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# Customer Validation in Cross-Dock

(Case study of cross-dock in Iran)

M. Aliakbarnia Omran*[a], F. Jolai[b]

[a] *Department of Industrial Engineering, Kish International Camp, University of Tehran, Tehran, Iran.*
[b] *School of Industrial Engineering, College of Engineering, University of Tehran, Tehran , Iran.*

## Abstract

Considering the importance of validation of customers in the cross-dock and since this is one of the problems of implementing cross-dock system in Iran, this study attempted to extract customer validation criteria. The purpose of the research is to eliminate the distrust of distributors in receiving the funds of the sent items and the statistical sample of this research is the experts of the system of distribution of goods and validation, indicators were collected by using Delphi method and questionnaire and AHP method was used to calculate the weight and the rank of indexes.

*Keywords:* Validation, Cross-Dock, Customer.

## 1. Introduction

Cross-dock is one of the most important ways of transferring materials and products to reduce transfer costs, inventory costs, cost of organizing orders, and time of responding to customers. Cross-Dock is a logistics technique that removes storage and packaging operations from the warehouse and coordinates goods for unloading from inbound vehicles and loading on unbound vehicles (sorting and reorganizing) [1]. A traditional distribution center stores products first and then organizes the order and prepares it for delivery to the customer. Cross-docking will significantly reduce the costs of arranging orders and inventory items. In the era of global competition, which has a massive amount of material moving around the world, this advantage of the cross-dock has been attracting increasing attention. In 2010, Vogt introduced a supply chain with a cross-dock as a supply chain that would include facilities of the cross-dock, and chain members share their facilities and capabilities for the entire supply chain, not just for a consumer [2]. The credit rating system was first developed in the 1950s. In fact, the idea of distinguishing between groups in a society based on the characteristics mentioned for its members derives from Fisher's paper in 1936. In 1938, Danham was the first whom provided a system for assessing applicants for the facilities. Durand, in 1941, identified

*Corresponding author
*Email address:* mehdiomran@ut.ac.ir, fjolai@ut.ac.ir (M. Aliakbarnia Omran*[a], F. Jolai[b] )

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key factors from the lenders point of view. He was the first to consider the statistical view and use the discriminant analysis model that focused on Fisher's results. In this way, he essentially created the motivation for developing theoretical framework that would determine the importance of each criterion. Therefore it can be consider that Durand is the founder of today's validation system. The high volume of credit demand led to the use of validation models in financial institutions.
One of the methods used to gain group knowledge is Delphi's technique, which is a process that has a predictive structure and contributes to decision making through surveys, information gathering and, finally, group consensus, while most surveys try to answer the question: "What is ?" Delphi can answers the question: "what can be /what should be?". For several years, multi-attribute decision making (MADM) methods have opened their place in decision making problems, Hierarchical analysis method (AHP) has been used more than other methods in management science. One of the most efficient decision-making techniques is the Analytical Hierarchy Process (AHP) process, first introduced by Thomas L. Saaty in 1980. It is based on pairwise comparisons and allows managers to review different scenarios. Hierarchical Analytic Process (AHP) in decision science, in which the choice of a solution from existing strategies or prioritization of solutions is posed Cross-dock industry is expanding and firms tend to reduce costs and send goods faster and better to customers. The success rate of cross-dock highly depends on the flow of information and appropriate communication to other members of the supply chain and customers. Due to the expansion of the cross-dock, the role of customers in its success is very effective. For successful performance, we must consider credit for each customer; for this reason, we consider the customer validation in this paper. The objectives of this research are to identify the components or indicators that by means of them measure the customers' credibility and Ranking the Indicators by AHP method.
A lot of research has been done on the cross-dock and validation. The various components of the cross-dock have been perused before, including: designing the layout of the components of the dock, scheduling of the inbound and outbound trucks, the use of various metaheuristic methods for resolving dock issues and validating customers for different banks etc. The subject of this research is to investigate the customer validation indices and their ranking with AHP method. So, in the literature review, some important and recent research has been pointed out. Kiss examined the relationship between the credit scoring models used and the development or preservation of organizational knowledge wealth; and introduced new category for credit scoring models with knowledge management approach [3]. Ong et al. with the aim of creating a credit scoring model using the genetic algorithm, they investigated two groups of customer credit data one from German and another from Australia. They concluded that the genetic algorithm was better in classification of the "good" and "bad" customers than the rest of the models [4].
Lee and Chen by using an artificial neural network and non-linear model of MARS, they surveyed 510 mortgage applicants in one of Taiwan's banks as an example. The results show that the hybrid models are less costly than the other methods, and the ability of these models to select independent variables is more than the rest of the models [5]. Šušteršicˇ et al. with limited data, they examined 581 customer data in a Slovenian bank from 1994 to 1998. The results showed that, given the questionable content of financial institution database information, the predictive power of the proposed model is roughly the same as recent studies.[6]. Abdou and Pointon with the goal of credit scoring and decision-making in Egyptian public sector banks, 1262 loan applicant examined. The results showed that neural network models were better than other models in the "average rate of correct classification (ACC)" criterion [7]. Abdou by examining alternative credit scoring models for loan applicants in private banking, he tried to increase the effectiveness and efficiency of the correct classification and identify the incorrect classification costs. using four techniques such as logistic regression, discriminant analysis, neural network and Weight of Evidence (WoE), and examining 360

cases of private bank customers in Egypt, he concluded that neural networks provide more accurately classification than other methods. And the cost of the incorrect categorization in this technique is less than traditional methods [8]. Psillaki et al. assessment credit risk based on company performance (using logistic regression and data envelopment analysis). Non-financial criteria have an important role in assessing credit risk [9]. Shin et al. peruse the risk of financial information fraud, an alert for industry using logistic regression and neural networks. Using financial variables, corporate governance variables, variables of cash flows and methods of logistic regression and neural network used to create a model for alerting companies with fraudulent and non-fraudulent operations [10].
Odeh et al. analyzed data by means of Fuzzy Simplex Algorithm, Neural Networks and Logistic Regression. The results showed that when the capacity of debt repayment and shareholders' equity are low and working capital is low or high, it is the best condition for non-repayment of loans from customers. Considering the importance of customer credit for cooperating with the cross-dock, we came to identify the important indicators for customer assessment. In this regard, we obtained a number of indicators by reviewing related articles and communicating with their authors and through interviewing distributors, banks and market experts. The primary indicators are listed in the table1

Table 1: Primary Indicators

| **Row** | **Indicators** | **Row** | **Indicators** |
|---|---|---|---|
| 1 | Age | 21 | Number of loans received at the bank |
| 2 | Sex | 22 | Past payment history |
| 3 | education | 23 | Number of Inquiries Loans from Other Banks |
| 4 | marital status | 24 | Customer's repute |
| 5 | Housing | 25 | Technical competence |
| 6 | Job | 26 | Fund |
| 7 | Number of years in this job | 27 | The general conditions of the economy and its impact on profitabilit |
| 8 | Income | 28 | Amount of requested loan |
| 9 | Work Experience | 29 | Amount of applicant's loan |
| 10 | Physical asset | 30 | Refund period |
| 11 | Current account balance | 31 | Interest rate of paid facility |
| 12 | Current account flow | 32 | Credit history |
| 13 | Check back | 33 | Customer Credit Status |
| 14 | Deferred obligations | 34 | Number of years elapsed |
| 15 | Monthly installments | 35 | Bank accounts |
| 16 | Average bank balance | 36 | Life insurance and deposit accounts |
| 17 | Loan amount | 37 | Type of ownership of the shop |
| 18 | Collateral | 38 | Shop location |
| 19 | Numbers of Co-signers | 39 | Payment type |
| 20 | Co-signer's credit status | | |

To get more realistic indexes using the Delphi method, we send indexes to several experts. Using a Delphi method, a number of indices were eliminated and the names of the indices made more appropriate in proportion to use on the dock and the following indices shown in table2 were used in the questionnaire:

Table 2: The remaining indicators after using the Delphi method

| Row | Indicators | Row | Indicators |
|---|---|---|---|
| 1 | Age | 12 | Technical competence |
| 2 | Sex | 13 | Fund |
| 3 | education | 14 | Interest rate of paid facility |
| 4 | marital status | 15 | Credit history |
| 5 | Matching the place of birth and residence | 16 | Negative records |
| 6 | Job | 17 | Status of respondents |
| 7 | Years of cooperation | 18 | Life insurance and deposit accounts |
| 8 | Income | 19 | Type of ownership of the shop |
| 9 | Work Experience | 20 | Shop location |
| 10 | Payment history | 21 | payment type |
| 11 | Reputation | 22 | Customer account turnover |

**The results of the questionnaire**

After collecting the questionnaire, due to the qualitative options, we turned them into quantitative numbers for careful examination. The alternatives are as follows: Very Important = 10, Important = 7.5, Normal = 5, Low Effective = 2.5, Ineffective = 0.
After quantization of the options, the order of the indicators in terms of importance is shown in the table3

Table 3: The importance of Indexes

| Row | Index | Importance |
|---|---|---|
| 1 | Customer Reputation Index | 5.50 |
| 2 | Customer payout Index | 5.20 |
| 3 | Customer Credit History Index | 2.765 |
| 4 | Customer Capital Index | 5.125 |
| 5 | Negative record of customer bank Index | 3.872 |
| 6 | Customer account turnover Index | 3.976 |
| 7 | Customer Revenue Index | 4.90 |
| 8 | Payment history Index | 4.65 |
| 9 | Customer Job Index | 2.43 |
| 10 | Customer Education Index | 4.625 |
| 11 | Years of cooperation Index | 4.625 |
| 12 | Customer Technical Competency Index | 4.50 |
| 13 | Customer respondents status Index | 4.475 |
| 14 | Customer Shop location Index | 3.45 |
| 15 | Customer Experience Index | 3.425 |
| 16 | Type of ownership of the customer's shop Index | 4.175 |
| 17 | customer payment facility Interest rate Index | 3.95 |

| | | |
|---|---|---|
| 18 | Customer Age Index | 3.975 |
| 19 | Matching the place of birth and the customer's location Index | 3.725 |
| 20 | Life insurance and deposit accounts Index | 3.15 |
| 21 | Customer Marital Status Index | 2.775 |
| 22 | Customer Sex Index | 2.70 |

We selected 10 indicators that had more points to analyze the hierarchy so that they can be ranked and weighted. By reducing the indices, we created the relative numbers table for AHP. In Table 4, which is obtained using the AHP method, both customer validation indicators are specified and the weight of each of the indices is expressed to define an equation that measures the customer's credibility.

Table 4: The weight of indicators in the validation of the cross-dock customers

| **Priority** | **Index** | **Weight of Index** |
|---|---|---|
| 1 | Reputation | 0.114721 |
| 2 | Payment type | 0.108506 |
| 3 | Customer Capital | 0.106928 |
| 4 | Customer revenues | 0.102244 |
| 5 | Payment history | 0.100177 |
| 6 | Education | 0.096502 |
| 7 | Years of cooperation | 0.096502 |
| 8 | Technical competence | 0.093908 |
| 9 | Status of respondents | 0.093386 |
| 10 | Type of ownership of the customer's shop | 0.087126 |

By analyzing, it is clear that customer validation is performed by examining the factors identified in Figure1.

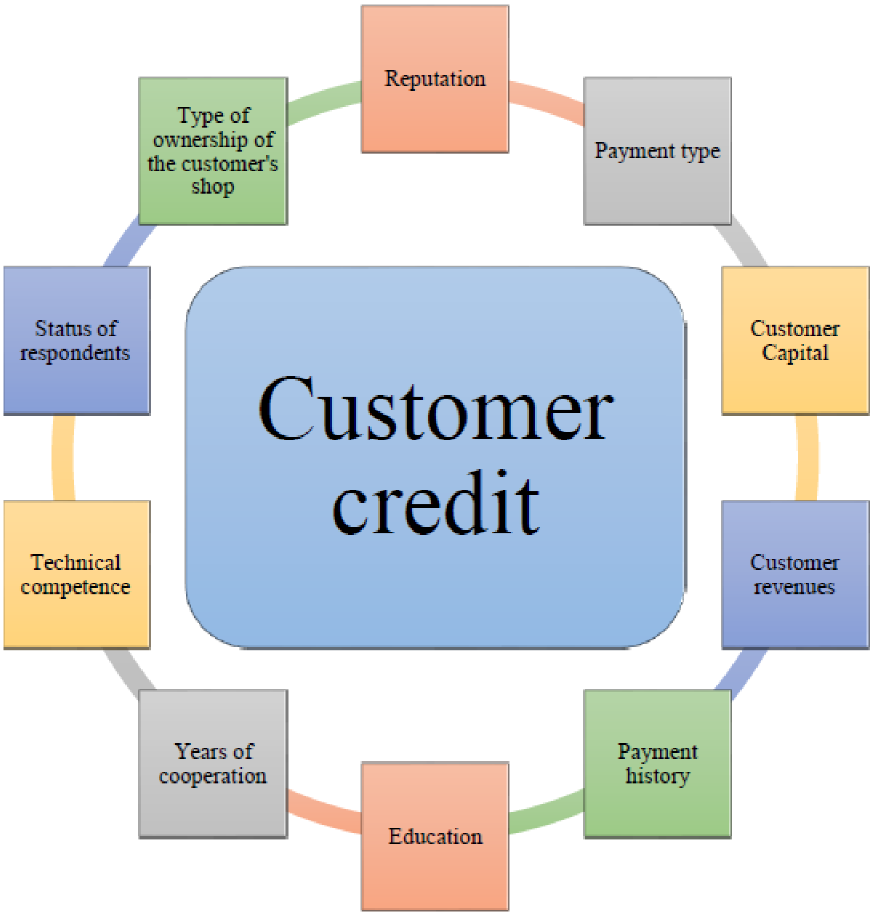


Figure 1: The proposed model for evaluating customer credit in cross-dock

## 2. Conclusion

1. According to Table 4, it is noted that the index of reputation with 0.071589197 importance as the highest weight in the customer's credit is important, therefore, despite the fact that indicators such as capital, income, etc. are considered, but the index of reputation has the highest importance. Therefore, it is suggested that before starting to cooperate with customers in cross-dock, develop a form to measure the customer's reputation to be able to get inform about the customer's reputation from several people.

2. The second indicator which has importance is the customer payment type, which ranked higher than other indicators. The type of payment for each customer can be cash, one-month payment, through a post-dated cheque. Certainly, cash payments are very considerable and the client who pays cash is very important, so try to do cash transaction or monthly payment in cross-dock , As a result, the payment should be either cash or short-term and refuse long-term repayment.

3. The next important indicator is capital. It is suggested that be aware of the amount of customer's capital in the cross-dock when buying the customer from the cross-dock, and according to the amount of customer's capital, define an upper limit on customer's purchase amount, and each customer has an interval defined for purchase based on the amount of his capital.

4. We see that the level of customer revenue, payment history, education, the duration of cooperation and etc., are important at a later stage, with a very small difference in weight, so a cross-dock should anticipate ways to properly measure these indicators, and with proper reporting and applying the results of reports in his sales decisions reduces the risk of return on investment.

While we expected that the indexes of store ownership, work experience and location to be among the top indicators, we found that these indicators are less important for respondents. Suggestions for future researches

1. Investigating other methods of validation and comparison with the results of this research
2. Perusing methods of measuring each of these indicators
3. Develop a sale strategy based on the amount of credit calculated for the customer based on the presented model

## References

[1] Ladier, A.-L. and G. Alpan, Robust cross-dock scheduling with time windows. Computers and Industrial Engineering, 99(2016) 16-28.
[2] J.J., Vogt, The successful cross-dock based supply chain, Journal of Business Logistics, 31(1) (2010) 99-119.
[3] Kiss, Ferenc, Credit scoring process from a knowledge management perspective", Periodica polytechnic ser.soc.man.scl, 11(1)(2003) 95-110.
[4] Ong Chorng-Shyong, Jih-Jeng Huang, Gwo-Hshiung Tzengb, Building credit scoring models using genetic programming, Expert Systems with Applications, 29(2005) 41–47.
[5] Lee ,Tian-Shyug and I-Fei Chen, A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines, Expert Systems with Applications, 28(2005)743–752.
[6] Šušteršicˇ, Maja, Jure Zupan, Dušan Mramor, Consumer credit scoring models with limited data, Expert Systems with Applications, 36 (2009) 4736–474.
[7] Abdou , Hussein A., John Pointon, Credit scoring and decision making in Egyptian public sector Banks, International Journal of Managerial Finance, 5(4) (2009), 391-406.
[8] Abdou, Hussein A., An evaluation of alternative scoring models in private banking, The Journal of Risk Finance, 10 (2009) 38-53.
[9] Maria Psillaki, Ioannis E.Tsolas, Dimitris Margaritis, Evaluation of credit risk based on firm performance, European Journal of Operational Research, 201(3) (2010) 873-881.
[10] Kuang-Hsum Shin, ching-Chan Cheng, Yi-Hsien Wang, Financial Information Fraud Risk Warning for Manufacturing Industry-Using Logistic Regression and Neural, (2011).