Design of Neuro-Fuzzy Controller for Water-Level Tank utilizing Genetic Algorithms

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Abstract

Fusion of Artificial Neural networks (ANNs) and Fuzzy Inference Systems (FIS) have attracted the growing interest of researchers in various scientific and engineering areas due to the growing needs of adaptive intelligent systems to solve real world problems. In this paper, Fuzzy Logic (FL), Neural Network (NN), and Genetic Algorithms (GAs) were combined to design and tune a neuro-fuzzy controller (NFC). This design is based on multi-layer neuro-fuzzy network. The adaptation of neuro-fuzzy rules consequents and tuning of NFC weights is accomplished utilizing genetic algorithms. Then ineffective rules are removed from the rule-base of the controller. A real code representation is used to encode the GA chromosome. Two selection methods are used, namely, Roulette wheel and Tournament selection methods. The steps of building, tuning, and the removal of the ineffective rules are accomplished in an off-line phase. In on-line phase, the resulting NFC is operated and it is noticed that the response of the system is not robust enough. So, to avoid any shortage that my happen in the system performance, an adaptive fuzzy controller is added to the NFC. Application of the NFC to a water-level tank is investigated in this paper.

الخلاصة

الشبكات العصبية الذكية وانظمة الاستنتاج المضبب جذبت الاهتمام المتزايد للباحثين في مختلف المجالات العلمية والهندسية نظراً للحاجة المتزايدة للانظمة المتكيفة الذكية لحل المعاضل الحقيقية في العالم. تم في هذا البحث دمج المنطق المضبب والشبكات العصبية الاصطناعية مع استخدام الخوارزميات الجينية لتصميم وتنغيم مسيطر عصبي مضبب وهذا التصميم مبني على اساس الشبكات العصبية – المضببة ذات المستويات المتعددة، اما تكييف نتائج القواعد العصبية المضببة مع تنغيم اوزان المسيطر العصبي المضبب فقد تم بواسطة الخوارزميات الجينية. واخيراً يتم ازالة القواعد غير الفعالة من اساس قواعد المسيطر. تم استخدام التمثيل الحقيقي للارقام من اجل ترميز كروموسومات الخوارزمية الجينية. تم استخدام طريقتين من طرق الاختيار الا وهي طريقة القرص الدوار (Roulette Wheel) وطريقة البقاء للاصلح (Tournament) . الخطوات المتبعة في بناء تنظيم وازالة القواعد غير الفعالة تم انجازها في طور الحسابات المفتوحة (OFF-Line Phase) . اما في طور التشغيل الحقيقي (On-Line Phase). فقد تم اشتغال المسيطر العصبي المضبب ولكن تم ملاحظة ان استجابة المنظومة غير كافية الصلادة. ولغرض معالجة مثل هذا التقصير في اداء المسيطر فقد تم اضافة مسيطر مضبب متكيف الى المسيطر العصبي المضبب. وكتطبيق عملي لمثل هكذا تصميم فقد تم فحص المسيطر المقترح على منظومة تحديد مستوى الماء في الخزانات.

Key Words

Artificial Neural Network, Fuzzy Logic, Genetic Algorithms, Neuro-Fuzzy Controller.

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1- Introduction

Artificial Neural Networks (ANN) have become popular models for a broad variety of modeling and control problems. However, ANN adaptive controllers cannot incorporate linguistic system descriptions, because it is difficult to extract knowledge from them in a comprehensive way. On the other hand, fuzzy inference systems represent knowledge using linguistic labels and may easily be interpreted. Recently, neuro-fuzzy approach has become a popular research area. In contrast to pure neural or fuzzy methods, the neuro-fuzzy method possesses both of their advantages the learning and adaptation capabilities of the neural networks and also providing an inference approach that enables approximate reasoning capabilities (Brown and Harris – 1994).

The integration of artificial neural network (ANN) learning and fuzzy logic (FL) approximate reasoning in One rchitecture, to overcome individual limitations and achieve synergetic effects through hybridization of these techniques, has in last ten years contributed to a large number of Neuro-Fuzzy (NF) rchitectures. NF techniques override the classical control methods in many aspects, such as algorithm simplicity, system robustness and the ability to handle imprecision and uncertainty (Abraham, and Nath – 2000)

2- Water-Level Tank System

As shown in figure 1, a storage tank is used as a buffer water supply and it is replenished from a mains water pipeline. The tank water level is controlled by float-valve mechanism which has frictional effects so that the relationship between the water level and the valve opening is non-linear (Harris - 2000). The relationship is broadly governed by the fact that the valve is fully open when the water level is below 10% of the set point, and, is fully closed when it is above the set point.

3- Neuro-Fuzzy Controller

Classical control theory is based on mathematical models that describe the behavior of a plant under consideration. The main idea of fuzzy control on the other hand is to build a model of a human control expert who is capable of controlling the plant without thinking in a mathematical model. The control expert specifies his control actions in the form of linguistic rules. These control rules are translated into the framework of fuzzy set theory providing a calculus which can simulate the behavior of the control expert.The combination of neural networks and fuzzy controllers to so called neuro-fuzzy models can help to enhance the performance of the controller by using special learning algorithms. There are several approaches to neuro-fuzzy systems from which a designer can choose (Nauck and Kruse - 1997).

Neural networks are used to tune membership functions of fuzzy systems that are employed as decision- making systems for controlling equipments. Although fuzzy logic can encode expert knowledge directly using rules with linguistic labels, it usually takes a lot of time to design and tune the membership functions which quantitatively define these linguistic labels. Neural networks learning techniques can automate this process and substantially reduce development time and cost while improving performance (Fuller - 2000).

4- Neuro-Fuzzy Controller (Nfc) structure

The NFC consists of four layers. Figure 2 shows the used neuro-fuzzy controller. Each layer performs a specific function. The first two layers represent the fuzzifier. Third layer represents rule-base (i.e., inference engine); the number of nodes in this layer is equal to the number of rules in the rule-base of the controller. Last layer (fourth layer), represents the defuzzifier, the output from this layer represents the control action.

The controller has two inputs and one output. The input variables are the error (e), and change rate of error (ce). The output variable is the control action (u). Each variable has five membership functions. They are: Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS), and Positive Big (PB). The error is computed as the difference between the reference signal and the output of the system.

$$e(k) = r(k) - y(k) \qquad ..(1)$$

While the change rate of error is computed as the difference between the current error and the previous one.

$$ce(k) = e(k) - e(k-1) \qquad ..(2)$$

The error Universe Of Discourse (UOD) for NFC controller is taken as [-1, 1], [-0.04, 0.04] for rate change of error, [-1, 1] for control action.

This structure includes a five by five rule fuzzy controller where the terms shown on the antecedent nodes represent linguistic variables; therefore, the number of rules is five by five which equals to 25-rules.

The term vj (j=1...5) represents the fuzzy sets describing the consequents or control action.

5- Neuro-Fuzzy Controller Based On Genetic Algorithms (Nfg)

The structure of neuro-fuzzy controller, which has been described in figure 2 previously, will be used in the design of NFG controller. GA was used to build this controller, for the properties that GA has in search operations when the data is huge and random.

Neuro-fuzzy controller consists of two main phases:

1- Off-line phase.

This phase includes three steps:

a- Step 1 - Finding the best consequents for connections between layer 3 and layer 4 (see figure 2) of the NFC, i.e., find the suitable consequents to have an acceptable response for the system.

b- Step 2 - Tune the membership function values to get acceptable results (i.e., minimum error).

c- Step 3 - Remove the don't care rules (i.e., the rules that are ineffective during the work of the system all the time).

Points a, and b, are accomplished utilizing GA, while point c is accomplished based on ineffective change on IAE (Ogata - 1997) (Integral Absolute-Error), which is given as:

$$J = \int_{0}^{\infty} |e(t)| dt \qquad ..(3)$$

Any GA starts with a population of randomly generated solutions, chromosomes, and advances toward better solutions by applying genetic operators, modeled on the genetic processes occurring in nature. In this work the length of the chromosome is specified according to the problem demands. Then many population sizes were tried to find the suitable one to give a proper solution. The population size was taken as replication of chromosome length which is named n, i.e., 4n, 6n, 8n, and 10n where tried to see their effects on the solution. Two selection methods were used in this work, namely, Roulette wheel and Tournament selection methods.

2- On-line phase.

An adaptive controller is added, to overcome the non-linearity of the system and to increase system robustness,

A learning control system is designed so that its learning controller has the ability to improve the performance of the closed loop system by generating command inputs to the plant and utilizing feedback information from the plant, the Fuzzy Model Reference Learning Controller (FMRLC) is a direct model reference adaptive controller. The block diagram for the FMRLC is shown in figure 3. It has four main parts; the plant (valve + water tank), the fuzzy controller, the reference model, and the learning mechanism (adaptive fuzzy controller) (Passino and Yurkovich - 1998).

The transfer function of the Reference Model (R.M) is chosen as 2 nd order model with ζ =0.9 and ω_n =1.6 rad/sec, and is given as in Equ.4. This model is selected to satisfy the required dynamic performance. The transfer function is:

$$G(s) = \frac{2.56}{s^2 + 2.88s + 2.56} \quad ..(4)$$

The adaptive fuzzy controller has two inputs, error (em) and change of error (cem), and one output. The error is computed as the difference between the reference model output and controlled plant output. Each variable has five fuzzy sets. So, the rules of adaptive fuzzy ontroller are 25 rules.

$$e_m(k) = y_{r.m}(k) - y_p(k) \quad ..(5)$$

$$ce_m(k) = e_m(k) - e_m(k-1) \quad ..(6)$$

The error Universe Of Discourse (UOD) for adaptive controller is taken as [-1, 1], [-0.04, 0.04] for rate change of error, [-1, 1] for control action.

6- Simulation Results

The used training signal is considered as:

$$r(k) = \begin{cases} 1.5 & 0 \le k \le 100 \\ 1 & 100 < k \le 200 \\ 1.7 & 200 < k \le 300 \\ 1.5 & 300 < k \le 400 \end{cases} \quad ..(7)$$

where r(k) is the training signal and k is sample number.

Four cases of initialization were used and as follows:

- Case 1 - Initial rule-base set and condition.
  In this case the first chromosome inthe population is equal to the initial rule-base. The rest is generated according to the condition stated above.
- Case 2 - No initial rule-base set and condition.
  In this case, all the chromosomes in the population are generated according to the condition stated above.
- Case 3 - Initial and no condition.
  In this case the first chromosome in the population is equal to the initial rule-base. The rest is generated randomly between 1 & 5.
- Case 4 - No initial and no condition.

In this case, all the chromosomes in the population are generated randomly between 1 & 5.

Figure 4 represents four cases, which are chosen to make a comparison among them and a rule-base set is chosen to be the result of step 1. This result would be used for step 2 to be tuned.

The previous figure represents the selected results from step 1. Data 1 represents the tested signal. Data 2 represents the result of roulette wheel selection method, case 1, training signal 1, and population size 6n. Data 3 represents the result of tournament selection method, case 1, training signal 1, and population size 4n. Data 4 represents the result of roulette wheel selection method, case 1, training signal 2, and population size 4n. Data 5 represents the result of tournament selection method, case 1, training signal 2, and population size 4n.

Table 1 gives the result summary of figure 4. And from which, it can be concluded that data 2, and data 3 are the best. So the rule-base of data 2 is taken as a result from step 1.

Table 1: System response parameters for figure 4.

	tr (sec)	tp (sec)	MP
data 2	4.2	4.7	1.5458
data 3	4.2	4.7	1.5458
data 4	4.2	4.7	1.5458
data 5	4.2	4.7	1.5720

In figure 5, two cases are chosen to make a comparison among them and tuned membership function values are chosen to be the result of step 2. This result would be used for step 3.

The previous figure represents the selected results from step 2. Data 1 represents the tested signal. Data 2 represents the result of roulette wheel selection method, and population size 6n. Data 3 represents the result of tournament selection method, and population size 4n.

Table 2: System response parameters for figure 5.

	tr (sec)	tp (sec)	MP
data 2	4.2	4.5	1.5341
data 3	4.2	4.5	1.5363

Table 2 gives the result summary of figure 5. And from which, it can be concluded that data 2, and data 3 are the same, but data 3 has greater Mp value. So the tuned membership function values data 2 is taken as a result from step 2.

In step 3, the ineffective rules are removed to minimize the amount of computations for the rule set evaluation. Figure 6 represents the result of step 3, and Table 3 gives the result summary of figure 6.

Table 3: System response parameters for figure 6.

tr (sec)	tp (sec)	MP
4.2	4.5	1.5341

Figure 7 represents the output of the system in on-line phase with and without the operating of the adaptive fuzzy controller.

Table 4: System response parameters for figure 7.

	tr (sec)	tp (sec)	Mp
NFG	4.2	4.5	1.5363
NFG with AFC	4.1	4.5	1.5546

From figure 7 and table 4, it can be seen that working with AFC is faster and and can respond properly to sudden changes.

7- Conclusions

From research results, it can be concluded that:

- The structure of the NFC represents the rules of the fuzzy control exactly. This allows some degree of flexibility in adjusting the fuzzy rules in order to achieve better performance.
- Accurate initial rule-base values are those values that are selected as close as possible to the solution. The choice of these values has a major effect on the response of the system.
- When accurate initial value is used. the increasing of the population size does not affect the results (system response).
- During the attempt to select the best partitioningof the UOD, it was found that tournament selection method is better than roulette wheel selection method when equal partitions of membership functions were applied. On the other hand, if asymmetric partitions were applied, then both of selection methods will give close results, i.e., no remarkable difference is sensed between the results of the two methods.

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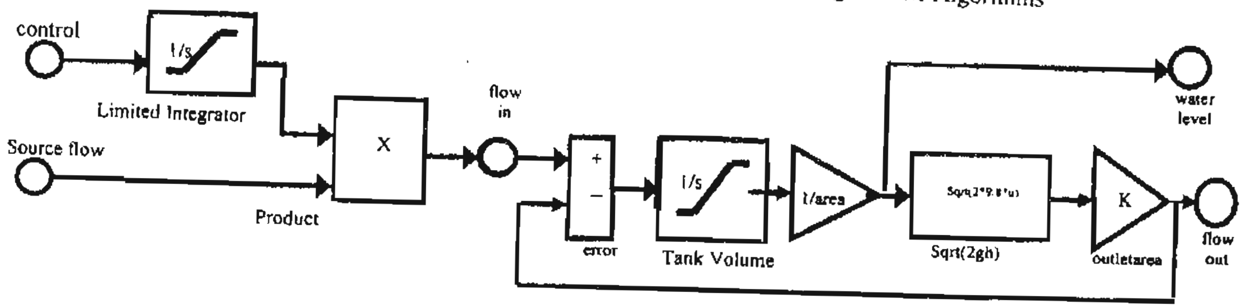

Figure 1: System model) (valve+water_tank)

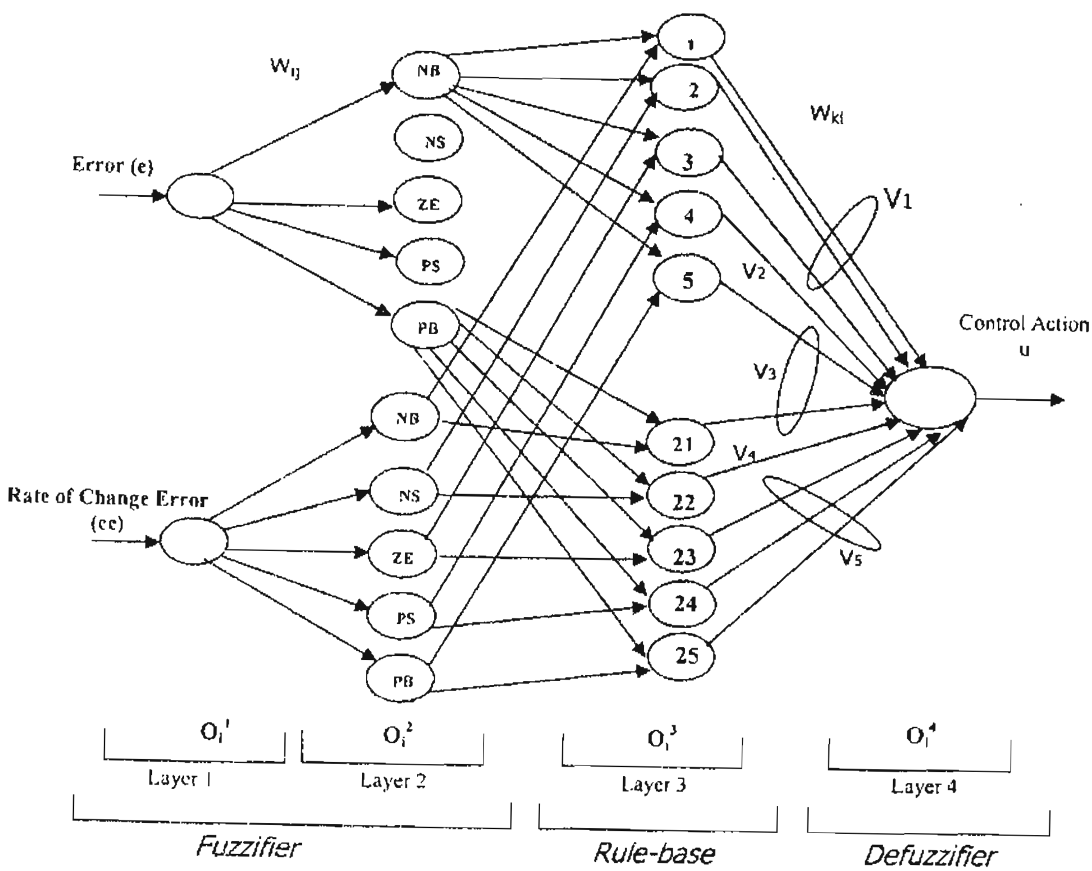

Figure 2: Basic structure of Neuro-Fuzzy Controller.

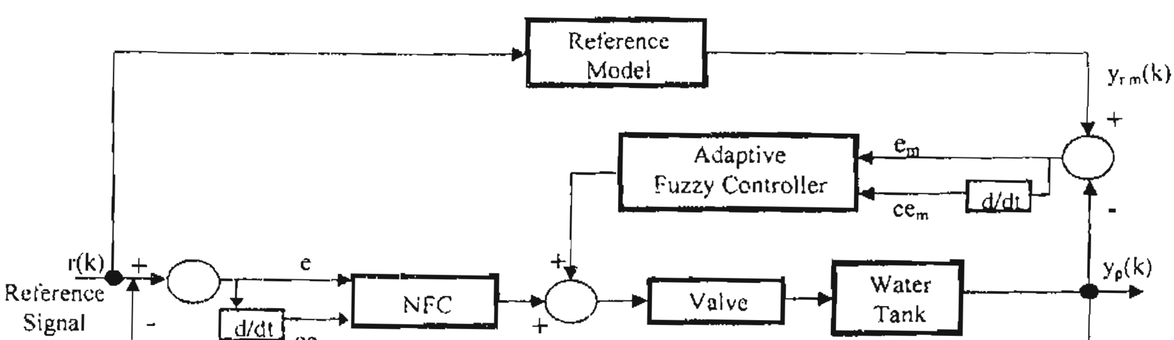

Figure 3: Fuzzy model Reference Learning control.

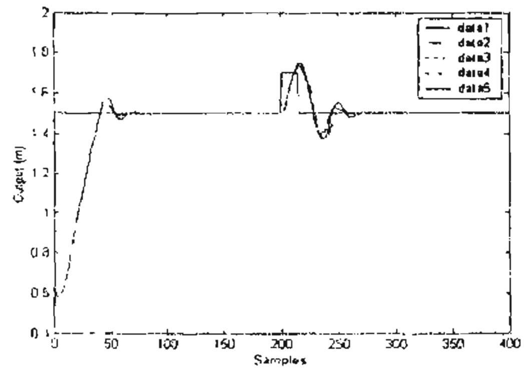

Figure 4: Comparison among four cases results from step 1.

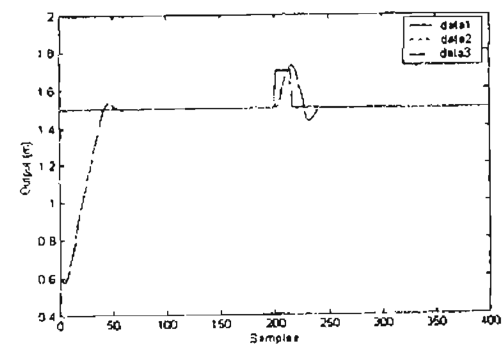

Figure 5: Comparison among tuning results from step 2.

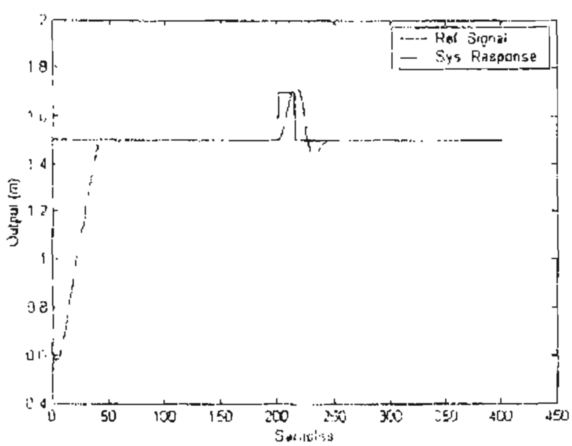

Figure 6: a. System response of step 3.

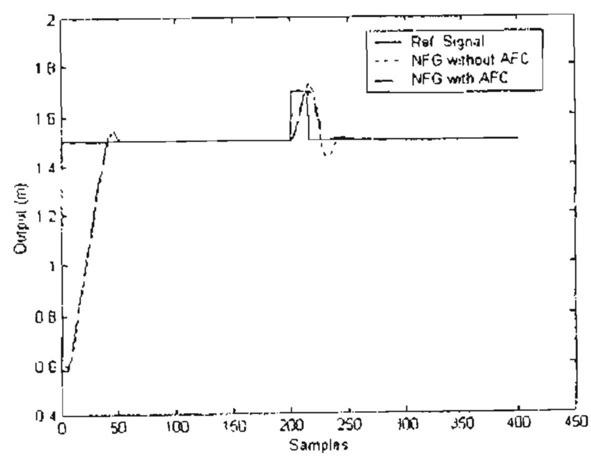

Figure 7: Robustness comparison between response without AFC and with AFC