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Estimating Unloading Time at Cross Docking Centre by Using Fuzzy Logic

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ABSTRACT

Cross docking is an alternative technique of warehousing that aims on eliminating the storage cost by significantly reducing handling and storage of inventory. One of the decision levels that requires vital attention to ensure the smooth and effective operation at cross docking terminal is the truck scheduling policy. Prior to that, an assignment decision of truck to door need to be decided first, hence the sequence of truck can be organized. The common practice was to assign the truck based on the availability of dock door and estimates the time of unloading based on intuition or experience from past record. Thus far, no systematic approach was found in the literature to estimate truck's unloading time. Paper on hand aims to tackle this issue by proposing a fuzzy logic approach to estimate truck's unloading time at retail cross docking warehouse. Refers to three orderly stages introduced in the literature of fuzzy logic inference system, seven steps were implemented in this study. With the help of Matlab software, all the input and output variables were set in the Fuzzy Logic Toolbox. Results obtained were analyzed and compared with the actual data gathered from the selected cross docking warehouse. The finding in this study is significant for the scheduling policy in cross docking terminal specifically to coordinate the assignment process for truck to door. Methodology proposed can also be adopted in any traditional warehouses, distribution centre or container terminal.

Key words: Cross docking, unloading time, fuzzy logic, truck-to-door assignment, scheduling

INTRODUCTION

Cross docking plays an integral part in the supply chain network of Fast Moving Consumer Goods (FMCG). It is an operational strategy that moved items through distribution centre without putting them into storage (Babics, 2005). Number of manufacturing companies, transportation service providers and also logistics providers are using cross docks as a consolidation or re-distribution point. Advantages of cross docking accrue from the reduction of the inventory holding cost, order picking cost, transportation cost and delivery time. In fact, cross docking system has been successfully applied in many industries and several famous companies such as Wal-Mart, Home Depot, Costco, Canadian Tire, FedEx Freight, Toyota, Goodyear GB Ltd. and Kodak C (Shakeri *et al*., 2008; Chen *et al*., 2009; Boysen, 2010).

According to Goliasa *et al*. (2010), one of the main problems in the cross docking centre is the problem concerning the main operations of the facility which involve inbound, staging and outbound operations. These operations include inbound operations which consist of assigning, scheduling and unloading inbound trucks, internal operations that involve the mixing and consolidation of goods and outbound operations which concerning on loading the goods to outbound trucks. When a supplier truck arrives at the facility, the respective operation manager faces two interrelated decisions which are; where and when the truck should be assigned to the dock (Boysen and Fliedner, 2010). The problem arises due to the inability of the operation manager to have complete information regarding the processing time (or unloading time) for each truck. Therefore, the truck is randomly assigned to the dock door just based on the availability of door and estimated truck's unloading time by the manager based on intuition, experienced and past records (Stock and Lambert, 2001).

The performance of goods transshipment in cross docking terminal is influenced by the effectiveness of the dock door assignment (Shuib and Wan Ahmad Fatthi, 2012). If an inbound operation is not being handled effectively, there will have a delay in completion of truck unloading task due to prolonged waiting and queuing time for the truck before being serviced. The total cross docking operation time (makespan) is define as the sum of total time for inbound operations, internal processing time and the total outbound operation time (Shakeri *et al*., 2008). Minimizing the dock-door assignment and scheduling time of inbound trucks will minimize the makespan, thus, contributes towards cost-savings of the cross docking operations.

This study presented a methodology for estimating the unloading time for the inbound operations in retail cross docking centre based on the fuzzy logic approach. The estimation was significant for the real time truck-to-door assignment model which was a part of the study on an optimization model of cross docking operations. It can be easily adapted for implementation in any cross docking or warehouse inbound trucks assignment and scheduling operations.

FUZZY LOGIC CONCEPT

Fuzzy logic has rapidly becoming an emerging technology for developing sophisticated control systems. Since it mimics human control logic with experience and expertise, fuzzy logic is not only recognized as a better approach for sorting and handling the data, but it is also proven as an excellent method for many control system applications in the field of business, industrial process, medical, electronics and engineering. Fuzzy logic control is derived from fuzzy set theory, first pioneered by Zadeh (1965). It is a theory which provides a framework for handling the vague, incomplete and imprecise qualitative data. In fuzzy logic control, a simple, plain language "IF X AND Y THEN RULE" is used to represent the desired system response in term of linguistic variable instead of mathematical formulation (Saini, 2005).

Fuzzy logic control involves three orderly stages (Cox 1992; Salama and Bartnikas, 2000; Cordon *et al*., 2004; Ganga and Carpinetti, 2011) as illustrated in Fig. 1, namely the fuzzification of the input variable, fuzzy inference engine with the application of If-Then rules and the defuzzification of the results.

During the fuzzification process, the numeric input variables are converted into their corresponding fuzzy sets via membership functions. The membership functions can take many forms included triangular, trapezoidal, bell shaped, Gaussian and etc. (Niraj and Kumar, 2011). These fuzzy inputs are called as antecedents and the real values which correspond to this antecedent can be changed interactively at runtime during the execution (Omara and Zohier, 2010). Once the inputs are fuzzified, the corresponding input fuzzy sets are passed to the inference engine that process the information to evaluate the actual value from the fuzzy rule base.

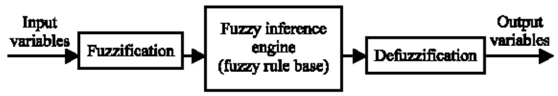

Fig. 1: Three orderly stages in fuzzy logic control

Fuzzy rule base is characterized in the form of IF-THEN rules where the IF statement is called as an antecedent and the THEN statement is called as consequent in which both involves the linguistic variables. For the case of multiple antecedents, they can be connected using 'AND' or 'OR' fuzzy operator (Rojas, 1996) to obtain the single number which indicates the result of antecedents evaluation. Refer to Yen (1999), fuzzy If-Then rules can be defined as:

If x is A and y is B then z is C

Schematically:

Rule	=	If x is A and y is B then z is C
Fact (antecedents)	=	x is A and y is B
Conclusion (consequent)	=	z is C

Where:

x and y	=	Input variables
z	=	Output variable

Each rule will produce an individual output and the outputs of all rules are unified in the aggregation process. The output of the inference process will always be the aggregated fuzzy set. However, for the implementation in a real world situation, the aggregated fuzzy output has to be converted into a crisp value. Here, the defuzzification process will play a certain role. The most common technique used in defuzzification is Centroid or Centre of Gravity Method (Saletic *et al.*, 2002; Eker and Torun, 2006; Azimirad *et al.*, 2010).

FUZZY LOGIC APPROACH FOR ESTIMATING TRUCK'S UNLOADING TIME

Data analysis: In retail cross docking terminal, each incoming truck is usually associated to one supplier. It is also a normal case for one supplier to send their products in many trucks. Upon arrival at the registration point of cross docking centre, each truck is required to present the purchase orders which contains details of the ordered products carried in the truck. In each purchase order, list of items along with the respective number of boxes per item associated to the predefined store were recorded.

In this study, the data was gathered from a selected logistic company which handles retail cross docking services. Data collected comprised of all information regarding the inbound operation. Data was then recorded in a database using Microsoft Excel. Data gathered included detail information of arrival time of truck, truck start time of service at dock door, time taken for unloading the freight and its departure time from the dock. Unloading time in this study refers to the total time taken for transferring the freight from truck to bay with the time for examining the correctness of the products. Besides that, information pertaining to variation of items and quantity of boxes were extracted from the information written in the copies of purchase orders. Sample of result from the data analysis for five trucks is shown in Table 1.

Table 1: Result of data analysis for five trucks

Truck	PO	I	B	AT	ST	DT	AUT (min)
1	1	3	11	11:44	11:45	11:55	10
2	21	54	59	8:51	9:11	10:46	94
3	42	211	314	9:56	11:12	14:27	185
4	77	345	694	8:09	9:06	14:17	310
5	120	382	728	13:25	15:20	20:16	296

PO: Purchase order, I: Item, B: Boxes, AT: Actual time, ST: Start time, DT: Departure time, AUT: Actual unloading time and Min: Minutes

Implementation steps: The fuzzy logic approach was used in this study to estimate the unloading time of trucks of inbound operation in retail cross docking facility. The estimation of unloading time was determined by measuring three main criteria which were, number of purchase orders carried by a truck, variation of items listed in each purchase order and quantity of boxes loaded in the truck. These criteria were considered in this study as they were the available information that can be obtained based on the purchase orders, presented by truck at the registration point. There were six steps to be followed in estimating unloading time using fuzzy logic:

- **Step 1: Identification of the input and output variables:** In this study, three input variables and one output variable were identified. The input variables were the number of purchase orders, varieties of items and the number of boxes while the output variable was the expected unloading time. For each linguistic variable, the linguistic value and range are represented in Table 2

Range was classified based on the data analyzed while the membership functions for the respective input and ouput variables were proposed based on this data analysis and approved by the experts from the company.

- **Step 2:** Rules generated in the Fuzzy Rules Base (FRB) from the linguistic values of input and output variables

Referring to step 1, there were three input variables with five linguistic values proposed for each input. Thus, total number of possible rules that could be obtained is given by:

$$l = k^n$$

Where:

l = Maximum possible number of rules
k = Fuzzy partition (lingustic values)
n = No. of inputs

Thus:

$$l = 5^3 = 125 \text{ rules}$$

However, 10 possible rules were excluded in this study due to illogical condition. Therefore, based on the 115 possible rules obtained, a Fuzzy Associative Memory (FAM) table was created to

Table 2: Linguistic variables, linguistic values and range of fuzzy numbers

Linguistic variables	Linguistic values	Range
Input variable		
No. of purchase order (PO)	Very few (VF)	[0,17]
	Few (F)	[14,52]
	Moderate (M)	[49,102]
	High (H)	[99,152]
	Very high (VH)	[149,252]
Variation of items (I)	Very few (VF)	[0,52]
	Few (F)	[49,152]
	Moderate (M)	[149,252]
	High (H)	[249,402]
	Very high (VH)	[399,900]
No. of boxes (B)	Very few (VF)	[0,102]
	Few (F)	[99,302]
	Moderate (M)	[299,802]
	High (H)	[799,1002]
	Very high (VH)	[999,4500]
Output variable		
Unloading time (UT)	Extremely short (ES)	[0,22]
	Very short (VS)	[20,42]
	Short (S)	[40,122]
	Moderate (M)	[120,242]
	Long (L)	[240,362]
	Very long (VL)	[360,482]
	Extremely long (EL)	[480,600]

Table 3: Fuzzy associative memory (FAM) table

	I		
PO_{VF}	I_{VF}	I_F	I_M
B			
B_{VF}	UT_{ES}	UT_{ES}	UT_{ES}
B_F	UT_S	UT_S	UT_S
B_M	UT_S	UT_S	UT_S
B_H	UT_M	UT_M	UT_M
B_{VH}	UT_M	UT_M	UT_M

PO: Purchase order, B: Box, I: Item, VF: Very few, F: Few, M: Moderate, H: High, VH: Very high, ES: Extremely short and S: Short

represent all possible outputs from all possible inputs. All possible input variables were combined using 'AND' operator. The Fuzzy Associative Memory (FAM) tables were referred to the experts from the company to be approved. Shown in Table 3 is an example of 15 rules in FAM. For example, Rule 1 can be represented in the form of IF-THEN rule as:

Rule 1: If number of purchase order is very few and variation of item is very few and number of boxes is very few, then unloading time is extremely short
Thus:

- Rule 1: $PO_{VF} \wedge I_{VF} \wedge B_{VF} \rightarrow UT_{ES}$

- **Step 3: Input fuzzification:** Trapezoidal membership function was used for the process of transforming the crisp values. By using the membership function, the fuzzifier would take the input values and determined the degree to which the values belonged to each of the fuzzy sets. For example, the membership functions of the linguistic values for the number of purchase orders is given in Fig. 2. Whereas, its trapezoidal fuzzy set can be illustrated as in Fig. 3

- Very few:

$$\mu_{PO_F}(w) = (0, 0, 14, 17) \quad = \begin{cases} 1 & \text{if } 0 \le w \le 14 \\ (17-w)/(17-14) & \text{if } 14 \le w \le 17 \\ 0 & \text{if Otherwise} \end{cases}$$

- Few:

$$\mu_{PO_F}(w) = (17, 17, 49, 52) \quad = \begin{cases} (w-14)/(17-14) & \text{if } 14 \le w \le 17 \\ 1 & \text{if } 17 \le w \le 49 \\ (52-w)/(52-49) & \text{if } 49 \le w \le 52 \\ 0 & \text{if Otherwise} \end{cases}$$

- Moderate:

$$\mu_{PO_M}(w) = (49, 52, 99, 102) \quad = \begin{cases} (w-49)/(52-49) & \text{if } 49 \le w \le 52 \\ 1 & \text{if } 52 \le w \le 99 \\ (102-w)/(102-09) & \text{if } 99 \le w \le 102 \\ 0 & \text{if Otherwise} \end{cases}$$

- High:

$$\mu_{PO_H}(w) = (99, 102, 149, 152) \quad = \begin{cases} (w-99)/(102-99) & \text{if } 99 \le w \le 102 \\ 1 & \text{if } 102 \le w \le 149 \\ (152-w)/(152-149) & \text{if } 149 \le w \le 152 \\ 0 & \text{if Otherwise} \end{cases}$$

- Very high:

$$\mu_{PO_H}(w) = (149, 152, 250, 250) \quad = \begin{cases} (w-149)/(152-149) & \text{if } 149 \le w \le 152 \\ 1 & \text{if } 152 \le w \le 250 \\ 0 & \text{if Otherwise} \end{cases}$$

Fig. 2: Membership function for number of purchase order, w: Number of purchase order

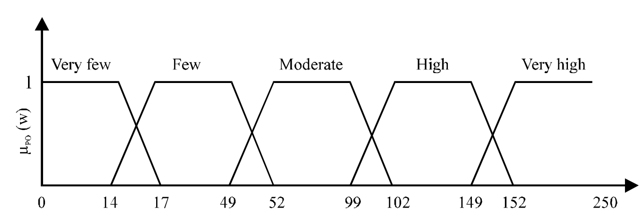

Fig. 3: Trapezoidal fuzzy set for number of purchase order

As an example, the fuzzification of crisp input for number of purchase order, w = 15 can be calculated as:

- The degree of membership function for w = 15 in fuzzy set very few:

$$\mu_{PO_F}(15) = \frac{17-15}{17-14} = 0.667$$

- The degree of membership function for w = 15 in fuzzy set few:

$$\mu_{PO_F}(15) = \frac{15-15}{17-14} = 0.33$$

Calculation performed indicates that the input value w belonged more to very few class of fuzzy set due to the degree of membership function which is closer to 1 compared to the result of membership function for few.

- **Step 4:** Combining the fuzzy inputs in step 3 with the rules in the Fuzzy Rule Base (FRB) obtained in step 2 to produce individual fuzzy output

When specific input values were received in the system, their compatibilities with the corresponding antecedents of all inference rules were determined. Only rules for which the values were compatible with the antecedents took place in determining the individual output. These rules were referred as rules that fired. For example, if two rules were utilized, then the step in estimating the unloading time is as in Fig. 4.

Let w be the number of purchase orders, x be the total variation of items and y be the number of boxes. Supposed that w = 15, x = 20 and y = 30 then the combination of the fuzzy inputs with the rules in the FRB can be illustrated as in Fig. 4.

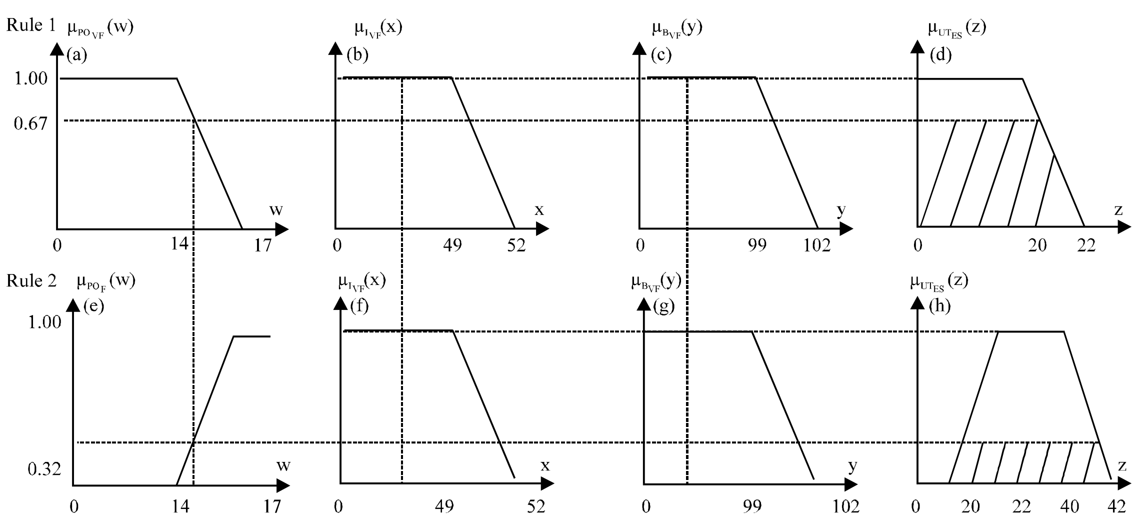

Fig. 4(a-h): Inference rule for w = 15, x = 20 and y = 30 (a) $\mu_{PO_{VF}}(w)$, (b) $\mu_{I_{VF}}(x)$, (c) $\mu_{B_{VF}}(y)$, (d) $\mu_{UT_{ES}}(z)$, (e) $\mu_{PO_F}(w)$, (f) $\mu_{I_{VF}}(x)$, (g) $\mu_{B_{VF}}(y)$ and (h) $\mu_{UT_S}(z)$

- **Step 5: Output aggregation:** Aggregation was the process of combining all individual fuzzy outputs into a single fuzzy set. Using the same example as in step 4, the aggregated fuzzy set of unloading time which the membership function had defined for the above example, $z \in [0, 42]$ is as shown in Fig. 5
- **Step 6: Aggregated output defuzzification:** The purposed of deffuzification was to convert the aggregated fuzzy output into a crisp value. Centre of gravity technique was used to determine the centre of the area for the combined membership function. The calculation was performed as shown in Fig. 6

  The position of the defuzzified value z* is shown in Fig. 7.

Matlab fuzzy logic toolbox: Matlab fuzzy logic toolbox was used in this study as a tool to find an estimated unloading time of the supplier truck. There are four primary Graphical User Interfaces (GUI) offered by the toolbox in order to build, edit and observe the fuzzy inference system. The GUI tools are:

- **Fuzzy inference system (FIS) editor:** FIS Editor displays general information about fuzzy inference system specifically what is the input and output variables. The method applied in this

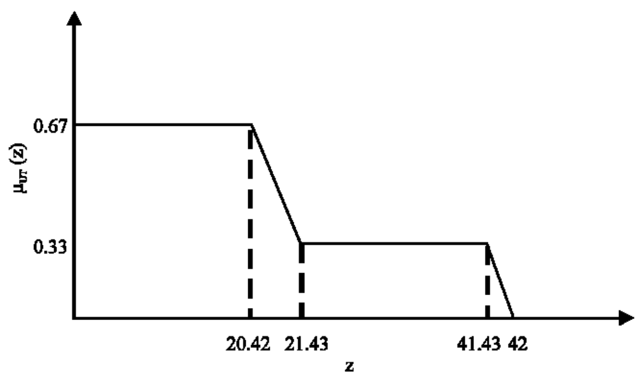

Fig. 5: Fuzzy set which represents the aggregated fuzzy output

$$z^* = \frac{\int z\mu_{UT}(z)dz}{\int \mu_{UT}(z)dz}$$

$$= \frac{\int_0^{20.42} 0.67zdz + \int_{20.42}^{21.43}(7.76-0.35z)zdz + \int_{21.43}^{41.43} 0.32zdz + \int_{41.43}^{42}(23.52-0.56z)zdz}{\int_0^{20.42} 0.67zdz + \int_{20.42}^{21.43}(7.76-0.35z)zdz + \int_{21.43}^{41.43} 0.32zdz + \int_{41.43}^{42}(23.52-0.56z)dz}$$

$$= \frac{\left[0.342z^2\right]_0^{20.42} + \left[3.88z^2\right]_{20.42}^{21.43} - \left[0.12z^3\right]_{20.42}^{21.43} + \left[0.16^2\right]_{21.43}^{41.43} + \left[11.76z^2\right]_{41.43}^{42} - \left[0.19z^3\right]_{41.43}^{42}}{\left[0.67\right]_0^{20.42} + \left[7.76z\right]_{20.42}^{21.43} - \left[0.18z^2\right]_{20.42}^{21.43} + \left[0.32z\right]_{21.43}^{41.43} + \left[23.52\right]_{41.43}^{42.00} - \left[0.28z^2\right]_{41.43}^{42}}$$

$$= \frac{\left[0.342z^2\right]_0^{20.42} + \left[3.88z^2\right]_{20.42}^{21.43} - \left[0.12z^3\right]_{20.42}^{21.43} + \left[0.16^2\right]_{21.43}^{41.43} + \left[11.76z^2\right]_{41.43}^{42} - \left[0.19z^3\right]_{41.43}^{42}}{\left[0.67\right]_0^{20.42} + \left[7.76z\right]_{20.42}^{21.43} - \left[0.18z^2\right]_{20.42}^{21.43} + \left[0.32z\right]_{21.43}^{41.43} + \left[23.52\right]_{41.43}^{42.00} - \left[0.28z^2\right]_{41.43}^{42}}$$

$$= \frac{341.36}{20.14}$$

$$= 16.73 \text{ min}$$

Fig. 6: Calculation based on Centre of Gravity Technique of area for the combined membership function

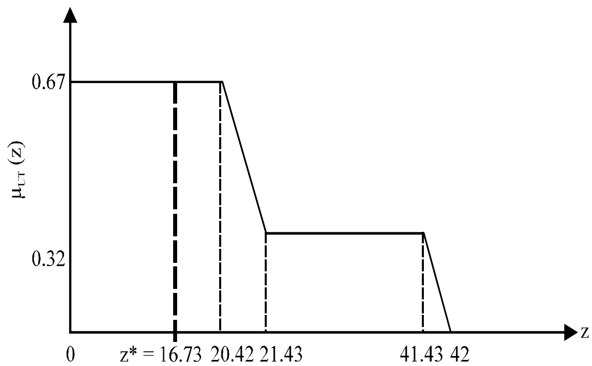

Fig. 7: Position of the defuzzified value z*

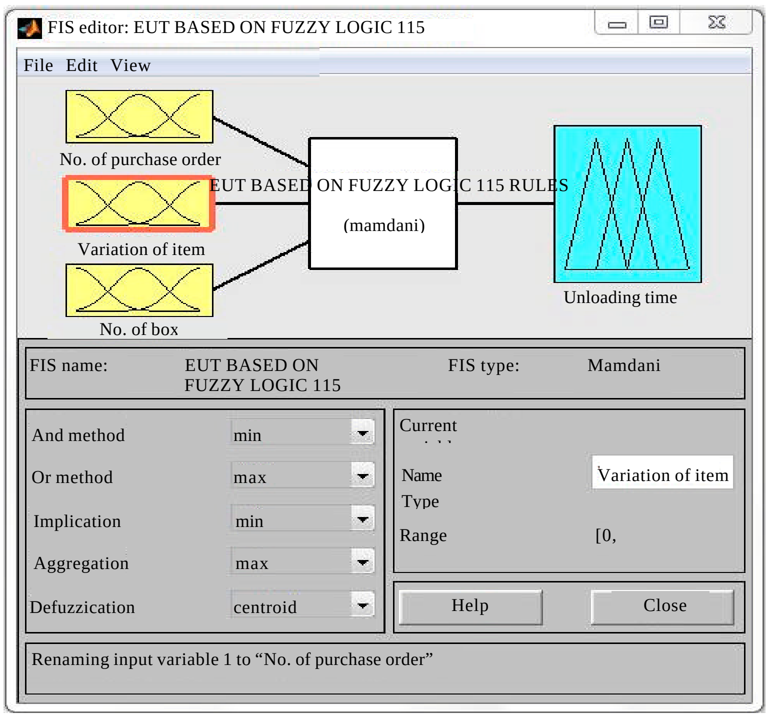

Fig. 8: FIS Editor for the input and output variables

study was the Mamdani method. Figure 8 displays three input variables processed by Mamdani fuzzy inference system in obtaining the output for this study

- **Membership function editor:** Membership function editor is the tool that allows the user to define the range, display and edit all membership functions associated to the input and output variables. In this study, trapezoidal form of membership function was utilized for all linguistic variables. Figure 9 shows the example of membership function editor associated with the linguistic values for one input variable
- **Rule editor:** Rule editor is used to construct the rule statements that define the relation between the input variables and the output variable. In this study, 115 rules were constructed automatically by clicking the buttons provided in the Rule Editor toolbox. Figure 10 represents a sample of several rules constructed

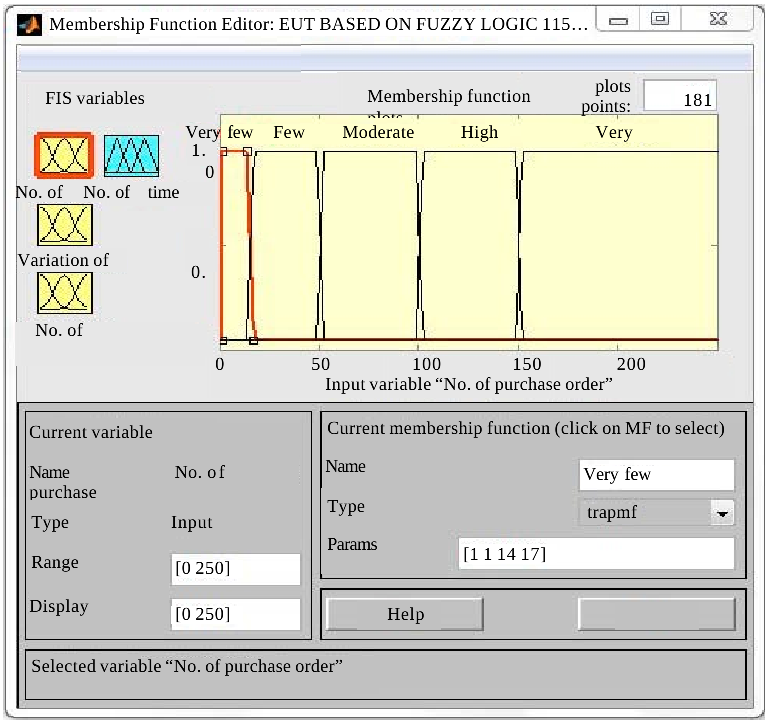

Fig. 9: Membership function editor for number of purchase order

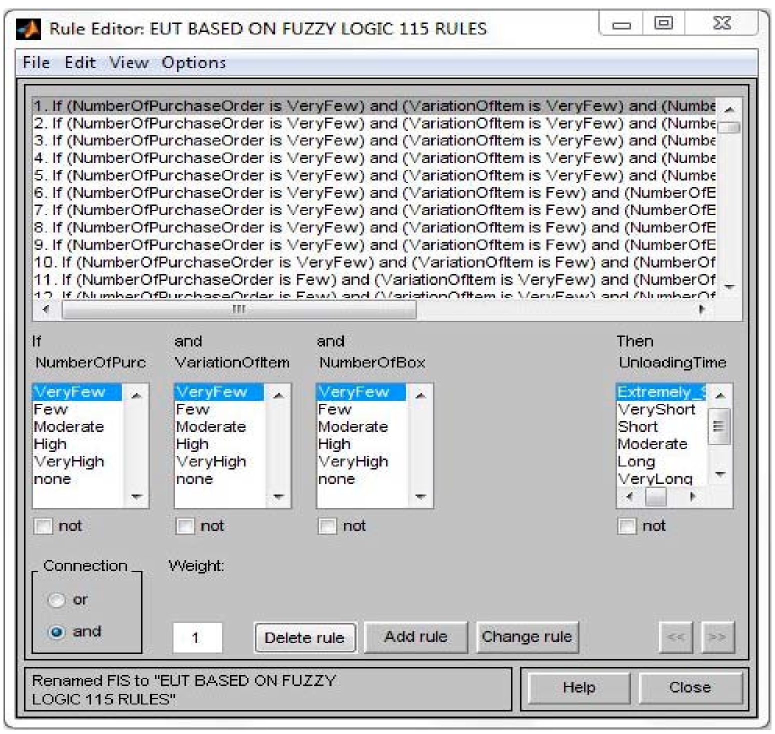

Fig. 10: Rule editor toolbox

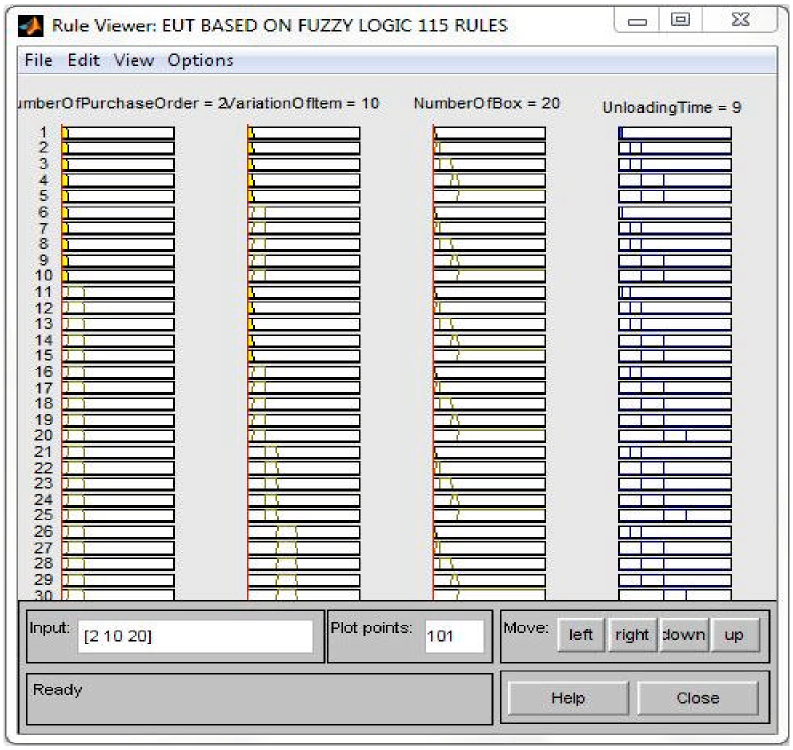

Fig. 11: Rule viewer for the fuzzy inference process for number of purchase order is 2, variation of item is 10 and number of boxes carried is 20 boxes

- **Rule viewer:** Rule viewer allows the user to view the whole fuzzy inference process. An output crisp answer will be displayed on top of the figure. For example, shown in Fig. 11, if the number of purchase order is 2, variation of item listed in the purchase order is 10 and number of box carried by truck is 20, the estimated unloading time for the truck is 9 min which lie under the category of Extremely Short

RESULTS AND DISCUSSION

In order to certify the applicability of the fuzzy logic method proposed in this study, comparison was made between the actual unloading time from real data gathered in this study with the estimated unloading time obtained from the fuzzy logic approach. Table 4 tabulates the comparison between the actual unloading time and the estimated unloading time for selected five supplier's truck. The first column in Table 1 represents the order of five different trucks followed by the number of purchase orders carried per truck in the second column. The third column shows the variation of items listed in the purchase orders while the fourth column indicates the number of boxes carried per truck. The fifth and sixth columns represent the actual unloading time obtained from the data collection and the value of estimated unloading time obtained from the fuzzy logic approach, respectively. The last column in Table 4 shows the difference between the actual unloading time and the estimated unloading time from the former columns in minutes.

The actual data for truck 1 which is associated with supplier 1 took 10 min for unloading the freight with 1 number of purchase order, 3 total of items and 11 boxes. With similar input case, the

Table 4: Comparison of estimated unloading time based on fuzzy logic and the actual unloading time for five supplier's truck

Truck	PO	I	B	AUT (min)	EUT (min)	DIFF (min)
1	1	3	11	10	9	1
2	21	54	59	94	93	1
3	42	211	314	185	183	2
4	77	345	694	310	303	7
5	120	382	728	296	303	-7

PO: Purchase order, I: Item, B: Boxes, AUT: Actual unloading time, Min: Minutes, EUT: Estimated unloading time and DIFF: Difference

estimated unloading time given by fuzzy logic is 10 min, where the difference of the estimated unloading time with the actual one is only 1 min. Truck from supplier 2 also represents the same difference as truck 1. For supplier 3, supplier 4 and supplier 5, the difference between an estimated value and the real value of recorded time are 2 min for truck 3, 7 min for truck 4 and 7 min for truck 4, respectively. Based on the result shown in table 4, an estimated unloading time obtained by using fuzzy logic approach shows the estimated value which was not slightly far from the actual ones. The difference was assumed to be acceptable and workable for the implementation in real world situations.

CONTRIBUTION TO CURRENT LITERATURE

In this study, a fuzzy logic method was adopted to estimate the unloading time of supplier's truck at retail cross docking terminal. Compared to previous models proposed by Oh *et al.* (2006), Goliasa *et al.* (2010), Boysen *et al.* (2010) and Boloori Arabani *et al.* (2012), the unloading time of products are assumed to take one unit of time for each box (if the products are carried by boxes) or one unit of time per pallet (if the products are carried on the pallet). However, refers to the real data from cross docking warehouse as shown in Table 1, these kind of assumptions are not appropriate in the real world situation, as different products might take different time in checking and verifying processes which also affected the total unloading time per truck.

Aside from that, studies carried out by Li *et al.* (2004), Song and Chen (2007), Shakeri *et al.* (2008) and Chen *et al.* (2009) treats the unloading time of truck as undetermined processing time where the value is unknown till the truck finish unloaded. In this case, incoming truck will be assigned based on the availability of dock door without any information of unloading time in advance. This scenario will result to the congestion of truck in the waiting area and delays the scheduling process at cross docking terminal. Also, in order to simplify the proposed scheduling model, several works on cross docking planning such as in Baptiste and Maknoon (2007), Bozer and Carlo (2008) and Wu *et al.* (2011) assumed the unloading time of truck to be constant; which means the unloading time for all trucks are similar and the contents of truck are disregarded . Based on reviewed works in cross docking planning, none of the studies has treated the unloading time as an estimated value specifically in the implementation of real world situation of retail cross docking problem.

CONCLUSION

This study proposed a multiple criteria decision model in fuzzy environment for estimating the unloading time of incoming truck in cross docking terminal which is considered as one of the critical decision making processes for effective planning of supply chain distribution center. Thus, far, no systematic approach had been found in the literature to estimate truck's unloading time. The outcome of this study enables us to estimate the unloading time based on three main factors namely the number of purchase order carried by supplier, variation of items listed in the purchase order and the quantity of boxes carried by the truck to be unloaded.

The ability to estimate a truck's unloading time enables operation managers of a cross docking center to determine more systematically where (to which dock door) should a truck be assigned and when the unloading process for a particular can begin. Thus, an effective scheduling strategy could be proposed that enables the truck's serviced time and the cross docking center's makespan to be minimized. The model proposed is highly feasible since all input criteria used are easily accessible from the information written in the purchase orders. Hence, the model could be easily implemented in any cross docking centres or warehouses.

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