Evolutionary temporal fuzzy control and fuzzy temporal rule-based control applied to adaptive distributed routing.

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Abstract

In this document we carry out a comparative analysis of the application of Fuzzy Logic Controllers, Temporal Fuzzy Logic Controllers, Faded Temporal fuzzy Logic Controllers, Fuzzy Temporal Rules-Based Controllers, and Hybrid Fuzzy Temporal Rules-Based Controllers, to improve the adaptive distributed routing. To obtain a good knowledge bases the controllers were evolved using Genetic Algorithms.

Key-Words: fuzzy logic controller, temporal fuzzy logic controllers, faded temporal fuzzy logic controller, temporal rule-based controllers, genetic algorithms, adaptive distributed routing.

1 Introduction

One of the major problems for most communications networks lies in defining an efficient packet routing policy. Many existing and planned network and protocols (e.g. Arpanet, and the IP routing protocol OSPF2), employ adaptive, distributed routing based on traditional routing algorithm such as the Dijkstra and the Ford and Fulkerson. These algorithms are employed in conjunction with periodic update, when information about link and node traffic conditions are transmitted between adjacent nodes or flooded throughout the entire network. However, since exchanging network status information uses link bandwidth, periodic updates are limited if overheads are to be acceptable. In addition the distributed nature of the system to be controlled means that state measurements are time delayed. In order to compound these difficulties, state measurements are not available continuously, but must necessarily be sampled at finite intervals [4, 9].

Some applications of the systems based on knowledge [8] need to manage facts that happen and vary as time goes by. That's why several models have been developed to represent and process the temporal knowledge [1,2,3].

Fuzzy Temporal Rules-Based Controllers (hereinafter FTRCs) presents a model for representation and handling of fuzzy temporal references, again using the formalism of possibility theory. They define a language (and associated grammar) for the expression of fuzzy temporal information and projected this representation of temporal entities onto fuzzy temporal constrain satisfaction network [1]. To obtain knowledge used in FTRCs, it is used Genetic Algorithms (hereinafter GA).

Temporal Fuzzy Logic Controllers (hereinafter TFLCs) are systems that incorporate in their knowledge bases (hereinafter KBs) the human knowledge, through their rules and membership functions of their fuzzy sets (hereinafter FSs) [2,5,6,7,8], and in which one part of the knowledge gives a place in a fuzzy way through the time to the realisation of the actions suggested by the inference engine [2].

In Faded Temporal fuzzy Logic Controllers (hereinafter FTFLCs) it is spread the TFLCs, which introduces the concept of temporal fading [5,6,7], which includes a non linear perception

L. Magdalena, M. Ojeda-Aciego, J.L. Verdegay (eds): Proceedings of IPMU'08, pp. 721–728
Torremolinos (Málaga), June 22–27, 2008

of time and gives a higher accuracy, reliability and certainty to the observations and actions near in the time. This effect is achieved by the “fading” of the temporal FSs.

In Hybrid Fuzzy Temporal Rules-Based Controllers (hereinafter Hybrid FTRCs) it is spread the FTRCs, which introduce the possibility of delay in the time the control action, and include the concept of temporal fading.

To obtain knowledge used in Hybrid FTRCs, TFLCs and FTFLCs, with a reasonable computational cost, it is used a method of genetic learning which combines:

a) The common GA applied over FTRCs, followed by GA applied over Hybrid FTRCs.

b) The common GA applied over Fuzzy Logic Controllers (hereinafter FLCs), followed by GA applied over TFLCs and over FTFLCs.

In GA applied over Hybrid FTRCs, TFLCs and FTFLCs the initial population has been developed from the best KB obtained in the first genetic process (GA over FTRCs or GA over FLCs).

The document is organised as following: in section 2 we present the use of FLC to improve the adaptive distributed routing performance. In section 3 we analyze the problems associated to the routing with FLCs, in addition, it is included a theoretical justification of the improvements added by the TFLCs. In section 4 we show the problems associated to the routing with TFLCs, in addition, it is presented a theoretical justification of the improvements added by the FTFLCs. In section 5 we analyze the other problems associated to the routing with FLCs, and it is included a theoretical justification of the improvements added by the FTRCs. In section 6 we analyze the problems associated to the routing with FTRCs, and it is included a theoretical justification of the improvements added by the Hybrid FTRCs. In section 7 we propose the application of GA over FLCs, GA over FTRCs, GA over Hybrid FTRCs, GA over TFLCs and GA over FTFLCs to optimise the network routing process. In section 8 we presents a experimental comparison of the network performance evaluation. In section 9 we spread the results of section 8.

2 Use of FLCs for adaptive distributed routing

The use of a single metric for adaptive routing is insufficient to reflect the actual state of the link. There is a limitation on the accuracy of the link state information obtained by the routing protocol, as the accuracy of the metric is usually predetermined by the network updating interval. Hence it becomes useful if two or more metrics can be associated to produce a single metric that can describe the state of the link more accurately. We propose the use of two metric: the average link packets delay and the link packets jitter delay (input variables), measurements from the previous sampling interval, to obtain a single metric, the output variable of the FLC. The metric link will be a constant in the next sampling interval. Each node runs the Dijkstra´s algorithm and calculates the shortest path routing table, every T seconds.

3 Justification of the improvements added by the TFLCs for adaptive distributed routing

3.1 Problems associated to FLCs

In a good routing systems, where the change of the input variables is spread with certain ease in the time (i.e. in networks with a large number of nodes), it will be necessary to adapt adequately the value given to the output variable in order to correct the detected failures in the states of the input variables when the temporal interval of spreading of each action finishes [5,6,7].

In all proposed fuzzy logic controller applied to routing systems, the link metric is the output variable of the inference engine. The input variables are the average link packets delay and the link packets jitter delay measurements, now, from the previous samplings intervals. Here each metric link will be a constant in the next sampling interval. Each node runs the Dijkstra´s algorithm and calculate the shortest path routing every T seconds. So that, the routes are calculated and updated only every T seconds. The problem is the impossibility to adapt adequately the value given to metric (to reroute traffic) at any time (e.g. to avoid a link congestion generates at this time).

3.2 Solutions proposed in TFLCs

To solve the previous problem, it is necessary that the routing system can change the value take to each metric link, at any instant. To achieve this target the TFLCs include in the rules list of the KB a series of rules with the same antecedent as that one we want to complement, with FSs values in the consequent that provoke the change in the states of the system, in the adequate way (change the metric links). At that time we include the temporal consequent where its FSs will take values that delay adequately the application of the support action, to permit the change of metric (reroute) at any instant.

4 Justification of the improvements added by the FTFLCs for adaptive distributed routing

4.1 Problems associated to TFLCs

The external noise (provoked by errors in the routing protocol, which introduces errors in routing tables) and the fired rules during the delay interval provoke the displacement of the moment in the time when the unwanted state (link state information) we wish to correct, is produced. The displacement will depend specially on the external actions suggested by the environmental noise during the delay interval.

4.2 Solutions proposed in FTFLCs

To solve this problem a good solution may consist in increasing the interval of temporal performance of the correcting action (metric link assignment), without increasing its global influence over the system. This effect is achieved distorting the temporal FSs, increasing their base and decreasing their height, so that their area will be the same as the original FS. The distortion will have to increase as the time among the observation of the system and the action programmed to its control passes, in order to compensate the decrease in the probability of placing adequately the correcting action (metric link assignment). That means a lack of accuracy in the temporal placing of the control actions, but supposes an increase in the probability of placing adequately such actions.

To place correctly the delayed actions it is necessary an adequate number of temporal FSs which covers all the possible delay interval of time, “period”.

To achieve that aim it is necessary:

a) A concentration of the closer temporal region.

Considering that the bases of the temporal FSs decrease as they come to their origin, a higher number of FSs with a lower separation between them will be necessary in that zone, if we want to maintain its overlap level.

b) A spreading of the farthest temporal region.

As the correcting action is delayed, the base of their associated temporal FSs will increase. Thus the temporal FSs will be overlapped for two rules which program actions placed in two far consecutive moments, therefore concerning to control effects, the temporal FSs would have almost the same temporal place. The target of programming two control actions with a different temporal performance will be only achieved if the time is spread (it is separated the placing of the consecutive moments). This spreading of time will have to be higher if the delay time of the rules is increased, in order to compensate the increase in the overlapping of the faded temporal FSs. [5,6,7].

5 Justification of the improvements added by the FTRCs for adaptive distributed routing

5.1 Problems associated to FLCs

In FLCs routing systems, the routes currently measured as heavily used (with high metric) are simultaneously avoided by all routing nodes, and routes measured as lightly loaded (with low metric) are simultaneously selected, thus causing unwanted oscillations in routing decisions. If the route is heavily used, the average packet link delay increase, if there are oscillations in routing, the jitter link delay increase, and so that the network performance evaluation decrease. Then, the problem is the oscillation in routing decision.

5.2 Solutions proposed in FTRCs

To avoid the above mentioned problem, is necessary to take into account the link state information (average packet link delay and packet jitter delay) from the previous sampling intervals, to obtain a metric without great oscillations.

For that, we propose the use of a model called fuzzy temporal rule-based routing controller (FTRC) presented by Barro [1]. This controller has been implemented using an explicit model for knowledge representation and reasoning. This model enables to explicitly incorporate time as a variable, due to which the evolution of variables in a temporal reference can be described. Using this routing controller we can obtain metric values that are adapted to each different circumstances, to avoid the link congestion and high routing oscillation.

6 Justification of the improvements added by the Hybrid FTRCs for adaptive distributed routing

6.1 Problems associated to FTRCs

In FLCs and FTRCs routing systems, the assigned value to each metric link (output variable) is calculated every updating interval, being the metric link a constant in the next sampling interval. The associated problem is the impossibility of change the metric link, at any instant (not necessarily at the updating instant), to reroute traffic over an other link and to avoid the link congestion.

6.2 Solutions proposed in Hybrid FTRCs

To solve the above mentioned problem, it is necessary that the routing system could change the value assigned to each metric link, at any instant. To achieve this target we can use the Hybrid FTRCs, which introduce the possibility of delay in the time the control action, and include the concept of temporal fading [5,6].

To characterize this controller the following elements are shown:

a) The KB, which is comprised of a data base and a rule base. Its structure is described in section 7.1.

b) The reasoning strategy, used in the inference engine, will have a common part with both FTRCs and FTFLCs:

The common part with FTRCs, is associated to the calculation of: the spatial compatibility *($ce(t_k)$)* [1], the degree of fulfillment of each linguistic proposition *(GDV)* [1] as well as the degree of fulfillment of the rule *(GDV)* [1]. The applied procedures will be the proposed in the FTRCs reasoning strategy [1].

In the common part with FTFLCs, after calculating $\mu_{Ai}(x)$ (degree of fulfillment of the rule i), we obtain the membership function of the fuzzy set inferred by the rule ($\mu_{B'i}(x)$), and then we run the following steps (also in the FTFLCs inference process): generation of a non-linear transformation through the time [5], generation of temporal transformed fuzzy sets [5], generation of Contributory Components [5], and defuzzification [5].

c) The structure of the controller, is the same as the FLCs structure [8].

7 Genetic learning over fuzzy controllers, applied to adaptive distributed routing

7.1 Structure of KB

In KBs used in GA_{FLCs}, the knowledge is stored in:

a) Groups of immediate application rules: groups of rules that present only one variable in the consequent, which is the same in all the rules.

b) The definition of membership function associated to antecedent and the consequent FSs variables.

c) The "fitness" parameter of the KB.

In the rule base of the KBs used in GA "heading" for TFLCs (hereinafter GAh_{TFLCs}) and GA "heading" for FTFLCs (hereinafter GAh_{FTFLCs}), the knowledge is stored in:

a) Duplicated groups of rules, set by:

1. A group of non temporal rules.

2. A group of deferred application temporal rules (forward temporal rules), set by rules with the same antecedent to any rule of the non temporal group, considering that its consequent is the same or different to the above mentioned rule, and those which a temporal consequent is added.

In the data base of the KBs used in GAh_{TFLCs}, in addition over GA_{FLCs}, the knowledge is stored in:

a) The definition of membership function associated to temporal FSs (triangular function).

b) The "forward period" parameter, that informs about maximum temporal operating interval of the rules.

In the data base of the KBs used in GAh_{FTFLCs}, in addition over GAh_{TFLCs}, the knowledge is stored in the fading parameters: "a", "b" and "c", which model the precision and temporal accuracy variation [5].

In the KBs used in GA_{FTRCs}, the knowledge is stored in:

a) Groups of immediate application rules: groups of fuzzy "back temporal rules" that present:

a.1) Only one variable in the consequent, which is the same in all the rules.

a.2) In the antecedent, propositions of the form "*X* is *A* <*in Q of* > *T*", where *X* is a linguistic variable, *A* represents a linguistic value of *X*, *T* is a temporal reference or entity and *Q* is a fuzzy quantifier [1].

b) The definition of membership function associated to antecedent and the consequent FSs variables.

c) The "fitness" parameter of the KB.

d) The definition of membership function associated to fuzzy quantifier (Q) FSs (trapezoidal function).

e) The "back period" parameter, that informs about maximum length of the temporal reference (T).

f) The definition of membership function associated to temporal reference (T) FSs (trapezoidal function).

In the rule base of the KBs used in GA "heading" for Hybrid FTRCs (hereinafter $Gah_{Hybrid\ FTRCs}$), the knowledge is stored in:

a) Duplicated groups of rules, set by:

a.1) A group of "back temporal rules", as the used in FTRCs.

a.2) A group of deferred application temporal rules (forward temporal rules), set by rules with the same antecedent to any rule of the back temporal group, considering that its consequent is the same or different to the above mentioned rule, and those which a temporal consequent is added.

In the data base of the KBs used in $GAh_{Hybrid\ FTRCs}$, in addition over GA_{FTRCs}, the knowledge is stored in:

c) The definition of membership function associated to temporal FSs (triangular function).

d) The "forward period" parameter.

e) The fading parameters.

7.2 New KB obtaining

To implement the GA_{FLCs}, GA_{FTRCs}, GAh_{TFLCs}, GAh_{FTFLCs}, and the $GAh_{Hybrid\ FTRCs}$, it has been used the Pittsburgh approach, taking as elements of the initial population 20 KBs filled at random and applying on each case the structure explained on the above section.

To achieve the KBs applying GA_{FLCs} or GA_{FTRCs} the genetic process is divided into four stages: 1. KB selection, proportionally to its “fitness”. 2. A crossover in rules and FSs definitions. 3. A mutation in variables, FSs in rules, and FS definition. 4. Old individual substitution by new ones, after comparing their “fitness”.

To achieve the KBs applying GAh_{TFLCs}, GAh_{FTFLCs} or $GAh_{Hybrid\ FTRCs}$ the genetic process is divided into four stages: 1. KB selection, proportionally to its “fitness”. 2. A crossover in forward temporal rules. 3. Mutation of variables in the rules, limited to the output variables and its associated temporal variable, and the forward period and fading parameters. 4. Old individual substitution by new ones, after comparing their “fitness”.

8 Experimental Results

8.1 Network and offered traffic simulate description

In order to test the viability of the approach of evolutionary temporal fuzzy logic controllers, applied to adaptive distributed routing, experiments were carried out on the simulated 6-node network shown in figure 1.

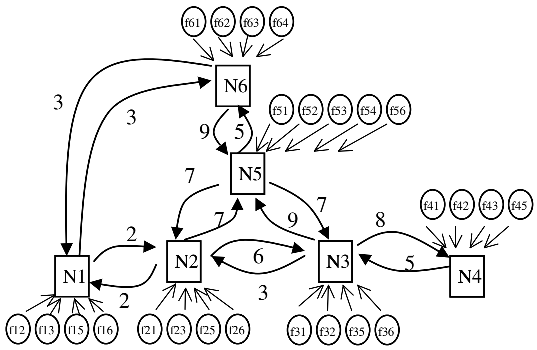

Figure 1. Network model.

We can see 6 nodes and 26 packets source (f_{ij}, “i” is the origin node, and “j” is the destination node of packets). All link data rates were set to 10 kbps, and each link is modelled as an M/M/1 queuing system and the numbers over the links are the initial metrics. For each packet source, we model the offered traffic with two stochastic processes:

1. The time between packets arrivals, is distributed exponentially, with average value “τ”. In this case $\tau = 0,1$ s.

2. The time of packet service, is distributed exponentially, with average value “s”. In this case s” is varied from 0,02 s. to 0,09 s. Thus the average packet size is varied from 200 to 900 b.

8.2 Network performance evaluation

Routing policies aim to optimise the network Quality of Service. The Quality of Service requirement, in a packet switching network, is given as a set of parameters: average delay packet , jitter delay packet (variance) , loss rate, bandwidth. In this case, we only take the average delay, the jitter delay and the loss rate, to obtain a network performance evaluation. To evaluate the network performance we use the following expression:

$$E = 0,7 \, . \, P + 0,3 . \left(1 - \left(0,8 \, . Rn + 0,2 \, . Vn \right) \right)$$

E: fitness function, whose coefficients especially penalize packets loss and reward a low delay packet. P: (successful arrival packets / total packets) (%). Rn: normalized average delay packet. Vn: normalized jitter delay packet. Where: R: average delay packet. V: jitter delay packet (variance). TAD: theoretical average delay packet. It is calculated for a M/M/1 system, with a traffic load level of 0,8.

To obtain R and V we take all packets in the network. And the parameters E and P can take values within the interval (0,1).

To obtain a right network performance evaluation, we use:

a) In the learning process:

a.1) Five traffic load levels, for all packets sources (ρ): 0,2; 0,35; 0,5; 0,65; 0,8.

a.2) Only one simulation for each traffic load level.

a.3) Simulation interval: 10 s., updating interval: 1 s.

a.4) $Rn = R / (4. TAD) \quad Vn = V / (4. TAD)$

b) In the final network performance evaluation:

b.1) Eight traffic load levels, for all packets sources (ρ): 0,2; 0,3; 0,4; 0,5; 0,6; 0,7; 0,8; 0,9.

b.2) For each traffic load level we run thirty network simulations, each one with a different seed. It is used to generate two pseudorandom number sequences, to model the traffic.

b.3) Simulation interval: 50 s., updating interval: 1 s.

b.4) $Rn = R / (9. TAD) \quad Vn = V / (9. TAD)$

In the final evaluation, for each load level, their evaluation is the average of the thirty individual evaluations. The global evaluation is the average of all load level evaluations.

8.3 Routing strategies used in the comparison

Seven alternative routing strategies were simulated to allow a final performance comparison:

a) The static shortest path routing (hereinafter SPR) [4].

The packets are routed along the fixed shortest path for each traffic session. Routes are established in advance using Dijkstra´s algorithms, and this routing method is not adaptive.

b) The adaptive shortest path routing (hereinafter APR) [4].

Each node run the Dijkstra´s algorithm every T seconds, using the average link packet delay and link packet jitter delay measurements from the previous sampling interval (updating interval). To obtain the metric link we use a lineal function [4].

c) The evolved fuzzy controller (FLC) [5].

d) The evolved temporal fuzzy controller (TFLC).

e) The evolved faded temporal fuzzy controller (FTFLC) [5].

f) The evolved fuzzy temporal rule-based controller (FTRC).

g) The evolved Hybrid Fuzzy Temporal Rules-Based Controllers (Hybrid FTRC).

For obtaining the experimental results:

a) We run thirty genetic learning process over all fuzzy controllers [5].

b) We run the experiments proposed to obtain the final network performance evaluation, in the:

b.1) Static and shortest path routing: one times.

b.2) Evolved fuzzy controllers: thirty times (one for each KB obtained genetically).

For a good adaptive distributed routing whit FTFLCs and Hybrid FTRCs, in each genetic learning process we must chose one KB, between the KBs obtained genetically. This KB must take, in the fading parameter, values that model the non linear transformation of time and the distortion of the temporal FSs, according to the concept of temporal fading [5,6].

To determine what routing strategy presents a better evaluation, it is necessary to compare the obtained results. In this comparison, given two data sets (network performance evaluation for each routing strategies), one of them characterized by their averages, standart deviation and number of data points (1 or 30), we use the Student's t tests to determine whether the averages are distinct or not.

Table 1. Routing strategies comparison

Comparison	Strategies	Evaluation (Average)	Improvement (%)	Test t
Sample 1	FLC	0,622	31,78	ok
Sample 2	SPR	0,472		
Sample 1	TFLC	0,647	1,25	ok
Sample 2	Hybrid	0,639		
Sample 1	FTFLC	0,648	1,41	ok
Sample 2	Hybrid	0,639		
Sample 1	TFLC	0,647	4,02	ok
Sample 2	FLC	0,622		
Sample 1	FTFLC	0,648	4,18	ok
Sample 2	FLC	0,622		
Sample 1	FTFLC	0,648	0,15	no
Sample 2	TFLC	0,647		
Sample 1	Hybrid	0,639	0,16	ok
Sample 2	FTRC	0,638		

The table 1, for each routing strategies comparison, shows the average, the improvement of the final network performance evaluation, and the Student’t test result.

Table 2. Ordered list of routing strategies.

Strategies	Evaluation (Average)
FTFLC	0,648
TFLC	0,647
Hybrid	0,639
FTRC	0,638
FLC	0,622
SPR	0,472
APR	0,245

The table 2, shows a list of the routing strategies, ordered by the average value of their obtained final network performance evaluation.

9 Conclusions

From the analysis of the experimental results obtained, we notice that, there is:

a) A moderate improvement on the network performance evaluation, obtained with the FTFLC and TFLC routing system, compared to the use of other routing systems.

This improvement (over SPR, APR, FLC and FTRC) is due to the FTFLC and TFLC systems can change the value assigned to each metric link, at any instant, to solve the impossibility to reroute traffic at any time.

This improvement (over Hybrid FTRC and FTRC) is due to this system introduce an inertia in the change of the metric link, which produces a decrease in their adaptation capacity.

b) A low improvement on the network performance evaluation, obtained with the FTFLC routing system compared to the use of TFLC routing system.

This improvement is due to the FTFLC system, to solve the uncertainty in the link state information, incorporates the concept of temporal fading, which includes a lack of accuracy in the temporal placing of the control actions, but supposes an increase in the probability of placing adequately such actions. This improvement is low because the used updating interval (1 s.) is not high, and therefore the probability of placing incorrectly the control action, in the moments where the unwanted state appears, decreases.

c) An improvement on the network performance evaluation, obtained with the Hybrid FTRC routing system compared to the use of FTRC routing system.

This improvement is due to the FTRC system, at each updating interval, for each packet destination (traffic session), uses only a routing path. However the Hybrid FTRC system, at each updating interval for each packet destination, can use several paths to avoid the links congestion.

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