

# **SOME APPROACHES FOR SOLVING FUZZY DATA ENVELOPMENT ANALYSIS MODELS**

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SUBMITTED BY

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# CERTIFICATE

This is to certify that the thesis entitled, “**Some Approaches for Solving Fuzzy Data Envelopment Analysis Models**”, submitted by Ms. Bindu Bhardwaj, in the fulfillment of the requirement for the award of the degree of Doctor of Philosophy in the LM Thapar School of Management, Thapar University, Patiala, is a record of candidate’s own work carried out by her under my supervision and guidance.

The matter presented in this thesis has not been submitted in part or full for the award of any degree in any other University or Institute.

Attestation by supervisor



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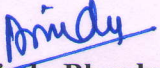
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# DECLARATION

It is certified that the thesis is entirely my own and the ideas and references cited herein have been duly acknowledged.

  
**Bindu Bhardwaj**

Attestation by supervisor



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**DECLARATION**

***DEDICATED***

***TO***

***MY SUPERVISOR***

***&***

***MY KIDS***

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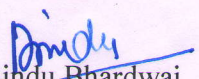
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# **Abstract**

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In this thesis, flaws in the existing fuzzy CCR DEA model as well as in some of the existing methods for solving fuzzy CCR DEA model are pointed out. Also, to resolve the flaws new fuzzy CCR DEA model and new approaches for solving it are proposed.

## **1.2 Organization of the thesis**

The chapter wise summary of the thesis is as follows:

### **Chapter 2**

Hatami-Marbini et al. [40] proposed a method to solve fuzzy CCR DEA model for evaluating the best relative fuzzy efficiency of decision making units (DMUs). In this chapter, it is pointed that the product of fuzzy numbers, used by Hatami-Marbini et al. [40], in their proposed method, is incorrect and hence, the method, proposed by Hatami-Marbini et al. [40], is not valid. To resolve this flaw, the method proposed by Hatami Marbini et al. [40], is modified by using correct product of fuzzy numbers.

### **Chapter 3**

Wang et al. [106] replaced the crisp output data and crisp input data of the crisp CCR DEA model with fuzzy data and proposed two methods for solving this fuzzy CCR DEA model. In this chapter, it is pointed out that the fuzzy CCR DEA model, proposed by Wang et al.[106], is not valid and hence the methods, proposed by Wang et al. [106] for evaluating the fuzzy efficiency of DMUs, are also not valid. Also, a new fuzzy CCR DEA model as well as a method to solve this fuzzy CCR DEA model is proposed.

### **Chapter 4**

Wang and Chin [105] proposed an optimistic as well as pessimistic fuzzy CCR DEA model and an approach for solving it to evaluate the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs. In this chapter, it is shown that the fuzzy CCR models, proposed by Wang and Chin [105], are

not valid and hence cannot be used to evaluate the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs. To resolve the flaws of the fuzzy CCR DEA model, proposed by Wang and Chin [105], new fuzzy CCR DEA models are proposed. Also, a new approach is proposed to solve the proposed fuzzy CCR DEA models for evaluating the relative geometric fuzzy efficiency of DMUs.

## **Chapter 5**

Puri and Yadav [83] proposed an optimistic as well as pessimistic intuitionistic fuzzy CCR DEA model and an approach to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of decision making units (DMUs). In this chapter, it is shown that the intuitionistic fuzzy CCR models, proposed by Puri and Yadav [83] are not valid and hence cannot be used to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of decision making units (DMUs). To resolve the flaws of the intuitionistic fuzzy CCR DEA model, proposed by Puri and Yadav [83], new intuitionistic fuzzy CCR DEA models are proposed. Also, a new approach is proposed to solve the proposed intuitionistic fuzzy CCR DEA models for evaluating the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs.

## **Chapter 6**

Finally, in this chapter, some future directions has been suggested.

## List of research papers

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- 1) **Bindu Bhardwaj**, Amit Kumar, A Note on the Paper “A simplified novel technique for solving fully fuzzy linear programming”. Journal of Optimization Theory and Applications, DOI: 10.1007/s10957-013-0505-3. **(Impact factor: 1.406)**
- 2) **Bindu Bhardwaj**, Amit Kumar, A Note on “A new algorithm to solve fully fuzzy linear programming problems using the MOLP problem”. Applied Mathematical Modelling. DOI: 10.1016/j.apm.2014.07.033 **(Impact factor: 2.195)**
- 3) **Bindu Bhardwaj**, Amit Kumar, Modified approach for solving fully fuzzy CCR DEA model, International Journal of Information and Decision Sciences (Communicated).
- 4) **Bindu Bhardwaj**, Amit Kumar, A new approach for solving fuzzy CCR DEA model, International Journal of Fuzzy Systems (Communicated).
- 5) **Bindu Bhardwaj**, Amit Kumar, A new approach for solving fully fuzzy CCR DEA model, Expert Systems with Applications (Communicated).
- 6) **Bindu Bhardwaj**, Amit Kumar, A new approach for solving intuitionistic fully fuzzy CCR DEA model, Expert Systems with Applications (Communicated).

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# Chapter 1

## Introduction

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### 1.1 Introduction

The efficiency evaluation of every system is important to find its weakness so that subsequent improvements can be made. The same has been practiced and studied for a long time. It has been recognized that the efficiency evaluation is a very complex problem. Two basic approaches used for evaluating efficiency are the parametric and nonparametric approaches. The parametric approach requires an assumption on the relationship between inputs and outputs while the nonparametric approach does not require any such assumption on the functional form. Numerous methods for measuring and evaluating productive efficiency have been developed. Data envelopment analysis (DEA), a non-parametric approach proposed by Charnes et al. [11], is an approach to measure the relative efficiency of homogenous units called decision making units (DMUs) which consume the same type of inputs and produce the same type of outputs.

A common measure of relative efficiency when there are multiple inputs and multiple outputs is a ratio of weighted sum of outputs to the weighted sum of inputs. DEA uses this concept and generalizes multiple-inputs and multiple-outputs for each DMU into a single virtual input and single virtual output, respectively. Specifically, it determines a set of weights such that the efficiency of the target DMU,  $DMU_0$  relative to the other DMUs is maximized. Thus, it provides an envelope for all considered DMUs rather than fitting a regression plane through the center of the data. Since, the pioneering work Charnes et al. [11], Data Envelopment Analysis (DEA) has been extensively used for evaluating the performance of many activities.

The reason of the DEA methodology being recommended widely in researches and applications is that it possess many merits which are not covered by traditional approaches [100].

For instance:

- (1) It is not only capable of deriving a single aggregated measure of the relative efficiency of DMUs in terms of their utilization of input factors to produce the desired outputs, but also able to provide suggestions on the possibility of increasing outputs and/ or conserving inputs to make the inefficient DMU become efficient.
- (2) In addition, DEA can handle non-commensurable multiple outputs and inputs without prior weight or prices.

Although, DEA methodology owns many advantages as stated above, it has some limitations which can be further improved [31]. The conventional DEA methods require accurate measurement of both the inputs and outputs. However, inputs and outputs of DMUs in real world problems are ever changeful. For example, for evaluating operation efficiencies of airlines, seat kilometers available, cargo-kilometers available, fuel and labor are regarded as inputs and passenger kilometers performed as the output. It is common sense that these inputs and output are easy to change because of weather, season, operating state and so on. Because DEA is a 'boundary' method sensitive to outliers, it is very difficult to evaluate the efficiency of DMU with varying inputs and outputs by conventional DEA models. Some researchers have proposed several models to challenge how to deal with the variation of data in efficiency evaluation problems by stochastic frontier models [28]. On the other hand, in more general cases, the data for evaluation are often collected from investigation by polling where the natural language such as good, medium and bad are used to reect a kind of general situation of the investigated entities rather than a specific case [79]. In the above example, the expert can make a general Conclusions

that airline A's passenger-kilometer is about 200 passenger-kilometers and fuel cost is high based on his rich experience.

Imprecise evaluations may be the result of unquantifiable, incomplete and non-obtainable information. In recent years, fuzzy set theory, established by Zadeh [113] has been proven to be useful as a way to quantify imprecise and vague data in DEA models. Fuzzy numbers are used to summarize the general situation of inputs and outputs and reacts the ambiguity of the expert's judgment. The center of a fuzzy number represents the most general case and the spread reacts some possibilities. The DEA model with fuzzy data, called “fuzzy DEA” models, can more realistically represent real world problems than the conventional DEA models. Fuzzy set theory also allows linguistic data to be used directly within the DEA model. Since, the original study by Sengupta [94, 95] there has been a continuous interest and increased development in fuzzy DEA (FDEA) literature. Several approaches have been developed and many new are coming for handling fuzzy input and output data in FDEA.

There are relatively a large number of papers in the fuzzy DEA literature. Since, summary development of the fuzzy DEA followed by a detailed description of the fuzzy DEA methods is easily available in the literature [25, 35]. So, to avoid the repetition of literature, the same is not described here and interested readers are requested to see the literature [25, 35]. However, research work done in four papers, published in last 6 years and base of this thesis work, is described in detailed manner in Chapter 2 to Chapter 5 of the thesis.

After reviewing the literature, it can be concluded that there are flaws in the existing fuzzy DEA models as well as in the existing methods for solving fuzzy DEA models. In this thesis, flaws in the existing fuzzy CCR DEA model as well as in some of the existing methods

for solving fuzzy CCR DEA model are pointed out. Also, to resolve the flaws new fuzzy CCR DEA model and new approaches for solving it are proposed.

## **1.2 Organization of the thesis**

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### **Chapter 2**

Hatami-Marbini et al. [40] proposed a method to solve fuzzy CCR DEA model for evaluating the best relative fuzzy efficiency of decision making units (DMUs). In this chapter, it is pointed that the product of fuzzy numbers, used by Hatami-Marbini et al. [40], in their proposed method, is incorrect and hence, the method, proposed by Hatami-Marbini et al. [40], is not valid. To resolve this flaw, the method proposed by Hatami Marbini et al. [40], is modified by using correct product of fuzzy numbers.

### **Chapter 3**

Wang et al. [106] replaced the crisp output data and crisp input data of the crisp CCR DEA model with fuzzy data and proposed two methods for solving this fuzzy CCR DEA model. In this chapter, it is pointed out that the fuzzy CCR DEA model, proposed by Wang et al.[106], is not valid and hence the methods, proposed by Wang et al. [106] for evaluating the fuzzy efficiency of DMUs, are also not valid. Also, a new fuzzy CCR DEA model as well as a method to solve this fuzzy CCR DEA model is proposed.

### **Chapter 4**

Wang and Chin [105] proposed an optimistic as well as pessimistic fuzzy CCR DEA model and an approach for solving it to evaluate the best relative fuzzy efficiency as well as

worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs. In this chapter, it is shown that the fuzzy CCR models, proposed by Wang and Chin [105], are not valid and hence cannot be used to evaluate the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs. To resolve the flaws of the fuzzy CCR DEA model, proposed by Wang and Chin [105], new fuzzy CCR DEA models are proposed. Also, a new approach is proposed to solve the proposed fuzzy CCR DEA models for evaluating the relative geometric fuzzy efficiency of DMUs.

## **Chapter 5**

Puri and Yadav [83] proposed an optimistic as well as pessimistic intuitionistic fuzzy CCR DEA model and an approach to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of decision making units (DMUs). In this chapter, it is shown that the intuitionistic fuzzy CCR models, proposed by Puri and Yadav [83] are not valid and hence cannot be used to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of decision making units (DMUs). To resolve the flaws of the intuitionistic fuzzy CCR DEA model, proposed by Puri and Yadav [83], new intuitionistic fuzzy CCR DEA models are proposed. Also, a new approach is proposed to solve the proposed intuitionistic fuzzy CCR DEA models for evaluating the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs.

## **Chapter 6**

Finally, in this chapter, some future directions has been suggested.



# Chapter 2

## Modified Approach for Solving Fully Fuzzy CCR

### DEA Model<sup>1</sup>

---

Hatami-Marbini et al. [40] proposed a method to solve fuzzy CCR DEA model for evaluating the best relative fuzzy efficiency of decision making units (DMUs). In this chapter, it is pointed that the product of fuzzy numbers, used by Hatami-Marbini et al. [40] in their proposed method, is incorrect and hence, the method, proposed by Hatami-Marbini et al. [40], is not valid. To resolve this flaw, the method proposed by Hatami Marbini et al. [40], is modified by using correct product of fuzzy numbers.

#### 2.1 Preliminaries

In this section, some basic definitions and arithmetic operations of fuzzy numbers are reviewed [123].

##### 2.1.1 Basic definitions

In this section, some basic definitions are reviewed [123].

**Definition 2.1** If the universal set is defined as  $X$  then a fuzzy set  $\tilde{A}$  of  $X$  can be defined by as a set of pairs of element  $x$  and  $\mu_{\tilde{A}}(x)$ ,  $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\}$ , where,  $\mu_{\tilde{A}}(x)$ , a real number in interval  $[0,1]$  represents the grade of membership function of  $x$  in  $\tilde{A}$ .

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<sup>1</sup> The contents of this chapter are communicated for the possible publication in International Journal of Information and Decision Sciences.

**Definition 2.2** A fuzzy set  $\tilde{A}$  is said to be convex if

$$\mu_{\tilde{A}}(\lambda x_1 + (1 - \lambda)x_2) \geq \text{minimum} \{\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2)\}, \forall x_1, x_2 \in X, \lambda \in [0,1].$$

**Definition 2.3** A fuzzy set  $\tilde{A}$  in  $X$  is said to be a normal fuzzy set if there exist at least a  $x \in X$  such that  $\mu_{\tilde{A}}(x) = 1$ .

**Definition 2.4** A fuzzy set  $\tilde{A}$  is a fuzzy number if  $\tilde{A}$  is normal and convex.

**Definition 2.5** A fuzzy number  $\tilde{A}$  is said to be non-negative (positive) if  $\mu_{\tilde{A}}(x) = 0, \forall x < 0$  ( $\forall x \leq 0$ ).

**Definition 2.6** A fuzzy number  $\tilde{A} = (a^M, a^\alpha, a^\beta), a^\alpha \geq 0, a^\beta \geq 0$ , is said to be a triangular fuzzy number if its membership function is given by

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{1}{a^\alpha}(x - a^M + a^\alpha), & a^M - a^\alpha \leq x < a^M \\ 1 & x = a^M \\ \frac{1}{a^\beta}(a^M - x + a^\beta), & a^M < x \leq a^M + a^\beta \\ 0, & \text{otherwise.} \end{cases}$$

**Definition 2.7** A triangular fuzzy number  $\tilde{A} = (a^M, a^\alpha, a^\beta)$  is said to be non-negative triangular fuzzy number if and only if  $a^M - a^\alpha \geq 0$ .

**Definition 2.8** A triangular fuzzy number  $\tilde{A} = (a^M, a^\alpha, a^\beta)$  is said to be positive triangular fuzzy number if and only if  $a^M - a^\alpha > 0$ .

**Definition 2.9** A fuzzy number  $\tilde{A} = (a^M, a^N, a^\alpha, a^\beta), a^M \leq a^N, a^\alpha > 0, a^\beta > 0$ , is said to be a trapezoidal fuzzy number if its membership function is given by

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{1}{a^\alpha}(x - a^M + a^\alpha), & a^M - a^\alpha \leq x < a^M \\ 1, & a^M \leq x \leq a^N \\ \frac{1}{a^\beta}(a^N - x + a^\beta), & a^N < x \leq a^N + a^\beta \\ 0, & \text{otherwise.} \end{cases}$$

**Definition 2.10** A trapezoidal fuzzy number  $\tilde{A} = (a^M, a^N, a^\alpha, a^\beta)$  is said to be non-negative trapezoidal fuzzy number if and only if  $a^M - a^\alpha \geq 0$ .

**Definition 2.11** A trapezoidal fuzzy number  $\tilde{A} = (a^M, a^N, a^\alpha, a^\beta)$  is said to be positive trapezoidal fuzzy number if and only if  $a^M - a^\alpha > 0$ .

**Definition 2.12** [40] A function  $\mathfrak{R} : F(R) \rightarrow R$  is a ranking function, where  $F(R)$  is a set of fuzzy numbers that is defined on the set of real numbers. This function maps each fuzzy number into real line.

Let  $\tilde{A} = (a^M, a^\alpha, a^\beta)$  and  $\tilde{B} = (b^M, b^\alpha, b^\beta)$  be two triangular fuzzy numbers. Then,

$$(i) \tilde{A} \succcurlyeq \tilde{B} \text{ iff } \mathfrak{R}(\tilde{A}) \geq \mathfrak{R}(\tilde{B})$$

$$(ii) \tilde{A} \approx \tilde{B} \text{ iff } \mathfrak{R}(\tilde{A}) = \mathfrak{R}(\tilde{B})$$

$$\text{where, } \mathfrak{R}(\tilde{A}) = a^M + \frac{a^\beta - a^\alpha}{4} \text{ and } \mathfrak{R}(\tilde{B}) = b^M + \frac{b^\beta - b^\alpha}{4}.$$

Let  $\tilde{A} = (a^M, a^N, a^\alpha, a^\beta)$  and  $\tilde{B} = (b^M, b^N, b^\alpha, b^\beta)$  be two trapezoidal fuzzy numbers.

Then,

$$(i) \tilde{A} \succcurlyeq \tilde{B} \text{ iff } \mathfrak{R}(\tilde{A}) \geq \mathfrak{R}(\tilde{B})$$

$$(ii) \tilde{A} \approx \tilde{B} \text{ iff } \mathfrak{R}(\tilde{A}) = \mathfrak{R}(\tilde{B})$$

$$\text{where, } \mathfrak{R}(\tilde{A}) = \frac{a^M + a^N}{2} + \frac{a^\beta - a^\alpha}{4} \text{ and } \mathfrak{R}(\tilde{B}) = \frac{b^M + b^N}{2} + \frac{b^\beta - b^\alpha}{4}.$$

**Remark 2.1** A triangular fuzzy number  $\tilde{A} = (a^M, a^\alpha, a^\beta)$  is also represented as  $\tilde{A} = (a, b, c)$ , where,  $a = a^M - a^\alpha, b = a^M, c = a^M + a^\beta$  and  $a \leq b \leq c$ . In Chapter 3, this representation is used.

**Remark 2.2** A trapezoidal fuzzy number  $\tilde{A} = (a^M, a^N, a^\alpha, a^\beta)$  is also represented as  $\tilde{A} = (a, b, c, d)$ , where,  $a = a^M - a^\alpha, b = a^M, c = a^N, d = a^N + a^\beta$  and  $a \leq b \leq c \leq d$ . In Chapter 4, this representation is used.

**Remark 2.3** Let  $\tilde{A} = (a, b, c, d)$  be a trapezoidal fuzzy number. Then,  $\mathfrak{R}(\tilde{A}) = \frac{a+b+c+d}{4}$ .

**Remark 2.4** Let  $\tilde{A} = (a, b, c)$  be a triangular fuzzy number. Then,  $\mathfrak{R}(\tilde{A}) = \frac{a+2b+c}{4}$ .

## 2.1.2 Arithmetic operations

In this section, arithmetic operations of triangular fuzzy numbers and trapezoidal fuzzy numbers are presented.

### 2.1.2.1 Arithmetic operations of triangular fuzzy numbers

Let  $\tilde{A} = (a^M, a^\alpha, a^\beta)$  and  $\tilde{B} = (b^M, b^\alpha, b^\beta)$  be two arbitrary triangular fuzzy numbers.

Then,

$$(i) \quad \tilde{A} + \tilde{B} = (a^M + b^M, a^\alpha + b^\alpha, a^\beta + b^\beta)$$

$$(ii) \quad \tilde{A} - \tilde{B} = (a^M - b^M, a^\alpha + b^\beta, a^\beta + b^\alpha)$$

$$(iii) \quad \tilde{A} \tilde{B} = (a^M b^M, a^M b^\alpha + b^M a^\alpha - a^\alpha b^\alpha, a^N b^\beta + b^N a^\beta + a^\beta b^\beta), \text{ where } \tilde{A} \text{ and}$$

$\tilde{B}$  are non-negative triangular fuzzy numbers.

$$(iv) \quad \frac{\tilde{A}}{\tilde{B}} = \left( \frac{a^M}{b^M}, \frac{a^M}{b^M} - \frac{a^M - a^\alpha}{b^M + b^\beta}, \frac{a^M + a^\beta}{b^M - b^\alpha} - \frac{a^M}{b^M} \right), \text{ where } \tilde{A} \text{ is a non-negative triangular fuzzy}$$

number and  $\tilde{B}$  is a positive triangular fuzzy number.

Let  $\tilde{A} = (a_1, b_1, c_1) = (a^M - a^\alpha, a^M, a^M + a^\beta)$  and  $\tilde{B} = (a_2, b_2, c_2) = (b^M - b^\alpha, b^M, b^M + b^\beta)$  be two arbitrary triangular fuzzy numbers. Then,

- (i)  $\tilde{A} + \tilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$
- (ii)  $\tilde{A} - \tilde{B} = (a_1 - c_2, b_1 - b_2, c_1 - a_2)$
- (iii)  $\tilde{A} \tilde{B} = (a_1 a_2, b_1 b_2, c_1 c_2)$ , where  $\tilde{A}$  and  $\tilde{B}$  are non-negative triangular fuzzy numbers.
- (iv)  $\frac{\tilde{A}}{\tilde{B}} = \left( \frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2} \right)$ , where  $\tilde{A}$  is a non-negative triangular fuzzy number and  $\tilde{B}$  is a positive triangular fuzzy number.

### 2.1.2.2 Arithmetic operations of trapezoidal fuzzy numbers

Let  $\tilde{A} = (a^M, a^N, a^\alpha, a^\beta)$  and  $\tilde{B} = (b^M, b^M, b^\alpha, b^\beta)$  be two arbitrary trapezoidal fuzzy numbers. Then,

- (i)  $\tilde{A} + \tilde{B} = (a^M + b^M, a^N + b^N, a^\alpha + b^\alpha, a^\beta + b^\beta)$
- (ii)  $\tilde{A} - \tilde{B} = (a^M - b^N, a^N - b^M, a^\alpha + b^\beta, a^\beta + b^\alpha)$
- (iii)  $\tilde{A} \tilde{B} = (a^M b^M, a^N b^N, a^M b^\alpha + b^M a^\alpha - a^\alpha b^\alpha, a^M b^\beta + b^M a^\beta + a^\beta b^\beta)$ , where  $\tilde{A}$  and  $\tilde{B}$  are non-negative trapezoidal fuzzy numbers.
- (iv)  $\frac{\tilde{A}}{\tilde{B}} = \left( \frac{a^M}{b^N}, \frac{a^N}{b^M}, \frac{a^M}{b^N} - \frac{a^M - a^\alpha}{b^N + b^\beta}, \frac{a^N + a^\beta}{b^M - b^\alpha} - \frac{a^N}{b^M} \right)$ , where  $\tilde{A}$  is a non-negative trapezoidal fuzzy number and  $\tilde{B}$  is a positive trapezoidal fuzzy number.

Let  $\tilde{A} = (a_1, b_1, c_1, d_1) = (a^M - a^\alpha, a^M, a^N, a^N + a^\beta)$  and  $\tilde{B} = (a_2, b_2, c_2, d_2) = (b^M - b^\alpha, b^M, b^N, b^N + b^\beta)$  be two arbitrary trapezoidal fuzzy numbers. Then,

- (i)  $\tilde{A} + \tilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2)$
- (ii)  $\tilde{A} - \tilde{B} = (a_1 - d_2, b_1 - c_2, c_1 - b_2, d_1 - a_2)$

(iii)  $\tilde{A} \tilde{B} = (a_1 a_2, b_1 b_2, c_1 c_2, d_1 d_2)$ , where  $\tilde{A}$  and  $\tilde{B}$  are non-negative trapezoidal fuzzy numbers.

(iv)  $\frac{\tilde{A}}{\tilde{B}} = \left( \frac{a_1}{d_2}, \frac{b_1}{c_2}, \frac{c_1}{a_2}, \frac{d_1}{b_2} \right)$ , where  $\tilde{A}$  is a non-negative trapezoidal fuzzy number and  $\tilde{B}$  is a positive trapezoidal fuzzy number.

## 2.2 Existing fuzzy DEA model

If there are  $n$  DMUs, then the best relative efficiency ( $E_p$ ) of  $p^{th}$  DMU can be obtained by solving the CCR DEA model-2.1 [11].

### CCR DEA model-2.1

$$\text{Maximize } \left[ E_p = \frac{\text{Virtual output of } p^{th} \text{ DMU}}{\text{Virtual input of } p^{th} \text{ DMU}} \right]$$

Subject to

$$\left[ \frac{\text{Virtual output of } j^{th} \text{ DMU}}{\text{Virtual input of } j^{th} \text{ DMU}} \right] \leq 1, \quad j = 1, \dots, n.$$

If each DMU have  $m$  inputs ( $x_{ij}; i = 1, 2, \dots, m; j = 1, 2, \dots, n$ ) and  $s$  outputs ( $y_{rj}; r = 1, 2, \dots, s; j = 1, 2, \dots, n$ ) then the CCR DEA model-2.1 can be transformed into the crisp CCR DEA model-2.2 [11].

### Crisp CCR DEA model-2.2

$$\text{Maximize } \left[ E_p = \frac{\sum_{r=1}^s u_r y_{rp}}{\sum_{i=1}^m v_i x_{ip}} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad \forall j,$$

$$u_r, v_i \geq 0, \quad \forall r, i.$$

where  $u_r$  ( $r = 1, \dots, s$ ) and  $v_i$  ( $i = 1, \dots, m$ ) are the weights assigned to the  $r^{th}$  output and  $i^{th}$  input, respectively.

The crisp CCR DEA model-2.2 can be transformed into the crisp CCR DEA model-2.3 [11].

### CCR crisp DEA model-2.3

$$\text{Maximize } \left[ E_p = \sum_{r=1}^s u_r y_{rp} \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip} = 1,$$

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, \quad \forall j,$$

$$u_r, v_i \geq 0, \quad \forall r, i.$$

where  $u_r$  ( $r = 1, \dots, s$ ) and  $v_i$  ( $i = 1, \dots, m$ ) are the weights assigned to the  $r^{th}$  output and  $i^{th}$  input, respectively.

Hatami Marbini et al. [40] pointed out that the crisp CCR DEA model-2.3, proposed by Charnes et al. [11] can be used only to evaluate the best relative efficiency ( $E_p$ ) of  $p^{th}$  DMU only if the collected data is precise. However, if the collected data is imprecise or vague then the

crisp CCR DEA model-2.3, proposed by Charnes et al. [11] cannot be used to obtain the best relative efficiency ( $E_p$ ) of  $p^{th}$  DMU. To overcome this limitation of the crisp CCR DEA model-2.3, proposed by Charnes et al. [11], Hatami Marbini et al. [40] transformed the crisp CCR DEA model-2.3 into fuzzy CCR DEA model-2.4 by replacing the crisp parameters  $u_r$ ,  $y_{rj}$ ,  $v_i$  and  $x_{ij}$  with triangular fuzzy numbers  $\tilde{u}_r = (u_r^M, u_r^\alpha, u_r^\beta)$ ,  $\tilde{y}_{rj} = (y_{rj}^M, y_{rj}^\alpha, y_{rj}^\beta)$ ,  $\tilde{v}_i = (v_i^M, v_i^\alpha, v_i^\beta)$  and  $\tilde{x}_{ij} = (x_{ij}^M, x_{ij}^\alpha, x_{ij}^\beta)$  respectively.

### Fuzzy CCR DEA model-2.4

$$\text{Maximize } \left[ \tilde{E}_p \approx \sum_{r=1}^s (u_r^M, u_r^\alpha, u_r^\beta) \otimes (y_{rp}^M, y_{rp}^\alpha, y_{rp}^\beta) \right]$$

Subject to

$$\sum_{i=1}^m (v_i^M, v_i^\alpha, v_i^\beta) \otimes (x_{ip}^M, x_{ip}^\alpha, x_{ip}^\beta) \approx (1, 0, 0)$$

$$\sum_{r=1}^s (u_r^M, u_r^\alpha, u_r^\beta) \otimes (y_{rj}^M, y_{rj}^\alpha, y_{rj}^\beta) - \sum_{i=1}^m (v_i^M, v_i^\alpha, v_i^\beta) \otimes (x_{ij}^M, x_{ij}^\alpha, x_{ij}^\beta) \leq (0, 0, 0), \forall j,$$

$$(u_r^M, u_r^\alpha, u_r^\beta), (v_i^M, v_i^\alpha, v_i^\beta) \geq (0, 0, 0), \forall r, i.$$

$(u_r^M, u_r^\alpha, u_r^\beta)$  and  $(v_i^M, v_i^\alpha, v_i^\beta)$  are non-negative triangular fuzzy numbers.

### 2.3 Existing method

Hatami-Marbini et al. [40], proposed the following method to solve the fuzzy CCR DEA model-2.4 for evaluating the best relative fuzzy efficiency of  $p^{th}$  DMU.

**Step 1:** The fuzzy CCR DEA model-2.4 can be transformed into the fuzzy CCR DEA model-2.5.

### Fuzzy CCR DEA model-2.5

$$\text{Maximize } \left[ \tilde{E}_p \approx \sum_{r=1}^s \left( u_r^M (y_{rp}^M + y_{rp}^\beta - y_{rp}^\alpha), u_r^\beta y_{rp}^M, u_r^\alpha y_{rp}^M \right) \right]$$

$$\sum_{i=1}^m \left( v_i^M (x_{ip}^M + x_{ip}^\beta - x_{ip}^\alpha), v_i^\beta x_{ip}^M, v_i^\alpha x_{ip}^M \right) = 1,$$

$$\sum_{r=1}^s \left( u_r^M (y_{rj}^M + y_{rj}^\beta - y_{rj}^\alpha), u_r^\beta y_{rj}^M, u_r^\alpha y_{rj}^M \right)$$

$$- \sum_{i=1}^m \left( v_i^M (x_{ij}^M + x_{ij}^\beta - x_{ij}^\alpha), v_i^\beta x_{ij}^M, v_i^\alpha x_{ij}^M \right) \leq (0,0,0), \forall j,$$

$$\left( u_r^M, u_r^\alpha, u_r^\beta \right), \left( v_i^M, v_i^\alpha, v_i^\beta \right) \geq (0,0,0), \forall r, i.$$

$\left( u_r^M, u_r^\alpha, u_r^\beta \right)$  and  $\left( v_i^M, v_i^\alpha, v_i^\beta \right)$  are non-negative triangular fuzzy numbers.

**Step 2:** The fuzzy CCR DEA model-2.5 can be transformed into the crisp CCR DEA model-2.6.

### Crisp CCR DEA model-2.6

$$\text{Maximize } \left[ E_p = \Re(\tilde{E}_p) = \sum_{r=1}^s \left[ \begin{array}{l} u_r^M \left( y_{rp}^M + \left(\frac{1}{4}\right) y_{rp}^\beta - \left(\frac{1}{4}\right) y_{rp}^\alpha \right) \\ + u_r^\beta \left( \left(\frac{1}{4}\right) y_{rp}^M \right) - u_r^\alpha \left( \left(\frac{1}{4}\right) y_{rp}^M \right) \end{array} \right] \right]$$

$$\sum_{i=1}^m \left[ v_i^M \left( x_{ip}^M + \left(\frac{1}{4}\right) x_{ip}^\beta - \left(\frac{1}{4}\right) x_{ip}^\alpha \right) + v_i^\beta \left( \left(\frac{1}{4}\right) x_{ip}^M \right) - v_i^\alpha \left( \left(\frac{1}{4}\right) x_{ip}^M \right) \right] = 1,$$

$$\sum_{r=1}^s \left[ u_r^M \left( y_{rj}^M + \left(\frac{1}{4}\right) y_{rj}^\beta - \left(\frac{1}{4}\right) y_{rj}^\alpha \right) + u_r^\beta \left( \left(\frac{1}{4}\right) y_{rj}^M \right) - u_r^\alpha \left( \left(\frac{1}{4}\right) y_{rj}^M \right) \right] -$$

$$\sum_{i=1}^m \left[ v_i^M \left( x_{ij}^M + \left( \frac{1}{4} \right) x_{ij}^\beta - \left( \frac{1}{4} \right) x_{ij}^\alpha \right) + v_i^\beta \left( \left( \frac{1}{4} \right) x_{ij}^M \right) - v_i^\alpha \left( \left( \frac{1}{4} \right) x_{ij}^M \right) \right] \leq 0 \quad \forall j,$$

$$u_r^M - u_r^\alpha \geq 0 \quad \forall r,$$

$$u_r^M - \left( \frac{1}{4} \right) u_r^\alpha + \left( \frac{1}{4} \right) u_r^\beta \geq 0, \quad \forall r,$$

$$v_i^M - v_i^\beta \geq 0, \quad \forall i,$$

$$v_i^M - \left( \frac{1}{4} \right) v_i^\alpha + \left( \frac{1}{4} \right) v_i^\beta \geq 0, \quad \forall i,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i.$$

**Step 3:** Find the optimal value crisp optimal value  $E_p = \Re(\tilde{E}_p)$ , representing ranking value of best relative fuzzy efficiency of  $p^{th}$  DMU, of the crisp CCR DEA model 2.6.

## 2.4 Flaws in the existing method

If  $\tilde{A} = (a^M, a^\alpha, a^\beta)$  and  $\tilde{B} = (b^M, b^\alpha, b^\beta)$  are two non-negative triangular fuzzy numbers then

$$\tilde{A} \otimes \tilde{B} = (a^M b^M, a^M b^\alpha + b^M a^\alpha - a^\alpha b^\alpha, a^M b^\beta + b^M a^\beta + a^\beta b^\beta).$$

However, it is obvious from Step 1 of the existing method [40], described in Section 2.3, that Hatami-Marbini et al. [40], have used the incorrect product  $\tilde{A} \otimes \tilde{B} = (a^M (b^M + b^\beta - b^\alpha), a^\beta b^M, a^\alpha b^M)$  to transform the fuzzy CCR DEA model-2.4 into the fuzzy CCR DEA model-2.5. Hence, the method, proposed by Hatami-Marbini et al. [40], is not valid in its present form.

## 2.5 Modified method

In this section, the existing method [40] is modified.

**Step 1:** Using the product of triangular fuzzy numbers, defined in Section 2.1.2.1, the fuzzy CCR DEA model-2.4 can be transformed into the fuzzy CCR DEA model-2.7.

### Fuzzy CCR DEA model-2.7

$$\text{Maximize } \left[ \tilde{E}_p \approx \sum_{r=1}^s \left( u_r^M y_{rp}^M, u_r^M y_{rp}^\alpha + y_{rp}^M u_r^\alpha - u_r^\alpha y_{rp}^\alpha, u_r^M y_{rp}^\beta + y_{rp}^M u_r^\beta + u_r^\beta y_{rp}^\beta \right) \right]$$

Subject to

$$\sum_{i=1}^m \left( v_i^M x_{ip}^M, v_i^M x_{ip}^\alpha + x_{ip}^M v_i^\alpha - v_i^\alpha x_{ip}^\alpha, v_i^M x_{ip}^\beta + x_{ip}^M v_i^\beta + v_i^\beta x_{ip}^\beta \right) \approx 1,$$

$$\sum_{r=1}^s \left( u_r^M y_{rj}^M, u_r^M y_{rj}^\alpha + y_{rj}^M u_r^\alpha - u_r^\alpha y_{rj}^\alpha, u_r^M y_{rj}^\beta + y_{rj}^M u_r^\beta + u_r^\beta y_{rj}^\beta \right)$$

$$\leq \sum_{i=1}^m \left( v_i^M x_{ij}^M, v_i^M x_{ij}^\alpha + x_{ij}^M v_i^\alpha - v_i^\alpha x_{ij}^\alpha, v_i^M x_{ij}^\beta + x_{ij}^M v_i^\beta + v_i^\beta x_{ij}^\beta \right), \forall j,$$

$$\left( u_r^M, u_r^\alpha, u_r^\beta \right), \left( v_i^M, v_i^\alpha, v_i^\beta \right) \geq (0,0,0), \forall r, i.$$

$\left( u_r^M, u_r^\alpha, u_r^\beta \right)$  and  $\left( v_i^M, v_i^\alpha, v_i^\beta \right)$  are non-negative triangular fuzzy numbers.

**Step 2:** Using Definition 2.12, the fuzzy CCR model-2.7 can be transformed into crisp CCR DEA model-2.8.

### Crisp CCR DEA model-2.8

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p) = \mathfrak{R} \left( \sum_{r=1}^s (u_r^M y_{rp}^M, u_r^M y_{rp}^\alpha + y_{rp}^M u_r^\alpha - u_r^\alpha y_{rp}^\alpha, u_r^M y_{rp}^\beta + y_{rp}^M u_r^\beta + u_r^\beta y_{rp}^\beta) \right) \right]$$

Subject to

$$\mathfrak{R} \left( \sum_{i=1}^m (v_i^M x_{ip}^M, v_i^M x_{ip}^\alpha + x_{ip}^M v_i^\alpha - v_i^\alpha x_{ip}^\alpha, v_i^M x_{ip}^\beta + x_{ip}^M v_i^\beta + v_i^\beta x_{ip}^\beta) \right) = \mathfrak{R}(1,1,1)$$

$$\begin{aligned} & \mathfrak{R} \left( \sum_{r=1}^s (u_r^M y_{rj}^M, u_r^M y_{rj}^\alpha + y_{rj}^M u_r^\alpha - u_r^\alpha y_{rj}^\alpha, u_r^M y_{rj}^\beta + y_{rj}^M u_r^\beta + u_r^\beta y_{rj}^\beta) \right) \\ & \leq \mathfrak{R} \left( \sum_{i=1}^m (v_i^M x_{ij}^M, v_i^M x_{ij}^\alpha + x_{ij}^M v_i^\alpha - v_i^\alpha x_{ij}^\alpha, v_i^M x_{ij}^\beta + x_{ij}^M v_i^\beta + v_i^\beta x_{ij}^\beta) \right), \forall j, \end{aligned}$$

$$\mathfrak{R}(u_r^M, u_r^\alpha, u_r^\beta) \geq \mathfrak{R}(0,0,0), \mathfrak{R}(v_i^M, v_i^\alpha, v_i^\beta) \geq \mathfrak{R}(0,0,0), \forall r, i.$$

$$u_r^M - u_r^\alpha \geq 0 \quad \forall r,$$

$$v_i^M - v_i^\beta \geq 0, \quad \forall i,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i.$$

**Step 3:** The crisp CCR DEA model-2.8 can be transformed into crisp CCR DEA model-2.9.

### Crisp CCR DEA model-2.9

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p) = \sum_{r=1}^s \mathfrak{R}(u_r^M y_{rp}^M, u_r^M y_{rp}^\alpha + y_{rp}^M u_r^\alpha - u_r^\alpha y_{rp}^\alpha, u_r^M y_{rp}^\beta + y_{rp}^M u_r^\beta + u_r^\beta y_{rp}^\beta) \right]$$

Subject to

$$\sum_{i=1}^m \mathfrak{R}(v_i^M x_{ip}^M, v_i^M x_{ip}^\alpha + x_{ip}^M v_i^\alpha - v_i^\alpha x_{ip}^\alpha, v_i^M x_{ip}^\beta + x_{ip}^M v_i^\beta + v_i^\beta x_{ip}^\beta) = \mathfrak{R}(1,1,1)$$

$$\sum_{r=1}^s \mathfrak{R}(u_r^M y_{rj}^M, u_r^M y_{rj}^\alpha + y_{rj}^M u_r^\alpha - u_r^\alpha y_{rj}^\alpha, u_r^M y_{rj}^\beta + y_{rj}^M u_r^\beta + u_r^\beta y_{rj}^\beta) \\ \leq \mathfrak{R}\left(\sum_{i=1}^m (v_i^M x_{ij}^M, v_i^M x_{ij}^\alpha + x_{ij}^M v_i^\alpha - v_i^\alpha x_{ij}^\alpha, v_i^M x_{ij}^\beta + x_{ij}^M v_i^\beta + v_i^\beta x_{ij}^\beta)\right), \forall j,$$

$$\mathfrak{R}(u_r^M, u_r^\alpha, u_r^\beta) \geq \mathfrak{R}(0,0,0), \mathfrak{R}(v_i^M, v_i^\alpha, v_i^\beta) \geq \mathfrak{R}(0,0,0), \forall r, i.$$

$$u_r^M - u_r^\alpha \geq 0 \quad \forall r,$$

$$v_i^M - v_i^\beta \geq 0, \quad \forall i,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i.$$

**Step 4:** Using the ranking formula  $\mathfrak{R}(a^M, a^\alpha, a^\beta) = a^M + \frac{a^\beta - a^\alpha}{4}$  and Definition 2.7, the crisp

CCR DEA model-2.9 can be transformed into the crisp CCR DEA model-2.10.

#### CCR crisp DEA model-2.10

$$\text{Maximize } \left[ E_p = \sum_{r=1}^s \left( u_r^M y_{rp}^M \right. \right. \\ \left. \left. + \frac{1}{4} \left[ \left( u_r^M y_{rp}^\beta + y_{rp}^M u_r^\beta + u_r^\beta y_{rp}^\beta \right) - \left( v_i^M x_{ip}^\alpha + x_{ip}^M v_i^\alpha - v_i^\alpha x_{ip}^\alpha \right) \right] \right) \right]$$

Subject to

$$\sum_{i=1}^m \left( v_i^M x_{ip}^M + \frac{1}{4} \left[ \left( v_i^M x_{ip}^\beta + x_{ip}^M v_i^\beta + v_i^\beta x_{ip}^\beta \right) - \left( v_i^M x_{ip}^\alpha + x_{ip}^M v_i^\alpha - v_i^\alpha x_{ip}^\alpha \right) \right] \right) = 1,$$

$$\sum_{r=1}^s \left( u_r^M y_{rj}^M + \frac{1}{4} \left[ (u_r^M y_{rj}^\beta + y_{rj}^M u_r^\beta + u_r^\beta y_{rj}^\beta) - (u_r^M y_{rj}^\alpha + y_{rj}^M u_r^\alpha - u_r^\alpha y_{rj}^\alpha) \right] \right) - \sum_{i=1}^m \left( v_i^M x_{ij}^M + \frac{1}{4} \left[ (v_i^M x_{ij}^\beta + x_{ij}^M v_i^\beta + v_i^\beta x_{ij}^\beta) - (v_i^M x_{ij}^\alpha + x_{ij}^M v_i^\alpha - v_i^\alpha x_{ij}^\alpha) \right] \right) \leq 0, \forall j,$$

$$u_r^M - u_r^\alpha \geq 0, \forall r,$$

$$u_r^M - \left(\frac{1}{4}\right)u_r^\alpha + \left(\frac{1}{4}\right)u_r^\beta \geq 0, \forall r,$$

$$v_i^M - v_i^\beta \geq 0, \quad \forall i,$$

$$v_i^M - \left(\frac{1}{4}\right)v_i^\alpha + \left(\frac{1}{4}\right)v_i^\beta \geq 0, \quad \forall i,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i.$$

**Step 5:** Find the optimal value  $E_p = \Re(\tilde{E}_p)$ , representing ranking value of relative fuzzy efficiency of  $p^{th}$  DMU, of the crisp CCR DEA model 2.6.

## 2.6 Exact best relative fuzzy efficiency of existing problem

Hatami-Marbini et al. [40] solved existing problem [31] to illustrate his proposed approach. However, as discussed in Section 2.3 that there are flaws in the existing method [40]. So, the results of this problem, obtained by Hatami Marbini et al. [40], is also not exact. In this section, the exact results of the same problem is obtained by the modified method.

### 2.6.1 Problem description

Hatami Marbini et al. [40] evaluated the best relative efficiency of each of five DMUs, each with two outputs and two inputs, to illustrate their proposed approach by considering the existing input and output data, represented by triangular fuzzy numbers, shown in Table 2.1.

**Table 2.1.** Input and output data

| (DMUs) | Input 1         | Input 2         | Output 1        | Output 2        |
|--------|-----------------|-----------------|-----------------|-----------------|
| 1      | (4, 0.5, 0.5)   | (2.1, 0.2, 0.2) | (2.6, 0.2, 0.2) | (4.1, 0.3, 0.3) |
| 2      | (2.9, 0, 0)     | (1.5, 0.1, 0.1) | (2.2, 0, 0)     | (3.5, 0.2, 0.2) |
| 3      | (4.9, 0.5, 0.5) | (2.6, 0.4, 0.4) | (3.2, 0.5, 0.5) | (5.1, 0.8, 0.8) |
| 4      | (4.1, 0.7, 0.7) | (2.3, 0.1, 0.1) | (2.9, 0.4, 0.4) | (5.7, 0.2, 0.2) |
| 5      | (6.5, 0.6, 0.6) | (4.1, 0.5, 0.5) | (5.1, 0.7, 0.7) | (7.4, 0.9, 0.9) |

### 2.6.2 Fuzzy CCR DEA models

Hatami Marbini et al. [40] solved the fuzzy CCR DEA model-2.11 to 2.15 to evaluate the best relative fuzzy efficiency of DMU<sub>1</sub> to DMU<sub>5</sub> respectively.

#### Fuzzy CCR DEA model-2.11

$$\text{Maximize } \left[ \tilde{E}_1 \approx (2.6, 0.2, 0.2)(u_1^M, u_1^\alpha, u_1^\beta) + (4.1, 0.3, 0.3)(u_2^M, u_2^\alpha, u_2^\beta) \right]$$

Subject to

$$(4, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.1, 0.2, 0.2)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1,$$

$$\begin{aligned} & \left[ (2.6, 0.2, 0.2)(u_1^M, u_1^\alpha, u_1^\beta) + (4.1, 0.3, 0.3)(u_2^M, u_2^\alpha, u_2^\beta) \right] - \left[ (4, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + \right. \\ & \left. (2.1, 0.2, 0.2)(v_2^M, v_2^\alpha, v_2^\beta) \right] \preceq (0, 0, 0), \end{aligned}$$

$$\begin{aligned} & \left[ (2.2, 0, 0)(u_1^M, u_1^\alpha, u_1^\beta) + (3.5, 0.2, 0.2)(u_2^M, u_2^\alpha, u_2^\beta) \right] \\ & - \left[ (2.9, 0, 0)(v_1^M, v_1^\alpha, v_1^\beta) + (1.5, 0.1, 0.1)(v_2^M, v_2^\alpha, v_2^\beta) \right] \preceq (0, 0, 0), \end{aligned}$$

$$\begin{aligned} & \left[ (3.2, 0.5, 0.5)(u_1^M, u_1^\alpha, u_1^\beta) + (5.1, 0.8, 0.8)(u_2^M, u_2^\alpha, u_2^\beta) \right] \\ & - \left[ (4.9, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.6, 0.4, 0.4)(v_2^M, v_2^\alpha, v_2^\beta) \right] \preceq (0, 0, 0), \end{aligned}$$

$$\begin{aligned} & \left[ (2.9, 0.4, 0.4)(u_1^M, u_1^\alpha, u_1^\beta) + (5.7, 0.2, 0.2)(u_2^M, u_2^\alpha, u_2^\beta) \right] \\ & - \left[ (4.1, 0.7, 0.7)(v_1^M, v_1^\alpha, v_1^\beta) + (2.3, 0.1, 0.1)(v_2^M, v_2^\alpha, v_2^\beta) \right] \preceq (0, 0, 0), \end{aligned}$$

$$\begin{aligned} & \left[ (5.1, 0.7, 0.7)(u_1^M, u_1^\alpha, u_1^\beta) + (7.4, 0.9, 0.9)(u_2^M, u_2^\alpha, u_2^\beta) \right] \\ & - \left[ (6.5, 0.6, 0.6)(v_1^M, v_1^\alpha, v_1^\beta) + (4.1, 0.5, 0.5)(v_2^M, v_2^\alpha, v_2^\beta) \right] \preceq (0, 0, 0), \end{aligned}$$

$$(u_1^M, u_1^\alpha, u_1^\beta) \succeq (0, 0, 0), (u_2^M, u_2^\alpha, u_2^\beta) \succeq (0, 0, 0),$$

$$(v_1^M, v_1^\alpha, v_1^\beta) \succeq (0, 0, 0), (v_2^M, v_2^\alpha, v_2^\beta) \succeq (0, 0, 0),$$

$(u_1^M, u_1^\alpha, u_1^\beta), (u_2^M, u_2^\alpha, u_2^\beta), (v_1^M, v_1^\alpha, v_1^\beta)$  and  $(v_2^M, v_2^\alpha, v_2^\beta)$  are non-negative triangular fuzzy numbers.

### Fuzzy CCR DEA model-2.12

$$\text{Maximize } \left[ \tilde{E}_2 \approx (2.2, 0, 0)(u_1^M, u_1^\alpha, u_1^\beta) + (3.5, 0.2, 0.2)(u_2^M, u_2^\alpha, u_2^\beta) \right]$$

Subject to

$$(2.9, 0, 0)(v_1^M, v_1^\alpha, v_1^\beta) + (1.5, 0.1, 0.1)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1,$$

and

All the constraints of fuzzy CCR DEA model-2.11 except the first constraint

$$“(4, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.1, 0.2, 0.2)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1”.$$

### **Fuzzy CCR DEA model-2.13**

$$\text{Maximize } [\tilde{E}_3 \approx (3.2, 0.5, 0.5)(u_1^M, u_1^\alpha, u_1^\beta) + (5.1, 0.8, 0.8)(u_2^M, u_2^\alpha, u_2^\beta)]$$

Subject to

$$(4.9, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.6, 0.4, 0.4)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1,$$

and

All the constraints of fuzzy CCR DEA model-2.11 except the first constraint

$$“(4, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.1, 0.2, 0.2)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1”.$$

### **Fuzzy CCR DEA model-2.14**

$$\text{Maximize } [\tilde{E}_4 \approx (2.9, 0.4, 0.4)(u_1^M, u_1^\alpha, u_1^\beta) + (5.7, 0.2, 0.2)(u_2^M, u_2^\alpha, u_2^\beta)]$$

Subject to

$$(4.1, 0.7, 0.7)(v_1^M, v_1^\alpha, v_1^\beta) + (2.3, 0.1, 0.1)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1,$$

and

All the constraints of fuzzy CCR DEA model-2.11 except the first constraint

$$“(4, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.1, 0.2, 0.2)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1”$$

### **Fuzzy CCR DEA model-2.15**

$$\text{Maximize } [\tilde{E}_5 \approx (5.1, 0.7, 0.7)(u_1^M, u_1^\alpha, u_1^\beta) + (7.4, 0.9, 0.9)(u_2^M, u_2^\alpha, u_2^\beta)]$$

Subject to

$$(6.5, 0.6, 0.6)(v_1^M, v_1^\alpha, v_1^\beta) + (4.1, 0.5, 0.5)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1,$$

and

All the constraints of fuzzy CCR DEA model-2.11 except the first constraint

$$“(4, 0.5, 0.5)(v_1^M, v_1^\alpha, v_1^\beta) + (2.1, 0.2, 0.2)(v_2^M, v_2^\alpha, v_2^\beta) \approx 1”$$

### **2.6.3 Exact best relative fuzzy efficiency of DMU<sub>1</sub>**

Using the method, modified in Section 2.5, the exact best relative fuzzy efficiency of DMU<sub>1</sub> can be obtained as follows:

**Step 1:** Using Step 1 of the modified method, fuzzy CCR DEA model-2.11 can be transformed into fuzzy CCR DEA model-2.16.

### **Fuzzy CCR DEA model-2.16**

$$\begin{aligned} \text{Maximize } [\tilde{E}_1 \approx & (2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta) \\ & + (4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta)] \end{aligned}$$

Subject to

$$\left(4v_1^M, 0.5v_1^M + 3.5v_1^\alpha, 0.5v_1^M + 4.5v_1^\beta\right) + \left(2.1v_2^M, 0.2v_2^M + 1.9v_2^\alpha, 0.2v_2^M + 2.3v_2^\beta\right) \approx 1,$$

$$\left(2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta\right) + \left(4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta\right)$$

$$- \left(4v_1^M, 0.5v_1^M + 3.5v_1^\alpha, 4.5v_1^\beta + 0.5v_1^M\right)$$

$$- \left(2.1v_2^M, 0.2v_2^M + 1.9v_2^\alpha, 0.2v_2^M + 2.3v_2^\beta\right) \leq (0,0,0),$$

$$\left(2.2u_1^M, 2.2u_1^\alpha, 2.2u_1^\beta\right) + \left(3.5u_2^M, 0.2u_2^M + 3.3u_2^\alpha, 0.2u_2^M + 3.7u_2^\beta\right) - \left(2.9v_1^M, 2.9v_1^\alpha, 2.9v_1^\beta\right)$$

$$- \left(1.5v_2^M, 0.1v_2^M + 1.4v_2^\alpha, 0.1v_2^M + 1.6v_2^\beta\right) \leq (0,0,0),$$

$$\left(3.2u_1^M, 0.5u_1^M + 2.7u_1^\alpha, 0.5u_1^M + 3.7u_1^\beta\right) + \left(5.1u_2^M, 0.8u_2^M + 4.3u_2^\alpha, 0.8u_2^M + 5.9u_2^\beta\right)$$

$$- \left(4.9v_1^M, 0.5v_1^M + 4.4v_1^\alpha, 0.5v_1^M + 5.4v_1^\beta\right)$$

$$- \left(2.6v_2^M, 0.4v_2^M + 2.2v_2^\alpha, 0.4v_2^M + 3.0v_2^\beta\right) \leq (0,0,0),$$

$$\left(2.9u_1^M, 0.4u_1^M + 2.5u_1^\alpha, 0.4u_1^M + 3.3u_1^\beta\right) + \left(5.7u_2^M, 0.2u_2^M + 5.5u_2^\alpha, 0.2u_2^M + 5.9u_2^\beta\right)$$

$$- \left(4.1v_1^M, 0.7v_1^M + 3.4v_1^\alpha, 0.7v_1^M + 4.8v_1^\beta\right)$$

$$- \left(2.3v_2^M, 0.1v_2^M + 2.2v_2^\alpha, 0.1v_2^M + 2.4v_2^\beta\right) \leq (0,0,0),$$

$$\left(5.1u_1^M, 0.7u_1^M + 4.4u_1^\alpha, 0.7u_1^M + 5.8u_1^\beta\right) + \left(7.4u_2^M, 0.9u_2^M + 6.5u_2^\alpha, 0.9u_2^M + 8.3u_2^\beta\right)$$

$$- \left(6.5v_1^M, 0.6v_1^M + 5.9v_1^\alpha, 0.6v_1^M + 7.1v_1^\beta\right)$$

$$- \left(4.1v_2^M, 0.5v_2^M + 3.6v_2^\alpha, 0.5v_2^M + 4.6v_2^\beta\right) \leq (0,0,0),$$

$$\left(u_1^M, u_1^\alpha, u_1^\beta\right) \geq (0,0,0), \left(u_2^M, u_2^\alpha, u_2^\beta\right) \geq (0,0,0),$$

$$(v_1^M, v_1^\alpha, v_1^\beta) \succcurlyeq (0,0,0), (v_2^M, v_2^\alpha, v_2^\beta) \succcurlyeq (0,0,0),$$

$(u_1^M, u_1^\alpha, u_1^\beta), (u_2^M, u_2^\alpha, u_2^\beta), (v_1^M, v_1^\alpha, v_1^\beta)$  and  $(v_2^M, v_2^\alpha, v_2^\beta)$  are non-negative triangular fuzzy numbers.

**Step 2:** Using Step 2 of the modified method, the fuzzy CCR DEA model-2.16 can be transformed into crisp CCR DEA model-2.17.

### Crisp CCR DEA model-2.17

$$\begin{aligned} \text{Maximize } & \left[ \mathfrak{R}(\tilde{E}_1) \right. \\ & = \mathfrak{R} \left( (2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta) \right. \\ & \left. \left. + (4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta) \right) \right] \end{aligned}$$

Subject to

$$\begin{aligned} & \mathfrak{R} \left( (4v_1^M, 0.5v_1^M + 3.5v_1^\alpha, 0.5v_1^M + 4.5v_1^\beta) + (2.1v_2^M, 0.2v_2^M + 1.9v_2^\alpha, 0.2v_2^M + 2.3v_2^\beta) \right) \\ & = \mathfrak{R}(1,1,1), \end{aligned}$$

$$\begin{aligned} & \mathfrak{R} \left( (2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta) + (4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta) \right. \\ & \quad \left. - (4v_1^M, 0.5v_1^M + 3.5v_1^\alpha, 4.5v_1^\beta + 0.5v_1^M) \right. \\ & \quad \left. - (2.1v_2^M, 0.2v_2^M + 1.9v_2^\alpha, 0.2v_2^M + 2.3v_2^\beta) \right) \leq \mathfrak{R}(0,0,0), \end{aligned}$$

$$\begin{aligned} & \mathfrak{R}\left(\left(2.2u_1^M, 2.2u_1^\alpha, 2.2u_1^\beta\right) + \left(3.5u_2^M, 0.2u_2^M + 3.3u_2^\alpha, 0.2u_2^M + 3.7u_2^\beta\right)\right) \\ & \quad - \left(2.9v_1^M, 2.9v_1^\alpha, 2.9v_1^\beta\right) - \left(1.5v_2^M, 0.1v_2^M + 1.4v_2^\alpha, 0.1v_2^M + 1.6v_2^\beta\right) \\ & \leq \mathfrak{R}(0,0,0), \end{aligned}$$

$$\begin{aligned} & \mathfrak{R}\left(\left(3.2u_1^M, 0.5u_1^M + 2.7u_1^\alpha, 0.5u_1^M + 3.7u_1^\beta\right) + \left(5.1u_2^M, 0.8u_2^M + 4.3u_2^\alpha, 0.8u_2^M + 5.9u_2^\beta\right)\right) \\ & \quad - \left(4.9v_1^M, 0.5v_1^M + 4.4v_1^\alpha, 0.5v_1^M + 5.4v_1^\beta\right) \\ & \quad - \left(2.6v_2^M, 0.4v_2^M + 2.2v_2^\alpha, 0.4v_2^M + 3.0v_2^\beta\right) \leq \mathfrak{R}(0,0,0), \end{aligned}$$

$$\begin{aligned} & \mathfrak{R}\left(\left(2.9u_1^M, 0.4u_1^M + 2.5u_1^\alpha, 0.4u_1^M + 3.3u_1^\beta\right) + \left(5.7u_2^M, 0.2u_2^M + 5.5u_2^\alpha, 0.2u_2^M + 5.9u_2^\beta\right)\right) \\ & \quad - \left(4.1v_1^M, 0.7v_1^M + 3.4v_1^\alpha, 0.7v_1^M + 4.8v_1^\beta\right) \\ & \quad - \left(2.3v_2^M, 0.1v_2^M + 2.2v_2^\alpha, 0.1v_2^M + 2.4v_2^\beta\right) \leq \mathfrak{R}(0,0,0), \end{aligned}$$

$$\begin{aligned} & \mathfrak{R}\left(\left(5.1u_1^M, 0.7u_1^M + 4.4u_1^\alpha, 0.7u_1^M + 5.8u_1^\beta\right) + \left(7.4u_2^M, 0.9u_2^M + 6.5u_2^\alpha, 0.9u_2^M + 8.3u_2^\beta\right)\right) \\ & \quad - \left(6.5v_1^M, 0.6v_1^M + 5.9v_1^\alpha, 0.6v_1^M + 7.1v_1^\beta\right) \\ & \quad - \left(4.1v_2^M, 0.5v_2^M + 3.6v_2^\alpha, 0.5v_2^M + 4.6v_2^\beta\right) \leq \mathfrak{R}(0,0,0), \end{aligned}$$

$$\mathfrak{R}(u_1^M, u_1^\alpha, u_1^\beta) \geq \mathfrak{R}(0,0,0), \mathfrak{R}(u_2^M, u_2^\alpha, u_2^\beta) \geq \mathfrak{R}(0,0,0),$$

$$\mathfrak{R}(v_1^M, v_1^\alpha, v_1^\beta) \geq \mathfrak{R}(0,0,0), \mathfrak{R}(v_2^M, v_2^\alpha, v_2^\beta) \geq \mathfrak{R}(0,0,0),$$

$$u_1^M - u_1^\alpha \geq 0, u_2^M - u_2^\alpha \geq 0, v_1^M - v_1^\alpha \geq 0, v_2^M - v_2^\alpha \geq 0,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, r = 1, 2, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i, i = 1, 2.$$

**Step 3:** Using Step 3 of the modified method, the fuzzy CCR DEA model-2.17 can be transformed into crisp CCR DEA model-2.18.

**Crisp CCR DEA model-2.18**

Maximize  $\left[ \mathfrak{R}(\tilde{E}_1) \right]$

$$= \mathfrak{R}\left(2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta\right) \\ + \mathfrak{R}\left(4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta\right)]$$

Subject to

$$\mathfrak{R}\left(4v_1^M, 0.5v_1^M + 3.5v_1^\alpha, 0.5v_1^M + 4.5v_1^\beta\right) + \mathfrak{R}\left(2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta\right) \\ + \mathfrak{R}\left(4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta\right) \left(2.1v_2^M, 0.2v_2^M + 1.9v_2^\alpha, 0.2v_2^M + 2.3v_2^\beta\right) \\ = \mathfrak{R}(1,1,1),$$

$$\mathfrak{R}\left(2.6u_1^M, 0.2u_1^M + 2.4u_1^\alpha, 0.2u_1^M + 2.8u_1^\beta\right) + \mathfrak{R}\left(4.1u_2^M, 0.3u_2^M + 3.8u_2^\alpha, 0.3u_2^M + 4.4u_2^\beta\right) \\ - \mathfrak{R}\left(4v_1^M, 0.5v_1^M + 3.5v_1^\alpha, 4.5v_1^\beta + 0.5v_1^M\right) \\ - \mathfrak{R}\left(2.1v_2^M, 0.2v_2^M + 1.9v_2^\alpha, 0.2v_2^M + 2.3v_2^\beta\right) \leq \mathfrak{R}(0,0,0),$$

$$\mathfrak{R}\left(2.2u_1^M, 2.2u_1^\alpha, 2.2u_1^\beta\right) + \mathfrak{R}\left(3.5u_2^M, 0.2u_2^M + 3.3u_2^\alpha, 0.2u_2^M + 3.7u_2^\beta\right) \\ - \mathfrak{R}\left(2.9v_1^M, 2.9v_1^\alpha, 2.9v_1^\beta\right) - \mathfrak{R}\left(1.5v_2^M, 0.1v_2^M + 1.4v_2^\alpha, 0.1v_2^M + 1.6v_2^\beta\right) \\ \leq \mathfrak{R}(0,0,0),$$

$$\begin{aligned}
& \left( \mathfrak{R}\left(3.2 u_1^M, 0.5u_1^M + 2.7u_1^\alpha, 0.5u_1^M + 3.7u_1^\beta\right) + \mathfrak{R}\left(5.1u_2^M, 0.8 u_2^M + 4.3u_2^\alpha, 0.8u_2^M + 5.9u_2^\beta\right) \right. \\
& \quad - \mathfrak{R}\left(4.9v_1^M, 0.5v_1^M + 4.4v_1^\alpha, 0.5v_1^M + 5.4v_1^\beta\right) \\
& \quad \left. - \mathfrak{R}\left(2.6v_2^M, 0.4v_2^M + 2.2 v_2^\alpha, 0.4v_2^M + 3.0v_2^\beta\right) \right) \leq \mathfrak{R}(0,0,0),
\end{aligned}$$

$$\begin{aligned}
& \mathfrak{R}\left(2.9u_1^M, 0.4u_1^M + 2.5u_1^\alpha, 0.4u_1^M + 3.3u_1^\beta\right) + \mathfrak{R}\left(5.7u_2^M, 0.2u_2^M + 5.5 u_2^\alpha, 0.2u_2^M + 5.9u_2^\beta\right) \\
& \quad - \mathfrak{R}\left(4.1 v_1^M, 0.7v_1^M + 3.4v_1^\alpha, 0.7v_1^M + 4.8v_1^\beta\right) \\
& \quad - \mathfrak{R}\left(2.3v_2^M, 0.1v_2^M + 2.2v_2^\alpha, 0.1v_2^M + 2.4v_2^\beta\right) \\
& \leq \mathfrak{R}(0,0,0), \mathfrak{R}\left(5.1u_1^M, 0.7u_1^M + 4.4 u_1^\alpha, 0.7u_1^M + 5.8u_1^\beta\right) \\
& \quad + \mathfrak{R}\left(7.4u_2^M, 0.9u_2^M + 6.5u_2^\alpha, 0.9u_2^M + 8.3u_2^\beta\right) \\
& \quad - \mathfrak{R}\left(6.5v_1^M, 0.6v_1^M + 5.9v_1^\alpha, 0.6v_1^M + 7.1v_1^\beta\right) \\
& \quad - \mathfrak{R}\left(4.1v_2^M, 0.5v_2^M + 3.6v_2^\alpha, 0.5v_2^M + 4.6v_2^\beta\right) \leq \mathfrak{R}(0,0,0),
\end{aligned}$$

$$\mathfrak{R}\left(u_1^M, u_1^\alpha, u_1^\beta\right) \geq \mathfrak{R}(0,0,0), \mathfrak{R}\left(u_2^M, u_2^\alpha, u_2^\beta\right) \geq \mathfrak{R}(0,0,0),$$

$$\mathfrak{R}\left(v_1^M, v_1^\alpha, v_1^\beta\right) \geq \mathfrak{R}(0,0,0), \mathfrak{R}\left(v_2^M, v_2^\alpha, v_2^\beta\right) \geq \mathfrak{R}(0,0,0),$$

$$u_1^M - u_1^\alpha \geq 0, u_2^M - u_2^\alpha \geq 0, v_1^M - v_1^\alpha \geq 0, v_2^M - v_2^\alpha \geq 0,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, r = 1,2, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i, i = 1,2.$$

**Step 4:** Using Step 4 of the modified method, the fuzzy CCR DEA model-2.18 can be transformed into crisp CCR DEA model-2.19.

### Crisp CCR DEA model-2.19

$$\text{Maximize } \left[ E_1 = \left( \frac{10.4 u_1^M - 2.4 u_1^\alpha + 2.8 u_1^\beta + 16.4 u_2^M - 3.8 u_2^\alpha + 4.4 u_2^\beta}{4} \right) \right]$$

Subject to

$$16 v_1^M - 3.5 v_1^\alpha + 4.5 v_1^\beta + 8.4 v_2^M - 1.9 v_2^\alpha + 2.3 v_2^\beta = 1,$$

$$10.4 u_1^M - 2.4 u_1^\alpha + 2.8 u_1^\beta + 16.4 u_2^M - 3.8 u_2^\alpha + 4.4 u_2^\beta - 18 v_1^M + 3.5 v_1^\alpha - 4.5 v_1^\beta -$$

$$8.4 v_2^M + 1.9 v_2^\alpha - 2.3 v_2^\beta \leq 0,$$

$$8.8 u_1^M - 2.2 u_1^\alpha + 2.2 u_1^\beta + 14 u_2^M - 3.3 u_2^\alpha + 3.7 u_2^\beta - 11.6 v_1^M + 2.9 v_1^\alpha - 2.9 v_1^\beta - 6 v_2^M$$

$$+ 1.4 v_2^\alpha - 1.6 v_2^\beta \leq 0,$$

$$12.8 u_1^M - 2.7 u_1^\alpha + 3.7 u_1^\beta + 20.4 u_2^M - 4.3 u_2^\alpha + 5.9 u_2^\beta - 19.6 v_1^M + 4.4 v_1^\alpha - 5.4 v_1^\beta - 10.4 v_2^M$$

$$- 2.2 v_2^\alpha - 3.0 v_2^\beta \leq 0,$$

$$11.6 u_1^M - 2.5 u_1^\alpha + 3.3 u_1^\beta + 22.8 u_2^M - 5.5 u_2^\alpha + 5.9 u_2^\beta - 16.4 v_1^M + 3.4 v_1^\alpha - 4.8 v_1^\beta - 9.2 v_2^M$$

$$+ 2.2 v_2^\alpha - 2.4 v_2^\beta \leq 0,$$

$$20.4 u_1^M - 4.4 u_1^\alpha + 5.8 u_1^\beta + 29.6 u_2^M - 6.5 u_2^\alpha + 8.3 u_2^\beta - 26 v_1^M + 5.9 v_1^\alpha - 7.1 v_1^\beta - 16.4 v_2^M$$

$$+ 3.6 v_2^\alpha - 4.6 v_2^\beta \leq 0,$$

$$u_1^M - u_1^\alpha \geq 0, u_2^M - u_2^\alpha \geq 0, v_1^M - v_1^\alpha \geq 0, v_2^M - v_2^\alpha \geq 0.$$

$$u_1^M - \left(\frac{1}{4}\right) u_1^\alpha + \left(\frac{1}{4}\right) u_1^\beta \geq 0, u_2^M - \left(\frac{1}{4}\right) u_2^\alpha + \left(\frac{1}{4}\right) u_2^\beta \geq 0,$$

$$v_1^M - \left(\frac{1}{4}\right) v_1^\alpha + \left(\frac{1}{4}\right) v_1^\beta \geq 0, v_2^M - \left(\frac{1}{4}\right) v_2^\alpha + \left(\frac{1}{4}\right) v_2^\beta \geq 0,$$

$$u_r^\alpha \geq 0, u_r^\beta \geq 0, \forall r, r = 1, 2, v_i^\alpha \geq 0, v_i^\beta \geq 0, \forall i, i = 1, 2.$$

**Step 5:** The optimal value  $E_1 = \mathfrak{R}(\tilde{E}_1)$ , representing the ranking value of fuzzy efficiency of DMU<sub>1</sub> is 0.23.

### 2.6.4 Exact best relative fuzzy efficiency of remaining DMUs

The ranking value of exact best relative fuzzy efficiency of DMU<sub>1</sub>, DMU<sub>2</sub>, DMU<sub>3</sub>, DMU<sub>4</sub> and DMU<sub>5</sub>, evaluated by solving the fuzzy CCR DEA model-2.12 to 2.15 with the modified method, is shown in Table 2.2.

**Table 2.2** The ranking value of exact best relative fuzzy efficiency of DMUs

| DMUs | Ranking value of best relative fuzzy efficiency |
|------|---|
| 1    | 0.23  |
| 2    | 0.25  |
| 3    | 0.245   |
| 4    | 0.25  |
| 5    | 0.25  |

It is obvious from Table 2.2 that  $\mathfrak{R}(\tilde{E}_2) = \mathfrak{R}(\tilde{E}_4) = \mathfrak{R}(\tilde{E}_5) > R(\tilde{E}_3) > R(\tilde{E}_1)$ . Therefore,  $\tilde{E}_2 \approx \tilde{E}_4 \approx \tilde{E}_5 > \tilde{E}_3 > \tilde{E}_1$ .

### 2.7 Conclusions

On the basis the present study, it can be concluded that there are flaws in the method, proposed by Hatami-Marbini et al. [40], and hence should not be used for evaluating the best relative fuzzy efficiency of DMUs. Also, to resolve the flaws, the method, proposed by Hatami-

Marbini et al. [40], is modified. Further, the exact best relative fuzzy efficiency of the DMUs, considered by Hatami-Marbini et al. [40], is evaluated by using the modified method.

# Chapter 3

## A New Approach for Solving Proposed Fuzzy CCR DEA Model<sup>2</sup>

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The existing fuzzy CCR DEA model, used in the previous chapter to evaluate the best relative fuzzy efficiency of DMUs, are obtained by replacing the crisp parameters of crisp CCR DEA model-2.3 with the fuzzy parameters. Wang et al. [106] replaced the crisp output data and crisp input data of the crisp CCR DEA model-2.2 with fuzzy data instead of crisp CCR DEA model-2.3 and proposed two methods for solving this fuzzy CCR DEA model. In this chapter, it is pointed out that the fuzzy CCR DEA model, proposed by Wang et al.[106] is not valid and hence the methods, proposed by Wang et al.[106], for evaluating the fuzzy efficiency of DMUs are also not valid. Also, a new fuzzy CCR DEA model as well as a method to solve this fuzzy CCR DEA model is proposed.

### 3.1 Existing fuzzy CCR DEA model

Wang et al. [106] transformed the crisp CCR DEA model-2.2 into fuzzy CCR DEA model-3.1 by replacing the crisp input data ( $x_{ij}$ ) and crisp output data ( $y_{rj}$ ) with triangular fuzzy numbers  $\tilde{x}_{ij} = (x_{ij}^L, x_{ij}^M, x_{ij}^U)$  and  $\tilde{y}_{rj} = (y_{rj}^L, y_{rj}^M, y_{rj}^U)$  respectively.

#### Fuzzy CCR DEA model-3.1

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \frac{\sum_{r=1}^s u_r (y_{rp}^L, y_{rp}^M, y_{rp}^U)}{\sum_{i=1}^m v_i (x_{ip}^L, x_{ip}^M, x_{ip}^U)} \right]$$

---

<sup>2</sup> The contents of this chapter are communicated for the possible publication in International Journal of Fuzzy Systems.

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^U) = \frac{\sum_{r=1}^s u_r (y_{rj}^L, y_{rj}^M, y_{rj}^U)}{\sum_{i=1}^m v_i (x_{ij}^L, x_{ij}^M, x_{ij}^U)} \preceq (1,1,1), \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### 3.2 Existing methods

Wang et al. [106] proposed the following two methods for solving the fuzzy CCR DEA model-3.1.

#### 3.2.1 First method

Wang et al. [106] proposed the following method for solving fuzzy CCR DEA model-3.1.

**Step 1:** Using the product of triangular fuzzy numbers, defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.1 can be transformed into fuzzy CCR DEA model-3.2.

#### Fuzzy CCR DEA model-3.2

$$\text{Maximize} \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \frac{(\sum_{r=1}^s u_r y_{rp}^L, \sum_{r=1}^s u_r y_{rp}^M, \sum_{r=1}^s u_r y_{rp}^U)}{(\sum_{i=1}^m v_i x_{ip}^L, \sum_{i=1}^m v_i x_{ip}^M, \sum_{i=1}^m v_i x_{ip}^U)} \right]$$

Subject to

$$\tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \frac{(\sum_{r=1}^s u_r y_{rj}^L, \sum_{r=1}^s u_r y_{rj}^M, \sum_{r=1}^s u_r y_{rj}^U)}{(\sum_{i=1}^m v_i x_{ij}^L, \sum_{i=1}^m v_i x_{ij}^M, \sum_{i=1}^m v_i x_{ij}^U)} \preceq (1,1,1), \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 2:** Using division of triangular fuzzy number, defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.2 can be transformed into fuzzy CCR DEA model-3.3.

### Fuzzy CCR DEA model-3.3

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\left[ \tilde{E}_p \approx (E_j^L, E_j^M, E_j^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) \right] \leq (1, 1, 1), \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 3:** Using the relation  $(a^L, a^M, a^U) \leq (b^L, b^M, b^U) \Rightarrow a^L \leq b^L, a^M \leq b^M, a^U \leq b^U$ ,

the fuzzy CCR DEA model-3.3 can be transformed into fuzzy CCR DEA model-3.4.

### Fuzzy CCR DEA model-3.4

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 4:** Since,  $E_j^L \leq E_j^M \leq E_j^U$ , So, if  $E_j^U \leq 1$  then automatically condition  $E_j^L \leq E_j^M \leq 1$  will be satisfied, so, the fuzzy CCR DEA model-3.4 can transformed into fuzzy CCR DEA model-3.5.

### Fuzzy CCR DEA model-3.5

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 5:** Transform the fuzzy CCR DEA model-3.5 into crisp CCR DEA model-3.6 to 3.8.

### Crisp CCR DEA model-3.6

$$\text{Maximize } \left[ E_p^L = \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Crisp CCR DEA model-3.7

$$\text{Maximize } \left[ E_p^M = \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Crisp CCR DEA model-3.8

$$\text{Maximize } \left[ E_p^U = \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 6:** The crisp CCR DEA models 3.6 to 3.8 can be transformed into crisp CCR DEA models 3.9 to 3.11 respectively.

### Crisp CCR DEA model-3.9

$$\text{Maximize } \left[ E_p^L = \sum_{r=1}^s u_r y_{rp}^L \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^U = 1,$$

$$\sum_{r=1}^s u_r y_{rj}^U - \sum_{i=1}^m v_i x_{ij}^L \leq 0, \forall j$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Crisp CCR DEA model-3.10

$$\text{Maximize } \left[ E_p^M = \sum_{r=1}^s u_r y_{rp}^M \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^M = 1,$$

$$\sum_{r=1}^s u_r y_{rj}^U - \sum_{i=1}^m v_i x_{ij}^L \leq 0, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Crisp CCR DEA model-3.11

$$\text{Maximize } \left[ E_p^U = \sum_{r=1}^s u_r y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^L = 1,$$

$$\sum_{r=1}^s u_r y_{rj}^U - \sum_{i=1}^m v_i x_{ij}^L \leq 0, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 7:** Find the optimal value  $E_p^L, E_p^M, E_p^U$  of crisp CCR DEA models 3.9 to 3.11 respectively.

**Step 8:** Using the optimal values of  $E_p^L, E_p^M, E_p^U$ , obtained in Step 6, the fuzzy optimal value (best relative fuzzy efficiency of DMU<sub>p</sub>) of fuzzy CCR DEA model-3.11 is  $(E_p^L, E_p^M, E_p^U)$ .

### 3.2.2 Second method

Wang et al. [106] proposed the following method for solving fuzzy CCR DEA model-3.1.

**Step 1:** Using the product of triangular fuzzy numbers, defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.1 can be transformed into fuzzy CCR DEA model-3.12.

#### Fuzzy CCR DEA model-3.12

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \frac{(\sum_{r=1}^s u_r y_{rp}^L, \sum_{r=1}^s u_r y_{rp}^M, \sum_{r=1}^s u_r y_{rp}^U)}{(\sum_{i=1}^m v_i x_{ip}^L, \sum_{i=1}^m v_i x_{ip}^M, \sum_{i=1}^m v_i x_{ip}^U)} \right]$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^U) \approx \frac{(\sum_{r=1}^s u_r y_{rj}^L, \sum_{r=1}^s u_r y_{rj}^M, \sum_{r=1}^s u_r y_{rj}^U)}{(\sum_{i=1}^m v_i x_{ij}^L, \sum_{i=1}^m v_i x_{ij}^M, \sum_{i=1}^m v_i x_{ij}^U)}, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 2:** Using the division of triangular fuzzy numbers, defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.12 can be transformed into fuzzy CCR DEA model-3.13.

#### Fuzzy CCR DEA model-3.13

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\left[ \tilde{E}_j \approx (E_j^L, E_j^M, E_j^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) \right] \preceq (1, 1, 1), \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 3:** Using the relation  $(a^L, a^M, a^U) \preceq (b^L, b^M, b^U) \Rightarrow a^L \leq b^L, a^M \leq b^M, a^U \leq b^U$ ,

the fuzzy CCR DEA model-3.13 can be transformed into fuzzy CCR DEA model-3.14.

#### Fuzzy CCR DEA model-3.14

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 4:** As for fuzzy CCR DEA model-3.14, since there are no restrictions imposed subjectively on the support of the fuzzy numbers  $\tilde{1}$ , its lower and upper bounds are therefore viewed as free. Based upon this point of view fuzzy CCR DEA model-3.14 can be transformed into fuzzy CCR DEA model-3.15.

#### Fuzzy CCR DEA model-3.15

$$\text{Maximize } \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j.$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 5:** Transform the fuzzy CCR DEA model-3.15 into crisp CCR DEA models-3.16 to 3.18.

**Crisp CCR DEA model-3.16**

$$\text{Maximize } \left[ E_p^L = \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Crisp CCR DEA model-3.17**

$$\text{Maximize } \left[ E_p^M = \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Crisp CCR DEA model-3.18**

$$\text{Maximize } \left[ E_p^U = \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 6:** The crisp CCR DEA models-3.16 to 3.18 can be transformed into crisp CCR DEA models-3.19 to 3.21 respectively.

**Crisp CCR DEA model-3.19**

$$\text{Maximize } \left[ E_p^L = \sum_{r=1}^s u_r y_{rp}^L \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^U = 1,$$

$$\sum_{r=1}^s u_r y_{rj}^M - \sum_{i=1}^m v_i x_{ij}^M \leq 0, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Crisp CCR DEA model-3.20**

$$\text{Maximize } \left[ E_p^M = \sum_{r=1}^s u_r y_{rp}^M \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^M = 1,$$

$$\sum_{r=1}^s u_r y_{rj}^M - \sum_{i=1}^m v_i x_{ij}^M \leq 0, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Crisp CCR DEA model-3.21

$$\text{Maximize } \left[ E_p^U = \sum_{r=1}^s u_r y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^L = 1,$$

$$\sum_{r=1}^s u_r y_{rj}^M - \sum_{i=1}^m v_i x_{ij}^M \leq 0, \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 7:** Find the optimal value  $E_p^L, E_p^M, E_p^U$  of crisp CCR DEA models 3.19 to 3.21 respectively.

**Step 8:** Using the optimal values of  $E_p^L, E_p^M, E_p^U$ , obtained in Step 6, the fuzzy optimal value (best relative fuzzy efficiency of  $DMU_p$ ) of fuzzy CCR DEA model 3.1 is  $(E_p^L, E_p^M, E_p^U)$ .

### 3.3 Flaws in the existing method

In this section, the flaws in the methods, proposed by Wang et al. [106] are pointed out.

1. In the fuzzy CCR DEA model-3.1,  $u_r, v_i$  are crisp numbers. Therefore, if these numbers are represented as triangular fuzzy numbers  $u_r = (u_r^L, u_r^M, u_r^U)$  and  $v_i = (v_i^L, v_i^M, v_i^U)$ , then the condition,  $u_r^L = u_r^M = u_r^U, v_i^L = v_i^M = v_i^U$ , should always be satisfied. However, in both the methods, proposed by Wang et al. [106] the values of  $E_p^L, E_p^M, E_p^U$  are obtained by solving the crisp CCR DEA models-3.19 to 3.21 independently. Since, all these models are solved independently, so, the optimal values of  $u_r$  and  $v_i$ , obtained on solving these models, will not necessarily be same, i.e., if  $u_r^L, v_i^L, u_r^M, v_i^M$  and  $u_r^U, v_i^U$

represents the optimal values of  $u_r$  and  $v_i$ , obtained on solving crisp CCR DEA models-3.19 to 3.21 respectively, then the condition  $u_r^L = u_r^M = u_r^U$  and  $v_i^L = v_i^M = v_i^U$  will not necessarily be satisfied. Hence, using the methods, proposed by Wang et al.[106] the obtained optimal solution  $\{u_r^L, v_i^L, u_r^M, v_i^M, u_r^U, v_i^U\}$  is not an optimal solution of fuzzy CCR DEA model-3.1 i.e., using the method, proposed by Wang et al. [106] it is not possible to find a crisp optimal solution  $\{u_r, v_i\}$  of fuzzy CCR DEA model-3.1.

2. It is well known that for a triangular fuzzy number  $(a, b, c)$ , the property  $a \leq b \leq c$  should always be satisfied. However, it is obvious from Step 6 of the existing method, presented in Section 3.2, that the values of  $E_p^L, E_p^M, E_p^U$  are obtained by solving three independent crisp CCR DEA models so the restriction  $E_p^L \leq E_p^M \leq E_p^U$  may or may not be satisfied.

### 3. 4 Flaws in the existing fuzzy DEA model

It is obvious from Step 2 and Step 3 of the existing method [106], presented in Section 3.2, that Wang et al. [106] have transformed the fuzzy constraints

$$\left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) \preceq (1,1,1)$$

in to the crisp constraints.

$$\frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j,$$

Since,  $\left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) \preceq (1,1,1), \forall j$ . So, there should exist a non-negative

triangular fuzzy number  $(S^L, S^M, S^U)$ ,  $S^L \leq S^M \leq S^U$  such that

$$\left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) + (S^L, S^M, S^U) = (1,1,1), \forall j.$$

However, the following clearly indicates that there will never exist a non-negative triangular fuzzy number  $(S^L, S^M, S^U)$ ,  $S^L \leq S^M \leq S^U$  and hence, the constraint

$\left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) \preceq (1,1,1), \forall j$  cannot be transformed into the constraints

$$\frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq 1, \forall j,$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \forall j.$$

$$\left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) \preceq (1,1,1)$$

$$\Rightarrow \left( \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U}, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M}, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \right) + (S^L, S^M, S^U) = (1,1,1)$$

$$\Rightarrow \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} + S^L = 1, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} + S^M = 1, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} + S^U = 1$$

$$\Rightarrow \frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} = 1 - S^L, \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} = 1 - S^M, \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} = 1 - S^U.$$

Now,

$$\frac{\sum_{r=1}^s u_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^U} \leq \frac{\sum_{r=1}^s u_r y_{rj}^M}{\sum_{i=1}^m v_i x_{ij}^M} \leq \frac{\sum_{r=1}^s u_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L}$$

$$\Rightarrow 1 - S^L \leq 1 - S^M \leq 1 - S^U$$

$$\Rightarrow -S^L \leq -S^M \leq -S^U$$

$$\Rightarrow S^L \geq S^M \geq S^U$$

$\Rightarrow (S^L, S^M, S^U)$  is not a triangular fuzzy number.

### 3.5 Proposed fuzzy CCR DEA model

Wang et al. [] transformed the crisp CCR DEA model-2.2 into fuzzy CCR DEA model-3.1 by replacing the crisp input data  $(x_{ij})$  and crisp output data  $(y_{rj})$  with triangular fuzzy numbers  $\tilde{x}_{ij} = (x_{ij}^L, x_{ij}^M, x_{ij}^U)$  and  $\tilde{y}_{rj} = (y_{rj}^L, y_{rj}^M, y_{rj}^U)$  respectively.

In this section, to resolve the flaws of the existing fuzzy DEA model, pointed out in Section 3.4, a modified fuzzy CCR DEA model is proposed.

If there are  $n$  DMUs then the best relative crisp efficiency  $(E_p)$  of  $p^{th}$  DMU can be obtained by solving the CCR DEA model-3.22

#### CCR DEA model-3.22

$$\text{Maximize } \left[ E_p = \frac{\text{Virtual output of } p^{th} \text{ DMU}}{\text{Virtual input of } p^{th} \text{ DMU}} \right]$$

Subject to

Virtual output of  $j^{th}$  DMU  $\leq$  Virtual input of  $j^{th}$  DMU,  $\forall j$ .

If each DMU have  $m$  inputs ( $x_{ij}; i = 1, 2, \dots, m; j = 1, 2, \dots, n$ ) and  $s$  outputs ( $y_{rj}; r = 1, 2, \dots, s; j = 1, 2, \dots, n$ ) then CCR DEA model-3.22 is transformed into crisp CCR DEA model-3.23

### Crisp CCR DEA model-3.23

$$\text{Maximize } \left[ E_p = \frac{\sum_{r=1}^s u_r y_{rp}}{\sum_{i=1}^m v_i x_{ip}} \right]$$

Subject to

$$\sum_{r=1}^s u_r y_{rj} \leq \sum_{i=1}^m v_i x_{ij} \quad \forall j,$$

$$u_r, v_i \geq 0, \forall r, i.$$

where  $u_r$  ( $r = 1, \dots, s$ ) and  $v_i$  ( $i = 1, \dots, m$ ) are the weights assigned to the  $r^{th}$  output and  $i^{th}$  input, respectively.

Replacing the crisp input data ( $x_{ij}$ ) and crisp output data ( $y_{rj}$ ) by triangular fuzzy numbers  $\tilde{x}_{ij} = (x_{ij}^L, x_{ij}^M, x_{ij}^U)$  and  $\tilde{y}_{rj} = (y_{rj}^L, y_{rj}^M, y_{rj}^U)$  respectively, the CCR DEA model-3.23 can be transformed into fuzzy CCR DEA model-3.24.

### Fuzzy CCR DEA model-3.24

$$\text{Maximize } \left[ \tilde{E}_j \approx (E_p^L, E_p^M, E_p^U) \approx \frac{\sum_{r=1}^s u_r (y_{rp}^L, y_{rp}^M, y_{rp}^U)}{\sum_{i=1}^m v_i (x_{ip}^L, x_{ip}^M, x_{ip}^U)} \right]$$

Subject to

$$\sum_{r=1}^s u_r (y_{rj}^L, y_{rj}^M, y_{rj}^U) \leq \sum_{i=1}^m v_i (x_{ij}^L, x_{ij}^M, x_{ij}^U), \quad j = 1, \dots, n,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### 3.6 Proposed approach

In Section 3.4, it is shown that the fuzzy CCR DEA model-3.5, proposed by Wang et al. [106] are not valid and hence cannot be used for evaluating the best relative fuzzy efficiency of DMUs. In this section, a new approach is proposed to evaluate the best relative fuzzy efficiency of DMUs by using the fuzzy CCR DEA model-3.24.

**Step 1:** Using the product of triangular fuzzy numbers, defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.24 can be transformed into fuzzy CCR DEA model-3.25.

#### Fuzzy CCR DEA model-3.25

$$\text{Maximize} \left[ \tilde{E}_j \approx (E_p^L, E_p^M, E_p^U) \approx \frac{\sum_{r=1}^s (u_r y_{rp}^L, u_r y_{rp}^M, u_r y_{rp}^U)}{\sum_{i=1}^m (v_i x_{ip}^L, v_i x_{ip}^M, v_i x_{ip}^U)} \right]$$

Subject to

$$\sum_{r=1}^s (u_r y_{rj}^L, u_r y_{rj}^M, u_r y_{rj}^U) \leq \sum_{i=1}^m (v_i x_{ij}^L, v_i x_{ij}^M, v_i x_{ij}^U), \quad \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 2:** Using the division of triangular fuzzy numbers defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.25 can be transformed into fuzzy CCR DEA model-3.26.

#### Fuzzy CCR DEA model-3.26

$$\text{Maximize} \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right) \right]$$

Subject to

$$\sum_{r=1}^s (u_r y_{rj}^L, u_r y_{rj}^M, u_r y_{rj}^U) \leq \sum_{i=1}^m (v_i x_{ij}^L, v_i x_{ij}^M, v_i x_{ij}^U), \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 3:** Using the relation  $(a^L, a^M, a^U) \leq (b^L, b^M, b^U) \Rightarrow a^L \leq b^L, a^M \leq b^M, a^U \leq b^U$ ,

the fuzzy CCR DEA model-3.26 can be transformed into fuzzy CCR DEA model-3.27.

### Fuzzy CCR DEA model-3.27

$$\text{Maximize} \left[ \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \approx \left( \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^L}, \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M}, \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^U} \right) \right]$$

Subject to

$$\sum_{r=1}^s u_r y_{rj}^L \leq \sum_{i=1}^m v_i x_{ij}^L, \quad \forall j,$$

$$\sum_{r=1}^s u_r y_{rj}^M \leq \sum_{i=1}^m v_i x_{ij}^M, \quad \forall j,$$

$$\sum_{r=1}^s u_r y_{rj}^U \leq \sum_{i=1}^m v_i x_{ij}^U, \quad \forall j,$$

$$u_r, v_i \geq 0, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 4:** The fuzzy optimal value  $\left( \tilde{E}_p \approx (E_p^L, E_p^M, E_p^U) \right)$ , representing the best relative fuzzy

efficiency of  $p^{th}$  DMU, can be obtained by solving the fuzzy CCR DEA model-3.27 as follows:

**Step 4(a)** Find the optimal value  $(E_p^L)$  of the crisp CCR DEA model-3.28a by solving crisp CCR

DEA model-3.28b equivalent to crisp CCR DEA model-3.28a

**Crisp CCR DEA model-3.28a**

$$\text{Maximize } \left[ E_p^L = \frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} \leq 1,$$

and

All the constraints of fuzzy crisp CCR DEA model-3.27.

**Crisp CCR DEA model-3.28b**

$$\text{Maximize } \left[ E_p^L = \sum_{r=1}^s u_r y_{rp}^L \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^U = 1,$$

$$\sum_{r=1}^s u_r y_{rp}^L \leq \sum_{i=1}^m v_i x_{ip}^U,$$

and

All the constraints of fuzzy crisp CCR DEA model-3.27.

**Step 4(b)** Find the optimal value ( $E_p^M$ ) of the crisp CCR DEA model-3.29a by solving crisp CCR DEA model-3.29b equivalent to crisp CCR DEA model-3.29a.

### Crisp CCR DEA model-3.29a

$$\text{Maximize } \left[ E_p^M = \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} = E_p^L,$$

$$E_p^L \leq \frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M} \leq 1,$$

and

All the constraints of fuzzy crisp CCR DEA model-3.27.

### Crisp CCR DEA model-3.29b

$$\text{Maximize } \left[ E_p^L = \sum_{r=1}^s u_r y_{rp}^M \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^M = 1,$$

$$\sum_{r=1}^s u_r y_{rp}^L = E_p^L \left( \sum_{i=1}^m v_i x_{ip}^U \right),$$

$$E_p^L \left( \sum_{i=1}^m v_i x_{ip}^M \right) \leq \sum_{r=1}^s u_r y_{rp}^M$$

and

All the constraints of fuzzy crisp CCR DEA model-3.27.

**Step 4(c)** Find the optimal value ( $E_p^U$ ) of the crisp CCR DEA model-3.30a by solving crisp CCR DEA model-3.30b equivalent to crisp CCR DEA model-3.30a

**Crisp CCR DEA model-3.30a**

$$\text{Maximize } \left[ E_p^U = \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r y_{rp}^L}{\sum_{i=1}^m v_i x_{ip}^U} = E_p^L$$

$$\frac{\sum_{r=1}^s u_r y_{rp}^M}{\sum_{i=1}^m v_i x_{ip}^M} = E_p^M,$$

$$E_p^M \leq \frac{\sum_{r=1}^s u_r y_{rp}^U}{\sum_{i=1}^m v_i x_{ip}^L} \leq 1,$$

and

All the constraints of fuzzy CCR DEA model-3.27.

**Crisp CCR DEA model-3.30b**

$$\text{Maximize } \left[ E_p^U = \sum_{r=1}^s u_r y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i x_{ip}^L = 1,$$

$$\sum_{r=1}^s u_r y_{rp}^U = E_p^L \left( \sum_{i=1}^m v_i x_{ip}^L \right),$$

$$\sum_{r=1}^s u_r y_{rp}^L = E_p^M \left( \sum_{i=1}^m v_i x_{ip}^U \right),$$

$$E_p^M \left( \sum_{i=1}^m v_i x_{ip}^L \right) \leq \sum_{r=1}^s u_r y_{rp}^U \leq \sum_{i=1}^m v_i x_{ip}^L,$$

and

All the constraints of fuzzy CCR DEA model-3.27.

**Step 5:** Using the optimal values of  $E_p^L, E_p^M, E_p^U$ , obtained in Step 4, the fuzzy optimal value (best relative fuzzy efficiency of  $DMU_p$ ) is  $(E_p^L, E_p^M, E_p^U)$ .

### 3.7 Exact fuzzy efficiency of real life problem

Wang et al. [106] solved a problem to illustrate his proposed approach. However, as discussed in Section 3.3 that there are flaws in the existing method [106]. So, the results of this problem, obtained by Wang et al. [106] is not exact. In this section, the exact results of the same problem is obtained by the proposed method.

#### 3.7.1 Problem description

Consider a performance assessment problem in China where eight manufacturing enterprises (DMUs) are to be evaluated in terms of two inputs and two outputs. The eight manufacturing enterprises all manufacture the same type of products but with different qualities. Both the gross output value (GOV) and product quality (PQ) are considered as outputs. Manufacturing cost (MC) and the number of employees (NOE) are considered as inputs. The data about the GOV and MC are uncertain due to the unavailability at the time of assessment and are therefore estimated as fuzzy numbers. The product quality is assessed by customers using fuzzy linguistic terms such as Excellent, Very Good, Average, Poor and Very Poor. The

assessment results by customers are weighted and averaged. Table 3.1 shows the input and output data for the eight manufacturing enterprises.

**Table 3.1: Input and output data for eight manufacturing enterprises**

| Enterprises |                    |      |                       |                 |
|-------------|--------------------|------|-----------------------|-----------------|
| (DMUs)      | Inputs (Two)       |      | Outputs (two)         |                 |
|             | MC                 | NOE  | GOV                   | PQ              |
| A           | (2120, 2170, 2210) | 1870 | (14500, 14790, 14860) | (3.1, 4.1, 4.9) |
| B           | (1420, 1460, 1500) | 1340 | (12470, 12720, 12790) | (1.2, 2.1, 3.0) |
| C           | (2510, 2570, 2610) | 2360 | (17900, 18260, 18400) | (3.3, 4.3, 5.0) |
| D           | (2300, 2350, 2400) | 2020 | (14970, 15270, 15400) | (2.7, 3.7, 4.6) |
| E           | (1480, 1520, 1560) | 1550 | (13980, 14260, 14330) | (1.0, 1.8, 2.7) |
| F           | (1990, 2030, 2100) | 1760 | (14030, 14310, 14400) | (1.6, 2.6, 3.6) |
| G           | (2200, 2260, 2300) | 1980 | (16540, 16870, 17000) | (2.4, 3.4, 4.4) |
| H           | (2400, 2460, 2520) | 2250 | (17600, 17960, 18100) | (2.6, 3.6, 4.6) |

### 3.7.2 Proposed fuzzy CCR DEA models

The best relative fuzzy efficiency of  $DMU_A$  to  $DMU_H$  respectively can be obtained by solving fuzzy CCR DEA model-3.31 to 3.39.

#### Fuzzy CCR DEA model-3.31

$$\text{Maximize } \left[ \tilde{E}_A \approx (E_A^L, E_A^M, E_A^U) \approx \left[ \frac{(14500, 14790, 14860)u_1 + (3.1, 4.1, 4.9)u_2}{(2120, 2170, 2210)v_1 + (1870, 1870, 1870)v_2} \right] \right]$$

Subject to

$$\begin{aligned} & (14500u_1 + 3.1u_2, 14790u_1 + 4.1u_2, 14860u_1 + 4.9u_2) \\ & \preceq (2120v_1 + 1870v_2, 2170v_1 + 1870v_2, 2210v_1 + 1870v_2), \end{aligned}$$

$$\begin{aligned}
& (12470u_1 + 1.2u_2, 12720u_1 + 2.1u_2, 12790u_1 + 3.0u_2) \\
& \quad \preceq (1420v_1 + 1340v_2, 1460v_1 + 1340v_2, 1500v_1 + 1340v_2), \\
& (17900u_1 + 3.3u_2, 18260u_1 + 4.3u_2, 18400u_1 + 5.0u_2) \\
& \quad \preceq (2510v_1 + 2360v_2, 2570v_1 + 2360v_2, 2610v_1 + 2360v_2), \\
& (14970u_1 + 2.7u_2, 15270u_1 + 3.7u_2, 15400u_1 + 4.6u_2) \\
& \quad \preceq (2300v_1 + 2020v_2, 2350v_1 + 2020v_2, 2400v_1 + 2020v_2), \\
& (13980u_1 + 1.0u_2, 14260u_1 + 1.8u_2, 14330u_1 + 2.7u_2) \\
& \quad \preceq (1480v_1 + 1550v_2, 1520v_1 + 1550v_2, 1560v_1 + 1550v_2), \\
& (14030u_1 + 1.6u_2, 14310u_1 + 2.6u_2, 14400u_1 + 3.6u_2) \\
& \quad \preceq (1990v_1 + 1760v_2, 2030v_1 + 1760v_2, 2100v_1 + 1760v_2), \\
& (16540u_1 + 2.4u_2, 16870u_1 + 3.4u_2, 17000u_1 + 4.4u_2) \\
& \quad \preceq (2200v_1 + 1980v_2, 2260v_1 + 1980v_2, 2300v_1 + 1980v_2), \\
& (17600u_1 + 2.6u_2, 17960u_1 + 3.6u_2, 18100u_1 + 4.6u_2) \\
& \quad \preceq (2400v_1 + 2250v_2, 2460v_1 + 2250v_2, 2520v_1 + 2250v_2), \\
& u_1, u_2, v_1, v_2 \geq 0.
\end{aligned}$$

**Fuzzy CCR DEA model-3.32**

$$\text{Maximize } \left[ \tilde{E}_B \approx (E_B^L, E_B^M, E_B^U) \approx \left[ \frac{(12470, 12720, 12790)u_1 + (1.2, 2.1, 3.0)u_2}{(1420, 1460, 1500)v_1 + (1340, 1340, 1340)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

**Fuzzy CCR DEA model-3.33**

$$\text{Maximize } \left[ \tilde{E}_C \approx (E_C^L, E_C^M, E_C^U) \approx \left[ \frac{(17900, 18260, 18400)u_1 + (3.3, 4.3, 5.0)u_2}{(2510, 2570, 2610)v_1 + (2360, 2360, 2360)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

**Fuzzy CCR DEA model-3.34**

$$\text{Maximize } \left[ \tilde{E}_D \approx (E_D^L, E_D^M, E_D^U) \approx \left[ \frac{(14970, 15270, 15400)u_1 + (2.7, 3.7, 4.6)u_2}{(2300, 2350, 2400)v_1 + (2020, 2020, 2020)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

**Fuzzy CCR DEA model-3.35**

$$\text{Maximize } \left[ \tilde{E}_E \approx (E_E^L, E_E^M, E_E^U) \approx \left[ \frac{(13980, 14260, 14330)u_1 + (1.0, 1.8, 2.7)u_2}{(1480, 1520, 1560)v_1 + (1550, 150, 150)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

**Fuzzy CCR DEA model-3.36**

$$\text{Maximize } \left[ \tilde{E}_F \approx (E_F^L, E_F^M, E_F^U) \approx \left[ \frac{(14030, 14310, 14400)u_1 + (1.6, 2.6, 3.6)u_2}{(1990, 2030, 2100)v_1 + (1760, 1760, 1760)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

**Fuzzy CCR DEA model-3.37**

$$\text{Maximize } \left[ \tilde{E}_G \approx (E_G^L, E_G^M, E_G^U) \approx \left[ \frac{(16540, 16870, 17000)u_1 + (2.4, 3.4, 4.4)u_2}{(2200, 2260, 2300)v_1 + (1980, 1980, 1980)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

### Fuzzy CCR DEA model-3.38

$$\text{Maximize } \left[ \tilde{E}_H \approx (E_H^L, E_H^M, E_H^U) \approx \left[ \frac{(17600, 17960, 18100)u_1 + (2.6, 3.6, 4.6)u_2}{(2400, 2460, 2520)v_1 + (2250, 2250, 2250)v_2} \right] \right]$$

Subject to

All the constraints of fuzzy CCR DEA model-3.31.

### 3.7.3 Exact best relative fuzzy efficiency of DMU<sub>A</sub>

Using the approach, proposed in Section 3.6, the exact best relative fuzzy efficiency of DMU<sub>A</sub> can be obtained as follows:

**Step 1:** Using the arithmetic operations of triangular fuzzy numbers, defined in Section 2.1.2.1, the fuzzy CCR DEA model-3.31 can be transformed into fuzzy CCR DEA model-3.39.

### Fuzzy CCR DEA model-3.39

$$\text{Maximize } \left[ \tilde{E}_A \approx (E_A^L, E_A^M, E_A^U) \approx \left[ \frac{(14500u_1 + 3.1u_2, 14790u_1 + 4.1u_2, 14860u_1 + 4.9u_2)}{(2120v_1 + 4.9u_2, 2170v_1 + 1870v_2, 2210v_1 + 1870v_2)} \right] \right]$$

Subject to

$$(14500u_1 + 3.1u_2, 14790u_1 + 4.1u_2, 14860u_1 + 4.9u_2) \preceq (2120v_1 + 1870v_2, 2170v_1 + 1870v_2, 2210v_1 + 1870v_2),$$

$$(12470u_1 + 1.2u_2, 12720u_1 + 2.1u_2, 12790u_1 + 3.0u_2)$$

$$\preceq (1420v_1 + 1340v_2, 1460v_1 + 1340v_2, 1500v_1 + 1340v_2),$$

$$(17900u_1 + 3.3u_2, 18260u_1 + 4.3u_2, 18400u_1 + 5.0u_2)$$

$$\preceq (2510v_1 + 2360v_2, 2570v_1 + 2360v_2, 2610v_1 + 2360v_2),$$

$$(14970u_1 + 2.7u_2, 15270u_1 + 3.7u_2, 15400u_1 + 4.6u_2)$$

$$\preceq (2300v_1 + 2020v_2, 2350v_1 + 2020v_2, 2400v_1 + 2020v_2),$$

$$\begin{aligned}
& (13980u_1 + 1.0u_2, 14260u_1 + 1.8u_2, 14330u_1 + 2.7u_2) \\
& \preceq (1480v_1 + 1550v_2, 1520v_1 + 1550v_2, 1560v_1 + 1550v_2), \\
& (14030u_1 + 1.6u_2, 14310u_1 + 2.6u_2, 14400u_1 + 3.6u_2) \\
& \preceq (1990v_1 + 1760v_2, 2030v_1 + 1760v_2, 2100v_1 + 1760v_2), \\
& (16540u_1 + 2.4u_2, 16870u_1 + 3.4u_2, 17000u_1 + 4.4u_2) \\
& \preceq (2200v_1 + 1980v_2, 2260v_1 + 1980v_2, 2300v_1 + 1980v_2), \\
& (17600u_1 + 2.6u_2, 17960u_1 + 3.6u_2, 18100u_1 + 4.6u_2) \\
& \preceq (2400v_1 + 2250v_2, 2460v_1 + 2250v_2, 2520v_1 + 2250v_2), \\
& u_1, u_2, v_1, v_2 \geq 0.
\end{aligned}$$

**Step 2:** The fuzzy CCR DEA model-3.39 can be transformed into fuzzy CCR DEA model-3.40.

#### Fuzzy CCR DEA model-3.40

$$\text{Maximize } \left[ \tilde{E}_A \approx (E_A^L, E_A^M, E_A^U) \approx \left[ \frac{(14500u_1 + 3.1u_2, 14790u_1 + 4.1u_2, 14860u_1 + 4.9u_2)}{(2120v_1 + 4.9u_2, 2170v_1 + 1870v_2, 2210v_1 + 1870v_2)} \right] \right]$$

Subject to

$$\begin{aligned}
14500u_1 + 3.1u_2 &\leq 2120v_1 + 1870v_2, & 14790u_1 + 4.1u_2 &\leq 2170v_1 + 1870v_2, \\
14860u_1 + 4.9u_2 &\leq 2210v_1 + 1870v_2, & 12470u_1 + 1.2u_2 &\leq 1420v_1 + 1340v_2, \\
12720u_1 + 2.1u_2 &\leq 1460v_1 + 1340v_2, & 12790u_1 + 3.0u_2 &\leq 1500v_1 + 1340v_2, \\
17900u_1 + 3.3u_2 &\leq 2510v_1 + 2360v_2, & 18260u_1 + 4.3u_2 &\leq 2570v_1 + 2360v_2, \\
18400u_1 + 5.0u_2 &\leq 2610v_1 + 2360v_2, & 14970u_1 + 2.7u_2 &\leq 300v_1 + 2020v_2, \\
15270u_1 + 3.7u_2 &\leq 2350v_1 + 2020v_2, & 15400u_1 + 4.6u_2 &\leq 2400v_1 + 2020v_2, \\
13980u_1 + 1.0u_2 &\leq 1480v_1 + 1550v_2, & 14260u_1 + 1.8u_2 &\leq 1520v_1 + 1550v_2, \\
14330u_1 + 2.7u_2 &\leq 1560v_1 + 1550v_2, & 14030u_1 + 1.6u_2 &\leq 1990v_1 + 1760v_2, \\
14310u_1 + 2.6u_2 &\leq 2030v_1 + 1760v_2, & 14400u_1 + 3.6u_2 &\leq 2100v_1 + 1760v_2,
\end{aligned}$$

$$16540u_1 + 2.4u_2 \leq 2200v_1 + 1980v_2,$$

$$16870u_1 + 3.4u_2 \leq 2260v_1 + 1980v_2,$$

$$17000u_1 + 4.4u_2 \leq 2300v_1 + 1980v_2,$$

$$17600u_1 + 2.6u_2 \leq 2400v_1 + 2250v_2,$$

$$17960u_1 + 3.6u_2 \leq 2460v_1 + 2250v_2,$$

$$18100u_1 + 4.6u_2 \leq 2520v_1 + 2250v_2.$$

$$u_1, u_2, v_1, v_2 \geq 0.$$

**Step 3:** The fuzzy CCR DEA model-3.40 can be transformed into fuzzy CCR DEA model-3.41.

### Fuzzy CCR DEA model-3.41

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_A \approx (E_A^L, E_A^M, E_A^U) \right. \\ & \left. \approx \left[ \left( \frac{14500u_1 + 3.1u_2}{2210v_1 + 1870v_2}, \frac{14790u_1 + 4.1u_2}{2170v_1 + 1870v_2}, \frac{14860u_1 + 4.9u_2}{2120v_1 + 4.9u_2} \right) \right] \right] \end{aligned}$$

Subject to

All the constraints of fuzzy CCR DEA model-3.40.

**Step 4:** The fuzzy optimal value  $\left( \tilde{E}_A \approx (E_A^L, E_A^M, E_A^U) \right)$ , representing the best relative fuzzy efficiency of  $A^{th}$  DMU, can be obtained by solving the CCR fuzzy DEA model-3.41 as follows

**Step (4a):** The optimal value  $(E_p^L)$  of the crisp CCR DEA model-3.43 and hence of crisp CCR DEA model-3.42 is 0.812.

### Crisp CCR DEA model-3.42

$$\text{Maximize } \left[ E_A^L = \frac{14500u_1 + 3.1u_2}{2210v_1 + 1870v_2} \right]$$

Subject to

$$\frac{14500u_1 + 3.1u_2}{2210v_1 + 1870v_2} \leq 1,$$

All the constraints of fuzzy CCR DEA model-3.40.

### **Crisp CCR DEA model-3.43**

$$\text{Maximize } [E_A^L = 14500u_1 + 3.1u_2]$$

Subject to

$$2210v_1 + 1870v_2 = 1,$$

$$14500u_1 + 3.1u_2 \leq 2210v_1 + 1870v_2,$$

and

All the constraints of fuzzy CCR DEA model-3.40.

**Step (4b):** The optimal value ( $E_p^M$ ) of the crisp CCR DEA model-3.45 and hence of crisp CCR DEA model-3.44 is 0.829.

### **Crisp CCR DEA model-3.44**

$$\text{Maximize } \left[ E_A^M = \frac{14790u_1 + 4.1u_2}{2170v_1 + 1870v_2} \right]$$

Subject to

$$\frac{14500u_1 + 3.1u_2}{2210v_1 + 1870v_2} = 0.812,$$

$$0.812 \leq \frac{14790u_1 + 4.1u_2}{2170v_1 + 1870v_2} \leq 1,$$

All the constraints of fuzzy CCR DEA model-3.40.

### **Crisp CCR DEA model-3.45**

$$\text{Maximize } [E_A^M = 14790u_1 + 4.1u_2]$$

Subject to

$$2170v_1 + 1870v_2 = 1,$$

$$14500u_1 + 3.1u_2 = 0.812(2210v_1 + 1870v_2),$$

$$0.812(2170v_1 + 1870v_2) \leq 14790u_1 + 4.1u_2 \leq 2170v_1 + 1870v_2,$$

All the constraints of fuzzy CCR DEA model-3.41.

**Step (4c):** The optimal value ( $E_p^U$ ) of the crisp CCR DEA model-3.47 and hence of crisp CCR DEA model-3.46 is 0.833.

#### **Crisp CCR DEA model-3.46**

$$\text{Maximize } \left[ E_A^U = \frac{14860u_1 + 4.9u_2}{2120v_1 + 4.9u_2} \right]$$

Subject to

$$\frac{14500u_1 + 3.1u_2}{2210v_1 + 1870v_2} = 0.812,$$

$$\frac{14790u_1 + 4.1u_2}{2170v_1 + 1870v_2} = 0.829,$$

$$0.829 \leq \frac{14860u_1 + 4.9u_2}{2120v_1 + 4.9u_2} \leq 1,$$

and

All the constraints of fuzzy CCR DEA model-3.40.

#### **Crisp CCR DEA model-3.47**

$$\text{Maximize } [E_A^U = 14860u_1 + 4.9u_2]$$

Subject to

$$2120v_1 + 4.9u_2 = 1,$$

$$14500u_1 + 3.1u_2 = 0.812(2210v_1 + 1870v_2),$$

$$14790u_1 + 4.1u_2 = 0.829(2170v_1 + 1870v_2),$$

$$0.829(2120v_1 + 4.9u_2) \leq 14860u_1 + 4.9u_2 \leq 2120v_1 + 4.9u_2,$$

All the constraints of fuzzy CCR DEA model-3.40.

**Step 5:** Using the optimal values of  $E_A^L, E_A^M, E_A^U$ , obtained in Step 4, the fuzzy optimal value (best relative fuzzy efficiency of DMU<sub>A</sub> of fuzzy CCR DEA model-3.31 is  $(E_A^L, E_A^M, E_A^U) = (0.812, 0.829, 0.833)$ ).

### 3.7.4 Results

The exact best relative fuzzy efficiency of all the DMUs, evaluated on solving fuzzy CCR DEA model-3.31 to 3.38 by the proposed method, are shown in Table 3.2. Also, the ranking value corresponding to best relative fuzzy efficiency, obtained by using the ranking formula defined in Remark 2.4, is shown in Table 3.2.

**Table 3.2 Exact best relative fuzzy efficiencies of DMUs**

| DMUs     | Exact best relative fuzzy efficiency of $j^{th}$ DMU<br>$(\tilde{E}_j)$ | Ranking Value $\mathfrak{R}(\tilde{E}_j)$ |
|----------|---|---|
| <b>A</b> | (.812, .829, .833)  | .826                                      |
| <b>B</b> | (.975, 1, 1)  | .994                                      |
| <b>C</b> | (.797, .815, .825)  | .813                                      |
| <b>D</b> | (.776, .792, .799)  | .790                                      |
| <b>E</b> | (.973, 1, 1)  | .993                                      |
| <b>F</b> | (.835, .852, .857)  | .849                                      |
| <b>G</b> | (.875, .893, .900)  | .890                                      |
| <b>H</b> | (.820, .836, .843)  | .833                                      |

It is obvious from Table 3.2 that  $\mathfrak{R}(\tilde{E}_B) > \mathfrak{R}(\tilde{E}_E) > \mathfrak{R}(\tilde{E}_G) > \mathfrak{R}(\tilde{E}_F) > \mathfrak{R}(\tilde{E}_H) > \mathfrak{R}(\tilde{E}_A) > \mathfrak{R}(\tilde{E}_C) > \mathfrak{R}(\tilde{E}_D)$ . Therefore,  $\tilde{E}_B > \tilde{E}_E > \tilde{E}_G > \tilde{E}_F > \tilde{E}_H > \tilde{E}_A > \tilde{E}_C > \tilde{E}_D$ .

### **3.8 Conclusions**

On the basis the present study, it can be concluded that there are flaws in the fuzzy CCR DEA model as well as in the method, proposed by Wang et al.[106] and hence neither the fuzzy CCR DEA model nor the method, proposed by Wang et al. [106] should be used for evaluating the best relative fuzzy efficiency of DMUs. Also, to resolve the flaws of the fuzzy CCR DEA model, a new fuzzy CCR model is proposed. Further, a new method is proposed to solve the proposed fuzzy CCR DEA model for evaluating the best relative fuzzy efficiency of DMUs. Further, the exact best relative fuzzy efficiency of the DMUs, considered by Wang et al. [106] is evaluated by using the proposed method.



# Chapter 4

## A New Approach for Solving Proposed Fully Fuzzy CCR DEA Model<sup>3</sup>

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Wang and Chin [105] proposed an optimistic as well as pessimistic fuzzy CCR DEA model and an approach for solving it to evaluate the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs. In this chapter, it is shown that the fuzzy CCR models, proposed by Wang and Chin [105] are not valid and hence cannot be used to evaluate the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs. To resolve the flaws of the fuzzy CCR DEA model, proposed by Wang and Chin [105] new fuzzy CCR DEA models are proposed. Also, a new approach is proposed to solve the proposed fuzzy CCR DEA models for evaluating the relative geometric crisp efficiency of DMUs.

### 4.1 Existing fuzzy DEA models

Wang and Chin [105] proposed the optimistic fuzzy CCR DEA model-4.1 and pessimistic fuzzy CCR DEA model-4.1 to evaluate the best relative fuzzy efficiency ( $\tilde{E}_p^{BEST}$ ) and worst relative fuzzy efficiency ( $\tilde{E}_p^{WORST}$ ) respectively of  $p^{th}$  DMU by incorporating the following modifications in the fuzzy CCR DEA model-4.1.

---

<sup>3</sup> The contents of this chapter are communicated for the possible publication in Expert Systems with Applications. The flaw pointed out in this chapter is published in Applied Mathematical Modelling.

1. Used trapezoidal fuzzy numbers instead of triangular fuzzy numbers to represent the input and output data.
2. Used trapezoidal fuzzy numbers instead of crisp numbers to represent the weights.

#### Optimistic fuzzy CCR DEA model-4.1

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_p^{BEST} \approx \left( (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right) \right. \\ & \left. \approx \frac{\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U) (y_{rp}^L, y_{rp}^M, y_{rp}^N, y_{rp}^U)}{\sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ip}^L, x_{ip}^M, x_{ip}^N, x_{ip}^U)} \right] \end{aligned}$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^N, E_j^U) = \frac{\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U) (y_{rj}^L, y_{rj}^M, y_{rj}^N, y_{rj}^U)}{\sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ij}^L, x_{ij}^M, x_{ij}^N, x_{ij}^U)} \leq (1,1,1,1), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

#### Pessimistic fuzzy CCR DEA model-4.1

$$\begin{aligned} \text{Minimize } & \left[ \tilde{E}_p^{WORST} \approx \left( E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST} \right) \right. \\ & \left. \approx \frac{\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U) (y_{rp}^L, y_{rp}^M, y_{rp}^N, y_{rp}^U)}{\sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ip}^L, x_{ip}^M, x_{ip}^N, x_{ip}^U)} \right] \end{aligned}$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^N, E_j^U) = \frac{\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U) (y_{rj}^L, y_{rj}^M, y_{rj}^N, y_{rj}^U)}{\sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ij}^L, x_{ij}^M, x_{ij}^N, x_{ij}^U)} \geq (1,1,1,1), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

## 4.2 Existing method

Wang and Chin [105] proposed the following method to evaluate best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, geometric crisp efficiency of DMUs.

**Step 1:** Using the product of trapezoidal fuzzy numbers, defined in Section 2.1.2.1, the optimistic fuzzy CCR DEA model-4.1 and the pessimistic fuzzy DEA model-4.1 can be transformed into optimistic fuzzy CCR DEA model-4.2 and the pessimistic fuzzy CCR DEA model-4.2 respectively.

### Optimistic fuzzy CCR DEA model-4.2

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \left( (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right) \approx \frac{\sum_{r=1}^s (u_r^L y_{rp}^L, u_r^M y_{rp}^M, u_r^N y_{rp}^N, u_r^U y_{rp}^U)}{\sum_{i=1}^m (v_i^L x_{ip}^L, v_i^M x_{ip}^M, v_i^N x_{ip}^N, v_i^U x_{ip}^U)} \right]$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^N, E_j^U) = \frac{\sum_{r=1}^s (u_r^L y_{rj}^L, u_r^M y_{rj}^M, u_r^N y_{rj}^N, u_r^U y_{rj}^U)}{\sum_{i=1}^m (v_i^L x_{ij}^L, v_i^M x_{ij}^M, v_i^N x_{ij}^N, v_i^U x_{ij}^U)} \leq (1, 1, 1, 1), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

### Pessimistic fuzzy CCR DEA model-4.2

$$\text{Minimize } \left[ \tilde{E}_p^{\text{WORST}} \approx (E_{p1}^{\text{WORST}}, E_{p2}^{\text{WORST}}, E_{p3}^{\text{WORST}}, E_{p4}^{\text{WORST}}) \right. \\ \left. \approx \frac{\sum_{r=1}^s (u_r^L y_{rp}^L, u_r^M y_{rp}^M, u_r^N y_{rp}^N, u_r^U y_{rp}^U)}{\sum_{i=1}^m (v_i^L x_{ip}^L, v_i^M x_{ip}^M, v_i^N x_{ip}^N, v_i^U x_{ip}^U)} \right]$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^N, E_j^U) = \frac{\sum_{r=1}^s (u_r^L y_{rj}^L, u_r^M y_{rj}^M, u_r^N y_{rj}^N, u_r^U y_{rj}^U)}{\sum_{i=1}^m (v_i^L x_{ij}^L, v_i^M x_{ij}^M, v_i^N x_{ij}^N, v_i^U x_{ij}^U)} \geq (1,1,1,1), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s$ , are non-negative trapezoidal fuzzy numbers.

**Step 2:** The optimistic fuzzy CCR DEA model-4.2 and the pessimistic fuzzy CCR DEA model-4.2 can be transformed into optimistic fuzzy CCR DEA model-4.3 and the pessimistic fuzzy CCR DEA model-4.3 respectively.

### Optimistic fuzzy CCR DEA model-4.3

$$\text{Maximize } \left[ \tilde{E}_p^{\text{BEST}} \approx ((E_{p1}^{\text{BEST}}, E_{p2}^{\text{BEST}}, E_{p3}^{\text{BEST}}, E_{p4}^{\text{BEST}})) \right. \\ \left. \approx \frac{(\sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U)}{(\sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U)} \right]$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^N, E_j^U) = \frac{(\sum_{r=1}^s u_r^L y_{rj}^L, \sum_{r=1}^s u_r^M y_{rj}^M, \sum_{r=1}^s u_r^N y_{rj}^N, \sum_{r=1}^s u_r^U y_{rj}^U)}{(\sum_{i=1}^m v_i^L x_{ij}^L, \sum_{i=1}^m v_i^M x_{ij}^M, \sum_{i=1}^m v_i^N x_{ij}^N, \sum_{i=1}^m v_i^U x_{ij}^U)} \leq (1,1,1,1), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

### Pessimistic fuzzy CCR DEA model-4.3

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right. \\ \left. \approx \frac{(\sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U)}{(\sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U)} \right]$$

Subject to

$$\tilde{E}_j \approx (E_j^L, E_j^M, E_j^N, E_j^U) = \frac{(\sum_{r=1}^s u_r^L y_{rj}^L, \sum_{r=1}^s u_r^M y_{rj}^M, \sum_{r=1}^s u_r^N y_{rj}^N, \sum_{r=1}^s u_r^U y_{rj}^U)}{(\sum_{i=1}^m v_i^L x_{ij}^L, \sum_{i=1}^m v_i^M x_{ij}^M, \sum_{i=1}^m v_i^N x_{ij}^N, \sum_{i=1}^m v_i^U x_{ij}^U)} \geq (1, 1, 1, 1), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

**Step 3:** The optimistic fuzzy CCR DEA model-4.3 and the pessimistic fuzzy CCR DEA model-4.3 can be transformed into optimistic crisp CCR DEA model-4.4 and the pessimistic crisp CCR DEA model-4.4 respectively.

### Optimistic crisp CCR DEA model-4.4

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = \mathfrak{R}((E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST})) \right. \\ \left. = \mathfrak{R} \left[ \frac{(\sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U)}{(\sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U)} \right] \right]$$

Subject to

$$\begin{aligned}\mathfrak{R}(\tilde{E}_j) &= \mathfrak{R}(E_j^L, E_j^M, E_j^N, E_j^U) = \mathfrak{R} \left[ \frac{(\sum_{r=1}^s u_r^L y_{rj}^L, \sum_{r=1}^s u_r^M y_{rj}^M, \sum_{r=1}^s u_r^N y_{rj}^N, \sum_{r=1}^s u_r^U y_{rj}^U)}{(\sum_{i=1}^m v_i^L x_{ij}^L, \sum_{i=1}^m v_i^M x_{ij}^M, \sum_{i=1}^m v_i^N x_{ij}^N, \sum_{i=1}^m v_i^U x_{ij}^U)} \right] \\ &\leq \mathfrak{R}(1,1,1,1), \forall, j,\end{aligned}$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

#### Pessimistic crisp CCR DEA model-4.4

$$\begin{aligned}\text{Minimize } &\left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = \mathfrak{R}(E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right. \\ &= \left. \mathfrak{R} \left[ \frac{(\sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U)}{(\sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U)} \right] \right]\end{aligned}$$

Subject to

$$\begin{aligned}\mathfrak{R}(\tilde{E}_j) &= \mathfrak{R}(E_j^L, E_j^M, E_j^N, E_j^U) = \mathfrak{R} \left[ \frac{(\sum_{r=1}^s u_r^L y_{rj}^L, \sum_{r=1}^s u_r^M y_{rj}^M, \sum_{r=1}^s u_r^N y_{rj}^N, \sum_{r=1}^s u_r^U y_{rj}^U)}{(\sum_{i=1}^m v_i^L x_{ij}^L, \sum_{i=1}^m v_i^M x_{ij}^M, \sum_{i=1}^m v_i^N x_{ij}^N, \sum_{i=1}^m v_i^U x_{ij}^U)} \right] \\ &\geq \mathfrak{R}(1,1,1,1), \forall, j,\end{aligned}$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 4:** The optimistic crisp CCR DEA model-4.4 and the pessimistic crisp CCR DEA model-4.4 can be transformed into optimistic crisp CCR DEA model-4.5 and the pessimistic crisp CCR DEA model-4.5 respectively.

### Optimistic crisp CCR DEA model-4.5

$$\begin{aligned} \text{Maximize } & \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = \mathfrak{R}(E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right. \\ & \left. = \frac{\mathfrak{R}(\sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U)}{\mathfrak{R}(\sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U)} \right] \end{aligned}$$

Subject to

$$\begin{aligned} \mathfrak{R}(\tilde{E}_j) = \mathfrak{R}(E_j^L, E_j^M, E_j^N, E_j^U) &= \frac{\mathfrak{R}(\sum_{r=1}^s u_r^L y_{rj}^L, \sum_{r=1}^s u_r^M y_{rj}^M, \sum_{r=1}^s u_r^N y_{rj}^N, \sum_{r=1}^s u_r^U y_{rj}^U)}{\mathfrak{R}(\sum_{i=1}^m v_i^L x_{ij}^L, \sum_{i=1}^m v_i^M x_{ij}^M, \sum_{i=1}^m v_i^N x_{ij}^N, \sum_{i=1}^m v_i^U x_{ij}^U)} \\ &\leq \mathfrak{R}(1,1,1,1), \forall j, \end{aligned}$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Pessimistic crisp CCR DEA model-4.5

$$\begin{aligned} \text{Minimize } & \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = \mathfrak{R}(E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right. \\ & \left. = \frac{\mathfrak{R}(\sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U)}{\mathfrak{R}(\sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U)} \right] \end{aligned}$$

Subject to

$$\begin{aligned} \mathfrak{R}(\tilde{E}_j) = \mathfrak{R}(E_j^L, E_j^M, E_j^N, E_j^U) &= \frac{\mathfrak{R}(\sum_{r=1}^s u_r^L y_{rj}^L, \sum_{r=1}^s u_r^M y_{rj}^M, \sum_{r=1}^s u_r^N y_{rj}^N, \sum_{r=1}^s u_r^U y_{rj}^U)}{\mathfrak{R}(\sum_{i=1}^m v_i^L x_{ij}^L, \sum_{i=1}^m v_i^M x_{ij}^M, \sum_{i=1}^m v_i^N x_{ij}^N, \sum_{i=1}^m v_i^U x_{ij}^U)} \\ &\geq \mathfrak{R}(1,1,1,1), \forall j, \end{aligned}$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 5:** The optimistic crisp CCR DEA model-4.5 and pessimistic crisp CCR DEA model-4.5 can be transformed into optimistic crisp CCR DEA model-4.6 and pessimistic crisp CCR DEA model-4.6 respectively.

**Optimistic crisp CCR DEA model-4.6**

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = \frac{(\sum_{r=1}^s u_r^L y_{rp}^L + \sum_{r=1}^s u_r^M y_{rp}^M + \sum_{r=1}^s u_r^N y_{rp}^N + \sum_{r=1}^s u_r^U y_{rp}^U)}{(\sum_{i=1}^m v_i^L x_{ip}^L + \sum_{i=1}^m v_i^M x_{ip}^M + \sum_{i=1}^m v_i^N x_{ip}^N + \sum_{i=1}^m v_i^U x_{ip}^U)} \right]$$

Subject to

$$\mathfrak{R} \left( \frac{(\sum_{r=1}^s u_r^L y_{rj}^L + \sum_{r=1}^s u_r^M y_{rj}^M + \sum_{r=1}^s u_r^N y_{rj}^N + \sum_{r=1}^s u_r^U y_{rj}^U)}{(\sum_{i=1}^m v_i^L x_{ij}^L + \sum_{i=1}^m v_i^M x_{ij}^M + \sum_{i=1}^m v_i^N x_{ij}^N + \sum_{i=1}^m v_i^U x_{ij}^U)} \right) \leq 1, \forall j,$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Pessimistic crisp CCR DEA model-4.6**

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = \frac{(\sum_{r=1}^s u_r^L y_{rp}^L + \sum_{r=1}^s u_r^M y_{rp}^M + \sum_{r=1}^s u_r^N y_{rp}^N + \sum_{r=1}^s u_r^U y_{rp}^U)}{(\sum_{i=1}^m v_i^L x_{ip}^L + \sum_{i=1}^m v_i^M x_{ip}^M + \sum_{i=1}^m v_i^N x_{ip}^N + \sum_{i=1}^m v_i^U x_{ip}^U)} \right]$$

Subject to

$$\mathfrak{R} \left( \frac{(\sum_{r=1}^s u_r^L y_{rj}^L + \sum_{r=1}^s u_r^M y_{rj}^M + \sum_{r=1}^s u_r^N y_{rj}^N + \sum_{r=1}^s u_r^U y_{rj}^U)}{(\sum_{i=1}^m v_i^L x_{ij}^L + \sum_{i=1}^m v_i^M x_{ij}^M + \sum_{i=1}^m v_i^N x_{ij}^N + \sum_{i=1}^m v_i^U x_{ij}^U)} \right) \geq 1, \forall j,$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 6:** The optimistic crisp CCR DEA model-4.6 and pessimistic crisp CCR DEA model-4.6 can be transformed into optimistic crisp CCR DEA model-4.7 and pessimistic crisp CCR DEA model-4.7 respectively.

### Optimistic crisp CCR DEA model-4.7

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = \sum_{r=1}^s u_r^L y_{rp}^L + \sum_{r=1}^s u_r^M y_{rp}^M + \sum_{r=1}^s u_r^N y_{rp}^N + \sum_{r=1}^s u_r^U y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i^L x_{ip}^L + \sum_{i=1}^m v_i^M x_{ip}^M + \sum_{i=1}^m v_i^N x_{ip}^N + \sum_{i=1}^m v_i^U x_{ip}^U = 1$$

$$\left( \sum_{r=1}^s u_r^L y_{rj}^L + \sum_{r=1}^s u_r^M y_{rj}^M + \sum_{r=1}^s u_r^N y_{rj}^N + \sum_{r=1}^s u_r^U y_{rj}^U \right) - \left( \sum_{i=1}^m v_i^L x_{ij}^L + \sum_{i=1}^m v_i^M x_{ij}^M + \sum_{i=1}^m v_i^N x_{ij}^N + \sum_{i=1}^m v_i^U x_{ij}^U \right) \leq 0, \forall j,$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

### Pessimistic crisp CCR DEA model-4.7

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = \sum_{r=1}^s u_r^L y_{rp}^L + \sum_{r=1}^s u_r^M y_{rp}^M + \sum_{r=1}^s u_r^N y_{rp}^N + \sum_{r=1}^s u_r^U y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i^L x_{ip}^L + \sum_{i=1}^m v_i^M x_{ip}^M + \sum_{i=1}^m v_i^N x_{ip}^N + \sum_{i=1}^m v_i^U x_{ip}^U = 1$$

$$\left( \sum_{r=1}^s u_r^L y_{rj}^L + \sum_{r=1}^s u_r^M y_{rj}^M + \sum_{r=1}^s u_r^N y_{rj}^N + \sum_{r=1}^s u_r^U y_{rj}^U \right) - \left( \sum_{i=1}^m v_i^L x_{ij}^L + \sum_{i=1}^m v_i^M x_{ij}^M + \sum_{i=1}^m v_i^N x_{ij}^N + \sum_{i=1}^m v_i^U x_{ij}^U \right) \geq 0, \forall j,$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 4:** Find the optimal value  $\left(\mathfrak{R}(\tilde{E}_p^{BEST})\right)$ , representing the best relative crisp efficiency of  $p^{th}$  DMU, by solving optimistic crisp CCR DEA model-4.7.

**Step 5:** Find the optimal value  $\left(\mathfrak{R}(\tilde{E}_p^{WORST})\right)$ , representing the worst relative crisp efficiency of  $p^{th}$  DMU, by solving pessimistic crisp CCR DEA model-4.7.

**Step 6:** Find the relative geometric average crisp efficiency  $E_p^{GEOMETRIC}$  of  $p^{th}$  DMU by putting the values  $E_p^{BEST}$  and  $E_p^{WORST}$ , obtained in Step 4 and Step 5, in

$$E_p^{GEOMETRIC} = \sqrt{E_p^{BEST} \times E_p^{WORST}}.$$

#### 4.3 Flaws in the existing method

If  $(a^L, a^M, a^N, a^U)$  &  $(b^L, b^M, b^N, b^U)$  are two trapezoidal fuzzy numbers then

$$\mathfrak{R}\left(\frac{(a^L, a^M, a^N, a^U)}{(b^L, b^M, b^N, b^U)}\right) = \mathfrak{R}\left(\frac{a^L}{b^U}, \frac{a^M}{b^N}, \frac{a^N}{b^M}, \frac{a^U}{b^L}\right) = \frac{\frac{a^L}{b^U} + \frac{a^M}{b^N} + \frac{a^N}{b^M} + \frac{a^U}{b^L}}{4}$$

and

$$\frac{\mathfrak{R}(a^L, a^M, a^N, a^U)}{\mathfrak{R}(b^L, b^M, b^N, b^U)} = \frac{a^L + a^M + a^N + a^U}{b^L + b^M + b^N + b^U}$$

It is obvious that

$$\mathfrak{R}\left(\frac{(a^L, a^M, a^N, a^U)}{(b^L, b^M, b^N, b^U)}\right) \neq \frac{\mathfrak{R}(a^L, a^M, a^N, a^U)}{\mathfrak{R}(b^L, b^M, b^N, b^U)}$$

However, Wang and Chin have used the property

$$\mathfrak{R}\left(\frac{(a^L, a^M, a^N, a^U)}{(b^L, b^M, b^N, b^U)}\right) = \frac{\mathfrak{R}(a^L, a^M, a^N, a^U)}{\mathfrak{R}(b^L, b^M, b^N, b^U)}$$

in Step 4 of their proposed method, therefore, the method proposed by Wang and Chin [105] is not valid.

#### 4.4 Proposed fuzzy DEA model

Wang and Chin [105] transformed the crisp CCR DEA model 2.2 into fuzzy CCR DEA model 4.1 by replacing the crisp input data  $(x_{ij})$ , crisp output data  $(y_{rj})$  and weights  $u_r$  and  $v_i$  with trapezoidal fuzzy numbers  $\tilde{x}_{ij} = (x_{ij}^L, x_{ij}^M, x_{ij}^N, x_{ij}^U)$ ,  $\tilde{y}_{rj} = (y_{rj}^L, y_{rj}^M, y_{rj}^N, y_{rj}^U)$  and  $(u_r^L, u_r^M, u_r^N, u_r^U)$ ,  $(v_i^L, v_i^M, v_i^N, v_i^U)$  respectively.

However, the flaws, pointed out in Section 3.3 of Chapter 3, is also existing in the optimistic fuzzy CCR DEA model-4.1 and pessimistic fuzzy CCR DEA model-4.2 proposed by Wang and Chin [105].

In this section, to resolve the flaws of the existing optimistic fuzzy CCR DEA model-4.1 and pessimistic fuzzy CCR DEA model-4.2, proposed by Wang and Chin [105] new optimistic fuzzy CCR DEA model-4.8 and pessimistic fuzzy CCR DEA model-4.8 are obtained by replacing the crisp weights  $u_r$  and  $v_i$  of the fuzzy DEA model, proposed in Section 3.5 of Chapter 3, with trapezoidal fuzzy numbers  $(u_r^L, u_r^M, u_r^N, u_r^U)$ ,  $(v_i^L, v_i^M, v_i^N, v_i^U)$  respectively.

#### Optimistic fuzzy CCR DEA model-4.8

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \approx \frac{\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U) (y_{rp}^L, y_{rp}^M, y_{rp}^N, y_{rp}^U)}{\sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ip}^L, x_{ip}^M, x_{ip}^N, x_{ip}^U)} \right]$$

Subject to

$$\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U)(y_{rj}^L, y_{rj}^M, y_{rj}^N, y_{rj}^U) \leq \sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ij}^L, x_{ij}^M, x_{ij}^N, x_{ij}^U), \forall, j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

#### Pessimistic fuzzy CCR DEA model-4.8

$$\begin{aligned} \text{Minimize } & \left[ \tilde{E}_p^{WORST} \approx (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right. \\ & \left. \approx \frac{\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U)(y_{rp}^L, y_{rp}^M, y_{rp}^N, y_{rp}^U)}{\sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ip}^L, x_{ip}^M, x_{ip}^N, x_{ip}^U)} \right] \end{aligned}$$

Subject to

$$\sum_{r=1}^s (u_r^L, u_r^M, u_r^N, u_r^U)(y_{rj}^L, y_{rj}^M, y_{rj}^N, y_{rj}^U) \geq \sum_{i=1}^m (v_i^L, v_i^M, v_i^N, v_i^U) (x_{ij}^L, x_{ij}^M, x_{ij}^N, x_{ij}^U), \forall, j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

#### 4.5 Proposed approach

In this section, a new approach is proposed to evaluate the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs by using the optimistic fuzzy CCR DEA model-4.8 and pessimistic fuzzy CCR DEA model-4.8.

**Step 1:** Using the product of trapezoidal fuzzy numbers, defined in Section 2.1.2.2, the optimistic fuzzy CCR DEA model-4.8 and pessimistic fuzzy CCR DEA model-4.8 can be

transformed into optimistic fuzzy CCR DEA model-4.9 and pessimistic fuzzy CCR DEA model-4.9 respectively.

#### Optimistic fuzzy CCR DEA model-4.9

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \approx \frac{\sum_{r=1}^s (u_r^L y_{rp}^L, u_r^M y_{rp}^M, u_r^N y_{rp}^N, u_r^U y_{rp}^U)}{\sum_{i=1}^m (v_i^L x_{ip}^L, v_i^M x_{ip}^M, v_i^N x_{ip}^N, v_i^U x_{ip}^U)} \right]$$

Subject to

$$\sum_{r=1}^s (u_r^L y_{rj}^L, u_r^M y_{rj}^M, u_r^N y_{rj}^N, u_r^U y_{rj}^U) \leq \sum_{i=1}^m (v_i^L x_{ij}^L, v_i^M x_{ij}^M, v_i^N x_{ij}^N, v_i^U x_{ij}^U), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s$ , are non-negative trapezoidal fuzzy numbers.

#### Pessimistic fuzzy CCR DEA model-4.9

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \approx \frac{\sum_{r=1}^s (u_r^L y_{rp}^L, u_r^M y_{rp}^M, u_r^N y_{rp}^N, u_r^U y_{rp}^U)}{\sum_{i=1}^m (v_i^L x_{ip}^L, v_i^M x_{ip}^M, v_i^N x_{ip}^N, v_i^U x_{ip}^U)} \right]$$

Subject to

$$\sum_{r=1}^s (u_r^L y_{rj}^L, u_r^M y_{rj}^M, u_r^N y_{rj}^N, u_r^U y_{rj}^U) \geq \sum_{i=1}^m (v_i^L x_{ij}^L, v_i^M x_{ij}^M, v_i^N x_{ij}^N, v_i^U x_{ij}^U), \forall j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s$ , are non-negative trapezoidal fuzzy numbers.

**Step 2:** Using the division of trapezoidal fuzzy numbers, defined in Section 2.1.2.2, the optimistic fuzzy CCR DEA model-4.9 and pessimistic fuzzy CCR DEA model-4.9 can be

transformed into optimistic fuzzy CCR DEA model-4.10 and pessimistic fuzzy CCR DEA model-4.10 respectively.

#### Optimistic fuzzy CCR DEA model-4.10

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_p^{BEST} \approx (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right. \\ & \left. \approx \left( \frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U}, \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N}, \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M}, \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \right) \right] \end{aligned}$$

Subject to

$$\begin{aligned} & \left( \sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U \right) \\ & \leq \left( \sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U \right), \forall, j, \end{aligned}$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

#### Pessimistic fuzzy CCR DEA model-4.10

$$\begin{aligned} \text{Minimize } & \left[ \tilde{E}_p^{WORST} \approx (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right. \\ & \left. \approx \left( \frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U}, \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N}, \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M}, \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \right) \right] \end{aligned}$$

Subject to

$$\left( \sum_{r=1}^s u_r^L y_{rp}^L, \sum_{r=1}^s u_r^M y_{rp}^M, \sum_{r=1}^s u_r^N y_{rp}^N, \sum_{r=1}^s u_r^U y_{rp}^U \right) \\ \succcurlyeq \left( \sum_{i=1}^m v_i^L x_{ip}^L, \sum_{i=1}^m v_i^M x_{ip}^M, \sum_{i=1}^m v_i^N x_{ip}^N, \sum_{i=1}^m v_i^U x_{ip}^U \right), \forall, j,$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, \dots, m, r = 1, \dots, s,$  are non-negative trapezoidal fuzzy numbers.

**Step 3:** Using the relation  $(a^L, a^M, a^N, a^U) \leq (b^L, b^M, b^N, b^U), a^L \leq b^L, a^M \leq b^M, a^N \leq b^N, a^U \leq b^U,$  the optimistic fuzzy CCR DEA model-4.10 and pessimistic fuzzy CCR DEA model-4.10 can be transformed into optimistic fuzzy CCR DEA model-4.11 and pessimistic fuzzy CCR DEA model-4.11 respectively.

#### Optimistic fuzzy CCR DEA model-4.11

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \left( (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right) \right. \\ \left. \approx \left( \frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U}, \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N}, \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M}, \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \right) \right]$$

Subject to

$$\sum_{r=1}^s u_r^L y_{rj}^L \leq \sum_{i=1}^m v_i^L x_{ij}^L, \forall, j,$$

$$\sum_{r=1}^s u_r^M y_{rj}^M \leq \sum_{i=1}^m v_i^M x_{ij}^M, \forall, j,$$

$$\sum_{r=1}^s u_r^N y_{rp}^N \leq \sum_{i=1}^m v_i^N x_{ip}^N, \forall, j,$$

$$\sum_{r=1}^s u_r^U y_{rp}^U \leq \sum_{i=1}^m v_i^U x_{ip}^U, \forall, j,$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

#### Pessimistic fuzzy CCR DEA model-4.11

$$\begin{aligned} \text{Minimize } & \left[ \tilde{E}_p^{WORST} \approx (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right. \\ & \left. \approx \left( \frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U}, \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N}, \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M}, \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \right) \right] \end{aligned}$$

Subject to

$$\sum_{r=1}^s u_r^L y_{rj}^L \geq \sum_{i=1}^m v_i^L x_{ij}^L, \forall, j,$$

$$\sum_{r=1}^s u_r^M y_{rj}^M \geq \sum_{i=1}^m v_i^M x_{ij}^M, \forall, j,$$

$$\sum_{r=1}^s u_r^N y_{rp}^N \geq \sum_{i=1}^m v_i^N x_{ip}^N, \forall, j,$$

$$\sum_{r=1}^s u_r^U y_{rp}^U \geq \sum_{i=1}^m v_i^U x_{ip}^U, \forall, j,$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U \quad i = 1, \dots, m, \quad r = 1, \dots, s.$$

**Step 4:** The fuzzy optimal value  $\left( \tilde{E}_p^{BEST} \approx \left( (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right) \right)$ , representing the

best relative fuzzy efficiency of  $p^{th}$  DMU, as well as the fuzzy optimal value  $\left( \tilde{E}_p^{WORST} \approx \right.$

$\left. (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}) \right)$ , representing the worst relative fuzzy efficiency of

$p^{th}$  DMU, can be obtained by solving the optimistic fuzzy CCR DEA model-4.11 and pessimistic fuzzy CCR DEA model-4.11 as follows:

**Step 4(a)** Find the optimal value  $(E_{p1}^{BEST})$  and  $(E_{p1}^{WORST})$  of the optimistic crisp CCR DEA model-4.12a and pessimistic CCR DEA model-4.12a by solving optimistic crisp CCR DEA model-4.12b and pessimistic CCR DEA model-4.12b equivalent to optimistic crisp CCR DEA model-4.12a and pessimistic CCR DEA model-4.12a respectively .

**Optimistic crisp CCR DEA model-4.12a**

$$\text{Maximize } \left[ E_{p1}^{BEST} = \frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} \leq 1,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

**Optimistic crisp CCR DEA model-4.12a**

$$\text{Maximize } \left[ E_{p1}^{BEST} = \sum_{r=1}^s u_r^L y_{rp}^L \right]$$

Subject to

$$\sum_{i=1}^m v_i^U x_{ip}^U = 1, \quad \sum_{r=1}^s u_r^L y_{rp}^L \geq \sum_{i=1}^m v_i^U x_{ip}^U,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

#### Pessimistic crisp CCR DEA model-4.12a

$$\text{Minimize } \left[ E_{p1}^{WORST} = \frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} \geq 1,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

#### Pessimistic crisp CCR DEA model-4.12b

$$\text{Minimize } \left[ E_{p1}^{WORST} = \sum_{r=1}^s u_r^L y_{rp}^L \right]$$

Subject to

$$\sum_{i=1}^m v_i^U x_{ip}^U = 1, \quad \sum_{r=1}^s u_r^L y_{rp}^L \geq \sum_{i=1}^m v_i^U x_{ip}^U,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

**Step 4(b):** Find the optimal value ( $E_{p2}^{BEST}$ ) and ( $E_{p2}^{WORST}$ ) of the optimistic crisp CCR DEA model-4.13a and pessimistic CCR DEA model-4.13a by solving optimistic crisp CCR DEA model-4.13b and pessimistic CCR DEA model-4.13b equivalent to optimistic crisp CCR DEA model-4.13a and pessimistic CCR DEA model-4.13a respectively .

### Optimistic crisp CCR DEA model-4.13a

$$\text{Maximize } \left[ E_{p2}^{BEST} = \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} = E_{p1}^{BEST},$$

$$E_{p1}^{BEST} \leq \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N},$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

### Optimistic crisp CCR DEA model-4.13b

$$\text{Maximize } \left[ E_{p2}^{BEST} = \sum_{r=1}^s u_r^M y_{rp}^M \right]$$

Subject to

$$\sum_{i=1}^m v_i^N x_{ip}^N = 1,$$

$$\sum_{r=1}^s u_r^L y_{rp}^L = E_{p1}^{BEST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right),$$

$$E_{p1}^{BEST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right) \leq \sum_{r=1}^s u_r^M y_{rp}^M \leq \sum_{i=1}^m v_i^M x_{ip}^M,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

**Pessimistic crisp CCR DEA model-4.13a**

$$\text{Minimize } \left[ E_{p2}^{WORST} = \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} = E_{p1}^{WORST},$$

$$E_{p1}^{WORST} \leq \frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N},$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

**Pessimistic crisp CCR DEA model-4.13b**

$$\text{Maximize } \left[ E_{p2}^{WORST} = \sum_{r=1}^s u_r^M y_{rp}^M \right]$$

Subject to

$$\sum_{i=1}^m v_i^N x_{ip}^N = 1,$$

$$\sum_{r=1}^s u_r^L y_{rp}^L = E_{p1}^{WORST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right),$$

$$E_{p1}^{WORST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right) \leq \sum_{r=1}^s u_r^M y_{rp}^M,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

**Step 4(c):** Find the optimal value ( $E_{p3}^{BEST}$ ) and ( $E_{p3}^{WORST}$ ) of the optimistic crisp CCR DEA model-4.14a and pessimistic CCR DEA model-4.14a by solving optimistic crisp CCR DEA model-4.14b and pessimistic CCR DEA model-4.14b equivalent to optimistic crisp CCR DEA model-4.14a and pessimistic CCR DEA model-4.14a respectively .

**Optimistic crisp CCR DEA model-4.14a**

$$\text{Maximize } \left[ E_{p3}^{BEST} = \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} = E_{p1}^{BEST},$$

$$\frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N} = E_{p2}^{BEST},$$

$$E_{p2}^{BEST} \leq \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M} \leq 1,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

**Optimistic crisp CCR DEA model-4.14b**

$$\text{Maximize } \left[ E_{p3}^{BEST} = \sum_{r=1}^s u_r^N y_{rp}^N \right]$$

Subject to

$$\sum_{i=1}^m v_i^M x_{ip}^M = 1,$$

$$\sum_{r=1}^s u_r^L y_{rp}^L = E_{p1}^{BEST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right),$$

$$\sum_{r=1}^s u_r^M y_{rp}^M = E_{p2}^{BEST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right),$$

$$E_{p2}^{BEST} \left( \sum_{i=1}^m v_i^M x_{ip}^M \right) \leq \sum_{r=1}^s u_r^N y_{rp}^N \leq \sum_{i=1}^m v_i^M x_{ip}^M,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

#### **Pessimistic crisp CCR DEA model-4.14a**

$$\text{Minimize } \left[ E_{p3}^{WORST} = \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M} \geq 1,$$

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} = E_{p1}^{WORST},$$

$$\frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N} = E_{p2}^{WORST},$$

$$E_{p2}^{WORST} \leq \frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M},$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

#### Pessimistic crisp CCR DEA model-4.14b

$$\text{Minimize } \left[ E_{p3}^{WORST} = \sum_{r=1}^s u_r^N y_{rp}^N \right]$$

Subject to

$$\sum_{i=1}^m v_i^M x_{ip}^M = 1,$$

$$\sum_{r=1}^s u_r^L y_{rp}^L = E_{p1}^{WORST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right),$$

$$\sum_{r=1}^s u_r^M y_{rp}^M = E_{p2}^{WORST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right),$$

$$E_{p2}^{WORST} \left( \sum_{i=1}^m v_i^M x_{ip}^M \right) \leq \sum_{r=1}^s u_r^N y_{rp}^N,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

**Step (4d):** Find the optimal value ( $E_{p4}^{BEST}$ ) and ( $E_{p4}^{WORST}$ ) of the optimistic crisp CCR DEA model-4.15a and pessimistic CCR DEA model-4.15a by solving optimistic crisp CCR DEA

model-4.15b and pessimistic CCR DEA model-4.15b equivalent to optimistic crisp CCR DEA model-4.15a and pessimistic CCR DEA model-4.15a respectively .

### Optimistic crisp CCR DEA model-4.15a

$$\text{Maximize } \left[ E_{p4}^{BEST} = \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \right]$$

Subject to

$$\frac{\sum_{r=1}^s u_r^L y_{rp}^L}{\sum_{i=1}^m v_i^U x_{ip}^U} = E_{p1}^{BEST},$$

$$\frac{\sum_{r=1}^s u_r^M y_{rp}^M}{\sum_{i=1}^m v_i^N x_{ip}^N} = E_{p2}^{BEST},$$

$$\frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M} = E_{p3}^{BEST},$$

$$E_{p3}^{BEST} \leq \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \leq 1,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

### Optimistic crisp CCR DEA model-4.15b

$$\text{Maximize } \left[ E_{p4}^{BEST} = \sum_{r=1}^s u_r^U y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i^L x_{ip}^L = 1,$$

$$\sum_{r=1}^s u_r^L y_{rp}^L = E_{p1}^{BEST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right),$$

$$\sum_{r=1}^s u_r^M y_{rp}^M = E_{p2}^{BEST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right),$$

$$\sum_{r=1}^s u_r^N y_{rp}^N = E_{p3}^{BEST} \left( \sum_{i=1}^m v_i^M x_{ip}^M \right),$$

$$E_{p3}^{BEST} \left( \sum_{i=1}^m v_i^L x_{ip}^L \right) \leq \sum_{r=1}^s u_r^U y_{rp}^U \leq \sum_{i=1}^m v_i^L x_{ip}^L,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.11.

#### **Pessimistic crisp CCR DEA model-4.15a**

$$\text{Minimize} \left[ E_{p4}^{WORST} = \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \right]$$

Subject to

$$\sum_{r=1}^s u_r^L y_{rp}^L = E_{p1}^{WORST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right),$$

$$\sum_{r=1}^s u_r^M y_{rp}^M = E_{p2}^{WORST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right),$$

$$\frac{\sum_{r=1}^s u_r^N y_{rp}^N}{\sum_{i=1}^m v_i^M x_{ip}^M} = E_{p3}^{WORST},$$

$$E_{p3}^{WORST} \leq \frac{\sum_{r=1}^s u_r^U y_{rp}^U}{\sum_{i=1}^m v_i^L x_{ip}^L} \leq 1,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

**Pessimistic crisp CCR DEA model-4.15b**

$$\text{Minimize } \left[ E_{p4}^{WORST} = \sum_{r=1}^s u_r^U y_{rp}^U \right]$$

Subject to

$$\sum_{i=1}^m v_i^L x_{ip}^L = 1,$$

$$\sum_{r=1}^s u_r^M y_{rp}^M = E_{p2}^{WORST} \left( \sum_{i=1}^m v_i^N x_{ip}^N \right),$$

$$\sum_{r=1}^s u_r^N y_{rp}^N = E_{p3}^{WORST} \left( \sum_{i=1}^m v_i^M x_{ip}^M \right),$$

$$\sum_{r=1}^s u_r^N y_{rp}^N = E_{p3}^{WORST} \left( \sum_{i=1}^m v_i^M x_{ip}^M \right)$$

$$E_{p3}^{WORST} \left( \sum_{i=1}^m v_i^U x_{ip}^U \right) \leq \sum_{r=1}^s u_r^U y_{rp}^U \leq 1,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.11.

**Step 5:** Using the values of  $E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}$  and  $E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}$ ,

obtained in Step (4a) to Step (4d), find the fuzzy optimal value

$\left( \tilde{E}_p^{BEST} = (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}, E_{p4}^{BEST}) \right)$  of optimistic fuzzy DEA model-4.11, representing the

best relative fuzzy efficiency of  $p^{th}$  DMU, as well as pessimistic fuzzy optimal value  $(\tilde{E}_p^{WORST} = (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}, E_{p4}^{WORST}))$  of pessimistic fuzzy DEA model-4.11, representing the worst relative fuzzy efficiency of  $p^{th}$  DMU.

**Step 5:** Find the crisp optimal value  $(E_p^{BEST} = \mathfrak{R}(\tilde{E}_p^{BEST}))$ , representing the best relative crisp efficiency of  $p^{th}$  DMU.

**Step 6:** Find the crisp optimal value  $(E_p^{WORST} = \mathfrak{R}(\tilde{E}_p^{WORST}))$ , representing the worst relative crisp efficiency of  $p^{th}$  DMU.

**Step 7:** Find the relative geometric crisp efficiency  $E_p^{GEOMETRIC}$  of  $p^{th}$  DMU by putting the values  $E_p^{BEST}$  and  $E_p^{WORST}$ , obtained in Step 5 and Step 6, in  $E_p^{GEOMETRIC} = \sqrt{E_p^{BEST} \times E_p^{WORST}}$ .

#### 4.6 Exact fuzzy efficiency of real life problem

Wang and Chin [105] evaluated the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of by considering eight manufacturing enterprises (DMUs) of China with two inputs and two outputs shown in Table 4.1 and using the optimistic fuzzy CCR DEA model-4.1 as well as pessimistic fuzzy CCR DEA model-4.1. The eight manufacturing enterprises, all manufacture the same type of products but with different qualities. Both the gross output value (GOV) and product quality (PQ) are considered as outputs. Manufacturing cost (MC) and the number of employees (NOE) are considered as inputs. The data about the GOV and MC are uncertain due to the unavailability at the time of assessment and are therefore estimated as fuzzy numbers. The product quality is

assessed by customers using fuzzy linguistic terms such as Excellent, Very Good, Average, Poor and Very Poor. The assessment results by customers are weighted and averaged.

However, as discussed in Section 4.4, that the optimistic fuzzy CCR DEA model-4.1 as well as pessimistic fuzzy CCR DEA model-4.1 are not valid. Therefore, the best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of 8 manufacturing enterprises, evaluated by Wang and Chin [105 ], is not exact. In this section, to illustrate the proposed method the exact best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence, relative geometric crisp efficiency of Enterprise A is evaluated by using the proposed method.

**Table 4.1: Input and output data for eight manufacturing enterprises [105]**

| (DMUs) | Inputs (Two)       |      | Outputs (two)         |                 |
|--------|--------------------|------|-----------------------|-----------------|
|        | MC                 | NOE  | GOV                   | PQ              |
| A      | (2120, 2170, 2210) | 1870 | (14500, 14790, 14860) | (3.1, 4.1, 4.9) |
| B      | (1420, 1460, 1500) | 1340 | (12470, 12720, 12790) | (1.2, 2.1, 3.0) |
| C      | (2510, 2570, 2610) | 2360 | (17900, 18260, 18400) | (3.3, 4.3, 5.0) |
| D      | (2300, 2350, 2400) | 2020 | (14970, 15270, 15400) | (2.7, 3.7, 4.6) |
| E      | (1480, 1520, 1560) | 1550 | (13980, 14260, 14330) | (1.0, 1.8, 2.7) |
| F      | (1990, 2030, 2100) | 1760 | (14030, 14310, 14400) | (1.6, 2.6, 3.6) |
| G      | (2200, 2260, 2300) | 1980 | (16540, 16870, 17000) | (2.4, 3.4, 4.4) |
| H      | (2400, 2460, 2520) | 2250 | (17600, 17960, 18100) | (2.6, 3.6, 4.6) |

#### 4.6.1 Proposed fuzzy CCR DEA models

The best relative fuzzy efficiency and worst relative fuzzy efficiency of  $DMU_A$  to  $DMU_H$  respectively can be obtained by solving the optimistic fuzzy CCR DEA models-4.16 to 4.23 and pessimistic CCR DEA models-4.16 to 4.23.

##### Optimistic fuzzy CCR DEA model-4.16

$$\text{Maximize } \left[ \tilde{E}_A^{BEST} = (E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}) \right. \\ \left. \approx \left[ \frac{(14500, 14790, 14860)(u_1^L, u_1^M, u_1^U) + (3.1, 4.1, 4.9)(u_2^L, u_2^M, u_2^U)}{(2120, 2170, 2210)(v_1^L, v_1^M, v_1^U) + (1870, 1870, 1870)(v_2^L, v_2^M, v_2^U)} \right] \right]$$

Subject to

$$(14500, 14790, 14860)(u_1^L, u_1^M, u_1^U) + (3.1, 4.1, 4.9)(u_2^L, u_2^M, u_2^U) \\ \leq (2120, 2170, 2210)(v_1^L, v_1^M, v_1^U) + (1870, 1870, 1870)(v_2^L, v_2^M, v_2^U)$$

$$(12470, 12720, 12790)(u_1^L, u_1^M, u_1^U) + (1.2, 2.1, 3.0)(u_2^L, u_2^M, u_2^U) \\ \leq (1420, 1460, 1500)(v_1^L, v_1^M, v_1^U) + (1340, 1340, 1340)(v_2^L, v_2^M, v_2^U)$$

$$(17900, 18260, 18400)(u_1^L, u_1^M, u_1^U) + (3.3, 4.3, 4.0)(u_2^L, u_2^M, u_2^U) \\ \leq (2510, 2570, 2610)(v_1^L, v_1^M, v_1^U) + (2360, 2360, 2360)(v_2^L, v_2^M, v_2^U)$$

$$(14970, 15270, 15400)(u_1^L, u_1^M, u_1^U) + (2.7, 3.7, 4.6)(u_2^L, u_2^M, u_2^U) \\ \leq (2300, 2350, 2400)(v_1^L, v_1^M, v_1^U) + (2020, 2020, 2020)(v_2^L, v_2^M, v_2^U)$$

$$(13980, 14260, 14330)(u_1^L, u_1^M, u_1^U) + (1.0, 1.8, 2.7)(u_2^L, u_2^M, u_2^U) \\ \leq (1480, 1520, 1560)(v_1^L, v_1^M, v_1^U) + (1550, 1550, 1550)(v_2^L, v_2^M, v_2^U)$$

$$(14030, 14310, 14400)(u_1^L, u_1^M, u_1^U) + (1.6, 2.6, 3.6)(u_2^L, u_2^M, u_2^U) \\ \leq (1990, 2030, 2100)(v_1^L, v_1^M, v_1^U) + (1760, 1760, 1760)(v_2^L, v_2^M, v_2^U)$$

$$\begin{aligned}
& (16540, 16870, 17000)(u_1^L, u_1^M, u_1^U) + (2.4, 3.4, 4.4)(u_2^L, u_2^M, u_2^U) \\
& \quad \preceq (2200, 2260, 2300)(v_1^L, v_1^M, v_1^U) + (1980, 1980, 1980)(v_2^L, v_2^M, v_2^U) \\
& (17600, 17960, 18100)(u_1^L, u_1^M, u_1^U) + (2.6, 3.6, 4.6)(u_2^L, u_2^M, u_2^U) \\
& \quad \preceq (2400, 2460, 2520)(v_1^L, v_1^M, v_1^U) + (2250, 2250, 2250)(v_2^L, v_2^M, v_2^U),
\end{aligned}$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, 2, r = 1, 2$ , are non-negative trapezoidal fuzzy numbers.

#### Pessimistic fuzzy CCR DEA model-4.16

$$\begin{aligned}
\text{Minimize } & \left[ \tilde{E}_A^{WORST} = (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}) \right. \\
& \left. \approx \left[ \frac{(14500, 14790, 14860)(u_1^L, u_1^M, u_1^U) + (3.1, 4.1, 4.9)(u_2^L, u_2^M, u_2^U)}{(2120, 2170, 2210)(v_1^L, v_1^M, v_1^U) + (1870, 1870, 1870)(v_2^L, v_2^M, v_2^U)} \right] \right]
\end{aligned}$$

Subject to

$$\begin{aligned}
& (14500, 14790, 14860)(u_1^L, u_1^M, u_1^U) + (3.1, 4.1, 4.9)(u_2^L, u_2^M, u_2^U) \\
& \quad \succeq (2120, 2170, 2210)(v_1^L, v_1^M, v_1^U) + (1870, 1870, 1870)(v_2^L, v_2^M, v_2^U) \\
& (12470, 12720, 12790)(u_1^L, u_1^M, u_1^U) + (1.2, 2.1, 3.0)(u_2^L, u_2^M, u_2^U) \\
& \quad \succeq (1420, 1460, 1500)(v_1^L, v_1^M, v_1^U) + (1340, 1340, 1340)(v_2^L, v_2^M, v_2^U) \\
& (17900, 18260, 18400)(u_1^L, u_1^M, u_1^U) + (3.3, 4.3, 4.0)(u_2^L, u_2^M, u_2^U) \\
& \quad \preceq (2510, 2570, 2610)(v_1^L, v_1^M, v_1^U) + (2360, 2360, 2360)(v_2^L, v_2^M, v_2^U) \\
& (14970, 15270, 15400)(u_1^L, u_1^M, u_1^U) + (2.7, 3.7, 4.6)(u_2^L, u_2^M, u_2^U) \\
& \quad \succeq (2300, 2350, 2400)(v_1^L, v_1^M, v_1^U) + (2020, 2020, 2020)(v_2^L, v_2^M, v_2^U) \\
& (13980, 14260, 14330)(u_1^L, u_1^M, u_1^U) + (1.0, 1.8, 2.7)(u_2^L, u_2^M, u_2^U) \\
& \quad \succeq (1480, 1520, 1560)(v_1^L, v_1^M, v_1^U) + (1550, 1550, 1550)(v_2^L, v_2^M, v_2^U)
\end{aligned}$$

$$\begin{aligned}
& (14030, 14310, 14400)(u_1^L, u_1^M, u_1^U) + (1.6, 2.6, 3.6)(u_2^L, u_2^M, u_2^U) \\
& \quad \geq (1990, 2030, 2100)(v_1^L, v_1^M, v_1^U) + (1760, 1760, 1760)(v_2^L, v_2^M, v_2^U) \\
& (16540, 16870, 17000)(u_1^L, u_1^M, u_1^U) + (2.4, 3.4, 4.4)(u_2^L, u_2^M, u_2^U) \\
& \quad \geq (2200, 2260, 2300)(v_1^L, v_1^M, v_1^U) + (1980, 1980, 1980)(v_2^L, v_2^M, v_2^U) \\
& (17600, 17960, 18100)(u_1^L, u_1^M, u_1^U) + (2.6, 3.6, 4.6)(u_2^L, u_2^M, u_2^U) \\
& \quad \geq (2400, 2460, 2520)(v_1^L, v_1^M, v_1^U) + (2250, 2250, 2250)(v_2^L, v_2^M, v_2^U),
\end{aligned}$$

$(u_r^L, u_r^M, u_r^N, u_r^U)$  and  $(v_i^L, v_i^M, v_i^N, v_i^U), i = 1, 2, r = 1, 2$ , are non-negative trapezoidal fuzzy numbers.

#### Optimistic fuzzy CCR DEA model-4.17

$$\begin{aligned}
\text{Maximize } & \left[ \tilde{E}_B^{BEST} = (E_{B1}^{BEST}, E_{B2}^{BEST}, E_{B3}^{BEST}) \right. \\
& \left. \approx \left[ \frac{(12470, 12720, 12790)(u_1^L, u_1^M, u_1^U) + (1.2, 2.1, 3.0)u_2}{(1420, 1460, 1500)v_1 + (1340, 1340, 1340)v_2} \right] \right]
\end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16.

#### Pessimistic fuzzy CCR DEA model-4.17

$$\begin{aligned}
\text{Minimize } & \left[ \tilde{E}_B^{WORST} = (E_{B1}^{WORST}, E_{B2}^{WORST}, E_{B3}^{WORST}) \right. \\
& \left. \approx \left[ \frac{(12470, 12720, 12790)(u_1^L, u_1^M, u_1^U) + (1.2, 2.1, 3.0)u_2}{(1420, 1460, 1500)v_1 + (1340, 1340, 1340)v_2} \right] \right]
\end{aligned}$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16

#### Optimistic fuzzy CCR DEA model-4.18

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_C^{BEST} = (E_{C1}^{BEST}, E_{C2}^{BEST}, E_{C3}^{BEST}) \right. \\ & \left. \approx \left[ \frac{(17900, 18260, 18400)(u_1^L, u_1^M, u_1^U) + (3.3, 4.3, 4.0)u_2}{(2510, 2570, 2610)v_1 + (2360, 2360, 2360)v_2} \right] \right] \end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16

#### Pessimistic fuzzy CCR DEA model-4.18

$$\begin{aligned} \text{Minimize } & \left[ \tilde{E}_C^{WORST} = (E_{C1}^{WORST}, E_{C2}^{WORST}, E_{C3}^{WORST}) \right. \\ & \left. \approx \left[ \frac{(17900, 18260, 18400)(u_1^L, u_1^M, u_1^U) + (3.3, 4.3, 4.0)u_2}{(2510, 2570, 2610)v_1 + (2360, 2360, 2360)v_2} \right] \right] \end{aligned}$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16.

#### Optimistic fuzzy CCR DEA model-4.19

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_D^{BEST} = (E_{D1}^{BEST}, E_{D2}^{BEST}, E_{D3}^{BEST}) \right. \\ & \left. \approx \left[ \frac{(14970, 15270, 15400)(u_1^L, u_1^M, u_1^U) + (2.7, 3.7, 4.6)u_2}{(2300, 2350, 2400)v_1 + (2020, 2020, 2020)v_2} \right] \right] \end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16

#### **Pessimistic fuzzy CCR DEA model-4.19**

$$\text{Minimize } \left[ \tilde{E}_D^{WORST} = (E_{D1}^{WORST}, E_{D2}^{WORST}, E_{D3}^{WORST}) \right. \\ \left. \approx \left[ \frac{(14970, 15270, 15400)(u_1^L, u_1^M, u_1^U) + (2.7, 3.7, 4.6)u_2}{(2300, 2350, 2400)v_1 + (2020, 2020, 2020)v_2} \right] \right]$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16

#### **Optimistic fuzzy CCR DEA model-4.20**

$$\text{Maximize } \left[ \tilde{E}_E^{BEST} = (E_{E1}^{BEST}, E_{E2}^{BEST}, E_{E3}^{BEST}) \right. \\ \left. \approx \left[ \frac{(13980, 14260, 14330)(u_1^L, u_1^M, u_1^U) + (1.0, 1.8, 2.7)u_2}{(1480, 1520, 1560)v_1 + (1550, 150, 150)v_2} \right] \right]$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16

#### **Pessimistic fuzzy CCR DEA model-4.20**

$$\text{Minimize } \left[ \tilde{E}_E^{WORST} = (E_{E1}^{WORST}, E_{E2}^{WORST}, E_{E3}^{WORST}) \right. \\ \left. \approx \left[ \frac{(13980, 14260, 14330)(u_1^L, u_1^M, u_1^U) + (1.0, 1.8, 2.7)u_2}{(1480, 1520, 1560)v_1 + (1550, 150, 150)v_2} \right] \right]$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16

### Optimistic fuzzy CCR DEA model-4.22

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_F^{BEST} = (E_{F1}^{BEST}, E_{F2}^{BEST}, E_{F3}^{BEST}) \right. \\ & \left. \approx \left[ \frac{(14030, 14310, 14400)(u_1^L, u_1^M, u_1^U) + (1.6, 2.6, 3.6)u_2}{(1990, 2030, 2100)v_1 + (1760, 1760, 1760)v_2} \right] \right] \end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16

### Pessimistic fuzzy CCR DEA model-4.22

$$\begin{aligned} \text{Minimize } & \left[ \tilde{E}_F^{WORST} = (E_{F1}^{WORST}, E_{F2}^{WORST}, E_{F3}^{WORST}) \right. \\ & \left. \approx \left[ \frac{(14030, 14310, 14400)(u_1^L, u_1^M, u_1^U) + (1.6, 2.6, 3.6)u_2}{(1990, 2030, 2100)v_1 + (1760, 1760, 1760)v_2} \right] \right] \end{aligned}$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16

### Optimistic fuzzy CCR DEA model-4.23

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_G^{BEST} = (E_{G1}^{BEST}, E_{G2}^{BEST}, E_{G3}^{BEST}) \right. \\ & \left. \approx \left[ \frac{(16540, 16870, 17000)(u_1^L, u_1^M, u_1^U) + (2.4, 3.4, 4.4)u_2}{(2200, 2260, 2300)v_1 + (1980, 1980, 1980)v_2} \right] \right] \end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16

### Pessimistic fuzzy CCR DEA model-4.23

$$\text{Minimize } \left[ \begin{aligned} \tilde{E}_G^{WORST} &= (E_{G1}^{WORST}, E_{G2}^{WORST}, E_{G3}^{WORST}) \\ &\approx \left[ \frac{(16540, 16870, 17000)(u_1^L, u_1^M, u_1^U) + (2.4, 3.4, 4.4)u_2}{(2200, 2260, 2300)v_1 + (1980, 1980, 1980)v_2} \right] \end{aligned} \right]$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16

### Optimistic fuzzy CCR DEA model-4.23

$$\text{Maximize } \left[ \begin{aligned} \tilde{E}_H^{BEST} &= (E_{H1}^{BEST}, E_{H2}^{BEST}, E_{H3}^{BEST}) \\ &\approx \left[ \frac{(17600, 17960, 18100)(u_1^L, u_1^M, u_1^U) + (2.6, 3.6, 4.6)u_2}{(2400, 2460, 2520)v_1 + (2250, 2250, 2250)v_2} \right] \end{aligned} \right]$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.16

### Pessimistic fuzzy CCR DEA model-4.23

$$\text{Minimize } \left[ \begin{aligned} \tilde{E}_H^{WORST} &= (E_{H1}^{WORST}, E_{H2}^{WORST}, E_{H3}^{WORST}) \\ &\approx \left[ \frac{(17600, 17960, 18100)(u_1^L, u_1^M, u_1^U) + (2.6, 3.6, 4.6)u_2}{(2400, 2460, 2520)v_1 + (2250, 2250, 2250)v_2} \right] \end{aligned} \right]$$

Subject to

All the constraints of pessimistic fuzzy CCR DEA model-4.16

#### 4.6.2 Exact relative geometric crisp efficiency of $DMU_A$

Using the method, proposed in Section 4.5, the exact best relative fuzzy efficiency as well as worst relative fuzzy efficiency and hence relative geometric crisp efficiency of  $DMU_A$  can be obtained as follows:

**Step 1:** Using the product of triangular fuzzy numbers, defined in Section 2.1.2.1, the optimistic fuzzy CCR DEA model-4.16 and pessimistic fuzzy CCR DEA model-4.16 can be transformed into optimistic fuzzy CCR DEA model-4.24 and pessimistic fuzzy CCR DEA model-4.24 respectively.

#### Optimistic fuzzy CCR DEA model-4.24

$$\text{Maximize } \left[ \tilde{E}_A^{BEST} = (E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}) \right. \\ \left. \approx \left[ \frac{(14500u_1^L + 3.1u_2^L, 14790u_1^L + 4.1u_2^L, 14860u_1^L + 4.9u_2^L)}{(2120v_1^L + 4.9v_2^L, 2170v_1^M + 1870v_2^M, 2210v_1^U + 1870v_2^U)} \right] \right]$$

Subject to

$$(14500u_1^L + 3.1u_2^L, 14790u_1^M + 4.1u_2^M, 14860u_1^U + 4.9u_2^U) \\ \leq (2120v_1^L + 1870v_2^L, 2170v_1^M + 1870v_2^M, 2210v_1^U + 1870v_2^U)$$

$$(12470u_1^L + 1.2u_2^L, 12720u_1^M + 2.1u_2^M, 12790u_1^U + 3.0u_2^U) \\ \leq (1420v_1^L + 1340v_2^L, 1460v_1^M + 1340v_2^M, 1500v_1^U + 1340v_2^U)$$

$$(17900u_1^L + 3.3u_2^L, 18260u_1^M + 4.3u_2^M, 18400u_1^U + 4.0u_2^U) \\ \leq (2510v_1^L + 2360v_2^L, 2570v_1^M + 2360v_2^M, 2610v_1^U + 2360v_2^U)$$

$$(14970u_1^L + 2.7u_2^L, 15270u_1^M + 3.7u_2^M, 15400u_1^U + 4.6u_2^U) \\ \leq (2300v_1^L + 2020v_2^L, 2350v_1^M + 2020v_2^M, 2400v_1^U + 2020v_2^U)$$

$$(13980u_1^L + 1.0u_2^L, 14260u_1^M + 1.8u_2^M, 14330u_1^U + 2.7u_2^U)$$

$$\leq (1480v_1^L + 1550v_2^L, 1520v_1^M + 1550v_2^M, 1560v_1^U + 1550v_2^U)$$

$$(14030u_1^L + 1.6u_2^L, 14310u_1^M + 2.6u_2^M, 14400u_1^U + 3.6u_2^U)$$

$$\leq (1990v_1^L + 1760v_2^L, 2030v_1^M + 1760v_2^M, 2100v_1^U + 1760v_2^U)$$

$$(16540u_1^L + 2.4u_2^L, 16870u_1^M + 3.4u_2^M, 17000u_1^U + 4.4u_2^U)$$

$$\leq (2200v_1^L + 1980v_2^L, 2260v_1^M + 1980v_2^M, 2300v_1^U + 1980v_2^U)$$

$$(17600u_1^L + 2.6u_2^L, 17960u_1^M + 3.6u_2^M, 18100u_1^U + 4.6u_2^U)$$

$$\leq (2400v_1^L + 2250v_2^L, 2460v_1^M + 2250v_2^M, 2520v_1^U + 2250v_2^U),$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, \quad i = 1, 2, \quad r = 1, 2,$$

#### Pessimistic fuzzy CCR DEA model-4.24

$$\text{Minimize } \left[ \tilde{E}_A^{WORST} = (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}) \right]$$

$$\approx \left[ \frac{(14500u_1^L + 3.1u_2^L, 14790u_1^M + 4.1u_2^M, 14860u_1^U + 4.9u_2^U)}{(2120v_1^L + 4.9v_2^L, 2170v_1^M + 1870v_2^M, 2210v_1^U + 1870v_2^U)} \right]$$

Subject to

$$(14500u_1^L + 3.1u_2^L, 14790u_1^M + 4.1u_2^M, 14860u_1^U + 4.9u_2^U)$$

$$\geq (2120v_1^L + 1870v_2^L, 2170v_1^M + 1870v_2^M, 2210v_1^U + 1870v_2^U)$$

$$(12470u_1^L + 1.2u_2^L, 12720u_1^M + 2.1u_2^M, 12790u_1^U + 3.0u_2^U)$$

$$\geq (1420v_1^L + 1340v_2^L, 1460v_1^M + 1340v_2^M, 1500v_1^U + 1340v_2^U)$$

$$(17900u_1^L + 3.3u_2^L, 18260u_1^M + 4.3u_2^M, 18400u_1^U + 4.0u_2^U)$$

$$\geq (2510v_1^L + 2360v_2^L, 2570v_1^M + 2360v_2^M, 2610v_1^U + 2360v_2^U)$$

$$(14970u_1^L + 2.7u_2^L, 15270u_1^M + 3.7u_2^M, 15400u_1^U + 4.6u_2^U)$$

$$\geq (2300v_1^L + 2020v_2^L, 2350v_1^M + 2020v_2^M, 2400v_1^U + 2020v_2^U)$$

$$(13980u_1^L + 1.0u_2^L, 14260u_1^M + 1.8u_2^M, 14330u_1^U + 2.7u_2^U)$$

$$\geq (1480v_1^L + 1550v_2^L, 1520v_1^M + 1550v_2^M, 1560v_1^U + 1550v_2^U)$$

$$(14030u_1^L + 1.6u_2^L, 14310u_1^M + 2.6u_2^M, 14400u_1^U + 3.6u_2^U)$$

$$\geq (1990v_1^L + 1760v_2^L, 2030v_1^M + 1760v_2^M, 2100v_1^U + 1760v_2^U)$$

$$(16540u_1^L + 2.4u_2^L, 16870u_1^M + 3.4u_2^M, 17000u_1^U + 4.4u_2^U)$$

$$\geq (2200v_1^L + 1980v_2^L, 2260v_1^M + 1980v_2^M, 2300v_1^U + 1980v_2^U)$$

$$(17600u_1^L + 2.6u_2^L, 17960u_1^M + 3.6u_2^M, 18100u_1^U + 4.6u_2^U)$$

$$\geq (2400v_1^L + 2250v_2^L, 2460v_1^M + 2250v_2^M, 2520v_1^U + 2250v_2^U),$$

$$0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, \quad i = 1, 2, \quad r = 1, 2,$$

**Step 2:** The optimistic fuzzy CCR DEA model-4.24 and pessimistic fuzzy CCR DEA model-4.24 can be transformed into optimistic fuzzy CCR DEA model-4.25 and pessimistic fuzzy CCR DEA model-4.25 respectively.

### Optimistic fuzzy CCR DEA model-4.25

$$\begin{aligned} \text{Maximize } & \left[ \tilde{E}_A^{BEST} = (E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}) \right. \\ & \left. \approx \left[ \frac{(14500u_1^L + 3.1u_2^L, 14790u_1^L + 4.1u_2^L, 14860u_1^L + 4.9u_2^L)}{(2120v_1^L + 4.9v_2^L, 2170v_1^M + 1870v_2^M, 2210v_1^U + 1870v_2^U)} \right] \right] \end{aligned}$$

Subject to

$$14500u_1^L + 3.1u_2^L \leq 2120v_1^L + 1870v_2^L, \quad 14790u_1^M + 4.1u_2^M \leq 2170v_1^M + 1870v_2^M,$$

$$14860u_1^U + 4.9u_2^U \leq 2210v_1^U + 1870v_2^U, \quad 12470u_1^L + 1.2u_2^L \leq 1420v_1^L + 1340v_2^L,$$

$$12720u_1^M + 2.1u_2^M \leq 1460v_1^M + 1340v_2^M, \quad 12790u_1^U + 3.0u_2^U \leq 1500v_1^U + 1340v_2^U,$$

$$17900u_1^L + 3.3u_2^L \leq 2510v_1^L + 2360v_2^L, \quad 18260u_1^M + 4.3u_2^M \leq 2570v_1^M + 2360v_2^M,$$

$$\begin{aligned}
18400u_1^U + 4.0u_2^U &\leq 2610v_1^U + 2360v_2^U, & 14970u_1^L + 2.7u_2^L &\leq 2300v_1^L + 2020v_2^L, \\
15270u_1^M + 3.7u_2^M &\leq 2350v_1^M + 2020v_2^M, & 15400u_1^U + 4.6u_2^U &\leq 2400v_1^U + 2020v_2^U, \\
13980u_1^L + 1.0u_2^L &\leq 1480v_1^L + 1550v_2^L, & 14260u_1^M + 1.8u_2^M &\leq 1520v_1^M + 1550v_2^M, \\
14330u_1^U + 2.7u_2^U &\leq 1560v_1^U + 1550v_2^U, & 14030u_1^L + 1.6u_2^L &\leq 1990v_1^L + 1760v_2^L, \\
14310u_1^M + 2.6u_2^M &\leq 2030v_1^M + 1760v_2^M, & 14400u_1^U + 3.6u_2^U &\leq 2100v_1^U + 1760v_2^U, \\
16540u_1^L + 2.4u_2^L &\leq 2200v_1^L + 1980v_2^L, & 16870u_1^M + 3.4u_2^M &\leq 2260v_1^M + 1980v_2^M, \\
17000u_1^U + 4.4u_2^U &\leq 2300v_1^U + 1980v_2^U, & 17600u_1^L + 2.6u_2^L &\leq 2400v_1^L + 2250v_2^L, \\
17960u_1^M + 3.6u_2^M &\leq 2460v_1^M + 2250v_2^M, & 18100u_1^U + 4.6u_2^U &\leq 2520v_1^U + 2250v_2^U. \\
0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; & 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, & i = 1,2, & r = 1,2,
\end{aligned}$$

**Pessimistic fuzzy CCR DEA model-4.25**

$$\begin{aligned}
\text{Minimize } & \left[ \tilde{E}_A^{WORST} = (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}) \right. \\
& \left. \approx \left[ \frac{(14500u_1^L + 3.1u_2^L, 14790u_1^L + 4.1u_2^L, 14860u_1^L + 4.9u_2^L)}{(2120v_1^L + 4.9v_2^L, 2170v_1^M + 1870v_2^M, 2210v_1^U + 1870v_2^U)} \right] \right]
\end{aligned}$$

Subject to

$$\begin{aligned}
14500u_1^L + 3.1u_2^L &\geq 2120v_1^L + 1870v_2^L, & 14790u_1^M + 4.1u_2^M &\geq 2170v_1^M + 1870v_2^M, \\
14860u_1^U + 4.9u_2^U &\geq 2210v_1^U + 1870v_2^U, & 12470u_1^L + 1.2u_2^L &\geq 1420v_1^L + 1340v_2^L, \\
12720u_1^M + 2.1u_2^M &\geq 1460v_1^M + 1340v_2^M, & 12790u_1^U + 3.0u_2^U &\geq 1500v_1^U + 1340v_2^U, \\
17900u_1^L + 3.3u_2 &\geq 2510v_1^L + 2360v_2^L, & 18260u_1^M + 4.3u_2^M &\geq 2570v_1^M + 2360v_2^M, \\
18400u_1^U + 4.0u_2^U &\geq 2610v_1^U + 2360v_2^U, & 14970u_1^L + 2.7u_2^L &\geq 2300v_1^L + 2020v_2^L, \\
15270u_1^M + 3.7u_2^M &\geq 2350v_1^M + 2020v_2^M, & 15400u_1^U + 4.6u_2^U &\geq 2400v_1^U + 2020v_2^U, \\
13980u_1^L + 1.0u_2^L &\geq 1480v_1^L + 1550v_2^L, & 14260u_1^M + 1.8u_2^M &\geq 1520v_1^M + 1550v_2^M, \\
14330u_1^U + 2.7u_2^U &\geq 1560v_1^U + 1550v_2^U, & 14030u_1^L + 1.6u_2^L &\geq 1990v_1^L + 1760v_2^L,
\end{aligned}$$

$$\begin{aligned}
14310u_1^M + 2.6u_2^M &\geq 2030v_1^M + 1760v_2^M, & 14400u_1^U + 3.6u_2^U &\geq 2100v_1^U + 1760v_2^U, \\
16540u_1^L + 2.4u_2^L &\geq 2200v_1^L + 1980v_2^L, & 16870u_1^M + 3.4u_2^M &\geq 2260v_1^M + 1980v_2^M, \\
17000u_1^U + 4.4u_2^U &\geq 2300v_1^U + 1980v_2^U, & 17600u_1^L + 2.6u_2^L &\geq 2400v_1^L + 2250v_2^L, \\
17960u_1^M + 3.6u_2^M &\geq 2460v_1^M + 2250v_2^M, & 18100u_1^U + 4.6u_2^U &\geq 2520v_1^U + 2250v_2^U. \\
0 \leq u_r^L \leq u_r^M \leq u_r^N \leq u_r^U; & 0 \leq v_i^L \leq v_i^M \leq v_i^N \leq v_i^U, & i = 1,2, & r = 1,2,
\end{aligned}$$

**Step 3:** The optimistic fuzzy CCR DEA model-4.25 and pessimistic fuzzy CCR DEA model-4.25 can be transformed into optimistic fuzzy CCR DEA model-4.26 and pessimistic fuzzy CCR DEA model-4.26 respectively.

#### Optimistic fuzzy CCR DEA model-4.26

$$\begin{aligned}
\text{Maximize } & \left[ \tilde{E}_A^{BEST} = (E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}) \right. \\
& \left. \approx \left[ \left( \frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U}, \frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M}, \frac{14860u_1^U + 4.9u_2^U}{2120v_1^L + 4.9v_2^L} \right) \right] \right]
\end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.25.

#### Pessimistic fuzzy CCR DEA model-4.26

$$\begin{aligned}
\text{Minimize } & \left[ \tilde{E}_A^{WORST} = (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}) \right. \\
& \left. \approx \left[ \left( \frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U}, \frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M}, \frac{14860u_1^U + 4.9u_2^U}{2120v_1^L + 4.9v_2^L} \right) \right] \right]
\end{aligned}$$

Subject to

All the constraints of optimistic fuzzy CCR DEA model-4.25.

**Step 4:** The fuzzy optimal value  $\left( \tilde{E}_A^{BEST} \approx \left( \left( (E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}) \right) \right) \right)$ , representing the best relative fuzzy efficiency of  $A^{th}$  DMU, as well as the fuzzy optimal value  $\left( \tilde{E}_A^{WORST} \approx (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}) \right)$ , representing the worst relative fuzzy efficiency of  $A^{th}$  DMU, can be obtained by solving the optimistic fuzzy CCR DEA model-4.26 and pessimistic fuzzy CCR DEA model-4.26 as follows:

**Step 4(a)** The optimal value  $(E_{A1}^{BEST})$  and  $(E_{A1}^{WORST})$  of the optimistic crisp CCR DEA model-4.27a and pessimistic CCR DEA model-4.27a by solving optimistic crisp CCR DEA model-4.27b and pessimistic CCR DEA model-4.27b equivalent to optimistic crisp CCR DEA model-4.27a and pessimistic CCR DEA model-4.27a are 0.812 and 1 respectively.

#### **Optimistic crisp CCR DEA model-4.27a**

$$\text{Maximize } \left[ E_{A1}^{BEST} = \frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} \right]$$

Subject to

$$\frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} \leq 1,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.16.

#### **Optimistic crisp CCR DEA model-4.27b**

$$\text{Maximize } [E_{A1}^{BEST} = 14500u_1^L + 3.1u_2^L]$$

Subject to

$$2210v_1^U + 1870v_2^U = 1$$

$$14500u_1^L + 3.1u_2^L \leq 2210v_1^U + 1870v_2^U,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.25.

**Pessimistic crisp CCR DEA model-4.27a**

$$\text{Minimize } \left[ E_{A1}^{WORST} = \frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} \right]$$

Subject to

$$\frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} \geq 1,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.25.

**Pessimistic crisp CCR DEA model-4.27b**

$$\text{Minimize } [E_{A1}^{WORST} = 14500u_1^L + 3.1u_2^L]$$

Subject to

$$2210v_1^U + 1870v_2^U = 1$$

$$14500u_1^L + 3.1u_2^L \geq 2210v_1^U + 1870v_2^U,$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.25.

**Step 4(b)** The optimal value ( $E_{A2}^{BEST}$ ) and ( $E_{A2}^{WORST}$ ) of the optimistic crisp CCR DEA model-4.28a and pessimistic CCR DEA model-4.28a by solving optimistic crisp CCR DEA model-4.28b and pessimistic CCR DEA model-4.28b equivalent to optimistic crisp CCR DEA model-4.28a and pessimistic CCR DEA model-4.28a are 0.833 and 1.046 respectively.

**Optimistic crisp CCR DEA model-4.28a**

$$\text{Maximize } \left[ E_{A2}^{BEST} = \frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M} \right]$$

Subject to

$$\frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} = 0.812$$

$$0.812 \leq \frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M} \leq 1$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.25.

**Optimistic crisp CCR DEA model-4.28b**

$$\text{Maximize } [E_{A2}^{BEST} = 14790u_1^M + 4.1u_2^M]$$

Subject to

$$2170v_1^M + 1870v_2^M = 1,$$

$$14500u_1^L + 3.1u_2^L = (0.812)(2210v_1^U + 1870v_2^U),$$

$$(0.812)(2170v_1^M + 1870v_2^M) \leq 14790u_1^M + 4.1u_2^M \leq 2170v_1^M + 1870v_2^M$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.25.

**Pessimistic crisp CCR DEA model-4.28a**

$$\text{Minimize } \left[ E_{A2}^{WORST} = \frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M} \right]$$

Subject to

$$\frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} = 1,$$

$$1 \leq \frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M}$$

All the constraints of pessimistic fuzzy CCR DEA model-4.25.

#### **Pessimistic crisp CCR DEA model-4.28b**

$$\text{Minimize}[E_{A2}^{BEST} = 14790u_1^M + 4.1u_2^M]$$

Subject to

$$2170v_1^M + 1870v_2^M = 1,$$

$$14500u_1^L + 3.1u_2^L = 2210v_1^U + 1870v_2^U,$$

$$2170v_1^M + 1870v_2^M \leq 14790u_1^M + 4.1u_2^M.$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.25.

**Step 4(c)** The optimal value ( $E_{A2}^{BEST}$ ) and ( $E_{A2}^{WORST}$ ) of the optimistic crisp CCR DEA model-4.29a and pessimistic CCR DEA model-4.29a by solving optimistic crisp CCR DEA model-4.29b and pessimistic CCR DEA model-4.29b equivalent to optimistic crisp CCR DEA model-4.29a and pessimistic CCR DEA model-4.29a are 0.854 and 1.072 respectively.

#### **Optimistic crisp CCR DEA model-4.29a**

$$\text{Maximize} \left[ E_{A3}^{BEST} = \frac{14860u_1^U + 4.9u_2^U}{2120v_1^L + 4.9v_2^L} \right]$$

Subject to

$$\frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} = 0.812$$

$$\frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M} = 0.833$$

$$0.833 \leq \frac{14860u_1^U + 4.9u_2^U}{2120v_1^L + 4.9v_2^L} \leq 1,$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.25.

#### **Optimistic crisp CCR DEA model-4.29b**

$$\text{Maximize } [E_{A3}^{BEST} = 14860u_1^U + 4.9u_2^U]$$

Subject to

$$2120v_1^L + 4.9v_2^L = 1,$$

$$14500u_1^L + 3.1u_2^L = (0.812)(2210v_1^U + 1870v_2^U)$$

$$14790u_1^M + 4.1u_2^M = (0.833)(2170v_1^M + 1870v_2^M),$$

$$(0.833)(2120v_1^L + 4.9v_2^L) \leq 14860u_1^U + 4.9u_2^U \leq 2120v_1^L + 4.9v_2^L.$$

and

All the constraints of optimistic fuzzy CCR DEA model-4.25.

#### **Pessimistic crisp CCR DEA model-4.29b**

$$\text{Minimize } \left[ E_{A3}^{WORST} = \frac{14860u_1^U + 4.9u_2^U}{2120v_1^L + 4.9v_2^L} \right]$$

Subject to

$$\frac{14500u_1^L + 3.1u_2^L}{2210v_1^U + 1870v_2^U} = 1,$$

$$\frac{14790u_1^M + 4.1u_2^M}{2170v_1^M + 1870v_2^M} = 1.046$$

$$1.046 \leq \frac{14860u_1^U + 4.9u_2^U}{2120v_1^L + 4.9v_2^L},$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.25.

**Pessimistic crisp CCR DEA model-4.29b**

$$\text{Minimize } [E_{A3}^{WORST} = 14860u_1^U + 4.9u_2^U]$$

Subject to

$$2120v_1^L + 4.9v_2^L = 1,$$

$$14500u_1^L + 3.1u_2^L = 2210v_1^U + 1870v_2^U$$

$$14790u_1^M + 4.1u_2^M = (1.046)(2170v_1^M + 1870v_2^M),$$

$$(1.046)(2120v_1^L + 4.9v_2^L) \leq 14860u_1^U + 4.9u_2^U \leq 2120v_1^L + 4.9v_2^L.$$

and

All the constraints of pessimistic fuzzy CCR DEA model-4.25.

**Step 5:** Using the values of  $E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}$  and  $E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}$ , obtained in Step

(4a) to Step (4c), the fuzzy optimal value  $(\tilde{E}_A^{BEST} = (E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}))$  of optimistic fuzzy

DEA model-4.16, representing the best relative fuzzy efficiency of  $A^{th}$  DMU, is  $(\tilde{E}_A^{BEST} =$

$(E_{A1}^{BEST}, E_{A2}^{BEST}, E_{A3}^{BEST}) = (0.812, 0.833, 0.854)$ ), as well as pessimistic fuzzy optimal value

$(\tilde{E}_A^{WORST} = (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}))$  of pessimistic fuzzy DEA model-4.16, representing the

worst relative fuzzy efficiency of  $A^{th}$  DMU, is  $(\tilde{E}_A^{WORST} = (E_{A1}^{WORST}, E_{A2}^{WORST}, E_{A3}^{WORST}) =$

$(1, 1.046, 1.072)$ ).

**Step 6:** The crisp optimal value  $(E_A^{BEST} = \mathfrak{R}(\tilde{E}_A^{BEST}) = \mathfrak{R}(0.812, 0.833, 0.854))$ , representing

the best relative crisp efficiency of  $A^{th}$  DMU is 0.833.

**Step 7:** The crisp optimal value ( $E_A^{WORST} = \Re(\tilde{E}_A^{WORST}) = \Re(1,1.046,1.072)$ ), representing the worst relative crisp efficiency of  $A^{th}$  DMU is 1.041.

**Step 8:** The geometric average crisp efficiency  $E_A^{GEOMETRIC}$  of  $A^{th}$  DMU by putting the values  $E_A^{BEST}$  and  $E_A^{WORST}$ , obtained in Step 5 and Step 6, in  $E_A^{GEOMETRIC} = \sqrt{E_A^{BEST} \times E_A^{WORST}}$  is 0.931.

### 4.6.3 Results

The exact best relative fuzzy efficiency, exact worst relative fuzzy efficiency and relative geometric crisp efficiency of all the DMUs evaluated on solving fuzzy CCR DEA by the proposed method are shown in Table 4.2.

**Table 4.2** Exact best relative fuzzy efficiency, exact worst relative fuzzy efficiency and relative geometric crisp efficiency of DMUs.

| DMU <sub>j</sub> | Best relative fuzzy efficiency | Worst relative fuzzy efficiency | Relative geometric crisp efficiency |
|------------------|--------------------------------|---------------------------------|-------------------------------------|
| <b>A</b>         | (.81238, .833217, .85407)      | (1, 1.04625, 1.07227))          | .931                                |
| <b>B</b>         | (.97498, 1, 1)                 | (1, 1.12689, 1.28793)           | 1.062                               |
| <b>C</b>         | (.79661, .815201, .83732)      | (1, 1.01738, 1.055204)          | .913                                |
| <b>D</b>         | (.77643, .79636, 81927)        | (1, 1, 1.028724)                | .898                                |
| <b>E</b>         | (.97303, 1, 1)                 | (1, 1, 1)                       | .996                                |
| <b>F</b>         | (.83517, .85653, .879205)      | (1, 1, 1.104026)                | .938                                |
| <b>G</b>         | (.87519, .89757, .92263)       | (1, 1.07384, 1.1585)            | .938                                |
| <b>H</b>         | (.819529, .84089, .86447)      | (1, 1.009602, 1.08548)          | .929                                |

It is obvious from Table 3.2 that  $\mathfrak{R}(\tilde{E}_B) > R(\tilde{E}_E) > R(\tilde{E}_G) = \mathfrak{R}(\tilde{E}_F) > R(\tilde{E}_H) > R(\tilde{E}_A) > R(\tilde{E}_C) > R(\tilde{E}_D)$ . Therefore,  $\tilde{E}_B > \tilde{E}_E > \tilde{E}_G \approx \tilde{E}_F > \tilde{E}_A > \tilde{E}_H > \tilde{E}_C > \tilde{E}_D$ .

#### 4.7 Conclusions

On the basis the present study, it can be concluded that there are flaws in the optimistic as well as pessimistic fuzzy CCR DEA model and in the method proposed by Wang et al. [105] and hence, neither the fuzzy CCR DEA model proposed by, Wang et al. [105] nor the method proposed by Wang et al. [105] should be used for evaluating the best relative geometric crisp efficiency of DMUs. Also, to resolve the flaws of the fuzzy CCR DEA models, new fuzzy CCR DEA models are proposed. Further, a new approach is proposed to solve the proposed fuzzy CCR DEA models for evaluating the best relative geometric crisp efficiency of DMUs.

# Chapter 5

## A New Approach for Solving Proposed Intuitionistic Fully Fuzzy CCR DEA Model<sup>4</sup>

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Puri and Yadav [83] proposed an optimistic as well as pessimistic intuitionistic fuzzy CCR DEA model and an approach to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of decision making units (DMUs). In this chapter, it is shown that the intuitionistic fuzzy CCR models, proposed by Puri and Yadav [83] are not valid and hence cannot be used to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of decision making units (DMUs). To resolve the flaws of the intuitionistic fuzzy CCR DEA model, proposed by Puri and Yadav [83], new intuitionistic fuzzy CCR DEA models are proposed. Also, a new approach is proposed to solve the proposed intuitionistic fuzzy CCR DEA models for evaluating the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs.

### 5.1 Preliminaries

Puri and Yadav [83] pointed out that the main characteristic of the fuzzy set theory is that in fuzzy sets/numbers, the degree of non-membership of an element is equal to one minus the

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<sup>4</sup> The contents of this chapter are communicated for the possible publication in Expert Systems with Applications.

degree of its membership and thus, the sum of membership and non-membership degrees of an element is equal to one. However, in real life applications, we deal with the information which is sometimes vague or inexact or insufficient and therefore, there is possibility that the sum of the membership and non-membership degrees of an element may come out to be less than one. It means there remains some degree of hesitation. Certainly, fuzzy sets theory is not appropriate to deal with such type of problems/situations; rather intuitionistic fuzzy set (IFS) theory is more suitable. Intuitionistic fuzzy set (IFS) [5] is an extension of fuzzy set and have been found to be highly useful to deal with vagueness. IFS considers both the degrees of membership (acceptance) and non-membership (rejection) of an element such that the sum of both values is less than or equal to 1.

### 5.1.1 Basic definitions

In this section, some basic definitions are reviewed [83].

**Definition 5.1** Let  $X$  be a universe of disclosure. Then an IFS  $\tilde{A}$  in  $X$  is given by  $\tilde{A} = \{(x, \mu_{\tilde{A}}(x), \nu_{\tilde{A}}(x)) : x \in X\}$ , where  $\mu_{\tilde{A}} : X \rightarrow [0,1]$  and  $\nu_{\tilde{A}} : X \rightarrow [0,1]$  with the condition,  $0 \leq \mu_{\tilde{A}}(x) + \nu_{\tilde{A}}(x) \leq 1, \forall x \in X$  represent the membership and non-membership functions respectively and the numbers  $\mu_{\tilde{A}}(x)$  and  $\nu_{\tilde{A}}(x)$  represent the membership degree and non-member-ship degree of the element  $x$  being in  $\tilde{A}$ . Further,  $\pi_{\tilde{A}}(x) = 1 - \mu_{\tilde{A}}(x) - \nu_{\tilde{A}}(x), \forall x \in X$  is a hesitation degree of  $x$  being in  $\tilde{A}$ . It is obvious that  $0 \leq \pi_{\tilde{A}}(x) \leq 1, \forall x \in X$ . If  $\pi_{\tilde{A}}(x) = 0, \forall x \in X$  then  $\tilde{A}$  becomes a fuzzy number.

**Definition 5.2** Let  $\tilde{A}$  be an IFS defined on the set of real numbers  $\mathbb{R}$  with its membership function  $\mu_{\tilde{A}}$  and non-membership function  $\nu_{\tilde{A}}$ , then  $\tilde{A}$  is said to be an intuitionistic fuzzy numbers (IFN) if

- (i) It is normal, i.e., there is any  $x_0 \in \mathbb{R}$  such that  $\mu_{\tilde{A}}(x_0) = 1$  (so  $v_{\tilde{A}}(x_0) = 0$ ).
- (ii) It is convex for  $\mu_{\tilde{A}}(x)$ , i.e.,  $\mu_{\tilde{A}}(\lambda x_1 + (1 - \lambda)x_2) \geq \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2))$ ,  
 $\forall x_1, x_2 \in \mathbb{R}, \lambda \in [0,1]$ .
- (iii) It is concave for  $v_{\tilde{A}}(x)$ , i.e.,  $v_{\tilde{A}}(\lambda x_1 + (1 - \lambda)x_2) \leq \max(v_{\tilde{A}}(x_1), v_{\tilde{A}}(x_2))$ ,  
 $\forall x_1, x_2 \in \mathbb{R}, \lambda \in [0,1]$ .

**Definition 5.3** An intuitionistic fuzzy number  $\tilde{A}$  is said to be a triangular intuitionistic fuzzy number if the membership function  $\mu_{\tilde{A}}$  and non-membership function  $v_{\tilde{A}}$  is defined as

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a_1}{a_2-a_1}, & a_1 < x \leq a_2, \\ 1, & x = a_2, \\ \frac{x-a_3}{a_2-a_3}, & a_2 \leq x < a_3, \\ 0, & \text{otherwise.} \end{cases} \quad \text{and} \quad v_{\tilde{A}}(x) = \begin{cases} \frac{x-a_4}{a_4-a_2}, & a_4 \leq x < a_2, \\ 0, & x = a_2, \\ \frac{x-a_2}{a_5-a_2}, & a_2 \leq x < a_5, \\ 1, & \text{otherwise.} \end{cases}$$

where  $a_4, a_1, a_2, a_3, a_5 \in \mathbb{R}$  such that  $a_4 \leq a_1 \leq a_2 \leq a_3 \leq a_5$ . It is denoted by  $(a_1, a_2, a_3; a_4, a_2, a_5)$ .

A triangular intuitionistic fuzzy number  $\tilde{A} = (a_1, a_2, a_3; a_4, a_2, a_5)$  becomes triangular fuzzy number  $\tilde{A} = (a_1, a_2, a_3)$  if  $a_1 = a_4, a_3 = a_5$  and  $v_{\tilde{A}}(x) = 1 - \mu_{\tilde{A}}(x), \forall x \in \mathbb{R}$  and it becomes a real number  $a$  if  $a_4 = a_1 = a_2 = a_3 = a_5 = a$ .

**Definition 5.4** A triangular intuitionistic fuzzy number  $\tilde{A} = (a_1, a_2, a_3; a_4, a_2, a_5)$  is said to be non-negative triangular intuitionistic fuzzy number, represented by  $\tilde{A} \succcurlyeq (0,0,0; 0,0,0)$ , if and only if  $a_4 \geq 0$ .

### 5.1.2 Arithmetic operations of triangular intuitionistic fuzzy numbers

Let  $\tilde{A} = (a_1, a_2, a_3; a_4, a_2, a_5)$  and  $\tilde{B} = (b_1, b_2, b_3; b_4, b_2, b_5)$  be two triangular intuitionistic fuzzy numbers. Then,

$$(i) \tilde{A} \oplus \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3; a_4 + b_4, a_2 + b_2, a_5 + b_5).$$

(ii)  $\tilde{A} \otimes \tilde{B} = (a_1 b_1, a_2 b_2, a_3 b_3; a_4 b_4, a_2 b_2, a_5 b_5)$  for  $\tilde{A}$  and  $\tilde{B}$  are non-negative triangular intuitionistic fuzzy numbers.

$$(iii) k\tilde{A} = \begin{cases} (ka_1, ka_2, ka_3; ka_4, ka_2, ka_5), k \geq 0, \\ (kb_3, kb_2, kb_1; kb_5, kb_2, kb_4), k \leq 0. \end{cases}$$

(iv)  $\frac{\tilde{A}}{\tilde{B}} = \left( \frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}; \frac{a_4}{b_5}, \frac{a_2}{b_2}, \frac{a_5}{b_4} \right)$ ,  $\tilde{A}^1$  is a non-negative triangular I.F.N and  $\tilde{B}$  is a positive triangular intuitionistic fuzzy number.

### 5.1.3. Comparison of triangular intuitionistic fuzzy numbers

Puri and Yadav [83] used the following method for comparing triangular intuitionistic fuzzy numbers.

If  $\tilde{A} = (a_1, a_2, a_3; a_4, a_2, a_5)$  and  $\tilde{B} = (b_1, b_2, b_3; b_4, b_2, b_5)$  are two triangular intuitionistic fuzzy numbers. Then,

$$(i) \tilde{A} \succcurlyeq \tilde{B} \Leftrightarrow \mathfrak{R}(\tilde{A}) \geq \mathfrak{R}(\tilde{B})$$

$$(ii) \tilde{A} \preccurlyeq \tilde{B} \Leftrightarrow \mathfrak{R}(\tilde{A}) \leq \mathfrak{R}(\tilde{B})$$

$$(iii) \tilde{A} \approx \tilde{B} \Leftrightarrow \mathfrak{R}(\tilde{A}) = \mathfrak{R}(\tilde{B})$$

where,

$$\mathfrak{R}(\tilde{A}) = \left( \frac{a_1 + a_3 + 4a_2 + a_4 + a_5}{8} \right) \text{ and } \mathfrak{R}(\tilde{B}) = \left( \frac{b_1 + b_3 + 4b_2 + b_4 + b_5}{8} \right)$$

## 5.2 Existing intuitionistic fuzzy DEA models

Puri and Yadav [83] proposed the optimistic intuitionistic fuzzy CCR DEA model-5.1 and pessimistic intuitionistic fuzzy CCR DEA model-5.1, respectively, to evaluate the best

relative intuitionistic fuzzy efficiency and the worst relative intuitionistic fuzzy efficiency of  $p^{th}$  DMU.

### Optimistic intuitionistic fuzzy CCR DEA model-5.1

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}; x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}) \approx (1,1,1; 1,1,1),$$

$$\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj})$$

$$- \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \leq (0,0,0; 0,0,0), \forall j,$$

$$= 1,2,3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1,2,3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1,2,3, \dots, m, \varepsilon > 0.$$

### Pessimistic intuitionistic fuzzy CCR DEA model-5.1

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}; x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}) \approx (1,1,1; 1,1,1),$$

$$\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rk}, y_2^{rk}, y_3^{rk}; y_4^{rk}, y_2^{rk}, y_5^{rk})$$

$$- \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ik}, x_2^{ik}, x_3^{ik}; x_4^{ik}, x_2^{ik}, x_5^{ik}) \geq (0,0,0; 0,0,0), \forall j,$$

$$= 1,2,3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1,2,3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1,2,3, \dots, m, \varepsilon > 0.$$

### 5.3 Existing method

Puri and Yadav [83] proposed the following method to evaluate the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of DMUs.

**Step 1:** Using the arithmetic operations of triangular intuitionistic fuzzy numbers, presented in Section 5.1.1, the optimistic intuitionistic fuzzy CCR DEA model-5.1 and the pessimistic intuitionistic fuzzy CCR DEA model-5.1 can be transformed into the optimistic intuitionistic fuzzy CCR DEA model-5.2 and the pessimistic intuitionistic fuzzy CCR DEA model-5.2 respectively.

#### Optimistic intuitionistic fuzzy CCR DEA model-5.2

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \sum_{r=1}^s (u_1^r y_1^{rp}, u_2^r y_2^{rp}, u_3^r y_3^{rp}; u_4^r y_4^r, u_2^r y_2^{rp}, u_5^r y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m (v_1^i x_1^{ip}, v_2^i x_2^{ip}, v_3^i x_3^{ip}; v_4^i x_4^{ip}, v_2^i x_2^{ip}, v_5^i x_5^{ip}) \approx (1,1,1; 1,1,1),$$

$$\sum_{r=1}^s (u_1^r y_1^{rk}, u_2^r y_2^{rk}, u_3^r y_3^{rk}; u_4^r y_4^{rk}, u_2^r y_2^{rk}, u_5^r y_5^{rk}) - \sum_{i=1}^m (v_1^i x_1^{ik}, v_2^i x_2^{ik}, v_3^i x_3^{ik}; v_4^i x_4^{ik}, v_2^i x_2^{ik}, v_5^i x_5^{ik}) \\ \leq (0,0,0; 0,0,0), \forall j = 1,2,3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1,2,3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1,2,3, \dots, m, \varepsilon > 0.$$

### Pessimistic intuitionistic fuzzy CCR DEA model-5.2

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx \sum_{r=1}^s (u_1^r y_1^{rp}, u_2^r y_2^{rp}, u_3^r y_3^{rp}; u_4^r y_4^r, u_2^r y_2^{rp}, u_5^r y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m (v_1^i x_1^{ip}, v_2^i x_2^{ip}, v_3^i x_3^{ip}; v_4^i x_4^{ip}, v_2^i x_2^{ip}, v_5^i x_5^{ip}) \approx (1,1,1; 1,1,1),$$

$$\sum_{r=1}^s (u_1^r y_1^{rj}, u_2^r y_2^{rj}, u_3^r y_3^{rj}; u_4^r y_4^r, u_2^r y_2^{rj}, u_5^r y_5^{rj}) - \sum_{i=1}^m (v_1^i x_1^{ij}, v_2^i x_2^{ij}, v_3^i x_3^{ij}; v_4^i x_4^i, v_2^i x_2^{ij}, v_5^i x_5^{ij}) \\ \geq (0,0,0; 0,0,0), \forall j = 1,2,3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r, u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1,2,3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1,2,3, \dots, m, \varepsilon > 0.$$

**Step 2:** Using Definition 5.4 and the method for comparing triangular intuitionistic fuzzy numbers, presented in Section 5.1.2, the optimistic intuitionistic fuzzy CCR DEA model-5.2 and

the pessimistic intuitionistic fuzzy CCR DEA model-5.2 can be transformed into optimistic crisp CCR DEA model-5.3 and the pessimistic crisp CCR DEA model-5.3 respectively.

### Optimistic crisp CCR DEA model-5.3

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = E_p^{BEST} = \sum_{r=1}^s \mathfrak{R}(u_1^r y_1^{rp}, u_2^r y_2^{rp}, u_3^r y_3^{rp}; u_4^r y_4^r, u_2^r y_2^{rp}, u_5^r y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m \mathfrak{R}(v_1^i x_1^{ip}, v_2^i x_2^{ip}, v_3^i x_3^{ip}; v_4^i x_4^{ip}, v_2^i x_2^{ip}, v_5^i x_5^{ip}) = \mathfrak{R}(1,1,1; 1,1,1),$$

$$\sum_{r=1}^s \mathfrak{R}(u_1^r y_1^{rk}, u_2^r y_2^{rk}; u_3^r y_3^{rk}, u_4^r y_4^{rk}, u_2^r y_2^{rk}, u_5^r y_5^{rk})$$

$$- \sum_{i=1}^m \mathfrak{R}(v_1^i x_1^{ik}, v_2^i x_2^{ik}, v_3^i x_3^{ik}; v_4^i x_4^{ik}, v_2^i x_2^{ik}, v_5^i x_5^{ik}) \leq \mathfrak{R}(0,0,0; 0,0,0), \forall j$$

$$= 1,2,3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1,2,3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1,2,3, \dots, m, \quad \varepsilon > 0.$$

### Pessimistic crisp CCR DEA model-5.3

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = E_p^{WORST} = \left( \sum_{r=1}^s \mathfrak{R}(u_1^r y_1^{rp}, u_2^r y_2^{rp}, u_3^r y_3^{rp}; u_4^r y_4^r, u_2^r y_2^{rp}, u_5^r y_5^{rp}) \right) \right]$$

Subject to

$$\left( \sum_{i=1}^m \mathfrak{R}(v_1^i x_1^{ip}, v_2^i x_2^{ip}, v_3^i x_3^{ip}; v_4^i x_4^{ip}, v_2^i x_2^{ip}, v_5^i x_5^{ip}) \right) = \mathfrak{R}(1,1,1; 1,1,1),$$

$$\left( \sum_{r=1}^s \mathfrak{R}(u_1^r y_1^{rk}, u_2^r y_2^{rk}, u_3^r y_3^{rk}, u_4^r y_4^{rk}, u_2^r y_2^{rk}, u_5^r y_5^{rk}) \right. \\ \left. - \sum_{i=1}^m \mathfrak{R}(v_1^i x_1^{ik}, v_2^i x_2^{ik}, v_3^i x_3^{ik}; v_4^i x_4^{ik}, v_2^i x_2^{ik}, v_5^i x_5^{ik}) \right) \geq \mathfrak{R}(0,0,0; 0,0,0), \forall j \\ = 1,2,3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1,2,3, \dots, s$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1,2,3, \dots, m, \quad \varepsilon > 0.$$

**Step 3:** The optimistic crisp CCR DEA model-5.3 and the pessimistic crisp CCR DEA model-5.3 can be transformed into optimistic crisp CCR DEA model-5.4 and the pessimistic crisp CCR DEA model-5.4 respectively.

#### Optimistic crisp CCR DEA model-5.4

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = E_p^{BEST} = \sum_{r=1}^s \left( \frac{u_1^r y_1^{rp} + u_3^r y_3^{rp} + 4u_2^r y_2^{rp} + u_4^r y_4^{rp} + u_5^r y_5^{rp}}{8} \right) \right]$$

Subject to

$$\sum_{i=1}^m \left( \frac{v_1^i x_1^{ip} + v_2^i x_2^{ip} + v_3^i x_3^{ip} + v_4^i x_4^{ip} + v_2^i x_2^{ip} + v_5^i x_5^{ip}}{8} \right) = 1,$$

$$\sum_{r=1}^s \left( \frac{u_1^r y_1^{rk} + u_3^r y_3^{rk} + 4u_2^r y_2^{rk} + u_4^r y_4^{rk} + u_5^r y_5^{rk}}{8} \right) \\ - \sum_{i=1}^m \left( \frac{v_1^i x_1^{ik} + v_3^i x_3^{ik} + 4v_2^i x_2^{ik} + v_4^i x_4^{ik} + v_5^i x_5^{ik}}{8} \right) \leq 0, \forall j = 1,2,3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1,2,3, \dots, s$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Pessimistic crisp CCR DEA model-5.4**

$$\text{Minimize} \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = E_p^{WORST} = \sum_{r=1}^s \left( \frac{u_1^r y_1^{rp} + u_3^r y_3^{rp} + 4u_2^r y_2^{rp} + u_4^r y_4^{rp} + u_5^r y_5^{rp}}{8} \right) \right]$$

Subject to

$$\sum_{i=1}^m \left( \frac{v_1^i x_1^{ip} + v_2^i x_2^{ip} + v_3^i x_3^{ip} + v_4^i x_4^{ip} + v_2^i x_2^{ip} + v_5^i x_5^{ip}}{8} \right) = 1$$

$$\sum_{r=1}^s \left( \frac{u_1^r y_1^{rk} + u_3^r y_3^{rk} + 4u_2^r y_2^{rk} + u_4^r y_4^{rk} + u_5^r y_5^{rk}}{8} \right)$$

$$- \sum_{i=1}^m \left( \frac{v_1^i x_1^{ik} + v_3^i x_3^{ik} + 4v_2^i x_2^{ik} + v_4^i x_4^{ik} + v_5^i x_5^{ik}}{8} \right) \geq 0, \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Step 4:** Find the optimal value ( $E_p^{BEST}$ ), representing the relative best crisp efficiency of  $p^{th}$

DMU, by solving optimistic crisp CCR DEA model-5.4.

**Step 5:** Find the optimal value ( $E_p^{WORST}$ ), representing the relative worst crisp efficiency of  $p^{th}$

DMU, by solving pessimistic crisp CCR DEA model-5.4.

**Step 6:** Find the relative geometric crisp efficiency  $E_p^{GEOMETRIC}$  of  $p^{th}$  DMU by putting the

$$\text{values } E_p^{BEST} \text{ and } E_p^{WORST}, \text{ obtained in Step 4 and Step 5, in } E_p^{GEOMETRIC} = \sqrt{E_p^{BEST} \times E_p^{WORST}}.$$

## 5.4 Flaws in the existing intuitionistic fuzzy CCR DEA models

In this section, it is pointed out that Puri and Yadav [83] have considered a mathematical incorrect assumption to obtain the optimistic intuitionistic fuzzy CCR DEA model 5.1 as well as pessimistic intuitionistic fuzzy CCR DEA model 5.1 hence these intuitionistic fuzzy CCR DEA mode, proposed by Puri and Yadav [83], are not valid and cannot be used to evaluate the relative geometric crisp efficiency of DMUs.

### 5.4.1 Origin of existing intuitionistic fuzzy CCR DEA models

The intuitionistic fuzzy CCR DEA models, proposed by Puri and Yadav [83], can be obtained as follows:

**Step 1:** If there are  $n$  DMUs then the best relative crisp efficiency ( $E_p^{BEST}$ ) and the worst relative crisp efficiency ( $E_p^{WORST}$ ) of the  $p^{th}$  DMU can be obtained by solving the optimistic CCR DEA model-5.5 and pessimistic CCR DEA model-5.5 respectively.

#### Optimistic CCR DEA model-5.5

$$\text{Maximize } \left[ E_p^{BEST} = \frac{\text{Virtual output of } p^{th} \text{ DMU}}{\text{Virtual input of } p^{th} \text{ DMU}} \right]$$

Subject to

$$\text{Virtual output of } j^{th} \text{ DMU} - \text{Virtual input of } j^{th} \text{ DMU} \leq 0, \forall j.$$

#### Pessimistic crisp CCR DEA model-5.5

$$\text{Minimize } \left[ E_p^{WORST} = \frac{\text{Virtual output of } p^{th} \text{ DMU}}{\text{Virtual input of } p^{th} \text{ DMU}} \right]$$

Subject to

Virtual output of  $j^{th}$  DMU – Virtual input of  $j^{th}$  DMU  $\geq 0, \forall j$ .

If each DMU have  $m$  inputs ( $x_{ij}; i = 1, 2, \dots, m; j = 1, 2, \dots, n$ ) and  $s$  outputs ( $y_{rj}; r = 1, 2, \dots, s; j = 1, 2, \dots, n$ ) then the optimistic crisp CCR DEA model-5.5 and the pessimistic CCR DEA model-5.5 can be transformed into the optimistic crisp CCR DEA model-5.6 and the pessimistic CCR DEA model-5.6 respectively.

### Optimistic crisp CCR DEA model-5.6

$$\text{Maximize } \left[ E_p^{BEST} = \frac{\sum_{r=1}^s u_r y_{rp}}{\sum_{i=1}^m v_i x_{ip}} \right]$$

Subject to

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0 \quad \forall j,$$

$$u_r, v_i \geq 0, \quad \forall r, i.$$

### Pessimistic crisp CCR DEA model-5.6

$$\text{Minimize } \left[ E_p^{WORST} = \frac{\sum_{r=1}^s u_r y_{rp}}{\sum_{i=1}^m v_i x_{ip}} \right]$$

Subject to

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \geq 0 \quad \forall j,$$

$$u_r, v_i \geq 0, \quad \forall r, i.$$

Replacing  $x_{ij}, y_{rj}, u_r$  and  $v_i$  by intuitionistic fuzzy numbers  $(x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}), (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}), (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r)$  and  $(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i)$  respectively, the optimistic crisp CCR DEA model-5.6 and the pessimistic crisp CCR DEA model-5.6 can be transformed into optimistic intuitionistic fuzzy CCR DEA model-5.7 and pessimistic intuitionistic fuzzy CCR DEA model-5.7 respectively.

### Optimistic intuitionistic fuzzy CCR DEA model-5.7

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \left( \frac{\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp})}{\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip})} \right) \right]$$

Subject to

$$\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) -$$

$$\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \leq (0,0,0; 0,0,0), \forall j = 1,2,3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1,2,3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1,2,3, \dots, m, \varepsilon > 0.$$

### Pessimistic intuitionistic fuzzy CCR DEA model-5.7

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx \left( \frac{\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp})}{\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip})} \right) \right]$$

Subject to

$$\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) -$$

$$\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r$$

$$= 1, 2, 3, \dots, s,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r), (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1, 2, 3, \dots, m, \varepsilon > 0.$$

**Step 2:** The optimistic intuitionistic fuzzy CCR DEA model-5.7 and pessimistic intuitionistic fuzzy CCR DEA model-5.7 can be transformed into optimistic crisp CCR DEA model-5.8 and pessimistic crisp CCR DEA model-5.8 respectively.

### Optimistic crisp CCR DEA model-5.8

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) \approx \mathfrak{R} \left( \frac{\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp})}{\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip})} \right) \right]$$

Subject to

$$\mathfrak{R} \left( \frac{\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) - \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij})}{\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij})} \right) \leq \varepsilon, \quad \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

### Pessimistic crisp CCR DEA model-5.8

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) \approx \mathfrak{R} \left( \frac{\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp})}{\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip})} \right) \right]$$

Subject to

$$\mathfrak{R} \left( \begin{array}{l} \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) - \\ \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \end{array} \right) \geq \varepsilon, \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Step 4:** The optimistic crisp CCR DEA model-5.8 and pessimistic crisp CCR DEA model-5.8 can be transformed into optimistic crisp CCR DEA model-5.9 and pessimistic crisp CCR DEA model-5.9 respectively.

#### Optimistic crisp CCR DEA model-5.9

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = \frac{\mathfrak{R}(\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}))}{\mathfrak{R}(\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}))} \right]$$

Subject to

$$\mathfrak{R} \left( \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) \right) -$$

$$\mathfrak{R} \left( \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \right) \leq \varepsilon, \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

### Pessimistic crisp CCR DEA model-5.9

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = \frac{\mathfrak{R}(\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}))}{\mathfrak{R}(\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}))} \right]$$

Subject to

$$\mathfrak{R} \left( \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) \right) -$$

$$\mathfrak{R} \left( \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \right) \geq \varepsilon, \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Step 5:** The optimistic crisp CCR DEA model-5.9 and pessimistic crisp CCR DEA model-5.9 can be transformed into optimistic crisp CCR DEA model-5.10 and pessimistic crisp CCR DEA model-5.10 respectively.

### Optimistic crisp CCR DEA model-5.10

$$\text{Maximize } \left[ \mathfrak{R}(\tilde{E}_p^{BEST}) = \mathfrak{R} \left( \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}) \right) \right]$$

Subject to

$$\mathfrak{R} \left( \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}) \right) = 1$$

$$\begin{aligned} & \mathfrak{R} \left( \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) \right) \\ & \quad - \mathfrak{R} \left( \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \right) \leq \varepsilon, \forall j \\ & \quad = 1, 2, 3, \dots, n, \end{aligned}$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

### Pessimistic crisp CCR DEA model-5.10

$$\text{Minimize } \left[ \mathfrak{R}(\tilde{E}_p^{WORST}) = \mathfrak{R} \left( \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}) \right) \right]$$

Subject to

$$\mathfrak{R} \left( \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}; x_3^{ip}, x_4^{ip}, x_2^{ip}, x_5^{ip}) \right) = 1$$

$$\begin{aligned} & \mathfrak{R} \left( \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj}) \right) \\ & \quad - \mathfrak{R} \left( \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \right) \leq \varepsilon, \forall j \\ & \quad = 1, 2, 3, \dots, n, \end{aligned}$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Step 6:** The optimistic crisp CCR DEA model-5.10 and pessimistic crisp CCR DEA model-5.10 can be transformed into optimistic intuitionistic fuzzy CCR DEA model-5.11 and pessimistic intuitionistic fuzzy CCR DEA model-5.11 respectively.

**Optimistic intuitionistic fuzzy CCR DEA model-5.11**

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \sum_{r=1}^s (u_1^r, u_2^r, u_3^r, u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}) \approx (1,1,1; 1,1,1)$$

$$\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj})$$

$$- \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \leq \varepsilon, \forall j = 1,2,3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1,2,3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1,2,3, \dots, m, \varepsilon > 0.$$

**Pessimistic intuitionistic fuzzy CCR DEA model-5.11**

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx \sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rp}, y_2^{rp}, y_3^{rp}; y_4^{rp}, y_2^{rp}, y_5^{rp}) \right]$$

Subject to

$$\sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ip}, x_2^{ip}, x_3^{ip}; x_4^{ip}, x_2^{ip}, x_5^{ip}) \approx (1,1,1,1)$$

$$\sum_{r=1}^s (u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \otimes (y_1^{rj}, y_2^{rj}, y_3^{rj}; y_4^{rj}, y_2^{rj}, y_5^{rj})$$

$$- \sum_{i=1}^m (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \otimes (x_1^{ij}, x_2^{ij}, x_3^{ij}; x_4^{ij}, x_2^{ij}, x_5^{ij}) \geq \varepsilon, \forall j = 1, 2, 3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1, 2, 3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1, 2, 3, \dots, m, \varepsilon > 0.$$

### 5.4.2 Mathematical incorrect assumptions

If  $(a_1, a_2, a_3; a_4, a_2, a_5)$  &  $(b_1, b_2, b_3; b_4, b_2, b_5)$  are two triangular intuitionistic fuzzy numbers then

$$\mathfrak{R} \left( \frac{(a_1, a_2, a_3; a_4, a_2, a_5)}{(b_1, b_2, b_3; b_4, b_2, b_5)} \right) = \mathfrak{R} \left( \frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}; \frac{a_4}{b_5}, \frac{a_2}{b_2}, \frac{a_5}{b_4} \right) = \frac{\frac{a_1}{b_3} + \frac{a_3}{b_1} + \frac{4a_2}{b_2} + \frac{a_4}{b_5} + \frac{a_5}{b_4}}{8}$$

and

$$\frac{\mathfrak{R}(a_1, a_2, a_3; a_4, a_2, a_5)}{\mathfrak{R}(b_1, b_2, b_3; b_4, b_2, b_5)} = \frac{a_1 + a_3 + 4a_2 + a_4 + a_5}{b_1 + b_3 + 4b_2 + b_4 + b_5}$$

It is obvious that

$$\mathfrak{R} \left( \frac{(a_1, a_2, a_3; a_4, a_2, a_5)}{(b_1, b_2, b_3; b_4, b_2, b_5)} \right) \neq \frac{\mathfrak{R}(a_1, a_2, a_3; a_4, a_2, a_5)}{\mathfrak{R}(b_1, b_2, b_3; b_4, b_2, b_5)}$$

However, Puri and Yadav have used the property

$$\mathfrak{R} \left( \frac{(a_1, a_2, a_3; a_4, a_2, a_5)}{(b_1, b_2, b_3; b_4, b_2, b_5)} \right) = \frac{\mathfrak{R}(a_1, a_2, a_3; a_4, a_2, a_5)}{\mathfrak{R}(b_1, b_2, b_3; b_4, b_2, b_5)}$$

in Step 4 of their proposed method to transform the optimistic crisp CCR DEA model-5.8 and pessimistic crisp CCR DEA model-5.8 into optimistic crisp CCR DEA model-5.9 and

pessimistic crisp CCR DEA model-5.9 respectively. Therefore, the optimistic intuitionistic fuzzy CCR DEA model-5.1 and pessimistic intuitionistic fuzzy CCR DEA model-5.1, proposed by Puri and Yadav, are not valid.

### **5.5 Proposed intuitionistic fuzzy DEA CCR models**

In Section 5.4, it is shown that the optimistic intuitionistic fuzzy CCR DEA model-5.1 and pessimistic intuitionistic fuzzy CCR DEA model-5.1, proposed by Puri and Yadav [83], are not valid and hence cannot be used for evaluating the relative geometric crisp efficiency of DMUs. In this section, new intuitionistic fuzzy CCR DEA models are proposed.

Replacing the trapezoidal fuzzy number with triangular intuitionistic fuzzy number in the optimistic fuzzy CCR DEA model-5.8 and pessimistic fuzzy CCR DEA model-5.8, proposed in Section-5.4 of Chapter 5, these models are transformed into optimistic intuitionistic fuzzy CCR DEA model 5.12 and the pessimistic intuitionistic fuzzy CCR DEA models-5.12

### **5.6 Proposed approach**

In this section, a new approach is proposed to evaluate the best relative intuitionistic fuzzy efficiency, worst relative intuitionistic fuzzy efficiency and hence, relative geometric efficiency of DMUs by using the optimistic intuitionistic fuzzy CCR DEA model-5.12 and pessimistic intuitionistic fuzzy CCR DEA model-5.12.

**Step 1:** Using the product of triangular intuitionistic fuzzy numbers, defined in Section 5.1.2, the optimistic intuitionistic fuzzy CCR DEA model-5.12 and pessimistic intuitionistic fuzzy CCR DEA model-5.12 can be transformed into optimistic intuitionistic fuzzy CCR DEA model-5.13 and pessimistic intuitionistic fuzzy CCR DEA model-5.13 respectively.

### Optimistic intuitionistic fuzzy CCR DEA model-5.13

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \approx \frac{\sum_{r=1}^s (u_1^r y_1^{rp}, u_2^r y_2^{rp}, u_3^r y_3^{rp}; u_4^r y_4^{rp}, u_2^r y_2^{rp}, u_5^r y_5^{rp})}{\sum_{i=1}^m (v_1^i x_1^{ip}, v_2^i x_2^{ip}, v_3^i x_3^{ip}; v_4^i x_4^{ip}, v_2^i x_2^{ip}, v_5^i x_5^{ip})} \right]$$

Subject to

$$\sum_{r=1}^s (u_1^r y_1^{rj}, u_2^r y_2^{rj}, u_3^r y_3^{rj}; u_4^r y_4^{rj}, u_2^r y_2^{rj}, u_5^r y_5^{rj}) \leq$$

$$\sum_{i=1}^m (v_1^i x_1^{ij}, v_2^i x_2^{ij}, v_3^i x_3^{ij}; v_4^i x_4^{ij}, v_2^i x_2^{ij}, v_5^i x_5^{ij}) \quad \forall j = 1, 2, 3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1, 2, 3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1, 2, 3, \dots, m, \varepsilon > 0.$$

### Pessimistic intuitionistic fuzzy CCR DEA model-5.13

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \approx \frac{\sum_{r=1}^s (u_1^r y_1^{rp}, u_2^r y_2^{rp}, u_3^r y_3^{rp}; u_4^r y_4^{rp}, u_2^r y_2^{rp}, u_5^r y_5^{rp})}{\sum_{i=1}^m (v_1^i x_1^{ip}, v_2^i x_2^{ip}, v_3^i x_3^{ip}; v_4^i x_4^{ip}, v_2^i x_2^{ip}, v_5^i x_5^{ip})} \right]$$

Subject to

$$\sum_{r=1}^s (u_1^r y_1^{rj}, u_2^r y_2^{rj}, u_3^r y_3^{rj}; u_4^r y_4^{rj}, u_2^r y_2^{rj}, u_5^r y_5^{rj}) \geq$$

$$\sum_{i=1}^m (v_1^i x_1^{ij}, v_2^i x_2^{ij}, v_3^i x_3^{ij}; v_4^i x_4^{ij}, v_2^i x_2^{ij}, v_5^i x_5^{ij}) \quad \forall j = 1, 2, 3, \dots, n,$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1, 2, 3, \dots, s,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1, 2, 3, \dots, m, \varepsilon > 0.$$

**Step 2:** Using the relation  $(a_1, a_2, a_3; a_4, a_2, a_5) \preceq (b_1, b_2, b_3; b_4, b_2, b_5), \Rightarrow a_1 \leq b_1, a_2 \leq b_2, a_3 \leq b_3, a_4 \leq b_4, a_5 \leq b_5$  and division of triangular intuitionistic fuzzy numbers, defined in Section 5.1.2, the optimistic intuitionistic fuzzy CCR DEA model-5.13 and pessimistic intuitionistic fuzzy CCR DEA model-5.13 can be transformed into optimistic intuitionistic fuzzy CCR DEA model-5.14 and pessimistic intuitionistic fuzzy CCR DEA model-5.14 respectively.

### Optimistic intuitionistic fuzzy CCR DEA model-5.14

$$\text{Maximize } \left[ \tilde{E}_p^{BEST} \right]$$

$$\approx \left( \frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}}, \frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}}, \frac{\sum_{r=1}^s u_3^r y_3^{rp}}{\sum_{i=1}^m v_1^i x_1^{ip}}, \frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}}, \frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}}, \frac{\sum_{r=1}^s u_5^r y_5^{rp}}{\sum_{i=1}^m v_4^i x_4^{ip}} \right)$$

Subject to

$$\sum_{r=1}^s u_1^r y_1^{rj} \leq \sum_{i=1}^m v_1^i x_1^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_2^r y_2^{rj} \leq \sum_{i=1}^m v_2^i x_2^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_3^r y_3^{rj} \leq \sum_{i=1}^m v_3^i x_3^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_4^r y_4^{rj} \leq \sum_{i=1}^m v_4^i x_4^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_5^r y_5^{rj} \leq \sum_{i=1}^m v_5^i x_5^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Pessimistic intuitionistic fuzzy CCR DEA model-5.14**

$$\text{Minimize } \left[ \tilde{E}_p^{WORST} \right.$$

$$\approx \left( \frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}}, \frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}}, \frac{\sum_{r=1}^s u_3^r y_3^{rp}}{\sum_{i=1}^m v_1^i x_1^{ip}}, \frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}}, \frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}}, \frac{\sum_{r=1}^s u_5^r y_5^{rp}}{\sum_{i=1}^m v_4^i x_4^{ip}} \right)$$

Subject to

$$\sum_{r=1}^s u_1^r y_1^{rj} \geq \sum_{i=1}^m v_1^i x_1^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_2^r y_2^{rj} \geq \sum_{i=1}^m v_2^i x_2^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_3^r y_3^{rj} \geq \sum_{i=1}^m v_3^i x_3^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_4^r y_4^{rj} \geq \sum_{i=1}^m v_4^i x_4^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\sum_{r=1}^s u_5^r y_5^{rj} \geq \sum_{i=1}^m v_5^i x_5^{ij} \quad \forall j = 1, 2, 3, \dots, n,$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2, 3, \dots, s,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \dots, m, \quad \varepsilon > 0.$$

**Step 3:** The intuitionistic fuzzy optimal value  $\left( \tilde{E}_p^{BEST} = \begin{pmatrix} E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}; \\ E_{p4}^{BEST}, E_{p2}^{BEST}, E_{p5}^{BEST} \end{pmatrix} \right)$ , representing

the best relative intuitionistic fuzzy efficiency of  $p^{th}$  DMU, as well as the intuitionistic fuzzy optimal value  $\left( \tilde{E}_p^{WORST} = \begin{pmatrix} E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}; \\ E_{p4}^{WORST}, E_{p2}^{WORST}, E_{p5}^{WORST} \end{pmatrix} \right)$ , representing the worst relative intuitionistic fuzzy efficiency of  $p^{th}$  DMU, can be obtained by solving the optimistic intuitionistic fuzzy CCR DEA model-5.14 and pessimistic intuitionistic fuzzy CCR DEA model-5.14 as follows:

**Step 3(a):** Find the optimal value  $(E_{p4}^{BEST})$  and  $(E_{p4}^{WORST})$  of the optimistic crisp CCR DEA model-5.15 and pessimistic CCR DEA model-5.15 respectively.

#### **Optimistic crisp CCR DEA model-5.15**

$$\text{Maximize } \left[ E_{p4}^{BEST} = \frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} \right]$$

Subject to constraints of optimistic intuitionistic fuzzy CCR DEA model-5.14 with the following additional constraint

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} \leq 1.$$

#### **Pessimistic crisp CCR DEA model-5.15**

$$\text{Minimize } \left[ E_{p4}^{WORST} = \frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} \right]$$

Subject to

All the constraints of pessimistic intuitionistic fuzzy CCR DEA model-5.14 with the following additional constraint

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} \geq 1,$$

**Step 3(b):** Find the optimal value ( $E_{p1}^{BEST}$ ) and ( $E_{p1}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.16 and pessimistic CCR DEA model-5.16 respectively.

### Optimistic crisp CCR DEA model-5.16

$$\text{Maximize } \left[ E_{p1}^{BEST} = \frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} \right]$$

Subject to

All Constraints of optimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{BEST},$$

$$E_{p4}^{BEST} \leq \frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} \leq 1.$$

### Pessimistic crisp CCR DEA model-5.16

$$\text{Minimize } \left[ E_{p1}^{WORST} = \frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} \right]$$

Subject to

All the constraints of pessimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{WORST},$$

$$E_{p4}^{WORST} \leq \frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}}.$$

**Step 3(c):** Find the optimal value ( $E_{p2}^{BEST}$ ) and ( $E_{p2}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.17 and pessimistic CCR DEA model-5.17 respectively.

#### Optimistic crisp CCR DEA model-5.17

$$\text{Maximize } \left[ E_{p2}^{BEST} = \sum_{r=1}^s \frac{u_2^r y_2^{rp}}{v_2^i x_2^{ip}} \right]$$

Subject to

Constraints of optimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{BEST},$$

$$\frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} = E_{p1}^{BEST},$$

$$E_{p1}^{BEST} \leq \sum_{r=1}^s \frac{u_2^r y_2^{rp}}{v_2^i x_2^{ip}} \leq 1.$$

### Pessimistic crisp CCR DEA model-5.17

$$\text{Minimize } \left[ E_{p2}^{WORST} = \sum_{r=1}^s \frac{u_2^r y_2^{rp}}{v_2^i x_2^{ip}} \right]$$

Subject to

Constraints of pessimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{WORST}$$

$$\frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} = E_{p1}^{WORST},$$

$$E_{p1}^{WORST} \leq \sum_{r=1}^s \frac{u_2^r y_2^{rp}}{v_2^i x_2^{ip}}.$$

**Step 3(d):** Find the optimal value ( $E_{p3}^{BEST}$ ) and ( $E_{p3}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.18 and pessimistic CCR DEA model-5.18 respectively.

### Optimistic crisp CCR DEA model-5.18

$$\text{Maximize } \left[ E_{p3}^{BEST} = \sum_{r=1}^s \frac{u_3^r y_3^{rp}}{v_1^i x_1^{ip}} \right]$$

Subject to

Constraints of optimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{BEST},$$

$$\frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} = E_{p1}^{BEST},$$

$$\frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}} = E_{p2}^{BEST},$$

$$E_{p2}^{BEST} \leq \sum_{r=1}^s \frac{u_3^r y_3^{rp}}{v_1^i x_1^{ip}} \leq 1.$$

### Pessimistic crisp CCR DEA model-5.18

$$\text{Minimize } \left[ E_{p3}^{WORST} = \sum_{r=1}^s \frac{u_3^r y_3^{rp}}{v_1^i x_1^{ip}} \right]$$

Subject to

Constraints of optimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{WORST}$$

$$\frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} = E_{p1}^{WORST},$$

$$\frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}} = E_{p2}^{WORST},$$

$$E_{p2}^{WORST} \leq \sum_{r=1}^s \frac{u_3^r y_3^{rp}}{v_1^i x_1^{ip}}.$$

**Step 3(e):** Find the optimal value ( $E_{p5}^{BEST}$ ) and ( $E_{p5}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.19 and pessimistic CCR DEA model-5.19 respectively.

### Optimistic crisp CCR DEA model-5.19

$$\text{Maximize } \left[ E_{p5}^{BEST} = \sum_{r=1}^s \frac{u_5^r y_5^{rp}}{v_4^i x_4^{ip}} \right]$$

Subject to

All the constraints of optimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{BEST},$$

$$\frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} = E_{p1}^{BEST},$$

$$\frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}} = E_{p2}^{BEST},$$

$$E_{p4}^{BEST} \leq \sum_{r=1}^s \frac{u_5^r y_5^{rp}}{v_4^i x_4^{ip}} \leq 1.$$

### Pessimistic crisp CCR DEA model-5.19

$$\text{Minimize } \left[ E_{p5}^{WORST} = \sum_{r=1}^s \frac{u_5^r y_5^{rp}}{v_4^i x_4^{ip}} \right]$$

Subject to

All the constraints of pessimistic crisp CCR DEA model-5.14 with the following additional constraints:

$$\frac{\sum_{r=1}^s u_4^r y_4^{rp}}{\sum_{i=1}^m v_5^i x_5^{ip}} = E_{p4}^{WORST}$$

$$\frac{\sum_{r=1}^s u_1^r y_1^{rp}}{\sum_{i=1}^m v_3^i x_3^{ip}} = E_{p1}^{WORST},$$

$$\frac{\sum_{r=1}^s u_2^r y_2^{rp}}{\sum_{i=1}^m v_2^i x_2^{ip}} = E_{p2}^{WORST},$$

$$E_{p3}^{WORST} \leq \sum_{r=1}^s \frac{u_5^r y_5^{rp}}{v_4^i x_4^{ip}}.$$

**Step 4:** Using the values of  $E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}; E_{p4}^{BEST}, E_{p5}^{BEST}$  and

$E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}; E_{p4}^{WORST}, E_{p2}^{WORST}, E_{p5}^{WORST}$ , obtained in Step (3a) to Step (3e), find the

intuitionistic fuzzy optimal value  $(\tilde{E}_p^{BEST} = (E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}; E_{p4}^{BEST}, E_{p5}^{BEST}))$  of optimistic

intuitionistic fuzzy DEA model-5.14, representing the best relative intuitionistic fuzzy efficiency

of  $p^{th}$  DMU, as well as intuitionistic fuzzy optimal value

$(\tilde{E}_p^{WORST} = (E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}; E_{p4}^{WORST}, E_{p2}^{WORST}, E_{p5}^{WORST}))$  of pessimistic intuitionistic

fuzzy DEA model-5.14, representing the worst relative intuitionistic fuzzy efficiency of

$p^{th}$  DMU.

**Step 5:** Find the crisp optimal value  $(E_p^{BEST} = \mathfrak{R}(\tilde{E}_p^{BEST}))$ , representing the best relative crisp efficiency of  $p^{th}$  DMU.

**Step 6:** Find the crisp optimal value  $(E_p^{WORST} = \mathfrak{R}(\tilde{E}_p^{WORST}))$ , representing the worst relative crisp efficiency of  $p^{th}$  DMU.

**Step 7:** Find the relative geometric crisp efficiency ( $E_p^{GEOMETRIC}$ ) of  $p^{th}$  DMU by putting the

values  $E_p^{BEST}$  and  $E_p^{WORST}$ , obtained in Step 5 and Step 6, in  $E_p^{GEOMETRIC} = \sqrt{E_p^{BEST} \times E_p^{WORST}}$ .

### 5.7 Exact relative geometric crisp efficiency of real life problem

Puri and Yadav [83] evaluated the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of 16 branches of State Bank of Patiala, Punjab, India by considering the input and output data shown in Table 5.1 and using the optimistic intuitionistic fuzzy CCR DEA model-5.1 as well as pessimistic intuitionistic fuzzy CCR DEA model-5.1. However, as discussed in Section 5.3, that the optimistic intuitionistic fuzzy CCR DEA model-5.1 as well as pessimistic intuitionistic fuzzy CCR DEA model-5.1 are not valid. Therefore, the best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of 16 branches of State Bank of Patiala, Punjab, India, evaluated by Puri and Yadav [83], is not exact.

In this section, to illustrate the proposed method the exact intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of these Banks is evaluated by using the proposed approach.

**Table 5.1 Input-Output for 16 bank branches**

| Sr.no. | Branch Name     | Inputs                 |                                |      | Outputs |       |
|--------|-----------------|------------------------|--------------------------------|------|---------|-------|
|        |                 | Labour                 | OE                             | IE   | II      | OI    |
| 1      | Amritsar (M.M)  | (15,17,19;13,17,21)    | (.39, .44, .46; .26, .44, .63) | 9.16 | 1.85    | 0.33  |
| 2      | Patti           | (14, 16, 18;12,16,20)  | (.46, .54, .65, .38, .54, .73) | 2.68 | 0.67    | 0.41  |
| 3      | Amritsar E.M.N. | (9, 11, 13; 6, 11, 15) | (.47, .54, .57; .42, .54, .60) | 4.24 | 10.73   | 0.49  |
| 4      | Verka           | (10, 13, 15; 8, 13,17) | (.19, .21, .24; .18, .21, .25) | 2.08 | 1       | 0.084 |
| 5      | Amritsar C.W.G. | (11, 14, 16; 9,14,19)  | (.25, .29, .31; .23, .29, .33) | 4.73 | 2.88    | 0.2   |
| 6      | Amritsar K.J.S  | (18,21,24; 15,21,27)   | (.28, .29, .30; .24,.29,.31)   | 4.58 | 4.97    | 0.85  |

|    |                              |                        |                                |      |      |       |
|----|------------------------------|------------------------|--------------------------------|------|------|-------|
| 7  | Mananwala<br>A. D. B         | (11, 14, 17; 9, 14,19) | (.21, .23, .24; .19, .23, .25) | 1.33 | 3.94 | 0.28  |
| 8  | Baba<br>Bakala               | (9, 12, 13; 7, 12, 16) | (.56, .60, .62; .52, .60, .64) | 2.98 | 2.16 | 0.3   |
| 9  | Chabhal                      | (6, 9, 12; 6, 9, 12)   | (.16, .17, .19; .13, .17, .20) | 1.48 | 2.58 | 0.15  |
| 10 | Lohaka                       | (5, 7, 9; 3, 7, 10)    | (.10, .11, .12; .08, .11, .13) | 0.75 | 1    | 0.13  |
| 11 | Harsha<br>Chhina             | (4, 6, 8; 3, 6, 9)     | (.15, .18, .20; .12, .18, .21) | 0.87 | 1.73 | 0.13  |
| 12 | Jhanjhoti                    | (8, 10, 13; 6, 10, 14) | (.18, .20, .22; .15, .20, .23) | 0.9  | 1.26 | 0.069 |
| 13 | Taran<br>Taran               | (9, 11, 13; 7, 11, 15) | (.19, .22, .24; .16, .22, .26) | 1.51 | 3.53 | 0.26  |
| 14 | Amritsar<br>(Textile)        | (9, 11, 14; 8, 11, 15) | (.20, .21, .23; .18, .21, .24) | 2.98 | 5.98 | 0.27  |
| 15 | Rayya<br>Mandi               | (7, 10, 12; 6, 10, 14) | (.21, .22, .24; .17, .22, .26) | 1.99 | 1.79 | 0.16  |
| 16 | Amritsar<br>(Civil<br>Lines) | (6, 8, 10; 5, 8, 12)   | (.25, .39, .44, .19, .39, .47) | 3.64 | 7.1  | 0.37  |

(OE; Operating Expenses, IE; Interest Expenses, II; Interest Income, OI; Other Income)

### 5.7.1 Proposed intuitionistic fuzzy CCR DEA models

The best relative intuitionistic fuzzy efficiency as well as worst best relative intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of  $DMU_1$  (1<sup>st</sup> Branch) can be obtained by solving optimistic intuitionistic fuzzy CCR DEA model-5.20 and pessimistic intuitionistic fuzzy CCR DEA model-5.20.

**Optimistic intuitionistic fuzzy CCR DEA model-5.20**

$$\text{Maximize } \left[ \begin{array}{l} \tilde{E}_A^{BEST} \approx ((E_A^{11})^{BEST}, (E_A^{12})^{BEST}, (E_A^{13})^{BEST}; (E_A^{14})^{BEST}, (E_A^{12})^{BEST}, (E_A^{15})^{BEST}) \\ \\ = \left( \frac{(1.85)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + (0.33)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25})}{(15,17,19; 13,17,21)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + (.39, .44, .46; .26, .44, .63)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + (9.16)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35})} \right) \end{array} \right]$$

Subject to

$$\left[ \begin{array}{l} (1.85)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.33)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \leq \left[ \begin{array}{l} (15,17,19; 13,17,21)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.39, .44, .46; .26, .44, .63)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (9.16)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (0.67)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.41)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \leq \left[ \begin{array}{l} (14, 16, 18; 12,16,20)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.46, .54, .65, .38, .54, .73)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.68)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (10.73)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.49)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \leq \left[ \begin{array}{l} (9, 11, 13; 6, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.47, .54, .57; .42, .54, .60)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (4.24)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.84)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (10, 13, 15; 8, 13, 17)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.19, .21, .24; .18, .21, .25)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.08)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.88)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.20)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (11, 14, 16; 9, 14, 19)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.25, .29, .31; .23, .29, .33)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (4.73)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (4.97)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.85)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (18, 21, 24; 15, 21, 27)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.28, .29, .30; .24, .29, .31)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (4.58)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.94)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.28)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (11, 14, 17; 9, 14, 19)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.21, .23, .24; .19, .23, .25)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.33)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.16)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.30)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (9, 12, 13; 7, 12, 16)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.56, .60, .62; .52, .60, .64)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.98)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.58)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.15)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (6, 9, 12; 6, 9, 12)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.16, .17, .19; .13, .17, .20)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.48)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.13)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (5, 7, 9; 3, 7, 10)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.10, .11, .12; .08, .11, .13)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (0.75)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.73)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.13)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (4, 6, 8; 3, 6, 9)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.15, .18, .20; .12, .18, .21)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (0.87)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.26)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.069)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (8, 10, 13; 6, 10, 14)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.18, .20, .22; .15, .20, .23)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (0.90)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.53)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.26)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \ll$$

$$\left[ \begin{array}{l} (9, 11, 13; 7, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.19, .22, .24; .16, .22, .26)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.51)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (5.98)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.27)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \leq$$

$$\left[ \begin{array}{l} (9, 11, 14; 8, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.20, .21, .23; .18, .21, .24)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.98)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.79)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.16)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \leq$$

$$\left[ \begin{array}{l} (7, 10, 12; 6, 7, 14)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.21, .22, .24; .17, .22, .26)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.99)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (7.10)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.37)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \leq$$

$$\left[ \begin{array}{l} (6, 8, 10; 5, 8, 12)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.25, .39, .44, .19, .39, .47)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (3.64)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \geq \varepsilon, \forall r = 1, 2, (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \geq \varepsilon, \forall i = 1, 2, 3, \varepsilon > 0.$$

### Pessimistic intuitionistic fuzzy CCR DEA model-5.20

$$\text{Minimize } \left[ \begin{array}{l} \tilde{E}_A^{BEST} \approx ((E_A^{11})^{BEST}, (E_A^{12})^{BEST}, (E_A^{13})^{BEST}; (E_A^{14})^{BEST}, (E_A^{12})^{BEST}, (E_A^{15})^{BEST}) \end{array} \right]$$

$$= \left( \frac{\begin{array}{l} (1.85)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.33)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array}}{\begin{array}{l} (15, 17, 19; 13, 17, 21)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.39, .44, .46; .26, .44, .63)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (9.16)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array}} \right)$$

Subject to

$$\left[ \begin{array}{l} (1.85)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.33)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (15,17,19; 13,17,21)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.39, .44, .46; .26, .44, .63)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (9.16)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (0.67)(u_1^{11}, u_2^{12}, u_3^{13}, u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.41)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (14, 16, 18; 12,16,20)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.46, .54, .65, .38, .54, .73)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.68)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (10.73)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.49)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9, 11, 13; 6, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.47, .54, .57; .42, .54, .60)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (4.24)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (.084)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (10, 13, 15; 8, 13, 17)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.19, .21, .24; .18, .21, .25)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.08)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.88)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.20)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (11, 14, 16; 9, 14, 19)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.25, .29, .31; .23, .29, .33)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (4.73)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (4.97)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.85)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (18, 21, 24; 15, 21, 27)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.28, .29, .30; .24, .29, .31)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (4.58)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.94)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.28)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (11, 14, 17; 9, 14, 19)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.21, .23, .24; .19, .23, .25)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.33)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.16)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.30)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9, 12, 13; 7, 12, 16)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.56, .60, .62; .52, .60, .64)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.98)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.58)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.15)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (6, 9, 12; 6, 9, 12)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.16, .17, .19; .13, .17, .20)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.48)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.13)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (5, 7, 9; 3, 7, 10)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.10, .11, .12; .08, .11, .13)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (0.75)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.73)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.13)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (4, 6, 8; 3, 6, 9)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.15, .18, .20; .12, .18, .21)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (0.87)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.26)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.069)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (8, 10, 13; 6, 10, 14)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.18, .20, .22; .15, .20, .23)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (0.90)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.53)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.26)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9, 11, 13; 7, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.19, .22, .24; .16, .22, .26)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.51)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (5.98)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.27)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9, 11, 14; 8, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.20, .21, .23; .18, .21, .24)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.98)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.79)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.16)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (7, 10, 12; 6, 7, 14)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.21, .22, .24; .17, .22, .26)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (1.99)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (7.10)(u_1^{11}, u_2^{12}, u_3^{13}; u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.37)(u_1^{21}, u_2^{22}, u_3^{23}; u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (6, 8, 10; 5, 8, 12)(v_1^{11}, v_2^{12}, v_3^{13}; v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.25, .39, .44, .19, .39, .47)(v_1^{21}, v_2^{22}, v_3^{23}; v_4^{24}, v_2^{22}, v_5^{25}) + \\ (3.64)(v_1^{31}, v_2^{32}, v_3^{33}; v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \succcurlyeq \varepsilon, \forall r = 1, 2,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \succcurlyeq \varepsilon, \forall i = 1, 2, 3, \varepsilon > 0.$$

### 5.7.2 Exact relative geometric crisp efficiency of $DMU_1$ (Amritsar Branch, M.M.)

Using the method, proposed in Section 5.6, the exact relative optimistic intuitionistic fuzzy efficiency as well as pessimistic intuitionistic fuzzy efficiency and hence, relative geometric crisp efficiency of  $DMU_1$  can be obtained as follows:

**Step 1:** Using the product of triangular intuitionistic fuzzy numbers, defined in Section 5.1.2, the optimistic intuitionistic fuzzy CCR DEA model-5.20 and pessimistic intuitionistic fuzzy CCR DEA model-5.20 can be transformed into optimistic intuitionistic fuzzy CCR DEA model-5.21 and pessimistic intuitionistic fuzzy CCR DEA model-5.21 respectively.

### Optimistic intuitionistic fuzzy CCR DEA model-5.21

$$\text{Maximize } \left[ \begin{array}{l} \tilde{E}_1^{BEST} \approx (E_{11}^{BEST}, E_{12}^{BEST}, E_{13}^{BEST}; E_{14}^{BEST}, E_{12}^{BEST}, E_{15}^{BEST}) \\ \\ = \left( \frac{\begin{array}{l} (1.85u_1^{11}, 1.85u_2^{12}, 1.85u_3^{13}; 1.85u_4^{14}, 1.85u_2^{12}, 1.85u_5^{15}) + \\ (0.33u_1^{21}, 0.33u_2^{22}, 0.33u_3^{23}; 0.33u_4^{24}, 0.33u_2^{22}, 0.33u_5^{25}) \\ (15v_1^{11}, 17v_2^{12}, 19v_3^{13}; 13v_4^{14}, 17v_2^{12}, 21v_5^{15}) + \\ (.39v_1^{21}, .44v_2^{22}, .46v_3^{23}; .26v_4^{24}, .44v_2^{22}, .63v_5^{25}) + \\ (9.16v_1^{31}, 9.16v_2^{32}, 9.16v_3^{33}; 9.16v_4^{34}, 9.16v_2^{32}, 9.16v_5^{35}) \end{array}}{\quad} \right) \end{array} \right]$$

Subject to

$$\left[ \begin{array}{l} (1.85u_1^{11}, 1.85u_2^{12}, 1.85u_3^{13}; 1.85u_4^{14}, 1.85u_2^{12}, 1.85u_5^{15}) + \\ (0.33u_1^{21}, 0.33u_2^{22}, 0.33u_3^{23}; 0.33u_4^{24}, 0.33u_2^{22}, 0.33u_5^{25}) \end{array} \right] \preceq \left[ \begin{array}{l} (15v_1^{11}, 17v_2^{12}, 19v_3^{13}; 13v_4^{14}, 17v_2^{12}, 21v_5^{15}) + \\ (.39v_1^{21}, .44v_2^{22}, .46v_3^{23}; .26v_4^{24}, .44v_2^{22}, .63v_5^{25}) + \\ (9.16v_1^{31}, 9.16v_2^{32}, 9.16v_3^{33}; 9.16v_4^{34}, 9.16v_2^{32}, 9.16v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (0.67u_1^{11}, 0.67u_2^{12}, 0.67u_3^{13}; 0.67u_4^{14}, 0.67u_2^{12}, 0.67u_5^{15}) + \\ (0.41u_1^{21}, 0.41u_2^{22}, 0.41u_3^{23}; 0.41u_4^{24}, 0.41u_2^{22}, 0.41u_5^{25}) \end{array} \right] \preceq \left[ \begin{array}{l} (14v_1^{11}, 16v_2^{12}, 18v_3^{13}; 12v_4^{14}, 16v_2^{12}, 20v_5^{15}) + \\ (.46v_1^{21}, .54v_2^{22}, .65v_3^{23}; .38v_4^{24}, .54v_2^{22}, .73v_5^{25}) + \\ (2.68v_1^{31}, 2.68v_2^{32}, 2.68v_3^{33}; 2.68v_4^{34}, 2.68v_2^{32}, 2.68v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (10.73u_1^{11}, 10.73u_2^{12}, 10.73u_3^{13}; 10.73u_4^{14}, 10.73u_2^{12}, 10.73u_5^{15}) + \\ (0.49u_1^{21}, 0.49u_2^{22}, 0.49u_3^{23}; 0.49u_4^{24}, 0.49u_2^{22}, 0.49u_5^{25}) \end{array} \right] \preceq \left[ \begin{array}{l} (9v_1^{11}, 11v_2^{12}, 13v_3^{13}; 6v_4^{14}, 11v_2^{12}, 15v_5^{15}) + \\ (.47v_1^{21}, .54v_2^{22}, .57v_3^{23}; .42v_4^{24}, .54v_2^{22}, .60v_5^{25}) + \\ (4.24v_1^{31}, 4.24v_2^{32}, 4.24v_3^{33}; 4.24v_4^{34}, 4.24v_2^{32}, 4.24v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00u_1^{11}, 1.00u_2^{12}, 1.00u_3^{13}; 1.00u_4^{14}, 1.00u_2^{12}, 1.00u_5^{15}) + \\ (.084u_1^{21}, .084u_2^{22}, .084u_3^{23}; .084u_4^{24}, .084u_2^{22}, .084u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (10v_1^{11}, 13v_2^{12}, 15v_3^{13}; 8v_4^{14}, 13v_2^{12}, 17v_5^{15}) + \\ (.19v_1^{21}, .21v_2^{22}, .24v_3^{23}; .18v_4^{24}, .21v_2^{22}, .25v_5^{25}) + \\ (2.08v_1^{31}, 2.08v_2^{32}, 2.08v_3^{33}; 2.08v_4^{34}, 2.08v_2^{32}, 2.08v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.88u_1^{11}, 2.88u_2^{12}, 2.88u_3^{13}; 2.88u_4^{14}, 2.88u_2^{12}, 2.88u_5^{15}) + \\ (0.20u_1^{21}, 0.20u_2^{22}, 0.20u_3^{23}; 0.20u_4^{24}, 0.20u_2^{22}, 0.20u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (11v_1^{11}, 14v_2^{12}, 16v_3^{13}; 9v_4^{14}, 14v_2^{12}, 19v_5^{15}) + \\ (.25v_1^{21}, .29v_2^{22}, .31v_3^{23}; .23v_4^{24}, .29v_2^{22}, .33v_5^{25}) + \\ (4.73v_1^{31}, 4.73v_2^{32}, 4.73v_3^{33}; 4.73v_4^{34}, 4.73v_2^{32}, 4.73v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (4.97u_1^{11}, 4.97u_2^{12}, 4.97u_3^{13}; 4.97u_4^{14}, 4.97u_2^{12}, 4.97u_5^{15}) + \\ (0.85u_1^{21}, 0.85u_2^{22}, 0.85u_3^{23}; 0.85u_4^{24}, 0.85u_2^{22}, 0.85u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (18v_1^{11}, 21v_2^{12}, 24v_3^{13}; 15v_4^{14}, 21v_2^{12}, 27v_5^{15}) + \\ (.28v_1^{21}, .29v_2^{22}, .30v_3^{23}; .24v_4^{24}, .29v_2^{22}, .31v_5^{25}) + \\ (4.58v_1^{31}, 4.58v_2^{32}, 4.58v_3^{33}; 4.58v_4^{34}, 4.58v_2^{32}, 4.58v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.94u_1^{11}, 3.94u_2^{12}, 3.94u_3^{13}; 3.94u_4^{14}, 3.94u_2^{12}, 3.94u_5^{15}) + \\ (0.28u_1^{21}, 0.28u_2^{22}, 0.28u_3^{23}; 0.28u_4^{24}, 0.28u_2^{22}, 0.28u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (11v_1^{11}, 14v_2^{12}, 17v_3^{13}; 9v_4^{14}, 14v_2^{12}, 19v_5^{15}) + \\ (.21v_1^{21}, .23v_2^{22}, .24v_3^{23}; .19v_4^{24}, .23v_2^{22}, .25v_5^{25}) + \\ (1.33v_1^{31}, 1.33v_2^{32}, 1.33v_3^{33}; 1.33v_4^{34}, 1.33v_2^{32}, 1.33v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.16u_1^{11}, 2.16u_2^{12}, 2.16u_3^{13}; 2.16u_4^{14}, 2.16u_2^{12}, 2.16u_5^{15}) + \\ (0.30u_1^{21}, 0.30u_2^{22}, 0.30u_3^{23}; 0.30u_4^{24}, 0.30u_2^{22}, 0.30u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (9v_2^{12}, 12v_2^{12}, 13v_3^{13}; 7v_4^{14}, 12v_2^{12}, 16v_5^{15}) + \\ (.56v_1^{21}, .60v_2^{22}, .62v_3^{23}; .52v_4^{24}, .60v_2^{22}, .64v_5^{25}) + \\ (2.98v_1^{31}, 2.98v_2^{32}, 2.98v_3^{33}; 2.98v_4^{34}, 2.98v_2^{32}, 2.98v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.58u_1^{11}, 2.58u_2^{12}, 2.58u_3^{13}; 2.58u_4^{14}, 2.58u_2^{12}, 2.58u_5^{15}) + \\ (0.15u_1^{21}, 0.15u_2^{22}, 0.15u_3^{23}; 0.15u_4^{24}, 0.15u_2^{22}, 0.15u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (6v_1^{11}, 9v_2^{12}, 12v_3^{13}; 6v_4^{14}, 9v_2^{12}, 12v_5^{15}) + \\ (.16v_1^{21}, .17v_2^{22}, .19v_3^{23}; .13v_4^{24}, .17v_2^{22}, .20v_5^{25}) + \\ (1.48v_1^{31}, 1.48v_2^{32}, 1.48v_3^{33}; 1.48v_4^{34}, 1.48v_2^{32}, 1.48v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00u_1^{11}, 1.00u_2^{12}, 1.00u_3^{13}; 1.00u_4^{14}, 1.00u_2^{12}, 1.00u_5^{15}) + \\ (0.13u_1^{21}, 0.13u_2^{22}, 0.13u_3^{23}; 0.13u_4^{24}, 0.13u_2^{22}, 0.13u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (5v_1^{11}, 7v_2^{12}, 9v_3^{13}; 3v_4^{14}, 7v_2^{12}, 10v_5^{15}) + \\ (.10v_1^{21}, .11v_2^{22}, .12v_3^{23}; .08v_4^{24}, .11v_2^{22}, .13v_5^{25}) + \\ (0.75v_1^{31}, 0.75v_2^{32}, 0.75v_3^{33}; 0.75v_4^{34}, 0.75v_2^{32}, 0.75v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.73u_1^{11}, 1.73u_2^{12}, 1.73u_3^{13}; 1.73u_4^{14}, 1.73u_2^{12}, 1.73u_5^{15}) + \\ (0.13u_1^{21}, 0.13u_2^{22}, 0.13u_3^{23}; 0.13u_4^{24}, 0.13u_2^{22}, 0.13u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (4v_1^{11}, 6v_2^{12}, 8v_3^{13}; 3v_4^{14}, 6v_2^{12}, 9v_5^{15}) + \\ (.15v_1^{21}, .18v_2^{22}, .20v_3^{23}; .12v_4^{24}, .18v_2^{22}, .21v_5^{25}) + \\ (0.87v_1^{31}, 0.87v_2^{32}, 0.87v_3^{33}; 0.87v_4^{34}, 0.87v_2^{32}, 0.87v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.26u_1^{11}, 1.26u_2^{12}, 1.26u_3^{13}; 1.26u_4^{14}, 1.26u_2^{12}, 1.26u_5^{15}) + \\ (0.069u_1^{21}, 0.069u_2^{22}, 0.069u_3^{23}; 0.069u_4^{24}, 0.069u_2^{22}, 0.069u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (8v_1^{11}, 10v_2^{12}, 13v_3^{13}; 6v_4^{14}, 10v_2^{12}, 14v_5^{15}) + \\ (.18v_1^{21}, .20v_2^{22}, .22v_3^{23}; .15v_4^{24}, .20v_2^{22}, .23v_5^{25}) + \\ (0.90v_1^{31}, 0.90v_2^{32}, 0.90v_3^{33}; 0.90v_4^{34}, 0.90v_2^{32}, 0.90v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.53u_1^{11}, 3.53u_2^{12}, 3.53u_3^{13}; 3.53u_4^{14}, 3.53u_2^{12}, 3.53u_5^{15}) + \\ (0.26u_1^{21}, 0.26u_2^{22}, 0.26u_3^{23}; 0.26u_4^{24}, 0.26u_2^{22}, 0.26u_5^{25}) \end{array} \right] \llbracket$$

$$\left[ \begin{array}{l} (9v_1^{11}, 11v_2^{12}, 13v_3^{13}; 7v_4^{14}, 11v_2^{12}, 15v_5^{15}) + \\ (.19v_1^{21}, .22v_2^{22}, .24v_3^{23}; .16v_4^{24}, .22v_2^{22}, .26v_5^{25}) + \\ (1.51v_1^{31}, 1.51v_2^{32}, 1.51v_3^{33}; 1.51v_4^{34}, 1.51v_2^{32}, 1.51v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (5.98, 5.98, 5.98; 5.98, 5.98, 5.98)(u_1^{11}, u_2^{12}, u_3^{13}, u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.27, 0.27, 0.27; 0.27, 0.27, 0.27)(u_1^{21}, u_2^{22}, u_3^{23}, u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \preceq$$

$$\left[ \begin{array}{l} (9, 11, 14; 8, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}, v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.20, .21, .23; .18, .21, .24)(v_1^{21}, v_2^{22}, v_3^{23}, v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.98, 2.98, 2.98; 2.98, 2.98, 2.98)(v_1^{31}, v_2^{32}, v_3^{33}, v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.79u_1^{11}, 1.79u_2^{12}, 1.79u_3^{13}; 1.79u_4^{14}, 1.79u_2^{12}, 1.79u_5^{15}) + \\ (0.16u_1^{21}, 0.16u_2^{22}, 0.16u_3^{23}; 0.16u_4^{24}, 0.16u_2^{22}, 0.16u_5^{25}) \end{array} \right] \preceq$$

$$\left[ \begin{array}{l} (7v_1^{11}, 10v_2^{12}, 12v_3^{13}; 6v_4^{14}, 10v_2^{12}, 14v_5^{15}) + \\ (.21v_1^{21}, .22v_2^{22}, .24v_3^{23}; .17v_4^{24}, .22v_2^{22}, .26v_5^{25}) + \\ (1.99v_1^{31}, 1.99v_2^{32}, 1.99v_3^{33}; 1.99v_4^{34}, 1.99v_2^{32}, 1.99v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (7.10u_1^{11}, 7.10u_2^{12}, 7.10u_3^{13}; 7.10u_4^{14}, 7.10u_2^{12}, 7.10u_5^{15}) + \\ (0.37u_1^{21}, 0.37u_2^{22}, 0.37u_3^{23}; 0.37u_4^{24}, 0.37u_2^{22}, 0.37u_5^{25}) \end{array} \right] \preceq$$

$$\left[ \begin{array}{l} (6v_1^{11}, 8v_2^{12}, 10v_3^{13}; 5v_4^{14}, 8v_2^{12}, 12v_5^{15}) + \\ (.25v_1^{21}, .39v_2^{22}, .44v_3^{23}; .19v_4^{24}, .39v_2^{22}, .47v_5^{25}) + \\ (3.64v_1^{31}, 3.64v_2^{32}, 3.64v_3^{33}; 3.64v_4^{34}, 3.64v_2^{32}, 3.64v_5^{35}) \end{array} \right]$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \succeq \varepsilon, \forall r = 1, 2, \quad (v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \succeq \varepsilon, \forall i = 1, 2, 3, \varepsilon > 0.$$

### Pessimistic intuitionistic fuzzy CCR DEA model-5.21

$$\text{Minimize } \left[ \begin{array}{l} \tilde{E}_1^{BEST} \approx (E_{11}^{BEST}, E_{12}^{BEST}, E_{13}^{BEST}; E_{14}^{BEST}, E_{12}^{BEST}, E_{15}^{BEST}) \end{array} \right]$$

$$= \left( \frac{\begin{array}{l} (1.85u_1^{11}, 1.85u_2^{12}, 1.85u_3^{13}; 1.85u_4^{14}, 1.85u_2^{12}, 1.85u_5^{15}) + \\ (0.33u_1^{21}, 0.33u_2^{22}, 0.33u_3^{23}; 0.33u_4^{24}, 0.33u_2^{22}, 0.33u_5^{25}) \end{array}}{\begin{array}{l} (15v_1^{11}, 17v_2^{12}, 19v_3^{13}; 13v_4^{14}, 17v_2^{12}, 21v_5^{15}) + \\ (.39v_1^{21}, .44v_2^{22}, .46v_3^{23}; .26v_4^{24}, .44v_2^{22}, .63v_5^{25}) + \\ (9.16v_1^{31}, 9.16v_2^{32}, 9.16v_3^{33}; 9.16v_4^{34}, 9.16v_2^{32}, 9.16v_5^{35}) \end{array}} \right)$$

Subject to

$$\left[ \begin{array}{l} (1.85u_1^{11}, 1.85u_2^{12}, 1.85u_3^{13}; 1.85u_4^{14}, 1.85u_2^{12}, 1.85u_5^{15}) + \\ (0.33u_1^{21}, 0.33u_2^{22}, 0.33u_3^{23}; 0.33u_4^{24}, 0.33u_2^{22}, 0.33u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (15v_1^{11}, 17v_2^{12}, 19v_3^{13}; 13v_4^{14}, 17v_2^{12}, 21v_5^{15}) + \\ (.39v_1^{21}, .44v_2^{22}, .46v_3^{23}; .26v_4^{24}, .44v_2^{22}, .63v_5^{25}) + \\ (9.16v_1^{31}, 9.16v_2^{32}, 9.16v_3^{33}; 9.16v_4^{34}, 9.16v_2^{32}, 9.16v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (0.67u_1^{11}, 0.67u_2^{12}, 0.67u_3^{13}; 0.67u_4^{14}, 0.67u_2^{12}, 0.67u_5^{15}) + \\ (0.41u_1^{21}, 0.41u_2^{22}, 0.41u_3^{23}; 0.41u_4^{24}, 0.41u_2^{22}, 0.41u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (14v_1^{11}, 16v_2^{12}, 18v_3^{13}; 12v_4^{14}, 16v_2^{12}, 20v_5^{15}) + \\ (.46v_1^{21}, .54v_2^{22}, .65v_3^{23}; .38v_4^{24}, .54v_2^{22}, .73v_5^{25}) + \\ (2.68v_1^{31}, 2.68v_2^{32}, 2.68v_3^{33}; 2.68v_4^{34}, 2.68v_2^{32}, 2.68v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (10.73u_1^{11}, 10.73u_2^{12}, 10.73u_3^{13}; 10.73u_4^{14}, 10.73u_2^{12}, 10.73u_5^{15}) + \\ (0.49u_1^{21}, 0.49u_2^{22}, 0.49u_3^{23}; 0.49u_4^{24}, 0.49u_2^{22}, 0.49u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9v_1^{11}, 11v_2^{12}, 13v_3^{13}; 6v_4^{14}, 11v_2^{12}, 15v_5^{15}) + \\ (.47v_1^{21}, .54v_2^{22}, .57v_3^{23}; .42v_4^{24}, .54v_2^{22}, .60v_5^{25}) + \\ (4.24v_1^{31}, 4.24v_2^{32}, 4.24v_3^{33}; 4.24v_4^{34}, 4.24v_2^{32}, 4.24v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00u_1^{11}, 1.00u_2^{12}, 1.00u_3^{13}; 1.00u_4^{14}, 1.00u_2^{12}, 1.00u_5^{15}) + \\ (.084u_1^{21}, .084u_2^{22}, .084u_3^{23}; .084u_4^{24}, .084u_2^{22}, .084u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (10v_1^{11}, 13v_2^{12}, 15v_3^{13}; 8v_4^{14}, 13v_2^{12}, 17v_5^{15}) + \\ (.19v_1^{21}, .21v_2^{22}, .24v_3^{23}; .18v_4^{24}, .21v_2^{22}, .25v_5^{25}) + \\ (2.08v_1^{31}, 2.08v_2^{32}, 2.08v_3^{33}; 2.08v_4^{34}, 2.08v_2^{32}, 2.08v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.88u_1^{11}, 2.88u_2^{12}, 2.88u_3^{13}; 2.88u_4^{14}, 2.88u_2^{12}, 2.88u_5^{15}) + \\ (0.20u_1^{21}, 0.20u_2^{22}, 0.20u_3^{23}; 0.20u_4^{24}, 0.20u_2^{22}, 0.20u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (11v_1^{11}, 14v_2^{12}, 16v_3^{13}; 9v_4^{14}, 14v_2^{12}, 19v_5^{15}) + \\ (.25v_1^{21}, .29v_2^{22}, .31v_3^{23}; .23v_4^{24}, .29v_2^{22}, .33v_5^{25}) + \\ (4.73v_1^{31}, 4.73v_2^{32}, 4.73v_3^{33}; 4.73v_4^{34}, 4.73v_2^{32}, 4.73v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (4.97u_1^{11}, 4.97u_2^{12}, 4.97u_3^{13}; 4.97u_4^{14}, 4.97u_2^{12}, 4.97u_5^{15}) + \\ (0.85u_1^{21}, 0.85u_2^{22}, 0.85u_3^{23}; 0.85u_4^{24}, 0.85u_2^{22}, 0.85u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (18v_1^{11}, 21v_2^{12}, 24v_3^{13}; 15v_4^{14}, 21v_2^{12}, 27v_5^{15}) + \\ (.28v_1^{21}, .29v_2^{22}, .30v_3^{23}; .24v_4^{24}, .29v_2^{22}, .31v_5^{25}) + \\ (4.58v_1^{31}, 4.58v_2^{32}, 4.58v_3^{33}; 4.58v_4^{34}, 4.58v_2^{32}, 4.58v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.94u_1^{11}, 3.94u_2^{12}, 3.94u_3^{13}; 3.94u_4^{14}, 3.94u_2^{12}, 3.94u_5^{15}) + \\ (0.28u_1^{21}, 0.28u_2^{22}, 0.28u_3^{23}; 0.28u_4^{24}, 0.28u_2^{22}, 0.28u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (11v_1^{11}, 14v_2^{12}, 17v_3^{13}; 9v_4^{14}, 14v_2^{12}, 19v_5^{15}) + \\ (.21v_1^{21}, .23v_2^{22}, .24v_3^{23}; .19v_4^{24}, .23v_2^{22}, .25v_5^{25}) + \\ (1.33v_1^{31}, 1.33v_2^{32}, 1.33v_3^{33}; 1.33v_4^{34}, 1.33v_2^{32}, 1.33v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.16u_1^{11}, 2.16u_2^{12}, 2.16u_3^{13}; 2.16u_4^{14}, 2.16u_2^{12}, 2.16u_5^{15}) + \\ (0.30u_1^{21}, 0.30u_2^{22}, 0.30u_3^{23}; 0.30u_4^{24}, 0.30u_2^{22}, 0.30u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9v_2^{12}, 12v_2^{12}, 13v_3^{13}; 7v_4^{14}, 12v_2^{12}, 16v_5^{15}) + \\ (.56v_1^{21}, .60v_2^{22}, .62v_3^{23}; .52v_4^{24}, .60v_2^{22}, .64v_5^{25}) + \\ (2.98v_1^{31}, 2.98v_2^{32}, 2.98v_3^{33}; 2.98v_4^{34}, 2.98v_2^{32}, 2.98v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (2.58u_1^{11}, 2.58u_2^{12}, 2.58u_3^{13}; 2.58u_4^{14}, 2.58u_2^{12}, 2.58u_5^{15}) + \\ (0.15u_1^{21}, 0.15u_2^{22}, 0.15u_3^{23}; 0.15u_4^{24}, 0.15u_2^{22}, 0.15u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (6v_1^{11}, 9v_2^{12}, 12v_3^{13}; 6v_4^{14}, 9v_2^{12}, 12v_5^{15}) + \\ (.16v_1^{21}, .17v_2^{22}, .19v_3^{23}; .13v_4^{24}, .17v_2^{22}, .20v_5^{25}) + \\ (1.48v_1^{31}, 1.48v_2^{32}, 1.48v_3^{33}; 1.48v_4^{34}, 1.48v_2^{32}, 1.48v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.00u_1^{11}, 1.00u_2^{12}, 1.00u_3^{13}; 1.00u_4^{14}, 1.00u_2^{12}, 1.00u_5^{15}) + \\ (0.13u_1^{21}, 0.13u_2^{22}, 0.13u_3^{23}; 0.13u_4^{24}, 0.13u_2^{22}, 0.13u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (5v_1^{11}, 7v_2^{12}, 9v_3^{13}; 3v_4^{14}, 7v_2^{12}, 10v_5^{15}) + \\ (.10v_1^{21}, .11v_2^{22}, .12v_3^{23}; .08v_4^{24}, .11v_2^{22}, .13v_5^{25}) + \\ (0.75v_1^{31}, 0.75v_2^{32}, 0.75v_3^{33}; 0.75v_4^{34}, 0.75v_2^{32}, 0.75v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.73u_1^{11}, 1.73u_2^{12}, 1.73u_3^{13}; 1.73u_4^{14}, 1.73u_2^{12}, 1.73u_5^{15}) + \\ (0.13u_1^{21}, 0.13u_2^{22}, 0.13u_3^{23}; 0.13u_4^{24}, 0.13u_2^{22}, 0.13u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (4v_1^{11}, 6v_2^{12}, 8v_3^{13}; 3v_4^{14}, 6v_2^{12}, 9v_5^{15}) + \\ (.15v_1^{21}, .18v_2^{22}, .20v_3^{23}; .12v_4^{24}, .18v_2^{22}, .21v_5^{25}) + \\ (0.87v_1^{31}, 0.87v_2^{32}, 0.87v_3^{33}; 0.87v_4^{34}, 0.87v_2^{32}, 0.87v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.26u_1^{11}, 1.26u_2^{12}, 1.26u_3^{13}; 1.26u_4^{14}, 1.26u_2^{12}, 1.26u_5^{15}) + \\ (0.069u_1^{21}, 0.069u_2^{22}, 0.069u_3^{23}; 0.069u_4^{24}, 0.069u_2^{22}, 0.069u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (8v_1^{11}, 10v_2^{12}, 13v_3^{13}; 6v_4^{14}, 10v_2^{12}, 14v_5^{15}) + \\ (.18v_1^{21}, .20v_2^{22}, .22v_3^{23}; .15v_4^{24}, .20v_2^{22}, .23v_5^{25}) + \\ (0.90v_1^{31}, 0.90v_2^{32}, 0.90v_3^{33}; 0.90v_4^{34}, 0.90v_2^{32}, 0.90v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (3.53u_1^{11}, 3.53u_2^{12}, 3.53u_3^{13}; 3.53u_4^{14}, 3.53u_2^{12}, 3.53u_5^{15}) + \\ (0.26u_1^{21}, 0.26u_2^{22}, 0.26u_3^{23}; 0.26u_4^{24}, 0.26u_2^{22}, 0.26u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9v_1^{11}, 11v_2^{12}, 13v_3^{13}; 7v_4^{14}, 11v_2^{12}, 15v_5^{15}) + \\ (.19v_1^{21}, .22v_2^{22}, .24v_3^{23}; .16v_4^{24}, .22v_2^{22}, .26v_5^{25}) + \\ (1.51v_1^{31}, 1.51v_2^{32}, 1.51v_3^{33}; 1.51v_4^{34}, 1.51v_2^{32}, 1.51v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (5.98, 5.98, 5.98; 5.98, 5.98, 5.98)(u_1^{11}, u_2^{12}, u_3^{13}, u_4^{14}, u_2^{12}, u_5^{15}) + \\ (0.27, 0.27, 0.27; 0.27, 0.27, 0.27)(u_1^{21}, u_2^{22}, u_3^{23}, u_4^{24}, u_2^{22}, u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (9, 11, 14; 8, 11, 15)(v_1^{11}, v_2^{12}, v_3^{13}, v_4^{14}, v_2^{12}, v_5^{15}) + \\ (.20, .21, .23; .18, .21, .24)(v_1^{21}, v_2^{22}, v_3^{23}, v_4^{24}, v_2^{22}, v_5^{25}) + \\ (2.98, 2.98, 2.98; 2.98, 2.98, 2.98)(v_1^{31}, v_2^{32}, v_3^{33}, v_4^{34}, v_2^{32}, v_5^{35}) \end{array} \right]$$

$$\left[ \begin{array}{l} (1.79u_1^{11}, 1.79u_2^{12}, 1.79u_3^{13}; 1.79u_4^{14}, 1.79u_2^{12}, 1.79u_5^{15}) + \\ (0.16u_1^{21}, 0.16u_2^{22}, 0.16u_3^{23}; 0.16u_4^{24}, 0.16u_2^{22}, 0.16u_5^{25}) \end{array} \right] \succcurlyeq$$

$$\left[ \begin{array}{l} (7v_1^{11}, 10v_2^{12}, 12v_3^{13}; 6v_4^{14}, 10v_2^{12}, 14v_5^{15}) + \\ (.21v_1^{21}, .22v_2^{22}, .24v_3^{23}; .17v_4^{24}, .22v_2^{22}, .26v_5^{25}) + \\ (1.99v_1^{31}, 1.99v_2^{32}, 1.99v_3^{33}; 1.99v_4^{34}, 1.99v_2^{32}, 1.99v_5^{35}) \end{array} \right]$$



$$\left( 15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}, 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}, \right. \\ \left. 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}; 13v_4^{14} + .26v_4^{24} + 9.16v_4^{34}, \right. \\ \left. 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}, 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35} \right),$$

$$\left( 0.67u_1^{11} + 0.41u_1^{21}, 0.67u_2^{12} + 0.41u_2^{22}, 0.67u_3^{13} + 0.41u_3^{23}; \right. \\ \left. 0.67u_4^{14} + 0.41u_4^{24}, 0.67u_2^{12} + 0.41u_2^{22}, 0.67u_5^{15} + 0.41u_5^{25} \right) \ll$$

$$\left( 14v_1^{11} + .46v_1^{21} + 2.68v_1^{31}, 16v_2^{12} + .54v_2^{22} + 2.68v_2^{32}, \right. \\ \left. 18v_3^{13} + .65v_3^{23} + 2.68v_3^{33}; 12v_4^{14} + .38v_4^{24} + 2.68v_4^{34}, \right. \\ \left. 16v_2^{12} + .54v_2^{22} + 2.68v_2^{32}, 20v_5^{15} + .73v_5^{25} + 2.68v_5^{35} \right),$$

$$\left( 10.73u_1^{11} + 0.49u_1^{21}, 10.73u_2^{12} + 0.49u_2^{22}, 10.73u_3^{13} + 0.49u_3^{23}; \right. \\ \left. 10.73u_4^{14} + 0.49u_4^{24}, 10.73u_2^{12} + 0.49u_2^{22}, 10.73u_5^{15} + 0.49u_5^{25} \right) \ll$$

$$\left( 9v_1^{11} + .47v_1^{21} + 4.24v_1^{31}, 11v_2^{12} + .54v_2^{22} + 4.24v_2^{32}, \right. \\ \left. 13v_3^{13} + .57v_3^{23} + 4.24v_3^{33}; 6v_4^{14} + .42v_4^{24} + 4.24v_4^{34}, \right. \\ \left. 11v_2^{12} + .54v_2^{22} + 4.24v_2^{32}, 15v_5^{15} + .60v_5^{25} + 4.24v_5^{32} \right),$$

$$\left( 1.00u_1^{11} + .084u_1^{21}, 1.00u_2^{12} + .084u_2^{22}, 1.00u_3^{13} + .084u_3^{23}; \right. \\ \left. 1.00u_4^{14} + .084u_4^{24}, 1.00u_2^{12} + .084u_2^{22}, 1.00u_5^{15} + .084u_5^{25} \right) \ll$$

$$\left( 10v_1^{11} + .19v_1^{21} + 2.08v_1^{31}, 13v_2^{12} + .21v_2^{22} + 2.08v_2^{32}, \right. \\ \left. 15v_3^{13} + .24v_3^{23} + 2.08v_3^{33}; 8v_4^{14} + .18v_4^{24} + 2.08v_4^{34}, \right. \\ \left. 13v_2^{12} + .21v_2^{22} + 2.08v_2^{32}, 17v_5^{15} + .25v_5^{25} + 2.08v_5^{32} \right),$$

$$\left( 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21}; \right. \\ \left. 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21} \right) \ll$$

$$\left( 11v_1^{11} + .25v_1^{21} + 4.73v_1^{31}, 14v_2^{12} + .29v_2^{22} + 4.73v_2^{32}, \right. \\ \left. 16v_3^{13} + .31v_3^{23} + 4.73v_3^{33}; 9v_4^{14} + .23v_4^{24} + 4.73v_4^{34}, \right. \\ \left. 14v_2^{12} + .29v_2^{22} + 4.73v_2^{32}, 19v_5^{15} + .33v_5^{25} + 4.73v_5^{34} \right),$$

$$\left( 4.97u_1^{11} + .85u_1^{21}, 4.97u_1^{11} + .85u_1^{21}, 4.97u_1^{11} + .85u_1^{21}; \right. \\ \left. 4.97u_1^{11} + .85u_1^{21}, 4.97u_1^{11} + .85u_1^{21}, 4.97u_1^{11} + .85u_1^{21} \right) \ll$$

$$\left( \begin{array}{l} 18v_1^{11} + .28v_1^{21} + 4.58v_1^{31}, 21v_2^{12} + .29v_2^{22} + 4.58v_2^{32}, \\ 24v_3^{13} + .30v_3^{23} + 4.58v_3^{33}; 15v_4^{14} + .24v_4^{24} + 4.58v_4^{34}, \\ 21v_2^{12} + .29v_2^{22} + 4.58v_2^{32}, 27v_5^{15} + .31v_5^{25} + 4.58v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 3.94u_1^{11} + 0.28u_1^{21}, 3.94u_2^{12} + 0.28u_2^{22}, 3.94u_3^{13} + 0.28u_3^{23}; \\ 3.94u_4^{14} + 0.28u_4^{24}, 3.94u_2^{12} + 0.28u_2^{22}, 3.94u_5^{15} + 0.28u_5^{25} \end{array} \right) \preceq$$

$$\left( \begin{array}{l} 11v_1^{11} + .21v_1^{21} + 1.33v_1^{31}, 14v_2^{12} + .23v_2^{22} + 1.33v_2^{32}, \\ 17v_3^{13} + .24v_3^{23} + 1.33v_3^{33}; 9v_4^{14} + .19v_4^{24} + 1.33v_4^{34}, \\ 14v_2^{12} + .23v_2^{22} + 1.33v_2^{32}, 19v_5^{15} + .25v_5^{25} + 1.33v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 2.16u_1^{11} + 0.30u_1^{21}, 2.16u_2^{12} + 0.30u_2^{22}, 2.16u_3^{13} + 0.30u_3^{23}; \\ 2.16u_4^{14} + 0.30u_4^{24}, 2.16u_2^{12} + 0.30u_2^{22}, 2.16u_5^{15} + 0.30u_5^{25} \end{array} \right) \preceq$$

$$\left( \begin{array}{l} 9v_1^{11} + .56v_1^{21} + 2.98v_1^{31}, 12v_2^{12} + .60v_2^{22} + 2.98v_2^{32}, \\ 13v_3^{13} + .62v_3^{23} + 2.98v_3^{33}; 7v_4^{14} + .52v_4^{24} + 2.98v_4^{34}, \\ 12v_2^{12} + .60v_2^{22} + 2.98v_2^{32}, 16v_5^{15} + .64v_5^{25} + 2.98v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 2.58u_1^{11} + 0.15u_1^{21}, 2.58u_2^{12} + 0.15u_2^{22}, 2.58u_3^{13} + 0.15u_3^{23}; \\ 2.58u_4^{14} + 0.15u_4^{24}, 2.58u_2^{12} + 0.15u_2^{22}, 2.58u_5^{15} + 0.15u_5^{25} \end{array} \right) \preceq$$

$$\left( \begin{array}{l} 6v_1^{11} + .16v_1^{21} + 1.48v_1^{31}, 9v_2^{12} + .17v_2^{22} + 1.48v_2^{32}, \\ 12v_3^{13} + .19v_3^{23} + 1.48v_3^{33}; 6v_4^{14} + .13v_4^{24} + 1.48v_4^{34}, \\ 9v_2^{12} + .17v_2^{22} + 1.48v_2^{32}, 12v_5^{15} + .20v_5^{25} + 1.48v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 1.00u_1^{11} + 0.13u_1^{21}, 1.00u_2^{12} + 0.13u_2^{22}, 1.00u_3^{13} + 0.13u_3^{23}; \\ 1.00u_4^{14} + 0.13u_4^{24}, 1.00u_2^{12} + 0.13u_2^{22}, 1.00u_5^{15} + 0.13u_5^{25} \end{array} \right) \preceq$$

$$\left( \begin{array}{l} 5v_1^{11} + .10v_1^{21} + .75v_1^{31}, 7v_2^{12} + .11v_2^{22} + .75v_2^{32}, \\ 9v_3^{13} + .12v_3^{23} + .75v_3^{33}; 3v_4^{14} + .08v_4^{24} + .75v_4^{34}, \\ 7v_2^{12} + .11v_2^{22} + .75v_2^{32}, 10v_5^{15} + .13v_5^{25} + .75v_5^{32} \end{array} \right),$$

$$\left( 1.73u_1^{11} + 0.13u_1^{21}, 1.73u_2^{12} + 0.13u_2^{22}, 1.73u_3^{13} + 0.13u_3^{23}; \right. \\ \left. 1.73u_4^{14} + 0.13u_4^{24}, 1.73u_2^{12} + 0.13u_2^{22}, 1.73u_5^{15} + 0.13u_5^{25} \right) \preceq$$

$$\left( 4v_1^{11} + .15v_1^{21} + .87v_1^{31}, 6v_2^{12} + .18v_2^{22} + .87v_2^{32}, \right. \\ \left. 8v_3^{13} + .20v_3^{23} + .87v_3^{33}; 3v_4^{14} + .12v_4^{24} + .87v_4^{34}, \right. \\ \left. 6v_2^{12} + .18v_2^{22} + .87v_2^{32}, 9v_5^{15} + .21v_5^{25} + .87v_5^{32} \right)$$

$$\left( 1.26u_1^{11} + 0.069u_1^{21}, 1.26u_2^{12} + 0.069u_2^{22}, 1.26u_3^{13} + 0.069u_3^{23}; \right. \\ \left. 1.26u_4^{14} + 0.069u_4^{24}, 1.26u_2^{12} + 0.069u_2^{22}, 1.26u_5^{15} + 0.069u_5^{25} \right) \preceq$$

$$\left( 8v_1^{11} + .18v_1^{21} + .90v_1^{31}, 10v_2^{12} + .20v_2^{22} + .90v_2^{32}, \right. \\ \left. 13v_3^{13} + .22v_3^{23} + .90v_3^{33}; 6v_4^{14} + .15v_4^{24} + .90v_4^{34}, \right. \\ \left. 10v_2^{12} + .20v_2^{22} + .90v_2^{32}, 14v_5^{15} + .23v_5^{25} + .90v_5^{32} \right)$$

$$\left( 3.53u_1^{11} + 0.26u_1^{21}, 3.53u_2^{12} + 0.26u_2^{22}, 3.53u_3^{13} + 0.26u_3^{23}; \right. \\ \left. 3.53u_4^{14} + 0.26u_4^{24}, 3.53u_2^{12} + 0.26u_2^{22}, 3.53u_5^{15} + 0.26u_5^{25} \right) \preceq$$

$$\left( 9v_1^{11} + .19v_1^{21} + 1.51v_1^{31}, 11v_2^{12} + .22v_2^{22} + 1.51v_2^{32}, \right. \\ \left. 13v_3^{13} + .24v_3^{23} + 1.51v_3^{33}; 7v_4^{14} + .16v_4^{24} + 1.51v_4^{34}, \right. \\ \left. 11v_2^{12} + .22v_2^{22} + 1.51v_2^{32}, 15v_5^{15} + .26v_5^{25} + 1.51v_5^{32} \right)$$

$$\left( 5.98u_1^{11} + 0.27u_1^{21}, 5.98u_2^{12} + 0.27u_2^{22}, 5.98u_3^{13} + 0.27u_3^{23}; \right. \\ \left. 5.98u_4^{14} + 0.27u_4^{24}, 5.98u_2^{12} + 0.27, 5.98u_5^{15} + 0.27u_5^{25} \right) \preceq$$

$$\left( 9v_1^{11} + .20v_1^{21} + 2.98v_1^{31}, 11v_2^{12} + .21v_2^{22} + 2.98v_2^{32}, \right. \\ \left. 14v_3^{13} + .23v_3^{23} + 2.98v_3^{33}; 8v_4^{14} + .18v_4^{24} + 2.98v_4^{34}, \right. \\ \left. 11v_2^{12} + .21v_2^{22} + 2.98v_2^{32}, 15v_5^{15} + .24v_5^{25} + 2.98v_5^{32} \right)$$

$$\left( 1.79u_1^{11} + 0.16u_1^{21}, 1.79u_2^{12} + 0.16u_2^{22}, 1.79u_3^{13} + 0.16u_3^{23}; \right. \\ \left. 1.79u_4^{14} + 0.16u_4^{24}, 1.79u_2^{12} + 0.16, 1.79u_5^{15} + 0.16u_5^{25} \right) \preceq$$

$$\left( 7v_1^{11} + .21v_1^{21} + 1.99v_1^{31}, 10v_2^{12} + .22v_2^{22} + 1.99v_2^{32}, \right. \\ \left. 12v_3^{13} + .24v_3^{23} + 1.99v_3^{33}; 6v_4^{14} + .17v_4^{24} + 1.99v_4^{34}, \right. \\ \left. 7v_2^{12} + .22v_2^{22} + 1.99v_2^{32}, 14v_5^{15} + .26v_5^{25} + 1.99v_5^{32} \right)$$



$$\left( 0.67u_1^{11} + 0.41u_1^{21}, 0.67u_2^{12} + 0.41u_2^{22}, 0.67u_3^{13} + 0.41u_3^{23}; \right. \\ \left. 0.67u_4^{14} + 0.41u_4^{24}, 0.67u_2^{12} + 0.41u_2^{22}, 0.67u_5^{15} + 0.41u_5^{25} \right) \succcurlyeq$$

$$\left( 14v_1^{11} + .46v_1^{21} + 2.68v_1^{31}, 16v_2^{12} + .54v_2^{22} + 2.68v_2^{32}, \right. \\ \left. 18v_3^{13} + .65v_3^{23} + 2.68v_3^{33}; 12v_4^{14} + .38v_4^{24} + 2.68v_4^{34}, \right. \\ \left. 16v_2^{12} + .54v_2^{22} + 2.68v_2^{32}, 20v_5^{15} + .73v_5^{25} + 2.68v_5^{35} \right),$$

$$\left( 10.73u_1^{11} + 0.49u_1^{21}, 10.73u_2^{12} + 0.49u_2^{22}, 10.73u_3^{13} + 0.49u_3^{23}; \right. \\ \left. 10.73u_4^{14} + 0.49u_4^{24}, 10.73u_2^{12} + 0.49u_2^{22}, 10.73u_5^{15} + 0.49u_5^{25} \right) \succcurlyeq$$

$$\left( 9v_1^{11} + .47v_1^{21} + 4.24v_1^{31}, 11v_2^{12} + .54v_2^{22} + 4.24v_2^{32}, \right. \\ \left. 13v_3^{13} + .57v_3^{23} + 4.24v_3^{33}; 6v_4^{14} + .42v_4^{24} + 4.24v_4^{34}, \right. \\ \left. 11v_2^{12} + .54v_2^{22} + 4.24v_2^{32}, 15v_5^{15} + .60v_5^{25} + 4.24v_5^{32} \right),$$

$$\left( 1.00u_1^{11} + .084u_1^{21}, 1.00u_2^{12} + .084u_2^{22}, 1.00u_3^{13} + .084u_3^{23}; \right. \\ \left. 1.00u_4^{14} + .084u_4^{24}, 1.00u_2^{12} + .084u_2^{22}, 1.00u_5^{15} + .084u_5^{25} \right) \succcurlyeq$$

$$\left( 10v_1^{11} + .19v_1^{21} + 2.08v_1^{31}, 13v_2^{12} + .21v_2^{22} + 2.08v_2^{32}, \right. \\ \left. 15v_3^{13} + .24v_3^{23} + 2.08v_3^{33}; 8v_4^{14} + .18v_4^{24} + 2.08v_4^{34}, \right. \\ \left. 13v_2^{12} + .21v_2^{22} + 2.08v_2^{32}, 17v_5^{15} + .25v_5^{25} + 2.08v_5^{32} \right),$$

$$\left( 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21}; \right. \\ \left. 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21}, 2.88u_1^{11} + .20u_1^{21} \right) \succcurlyeq$$

$$\left( 11v_1^{11} + .25v_1^{21} + 4.73v_1^{31}, 14v_2^{12} + .29v_2^{22} + 4.73v_2^{32}, \right. \\ \left. 16v_3^{13} + .31v_3^{23} + 4.73v_3^{33}; 9v_4^{14} + .23v_4^{24} + 4.73v_4^{34}, \right. \\ \left. 14v_2^{12} + .29v_2^{22} + 4.73v_2^{32}, 19v_5^{15} + .33v_5^{25} + 4.73v_5^{34} \right),$$

$$\left( 18v_1^{11} + .28v_1^{21} + 4.58v_1^{31}, 21v_2^{12} + .29v_2^{22} + 4.58v_2^{32}, \right. \\ \left. 24v_3^{13} + .30v_3^{23} + 4.58v_3^{33}; 15v_4^{14} + .24v_4^{24} + 4.58v_4^{34}, \right. \\ \left. 21v_2^{12} + .29v_2^{22} + 4.58v_2^{32}, 27v_5^{15} + .31v_5^{25} + 4.58v_5^{32} \right),$$

$$\left( 3.94u_1^{11} + 0.28u_1^{21}, 3.94u_2^{12} + 0.28u_2^{22}, 3.94u_3^{13} + 0.28u_3^{23}; \right. \\ \left. 3.94u_4^{14} + 0.28u_4^{24}, 3.94u_2^{12} + 0.28u_2^{22}, 3.94u_5^{15} + 0.28u_5^{25} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 11v_1^{11} + .21v_1^{21} + 1.33v_1^{31}, 14v_2^{12} + .23v_2^{22} + 1.33v_2^{32}, \\ 17v_3^{13} + .24v_3^{23} + 1.33v_3^{33}; 9v_4^{14} + .19v_4^{24} + 1.33v_4^{34}, \\ 14v_2^{12} + .23v_2^{22} + 1.33v_2^{32}, 19v_5^{15} + .25v_5^{25} + 1.33v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 2.16u_1^{11} + 0.30u_1^{21}, 2.16u_2^{12} + 0.30u_2^{22}, 2.16u_3^{13} + 0.30u_3^{23}; \\ 2.16u_4^{14} + 0.30u_4^{24}, 2.16u_2^{12} + 0.30u_2^{22}, 2.16u_5^{15} + 0.30u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 9v_1^{11} + .56v_1^{21} + 2.98v_1^{31}, 12v_2^{12} + .60v_2^{22} + 2.98v_2^{32}, \\ 13v_3^{13} + .62v_3^{23} + 2.98v_3^{33}; 7v_4^{14} + .52v_4^{24} + 2.98v_4^{34}, \\ 12v_2^{12} + .60v_2^{22} + 2.98v_2^{32}, 16v_5^{15} + .64v_5^{25} + 2.98v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 2.58u_1^{11} + 0.15u_1^{21}, 2.58u_2^{12} + 0.15u_2^{22}, 2.58u_3^{13} + 0.15u_3^{23}; \\ 2.58u_4^{14} + 0.15u_4^{24}, 2.58u_2^{12} + 0.15u_2^{22}, 2.58u_5^{15} + 0.15u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 6v_1^{11} + .16v_1^{21} + 1.48v_1^{31}, 9v_2^{12} + .17v_2^{22} + 1.48v_2^{32}, \\ 12v_3^{13} + .19v_3^{23} + 1.48v_3^{33}; 6v_4^{14} + .13v_4^{24} + 1.48v_4^{34}, \\ 9v_2^{12} + .17v_2^{22} + 1.48v_2^{32}, 12v_5^{15} + .20v_5^{25} + 1.48v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 1.00u_1^{11} + 0.13u_1^{21}, 1.00u_2^{12} + 0.13u_2^{22}, 1.00u_3^{13} + 0.13u_3^{23}; \\ 1.00u_4^{14} + 0.13u_4^{24}, 1.00u_2^{12} + 0.13u_2^{22}, 1.00u_5^{15} + 0.13u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 5v_1^{11} + .10v_1^{21} + .75v_1^{31}, 7v_2^{12} + .11v_2^{22} + .75v_2^{32}, \\ 9v_3^{13} + .12v_3^{23} + .75v_3^{33}; 3v_4^{14} + .08v_4^{24} + .75v_4^{34}, \\ 7v_2^{12} + .11v_2^{22} + .75v_2^{32}, 10v_5^{15} + .13v_5^{25} + .75v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 1.73u_1^{11} + 0.13u_1^{21}, 1.73u_2^{12} + 0.13u_2^{22}, 1.73u_3^{13} + 0.13u_3^{23}; \\ 1.73u_4^{14} + 0.13u_4^{24}, 1.73u_2^{12} + 0.13u_2^{22}, 1.73u_5^{15} + 0.13u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 4v_1^{11} + .15v_1^{21} + .87v_1^{31}, 6v_2^{12} + .18v_2^{22} + .87v_2^{32}, \\ 8v_3^{13} + .20v_3^{23} + .87v_3^{33}; 3v_4^{14} + .12v_4^{24} + .87v_4^{34}, \\ 6v_2^{12} + .18v_2^{22} + .87v_2^{32}, 9v_5^{15} + .21v_5^{25} + .87v_5^{32} \end{array} \right)$$

$$\left( \begin{array}{l} 1.26u_1^{11} + 0.069u_1^{21}, 1.26u_2^{12} + 0.069u_2^{22}, 1.26u_3^{13} + 0.069u_3^{23}; \\ 1.26u_4^{14} + 0.069u_4^{24}, 1.26u_2^{12} + 0.069u_2^{22}, 1.26u_5^{15} + 0.069u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 8v_1^{11} + .18v_1^{21} + .90v_1^{31}, 10v_2^{12} + .20v_2^{22} + .90v_2^{32}, \\ 13v_3^{13} + .22v_3^{23} + .90v_3^{33}; 6v_4^{14} + .15v_4^{24} + .90v_4^{34}, \\ 10v_2^{12} + .20v_2^{22} + .90v_2^{32}, 14v_5^{15} + .23v_5^{25} + .90v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 3.53u_1^{11} + 0.26u_1^{21}, 3.53u_2^{12} + 0.26u_2^{22}, 3.53u_3^{13} + 0.26u_3^{23}; \\ 3.53u_4^{14} + 0.26u_4^{24}, 3.53u_2^{12} + 0.26u_2^{22}, 3.53u_5^{15} + 0.26u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 9v_1^{11} + .19v_1^{21} + 1.51v_1^{31}, 11v_2^{12} + .22v_2^{22} + 1.51v_2^{32}, \\ 13v_3^{13} + .24v_3^{23} + 1.51v_3^{33}; 7v_4^{14} + .16v_4^{24} + 1.51v_4^{34}, \\ 11v_2^{12} + .22v_2^{22} + 1.51v_2^{32}, 15v_5^{15} + .26v_5^{25} + 1.51v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 5.98u_1^{11} + 0.27u_1^{21}, 5.98u_2^{12} + 0.27u_2^{22}, 5.98u_3^{13} + 0.27u_3^{23}; \\ 5.98u_4^{14} + 0.27u_4^{24}, 5.98u_2^{12} + 0.27, 5.98u_5^{15} + 0.27u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 9v_1^{11} + .20v_1^{21} + 2.98v_1^{31}, 11v_2^{12} + .21v_2^{22} + 2.98v_2^{32}, \\ 14v_3^{13} + .23v_3^{23} + 2.98v_3^{33}; 8v_4^{14} + .18v_4^{24} + 2.98v_4^{34}, \\ 11v_2^{12} + .21v_2^{22} + 2.98v_2^{32}, 15v_5^{15} + .24v_5^{25} + 2.98v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 1.79u_1^{11} + 0.16u_1^{21}, 1.79u_2^{12} + 0.16u_2^{22}, 1.79u_3^{13} + 0.16u_3^{23}; \\ 1.79u_4^{14} + 0.16u_4^{24}, 1.79u_2^{12} + 0.16, 1.79u_5^{15} + 0.16u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 7v_1^{11} + .21v_1^{21} + 1.99v_1^{31}, 10v_2^{12} + .22v_2^{22} + 1.99v_2^{32}, \\ 12v_3^{13} + .24v_3^{23} + 1.99v_3^{33}; 6v_4^{14} + .17v_4^{24} + 1.99v_4^{34}, \\ 7v_2^{12} + .22v_2^{22} + 1.99v_2^{32}, 14v_5^{15} + .26v_5^{25} + 1.99v_5^{32} \end{array} \right),$$

$$\left( \begin{array}{l} 7.10u_1^{11} + 0.37u_1^{21}, 7.10u_2^{12} + 0.37u_2^{22}, 7.10u_3^{13} + 0.37u_3^{23}; \\ 7.10u_4^{14} + 0.37u_4^{24}, 7.10u_2^{12} + 0.37, 7.10u_5^{15} + 0.37u_5^{25} \end{array} \right) \succcurlyeq$$

$$\left( \begin{array}{l} 6v_1^{11} + .25v_1^{21} + 3.64v_1^{31}, 8v_2^{12} + .39v_2^{22} + 3.64v_2^{32}, \\ 10v_3^{13} + .44v_3^{23} + 3.64v_3^{33}; 5v_4^{14} + .19v_4^{24} + 3.64v_4^{34}, \\ 8v_2^{12} + .39v_2^{22} + 3.64v_2^{32}, 12v_5^{15} + .47v_5^{25} + 3.64v_5^{32} \end{array} \right),$$

$$(u_1^r, u_2^r, u_3^r; u_4^r, u_2^r, u_5^r) \succcurlyeq \varepsilon, \forall r = 1, 2,$$

$$(v_1^i, v_2^i, v_3^i; v_4^i, v_2^i, v_5^i) \succcurlyeq \varepsilon, \forall i = 1, 2, 3, \varepsilon > 0.$$

**Step 2:** Using the relation  $(a_1, a_2, a_3; a_4, a_2, a_5) \preceq (b_1, b_2, b_3; b_4, b_2, b_5) \Rightarrow a_1 \leq b_1, a_2 \leq b_2, a_3 \leq b_3, a_4 \leq b_4, a_5 \leq b_5$  and the division of triangular intuitionistic fuzzy numbers, defined in Section 5.1.2, the optimistic intuitionistic fuzzy CCR DEA model-5.22 and pessimistic intuitionistic fuzzy CCR DEA model-5.22 can be transformed into optimistic intuitionistic fuzzy CCR DEA model-5.23 and pessimistic intuitionistic fuzzy CCR DEA model-5.23 respectively.

**Optimistic intuitionistic fuzzy CCR DEA model-5.23**

$$\text{Maximize } \left[ \tilde{E}_1^{BEST} \approx (E_{11}^{BEST}, E_{12}^{BEST}, E_{13}^{BEST}; E_{14}^{BEST}, E_{12}^{BEST}, E_{15}^{BEST}) \right.$$

$$\approx \left( \frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}}, \frac{1.85u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}}, \frac{1.85u_3^{13} + 0.33u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}}; \right.$$

$$\left. \frac{1.85u_4^{14} + 0.33u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}}, \frac{1.85u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}}, \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26v_4^{24} + 9.16v_4^{34}} \right)$$

Subject to

$$1.85u_1^{11} + 0.33u_1^{21} \leq 15v_1^{11} + .39v_1^{21} + 9.16v_1^{31},$$

$$1.85u_1^{12} + 0.33u_1^{22} \leq 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32},$$

$$1.85u_1^{13} + 0.33u_1^{23} \leq 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33},$$

$$1.85u_1^{14} + 0.33u_1^{24} \leq 13v_4^{14} + .26v_4^{24} + 9.16v_4^{34},$$

$$1.85u_1^{15} + 0.33u_1^{25} \leq 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}$$

$$0.67u_1^{11} + 0.41u_1^{21} \leq 14v_1^{11} + .46v_1^{21} + 2.68v_1^{31},$$

$$0.67u_1^{12} + 0.41u_1^{22} \leq 16v_2^{12} + .54v_2^{22} + 2.68v_2^{32}$$

$$0.67u_1^{13} + 0.41u_1^{23} \leq 18v_3^{13} + .65v_3^{23} + 2.68v_3^{33},$$

$$0.67u_1^{14} + 0.41u_1^{24} \leq 12v_4^{14} + .38v_4^{24} + 2.68v_4^{34},$$

$$0.67u_1^{15} + 0.41u_1^{25} \leq 20v_5^{15} + .73v_5^{25} + 2.68v_5^{35},$$

$$10.73u_1^{11} + 0.49u_1^{21} \leq 9v_1^{11} + .47v_1^{21} + 4.24v_1^{31},$$

$$10.73u_1^{12} + 0.49u_1^{22} \leq 11v_2^{12} + .54v_2^{22} + 4.24v_2^{32},$$

$$10.73u_1^{13} + 0.49u_1^{23} \leq 13v_3^{13} + .57v_3^{23} + 4.24v_3^{33};$$

$$10.73u_1^{14} + 0.49u_1^{24} \leq 6v_4^{14} + .42v_4^{24} + 4.24v_4^{34},$$

$$10.73u_1^{15} + 0.49u_1^{25} \leq 15v_5^{15} + .60v_5^{25} + 4.24v_5^{35},$$

$$1.00u_1^{11} + .084u_1^{21} \leq 10v_1^{11} + .19v_1^{21} + 2.08v_1^{31},$$

$$1.00u_1^{12} + .084u_1^{22} \leq 13v_2^{12} + .21v_2^{22} + 2.08v_2^{32},$$

$$1.00u_1^{13} + .084u_1^{23} \leq 15v_3^{13} + .24v_3^{23} + 2.08v_3^{33};$$

$$1.00u_1^{14} + .084u_1^{24} \leq 8v_4^{14} + .18v_4^{24} + 2.08v_4^{34},$$

$$1.00u_1^{15} + .084u_1^{25} \leq 17v_5^{15} + .25v_5^{25} + 2.08v_5^{35},$$

$$2.88u_1^{11} + .20u_1^{21} \leq 11v_1^{11} + .25v_1^{21} + 4.73v_1^{31},$$

$$2.88u_1^{12} + .20u_1^{22} \leq 14v_2^{12} + .29v_2^{22} + 4.73v_2^{32},$$

$$2.88u_1^{13} + .20u_1^{23} \leq 16v_3^{13} + .31v_3^{23} + 4.73v_3^{33};$$

$$2.88u_1^{14} + .20u_1^{24} \leq 9v_4^{14} + .23v_4^{24} + 4.73v_4^{34},$$

$$2.88u_1^{15} + .20u_1^{25} \leq 19v_5^{15} + .33v_5^{25} + 4.73v_5^{35}$$

$$4.97u_1^{11} + .85u_1^{21} \leq 18v_1^{11} + .28v_1^{21} + 4.58v_1^{31},$$

$$4.97u_1^{12} + .85u_1^{22} \leq 21v_2^{12} + .29v_2^{22} + 4.58v_2^{32},$$

$$4.97u_1^{13} + .85u_1^{23} \leq 24v_3^{13} + .30v_3^{23} + 4.58v_3^{33};$$

$$4.97u_1^{14} + .85u_1^{24} \leq 15v_4^{14} + .24v_4^{24} + 4.58v_4^{34},$$

$$4.97u_1^{15} + .85u_1^{25} \leq 27v_5^{15} + .31v_5^{25} + 4.58v_2^{35},$$

$$3.94u_1^{11} + 0.28u_1^{21} \leq 11v_1^{11} + .21v_1^{21} + 1.33v_1^{31},$$

$$3.94u_1^{12} + 0.28u_1^{22} \leq 14v_2^{12} + .23v_2^{22} + 1.33v_2^{32},$$

$$3.94u_1^{13} + 0.28u_1^{23} \leq 17v_3^{13} + .24v_3^{23} + 1.33v_3^{33};$$

$$3.94u_1^{14} + 0.28u_1^{24} \leq 9v_4^{14} + .19v_4^{24} + 1.33v_4^{34},$$

$$3.94u_1^{15} + 0.28u_1^{25} \leq 19v_5^{15} + .25v_5^{25} + 1.33v_2^{35}$$

$$2.16u_1^{11} + 0.30u_1^{21} \leq 9v_1^{11} + .56v_1^{21} + 2.98v_1^{31},$$

$$2.16u_1^{12} + 0.30u_1^{22} \leq 12v_2^{12} + .60v_2^{22} + 2.98v_2^{32},$$

$$2.16u_1^{13} + 0.30u_1^{23} \leq 13v_3^{13} + .62v_3^{23} + 2.98v_3^{33};$$

$$2.16u_1^{14} + 0.30u_1^{24} \leq 7v_4^{14} + .52v_4^{24} + 2.98v_4^{34},$$

$$2.16u_1^{15} + 0.30u_1^{25} \leq 16v_5^{15} + .64v_5^{25} + 2.98v_2^{35},$$

$$2.58u_1^{11} + 0.15u_1^{21} \leq 6v_1^{11} + .16v_1^{21} + 1.48v_1^{31},$$

$$2.58u_1^{12} + 0.15u_1^{22} \leq 9v_2^{12} + .17v_2^{22} + 1.48v_2^{32},$$

$$2.58u_1^{13} + 0.15u_1^{23} \leq 12v_3^{13} + .19v_3^{23} + 1.48v_3^{33};$$

$$2.58u_1^{14} + 0.15u_1^{24} \leq 6v_4^{14} + .13v_4^{24} + 1.48v_4^{34},$$

$$2.58u_1^{15} + 0.15u_1^{25} \leq 12v_5^{15} + .20v_5^{25} + 1.48v_2^{35},$$

$$1.00u_1^{11} + 0.13u_1^{21} \leq 5v_1^{11} + .10v_1^{21} + .75v_1^{31},$$

$$1.00u_1^{12} + 0.13u_1^{22} \leq 7v_2^{12} + .11v_2^{22} + .75v_2^{32},$$

$$1.00u_1^{13} + 0.13u_1^{23} \leq 9v_3^{13} + .12v_3^{23} + .75v_3^{33};$$

$$1.00u_1^{14} + 0.13u_1^{24} \leq 3v_4^{14} + .08v_4^{24} + .75v_4^{34},$$

$$1.00u_1^{15} + 0.13u_1^{25} \leq 10v_5^{15} + .13v_5^{25} + .75v_2^{35}$$

$$1.73u_1^{11} + 0.13u_1^{21} \leq 4v_1^{11} + .15v_1^{21} + .87v_1^{31},$$

$$1.73u_1^{12} + 0.13u_1^{22} \leq 6v_2^{12} + .18v_2^{22} + .87v_2^{32},$$

$$1.73u_1^{13} + 0.13u_1^{23} \leq 8v_3^{13} + .20v_3^{23} + .87v_3^{33};$$

$$1.73u_1^{14} + 0.13u_1^{24} \leq 3v_4^{14} + .12v_4^{24} + .87v_4^{34},$$

$$1.73u_1^{15} + 0.13u_1^{25} \leq 9v_5^{15} + .21v_5^{25} + .87v_2^{35}$$

$$1.26u_1^{11} + 0.069u_1^{21} \leq 8v_1^{11} + .18v_1^{21} + .90v_1^{31},$$

$$1.26u_1^{12} + 0.069u_1^{22} \leq 10v_2^{12} + .20v_2^{22} + .90v_2^{32},$$

$$1.26u_1^{13} + 0.069u_1^{23} \leq 13v_3^{13} + .22v_3^{23} + .90v_3^{33};$$

$$1.26u_1^{14} + 0.069u_1^{24} \leq 6v_4^{14} + .15v_4^{24} + .90v_4^{34},$$

$$1.26u_1^{15} + 0.069u_1^{25} \leq 14v_5^{15} + .23v_5^{25} + .90v_2^{35}$$

$$3.53u_1^{11} + 0.26u_1^{21} \leq 9v_1^{11} + .19v_1^{21} + 1.51v_1^{31},$$

$$3.53u_1^{12} + 0.26u_1^{22} \leq 11v_2^{12} + .22v_2^{22} + 1.51v_2^{32},$$

$$\begin{aligned}
3.53u_1^{13} + 0.26u_1^{23} &\leq 13v_3^{13} + .24v_3^{23} + 1.51v_3^{33} \\
3.53u_1^{14} + 0.26u_1^{24} &\leq 7v_4^{14} + .16v_4^{24} + 1.51v_4^{34}, \\
3.53u_1^{15} + 0.26u_1^{25} &\leq 15v_5^{15} + .26v_5^{25} + 1.51v_2^{35} \\
5.98u_1^{11} + 0.27u_1^{21} &\leq 9v_1^{11} + .20v_1^{21} + 2.98v_1^{31}, \\
5.98u_1^{12} + 0.27u_1^{22} &\leq 11v_2^{12} + .21v_2^{22} + 2.98v_2^{32}, \\
5.98u_1^{13} + 0.27u_1^{23} &\leq 14v_3^{13} + .23v_3^{23} + 2.98v_3^{33}; \\
5.98u_1^{14} + 0.27u_1^{24} &\leq 8v_4^{14} + .18v_4^{24} + 2.98v_4^{34}, \\
5.98u_1^{15} + 0.27u_1^{25} &\leq 15v_5^{15} + .24v_5^{25} + 2.98v_2^{35} \\
1.79u_1^{11} + 0.16u_1^{21} &\leq 7v_1^{11} + .21v_1^{21} + 1.99v_1^{31}, \\
1.79u_1^{12} + 0.16u_1^{22} &\leq 10v_2^{12} + .22v_2^{22} + 1.99v_2^{32}, \\
1.79u_1^{13} + 0.16u_1^{23} &\leq 12v_3^{13} + .24v_3^{23} + 1.99v_3^{33}; \\
1.79u_1^{14} + 0.16u_1^{24} &\leq 6v_4^{14} + .17v_4^{24} + 1.99v_4^{34}, \\
1.79u_1^{15} + 0.16u_1^{25} &\leq 14v_5^{15} + .26v_5^{25} + 1.99v_2^{35}, \\
7.10u_1^{11} + 0.37u_1^{21} &\leq 6v_1^{11} + .25v_1^{21} + 3.64v_1^{31}, \\
7.10u_2^{12} + 0.37u_2^{22} &\leq 8v_2^{12} + .39v_2^{22} + 3.64v_2^{32}, \\
7.10u_3^{13} + 0.37u_3^{23} &\leq 10v_3^{13} + .44v_3^{23} + 3.64v_3^{33}, \\
7.10u_4^{14} + 0.37u_4^{24} &\leq 5v_4^{14} + .19v_4^{24} + 3.64v_4^{34}, \\
7.10u_5^{15} + 0.37u_5^{25} &\leq 12v_5^{15} + .47v_5^{25} + 3.64v_2^{35}
\end{aligned}$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \quad \varepsilon > 0.$$

**Pessimistic intuitionistic fuzzy CCR DEA model-5.23**

$$\text{Minimize } \left[ \begin{array}{l} \tilde{E}_1^{BEST} \approx (E_{11}^{BEST}, E_{12}^{BEST}, E_{13}^{BEST}, E_{14}^{BEST}, E_{12}^{BEST}, E_{15}^{BEST}) \\ \\ \approx \left( \frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}}, \frac{1.85u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}}, \frac{1.85u_3^{13} + 0.33u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}}; \right. \\ \left. \frac{1.85u_4^{14} + 0.33u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}}, \frac{1.85u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}}, \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26v_4^{24} + 9.16v_4^{34}} \right) \end{array} \right]$$

Subject to

$$1.85u_1^{11} + 0.33u_1^{21} \geq 15v_1^{11} + .39v_1^{21} + 9.16v_1^{31},$$

$$1.85u_1^{12} + 0.33u_1^{22} \geq 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32},$$

$$1.85u_1^{13} + 0.33u_1^{23} \geq 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33},$$

$$1.85u_1^{14} + 0.33u_1^{24} \geq 13v_4^{14} + .26v_4^{24} + 9.16v_4^{34},$$

$$1.85u_1^{15} + 0.33u_1^{25} \geq 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}$$

$$0.67u_1^{11} + 0.41u_1^{21} \geq 14v_1^{11} + .46v_1^{21} + 2.68v_1^{31},$$

$$0.67u_1^{12} + 0.41u_1^{22} \geq 16v_2^{12} + .54v_2^{22} + 2.68v_2^{32}$$

$$0.67u_1^{13} + 0.41u_1^{23} \geq 18v_3^{13} + .65v_3^{23} + 2.68v_3^{33},$$

$$0.67u_1^{14} + 0.41u_1^{24} \geq 12v_4^{14} + .38v_4^{24} + 2.68v_4^{34},$$

$$0.67u_1^{15} + 0.41u_1^{25} \geq 20v_5^{15} + .73v_5^{25} + 2.68v_5^{35},$$

$$10.73u_1^{11} + 0.49u_1^{21} \geq 9v_1^{11} + .47v_1^{21} + 4.24v_1^{31},$$

$$10.73u_1^{12} + 0.49u_1^{22} \geq 11v_2^{12} + .54v_2^{22} + 4.24v_2^{32},$$

$$10.73u_1^{13} + 0.49u_1^{23} \geq 13v_3^{13} + .57v_3^{23} + 4.24v_3^{33};$$

$$10.73u_1^{14} + 0.49u_1^{24} \geq 6v_4^{14} + .42v_4^{24} + 4.24v_4^{34},$$

$$10.73u_1^{15} + 0.49u_1^{25} \geq 15v_5^{15} + .60v_5^{25} + 4.24v_5^{35},$$

$$1.00u_1^{11} + .084u_1^{21} \geq 10v_1^{11} + .19v_1^{21} + 2.08v_1^{31},$$

$$1.00u_1^{12} + .084u_1^{22} \geq 13v_2^{12} + .21v_2^{22} + 2.08v_2^{32},$$

$$1.00u_1^{13} + .084u_1^{23} \geq 15v_3^{13} + .24v_3^{23} + 2.08v_3^{33};$$

$$1.00u_1^{14} + .084u_1^{24} \geq 8v_4^{14} + .18v_4^{24} + 2.08v_4^{34},$$

$$1.00u_1^{15} + .084u_1^{25} \geq 17v_5^{15} + .25v_5^{25} + 2.08v_5^{35},$$

$$2.88u_1^{11} + .20u_1^{21} \geq 11v_1^{11} + .25v_1^{21} + 4.73v_1^{31},$$

$$2.88u_1^{12} + .20u_1^{22} \geq 14v_2^{12} + .29v_2^{22} + 4.73v_2^{32},$$

$$2.88u_1^{13} + .20u_1^{23} \geq 16v_3^{13} + .31v_3^{23} + 4.73v_3^{33};$$

$$2.88u_1^{14} + .20u_1^{24} \geq 9v_4^{14} + .23v_4^{24} + 4.73v_4^{34},$$

$$2.88u_1^{15} + .20u_1^{25} \geq 19v_5^{15} + .33v_5^{25} + 4.73v_5^{35}$$

$$4.97u_1^{11} + .85u_1^{21} \geq 18v_1^{11} + .28v_1^{21} + 4.58v_1^{31},$$

$$4.97u_1^{12} + .85u_1^{22} \geq 21v_2^{12} + .29v_2^{22} + 4.58v_2^{32},$$

$$4.97u_1^{13} + .85u_1^{23} \geq 24v_3^{13} + .30v_3^{23} + 4.58v_3^{33};$$

$$4.97u_1^{14} + .85u_1^{24} \geq 15v_4^{14} + .24v_4^{24} + 4.58v_4^{34},$$

$$4.97u_1^{15} + .85u_1^{25} \geq 27v_5^{15} + .31v_5^{25} + 4.58v_2^{35},$$

$$3.94u_1^{11} + 0.28u_1^{21} \geq 11v_1^{11} + .21v_1^{21} + 1.33v_1^{31},$$

$$3.94u_1^{12} + 0.28u_1^{22} \geq 14v_2^{12} + .23v_2^{22} + 1.33v_2^{32},$$

$$3.94u_1^{13} + 0.28u_1^{23} \geq 17v_3^{13} + .24v_3^{23} + 1.33v_3^{33};$$

$$3.94u_1^{14} + 0.28u_1^{24} \geq 9v_4^{14} + .19v_4^{24} + 1.33v_4^{34},$$

$$3.94u_1^{15} + 0.28u_1^{25} \geq 19v_5^{15} + .25v_5^{25} + 1.33v_2^{35}$$

$$2.16u_1^{11} + 0.30u_1^{21} \geq 9v_1^{11} + .56v_1^{21} + 2.98v_1^{31},$$

$$2.16u_1^{12} + 0.30u_1^{22} \geq 12v_2^{12} + .60v_2^{22} + 2.98v_2^{32},$$

$$2.16u_1^{13} + 0.30u_1^{23} \geq 13v_3^{13} + .62v_3^{23} + 2.98v_3^{33};$$

$$2.16u_1^{14} + 0.30u_1^{24} \geq 7v_4^{14} + .52v_4^{24} + 2.98v_4^{34},$$

$$2.16u_1^{15} + 0.30u_1^{25} \geq 16v_5^{15} + .64v_5^{25} + 2.98v_2^{35},$$

$$2.58u_1^{11} + 0.15u_1^{21} \geq 6v_1^{11} + .16v_1^{21} + 1.48v_1^{31},$$

$$2.58u_1^{12} + 0.15u_1^{22} \geq 9v_2^{12} + .17v_2^{22} + 1.48v_2^{32},$$

$$2.58u_1^{13} + 0.15u_1^{23} \geq 12v_3^{13} + .19v_3^{23} + 1.48v_3^{33};$$

$$2.58u_1^{14} + 0.15u_1^{24} \geq 6v_4^{14} + .13v_4^{24} + 1.48v_4^{34},$$

$$2.58u_1^{15} + 0.15u_1^{25} \geq 12v_5^{15} + .20v_5^{25} + 1.48v_2^{35},$$

$$1.00u_1^{11} + 0.13u_1^{21} \geq 5v_1^{11} + .10v_1^{21} + .75v_1^{31},$$

$$1.00u_1^{12} + 0.13u_1^{22} \geq 7v_2^{12} + .11v_2^{22} + .75v_2^{32},$$

$$1.00u_1^{13} + 0.13u_1^{23} \geq 9v_3^{13} + .12v_3^{23} + .75v_3^{33};$$

$$1.00u_1^{14} + 0.13u_1^{24} \geq 3v_4^{14} + .08v_4^{24} + .75v_4^{34},$$

$$1.00u_1^{15} + 0.13u_1^{25} \geq 10v_5^{15} + .13v_5^{25} + .75v_2^{35}$$

$$1.73u_1^{11} + 0.13u_1^{21} \geq 4v_1^{11} + .15v_1^{21} + .87v_1^{31},$$

$$1.73u_1^{12} + 0.13u_1^{22} \geq 6v_2^{12} + .18v_2^{22} + .87v_2^{32},$$

$$1.73u_1^{13} + 0.13u_1^{23} \geq 8v_3^{13} + .20v_3^{23} + .87v_3^{33};$$

$$1.73u_1^{14} + 0.13u_1^{24} \geq 3v_4^{14} + .12v_4^{24} + .87v_4^{34},$$

$$1.73u_1^{15} + 0.13u_1^{25} \geq 9v_5^{15} + .21v_5^{25} + .87v_2^{35}$$

$$1.26u_1^{11} + 0.069u_1^{21} \geq 8v_1^{11} + .18v_1^{21} + .90v_1^{31},$$

$$1.26u_1^{12} + 0.069u_1^{22} \geq 10v_2^{12} + .20v_2^{22} + .90v_2^{32},$$

$$1.26u_1^{13} + 0.069u_1^{23} \geq 13v_3^{13} + .22v_3^{23} + .90v_3^{33};$$

$$1.26u_1^{14} + 0.069u_1^{24} \geq 6v_4^{14} + .15v_4^{24} + .90v_4^{34},$$

$$1.26u_1^{15} + 0.069u_1^{25} \geq 14v_5^{15} + .23v_5^{25} + .90v_2^{35}$$

$$3.53u_1^{11} + 0.26u_1^{21} \geq 9v_1^{11} + .19v_1^{21} + 1.51v_1^{31},$$

$$3.53u_1^{12} + 0.26u_1^{22} \geq 11v_2^{12} + .22v_2^{22} + 1.51v_2^{32},$$

$$3.53u_1^{13} + 0.26u_1^{23} \geq 13v_3^{13} + .24v_3^{23} + 1.51v_3^{33}$$

$$3.53u_1^{14} + 0.26u_1^{24} \geq 7v_4^{14} + .16v_4^{24} + 1.51v_4^{34},$$

$$3.53u_1^{15} + 0.26u_1^{25} \geq 15v_5^{15} + .26v_5^{25} + 1.51v_2^{35}$$

$$5.98u_1^{11} + 0.27u_1^{21} \geq 9v_1^{11} + .20v_1^{21} + 2.98v_1^{31},$$

$$5.98u_1^{12} + 0.27u_1^{22} \geq 11v_2^{12} + .21v_2^{22} + 2.98v_2^{32},$$

$$\begin{aligned}
5.98u_1^{13} + 0.27u_1^{23} &\geq 14v_3^{13} + .23v_3^{23} + 2.98v_3^{33}; \\
5.98u_1^{14} + 0.27u_1^{24} &\geq 8v_4^{14} + .18v_4^{24} + 2.98v_4^{34}, \\
5.98u_1^{15} + 0.27u_1^{25} &\geq 15v_5^{15} + .24v_5^{25} + 2.98v_2^{35} \\
1.79u_1^{11} + 0.16u_1^{21} &\geq 7v_1^{11} + .21v_1^{21} + 1.99v_1^{31}, \\
1.79u_1^{12} + 0.16u_1^{22} &\geq 10v_2^{12} + .22v_2^{22} + 1.99v_2^{32}, \\
1.79u_1^{13} + 0.16u_1^{23} &\geq 12v_3^{13} + .24v_3^{23} + 1.99v_3^{33}; \\
1.79u_1^{14} + 0.16u_1^{24} &\geq 6v_4^{14} + .17v_4^{24} + 1.99v_4^{34}, \\
1.79u_1^{15} + 0.16u_1^{25} &\geq 14v_5^{15} + .26v_5^{25} + 1.99v_2^{35}, \\
7.10u_1^{11} + 0.37u_1^{21} &\geq 6v_1^{11} + .25v_1^{21} + 3.64v_1^{31}, \\
7.10u_2^{12} + 0.37u_2^{22} &\geq 8v_2^{12} + .39v_2^{22} + 3.64v_2^{32}, \\
7.10u_3^{13} + 0.37u_3^{23} &\geq 10v_3^{13} + .44v_3^{23} + 3.64v_3^{33}, \\
7.10u_4^{14} + 0.37u_4^{24} &\geq 5v_4^{14} + .19v_4^{24} + 3.64v_4^{34}, \\
7.10u_5^{15} + 0.37u_5^{25} &\geq 12v_5^{15} + .47v_5^{25} + 3.64v_2^{35},
\end{aligned}$$

$$\varepsilon \leq u_4^r \leq u_1^r \leq u_2^r \leq u_3^r \leq u_5^r \quad \forall, r = 1, 2,$$

$$\varepsilon \leq v_4^i \leq v_1^i \leq v_2^i \leq v_3^i \leq v_5^i \quad \forall, i = 1, 2, 3, \quad \varepsilon > 0.$$

**Step 3:** The intuitionistic fuzzy optimal value

$$\left( \tilde{E}_1^{BEST} = (E_{11}^{BEST}, E_{12}^{BEST}, E_{13}^{BEST}; E_{14}^{BEST}, E_{12}^{BEST}, E_{15}^{BEST}) \right),$$

representing the best relative intuitionistic fuzzy efficiency of 1<sup>st</sup> DMU, as well as the intuitionistic fuzzy optimal value

$$\left( \tilde{E}_1^{WORST} = (E_{11}^{WORST}, E_{12}^{WORST}, E_{13}^{WORST}; E_{14}^{WORST}, E_{12}^{WORST}, E_{15}^{WORST}) \right),$$

representing the worst relative intuitionistic fuzzy efficiency of 1<sup>st</sup> DMU, can be obtained by solving the optimistic

intuitionistic fuzzy CCR DEA model-5.23 and pessimistic intuitionistic fuzzy CCR DEA model-5.23 as follows:

**Step 3(a):** The optimal value ( $E_{14}^{BEST}$ ) and ( $E_{14}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.24a and pessimistic crisp CCR DEA model-5.24a by solving optimistic crisp CCR DEA model-5.24b and pessimistic crisp CCR DEA model-5.24b equivalent to optimistic crisp CCR DEA model-5.24a and pessimistic crisp CCR DEA model-5.24a are 0.292 and 1 respectively .

**Optimistic crisp CCR DEA model-5.24a**

$$\text{Maximize } \left[ E_{14}^{BEST} = \frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} \right]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.38 with the following additional constraint:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} \leq 1.$$

**Optimistic crisp CCR DEA model-5.24b**

$$\text{Maximize } [E_{14}^{BEST} = 1.85u_4^{14} + 0.33 u_4^{24}]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR DEA model-5.24 with the following additional constraint:

$$21v_5^{15} + .63v_5^{25} + 9.16v_5^{35} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} \leq 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}.$$

**Pessimistic crisp CCR DEA model-5.24a**

$$\text{Minimize} \left[ E_{14}^{WORST} = \frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} \right]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraint:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} \geq 1.$$

**Pessimistic crisp CCR DEA model-5.24b**

$$\text{Minimize} [E_{14}^{WORST} = 1.85u_4^{14} + 0.33 u_4^{24}]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.24 with the following additional constraints:

$$21v_5^{15} + .63v_5^{25} + 9.16v_5^{35} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} \geq 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}.$$

**Step (3b):** The optimal value ( $E_{11}^{BEST}$ ) and ( $E_{11}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.25a and pessimistic CCR DEA model-5.25a by solving optimistic crisp CCR DEA model-5.25b and pessimistic CCR DEA model-5.25b equivalent to optimistic crisp CCR DEA model-5.25a and pessimistic CCR DEA model-5.25a are 0.416 and 1 respectively .

### Optimistic crisp CCR DEA model-5.25a

$$\text{Maximize } \left[ E_{11}^{BEST} = \frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} \right]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 0.292,$$

$$0.292 \leq \frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} \leq 1.$$

### Optimistic crisp CCR DEA model-5.25b

$$\text{Maximize } [E_{11}^{BEST} = 1.85u_1^{11} + 0.33u_1^{21}]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$19v_3^{13} + .46v_3^{23} + 9.16v_3^{33} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 0.292(21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}),$$

$$0.292(19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}) \leq 1.85u_1^{11} + 0.33u_1^{21} \leq 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}.$$

### Pessimistic crisp CCR DEA model-5.25a

$$\text{Minimize } \left[ E_{11}^{WORST} = \frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} \right]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 1,$$

$$1 \leq \frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}}.$$

### **Pessimistic crisp CCR DEA model-5.25b**

$$\text{Minimize}[E_{11}^{WORST} = 1.85u_1^{11} + 0.33u_1^{21}]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$19v_3^{13} + .46v_3^{23} + 9.16v_3^{33} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35},$$

$$19v_3^{13} + .46v_3^{23} + 9.16v_3^{33} \leq 1.85u_1^{11} + 0.33u_1^{21}.$$

**Step (3c):** The optimal value ( $E_{12}^{BEST}$ ) and ( $E_{12}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.26a and pessimistic CCR DEA model-5.26a by solving optimistic crisp CCR DEA model-5.26b and pessimistic CCR DEA model-5.26b equivalent to optimistic crisp CCR DEA model-5.26a and pessimistic CCR DEA model-5.26b are 0.464 and 1 respectively .

**Optimistic crisp CCR DEA model-5.26a**

$$\text{Maximize } \left[ E_{12}^{BEST} = \frac{1.85 u_2^{12} + 0.33 u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} \right]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraint:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 0.292,$$

$$\frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} = .416,$$

$$0.416 \leq \frac{1.85 u_2^{12} + 0.33 u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} \leq 1.$$

**Optimistic crisp CCR DEA model-5.26b**

$$\text{Maximize } [E_{12}^{BEST} = 1.85 u_2^{12} + 0.33 u_2^{22}]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$17v_2^{12} + .44v_2^{22} + 9.16v_2^{32} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 0.292(21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}),$$

$$1.85u_1^{11} + 0.33u_1^{21} = 0.416(19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}),$$

$$0.416(17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}) \leq 1.85 u_2^{12} + 0.33u_2^{22} \leq 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}.$$

**Pessimistic crisp CCR DEA model-5.26a**

$$\text{Minimize} \left[ E_{12}^{BEST} = \frac{1.85 u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} \right]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.38 with the following additional constraint:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 1,$$

$$\frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} = 1,$$

$$0.416 \leq \frac{1.85 u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}}$$

**Pessimistic crisp CCR DEA model-5.40b**

$$\text{Minimize}[E_{12}^{BEST} = 1.85 u_2^{12} + 0.33u_2^{22}]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$17v_2^{12} + .44v_2^{22} + 9.16v_2^{32} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35},$$

$$1.85u_1^{11} + 0.33u_1^{21} = 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33},$$

$$17v_2^{12} + .44v_2^{22} + 9.16v_2^{32} \leq 1.85 u_2^{12} + 0.33u_2^{22}.$$

**Step (3d):** The optimal value ( $E_{13}^{BEST}$ ) and ( $E_{13}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.27a and pessimistic CCR DEA model-5.27a by solving optimistic crisp CCR DEA model-5.27b and pessimistic CCR DEA model-5.27b equivalent to optimistic crisp CCR DEA model-5.27a and pessimistic CCR DEA model-5.27a are 0.464 and 1 respectively .

### Optimistic crisp CCR DEA model-5.27a

$$\text{Maximize} \left[ E_{13}^{BEST} = \frac{1.85u_3^{13} + 0.33 u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}} \right]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 0.292,$$

$$\frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} = 0.416,$$

$$\frac{1.85 u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} = 0.464,$$

$$0.464 \leq \frac{1.85u_3^{13} + 0.33 u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}} \leq 1.$$

### Optimistic crisp CCR DEA model-5.27b

$$\text{Maximize}[E_{13}^{BEST} = 1.85u_3^{13} + 0.33 u_3^{23}]$$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraint:

$$15v_1^{11} + .39v_1^{21} + 9.16v_1^{31} = 1,$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 0.292(21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}),$$

$$1.85u_1^{11} + 0.33u_1^{21} = 0.416(19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}),$$

$$1.85 u_2^{12} + 0.33u_2^{22} = 0.464(17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}),$$

$$0.464(15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}) \leq 1.85u_3^{13} + 0.33 u_3^{23} \leq 15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}.$$

#### **Pessimistic crisp CCR DEA model-5.27a**

$$\text{Minimize } \left[ E_{13}^{WORST} = \frac{1.85u_3^{13} + 0.33 u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}} \right]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraint:

$$\frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} = 1,$$

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 1,$$

$$\frac{1.85 u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} = 1,$$

$$1 \leq \frac{1.85u_3^{13} + 0.33 u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}}$$

**Pessimistic crisp CCR DEA model-5.27b**

Minimize [ $E_{13}^{WORST} = 1.85u_3^{13} + 0.33 u_3^{23}$ ]

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$15v_1^{11} + .39v_1^{21} + 9.16v_1^{31} = 1$$

$$1.85u_1^{11} + 0.33u_1^{21} = 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}$$

$$1.85 u_2^{12} + 0.33u_2^{22} = 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}$$

$$15v_1^{11} + .39v_1^{21} + 9.16v_1^{31} \leq 1.85u_3^{13} + 0.33 u_3^{23}$$

**Step 3:** The optimal value ( $E_{15}^{BEST}$ ) and ( $E_{15}^{WORST}$ ) of the optimistic crisp CCR DEA model-5.28a and pessimistic CCR DEA model-5.28a by solving optimistic crisp CCR DEA model-5.28b and pessimistic CCR DEA model-5.28b equivalent to optimistic crisp CCR DEA model-5.28a and pessimistic CCR DEA model-5.28a are 0.464 and 1 respectively .

**Optimistic crisp CCR DEA model-5.28a**

Maximize  $\left[ E_{15}^{BEST} = \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}} \right]$

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 0.292,$$

$$\frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} = 0.416,$$

$$\frac{1.85 u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} = 0.464,$$

$$\frac{1.85u_3^{13} + 0.33 u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}} = 0.464,$$

$$0.464 \leq \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}} \leq 1.$$

**Optimistic crisp CCR DEA model-5.28b**

Maximize [ $E_{15}^{BEST} = 1.85u_5^{15} + 0.33u_5^{25}$ ]

Subject to

Constraints of optimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34} = 1,$$

$$1.85u_1^{11} + 0.33u_1^{21} = 0.416(19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}),$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 0.292(21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}),$$

$$1.85 u_2^{12} + 0.33u_2^{22} = 0.464(17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}),$$

$$1.85u_3^{13} + 0.33 u_3^{23} = 0.464(15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}),$$

$$0.464(13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}) \leq 1.85u_5^{15} + 0.33u_5^{25} \leq 13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}.$$

**Pessimistic crisp CCR DEA model-5.28a**

$$\text{Minimize } \left[ E_{15}^{WORST} = \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}} \right]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraints:

$$\frac{1.85u_1^{11} + 0.33u_1^{21}}{19v_3^{13} + .46v_3^{23} + 9.16v_3^{33}} = 1,$$

$$\frac{1.85u_4^{14} + 0.33 u_4^{24}}{21v_5^{15} + .63v_5^{25} + 9.16v_5^{35}} = 1,$$

$$\frac{1.85 u_2^{12} + 0.33u_2^{22}}{17v_2^{12} + .44v_2^{22} + 9.16v_2^{32}} = 1,$$

$$\frac{1.85u_3^{13} + 0.33 u_3^{23}}{15v_1^{11} + .39v_1^{21} + 9.16v_1^{31}} = 1,$$

$$1 \leq \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}}.$$

**Pessimistic crisp CCR DEA model-5.28b**

$$\text{Minimize } \left[ E_{15}^{WORST} = \frac{1.85u_5^{15} + 0.33u_5^{25}}{13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34}} \right]$$

Subject to

Constraints of pessimistic intuitionistic fuzzy CCR fuzzy DEA model-5.23 with the following additional constraint:

$$13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34} = 1,$$

$$1.85u_1^{11} + 0.33u_1^{21} = 19v_3^{13} + .46v_3^{23} + 9.16v_3^{33},$$

$$1.85u_4^{14} + 0.33 u_4^{24} = 21v_5^{15} + .63v_5^{25} + 9.16v_5^{35},$$

$$1.85 u_2^{12} + 0.33u_2^{22} = 17v_2^{12} + .44v_2^{22} + 9.16v_2^{32},$$

$$1.85u_3^{13} + 0.33 u_3^{23} = 15v_1^{11} + .39v_1^{21} + 9.16v_1^{31},$$

$$13v_4^{14} + .26 v_4^{24} + 9.16v_4^{34} \leq 1.85u_5^{15} + 0.33u_5^{25}.$$

**Step 4:** Using the values of  $E_{p1}^{BEST}, E_{p2}^{BEST}, E_{p3}^{BEST}; E_{p4}^{BEST}, E_{p5}^{BEST}$  and

$E_{p1}^{WORST}, E_{p2}^{WORST}, E_{p3}^{WORST}; E_{p4}^{WORST}, E_{p2}^{WORST}, E_{p5}^{WORST}$ , obtained in Step (3a) to Step (3e), the

intuitionistic fuzzy optimal value  $(\tilde{E}_1^{BEST} = (E_{11}^{BEST}, E_{12}^{BEST}, E_{13}^{BEST}; E_{14}^{BEST}, E_{12}^{BEST}, E_{15}^{BEST}))$  of

optimistic intuitionistic fuzzy DEA model-5.23, representing the best relative intuitionistic fuzzy

efficiency of I<sup>st</sup> DMU, is (0.416,0.464,0.464; 0.292,0.464,0.464) as well as intuitionistic

fuzzy optimal value  $(\tilde{E}_1^{WORST} = (E_{11}^{WORST}, E_{12}^{WORST}, E_{13}^{WORST}; E_{14}^{WORST}, E_{12}^{WORST}, E_{15}^{WORST}))$  of

pessimistic intuitionistic fuzzy DEA model-5.23, representing the worst relative intuitionistic

fuzzy efficiency of I<sup>st</sup> DMU is (1,1,1; 1,1,1).

**Step 5:** The crisp optimal value

$(E_1^{BEST} = \mathfrak{R}(\tilde{E}_1^{BEST}) = \mathfrak{R}(0.416,0.464,0.464; 0.292,0.464,0.464))$ , representing the best

relative crisp efficiency of I<sup>st</sup> DMU is 0.437.

**Step 6:** The crisp optimal value  $(E_1^{WORST} = \mathfrak{R}(\tilde{E}_1^{WORST}) = \mathfrak{R}(1,1,1; 1,1,1))$ , representing the worst relative crisp efficiency of 1<sup>st</sup> DMU is 1.

### 5.7.3 Results

The best relative intuitionistic fuzzy efficiency as well as worst relative intuitionistic fuzzy efficiency and hence, the relative geometric crisp efficiency of all the DMUs, obtained by the proposed approach, are shown in Table 5.2.

**Table 5.2** Best relative intuitionistic fuzzy efficiency, worst relative intuitionistic fuzzy efficiency and the relative geometric crisp efficiency of all the DMUs.

| DMUs | Best relative intuitionistic fuzzy efficiency | Worst relative intuitionistic fuzzy efficiency | Relative crisp geometric efficiency |
|------|---|--|-------------------------------------|
| 1    | (.416, .464, .464; .292, .464, .464)          | (1, 1, 1; 1, 1, 1)                             | .661                                |
| 2    | (.742, .751, .763; .727, .751, .768)          | (1, 1.243, 1.532; 1, 1.243, 1.352)             | .970                                |
| 3    | (.940, .946, .949; .937, .947, .958)          | (1.023, 1.245, 2.034; 1, 1.243, 3.65)          | 1.225                               |
| 4    | (.238, .278, .305; .216, .278, .325)          | (1, 1, 1.554; 1, 1, 1.554)                     | .544                                |
| 5    | (.345, .351, .353; .339, .351, .360)          | (1, 1, 1; 1, 1, 1)                             | .591                                |
| 6    | (1, 1, 1; 1, 1, 1)                            | (1, 1, 1.582; 1, 1, 1.603)                     | 1.07                                |
| 7    | (1, 1, 1; 1, 1, 1)                            | (1, 2.63, 3.96; 1, 2.63, 10.21)                | 1.825                               |
| 8    | (.525, .525, .525; .525, .525, .525)          | (1, 1.234, 1.952; 1, 1.234, 2.018)             | .809                                |
| 9    | (.623, .630, .635; .604, .630, .639)          | (1, 2.349, 3.809; 1, 2.349, 6.023)             | 1.268                               |
| 10   | (.825, .830, .838; .823, .830, .842)          | (1, 1, 1; 1, 1, 5.508)                         | 1.074                               |

|    |                                 |                                     |       |
|----|---------------------------------|-------------------------------------|-------|
| 11 | (.716,.718,.723;.710,.718,.728) | (1, 2.938, 3.809; 1, 2.938, 4.432)  | 1.405 |
| 12 | (.473,.473,.473;.473,.473,.473) | (1, 1, 1.247; 1,1, 1.513)           | .720  |
| 13 | (.820,.827,.830;.818,.827,.837) | (1, 3.253, 3.997; 1, 3.253, 10.908) | 1.758 |
| 14 | (.679,.685,.690;.672,.685,.693) | (1, 3.040, 4.411; 1, 3.040, 4.411 ) | 1.402 |
| 15 | (.732,.735,.739;.727,.735,.748) | (1, 1.853, 2.092; 1, 1.853, 3.453)  | 1.173 |
| 16 | (.733,.737,.740;.730,.737,.742) | (1, 3.973, 5.298; 1, 3.973, 8.416)  | 1.706 |

## 5.8 Conclusions

On the basis the present study, it can be concluded that there are flaws in the optimistic as well as pessimistic intuitionistic fuzzy CCR DEA model and in the method proposed by Puri and Yadav [83] and hence neither the intuitionistic fuzzy CCR DEA model proposed by, Puri and Yadav [83] nor the method proposed by Puri and Yadav [83] should be used for evaluating the best relative geometric crisp efficiency of DMUs. Also, to resolve the flaws of the intuitionistic fuzzy CCR DEA models, new intuitionistic fuzzy CCR DEA models are proposed. Further, a new approach is proposed to solve the proposed intuitionistic fuzzy CCR DEA models for evaluating the best relative geometric crisp efficiency of DMUs.



# Chapter 6

## Future Scope

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The following may be treated as future directions:

1. The fuzzy/intuitionistic fuzzy CCR DEA models, proposed in thesis, are valid only if positive fuzzy/intuitionistic fuzzy numbers represents input and output data. However, in real life problem, there exist several real life problems in which some of the input data and/ or output data may be negative e.g., investment returns of mutual funds may be negative. Some researchers have developed some fuzzy DEA models to deal with negative data. However, after a deep study of these methods, it is concluded that there are some flaws in these methods. In future, it may be tried to develop new fuzzy/intuitionistic fuzzy DEA models to deal with negative data.
2. In the thesis, the flaws in the exiting fuzzy/ intuitionistic fuzzy CCR DEA models are pointed out and to resolve the flaws, new fuzzy/ intuitionistic fuzzy CCR DEA models are proposed. There are several other fuzzy DEA models which are extension of fuzzy CCR DEA models. It can be easily verified that the flaws, pointed out in the fuzzy/intuitionistic fuzzy CCR DEA models, also exists in the other fuzzy DEA models. In future, new fuzzy/ intuitionistic fuzzy DEA models may be developed to resolve the flaws of other existing fuzzy DEA models.
3. The approaches, proposed in this thesis, may be used to evaluate the exact best relative geometric crisp efficiency of real life problems.



# Bibliography

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1. Abtahi, A-R., Khalili-Damghani, K., Fuzzy data envelopment analysis for measuring agility performance of supply chains, *Int. J. Model. Operat. Manag.*, 1, 263–288 (2011).
2. Ahmady, N., Azadi, M., Sadeghi, S.A.H., Saen, R.F., A novel fuzzy data envelopment algorithm for efficiency assessment and optimization of wireless communication sectors analysis model with double frontiers for supplier selection, *Int. J. Logist. Res. Appl.*, 16, 87–98 (2013).
3. Angiz, L., Emrouznejad, M.Z., Mustafa, A., Fuzzy data envelopment analysis: a discrete approach, *Expert Syst. Appl.*, 39, 2263–2269 (2012).
4. Asbullah, M.A., A new approach to estimate the mix efficiency in data envelopment analysis, *Appl. Math. Sci.*, 4, 2135–2143 (2010).
5. Atanassov, K.T., Intuitionistic fuzzy sets, *Fuzzy Sets Syst.*, 20, 87-96 (1996).
6. Banker, R.D., Charnes, A., Cooper, W.W., Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Manage. Sci.*, 30, 1078–1092 (1984).
7. Bazaraa, M.S., J.J Jarvis, H.D Sherali, *Linear Programming and Network Flows*, Second Edition, Wiley, New York, 1990.
8. Bector, C.R., S. Chandra, On duality in linear programming under fuzzy environment, *Fuzzy Sets Syst.*, 125, 317-325 (2002).
9. Bellman, R.E., Zadeh, L.A., Decision making in a fuzzy environment, *Manag. Sci.*, 17, 141–164 (1970).
10. Charnes, A., Cooper, W.W., The non-Archimedean CCR ratio for efficiency analysis: a rejoinder to Boyd and Fare, *Eur. J. Oper. Res.*, 15, 333–334 (1984).

11. Charnes, A., Cooper, W.W., Rhodes, E., Measuring the efficiency of decision making units, *Eur. J. Oper. Res.*, 2, 429–444 (1978).
12. Cook, W.D., Kress, M., Seiford, L.M., Data envelopment analysis in the presence of both quantitative and qualitative factors, *J. Oper. Res. Soc.*, 47, 945–953 (1996).
13. Cook, W.D., Kress, M., Seiford, L.M., On the use of ordinal data in data envelopment analysis, *J. Oper. Res. Soc.*, 44, 133–140 (1993).
14. Cook, W.D., Seiford, L.M., Data envelopment analysis (DEA)—Thirty years on, *Eur. J. Oper. Res.*, 192, 1–17 (2009).
15. Cooper, W.W., Park, K.S., Yu, G., An illustrative application of IDEA (Imprecise Data Envelopment Analysis) to a Korean mobile telecommunication company, *Oper. Res.*, 49, 807–820 (2001).
16. Cooper, W.W., Park, K.S., Yu, G., IDEA (imprecise data envelopment analysis) with CMDs (column maximum decision making units), *J. Oper. Res. Soc.*, 52, 176–181 (2001).
17. Cooper, W.W., Park, K.S., Yu, G., IDEA and AR-IDEA: models for dealing with imprecise data in DEA, *Manage. Sci.*, 45, 597–607 (1999).
18. Cooper, W.W., Seiford, L.M., Tone, K., *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*, 2nd edition. Springer, NewYork (2007).
19. Despotis, D.K., Smirlis, Y.G., Data envelopment analysis with imprecise data, *Eur. J. Oper. Res.*, 140, 24–36 (2002).
20. Dahiya, K., Verma, V., Positive sensitivity analysis in linear programming with bounded variables, *ASOR Bulletin*, 26, 2-26 (2007).

21. Dia, M., A model of fuzzy data envelopment analysis, *INFOR*, 42, 267–279 (2004).
22. Dyson, R.G., Shale, E.A., Data envelopment analysis, operational research and uncertainty, *J. Oper. Res. Soc.*, 61, 25–34 (2010).
23. Emrouznejad, A., Parker, B.R., Tavares, G., Evaluation of research in efficiency and productivity: a survey and analysis of the first 30 years of scholarly literature in DEA, *Socioecon.Plan. Sci.*, 42, 151–157 (2008).
24. Emrouznejad, A., Rostamy-Malkhalifeh, M., Hatami-Marbini, A., Tavana, M., Aghayi, N.: An overall profit Malmquist productivity index with fuzzy and interval data. *Math. Comput. Model.*, 54, 2827–2838 (2011).
25. Emrouznejad, A., Tavana, M., Performance Measurement with Fuzzy Data Envelopment Analysis, *Studies in Fuzziness and Soft Computing* 309, DOI: 10.1007/978-3-642-4137-8\_1, Springer-Verlag Berlin Heidelberg 2014.
26. Garcia, P.A.A., Schirru, R., Melo, P.F.F.E., A fuzzy data envelopment analysis approach for FMEA, *Prog. Nucl. Energy*, 46, 359–373 (2005).
27. Gattoufi, S., Oral, M., Reisman, A., A taxonomy for data envelopment analysis, *Socioecon. Plan. Sci.*, 38, 141–158 (2004).
28. Greene, W.H., A Gamma-distributed stochastic frontier model, *J. Econometrics*, 46, 141-163 (1990).
29. Guh, Y.Y., Data envelopment analysis in fuzzy environment, *Inf. Manag. Sci.*, 12, 51–65 (2001).
30. Guo, P., Fuzzy data envelopment analysis and its application to location problems, *Inf. Sci.*, 179, 820–829 (2009).

31. Guo, P., Tanaka, H., Fuzzy DEA: a perceptual evaluation method, *Fuzzy Sets Syst.*, 119 149–160 (2001).
32. Gupta, S. K., Dangar, D., Duality for a class of nonlinear optimization problem under generalized convexity, *Fuzzy Opt. Dec. Making*, 13, 131–150 (2014).
33. Gupta, P., Mehlawat, M.K., Bector-Chandra type duality in fuzzy linear programming with exponential membership functions *Fuzzy Sets Syst.*, 160 (2009) 3290-3308.
34. Gupta, A., Mehra , A., Appadoo , S. S., Mixed solution strategy for MCGDM problems using entropy/ class entropy in interval valued intuitionistic fuzzy environment, *International Game Theory Review*, 17, doi: 10.1142/S0219198915400071 (2015).
35. Hatami-Marbini, A., Emrouznejad, A., Tavana, M., A taxonomy and review of the fuzzy data envelopment analysis literature: two decades in the making, *Eur. J. Oper. Res.*, 214, 457–472 (2011).
36. Hatami-Marbini, A., Saati, S., Makui, A., Ideal and anti-Ideal decision making units: a fuzzy DEA approach, *J. Ind. Eng. Int.*, 6, 31–41 (2010).
37. Hatami-Marbini, A., Saati, S., Tavana, M., An ideal-seeking fuzzy data envelopment analysis framework, *Appl. Soft Comput.*, 10, 1062–1070 (2010).
38. Hatami-Marbini, A., Saati, S., Tavana, M., Data envelopment analysis with fuzzy parameters: an interactive approach, *Int. J. Oper. Res. Inf. Syst.*, 2, 39–53 (2011).
39. Hatami-Marbini, A., Tavana, M., Agrell, P.J., Saati, S., Positive and normative use of fuzzy DEA-BCC models: a critical view on NATO enlargement, *Int. Trans. Oper. Res.*, 20, 411–433 (2013).
40. Hatami-Marbini, A., Tavana, M., Ebrahimi, A., A fully fuzzified data envelopment analysis model, *Int. J. Inf. Decis. Sci.*, 3, 252–264 (2011).

41. Hatami-Marbini, A., Tavana, M., Emrouznejad, A., Saati, S., Efficiency measurement in fuzzy additive data envelopment analysis, *Int. J. Ind. Syst. Eng.*, 10, 1–20 (2012).
42. Hosseinzadeh Lotfi, F., Adabitarbar Firozja, M., Erfani, V., Efficiency measures in data envelopment analysis with fuzzy and ordinal data, *Int. Math. Forum*, 4, 995–1006 (2009a).
43. Hosseinzadeh Lotfi, F., Jahanshahloo, G.R., Alimardani, M., A new approach for efficiency measures by fuzzy linear programming and application in insurance organization, *Appl. Math. Sci.*, 1, 647–663 (2007).
44. Hosseinzadeh Lotfi, F., Jahanshahloo, G.R., Vahidi, A.R., Dalirian, A., Efficiency and effectiveness in multi-activity network DEA model with fuzzy data, *Appl. Math. Sci.*, 3, 2603–2618 (2009).
45. Hosseinzadeh Lotfi, F., Mansouri, B., The extended data envelopment analysis /discriminant analysis approach of fuzzy models, *Appl. Math. Sci.*, 2, 1465–1477 (2008).
46. Jahanshahloo, G.R., Hosseinzadeh Lotfi, F., Adabitarbar Firozja, M., Allahviranloo, T., Ranking DMUs with fuzzy data in DEA, *Int. J. Contemp. Math. Sci.*, 2, 203–211 (2007b).
47. Juan, Y.K., A hybrid approach using data envelopment analysis and case-based reasoning for housing refurbishment contractors selection and performance improvement, *Expert Syst. Appl.*, 36, 5702–5710 (2009).
48. Kao, C., Efficiency measurement for parallel production systems, *Eur. J. Oper. Res.*, 196, 1107–1112 (2009).

49. Kao, C., Hwang, S.N., Efficiency decomposition in two-stage data envelopment analysis: an application to non-life insurance companies in Taiwan, *Eur. J. Oper. Res.*, 185, 418–429 (2008).
50. Kao, C., Hwang, S.N., Efficiency measurement for network systems: IT impact on firm performance, *Decis. Support Syst.*, 48, 437–446 (2010).
51. Kao, C., Interval efficiency measures in data envelopment analysis with imprecise data, *Eur. J. Oper. Res.*, 174, 1087–1099 (2006).
52. Kao, C., Lin, P.H., Efficiency of parallel production systems with fuzzy data, *Fuzzy Sets Syst.*, 198, 83–98 (2012).
53. Kao, C., Lin, P.H., Qualitative factors in data envelopment analysis: a fuzzy number approach, *Eur. J. Oper. Res.*, 211, 586–593 (2011).
54. Kao, C., Liu, S.T., A mathematical programming approach to fuzzy efficiency ranking, *Int. J. Prod. Econ.*, 86, 145–154 (2003).
55. Kao, C., Liu, S.T., Data envelopment analysis with imprecise data: An application of Taiwan machinery firms, *Int. J. Uncertain. Fuzziness Knowl. Based Syst.*, 13, 225–240 (2005).
56. Kao, C., Liu, S.T., Data envelopment analysis with missing data: an application to university libraries in Taiwan, *J. Oper. Res. Soc.*, 51, 897–905 (2000).
57. Kao, C., Liu, S.T., Efficiencies of two-stage systems with fuzzy data, *Fuzzy Sets Syst.*, 176, 20–35 (2011).
58. Kao, C., Liu, S.T., Fuzzy efficiency measures in data envelopment analysis, *Fuzzy Sets Syst.*, 113, 427–437 (2000).

59. Kao, C., Liu, S.T., Fuzzy efficiency measures in data envelopment analysis, *Fuzzy Sets and Sys.*, 113, 427–437 (2000).
60. Karsak, E.E., Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of imprecise data, *Int. J. Adv. Manuf. Technol.*, 35, 867–874 (2008).
61. Kasana, H. S., K. D. Kumar, *Introductory Operations Research: Theory and Applications*, Springer-Verlag, Berlin Heidelberg, New York, 2004.
62. Kaufmann, A., Gupta, M.M., *Introduction to Fuzzy Arithmetic: Theory and Applications*, Van Nostrand Reinhold, New York, 1985.
63. A. Kaufmann, Gupta, M.M., *Fuzzy Mathematical Models in Engineering and Management Science*, Amsterdam Netherland, Elsevier, 1988.
64. Khalili-Damghani, K., Abtahi, A-R., Measuring efficiency of just in time implementation using a fuzzy data envelopment analysis approach: real case of Iranian dairy industries, *Int. J. Adv. Oper. Manag.*, 3, 337–354 (2011).
65. Khan, F.I., Sadiq, R., Risk-based prioritization of air pollution monitoring using fuzzy synthetic evaluation technique, *Environmental Monitoring and Assessment*, 105, 26-283 (2005).
66. Khodabakhshi, M., Gholami, Y., Kheirollahi, H., An additive model approach for estimating returns to scale in imprecise data envelopment analysis, *Appl. Math. Model.*, 34, 1247–1257 (2010).
67. Khoshfetrat, S., Daneshvar, S., Improving weak efficiency frontiers in the fuzzy data envelopment analysis models, *Appl. Math. Model.*, 35, 339–345 (2011).
68. G.J. Klir, B. Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, Prentice-Hall,

Inc., New Jersey, USA, 1996.

69. Leon, T., Liern, V., Ruiz, J.L., Sirvent, I., A fuzzy mathematical programming approach to the assessment of efficiency with DEA models, *Fuzzy Sets Syst.*, 139, 407–419 (2003).
70. Lertworasirikul, S., Fang, S.C., Joines, J.A., Nuttle, H.L.W., Fuzzy data envelopment analysis (DEA): a possibility approach, *Fuzzy Sets Syst.*, 139, 379–394 (2003).
71. Lertworasirikul, S., Fang, S.C., Nuttle, H.L.W., Joines, J.A., Fuzzy BCC model for data envelopment analysis, *Fuzzy Opt. Dec. Making*, 2, 337–358 (2003).
72. Lertworasirikul, S.: *Fuzzy Data Envelopment Analysis (DEA)*. Ph.D. Dissertation, Department of Industrial Engineering, North Carolina State University (2002).
73. Lin, H.T., Personnel selection using analytic network process and fuzzy data envelopment analysis approaches, *Comput. Ind. Eng.*, 59, 937–944 (2010).
74. Liu, S., Chuang, M., Fuzzy efficiency measures in fuzzy DEA-AR with application to university libraries, *Expert Syst. Appl.*, 36, 1105–1113 (2009).
75. Mansourirad, E., Rizam, M.R.A.B., Lee, L.S., Jaafar, A., Fuzzy weights in data envelopment analysis, *Int. Math. Forum*, 5, 1871–1886 (2010).
76. Mohanty, B.K., A procedure for measuring uncertainties due to lack of information in a fuzzy game theory problem, *International Journal of Systems Science*, 25, 2309–2317 (1994).
77. Moheb-Alizadeh, H., Rasouli, S.M., Tavakkoli-Moghaddam, R., The use of multi-criteria data envelopment analysis (MCDEA) for location–allocation problems in a fuzzy environment, *Expert Syst. Appl.*, 38, 5687–5695 (2011).
78. Mostafaei, A., Saljooghi, F.H., Cost efficiency measures in data envelopment analysis with data uncertainty, *Eur. J. Oper. Res.*, 202, 595–603 (2010).

79. Nagano, F., T. Yamaguchi, T. Fukukawa, DEA with fuzzy output data, *J. Oper. Res. Soc. Jpn.*, 40, 425-429 (1995).
80. Nedeljkovic', R.R., Drenovac, D., Efficiency measurement of delivery post offices using fuzzy data envelopment analysis (Possibility approach), *Int. J. Traffic Transp. Eng.*, 2, 22–29 (2012).
81. Park, K.S., Efficiency bounds and efficiency classifications in DEA with imprecise data, *J. Oper. Res. Soc.*, 58, 533–540 (2007).
82. Puri, J., Yadav, S.P., A concept of fuzzy input mix-efficiency in fuzzy DEA and its application in banking sector, *Expert Syst. Appl.*, 40, 1437–1450 (2013).
83. Puri, J., S.P. Yadav, Intuitionistic fuzzy data envelopment analysis: An application to the banking sector in India, *Expert Syst. Appl.*, 42, 4982-4998 (2015).
84. Qin, R., Liu, Y., Liu, Z.-Q., Modeling fuzzy data envelopment analysis by parametric programming method, *Expert Syst. Appl.*, 38, 8648–8663 (2011).
85. Ramón, N., Ruiz, J.L., Sirvent, I., On the choice of weights profiles in cross-efficiency evaluations, *Eur. J. Oper. Res.*, 207, 1564–1572 (2009).
86. Ray, S.C., *Data envelopment analysis: theory and techniques for economics and operations research*, Cambridge University Press, Cambridge (2004).
87. Razavi Hajiagha, S.H., Akrami, H., Zavadskas, E.K., Hashemi, S.S., An intuitionistic fuzzy data envelopment analysis for efficiency evaluation under uncertainty: case of a finance and credit institution, *E a M: Ekonomie a Management*, 161, 128–137 (2013).
88. Saati, S., Hatami-Marbini, A., Tavana, M., A data envelopment analysis model with discretionary and non-discretionary factors in fuzzy environments, *Int. J. Prod. Qual.Manag.*, 8, 45–63 (2011).

89. Saati, S., Hatami-Marbini, A., Tavana, M., Agrell, P.J., A fuzzy data envelopment analysis for clustering operating units with imprecise data, *Int. J. Uncertain. Fuzziness Knowl. Based Syst.*, 21, 29–54 (2013).
90. Saati, S., Memariani, A., Jahanshahloo, G.R., Efficiency analysis and ranking of DMUs with fuzzy data., *Fuzzy Optim.Decis. Making*, 1, 255–267 (2002).
91. Saneifard, R., Allahviranloo T., Hosseinzadeh Lotfi, F., Mikaeilvand, N., Euclidean ranking DMUs with fuzzy data in DEA, *Appl. Math. Sci.*, 1, 2989–2998 (2007).
92. Sefeedpari, P., Rafiee, S., Akram, A., Selecting energy efficient poultry egg producers: a fuzzy data envelopment analysis approach, *Int. J. Appl. Oper. Res.*, 2, 77–88 (2012).
93. Seiford, L.M., Data envelopment analysis: the evolution of the state of the art (1978–1995), *J. Prod. Anal.*, 7, 99–137 (1996).
94. Sengupta, J.K., A fuzzy systems approach in data envelopment analysis, *Comput. Math. Appl.*, 24, 259–266 (1992).
95. Sengupta, J.K., Measuring efficiency by a fuzzy statistical approach, *Fuzzy Sets Syst.*, 46, 73–80 (1992).
96. Sheth, N., Triantis, K., Measuring and evaluating efficiency and effectiveness using goal programming and data envelopment analysis in a fuzzy environment, *Yugoslav J. Oper. Res.*, 13, 35–60 (2003).
97. Srinivasa Raju, K., Nagesh Kumar, D., Fuzzy data envelopment analysis for performance evaluation of an irrigation system, *Irrigation Drainage*, 62, 170–180 (2013).
98. Stancu-Minasian, I.M., Pop, B., On a fuzzy set approach to solving multiple objective linear fractional programming problem, *Fuzzy Sets Syst*, 134, 397-405 (2003).
99. Taha, H.A., *Operations Research: An Introduction*, Prentice-Hall, New Jersey, 2003.

100. Thanassoulis, E., A comparison of regression analysis and data envelopment analysis as alternative methods for performance assessments, *J. Oper. Res. Soc.*, 44, 1129-1144 (1993).
101. Tlig, H., Rebai, A., A mathematical approach to solve data envelopment analysis models when data are LR fuzzy numbers, *Appl. Math. Sci.*, 3, 2383–2396 (2009).
102. Tone, K., A slacks-based measure of efficiency in data envelopment analysis, *Eur. J. Oper. Res.*, 130, 498–509 (2001).
103. Triantis, K., Fuzzy non-radial data envelopment analysis (DEA) measures of technical efficiency in support of an integrated performance measurement system, *Int. J. Automat. Technol. Manag.*, 3, 328–353 (2003).
104. Verma, A.K., Srividya, A., Deka, B.C. Composite system reliability assessment using fuzzy linear programming, *Electric Power Systems Research*, 73 (2005) 143-149.
105. Wang, Y.-M., Chin, K.-S., Fuzzy data envelopment analysis: a fuzzy expected value approach, *Expert Syst. Appl.*, 38, 11678–11685 (2011).
106. Wang, Y.M., Luo, Y., Liang, L., Fuzzy data envelopment analysis based upon fuzzy arithmetic with an application to performance assessment of manufacturing enterprises, *Expert Syst. Appl.*, 36, 5205–5211 (2009).
107. Wen, M., Li, H., Fuzzy data envelopment analysis (DEA): model and ranking method, *J. Comput. Appl. Math.*, 223, 872–878 (2009).
108. Wen, M., You, C., Kang, R., A new ranking method to fuzzy data envelopment analysis, *Comput. Math. Appl.*, 59, 3398–3404 (2010).
109. W. L. Winston (2007). *Operations Research: Applications and Algorithms*, fourth edition, Thomson, Australia.

110. Wu, D.D., Performance evaluation: an integrated method using data envelopment analysis and fuzzy preference relations, *Eur. J. Oper. Res.*, 194, 227–235 (2005).
111. Wu, D., Yang, Z., Liang, L., Efficiency analysis of cross-region bank branches using fuzzy data envelopment analysis, *Appl. Math. Comput.*, 181, 271–281 (2006).
112. Zadeh, L.A., Fuzzy sets as a basis for a theory of possibility, *Fuzzy Sets Syst.*, 1, 3–28 (1999).
113. Zadeh, L.A., Fuzzy sets, *Inf. Control*, 8, 338–353 (1965).
114. Zerafat Angiz L., M., Emrouznejad, A., Mustafa, A., Fuzzy data envelopment analysis: A discrete approach, *Expert Syst. Appl.*, 39, 2263–2269 (2012).
115. Zerafat Angiz L., M., Tajaddini, A., Mustafa, A., Jalal Kamali, M., Ranking alternatives in a preferential voting system using fuzzy concepts and data envelopment analysis, *Computers & Industrial Engineering*, 63, 784–790 (2012).
116. Zerafat Angiz, L.M., Emrouznejad, A., Mustafa, A., Aggregating preference ranking with fuzzy data envelopment analysis, *Knowl. Based Syst.*, 23, 512–519 (2010a).
117. Zerafat Angiz, L.M., Mustafa, A., Emrouznejad, A., Ranking efficient decision making unit sin data envelopment analysis using fuzzy concept, *Comput. Ind. Eng.*, 59, 712–719 (2010).
118. Zhang, Q., Yang, S.X., Mittal, G.S., Yi, S., Prediction of performance indices and optimal parameters of rough rice drying using neural networks, *Biosystems Engg.*, 83, 281-290 (2002).
119. Zhao, X., Yue, W., A multi-subsystem fuzzy DEA model with its application in mutual funds management companies' competence evaluation, *Procedia Comput. Sci.*, 1, 2469–2478 (2012).

120. Zhou, Z., Lui, S., Ma, C., Liu, D., Liu, W., Fuzzy data envelopment analysis models with assurance regions: a note, *Expert Syst. Appl.*, 39, 2227–2231 (2012).
121. Zhu, J., Imprecise data envelopment analysis (IDEA): a review and improvement with an application, *Eur. J. Oper. Res.*, 144, 513–529 (2003).
122. Zhu, J., Imprecise DEA via standard linear DEA models with a revisit to a Korean mobile telecommunication company, *Opns. Res.*, 52, 323–329 (2004).
123. Zimmermann, H.Z., *Fuzzy Set Theory and Its Applications*, 3rd edn., Kluwer Nijhoff, Boston (1996).