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A type-2 fuzzy system model for reducing bullwhip effects in supply chains and its application in steel manufacturing

M.H. Fazel Zarandi *, **R. Gamasaee**

Department of Industrial Engineering, Amirkabir University of Technology, Tehran, P.O. Box 15875-4413, Iran

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Abstract The purpose of this paper is to evaluate and reduce the bullwhip effect in fuzzy environments by means of type-2 fuzzy methodology. In order to reduce the bullwhip effect in a supply chain, we propose a new method for demand forecasting. First, the demand data of a real steel industry in Canada is clustered with an interval type-2 fuzzy c-regression clustering algorithm. Then, a novel interval type-2 fuzzy hybrid expert system is developed for demand forecasting. This system uses Fuzzy Disjunctive Normal Forms (FDNF) and Fuzzy Conjunctive Normal Forms (FCNF) for the aggregation of antecedents. An interval type-2 fuzzy order policy is developed to determine orders in the supply chain. Then, the results of the proposed method are compared with the type-1 fuzzy expert system as well as the type-1 fuzzy time series method in the literature. The results show that the bullwhip effect is significantly reduced; also, the system has less error and high accuracy.

1. Introduction

Customer demand information is very important in supply chains because of the competitive nature of industries. So, each entity in a supply chain tries to gather the demand information of its downstream customers. Demands of the downstream customers are considered as orders for their upstream suppliers. When an end customer places an order, this order is amplified as it moves through the chain. Such a phenomenon is recognized and described by Forrester [1]. He named this effect "demand amplification", which is now known as the bullwhip effect [2]. The next research is related to Sterman [3], who described this effect in a popular beer game.

Five reasons for bullwhip effect occurrence have been introduced by Lee et al. [4,5]. These reasons are: demand forecasting, order batching, price fluctuation, rationing and shortage gaming, and none-zero lead time. Metters [6], Baganha and Cohen [7], Chen et al. [8], and Campuzano et al. [9] focused on demand forecasting. Kelle and Milne [10], and Lee and Wu [11] studied order batching as one of the causes of the bullwhip effect. Pricing is considered by Özelkan and Cakanyıldırım [12] as the other reason for bullwhip occurrence. Cachon and Lariviere [13] studied shortage gaming. Agrawal et al. [14] investigated the effect of information sharing and lead time on the bullwhip effect, as well as on hand inventory.

In some situations, we encounter vague information in supply chains, which is represented by linguistic terms. Fuzzy logic is a proper method to model and solve those linguistic problems. For the first time, Carlsson and Fuller [15] used fuzzy logic in bullwhip effect problems. Fazel Zarandi et al. [16] presented an intelligent agent-based system for reducing the bullwhip effect in supply chains, in which all demands, lead times, and ordering quantities are fuzzy variables. Other work in the area of bullwhip effects in fuzzy environments is related to Fazel Zarandi et al. [17] and Campuzano et al. [9]. Fazel Zarandi et al. [17] used a multi-agent system for reducing the bullwhip effect. Campuzano et al. [9] considered a system dynamics model with type-1 fuzzy estimations of demand.

In some situations, the information is too vague to model the problem with type-1 fuzzy sets. In type-2 fuzzy systems, each membership degree, itself, is represented by another membership degree, which is called the secondary membership [18]. The method used for modeling and solving these kinds of problem is type-2 fuzzy theory, which was introduced by Zadeh [19].

* Corresponding author. Tel.: +98 2164545378; fax: +98 2166954569.
E-mail addresses: zarandi@aut.ac.ir (M.H. Fazel Zarandi), gamasaee@aut.ac.ir (R. Gamasaee).

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Turksen [20] and Gorzalczany [21] are pioneers of interval type-2 fuzzy sets. This fact that fuzzy normal forms can be generated from fuzzy truth tables has been presented by Turksen [20]. Turksen [22] introduced the Fuzzy Disjunctive Normal Form (FDNF) and the Fuzzy Conjunctive Normal Form (FCNF) for type-2 fuzzy sets, which are obtained from the fuzzy truth table. One controversial issue in type-2 fuzzy theory has been the complexity of the system. However, Sepúlveda et al. [23] showed that interval type-2 fuzzy systems can accelerate the computation process and control uncertainty better than type-1 fuzzy systems. Moreover, Melin et al. [24] showed that the most conspicuous images are obtained by using interval type-2 fuzzy systems. Interval type-2 fuzzy systems consist of three steps: structure identification, inference engine, and parameter tuning.

Rhee and Hwang [25–27] presented a Interval Type-2 Fuzzy C-Means clustering algorithm (IT2 FCM) for the structure identification phase of type-2 fuzzy systems. This method is used for Mamdani's systems. However, the Fuzzy C-Regression clustering Model (FCRM) is utilized in the structure identification phase of Takagi–Sugeno's systems.

In Mamdani's systems, all variables in consequents and antecedents have linguistic variables. In contrast, T–S systems have linguistic variables, not in the consequent part, but in their antecedents. On the other hand, the consequent of a T–S system is a function. Therefore, they require different reasoning and structure identification techniques. Hidalgo et al. [28] used the genetic algorithm for designing a type-2 fuzzy inference system with the Mamdani method.

Reviewing the literature of bullwhip problems shows that there is no research work on the bullwhip effect in type-2 fuzzy environments. So, this paper is the first to focus on bullwhip effect reduction, in which all demands, orders, and lead times are type-2 fuzzy sets. In order to model the problem, we extend a method introduced by Li et al. [29]. The method presented in [29] is FCRM for a type-1 fuzzy system, and we extend it to interval type-2 FCRM. A Gaussian Mixture Model (GMM) is developed to generate a partition matrix in the clustering algorithm. Regression coefficients are generated with a Weighted Least Square (WLS). After applying the interval type-2 fuzzy c-regression method, a new hybrid interval type-2 fuzzy inference system is used for demand prediction. This system is a combination of the Mamdani and Sugeno inference mechanism. We modify the FDNF and FCNF method, proposed by Turksen [30], for the reasoning phase of this system. In addition, the Adaptive-Network-Based Fuzzy Inference System (ANFIS) is used for the parameter tuning phase.

The rest of this paper is organized as follows: In Section 2, the background is presented. Section 3 addresses problem definition. In this section, the structure of the proposed supply chain, the bullwhip effect in this chain and the method of reducing this effect, with numerical examples, are illustrated. Finally, in Section 4, conclusions and future work are presented.

2. Background

In this section, first, the interval type-2 fuzzy C-regression clustering model for structure identification is described [31]. Then, Turksen's FCNF and FDNF methods [30] are explained. Finally, the type-2 fuzzy inference system is presented.

2.1. Interval type-2 fuzzy c-regression clustering model

The first step in developing a fuzzy expert system is structure identification. A technique that is used in the literature for this phase is Fuzzy C-Means clustering (FCM). It was introduced by Bezdek [32], whose objective was to minimize total error and to put similar data in the same clusters. This algorithm is developed for the structure identification of Mamdani expert systems. Since our proposed method uses Interval Type-2 Fuzzy Takagi–Sugeno–Kang (IT2F TSK) expert systems, we propose an Interval Type-2 Fuzzy C-Regression clustering Model (IT2 FCRM) [31]. This method is the extended model of the type-1 FCRM proposed by Li et al. [29].

In contrast to FCM, in which the shapes of clusters are hyper-spheres, the clusters are hyper-planes [29] in FCRM. The hyper-planes are generated from the regression function. In the FCRM algorithm, the distance between data and the cluster representative is obtained by calculating the total error of the system. This error is defined as the difference between actual output and estimated output [33]. For generating the partition matrix, in the FCRM algorithm, we use the Gaussian Mixture Model (GMM). The Weighted Least Square algorithm (WLS) is applied for calculating regression coefficients. As stated by Hwang and Rhee [34], interval type-2 FCM is generated with two fuzzifiers, m_1 and m_2. We extend the IT2 FCM algorithm proposed by Hwang and Rhee [34] to IT2 FCRM [31].

Eq. (1) represents the regression function:

$$y_i = f^z\left(x_i, \alpha_j\right) = \sum_{q=1}^{M} a_1^z x_{kq} + b_0^z, \tag{1}$$

where, $x_i = \left[x_{1,i}, x_{2,i}, \ldots, x_{M,i}\right]^T$ denotes the data points, $i = 1, \ldots, n$ is the number of data, $j = 1, \ldots, c$ is the number of clusters (or rules), $z = 1, \ldots, r$ is the number of regression functions, b is a constant number, and $q = 1, \ldots, M$ is the number of variables in each regression. Regression coefficients are represented by α_j, and the Weighted Least Square method (WLS) is used to calculate them in Eq. (2) [35]:

$$\begin{cases} X_i = \begin{bmatrix} x_{1,i} \\ x_{2,i} \\ \vdots \\ x_{M,i} \end{bmatrix}^T, \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix}^T, \\ W_i = \begin{bmatrix} w_j(x_1) & 0 & \cdots & 0 \\ 0 & w_j(x_2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_j(x_M) \end{bmatrix} \\ \alpha_i = \left[X^T W_i X\right]^{-1} X^T W_i y \end{cases} \tag{2}$$

where x is a data point matrix for inputs, and y is a data point matrix for outputs.

Gaussian mixture distribution is used for generating the partition matrix in Eq. (3). This method can be used in clustering [36]:

$$N\left(x; \bar{x}, C\right) = \frac{1}{(2\pi)^{\frac{|x|}{2}} \sqrt{|C|}} \times \exp\left(\frac{-1}{2}\left(x - \bar{x}\right)^T C^{-1}\left(x - \bar{x}\right)\right), \tag{3}$$

where $\bar{x}$ is the mean and C is the covariance matrix of the Gaussian distribution. C is often diagonal [37]. The likelihood of a given x being determined by a GMM is [37]:

$$P(x) = \sum_{i=1}^{N} w_i N\left(x; \bar{x}, C\right), \tag{4}$$