range. Therefore, it is necessary to ascertain the maximum and minimum values. The extent of these ranges can be expanded or contracted according to the specific circumstances of the given occurrence. Equation (1) can be utilized for the computation of the X_R value.

$$X_R = (X_{\max}) - (X_{min}). \quad (1)$$

For each variable, the maximum (X_{max}) and minimum (X_{min}) values were assigned. These intervals can remain as large as desired. After analyzing the dataset, the minimum and maximum precipitation ranges were determined to be (200 mm – 2000 mm, respectively) for temperatures (0-50)°C and relative-humidity percentages (0-100)%.

2. It is necessary to define a minimum of three membership functions that are temporary for every independent variable. Increasing the number of membership functions has been found to reduce the error of the model, according to Toprak (2009). However, this also results in an increase in program load, which refers to the processing volume. The present investigation utilized five distinct membership functions denoted as Very Low (VL), Low (L), Medium (M), High(H) and Very High (VH).

3. The triangular membership functions (MFs) were intentionally created. According to Toprak (2009), it is recommended that the initial and final membership functions be represented as right-angled triangles, whereas the middle membership functions should be depicted as isosceles triangles. The validity of a fuzzy system is contingent upon the distribution of data falling within the range of the first and last membership functions for each independent variable, as shown in Figure (1).

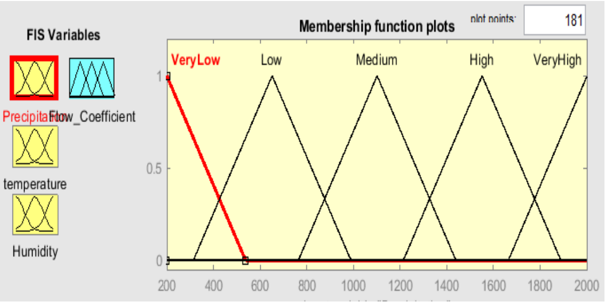

Figure (1): MATLAB view of the fuzzy membership functions (MFs)

4. For each variable, the key values (K_1, K_2... K_N) and core value (C_i) of the membership functions, the unit width (UW), the symmetrically extended unit width (EUW) and the value (O) of the two intersecting neighbour membership functions are determined. Furthermore, the number of right-angled triangles (nu) in the triangular fuzzy set was determined. Parameters used in the construction of the triangular MFs are shown in Figure 2. Equations (2–10) were used to calculate the key values (Toprak 2009).

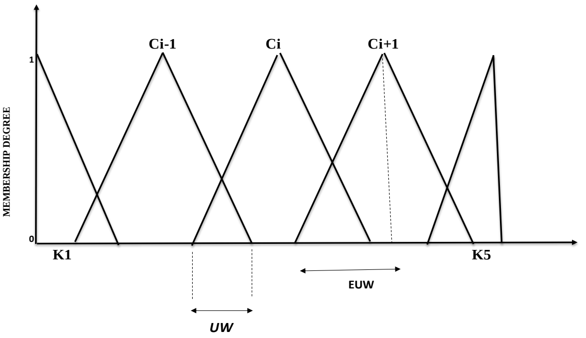

Figure (2): Parameters used in the construction of triangular MFs

$$\mathrm{Vr} = (\mathrm{P,T,H})\max - (\mathrm{P,T,H})\min \quad (2)$$

$$\mathrm{Ci} = \mathrm{K3} = \frac{\mathrm{Vr}}{2} - (\mathrm{P,T,H})\min \quad (3)$$

$$\mathrm{UW} = \frac{\mathrm{Vr}}{\mathrm{nu}} \quad (4)$$

$$\mathrm{O} = \frac{\mathrm{UW}}{2} \quad (5)$$

$$\mathrm{EUW} = \mathrm{UW} + \mathrm{O} \quad (6)$$

$$\mathrm{K4} = \mathrm{Ki} = \mathrm{Ci} + 1 = \left(\frac{\mathrm{Ci} - (\mathrm{P,T,H})\min}{2}\right) + (\mathrm{P,T,H})\min \quad (7)$$

$$K2 = Ci - 1 = (P, T, H)max - \left((P, T, H)\ max - \frac{Ki}{2}\right) \tag{8}$$

$$K1 = (P, T, H)min + \left(\frac{EUW}{3}\right) \tag{9}$$

$$K5 = (P, T, H)max - \frac{EUW}{3} \tag{10}$$

5. These key values are the fuzzy model's inputs. Note that the key values for the inputs are highlighted in Figures 3, 4 and 5. The decision was made to ensure that the number of key values assigned to each independent variable corresponds to the number of membership functions (MFs). It is advantageous to select the same number of membership functions (MFs) as fuzzy rules for the outputs (FRs).

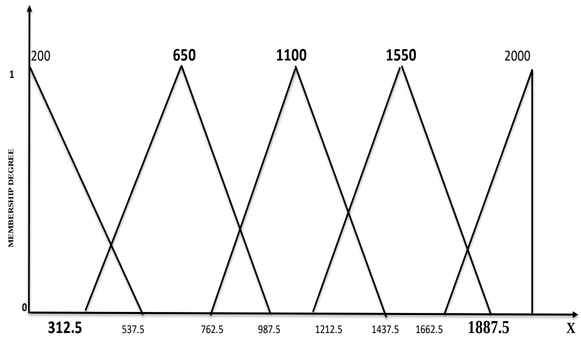

Figure (3): Key values of precipitation

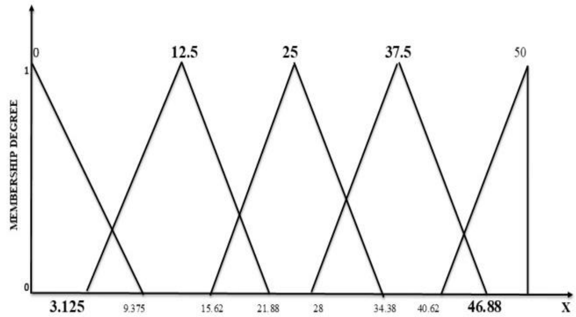

Figure (4): Key values of temperature

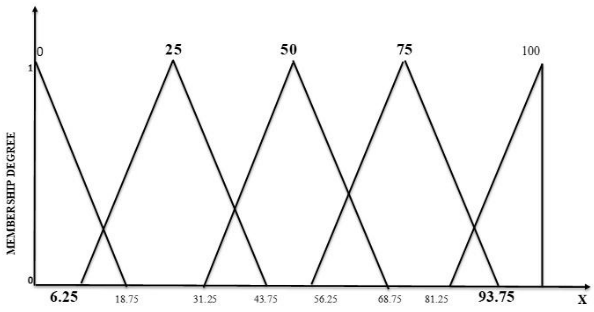

Figure (5): Key values of relative humidity

6. After the fuzzification process is completed, the fuzzy rules' base is created. The fuzzy rules' base is determined by factoring in pertinent physical conditions, such as "IF", "AND" and "THEN." Fuzzy rules are generated for each parameter. To avoid overlooking any possibilities, the number of fuzzy rules depends on the number of fuzzy sets in the independent variables and their membership functions, as expressed by Eq. (11).

$$N = (m)^{r} \tag{11}$$

where: N is the number of fuzzy rules, m is the number of membership functions and r is the number of inputs. The number of fuzzy rules for this study is 125 rules.

7. The MATLAB software was configured to contain the fuzzy set. The Mamdani algorithm was utilized as an operator. The defuzzification process was carried out using the centroid method (Toprak, 2009). The program has been equipped with input and output files, which have been formatted with the (.dat) extension. Then, the program with the (.fis) extension is loaded. The file extension (.m) is utilized for the execution of a prearranged program. The generation of model outcomes can be achieved through the execution of the present file with the (.m) extension. By following this procedure, the program preparation can be streamlined and the need for trial and error can be minimized. Subsequently, the table representing the fuzzy set was generated.
8. According to Toprak (2009) and Toprak et al. (2017a), in cases where the output membership functions exhibit excessive intertwining, it is recommended to reduce their number by merging two or more functions into a single one.

RESULTS AND DISCUSSION

A significant association exists between the precision of hydrological computations and the efficiency of hydraulic planning for water-drainage systems. The inclusion of this factor is essential in order to obtain a precise calculation of the flow coefficient. On the other hand, the current method for calculating this coefficient involves using tables that contain only a sub-set of the available data. The flow coefficient is not precisely at the desired value due to ignoring the study area's unique conditions, which results in designs that are not as effective as they should be. This study aimed to determine the flow-coefficient value of the study area, which consisted primarily of residential and agricultural land (Aksu river basin). This was accomplished with the help of the MATLAB computer program and the fuzzy-logic module. In order to arrive at the most accurate conclusion using the SMRGT method, membership functions and fuzzy rules were applied to the variables that served as inputs and those that served as outputs. Mamdani's method is used as an operating system, the centroid method was selected for defuzzification and specific formulae were used to determine input and output key values, as shown in Table 1.

Table 1. The calculated key values of the inputs and output

Inputs	X_R	UW	EUW	O	K_1	K_2	K_3	K_4	K_5
P	1800	225	337.5	112.5	312.5	650	1100	1550	1887.5
T	50	6.25	9.375	3.125	3.125	12.5	25	37.5	46.88
Rh	100	12.5	18.75	6.25	6.25	25	50	75	93.75
a	1	0.125	0.1875	0.0625	0	0.125	0.5	0.25	1

A specialist must be consulted to calculate the unique equation needed to ascertain the flow coefficient in light of the different features of the basin. According to the SMRGT method, the model output (flow coefficient) should equal the number of rules, which in this study is determined to be 125. If there is no precipitation, the flow coefficient's smallest and largest value ranges are interpreted as 0 and 1, respectively. To generalize the model, all probabilities of precipitation events are accounted for, resulting in the development of a model of flow coefficient. In the generated model, the effects of precipitation, temperature and relative humidity on the flow coefficient were not identical; each independent variable's contribution was assumed to be distinct.

Upon examination of the created fuzzy rules, it is evident that the flow coefficient attains a value of zero under conditions of minimal precipitation and relative humidity, specifically at 200 mm and 0%, respectively, while the temperature is at an exceedingly elevated level of 50 C°. Furthermore, the flow coefficient attains a value of unity under conditions of maximum precipitation and relative humidity; i.e., 2000 mm and 100%, respectively, coupled with an extremely low temperature of zero Celsius. The aforementioned instances serve as an evidence that the model possesses both mathematical precision and physical validity. This conclusion is supported by the research presented in Toprak (2009), Bayri (2018), Sevgin (2021), Unes et al. (2019), … etc. The volume of water passing through a given area will be maximized under heavy precipitation and low temperature accompanied by elevated relative humidity. The analysis reveals the presence of statistically significant positive and negative correlations between the output variable and the input variables. Stated differently, there exists a positive correlation between the flow coefficient and the quantity of precipitation and relative humidity present in the atmosphere, while a negative correlation exists between the flow coefficient and temperature.

Figures 6 and 7 show, respectively, how the model result (the dependent variable, the flow coefficient) varies in three dimensions (3D) as a function of the variables that are considered independent (precipitation, temperature and relative humidity). Generating a 3-dimensional surface involves evaluating the membership functions of each input variable and then combining them using fuzzy inference rules to determine the degree of membership in the output fuzzy sets. The results are commonly articulated in the shape of a degree of membership with imprecision or a definite output quantity achieved *via* the process of defuzzification. Each point situated on the surface represents a distinct combination of input variables and their corresponding output values, as ascertained by the fuzzy inference process. The presence of complex patterns, associations that are not linear or boundaries that are unclear is dependent on the membership functions and fuzzy inference rules that have been chosen. The analysis of the tri-dimensional surface has the capability of enhancing understanding of the effects of modifications in the input parameters on the output, thus aiding in the creation of determinations or the establishment of management systems based on the fuzzy-logic model.

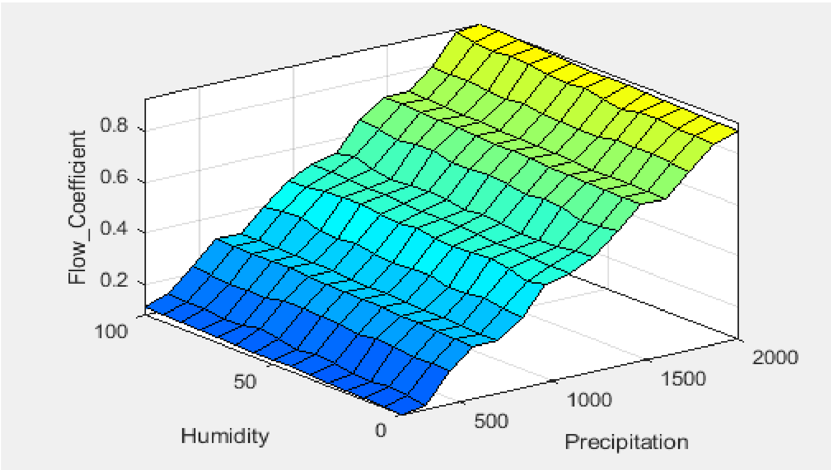

Figure (6): The 3D variation of the flow coefficient due to precipitation and relative humidity

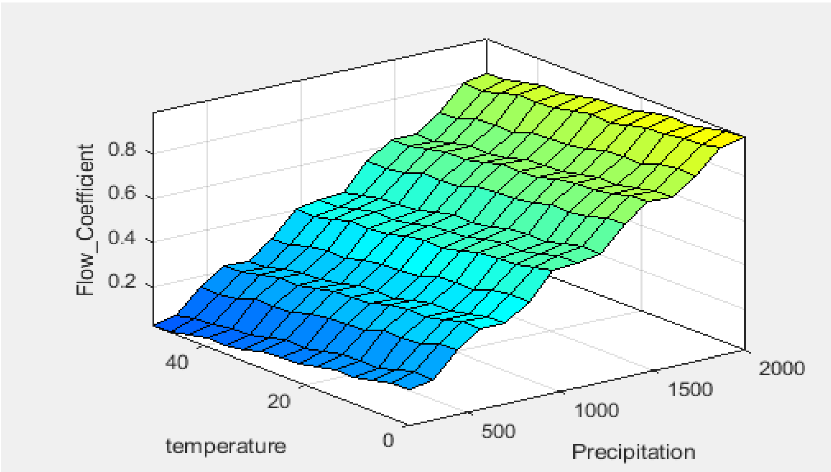

Figure (7): The 3D variation of the flow coefficient due to precipitation and temperature

The statistical parameters' minimum (X_{min}), mean (X_m), maximum (X_{max}), standard deviation (σ), coefficient of variation (C_{vx}), coefficient of skewness (C_{sx}) and correlation coefficient (r) were used to compare the model's output with the data to test the model's predictions. Error types also included Mean Absolute Relative Error (MARE), Mean Square Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results of statistical comparisons are shown in Table 2. In addition, a scatter diagram (Figure 8) was used to illustrate the comparison. The scatter diagram reveals that the regression line intersects the horizontal axis at an angle of approximately 45 degrees. This means that the model is not skewed. In other words, the model does not produce consistently larger or smaller predictions than the observed data. The high coefficient of determination (R^2 = 0.963) indicates that the statistical relationship between the model and data outcomes can be expressed mathematically. In other words, the model identifies the trend in the data. Most points lie close to the regression line, indicating that the model results and actual data are numerically comparable. Table 3 displays the number of FRs and the output's key values. The table depicts the generation of fuzzy rules for a fuzzy model.

Table 2. Comparison of statistical parameters and rates of errors

Statistical Parameters	Data	Model
Max.	1.00	1.00
Min.	0.00	0.00
Mean	0.56	0.50
Standard Deviation	0.31	0.29
Skewness	0.00045	-0.00029
Coefficient of Variance (CV)	0.56	0.586
Correlation Coefficient (r)	0.98	
Nash-Sutcliffe Efficiency Coefficient (NSE)	0.90	
Mean Absolute Error (MAE)	0.081	
Mean Absolute Relative Error (MARE)	17.3	
Root Mean Square Error (RMSE)	0.096	

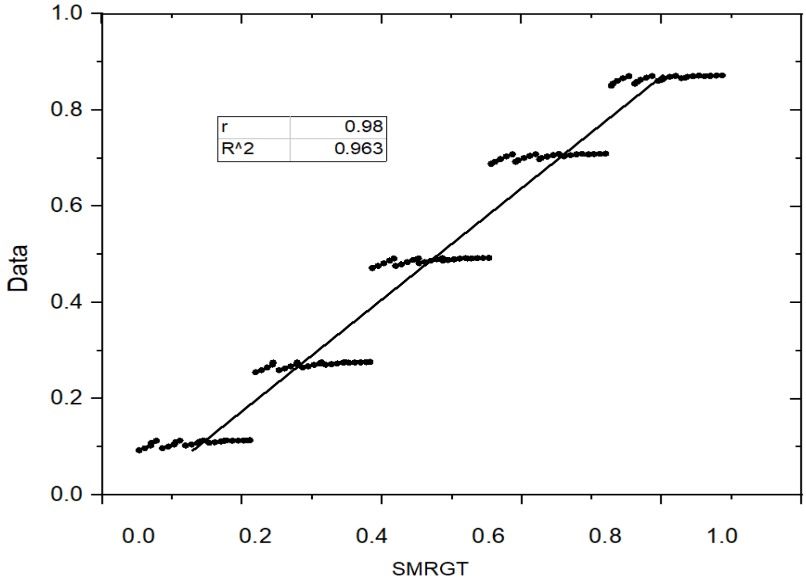

Figure (8): The scatter diagram of the SMRGT model and data results

Table 3. Fuzzy-set generation

Precipitation (mm)		Temperature (°C)		Relative Humidity (%)		Flow Coefficient	Flow Coefficient	Mean Absolute Relative Error
Numerical	Verbal	Numerical	Verbal	Numerical	Verbal	(Data)	(Model)	MARE
312.5	Very low	46.88	Very High	6.25	Very low	0.0000	0	0.00
312.5	Very low	46.88	Very High	25	Low	0.0210	0.01	0.42
312.5	Very low	46.88	Very High	50	Medium	0.0290	0.02	0.25
312.5	Very low	46.88	Very High	75	High	0.0340	0.0212	0.30

312.5	Very low	46.88	Very High	93.75	Very high	0.0410	0.03	0.21
312.5	Very low	37.5	High	6.25	Very low	0.0591	0.04	0.26
312.5	Very low	37.5	High	25	Low	0.0682	0.05	0.21
312.5	Very low	37.5	High	50	Medium	0.1360	0.06	0.45
312.5	Very low	37.5	High	75	High	0.1410	0.0627	0.44
312.5	Very low	37.5	High	93.75	Very high	0.1447	0.07	0.41
312.5	Very low	25	Medium	6.25	Very low	0.1401	0.08	0.34
312.5	Very low	25	Medium	25	Low	0.1426	0.09	0.30
312.5	Very low	25	Medium	50	Medium	0.1460	0.1	0.25
312.5	Very low	25	Medium	75	High	0.1493	0.104	0.24
312.5	Very low	25	Medium	93.75	Very high	0.1518	0.11	0.22
312.5	Very low	12.5	Low	6.25	Very low	0.1530	0.12	0.17
312.5	Very low	12.5	Low	25	Low	0.1542	0.13	0.13
312.5	Very low	12.5	Low	50	Medium	0.1559	0.14	0.08
312.5	Very low	12.5	Low	75	High	0.1576	0.146	0.06
312.5	Very low	12.5	Low	93.75	Very high	0.1588	0.15	0.04
312.5	Very low	3.125	Very low	6.25	Very low	0.1626	0.16	0.01
312.5	Very low	3.125	Very low	25	Low	0.1630	0.17	0.03
312.5	Very low	3.125	Very low	50	Medium	0.1634	0.18	0.08
312.5	Very low	3.125	Very low	75	High	0.1638	0.187	0.11
312.5	Very low	3.125	Very low	93.75	Very high	0.1641	0.19	0.13
650	Low	46.88	Very High	6.25	Very low	0.2968	0.2	0.26
650	Low	46.88	Very High	25	Low	0.3014	0.21	0.24
650	Low	46.88	Very High	50	Medium	0.3077	0.22	0.23
650	Low	46.88	Very High	75	High	0.3139	0.229	0.22
650	Low	46.88	Very High	93.75	Very high	0.3185	0.23	0.22
650	Low	37.5	High	6.25	Very low	0.3064	0.24	0.17
650	Low	37.5	High	25	Low	0.3101	0.25	0.16
650	Low	37.5	High	50	Medium	0.3151	0.26	0.14
650	Low	37.5	High	75	High	0.3201	0.27	0.13
650	Low	37.5	High	93.75	Very high	0.3238	0.271	0.13
650	Low	25	Medium	6.25	Very low	0.3193	0.28	0.10
650	Low	25	Medium	25	Low	0.3218	0.29	0.08
650	Low	25	Medium	50	Medium	0.3251	0.3	0.06
650	Low	25	Medium	75	High	0.3284	0.31	0.04
650	Low	25	Medium	93.75	Very high	0.3309	0.313	0.04
650	Low	12.5	Low	6.25	Very low	0.3321	0.32	0.03
650	Low	12.5	Low	25	Low	0.3334	0.33	0.01
650	Low	12.5	Low	50	Medium	0.3350	0.34	0.01
650	Low	12.5	Low	75	High	0.3367	0.35	0.03
650	Low	12.5	Low	93.75	Very high	0.3379	0.354	0.04
650	Low	3.125	Very low	6.25	Very low	0.3418	0.36	0.04
650	Low	3.125	Very low	25	Low	0.3421	0.37	0.07
650	Low	3.125	Very low	50	Medium	0.3425	0.38	0.09
650	Low	3.125	Very low	75	High	0.3429	0.39	0.11
650	Low	3.125	Very low	93.75	Very high	0.3432	0.396	0.12

1100	Medium	46.88	Very High	6.25	Very low	0.5356	0.4	0.20
1100	Medium	46.88	Very High	25	Low	0.5403	0.41	0.19
1100	Medium	46.88	Very High	50	Medium	0.5465	0.42	0.19
1100	Medium	46.88	Very High	75	High	0.5527	0.43	0.18
1100	Medium	46.88	Very High	93.75	Very high	0.5574	0.437	0.17
1100	Medium	37.5	High	6.25	Very low	0.5452	0.44	0.15
1100	Medium	37.5	High	25	Low	0.5490	0.45	0.14
1100	Medium	37.5	High	50	Medium	0.5540	0.46	0.14
1100	Medium	37.5	High	75	High	0.5589	0.47	0.13
1100	Medium	37.5	High	93.75	Very high	0.5627	0.479	0.12
1100	Medium	25	Medium	6.25	Very low	0.5581	0.48	0.11
1100	Medium	25	Medium	25	Low	0.5606	0.49	0.10
1100	Medium	25	Medium	50	Medium	0.5639	0.5	0.09
1100	Medium	25	Medium	75	High	0.5672	0.51	0.08
1100	Medium	25	Medium	93.75	Very high	0.5697	0.52	0.07
1100	Medium	12.5	Low	6.25	Very low	0.5710	0.521	0.07
1100	Medium	12.5	Low	25	Low	0.5722	0.53	0.06
1100	Medium	12.5	Low	50	Medium	0.5739	0.54	0.05
1100	Medium	12.5	Low	75	High	0.5755	0.55	0.04
1100	Medium	12.5	Low	93.75	Very high	0.5768	0.56	0.02
1100	Medium	3.125	Very low	6.25	Very low	0.5806	0.563	0.02
1100	Medium	3.125	Very low	25	Low	0.5809	0.57	0.02
1100	Medium	3.125	Very low	50	Medium	0.5813	0.58	0.00
1100	Medium	3.125	Very low	75	High	0.5817	0.59	0.01
1100	Medium	3.125	Very low	93.75	Very high	0.5820	0.6	0.02
1550	High	46.88	Very High	6.25	Very low	0.7744	0.604	0.18
1550	High	46.88	Very High	25	Low	0.7791	0.61	0.17
1550	High	46.88	Very High	50	Medium	0.7853	0.62	0.17
1550	High	46.88	Very High	75	High	0.7915	0.63	0.16
1550	High	46.88	Very High	93.75	Very high	0.7962	0.64	0.16
1550	High	37.5	High	6.25	Very low	0.7841	0.646	0.14
1550	High	37.5	High	25	Low	0.7878	0.65	0.14
1550	High	37.5	High	50	Medium	0.7928	0.66	0.13
1550	High	37.5	High	75	High	0.7978	0.67	0.13
1550	High	37.5	High	93.75	Very high	0.8015	0.68	0.12
1550	High	25	Medium	6.25	Very low	0.7969	0.687	0.11
1550	High	25	Medium	25	Low	0.7994	0.69	0.11
1550	High	25	Medium	50	Medium	0.8027	0.7	0.10
1550	High	25	Medium	75	High	0.8061	0.71	0.10
1550	High	25	Medium	93.75	Very high	0.8085	0.72	0.09
1550	High	12.5	Low	6.25	Very low	0.8098	0.729	0.08
1550	High	12.5	Low	25	Low	0.8110	0.73	0.08
1550	High	12.5	Low	50	Medium	0.8127	0.74	0.07
1550	High	12.5	Low	75	High	0.8143	0.75	0.06
1550	High	12.5	Low	93.75	Very high	0.8156	0.76	0.05
1550	High	3.125	Very low	6.25	Very low	0.8194	0.77	0.05

1550	High	3.125	Very low	25	Low	0.8197	0.771	0.05
1550	High	3.125	Very low	50	Medium	0.8202	0.78	0.04
1550	High	3.125	Very low	75	High	0.8206	0.79	0.03
1550	High	3.125	Very low	93.75	Very high	0.8209	0.8	0.02
1887.5	Very High	46.88	Very High	6.25	Very low	0.9536	0.81	0.12
1887.5	Very High	46.88	Very High	25	Low	0.9582	0.813	0.12
1887.5	Very High	46.88	Very High	50	Medium	0.9644	0.82	0.12
1887.5	Very High	46.88	Very High	75	High	0.9707	0.83	0.12
1887.5	Very High	46.88	Very High	93.75	Very high	0.9753	0.84	0.11
1887.5	Very High	37.5	High	6.25	Very low	0.9632	0.85	0.09
1887.5	Very High	37.5	High	25	Low	0.9669	0.854	0.09
1887.5	Very High	37.5	High	50	Medium	0.9719	0.86	0.09
1887.5	Very High	37.5	High	75	High	0.9769	0.87	0.09
1887.5	Very High	37.5	High	93.75	Very high	0.9806	0.88	0.08
1887.5	Very High	25	Medium	6.25	Very low	0.9761	0.89	0.07
1887.5	Very High	25	Medium	25	Low	0.9785	0.896	0.07
1887.5	Very High	25	Medium	50	Medium	0.9819	0.9	0.07
1887.5	Very High	25	Medium	75	High	0.9852	0.91	0.06
1887.5	Very High	25	Medium	93.75	Very high	0.9877	0.92	0.05
1887.5	Very High	12.5	Low	6.25	Very low	0.9889	0.93	0.05
1887.5	Very High	12.5	Low	25	Low	0.9902	0.937	0.04
1887.5	Very High	12.5	Low	50	Medium	0.9918	0.94	0.04
1887.5	Very High	12.5	Low	75	High	0.9935	0.95	0.04
1887.5	Very High	12.5	Low	93.75	Very high	0.9947	0.96	0.03
1887.5	Very High	3.125	Very low	6.25	Very low	0.9985	0.97	0.02
1887.5	Very High	3.125	Very low	25	Low	0.9989	0.979	0.02
1887.5	Very High	3.125	Very low	50	Medium	0.9993	0.98	0.02
1887.5	Very High	3.125	Very low	75	High	0.9997	0.99	0.01
1887.5	Very High	3.125	Very low	93.75	Very high	1.0000	1	0.00

Table 3 demonstrates the efficacy of the SMRGT approach in augmenting the interpretability and reducing the opacity of the fuzzy-logic system. This is achieved through the utilization of linguistic labels that are more readily comprehensible, such as "low," "medium " and "high," as opposed to labels that are highly subjective. The process of simplifying fuzzy rules, which were originally established based on expert experience and included physical cause-and-effect relationships, resulted in a reduction in the complexity of the fuzzy rule set and improved its comprehensibility.

CONCLUSIONS

The present study utilized a fuzzy logic-based artificial-intelligence model to determine the flow coefficient. The utilization of a straightforward membership function and fuzzy rules' generation technique (SMRGT) was introduced and implemented for fuzzy modeling. The Mamdani fuzzy models have been established using MATLAB software. The present investigation revolves around the concept and its sub-models, which have demonstrated considerable success when evaluated against the aforementioned criteria. The suitability of its usage in the computation of the flow coefficient is supported by the impartiality and linearity of the scatter diagram, as well as the high correlation coefficient (R^2) and Nash-Sutcliffe efficiency coefficient (NSE) observed between the data and the model valuation.

Additionally, the model exhibits low values of Mean Absolute Relative Error (MARE), Mean Square Error

(MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Statistical parameters are similar to the observed data. The algorithm's application segment indicates that model calibration does not necessitate any data. The development of the model by SMRGT solely necessitates the expertise of the modeller. Moreover, it is not necessary to perform model calibration through trial and error. Consequently, there exists no necessity to partition the datasets into two distinct categories; namely, the training and model-testing sets. Moreover, it is unnecessary to utilize either software or a sub-program for the purpose of calibrating the model.

The study presented herein provides an evidence on that fuzzy logic exhibits a dynamic architecture and possesses the ability to deduce with ease when novel data is incorporated into the framework. In contrast to classical analysis, it is believed that the utilization of this method has a beneficial impact on engineering design, as it has the capacity to present all experimental outcomes within a precise mechanism. The fuzzy SMRGT model's ability to account for the physical cause-effect relationship allows for its generalizability across various basins, regions and time periods. As per the data provided by the State Hydraulic Works, the mean flow coefficient of the basins located in Turkey is 0.37. The Aksu basin's water-storage capacity is comparatively low, as evidenced by its value of 0.49 in relation to the average for Turkey. This indicates a heightened susceptibility to flooding within the basin. The hypothesis posits that the utilization of the fuzzy SMRGT approach, in conjunction with other analogous physics-oriented methodologies, ought to be more prevalently employed in the modeling of the flow coefficient, given the sensitivity and uncertainty associated with flood disasters. This enables the contemplation of an authoritative viewpoint regarding the model in comparison to alternative approaches documented in the literature. The existing literature reveals a limited number of studies focused on the determination of the flow coefficient. Several of the aforementioned studies are classical in nature, while the majority of the more recent ones suggest a black-box model. However, the generalization of such models may result in a decrease in precision when determining the flow coefficient.

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