

Neuro-Fuzzy Programming to Finding Fuzzy Multiple Objective Linear Programming Problems

¹Anil Kumar Yadav

¹Research Scholar

University Department of Mathematics,
Kolhan University, Chaibasa, Jharkhand, India

²Dr. Savita Mishra

²Assistant professor

Department of Mathematics, The Graduate School College
For Women, Jamshedpur, Kolhan University, Jharkhand,

³Dr. B. N. Prasad

³Principal Singhbhum College Chandil, Jharkhand, India

Abstract:- A neural network for solving fuzzy multiple objective linear programming problems is proposed in this paper. The distinguishing features of the proposed Neural network are that the primal and dual problems can be solved simultaneously, all necessary and sufficient optimality conditions are incorporated, and no penalty parameter is involved. We prove strictly an important theoretical result so that, for an arbitrary initial point, the trajectory of the proposed network does converge to the set of its equilibrium points, regardless of whether a multiple objective linear programming problem has unique or infinitely many optimal solutions. Numerical simulation results also show that the proposed network is feasible and efficient. In addition, a general method for transforming nonlinear programming problems into unconstrained problems is also proposed.

Keywords:- Fuzzy Neural Network, Fuzzy Multiple objective, Neuro-fuzzy, Constraint satisfaction Learning Fuzzy constraints, Linear Programming Problems.

I. INTRODUCTION

Fuzzy logic systems can deal with incomplete knowledge of an environment with a vague nature. This makes fuzzy logic a powerful tool for reasoning in imprecise knowledge based systems[2]. Due to continuous-valued logic nature, fuzzy logic is much closer to human thinking than the conventional two-valued logic. Problems with need to reasoning on imprecise knowledge are called fuzzy programming problems. Neuro Fuzzy programming problems have many utilization, such as in the biological field, artificial intelligence, operations research field. In this so many researcher and research scholar are emphasized on these field [4].

The Fuzzy systems propose a mathematic calculus to translate the subjective human knowledge of the real processes. This is a way to manipulate practical knowledge with some level of uncertainty. The fuzzy sets theory was initiated by Lofti Zadeh in 1965. Since the moment that fuzzy systems become popular in industrial application, the engineers designer perceived that the development of a fuzzy system with good performance is not an easy task. Thus, appears the idea of applying learning algorithms to the

fuzzy systems. The neural networks, that have efficient learning algorithms, had been presented as an alternative to automates or to support the development of tuning fuzzy systems. The first studies of the Neuro-fuzzy systems date of the beginning of the 90's decade, with Jang, Lin and Lee in 1991, Berenji in 1992[8,12] and Nauck from 1993[4,7,11].

Fuzzy Neural networks try to make the biological functions of the human brain. The main advantages of the neural networks is the fact of these structures could learn with examples (training vectors, input and output samples of the system). The main characteristics of the neural networks are: • learning capacity • generalization capacity • robustness in relation to disturbances.

II. STATE OF THE ART

Let us consider fuzzy decision problems in the form of

$$\max_x (C_1x, \dots, C_kx) \quad (1)$$

Where $C_i = (C_{i1}, \dots, C_{in})$ is a vector of fuzzy numbers and $x \in R^n$ is the vector of 'crisp decision variables. Suppose that for each objects e function of (1) we have two references fuzzy numbers. denoted be m_i and M_i , which represent undesired and desired levels for the i -th objective, respectively.

We now can state (1) as follows: find an $x^* \in R^n$ such that $C_i x^*$ is as close as possible to the desired point M_i , and it is as far as possible from the undesired point in m_i for each i .

III. FUZZY NEURAL NETWORKS

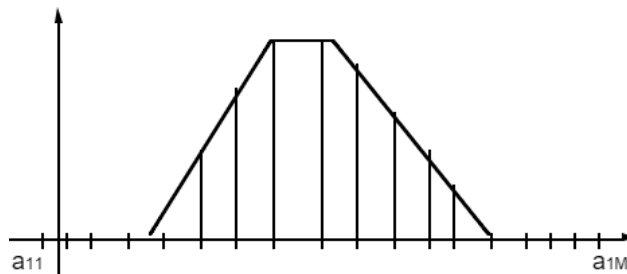
Suppose that there is a fuzzy neural network with the set of input-output pairs $\{(A_i, B_i), i = 1, \dots, m\}$, where $A_i = (A_{i1}, \dots, A_{in})$ is a vector of fuzzy numbers and the output B_i is a fuzzy numbers. In computer applications we usually use discrete versions of the continuous fuzzy sets. The discrete version of the above system is

$$\begin{array}{cc}
 \text{Inputs} & \text{Outputs} \\
 A_1(x_1), \dots, A_1(x_M) & B_1(y_1), \dots, B_1(y_N) \\
 \dots & \dots \\
 A_m(x_1), \dots, A_m(x_M) & B_m(y_1), \dots, B_m(y_N)
 \end{array}$$

where (x_1, \dots, x_M) and (y_1, \dots, y_N) are well-chosen partitions of the input and output spaces.

$$A_m(x_1), \dots, A_m(x_M) \quad B_m(y_1), \dots, B_m(y_N)$$

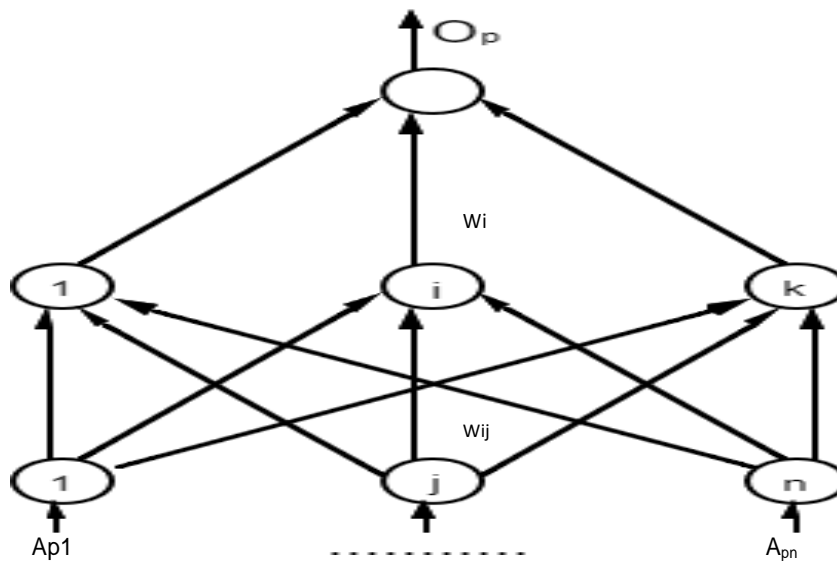
Other possibility is to input the α -level sets of fuzzy numbers [6]. We need to find weights, such that for all input vectors A_i all the computed α -level sets are as close as possible to the α -level sets of the target fuzzy numbers B_i . The number of inputs and outputs depend on the number of α -level sets considered.



A discretization of fuzzy input A_{ij} where $a_{ij} = A_i(x_j)$

In the architecture [5] input vectors and target outputs where given by fuzzy numbers. Weights and biases, however were , given by real numbers as in the case of standard back propagation algorithm.

The following extension of back propagation algorithm to train neural networks from fuzzy training pattern was proposed by [5].



The structure of Neural fuzzy networks is proposed in [5].

The output of the i -th hidden unit is

$$O_{pi} = f\left(\sum^n w_{ij} A_{pj}\right)$$

For the output unit

$$O_p = f\left(\sum^k w_i O_{pi}\right)$$

Let us denote the α -level sets of the computed output O_p and the target output B_p

$$[O_p]^\alpha = [O_p^L(\alpha), O_p^R(\alpha)]$$

$$[B_p]^\alpha = [B_p^L(\alpha), B_p^R(\alpha)]$$

The cost function to be minimized can be stated as follows

$$e_p(\alpha) := e_p^L(\alpha) + e_p^R(\alpha)$$

Where

$$e_p^L(\alpha) = (B_p^L(\alpha) - O_p^L(\alpha))^2 / 2$$

$$e_p^R(\alpha) = (B_p^R(\alpha) - O_p^R(\alpha))^2 / 2$$

The cost function for the training pattern p is

$$e_p = \sum_\alpha \alpha e_p(\alpha)$$

From the cost function $e_p(\alpha)$ the following learning rules can be derived

$$\begin{aligned} \Delta w_i(t+1) &= \Omega \alpha (-\partial e_p(\alpha) / \partial w_i + \alpha \Delta w_i(t)) \\ \Delta w_{ij}(t+1) &= \Omega \alpha (-\partial e_p(\alpha) / \partial w_{ij} + \alpha \Delta w_{ij}(t)) \end{aligned}$$

IV. FUZZY LINEAR EQUATIONS

Let us consider the system of fuzzy linear equations

$$A_{11}x_1 + \dots + A_{1n}x_n = B_1 \quad \dots \quad \dots \quad (2)$$

$$A_{m1}x_1 + \dots + A_{mn}x_n = B_m$$

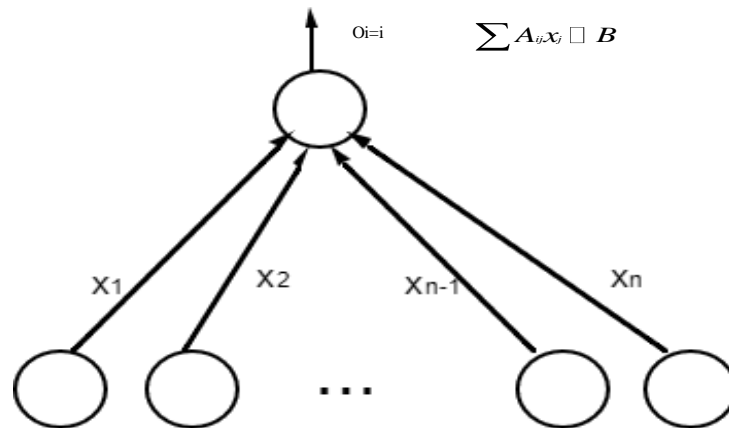
where A_{ij} and B_i are fuzzy numbers.

The problem is to find a crisp vector $x \in \mathbb{R}^n$ satisfying this system of equations as far as possible. We use the following single layer fuzzy neural network for finding an approximate solution to (2).

where the training set is $\{(A_{i1}, \dots, A_{in}, B_i), i = 1, \dots, m\}$ the coordinates of decision variable x .

It is clear that in the end of the learning we get an x satisfying bestly (in the sense of closeness of α -level sets) the system of equations (2).

It is well-known that fuzzy expert systems and neural networks are universal approximators. However, as was pointed out by Buckley and Hayashi [1], fuzzy neural networks can not approximate all continuous fuzzy functions, which means that the extended backpropagation algorithm from [5] can not be always used in the process of finding approximate solutions to systems of fuzzy equations.



V. APPLICATION OF FUZZY NEURAL NETWORKS TO FMOLP

Let us Consider the following FMOLP

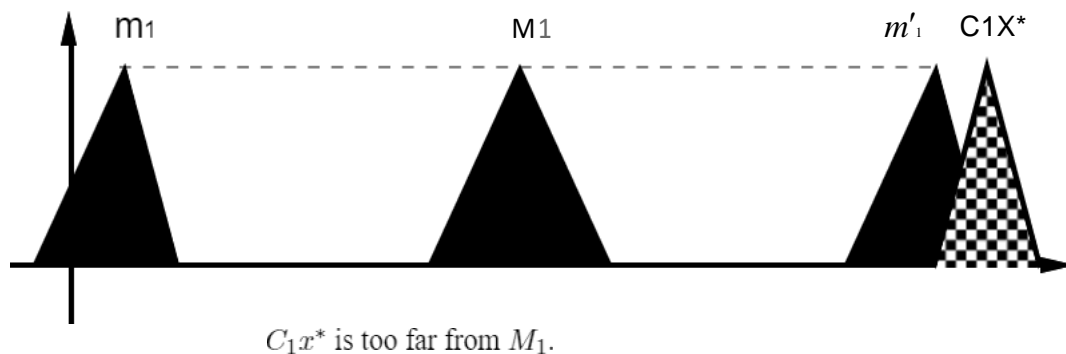
$$\max \{ (C_1x, \dots, C_kx) | x \in R^n \} \tag{3}$$

Where C_i is a vector of fuzzy numbers $i = 1, \dots, k$.

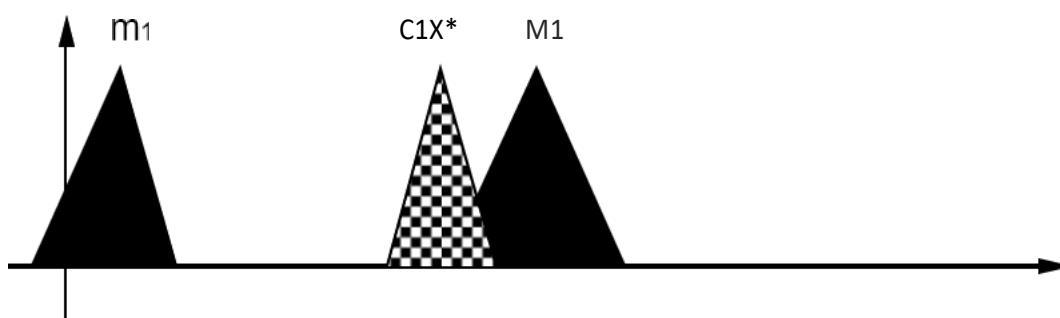
Suppose that for each objective function of (3) we have two references fuzzy numbers, denoted by m_i , and M_i , which represents undesired and desired levels for the i -th objective respectively.

Now we should find an $x^* \in R^n$, such that $C_i x^*$ is as close as possible to the desired point M_i , and it is as far as possible from the undesired point m_i , for each i .

Let d_i denote the maximal distance between the α -level sets of m_i and M_i and let m'_i be the fuzzy number obtained by shifting m_i by the value of d_i , in the direction of M_i . Then we consider m'_i as the reference level for the biggest acceptable value for the i -th objective function.



It is clear that good compromise solutions should be searched between M_i and m'_i we can introduce weights measuring the importance of "closeness" and "farness".

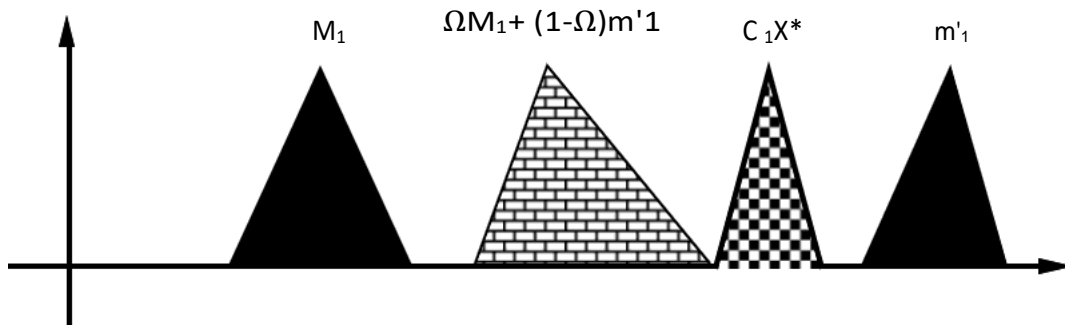


C_1x^* is close to M_1 , but not far enough from m_1

Let $\Omega \in [0, 1]$ be the grade of importance of "closeness" to the desired level and then $(1 - \Omega)$ denotes the importance of "farness" from the undesired level.

Then we can use the following training set for Our single layer fuzzy neural network:

Input	Output
C_1	$\Omega M_1 + (1 - \Omega)m'_1$
.....
C_k	$\Omega M_k + (1 - \Omega)m'_k$



VI. A GOOD COMPROMISE SOLUTION

It is clear that in the end of training we set the optimal weights (decision variables), for which the values of the fuzzy objectives are as close as possible to the desired levels and and far from the undesired levels in the sense of the chosen importance degrees.

VII. CONCLUSION

An effort has been made to solve FMLOP based on Neuro- fuzzy theory. This paper presented a approach that was adopted while figure compromise the solution .The major benefit of this paper is that the finding approximate solutions to systems of fuzzy equations. The proposed approach can be extended to solve fuzzy multi-objective linear programming problems FMOLPPs.

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