# COMPARISION OF FUZZY AND NEURAL FUZZY CONTROLLER IN SOLUTION OF THE VEHICLE PARKING PROBLEM

Ersen Yılmaz
e-mail: *ersen@uludag.edu.tr*

Arzu Babaev
e-mail: *babaev@uludag.edu.tr*

*Uludağ University, Faculty of Engineering and Architecture, Department of Electronics Engineering, 16059 Bursa, Turkey*

*Key words: Neural fuzzy controller, fuzzy controller, vehicle parking problem*

## ABSTRACT

**In control applications, controllers are preferred to have a basic decision mechanism, less number of iterations and minimum error rate. In this study, Fuzzy Controller (FC) and Neural Fuzzy Controller (NFC) are compared according to design complexity, decision mechanism, number of iterations and duration of iterations in solution of the vehicle parking problem.**

## I. INTRODUCTION

In designing control systems, one of the important challenges frequently encountered deals with how to model such a system. Human experience represented with a set of linguistic rules is generally the best model for control systems [1]. Fuzzy logic controllers are mimic experts but deriving and fine-tuning the rule set and membership functions are often difficult [2]. Neural controllers learn but sufficient training patterns are usually difficult to obtain and training time for network is very long. NFC takes advantage of the best of fuzzy logic and neural networks -integrates the fuzzy logic representation of human knowledge with the learning capability of neural networks [3]. In this study, (FC) and (NFC) are compared according to design complexity, decision mechanism, number of iterations and duration of iterations in solution of the vehicle parking problem. This paper is organized as follows. Section 2 gives basic NFC architecture. Section 3 defines vehicle parking problem. Section 4 and 5 present solution stages of the problem and simulation results, respectively.

## II. NFC ARCHITECTURE

NFC is realized by representation of FC process units with neural networks. Constructing a FC from data is proposed by Klawonn and Kruse [4]. The NFC model shown in Fig.1 has three main parts; Fuzzification Neural Network (FNN), Inference Neural Network (INN) and Defuzzification Neural Network (DNN). All of these are feedforward neural networks that use backpropagation .

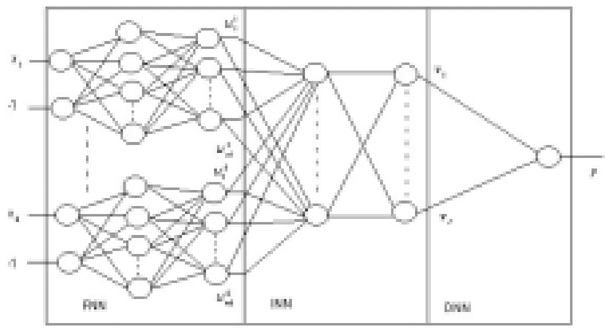

Figure 1. Neural fuzzy controller

FNN shown in Fig.2 has two input nodes; numerical data (x) and bias input. Numerical data is obtained from controller output and defined on the universal set $U = \{u_1, u_2 ......u_n\}$. Number of FNN's output nodes are equal to number of elements of the universal set U. Training set for FNN is given Table 1. FNN's output nodes are INN's input nodes.

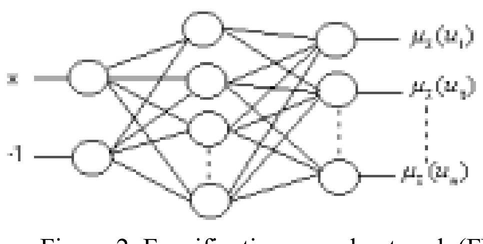

Figure 2. Fuzzification neural network (FNN)

INN is used to learn rule set and maps input vectors to output vectors. Input and output vectors are membership value pairs. INN's output nodes are DNN's input nodes.

Table 1. Training set for FNN

| input | | output | | | |
|---|---|---|---|---|---|
| $u_1$ | -1 | $\mu_{\tilde{u}_1}(u_1)$ | $\mu_{\tilde{u}_1}(u_2)$ | . | $\mu_{\tilde{u}_1}(u_n)$ |
| $u_2$ | -1 | $\mu_{\tilde{u}_2}(u_1)$ | . | . | . |
| . | . | . | . | . | . |
| $u_n$ | -1 | $\mu_{\tilde{u}_n}(u_1)$ | $\mu_{\tilde{u}_n}(u_2)$ | . | $\mu_{\tilde{u}_n}(u_n)$ |

Defuzzification of INN's output is realized by using DNN. Controller output y is defined on the universal set $V = \{v_1, v_2 .....v_l\}$ and takes values of the linguistic term set $P = \{P_1, P_2,.....P_t\}$. DNN is shown in Fig.3 and training set for DNN is given in Table 2.

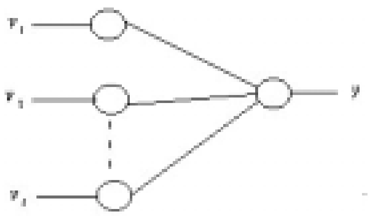

Figure 3. Defuzzification neural network (DNN)

Table 2. Training set for DNN

| input | | | output |
|---|---|---|---|
| $\mu_{p1}(v_1)$ | . | $\mu_{p1}(v_l)$ | $v_1^0$ |
| $\mu_{p2}(v_1)$ | . | . | |
| . | . | . | |
| $\mu_{pt}(v_1)$ | . | $\mu_{pt}(v_l)$ | $v_t^0$ |

where, $$v_i^0 = \frac{\sum_{j=1}^{m} \mu_{pi}(v_j) v_j}{\sum_{j=1}^{m} \mu_{pi}(v_j)} \tag{1}$$

## III. DEFINITION OF THE VEHICLE PARKING PROBLEM

Let's absolutely explain the problem. Position of the vehicle is defined by the (x,y,φ) parameters. Our aim is to put forward the vehicle to the desired position (0, $y_a$ ,90) where x and y are coordinates of the position, φ is the angle of position (Figure 4). First position is taken as any (x,0, φ) point on the x coordinate. y coordinate is assumed as adequately large and not considered in this problem. Consequently, a two-input (x: position, φ: position angle) and one-output (θ - rotation angle of steering wheel) controller is obtained.

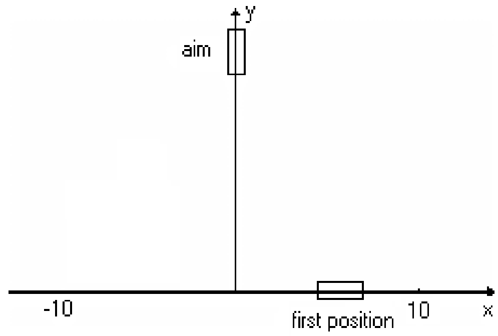


Figure 4. Graphical comment of problem

To solve this problem, intervals of parameters of the controller are chosen as;

$$x \in [-10,10], \quad \varphi \in [0,180], \quad \theta \in [-90,90]$$

## IV. SOLUTION OF THE VEHICLE PARKING PROBLEM

To solve the problem, initially FC was realized. In designing FC, we chose same universal sets and same membership functions for inputs and output.
The chosen universal set ($U$) and membership function $(F)$ are given as;

$$U = \{-10,-9,-8,-7,-6,-5,-4,-3,-2,-1,0,1,2,3,4,5,6,7,8,9,10\}$$

$$F(e) = \begin{cases} e \le a-5 & y = 0 \\ e \rangle a-5 \,\&\, e \le a & y = 1+(e-a)/5 \\ e \rangle a \,\&\, e \langle a+5 & y = 1-(e-a)/5 \\ e \ge a+5 & y = 0 \end{cases} \tag{2}$$

where a is the input value which will be fuzzificated and e is any element of the universal set.
We defined five linguistic terms. These linguistic terms and their membership functions obtained by using $F$ are given below;

Negative Big
$NB = \{1,0.8,0.6,0.4,0.2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0\}$
Negative Small
$NS = \{0,0.2,0.4,0.6,0.8,1,0.8,0.6,0.4,0.2,0,0,0,0,0,0,0,0,0,0,0\}$
Zero
$Z = \{0,0,0,0,0,0.2,0.4,0.6,0.8,1,0.8,0.6,0.4,0.2,0,0,0,0,0,0\}$
Positive Small
$PS = \{0,0,0,0,0,0,0,0,0,0,0.2,0.4,0.6,0.8,1,0.8,0.6,0.4,0.2,0\}$
Positive Big
$PB = \{0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0.2,0.4,0.6,0.8,1\}$

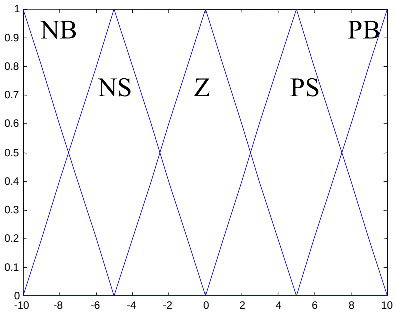


Figure 5. Membership func. for vehicle parking behavior

Since inputs and the output use the same universal set $U$, their intervals should be adequate with $U$. Our chosen universal set is adequte with position interval. To achieve the adequacy between the position angle and the universal set U, the transform $\varphi = \frac{\varphi - 90}{9}$ was used.

Fuzzy rule base that characterized vehicle parking behavior was generated by using five linguistic terms. The generated fuzzy rule base is given in Table 3.

Table 3. Fuzzy rule base for solution of the prob.

| P \ A | NB | NS | Z | PS | PB |
|---|---|---|---|---|---|
| NB | PB | PB | PB | PK | Z |
| NS | PB | PB | PK | Z | NS |
| Z | PB | PK | Z | NS | NB |
| PS | PK | Z | NS | NB | NB |
| PB | PK | Z | NS | NB | NB |

In Table 3, P is the position and A is the position angle.

NFC used in solution of the problem is given Figure 6. Training set for NFC is obtained from FC rule base.

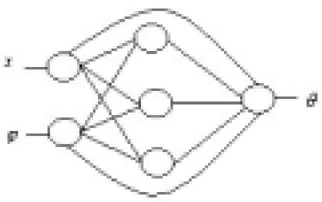

Figure 6. NFC used for solving the problem

Same problem was solved by possibility theory approach in [5] and by sugeno approach in [6].

## V. SIMULATION RESULTS

Simulation program has been developed in C++ Builder. Simulation results of FC and NFC for different vehicle positions are given in below figures.

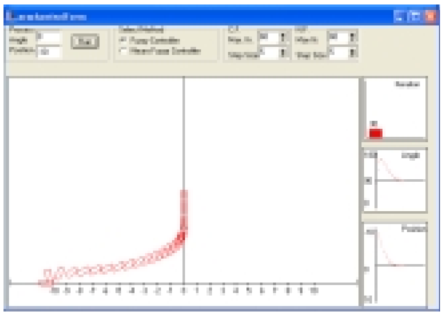

Figure 7. FC solution for x=-10 and φ=0

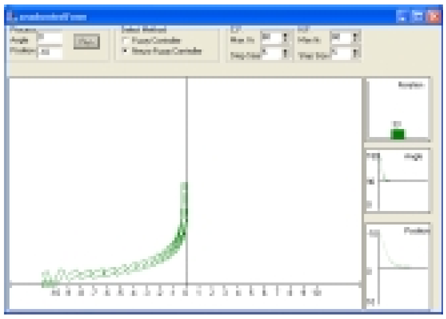

Figure 8. NFC solution for x=-10 and φ=0

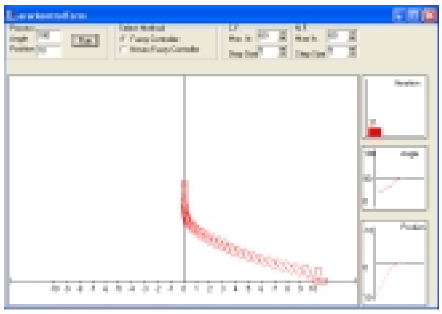

Figure 9. FC solution for x=10 and φ=180

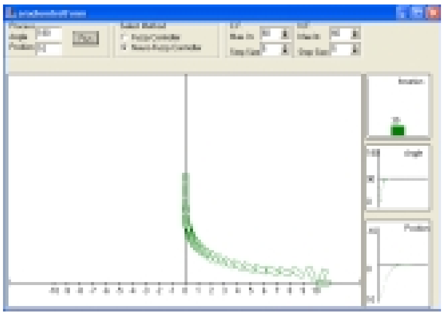

Figure 10. NFC solution for x=10 and φ=180

## VI. CONCLUSION

In this study, compared results are obtained for FC and NFC according to design complexity, decision mechanism, number of iterations and duration of iterations.

Design of NFC is realized by representation of FC process units with neural networks. Selection and training of an adequate neural network can increase stage and duration of design. Therefore, design of NFC is more complex than that of FC.

Decision mechanism of FC is the fuzzy rule base. During each decision time, inference is performed by using the whole rule base. Decision mechanism of NFC is composed of a trained neural network and during each decision time, only matrix products are computed. Therefore, decision of NFC is faster than FC.

Although FC solves the problem in less number of iterations, it requires more processes and consequently longer processing time than NFC since it uses the rule base for every iteration.

## REFERENCES

1. L-X. Wang, Adaptive Fuzzy Systems and Control, Prentice Hall, 1994.
2. B. Kosko, Neural Networks and Fuzzy Systems, Prentice Hall Inc, 1992.
3. K.C. NG. M.M. Trivedi, A Neuro-Fuzzy Controller for Mobile Robot Navigation and Multirobot Convoying, IEEE Transactions on Systems, Man , and Cybernetics-Part B: Cybernetics , Vol.28,No.6,pp. 829-840,1998.
4.F. Klawonn, R. Kruse. Constructing a Fuzzy Controller from Data, Fuzzy Sets and Systems, Vol.85,pp.177-193,1997.
5. A. Babaev, B. Güler, Possibility Theory Approach to Inference Problem in Fuzzy Controller,Bilişim′98, İstanbul, pp.107-111,1998 (in Turkish).
6.A. Babaev, E. Yılmaz, Obtaining Sugeno Type Rule Base by Using Experiment Planning, TAINN'99 8.th Turkish Symposium on Artificial Intelligence and Neural Networks,pp 238-246,1999 (in Turkish).