Real Time Flow Prediction using Fuzzy Logic Models

Aschalew Debebe and Willy Bauwens

Models to predict flows in different parts of an urban catchment are developed using so-called Fuzzy Logic in combination with artificial neural networks. These models are developed to be used as part of a real time control system so that flows at various horizons can be computed and used as inputs to the controller. These models showed excellent performance both in their accuracy and execution time and proved to be very helpful in supplying the necessary forecasts for the real time controller. Another advantage of such models is that they can be developed in a relatively short time.

10.1 Introduction

Real-time control in hydrologic systems involves mainly the operation of a reservoir system by making decisions on reservoir releases as information become available, with relatively short time interval, which may vary between several minutes to several hours. In order to have sufficient time to set the control points, there is a need for determining the appropriate control action ahead of time. That in most cases requires forecasts of rainfall or flow at different critical sections in the system.

Some of the most commonly used techniques for flow forecasting include techniques based on deterministic catchment models, flood routing models, and time series models. Although it is often assumed that the more complex model will yield better results, this is often not true. It is thus advisable to use the simpler and more understood models as long as there is no proven benefit of a more complex model. Existing flood forecasting models are highly data specific and their operational performance depends upon the science used to build and operate these models as well as their ability to respond to dynamic and rapidly changing events (See and Openshaw, 1998).

Since the lead-time of the forecast often determines the quality of the forecast, techniques that extend the lead-time while giving reasonable accuracy are of growing importance. In traditional hydrology, extensive use of time series prediction models has been made to this effect. However, these models, although known to be good for their execution speed, they fail to represent the non-linearity that exists in hydrological systems. Moreover, for larger lead-times their forecasting accuracy diminishes considerably.

It is clear that accurate system models can be very useful but identifying them is not necessarily simple. Consider the way humans develop models of systems found in everyday life. These usually come from two fundamental sources; a priori knowledge acquired from education, communication etc., and personal experiences. These two should be utilized, while inadequacies found in this knowledge can be compensated for by the ability to learn from observations of the true system.

10.2 Soft Computing (Intelligent) Techniques

Soft computing is the name that is being put forth as an alternative to artificial intelligence for the plethora of advanced information processing technologies that have emerged in the past decade. Soft computing, unlike hard computing, is tolerant of imprecision, uncertainty and partial truth. In effect, the model for soft computing is the human mind. The guiding principle of soft computing is exploiting the tolerance for imprecision, uncertainity and partial truth to achieve tractability, robustness and low solution cost. A characteristic of soft computing is its capability of modeling uncertainties by different methods of probability, fuzziness, and possibility.

The principal constituents of Soft Computing (SC) are Fuzzy Logic (FL), Artificial Neural Network (ANN) and Probabilistic Reasoning (PR), with the latter subsuming belief networks, genetic algorithms, chaos theory and parts of learning theory. What is important to note is that SC is not a melange of FL, ANN
and PR. Rather, it is a partnership in which each of the partners contributes a distinct methodology for addressing problems in its domain. In this perspective, the principal contributions of FL, ANN and PR are complementary rather than competitive. However, in this chapter only the application of Fuzzy Logic Models for real time flow forecasting will be presented.

10.3 Fuzzy Logic Models

Fuzzy Logic is a rule-based method capable of dealing with uncertainty in knowledge (Stundner & Zangl, 1998). Fuzzy systems, the basis of fuzzy logic models, can be considered as a super-set of conventional (Boolean) logic that has been extended to handle the concept of partial truth, which are truth values between “completely true” and “completely false”. Classical logic or Boolean logic has two values or states often expressed as true or false, yes or no, on or off, black or white, start or stop. Yet in the real world it is known that there are many situations where events are not black or white but some shade of gray. Fuzzy logic is a continuous form of logic that allows describing the shades of gray.

At present, fuzzy logic models are successfully being used in many engineering applications involving process control (Jang, Sun and Mizutani, 1997). In their application to system identification, a number of rules are employed to work on the fuzzy sets of inputs in parallel in order to compute the relevant output. In the area of flow forecasting, the sets of inputs could be past flows and/or present and past rainfall if available.

10.4 Real Time Flow Forecasting

In the presence of flow (level) measuring devices, the information, if it can be transmitted to control sections through telemetry, can be used by the real time controller. If this is not the case, however, the use of flow forecasting models is inevitable. The need for the forecasting model discussed in this chapter rose from the ongoing research in the area of adaptive real time controller development for flood and pollution reduction in urban drainage.

The adaptive real time controller itself is based on fuzzy logic techniques coupled with artificial neural networks and other optimization techniques. Fuzzy Logic techniques were also chosen for the forecasting models, mainly due to their speed of execution, ability to model non-linear relationships and forecast accuracy even under circumstances where information could be inaccurate.
10.5 Description of the Bellebeek Catchment

The Bellebeek catchment, chosen for the present study, is located in the central part of Belgium west of Brussels. The catchment to the last gaging station close to the confluence with the Dender River has a total area of ca. 100 km$^2$ and a main stream length of 15.5 km. The Bellebeek River is a tributary of the Dender River joining it some 3 km downstream of the last gaging station. The elevation at the gaging station is about 12 m and the elevation at the junction with the Dender River is about 8 m above sea level. The highest point in the watershed is at an elevation of 100 m above sea level.

The Bellebeek catchment has a hilly landscape, which is characterized by relatively high upper regions, sloping surfaces covered by colluvium material, and valleys filled with alluvium. The proximity of Brussels has induced intermittent dispersed urbanization in the area, which was originally only agricultural land. Flooding has shown a too frequent occurrence, which is the motivation for investigating applications of real time control in order to tackle this problem.

10.6 Model Development

One of the requirements for a real time control, specially at a feasibility stage, where installations of measuring stations are not economical, is an information about future flows at control sections. This is important since there should be enough time between taking a control action and its effect at the critical sections.

Real time flow forecasting is basically a system identification problem where sets of input and output variables are available and a model which mimics the behavior of the underlying system across the complete envelope of its operation is sought. Essentially, system identification is the task of building system models from a combination of a priori knowledge and empirical data. In this chapter, we assume that a priori knowledge about the relationship between past and future inflows is not available, and an automated identification using fuzzy logic coupled with a fuzzy clustering technique is employed.

The future flows of a chosen horizon are modeled as a function of present and relevant past flows \( Q(t), Q(t-1), ..., Q(t-n) \), where 'n' is the relevant lag time) through a rule base which relates the fuzzified inputs to a series of linear equations representing the Sugeno type fuzzy inference system. In the design of fuzzy logic models, the first step is deciding on the number and shape of membership functions for all inputs into and outputs from the system (Figure 10.1), which very loosely speaking could be considered as dividing the range of the variables into intervals. Once this is decided, the rule base can be established either manually or automatically depending on the extent of available knowledge. In this
10.6 Model Development

chapter, a mesh of rules involving all inputs and all membership functions is used. The parameters of the model are then tuned using artificial neural networks.

![Fuzzification of inputs](image)

Figure 10.1 Fuzzification of inputs.

Three of the rules of the Sugeno type fuzzy controller used in the model are:

1. if \((Q(t) \text{ is Low})\) and \((Q(t-1) \text{ is Low})\) and \((Q(t-2) \text{ is Low})\) then \(Q(t+6) = Q_1\)
2. if \((Q(t) \text{ is Low})\) and \((Q(t-1) \text{ is Low})\) and \((Q(t-2) \text{ is Med})\) then \(Q(t+6) = Q_2\)
3. if \((Q(t) \text{ is Low})\) and \((Q(t-1) \text{ is Low})\) and \((Q(t-2) \text{ is High})\) then \(Q(t+6) = Q_3\)

... where \(Q_1, Q_2, \ldots, Q_n\) are the consequent parts which are linear functions of the inputs having the form:

\[
Q_i = a_{i1}Q(t) + a_{i2}Q(t-1) + a_{i3}Q(t-2) + b_i \tag{10.1}
\]

where \(a_{i1}, a_{i2}, a_{i3}\) and \(b_i\) are the parameters of the fuzzy consequent part. The final value of \(Q(t+6)\) at every time step can be calculated from equation 10.2 which results in a piece wise linear approximation of the non linear relationship.

\[
Q(t + 6) = \frac{\sum_{i=1}^{n} w_i Q_i}{\sum_{i=1}^{n} w_i} \tag{10.2}
\]
where:

\[ n = \text{number of rules} \]
\[ w_i = \text{weights, degree to which each rule is satisfied} \]

The consequent parameters are identified for the fuzzy inference system as shown in Table 10.1 for some of the rules, while Figure 10.1 gives the input membership functions:

**Table 10.1** Part of the fuzzy logic parameters used in the model.

<table>
<thead>
<tr>
<th>Rule</th>
<th>&quot;a_1&quot;</th>
<th>&quot;a_2&quot;</th>
<th>&quot;a_3&quot;</th>
<th>&quot;b&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-46.03</td>
<td>-42.6</td>
<td>27.86</td>
<td>0.3385</td>
</tr>
<tr>
<td>2</td>
<td>-47.84</td>
<td>-12.77</td>
<td>31.05</td>
<td>-68.7</td>
</tr>
<tr>
<td>3</td>
<td>0.1672</td>
<td>0.1783</td>
<td>0.2068</td>
<td>0.06284</td>
</tr>
</tbody>
</table>

The model parameters, which are basically the membership functions for the inputs, the rules and the consequent parameters of the Sugeno type fuzzy controller constitute the model. The major task in using such models is then to identify these parameters since transfer of knowledge, if any, into such systems is not that obvious.

Different techniques including statistical clustering and artificial neural networks are used in order to tackle the identification of the fuzzy logic controller parameters whenever there is a lack of knowledge that could directly be encoded into such systems or transforming the *a priori* knowledge is difficult.

The 6-time step ahead (1 h) forecast of inflows into one of the reservoirs in the Belbeek catchment using the present and past inflows as inputs is shown in Figure 10.2. The plot shows the output of the model on a training data set. Application of the trained model is then made on another set of data and for different horizons as shown in Figure 10.3.

![Figure 10.2](image-url) Real time flow forecast of reservoir inflows (1-hour ahead forecast).
10.7 Conclusion

A mathematical relationship of the inputs and the forecasted output may be inferred from the identified model (although it does not seem obvious from the values of the parameters such as those shown in Table 10.1).

10.7 Conclusion

The so-called intelligent or soft computing techniques include different independent components including fuzzy logic, artificial neural networks, and genetic algorithms and others. These components have their advantages and disadvantages and as a result applications based on a hybrid approach are becoming more and more common. Application of Neuro-Fuzzy techniques are made in this chapter to forecast flows in small catchments. However, it is known that the training procedure of an artificial neural network may be stacked in a local minima and may not have an optimal solution. Genetic algorithms, which are basically stochastic searching algorithms, can be used to tune the parameters of the fuzzy logic model.
References

