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# Optimization of adaptive fuzzy logic controller using novel combined evolutionary algorithms, and its application in Diez Lagos flood controlling system, Southern New Mexico

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ABSTRACT

In fuzzy logic controllers (FLCs), optimal performance can be defined as performance that minimizes the deviation (error term) between the decisions of the fuzzy logic systems and the decisions of experts. A range of approaches – such as genetic algorithms (GA), particle swarm optimization (PSO), artificial neural networks (ANN), and adaptive network based fuzzy inference systems (ANFIS) – can be used to pursue optimal performance for FLCs by refining the membership function parameters (MFPs) that control performance. Multiple studies have been conducted to refine MFPs and improve the performance of fuzzy logic systems through the application of a single optimization approach, but since different optimization approaches yield different error terms under different scenarios, the use of a single optimization approach does not necessarily produce truly optimal results. Therefore, this study employed several optimization approaches – ANFIS, GA, and PSO – within a defined search engine unit that compared the error values from the different approaches under different scenarios and, in each scenario, selected the results that had the minimum error value. Additionally, appropriate initial variables for the optimization process were introduced through the Takagi–Sugeno method. This system was applied to a case study of the Diez Lagos (DL) flood controlling system in southern New Mexico, and we found that it had lower average error terms than a single optimization approach in monitoring a flood control gate and pump across a range of scenarios. Overall, using evolutionary algorithms in a novel search engine led to superior performance, using the Takagi–Sugeno method led to near-optimum initial values for the MFPs, and developing a feedback monitoring system consistently led to reliable operating rules. Therefore, we recommend the use of different methods in the search engine unit for finding the optimal MFPs, and selecting the MFPs from the method which has the lowest error value among them.




## 1. Introduction

Fuzzy sets and fuzzy logic were proposed by Zadeh in 1965 (Zadeh, 1965), and these concepts have been used widely in control systems. Generally, fuzzy logic controllers (FLCs) utilize linguistic expressions to develop a quantitative relationship between the input and output elements of the model. In order to gain output values that are acceptably near the expected outputs, FLCs should be tuned and optimized. To achieve this, evolutionary algorithms have been used widely by Q2 several researchers. Khan et al. (2015) used a genetic algorithm for tuning the adaptive fuzzy multivariable controller applied in an air handling unit. Collotta, Bello, and Pau (2015) have developed a combined system that uses a wireless sensor network and multiple FLCs to dynamically control the green time of traffic lights. Instead of one single FLC, Collotta et al. (2015) applied multiple FLCs for controlling different traffic phases. As compared to the use of a single FLC, the approach developed by Collotta et al. led to a higher fault tolerance, shorter waiting times for arriving vehicles, higher scalability, and higher flexibility with unbalanced arrival rates. Muthukaruppan and Er (2012) used the PSO method to tune the developed MFPs of a fuzzy expert system, which was being used to diagnose coronary artery diseases. They used a decision tree model to unravel the contributing attributes in coronary artery diseases and transfer into fuzzy based rules (fuzzy expert system); then, the fuzzy expert system was tuned by PSO. The fuzzy expert system tuned by PSO showed

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higher classification accuracy (93.27%) between heart diseases and health conditions. Muthukaruppan and Er's approach in using a hybrid model that incorporated both a decision tree model and PSO led them to higher accuracy. Wang and Altunkaynak (2011) utilized FLCs for simulating the rainfall-runoff of a system, and Saghaei and Didekhani (2011) used an ANFIS to derive overall utilities of projects by considering the interrelations among the involved criteria. Bingul and Karahan (2011) used PSO for tuning an FLC that was used for controlling a robot trajectory in two dimensional movement. Deka and Chandramouli (2009) developed a hybrid model of artificial neural network and fuzzy inference systems to find the optimized reservoir releases. Cheng, Tsai, Ko, and Chang (2008) used a fuzzy neural inference system to optimize the decision-making processes in geotechnical engineering. Shoorehdeli, Teshnehlab, and Sedigh (2007), by using the PSO method, developed a hybrid learning approach for tuning the parameters of ANFIS. Ahlawat and Ramaswamy (2004) developed an optimal FLC to predict a tall building's displacement in windy conditions. Karaboga, Bagis, and Haktanir (2004) used a fuzzy inference system for operating the spillway gates in a flood controlling reservoir. Navale and Nelson (2010), Chen and Rine (2003), and Yang and Soh (2000) used a GA for finding the optimal parameters of FLCs in different engineering systems. Russell and Campbell (1996) used fuzzy inference for finding the optimal operating rule of a reservoir.

In most studies, researchers used a single evolutionary algorithm in tuning and optimizing FLCs. However, it is unlikely that a single evolutionary algorithm will find the optimal solution for all encountered scenarios, and may even select a locally optimal solution rather than a globally optimal solution. There is a crucial lack of a search engines for comparing the results of different evolutionary algorithms to ensure that the parameters of the FLCs are, in fact, optimal. This study attempts to minimize the uncertainty level of FLC's optimality by defining a search engine that includes three popular evolutionary methods. By using and comparing multiple evolutionary algorithms, this approach increases the likelihood of identifying truly optimal conditions and reduces the risk of selecting locally optimal conditions rather than globally optimal conditions. In order to achieve an accurate and optimal fuzzy inference system (FIS), two key factors are significantly important: (1) discovering appropriate fuzzy rules, and (2) applying an appropriate tuning method. Considering the input and output values of an FIS, selecting the appropriate techniques to define the optimal phases is crucially important; therefore, selecting the appropriate fuzzy intervals (phases) of input and output values is as important as tuning the membership functions of those intervals. One of the best approaches to investigate the required structure for a fuzzy inference system is plotting the output and input values. The graphical behavior facilitates the selection of an appropriate structure for the FLC (an FIS). Then, the membership function parameters of that structure can be optimized through an optimization process.

For this study, initial membership function parameters were defined based on Takagi–Sugeno fuzzy inference systems instead of linguistic expressions. The Takagi–Sugeno method was chosen due to the effect exerted by inference systems on the accuracy of FLC-derived output values. In Takagi–Sugeno systems, input variables typically are defined in the form of Gaussian distributions, and output variables are defined in the form of linear intervals or constant output values. Increasing the number of membership functions and intervals in the input and output values also increases the inference system's accuracy in deriving output values for specific input values.

After using the Takagi–Sugeno method to select appropriate initial membership function parameters, the FLCs utilized in the Diez Lagos (DL) flood control system were tuned and optimized through a novel dynamic tuning system that was developed in this study. This dynamic tuning system simultaneously utilizes three evolutionary algorithms in finding the MFPs of the FLCs. Additionally, this study developed several optimized operational plans for gate and pump operations under different flooding conditions. These plans were derived by optimizing two FLCs, one for pump operations and the other for gate operations.

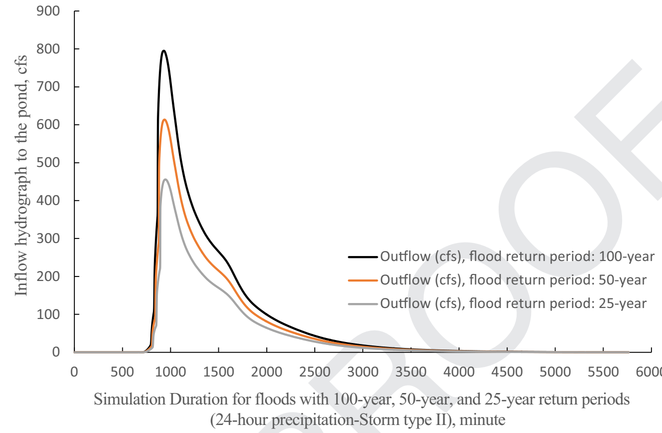


**Fig. 1.** Inflow hydrographs to the pond for floods with 100-year, 50-year, and 25-year return periods (24-h precipitation, Storm type II).

The aim of DL pond system is to capture a total runoff volume of about 250,000 $m^3$. For floods that exceed the pond system's capacity, excess runoff must be transferred to the drainage system through the controllable gate and pump to protect downstream residential areas. Additionally, a significant percentage of the total captured runoff is infiltrated to the existing aquifer system through seepage.

## 2. Material and methods

In this study, runoff hydrographs for the DL system were obtained by using the soil conservation service method (SCS) for 24-h rainfall flood events with the various return periods of 25-years, 50-years, and 100 years.

In a previous study, Zamani and King (2015) developed a dynamic operating system for the flood control pond in DL, simulating the pond as a control volume where the volume change in the control volume equals inflow to the pond minus outflow from the pond. The outflow from the pond is considered to take three forms: outflow as seepage to the underground aquifer, outflow through the gate to the drainage system, and outflow through the pump to the drainage system. The pump system and gate have not yet been installed, but river aggradation has severely limited the ability to release water by gravity through the drainage system. Part of the objective of this study was to provide a basis for sizing the proposed gate and pump systems. Although evapotranspiration could have been considered as another outflow, it was neglected in Zamani and King's simulation process in order to develop a conservative scenario that minimized risk to the downstream residential area. Therefore, the general control volume was formulated as follows:

$$Q_{in} - Q_{out} = A\frac{dh}{dt} = Q_{in} - Q_{seepage} - Q_{gate} - Q_{pump} \quad (1)$$

where, for a specific simulation duration, $Q_{in}$ is the inflow to the pond and $Q_{out}$ is total outflow from the pond. $Q_{out}$, in turn, includes seepage ($Q_{seepage}$), outflow from the gates ($Q_{gates}$), and outflow from the pump ($Q_{pump}$).

The inflow hydrographs to the DL pond for return periods of 100-year, 50-year, and 25-year for 24-h duration are shown in Fig. 1. The variation of accumulated outflows from the gate against accumulated inflow to the pond for flood return periods of 100-years, 50-years, and 25-years is shown in Fig. 2. Those variations were simulated for simulation duration. For return periods of 100-years, 50-years, and 25-years, Fig. 2 shows, the dynamics of accumulated inflow to the