Intelligent model for reservoir operation through data mining- A Case study

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Abstract. Classical discrete mathematics could not model complex and uncertain systems effectively. These discrete mathematical equations can be replaced by a method of fuzzy logic systems wherein the operational laws are expressed in linguistic terms. Fuzzy logic means it is the form of knowledge acquisition to be suitable for notions that cannot be defined as precisely as discrete mathematics would do. But it depends upon their context, knowledge acquisition to enable the computerized devices to think like humans. The Matlab was employed to develop the operation model of the Vaigai reservoir which is in South India. Fuzzy logic control was successfully found to be a logical way for mapping between input and output variables of the operation of a reservoir. The objective of the study was to capture the experience gained over past years of operation of the Vaigai system so that the experiential knowledge was made available to the operator for assisting him inefficient management of the reservoir. The data mining helped to develop an improved database for heuristic models such as the non-crisp model for deriving an effective monthly operational policy for Vaigai reservoir.

Key words: Fuzzy models, Fuzzy logic toolbox, Vaigai reservoir, Fuzzy logic control, Takagi-Sugeno (TSK) fuzzy model.

1. Introduction
Water resources system modelling using scientific and analytical models are not the choice of engineers. This is mainly because of its ill-defined and uncertain information or the pattern existing amongst the variables. In contrast, a new intelligent approach namely, a fuzzy inference system applying “if-then-else” rules can be used to model the linguistic, human knowledge and thinking qualitative method. Moreover, this method does not require precise quantitative data, pre-process, and analyses. In fuzzy logic, the inference could be non-crisp and unclear information. For example, while the water demand is ‘very high’ i.e. in qualitative data form, the crisp value is essential for developing its inference system.

However, intelligent methods can be used to process this type of information as well. Most of the natural, environmental, applied, hydrogeological, sociological, biological, hydrological, and ecological processes are non-linear phenomena i.e. the relationship between the cause and effect of these processes is not clear and is of non-linear distribution. They used Stochastic Dynamic Programming (SDP) to frame the rule base in their approach. For the unsaturated zone, fuzzy control is used to represent water movement and seepage [1]. The triangle fuzzy classifier for storage intervals produces a more flexible...
interpretation technique than the trapezoidal classifier, which produces operating policies that mimic those defined by probabilistic stochastic dynamic programmes more closely [2]. In comparison to C5.0, NDT, and current Dam operating standards, the FIDs model has shown greater performance. This researcher utilised fuzzy logic to determine the best operating rules and allocations for the dam based on water demand [3].

The linear regression models are not sufficient to explain the uncertain and non-linear system’s behaviours [4]. Artificial neural networks (ANN), Fuzzy Loci Controls (FLC), rule-based systems, genetic programming, and cellular automata are some of the most proven non-linear modelling tools and are used to a greater extent in natural process modelling than any others. For single flow control, a fuzzy rule-based equation was developed [5]. The fuzzy rule-based model gives only approximate values of the flow which can be estimated and interpolated with better accuracy than other mathematical methods. An irrigation system was modelled to estimate the system's hydraulic efficiency's optimum variables. The principal source of electricity in this system is a small-scale wind turbine, with the electricity being stored in a cell battery. A water pump is also included in the system to keep the water reservoir topped off. This pumping mechanism has the advantage of not requiring any maintenance [9].

The examination of questionnaires is a complicated procedure that must account for inherent subjectivity and ambiguity in data sets. A fuzzy signatures (FSigs)-based system was developed for analysing questionnaires with hierarchically connected (partially) unclear replies, and its usefulness a real-world problem was used to demonstrate this: a robot performing a partial analysis of current research [10]. The study aimed to use correlation, R and linear fitting regression coefficient to assess the influence between watermelon performance as well as the density of its primary pests, resulting in models for predicting crop performance based on pest density for better pest management. Watermelon is infested with a variety of pests that vary in formulation and intensity depending on the season [11].

Crop growth models of various levels of complexity were already developed to anticipate the impacts of water, soil, and nutrients and biofuel yields, as well as irrigation management, in a range of crops. For GY and BY, the Root Mean Square Error - RMSE and system performance was 0.87 to 0.96, 0.1 to 1.2, and 0.87 to 0.96, accordingly. As an outcome, the Aquacrop model is a useful tool for making agricultural development decisions for soybeans. [12]. A proportional integral was used to manage the fluid pressure in an uncertain system such as over-head tanks of non-axis symmetric objects. It does not, however, provide a precise result. Therefore, the fuzzy logic controller adds intelligence to the machine, allowing for a more accurate and effective reaction (FLC). The Kalman method, which uses fuzzy logic rules, automatically adjusts the state variables during system operation, and the controller is used to reduce error in poor circumstances.

A conical tank system is used to perform this strategy. A conical tank structure is used to perform this strategy. When using fuzzy regulators, this strategy appears to be effective, according to modelling findings [13]. It is described how a heuristic method was applied to monitor the bending strength of welds. A Mamdani-type fuzzy model was created with experimental results to predict the bending strength of welding was developed and tested in the lab. The fuzzy outputs for weld tensile strength and nugget hardness show errors of 2.13 and 1.31 per cent, respectively, when comparing to the experimental data. The developed methodology was used for real-time operation and assessment of the FSW operation within the limit of operational factors [14].

A fuzzy aided grey Taguchi technique was presented for numerous weld performance criteria. Using the fuzzy inference system, the Taguchi methodology in the early stage was employed for multi-response programming issues against its analogous issue. The input performance was altered for knowing how the outcomes properties are affected. The proposed method can effectively be applied in the FSW process to maximize numerous weld quality attributes, according to a confirmation test [15]. The authors presented fuzzy operation of controllers which are self-programming and adjusting to get an optimal value [16].
An identity approach to address constantly changing operating conditions and poor ratios were modelled using other forms of fuzzy controls. The found by dynamic simulation and characteristics analysis and the grate cooler channel condition was generated through system modelling [17]. This paper uses a diary methodology to study the impacts of air pollution ratings on employees' routine physical resources and behaviour. According to multilevel data obtained over 2 metropolitan cities, affects workers badly [18]. The algorithm, and a parallel version, are detailed in the Fuzzy module of the free computer algebra software Sage Math. Solve Fuzzy System, or SFS, is an efficient technique for finding actual solutions of computation systems with symmetrical L-R fuzzy numbers as coefficients and constrained support and objective distribution functions are L and R. The real solutions of a system can be derived from the solutions of some polynomial systems with real coefficients [19].

It presented a numerical approach for generating this index as well as a way of computing them. When comparing two fuzzy sets, the comparison should be available to respond by ignoring the order. Two crisp relations with shared factors over a collection of classifiers were generated by the preferred density function. There exist a stringent order relation and the rest is a relation that reflects order indifference, based on the parameter value [20]. A distance in between the sum of upper semicontinuous fuzzy subsets of a finite-dimensional Euclidean space but also its T-convex hull has an upper limitation. As a result of this discovery, we describe an iterative approach for generating a T-convex hull of an upper semicontinuous fuzzy set. As an extension of the conclusions about t-norm fuzzy sets, we offer an example from a game-theoretic situation where t-norm fuzzy sets were utilised to handle uncertainty in a recurring two-player game [21].

2. Materials and methods
The methodology entails the fuzzy logic control (FLC) approach for tackling the problem of reservoir operation. To start with, the results of optimization were used for creating the input database of the model. Input data of Inflows (I), Initial Storage (S), Demand (D), and Release (R) were collected for the study period 1969-1997 and used in programming reservoir operation. The system has input and output engines. Hence the first task of preparing the data set was completed in this study. The logical steps involved in the development in the form of a diagram of the developed model development are shown in Figure 1. The model is to derive the operational policies for the reservoir system chosen. These systems also utilized the knowledge of experts and attempted to incorporate the imprecision and uncertainty associated with various aspects of developing rules of this integrated modelling system. The model was developed in Matlab with a Fuzzy toolbox. In this present work, explicit considerations on variability in inflow pattern, storage non-specificity, imperfection of the demand level, and fuzzy constraints on the releases were implemented in the concept of developing membership functions.

2.1. Methodology of Fuzzy Logic Model Development
The fuzzy logic system using linguistic terms is generally expressed in the form of logical implications, such as “if-then rules”. The crisp constraints are fuzzified to non-crisp constraints in several water resource-related applications. But this approach is a usual refinement to conventional optimization techniques using fuzzy logic. “Tsebyschev Polynomial transformation was applied to transform the fuzzy constraints” in the study area chosen to develop a fuzzy inference system. MATLAB is a numeric computing environment hosting Fuzzy logic which has a collection of built-in functions for programming as per problem needs. The procedure for developing the fuzzy model for reservoir operation is as follows. i) Firstly, construct membership function for the variable; inflow, ii) membership function for the initial storage, iii) membership function for demand and iv) membership function for release, vi) formulation of fuzzy rules and implication. The operation of the reservoir has been represented by simulating a fuzzy model and its defuzzification of the output. The results are compared with that of the actual operation to check for suitability, adaptability, and applicability of the fuzzy logic model for reservoir operation.

The steps involved are as follows:
1. Fuzzification of Inputs
2. Fuzzy membership function derivation
3. Fuzzy Inference System (Rule Base)
4. Aggregation
5. Crisp values and output
6. Fuzzification of Inputs

For deriving operation policies in this study Type I Sugeno fuzzy inference system was used. It was attempted to show how the Sugeno type system gave freedom to incorporate a constant/linear system into a fuzzy system. The initial step of the fuzzy inferencing system is to select the input and evaluate the degree to which it will form a range of classes. Each class will then fall into different fuzzy sets for which membership functions will be developed.

![Flow Diagram of Reservoir Operation policy using FLC](image1)

**Figure 1.** Flow Diagram of Reservoir Operation policy using FLC

The input parameters are grouped into many fuzzy linguistic sets of different types. The possible max and min size of the fuzzy variables (3-3-3-3, 3-5-3-3, 3-3-5-3, 3-3-3-5, 5-5-3-3, 3-5-5-3, 3-3-5-5 and 5-3-3-5) are chosen based on the testing of various topologies of fuzzy variables. When their performances of meeting the target demands were compared, 5-3-3-5 topology had given a better performance than other topologies. Hence the topology of the fuzzy model had been chosen as 5-3-3-5. The reservoir
operation variables such as inflow, demand, initial storage, and release are considered in the current study. The fuzzy sets are chosen to be between the ranges of very low to very high. Some parameters are taken from low to high and some very low to very high according to their physical nature and the records. The model is developed using inputs that are a numerical value within the database and are criss sets. For example, the June month interval was 1–17 for inflow, 16–193 for storage, 33–43 for demand, and 7–52 for release in a year and vary over different months.

2.2. Fuzzy membership function derivation
It is mentioned that the fuzzy method is a more convenient way for modelling to accept the opinions of experts and is expected by the water operators [6]. A new type of Takagi-Sugeno-Kang fuzzy algorithm, known as the Takagi-Sugeno (TSK) fuzzy model, was used to create a fuzzy model for reservoir operation. The TSK fuzzy model combines linguistic and mathematical regression analysis. The TSK model's primary goal is to create fuzzy models for measured data automatically. To construct a fuzzy engine and aggregate the corresponding results, the model is used to release, inflow, demand, and storage [7]. As a result, this study relied on triangular membership functions. After fuzzification of input data, the degree of belongingness of the antecedent (membership function) may be determined [8].

2.3. Fuzzy logic modelling
Choice of membership function: The predictor's main feature was a sharp part of the subsequent rule. In general, the fuzzy logic rule base in Takagi Sugeno coding looks like this (Takagi and Sugeno 1985):

\[
\text{If } \text{'xx} \text{ is "AA and 'yy is "BB then 'zz = "f (xx, yy)} \hfill (1)
\]

In the antecedent, A and B were fuzzy sets, while \( z = f(xx, yy) \) was a crisp function in the consequent. In most cases, \( f(xx, yy) \) was a polynomial in the \( xx \) and \( yy \) input variables. The model is a first-order polynomial as in Eq.1. This study used the fuzzy logic inferencing method for a linear degree of the Takagi-Sugeno fuzzy model with crisp inputs.

The crucial modelling fact in fuzzy logic is that this approach permits some to be partial and others to be other partial; rather than saying either everything or nothing; and thus, the degree of “fitting” to a particular fuzzy set could be quantitatively by a membership ranging from 0 - 1.0. Hence the definition for fuzzy sets for inflow, initial storage, demand, and release was obtained through historical data instead of expert’s opinion for reservoir operation and are shown in Figure 2.

![Fuzzy Model on reservoir operation](image)
Fuzzy set membership functions are plotted using many different functions. The simple straight-line forming the triangular functions are shown in Figure 3- Figure 5. They are the simplest possible and are often preferred for water resources and environmental applications. In this problem, a statistical method was adopted to discretize the variables into different fuzzy sets. Standard deviations of the database were calculated. The average deviation of each set formed the pivotal value and from which further classifications of the variables were done on both sides. For example, in the discretization of the fuzzy set for initial storage, 0 was low, 112 was medium and 193 was high. “But a class size of, say 50 is in middle, i.e., it is partly belonging to two categories “low” and “medium”. In fuzzy system terms, 50 had a value of 0.4 of low, 0.65 of the medium, and 0.0 of high.” Similarly, other variables as inflow, demand, and release were fuzzified and are shown in Figure 3 to Figure 6.

Figure 3. Membership Function for Inflow

Figure 4. Membership function for Initial Storage
2.4. The Fuzzy Inference System

Imprecise data can be modelled conveniently and diagnosed suitably in the fuzzy logic method. The operating policies developed using the Linear-programming (LP) model was used for deriving the fuzzy rule base of the system. All smaller diagrams of all fuzzy sets are used to compile for a fuzzy inference diagram. Figure 2 shows the model of the fuzzy inference system which was used in deriving the present reservoir operation policies. It could examine simultaneously all parts of the fuzzy inference process automatically. This had all the input membership functions as inflow, initial storage, and demand on one side, output membership function on the other side with fuzzy inference engine at the middle. Information flew through the fuzzy inference diagram. For example; from Figure 2, the particular inputs as inflow, initial storage and demand have helped to easily see that the minimum function was the truncation rule. The pairs of input-output sequences generated from the simulation are employed to derive the fuzzy logic rules. The rules were formed based on the pairs of input-output data sequences from the actual historic operation of the reservoir and the expert's opinion on the values of fuzzy sets. The error seemed to decrease when the membership functions for input parameter and output parameters is slowly increased. Eventually, the rule base also got changed due to this effect. The number of rule

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**Figure 5.** Membership function for Demand

**Figure 6.** Membership Function for Release
bases had increased as the number of membership functions was increased. Hence to achieve an optimal solution from the model, a trade-off was executed. The number of derived rules and their membership functions complement each other to achieve near-optimal solutions from the model.

3. Development of Fuzzy Rules
Many decisions are made by humans and hence it is necessary to use expert’s opinions if a realistic model is to be constructed of a process. For capturing the knowledge and experience of senior professionals and making use of the expert's wisdom in the model a questionnaire survey was conducted for developing the rules. The methodology for building the fuzzy rules was dependent on the linear programming model and of the expert’s opinion. A questionnaire survey was conducted, and the results obtained from 35 responses were aggregated suitably for developing fuzzy rules. In this study 45 rules, several different fuzzy sets were developed by resolving the inputs of each rule. For example, “inflow was very low”, “inflow was low”, “inflow was medium”, “inflow was high”, “inflow was very high”, “initial storage was low”, “initial storage was medium”, “initial storage was high” and so on.

Fuzzy operation rules were constructed for all twelve months. The inputs were fuzzified based on each linguistic set before the rules could be evaluated. For example, what would be the extent of the inflow to be very low? Figure 3 shows how well the inflow into the reservoir qualified, in June (via its membership system function). In this case, the inflow rated as 9, which, had given graphical definition of low, corresponds to a degree \( m = 0.6 \) for the “low” membership function. The counterpart to the operation manager will be “the inflow was low. Likewise, each set of input was studied fuzzified against the qualifying membership functions that are required by the rules. The complete sets of fuzzy system rules developed for reservoir operation are presented in the following sections.

4. Results and discussion
The fuzzy operator was chosen carefully to result in one value that represented the consequence of any rule applied. Since the antecedent of any rule has more than one output it should result in any one number. That number became an output function in the system.

4.1. Aggregation method
The output is always one true value, whereas the fuzzy operators are always few or many values from fuzzified input factors. All of the designed rules made use of the AND operation. The model, for example, has evaluated the antecedent of rule 17 and for release computation in the following month, June month. The fuzzy membership scores 0.65, 1, and 0.5 were obtained from the three different elements of the antecedent (low inflow, low beginning storage, and medium demand). The fuzzy AND operator simply chose the lowest of the three values, 0.5 (the release was very low), and therefore fuzzy logic simulation finished operation rule number 17. Similarly, all the other rules were evaluated using the AND operator. The complete sets of fuzzy system rules developed for reservoir operation are shown in Table 1.

| Rule No. | Fuzzy Rules for Vaigai reservoir operation |
|----------|------------------------------------------|
| 1        | If IW is very low & S is low & D is low then R is very low |
| 2        | If IW is very low & S is low & D is medium then release is very low |
| 3        | If IW is very low & S is low & D is high then release is very low |
| 4        | If IW is very low & S is medium & D is low then release is low |
| 5        | If IW is very low & S is medium & D is medium then release is low |
| 6        | If IW is very low and S is medium and D is high then release is low |
| 7        | If IW is very low and S is high and D is low then release is low |
| 8        | If IW is very low and S is high and D is medium then release is low |
boundary conditions for the reservoir operation were also incorporated in this model using fuzzy logic control. The fuzzy logic model had enhanced the generalization capability of the system by providing constraints involved, and discretisation of variables such as storage and inflows. The way to couple an input domain to an output space. The Takagi-Sugeno-type fuzzy inference system was used in this model. The fuzzy model was validated for a system of continuity equations. Its physical or all three above rules of the antecedent part had been placed together to combine and aggregate the output of each into a single crisp set. FLC stands for Fuzzy logic control was found to be a convenient way to couple an input domain to an output space. The Takagi-Sugeno-type fuzzy inference system was used in this model. The fuzzy model was validated for a system of continuity equations. Its physical or boundary conditions for the reservoir operation were also incorporated in this model using fuzzy logic control. The fuzzy logic model had enhanced the generalization capability of the system by providing more reliable output when extrapolation was needed beyond the limits of the data which were used for developing them. The factors that contributed to the performance were the objective function, constraints involved, and discretisation of variables such as storage and inflows.

4.2. Crisp values and output

All three above rules of the antecedent part had been placed together to combine and aggregate the output of each into a single crisp set. FLC stands for Fuzzy logic control was found to be a convenient way to couple an input domain to an output space. The Takagi-Sugeno-type fuzzy inference system was used in this model. The fuzzy model was validated for a system of continuity equations. Its physical or boundary conditions for the reservoir operation were also incorporated in this model using fuzzy logic control. The fuzzy logic model had enhanced the generalization capability of the system by providing more reliable output when extrapolation was needed beyond the limits of the data which were used for developing them. The factors that contributed to the performance were the objective function, constraints involved, and discretisation of variables such as storage and inflows.
It was found that the fuzzy logic approach proves to be a reliable tool in analysing problems like reservoir operation, like LP, DP, and SDP alone were not essential for this approach. It was very well demonstrated that the fuzzy logic approach is a promising alternative for reservoir operation modelling among the methods discussed in previous sections.

4.3. Validation of the model

A new set of data pattern which was not used for training the Fuzzy logic reservoir operation model was subjected to the validation process. The new data set were presented to the trained FIS model, to see how well the FIS model predict the corresponding output values. The period of this validation was from 1994-’95 to 1997-’98. The releases obtained through the FIS model were plotted against actual releases. The plot is shown in Figure 7.

![Figure 7. Performance of Fuzzy model for reservoir operation](image)

Fuzzy releases have adequately met the demand throughout the year whereas there were excess releases in actual practice. The modelling approach used for developing reservoir operation was much similar to many system identification techniques, but the case study model developed would support the functioning of the operation to a great extent. Further, the performance criteria such as the amount of deficit and percentage of deficit were estimated to validate the model. The results of this validation and the selection of a fuzzy model for reservoir operation are exhibited in Table 2.
Table 2. Comparison of the Performance of FLC Model with Other Models of Reservoir Operation

| Method | Period | 1994-'95 | 1995-'96 | 1996-'97 | 1997-'98 | Average Deficit (%) |
|--------|--------|----------|----------|----------|----------|---------------------|
| ACTUAL | Amount of deficit in Mm3 | 236.9 | 365.7 | 178.9 | 145.9 | |
|        | % deficit | 36.8 | 44.3 | 30.5 | 27.0 | 34.6 |
| LP     | Amount of deficit in Mm3 | 231.4 | 253.5 | 184.2 | 127.7 | |
|        | % deficit | 35.9 | 30.7 | 31.3 | 23.6 | 30.4 |
| EANN   | Amount of deficit in Mm3 | 74.7 | 170.7 | 34.4 | 12.0 | |
|        | % deficit | 11.6 | 20.7 | 5.9 | 2.2 | 10.1 |
| FLC    | Amount of deficit in Mm3 | 25.1 | 94.0 | 22.7 | 9.3 | |
|        | % deficit | 3.9 | 11.4 | 3.9 | 1.7 | 5.2 |

Figure 8. Comparison of performance of Fuzzy model and ANN model
The results had shown a good improvement in meeting the demand as compared with the artificial neural network model, EANN, and actual historic operation and as seen from Table 2. In addition, the percentages of demand met by these models during the validation period were compared in Figure 8. This encouraged the selection of the Fuzzy model over EANN. This has accomplished to state that this type of fuzzy model will provide guidelines for future studies. The developed model can be extended to construct a fuzzy inference system that operates between several optimal controllers. It can also be transformed into a highly nonlinear model within its operating space.

The main improvement in FIS/ FLC systems is its intelligence to imprecise data and tolerance towards insufficient information about the data. FLC can model uncertain functions of mere or arbitrary complexity as well. Hence fuzzy logic is well recommended for developing models on reservoir operation. The next approach may be the modelling of reservoir operation using Neuro-Fuzzy logic which is an integrated model of two heuristic methods namely artificial neural network and fuzzy logic system.

5. Conclusions

The developed FLC model for reservoir operation has produced better results than the system's current operational procedure. For the Vaigai reservoir in South India, FLC was developed to represent reservoir operation by carefully extracting knowledge through data mining. The consequences of a proper set of decisions or set of operating rules were evaluated using detailed data mining on developed models. The following was discovered when the results of data mining and the corresponding results were compared across various modelling methods. The fuzzy reservoir operation model produced a 5% average deficit, whereas EANN produced a maximum of a 10% average deficit. It demonstrates that fuzzy logic is more robust in processing uncertainty than artificial neural networks, with a 5 percent advantage over ANNs.

Heuristic models prescribe procedures that best achieve a pre-defined purpose, even though they describe the system in a more simplified form. They serve as starting points for a more in-depth investigation. These codes can be used in a variety of ways and with a variety of modifications. One of them will be used for the input data in the form of a variable, i.e. points generated before in the model. This will increase the operational flexibility of the proposed model. Traditional methodologies demonstrated to be a better way for extracting knowledge from data for creating optimal operational policies for the reservoir system using available data and information when reinforced by techniques such as neural networks and fuzzy logic. The model's success in capturing knowledge in the reservoir operating domain highlighted a promising study field. As a result, the inquiry will be used to build a method for dealing with different types of fuzzy and neuro-fuzzy systems, as well as combining them with other soft computing techniques such as artificial neural network systems.

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