PERFORMANCE ASSESSMENT OF A SPARE PART DEALER NETWORK USING DATA ENVELOPMENT ANALYSIS

by

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Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Master of Science
in
Industrial Engineering

Boğaziçi University

2006

ACKNOWLEDGEMENTS

I would like to express my sincere appreciation to my thesis supervisor, Assoc. Prof. Taner Bilgiç, for his valuable guidance, support, motivation and patience throughout this study. Without his help, I would have not been able to complete this study.

I would also wish to express my sincere thanks to Levend Beriker and Yusuf Şire for the providing the data set that is used in this thesis and for their suggestions. Special thanks go to Nuri Bilensoy, Mehmet Güray Güler, and Emre Demir for their support.

Finally, I would like to thank to my family for their never-ending support, encouragement and patience. I also appreciate all of my friends for their good friendships, assistance and moral support.

ABSTRACT

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In this study, we analyze comparative dealer efficiency of a spare part distributor, using data envelopment analysis. In order to ensure homogeneity in the data sets, five different clusters are formed, and for each cluster, BCC-Output and CCR-Output oriented models are applied. The results of all models are interpreted and the comparison of the results is provided. The comparison is made in two perspectives: One perspective is related with different clusters of the same data set under the same data envelopment analysis model. The other perspective compares different types of the efficient frontiers under two different data envelopment analysis models. The results provide insight about the nature of Data Envelopment Analysis as well as about the practical problem at hand.

ÖZET

VERİ ZARFLAMA ANALİZİ KULLANILARAK BİR YEDEK PARÇA BAYİ AĞININ PERFORMANS DEĞERLENDİRMESİNİN YAPILMASI

Bu tezde, bir yedek parça dağıtıcısının bayilerinin veri zarflama analizi kullanılarak yapılan karşılaştırmalı verimlilik analizleri sunulmaktadır. Bu çalışmada, veri setlerinde homojenliği sağlayabilmek için beş farklı veri kümesi oluşturulmuştur. Her bir veri kümesi için BCC-Çıktı ve CCR-Çıktı modelleri kullanılmıştır. Daha sonra bu modellerin sonuçları tartışılarak modellerin kıyaslamaları gerçekleştirilmiştir. Kıyaslamalar iki açıdan sunulmuştur: Birincisi, veri setlerinin değişmesinden kaynaklanan verimlilik değişikliklerinin kıyaslanması, yani veri zarflama analizi modelleri aynı, veri kümeleri farklı olan modellerin kıyaslanması. Diğeri ise, verimlilik sınırı tipinin değişmesinden kaynaklanan verimlilik değişikliklerinin kıyaslanmasıdır. Sonuçlar hem veri zarflama yöntemi hakkında hem de incelenen dağıtıcı hakkında çeşitli gözlemler yapılmasını sağlamıştır.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS/ABBREVIATIONS

BCC	Banker-Charnes-Cooper
BCC-O	Banker-Charnes-Cooper-Output
CCR	Charnes-Cooper-Rhodes
CCR-O	Charnes-Cooper-Rhodes-Output
CRS	Constant returns to scale
DEA	Data envelopment analysis
DRS	Decreasing returns to scale
IRS	Increasing returns to scale
RTS	Returns to scale
VRS	Variable returns to scale

1. INTRODUCTION

In the last few years, Turkish economy has got into an evolution. During the European Union negotiations period, the inflation rates have decreased dramatically. Foreign trade volumes went up, although employment values of our country did not change with respect to crisis in 2001, the gross national product (GNP) of Turkey increased during the last four years. After recession in GNP at 9.5% in 2001, the growth rates have been 7.9%, 5.9%, 9.9% in 2002, 2003, 2004, respectively (www.die.gov.tr). Although the official results have not been issued yet, the GNP increase for 2005 is expected to be around 5.5 %. On the other hand, unemployment ratios have been 8.4%, 10.3%, 10.5%, 10.3%, and 10.3% from 2001 to 2005 respectively according to State Statistical Institute (DIE) statistics.

It is interesting to note that although GNP increased significantly, the unemployment ratio did not show any improvement. It could be conjectured that, one of the most important reasons for this situation is the increase in the production efficiencies of the firms. There are some facts behind the efficiency growth of domestic companies. First of all, they need to work more effectively to survive in such a competitive business environment. The competition is increasing day by day during the EU negotiation process. Secondly, Turkish companies disregarded efficiency during the last two decades under high inflation rates where large financial gains were possible in financial markets. The incredible profits originated from financial instruments under high inflation rates, and pushed the companies to neglect the production based or operational efficiency. However, the decrease in inflation rates and competition forced the companies to think more carefully about efficiency.

Data Envelopment Analysis (DEA) is one of the successful methodologies that can be used for performance evaluation. The use of DEA is in assessing the performance values of many different kinds of entities related with many different activities in many different contexts in many different countries (Cooper et al., 2000).

Managers are often under great pressure to improve the performance of their organizations. To improve performance, one needs to constantly evaluate operations or processes related to producing products, providing services and marketing and selling products. Benchmarking and performance evaluation are widely used to improve performance and increase productivity. In fact, it is more useful when no objective or engineered standard is available to define efficient and effective performance. Benchmarking is commonly used in managing service operations, because service standards are more complex than assessing the manufacturing standards. However, it is becoming much more complex to evaluate an organization's performance when there are multiple inputs and outputs. Of course, when the relationships between the inputs and outputs are complicated and involve some indefinite tradeoffs, the difficulties will be further enhanced.

In this study, we investigate a spare part distribution firm. The distributor has more than ten thousand dealers all over Turkey. At the beginning of the study, we obtained 16 attributes which are potentially input or output variables to achieve a performance assessment for all dealers of the distributor. The distributor has different spare part suppliers such as Mako, Otoyol and Tofas.

Since the distributor needs to manage its dealers successfully, it should give right decisions for the right dealer at the right time. We first construct an input-output model as a guide for the distributor. The model is composed of four inputs and two outputs. After that, five different dealer clusters are generated in order to evaluate the dealers with the equivalent units. Finally, two different DEA models which are CCR-Output and BCC-Output models are applied for each data set.

The distributor may be interested in dealers' performance analysis for a variety of reasons. First, distributor can concentrate on certain dealers for decreasing the operational costs. Second, distributor should control accessibility of spare parts in all over the locations.

The thesis is organized as follows: methodology of DEA is introduced in Chapter 2. Chapter 3 is devoted to reviewing different data envelopment analysis studies. The characteristics of our problem are defined and the model selection process is discussed in Chapter 4. In Chapter 5, we represent results of our analysis and interpret the results. Finally we conclude the study in Chapter 6.

2. DATA ENVELOPMENT ANALYSIS METHODOLOGY

Operations/processes in all businesses involve transformation-adding values and changes to raw material and converting them into goods and services that customers ask for. In the transformation level, there are inputs which must be used to provide some outputs. Inputs comprise materials, labor, machines, energy, and other resources and outputs are made up of services, finished products, customer satisfaction, and other outcomes. Evaluating how efficiently various processes operate with respect to multiple input and output is a usual interest of managers. Benchmarking and performance evaluation make good job in making business operations/processes more productive.

Performance evaluation, as a continuous improvement tool, is highly important for firms which want to stay competitive since performance evaluation and benchmarking positively force any business unit to constantly evolve and improve in order to survive and prosper in a business environment facing global competition. In the light of performance analysis, one can learn about;

- The strengths and the weaknesses of business operations, activities, and processes;
- How to prepare the business to meet its' customers' needs and requirements
- Identifying opportunities to improve current operations and processes, and produce new services, products and processes.

Gap analysis is a single measure based fundamental method in performance evaluation and benchmarking. However we face a problem when we have multiple measurements while benchmarking. One single measure generally will not be sufficient for the purpose of performance evaluation. Return on investment (ROI) and return on sales (ROS) are some single output to input financial ratios which can be used as indices to characterize financial performance. Although, the bi-variate financial ratios mostly used in extant research are simpler to conceptualize and easier to calculate, they ignore the multi-dimensional aspects of performance. They give only a restricted, incomplete picture of the process and fail to account for the interactions between the different factors, leading to contradictory results (Mukherjee and Nath, 2002).

Moreover, any substitutions or tradeoffs among various performance measures are ignored by using single measures. Each business operation has specific performance measures with tradeoffs.

Efficient Frontier can be estimated by using optimization techniques if we know about the functional forms for the relationships among various performance measures. Without a priori information on the tradeoffs, the functional forms cannot be specified. As a result, it is not possible for us to characterize the business operations and processes completely. Note that the objective of performance evaluation is to evaluate the current business operation internally and to benchmark against similar business operations externally to identify the best practice. We can identify such best-practices empirically. Efficient frontier can be estimated relying on observations on one business operation/process over time or similar business operations at a specific time period.

We will use decision making units (DMU) to represent business operations or processes. Each DMU has a set of inputs and outputs, representing multiple performance measures. Assume that, there are n DMUs which are denoted as DMU_j (j=1,....,n) and each of DMUs uses m inputs x_{ij} (i=1,2,...,m) to produce s outputs y_{rj} (r=1,2,...,s). By using these n observations we obtain the efficient frontier.

Data Envelopment Analysis (DEA) is an effective tool in identifying such empirical frontiers and in evaluating *comparative* or *relative* efficiency (Thanassoulis, 2001). We speak of relative efficiency because its measurement by DEA is with reference to some set of units we are comparing with each other. Absolute measure of efficiency cannot be derived by means of DEA unless we make some additional assumptions. For that reason, in a practical setting units which we may find efficient by DEA may in fact be capable of improving their performance even further.

DEA employs mathematical programming to estimate the tradeoffs inherent in the empirical efficient frontier. Although DEA was designed to measure relative efficiency where market prices are not available, it has also been used in very different areas, because it has no need for a priori underlying form assumption to model multiple-input and multiple-output relationship.

We briefly introduce the DEA approaches used in this thesis that can be used in empirical efficient frontier estimation and also in performance evaluation and benchmarking, after a general discussion of performance measurement methods.

2.1. Performance Measurement Methods

Before further discussion about DEA, we want to give brief information about performance measurement methods.

Comparative performance measurement must begin with the definition of the unit of assessment. The unit of assessment is the entity we propose to compare on performance with other entities of its kind. Bank branches, schools, hospitals, retail stores can be given as examples for entities. The unit of assessment uses a set of resources referred as *inputs* which it changes into a set of outcomes referred to as *outputs.* The definition of unit of assessment and identification of the corresponding input-output factors are of crucial significance in assessing performance.

2.1.1. Performance Indicators

Performance indicator is a frequently used method for measuring the performance of an operating unit. A performance indicator can be defined as a ratio of some output to input belonging to the unit being discussed. Return on investment (ROI) and return on sales (ROS) are two examples for performance indicators that are mentioned before. Unfortunately, a single performance indicator of this kind is generally not enough to convey the relative efficiencies of real operating units. In fact, we may have economies or diseconomies of scale in addition to multiple inputs and/or multiple outputs characterizing the operations of the units being compared. In cases which have multiple performance indicators, we have no benchmark of minimum input to output ratio to be used for measuring the performance of each operating unit. Ratio style performance indicators can only be successful in a process when a single resource and a single output are involved. Once we move to more realistic contexts which involve multiple inputs and/or multiple outputs we need a *modeling approach* for measuring performance.

2.1.2. Modeling Methods of Comparative Performance Measurement

The goal of the modeling approach for measuring comparative performance is to build a better understanding of the production process operated by units being assessed rather than simply compute indices of their comparative performance measurement. Basically there are two types of modeling methods of comparative performance measurement, parametric and non-parametric methods.

Data envelopment analysis (DEA) is the main method in the non-parametric category. DEA is an operations research based method for measuring the performance efficiency of decision units that are characterized by multiple inputs and outputs. DEA converts multiple inputs and outputs of a decision unit into a single measure of performance which is called relative efficiency (Donthu, 1998).

2.2. Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) Data Envelopment Analysis Models

In this section we introduce the CCR and BCC envelopment models. We use CCR-output oriented and BCC-output oriented models in performance evaluation of our data set, in this thesis. For that reason, we prefer to discuss more about the CCR and BCC approaches.

2.2.1. CCR Models

Although we use CCR-Output and BCC-Output Models in our application it is important to clarify the CCR-Input model for better understanding of both CCR and BCC output models. So the idea behind the CCR is explained before proceeding.

2.2.1.1. CCR-Input Oriented Models. First, for each DMU we form the virtual input output by (yet unknown) weights v_i and u_r:

$$\text{Virtual input} = v_1 x_{10} + v_2 x_{20} + \dots\dots\dots\dots + v_m x_{m0}$$

$$\text{Virtual output} = u_1 y_{10} + u_2 y_{20} + \dots\dots\dots\dots + u_s y_{s0}$$

The goal is to maximize the $\dfrac{VirtualOutput}{VirtualInput}$ ratio.

In the light of criteria above the weights are determined. Notice that, the weights differ from one DMU to another.

Assume that we have *m* inputs and *s* outputs. Let the input and output data for DMU_j be (x_{1j}, x_{2j}, $x_{3j},\dots\dots$, xm_j) and (y_{1j}, y_{2j}, $y_{3j},\dots\dots$, ys_j). The input data matrix X and output data matrix Y can be arranged as follows,

$$X = \begin{pmatrix} x_{11} & x_{12} & \dots\dots & x_{1n} \\ x_{21} & x_{22} & \dots\dots & x_{2n} \\ . & . & & . \\ & & \dots\dots & \\ . & . & & . \\ x_{m1} & x_{m2} & \dots\dots & x_{mn} \end{pmatrix} \tag{2.1}$$

$$Y = \begin{pmatrix} y_{11} & y_{12} & \dots\dots & y_{1n} \\ y_{21} & y_{22} & \dots\dots & y_{2n} \\ . & . & . & . \\ . & . & . & . \\ y_{s1} & y_{s2} & y_{s3} & y_{sn} \end{pmatrix} \tag{2.2}$$

Where X is an $(m \times n)$ matrix and Y is an $(s \times n)$ matrix.

Now assume that we have n DMUs, we solve the following fractional programming problem to obtain values for the input weights v_i and output weights u_r for (i=1,……m) and (r=1,……,s) respectively. Note that the calculation below is for DMU_0.

$$(FP_o) \qquad \max \qquad \theta = \frac{u_1 y_{10} + u_2 y_{20} + ... + u_s y_{s0}}{v_1 x_{10} + v_2 x_{20} + ... + v_m x_{m0}} \tag{2.3}$$

$$s.t \qquad \frac{u_1 y_{1j} + u_2 y_{2j} + ... + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + ... + v_m x_{mj}} \leq 1 \qquad (j = 1, ..., n) \tag{2.4}$$

$$\begin{aligned} &v_1, v_2, ..., v_m \geq 0 \\ &u_1, u_2, ..., u_m \geq 0 \end{aligned} \tag{2.5}$$

The point here is that the ratio of virtual output to virtual input should not exceed 1 for any DMU. The objective to obtain the weights (v_i) and (u_r) that maximize the ratio of DMU_0. Because of the constraints, θ can not exceed 1.

As a second step we transform the fractional program (FP_o) to a linear program (LP_o),

$$(LP_o) \qquad \max \qquad \theta = u_1 y_{10} + u_2 y_{20} + ... + u_s y_{s0} \tag{2.6}$$

$$s.t \qquad v_1 x_{10} + v_2 x_{20} + ... + v_m x_{m0} = 1 \tag{2.7}$$

$$\begin{gathered} u_1 y_{1j} + u_2 y_{2j} + ... + u_s y_{sj} \leq v_1 x_{1j} + v_2 x_{2j} + ... + v_m x_{mj} \\ (j = 1, ..., n) \end{gathered} \tag{2.8}$$

$$\begin{aligned} &v_1, v_2, ..., v_m \geq 0 \\ &u_1, u_2, ..., u_m \geq 0 \end{aligned} \tag{2.9}$$

Note the fact that the fractional program (FP_o) is equivalent to linear program (LP_o).

Definition 2.1

CCR Efficiency

1. DMU_0 is CCR-efficient if θ^* =1 and there exists at least one optimal (v^* , u^*) with v^*>0 and u^*>0.
2. Otherwise, DMU_0 is CCR-inefficient.

We consider these criteria for efficiency evaluation. The definition says CCR-inefficiency means that either (i) θ^* <1 or (ii) θ^* =1 and at least one element of (v^*, u^*) is zero for every optimal solution of (LP_o).

There are two basic CCR models. First one is the input oriented model which is minimizing inputs while producing same amount of output and the second is output oriented model that tries to maximize the output by using the same amount of inputs.

<u>2.2.1.2. The Dual of CCR-Input Oriented Model.</u> Here we rewrite the (LP_0) which we have introduced before. However, this time it is expressed in vector-matrix notation, v is a row vector for input multipliers and u is a row vector for output multipliers.

$$(LP_0) \quad \max \quad uy_0 \tag{2.10}$$

$$s.t \quad vx_0 = 1 \tag{2.11}$$

$$-vX + uY \leq 0 \tag{2.12}$$

$$v \geq 0, \quad u \geq 0 \tag{2.13}$$

The dual problem of (LP_0) can be expressed as follows,

$$(DLP_0) \quad \min \quad \theta \tag{2.14}$$

$$\text{s.t} \quad \theta x_0 - X\lambda \geq 0 \tag{2.15}$$

$$Y\lambda \geq y_0 \tag{2.16}$$

$$\lambda \geq 0 \tag{2.17}$$

$$\theta \quad (unrestricted)$$

Here θ in (2.14) a real variable and λ is a non-negative vector $\lambda = (\lambda_1 + \lambda_2 + ... + \lambda_n)^T$.

(DLP_0) has a feasible solution $\theta = 1$, $\lambda_0 = 1$, $\lambda_j = 0\ (j \neq 0)$. Hence the optimal θ, denoted by θ^*, is not greater than 1. On the other hand, due to the nonnegativity assumption for the data, the constraint (2.16) forces λ to be non-zero because $y_0 \geq 0$ and $y_0 \neq 0$. Hence, from (2.15) θ must be greater than zero.

As a result of penultimate paragraph, we have $0 < \theta^* \leq 1$, and the relation between the production possibility set and (DLP_0) is like that; the constraints of (DLP_0) require the activity $(\theta x_0, y_0)$ to belong to production probability set (PPS) meanwhile the objective seeks the minimum θ that reduces the input vector x_0 radially to θx_0 on condition that remaining in P. In other words, we can say that in dual problem we are looking for an activity in P that guarantees at least the output level of y_0 of DMU_0 in all components while reducing the input vector x_0 proportionally to a value as small as possible.

Also slack vectors, input excesses $s^- \in R^m$ and output shortfalls $s^+ \in R^s$ can be expressed as below:

$$s^- = \theta x_0 - X\lambda \tag{2.18}$$

$$s^+ = Y\lambda - y_0 \tag{2.19}$$

both s^- and s^+ have values greater or equal to zero for any feasible solution (θ, λ) of (DLP_0).

The formulations indicate that DMU_0 which has (x_0, y_0) as input and output values can improve its inputs by reducing radially with θ^*. Also it can diminish its inputs by s^{-*}. Likewise output can be increased by adding s^{+*} to y_0. So, the *CCR projection* or *efficient targets* can be expressed as:

$$\begin{aligned} \hat{x}_0 &= \theta^* x_0 - s^{-*} \leq x_0 \\ \hat{y}_0 &= y_0 + s^{+*} \geq y_0 \end{aligned} \tag{2.20}$$

2.2.1.3. The CCR-Output Oriented Model. The objective of input-oriented model is to minimize inputs while producing no less output. Here we analyze output-oriented model. This model tends to maximize output level while using no more input.

$$(\text{LPO}_0)\quad \min \quad px_0 \tag{2.21}$$

$$\text{s.t} \quad qy_0 = 1 \tag{2.22}$$

$$-pX + qY \le 0 \tag{2.23}$$

$$p \ge 0, \quad q \ge 0 \tag{2.24}$$

In (LPO_0) the variables p and q are vector variables that expressing weights of inputs and outputs respectively. Let an optimal solution of (LP_0) be (v^*, u^*), then an optimal solution can be obtained from these values:

$$p^* = v^* / \theta^* \tag{2.25}$$

$$q^* = u^* / \theta^* \tag{2.26}$$

Dual of (LPO_0) is named as ($DLPO_0$):

$$(\text{DLPO}_0)\quad \max \quad \eta \tag{2.27}$$

$$\text{s.t} \quad x_0 - X\mu \ge 0 \tag{2.28}$$

$$\eta y_0 - Y\mu \le 0 \tag{2.29}$$

$$\mu \ge 0 \tag{2.30}$$

Also the optimal value of the output-oriented model relates to that of the input oriented model:

$$\eta^* = 1/\theta^* \tag{2.31}$$

$$\mu^* = \lambda^* / \theta^* \tag{2.32}$$

The slack values (t^-, t^+) also can be related that of the input-oriented model:

$$t^{-*} = s^{-*} / \theta^* \tag{2.33}$$

$$t^{+*} = s^{+*} / \theta^* \tag{2.34}$$

Finally, the CCR projection or efficient target values output-oriented model is:

$$\hat{x}_0 = x_0 - t^{-*} \tag{2.35}$$

$$\hat{y}_0 = \eta^* y_0 + t^{+*} \tag{2.36}$$

As can be seen in above explanation there are simple transformations between values of input and output models' results and the objective functions of both models give the same result. However this does not imply that there is no managerial significance to be assigned to the choice of models.

2.2.2. BCC Models

The CCR models based on the constant returns to scale (CRS) which means if an activity (x, y) is feasible, then for every positive scalar t, the activity (tx, ty) is also feasible. However, the BCC model has its production frontiers spanned by the convex hull of the existing DMUs. The frontiers have piecewise linear and concave characteristics which leads to variable returns to scale (VRS) characterizations with increasing returns to scale (IRS), decreasing returns to scale (DRS) and CRS. In this part we introduce the basic properties of output oriented BCC model.

2.2.2.1. BCC Output Oriented Model. The primal linear programming model of BCC output-oriented model is:

$$(\text{BCCO}_0) \quad \max \quad \eta_B \tag{2.37}$$

$$\text{s.t.} \quad X\lambda \leq x_0 \tag{2.38}$$

$$\eta_B y_0 - Y\lambda \leq 0 \tag{2.39}$$

$$e\lambda = 1 \tag{2.40}$$

$$\lambda \geq 0 \tag{2.41}$$

The dual form of the ($BCCO_0$) is formulated as:

$$(DBCCO_0)\quad \min \quad z = vx_0 - v_0 \tag{2.42}$$

$$\text{s.t.} \quad uy_0 = 1 \tag{2.43}$$

$$vX - uY - v_0 e \geq 0 \tag{2.44}$$

$$v \geq 0, \quad u \geq 0, \quad v_0 \text{ free in sign} \tag{2.45}$$

Cooper et al.(2000), Zhu (2003) and Thanassoulis (2001) are some of the sources that can be used as references for further information about the DEA models.

3. LITERATURE REVIEW

Data Envelopment Analysis is a technique that uses mathematical programming methods and models. These methods and models are used to assess the performance of peer units that have multiple inputs and multiple outputs. Since the pioneering work by Charnes et al. (1978), DEA has been extensively applied to the study of the efficiency of homogenous units. Empirical orientation and no need of prior assumptions are the properties of DEA which enable it to be used in very different studies such as; banking (Cook and Hababou, 2001), retail stores (Keh and Chu, 2003), educational institutions (Sarrico and Dyson, 2000), manufacturing (Ertay and Ruan, 2005), hospitals (Harris et al., 2000), police force (Thanassoulis, 1995), steel industry productivity (Ray, Seiford and Zhu, 1998), highway maintenance efficiency (Cook, Roll and Kazakov, 1990), software development (Banker and Kemerer, 1989), logistics systems (Kleinsorge, Schary and Tanner 1989).

In this chapter, brief information is provided about some related researches that contain detailed work on DEA as a first step. Then, the major differences between our work and above mentioned researches are stated. Finally, we make some comments about the possible extensions.

Dyson et al. (2001) is one of the papers that concentrate on some problematic issues and possible traps during the study of DEA application. Some of the issues are the selection of input/output variables, homogeneity of units under assessment, the measurement of input/output variables, weights of these variables. Although, some pitfalls remain problematic, some pitfalls have been mentioned with their possible solutions as protocols.

It is mentioned that variable returns to scale (VRS) model always envelops the data more closely than constant returns to scale (CRS) model, irrespective of whether VRS exists. It also means that if the VRS model is used, where there are no inherent scale effects, small and large units tend to be over-rated in the efficiency assessment.

Furthermore, according to the authors, there are some key points during the selection of input/output set:

- The set of factors must be common for all DMUs.
- It must capture all activity levels and performance measures.
- Environmental variations for DMUs should be regarded
- It must cover full range of resources used

Barros and Alves (2003) focus on retail store efficiency assessment by using DEA. A supermarket chain group of 47 retail outlets of Portugal is studied by the researchers. The VRS hypothesis is chosen, because scale size is controllable by the retail chain's central management. However CRS hypothesis is also applied for comparison. The choice of input or output-oriented DEA is based on the market conditions. As a general rule of thumb, in competitive markets, the DMUs are output oriented. For that reason, output oriented model is selected in this study. Output oriented DEA method is preferred in both VRS and CRS models. There are 9 inputs and 2 outputs for each dealer to assess the efficiency level. Inputs are assumed to be full-time employees, part-time employees, cost of labor, absenteeism, area of outlets, number of points of sale (POS), age of the outlets, inventory, and other costs. Outputs are arranged as sales and operational results (profit). There are two types of DEA in respect of time period: time series and cross section. Cross sectional data of the year 2000 were used for the research.

The results of the study suggest that economies of scale are determinant factors of efficiency in this sector. It is determined that several outlets have efficiency level of 1 when CRS assumption is used; however number of efficient outlets, including all CRS-efficient outlets, increases when VRS model is used. In other words, the dominant source of inefficiency is economies of scale. Another result of the study is the fact that, the outlets' dominant character is increasing returns to scale (IRS) as it was in all retail store studies of DEA.

Keh and Chu (2002) study a grocery retailer chain. DEA is used to assess the performance level of grocery retailers. The model used for study is constructed as follows: There are three groups of data which are raw input (capital, labor), intermediate output (accessibility, assortment, assurance of product delivery, product information, and ambiance) and final output (sales, revenue) for 13 DMUs in 10 year period.

The study is founded on 3 stages: Stage 1 (raw input→ intermediate output), Stage 2 (intermediate output→ final output), Stage 3 (raw input→ final output). These three stages are discussed and correlations between them are explained. Also it is shown that there is increasing returns to scale in grocery retailing stores.

Banking institutions are one of the most important issues of DEA contexts. Mukherjee, Nath and Pal (2002) introduce a comprehensive study on Indian banks. The authors try to obtain a connection between performance benchmarking and strategic homogeneity of Indian commercial banks. As a first step, they put ahead these questions for answering: 1- how to obtain a performance benchmarking of the Indian banking. 2- Whether any groupings of the Indian banks can be obtained based on the homogeneity in business strategy.

Having asked these questions, they start to apply the solutions. DEA methodology is preferred for performance benchmarking of 68 Indian banks which can be classified as publicly owned, privately owned and foreign capital. They decide to use an intermediation approach, in which financial institutions are assumed to be intermediaries between the depositors and the investors where the outputs are considered in terms of the value of loans rather than the number of loan accounts. This approach is more suitable for evaluating the performance of an entire institution (Berger and Humphery, 1997). CCR output oriented model is used for the performance evaluation. Finally, it is found that, publicly owned banks have higher efficiency scores and more stable performance during the observed periods.

Another research related to banking is performed by Cook and Hababou (2000). In this research, an additive model is introduced to evaluate sales and service efficiency of a major Canadian Bank. The authors struggle with some technical difficulties such as sharing resources between the sales and service functions. A goal programming version of the additive model is developed to evaluate the 20 branches and results are interpreted.

Seiford et al. (1998) provide one of the basic studies about returns to scale (RTS) concept. Although the study is not directly related to retail store/dealer efficiency assessment, it is an effective guide for any DEA research. In this paper, determination of RTS in DEA is presented. The three basic RTS methods, which are scale efficiency index method, CCR RTS method and BCC RTS method, are discussed. The point that the alternate optimal solutions only affect the definition of RTS on DMUs which should be classified as constant returns to scale (CRS) is reviewed. Some modifications of these basic RTS methods are introduced to eliminate the effects of multiple optimal DEA solutions on the RTS estimation. Consequently, the basic RTS methods, their modifications and the relations between them are clarified to enable the DEA users to select the most suitable RTS method.

Donthu and Yoo (1998) is one of the most important articles among the retail store related DEA studies. In this study, DEA methodology is applied to 24 stores of a fast food restaurant chain. The authors introduce a model of 4 inputs (store size, store manager experience with the chain, store location, promotion/give-away expenses) and 2 outputs (sales, customer satisfaction). The data of three years are used for that research.

According to these three year data, they present the first year's efficiency scores and they compare these results with regression analysis of the same year. After that, the DEA efficiencies of year1, year2 and year3 are introduced and discussed. Finally, the total data of three years (3 year * 24 DMU) are pooled and DEA efficiencies are calculated for the DMUs according to the pooled data and the results are interpreted. Using the customer satisfaction, a five point scale measure, as one of the output variable in the retail store productivity assessment makes this study exceptional.

Herrero et al. (2005) provide good insights for the usage area of DEA methodology. The study assumes only one input that is the size of folder in bytes to be compressed and the input value is fixed for all compressors. The model is composed of three outputs which are the speed (in bytes per second) at compressing input files, the speed at extracting files, and the compress ratio.

Three analyses are applied: technical efficiency of compressors relative to *text files,* efficiency of compressors relative to *exe. files* and efficiency of compressors relative to *both types of files*. In all of the three analyses, it is shown that the speed of compressing is the main source of inefficiency. For that reason, they advise that the compressors should focus on improving this attribute.

Thanassoulis (1993) is an important article that compares *DEA* and *Regression Analysis* as the alternative methods for performance assessments. The comparison is restricted to homogenous units that use single input or produce single output. Relative efficiency scores, marginal input-output values and target input-output levels are assumed to be concerning points for the two methods. The results of the study are as follows; generally, DEA outperforms regression analysis on accuracy of estimates. However, regression analysis offers better stability of accuracy.

In this thesis, we conceptualize dealer efficiency, as the relative performance efficiency of a dealer characterized by multiple inputs and outputs and present an operations research-based methodology, namely Data Envelopment Analysis. This method accommodates multiple inputs and outputs and produces a single measure of efficiency that is relative in nature (Donthu and Yoo, 1998). Moreover, best performers are used as bases in this relative efficiency computation.

As indicated before, two different types of DEA models can be constructed with respect to time period as: time series and cross-section. Time series models allow tracking of decision making unit's efficiency over time. On the other hand, cross-section models only reflect the snapshot of that period. Time series generally are preferred in previous DEA studies. We use cross-section data of year 2004, because prior years' data are not available. This study can be further improved by using the data of the consecutive years.

Choosing DEA model is another important point of the study. As a general rule of thumb, in competitive markets, the DMUs are output oriented (Barros et al., 2003). We also prefer output oriented DEA model. While (Mukherjee et al, 2002) prefer to use CCR output oriented model in the banking study, (Barros et al., 2003) prefer to use BCC model in the retail store efficiency study and also apply CCR for comparison. On the other hand, (Cook and Hababou, 2001) use an Additive model in their bank branches' sales performance analysis study. We also decide to use BCC-Output oriented model and CCR-Output oriented model for comparison.

A basic pitfall in the application of DEA arises simply from attempting to compare non-homogenous units. Clustering the units into homogenous sets is the one of the solutions to that problem (Dyson et al., 2001). (Mukherjee et al., 2002) use such clustering method. We prefer to compose a general model and four other clusters to overcome the above mentioned pitfall.

4. PROBLEM DEFINITION AND DATA PREPARATION

This chapter is dedicated to define the problem and introduce the attributes which are obtained in the raw data set. Also, data refinement and preparation steps are presented. Data refinement is necessary to prepare the data for a proper analysis. Refinement comprises of cleaning data rows which have null values, converting units (for example TL to YTL). Data preparation covers generating new attributes and clustering whole data set into sub-groups to make more realistic evaluations.

Assessment of comparative efficiency of spare part dealers is targeted in the study. For that purpose, DEA methodology is applied to the data set of 10624 spare part dealers of an automobile spare parts distributor. At the beginning of the study, a raw data set which covers the yearly records of 2004 are treated (note that each spare part dealer represents a DMU). Firstly, raw data set is passed through some data refinement steps. Such as; eliminating null valued data rows (each row represents a dealer/DMU) out of 10624 rows and converting Turkish Lira (TL) values to New Turkish Lira (YTL). After that, newly derived attributes are generated. These new attributes except "Market share" are used as reference points for forming clusters in the study. "Market share" is used as one of the output variables in the input-output model. "Market share", "Tofas ratio", "Otoyol ratio" are some examples for new attributes which are obtained by using existing attributes. It is important to mention that clusters are composed to obtain more homogeneous sub-groups.

After obtaining the clusters, there are two decisions to be made;

1. Composing an input-output variable model
2. Choosing a DEA model

Input-output variable model is created according to the previous studies that appear in the literature and the performance criteria of the distributor. Also, correlation levels within input variables and output variables are taken into consideration during this step. Low correlation between input variables and output variables is preferred. Choosing a proper DEA model for the problem is another vital point of the study. Related previous studies are also taken into account during selection of the DEA model, beside the managerial policy of the distributor.

In Table 4.1 the main attributes that are available in raw data set, units of the variables, max and min values, and number of non-blank rows for each attribute are given.

Table 4.1. Attributes, units, range and number of non-blank rows in the raw data set

Attributes	Unit	Min. Value	Max. Value	Number of non-blank rows
Location	-	2	13	10624
Debt cost	TL	15,000	11,134,900,683	6622
Invoice term	Days	1	152	6609
Number of orders	Times	1	2903	10624
Invoice cost	TL	3,030,000	877,876,782,540	10614
Discount	TL	-11,960,000	225,197,097,226	2671
Accessory	TL	750,000	225,197,097,226	8320
Accumulator	TL	20,000,000	98,736,023,821	854
Epidemic-Tofas	TL	169,200,000	48,550,444,034	65
Exterior part	TL	48,600,000	1,107,484,000	6
Mako	TL	1,260,000	679,703,853,794	1488
Otoyol	TL	570,000	349,757,625,360	672
Tofas	TL	1,800,000	793,049,137,762	4337
Trendy	TL	863,500,000	863,500,000	1
Motor oil	TL	2,720,000	299,573,746,715	846
Sales	TL	3,125,000	922,632,668,345	10624

The attributes given in Table 4.1 can be described as follows:

- “Location” is the region where the spare part dealer performs its business. In this study, there are 12 regions that are defined by the distributor and these locations are coded from 2 to 13.
- “Debt cost” is the cost that is caused by the deferral of the payments by the dealers. If this value is high, it indicates a weak financial status for the dealer. That variable is a function of “Invoice term”, because “Debt cost” is calculated as a function of *invoice term* and *inflation rate*.

- "Invoice term" is the number of remaining days for the due date of the invoice. The higher the *invoice term* value, the later the distributor will take the money against sold goods. So, a high value for that variable is also an indicator of a negative financial status for the dealer.
- "Number of orders" shows how many orders the dealer gives to the distributor in that period. The larger the orders, the more operational and transportation cost for the distributor. Namely, high *number of orders* variable is a negative indicator for dealer efficiency. Note that, although high *number of orders* generally means that high amount of spare parts are purchased from the distributor; here it is assumed that *number of orders* does not change the "Sales" amount of the distributor to the corresponding dealer.
- "Invoice cost" is the total cost of the all goods sold to the dealer in a given period. Note that, this cost is the cost of goods for the distributor. The lower the *invoice cost* the more positively it affects the efficiency of the dealer.
- "Discount" is the discount amount that is given to the corresponding dealer. Since the efficiency of the dealers is analyzed from the distributor perspective, the lower *discount* value signifies a positive effect on efficiency.

All attributes given below are sales related variables. High values of these variables indicate high efficiency for the dealers. In DEA methodology, output variables are chosen out of such variables that indicate high efficiency if the value of the variable increases. For that reason, these attributes can be presented as potential output variables for the input-output model. The input-output model is presented in this chapter.

- "Accessory" column gives information about the total sales volume of accessories in each dealer.
- "Accumulator" column informs us about the total accumulator sales.
- "Epidemic-Tofas" represents the sales of engine parts which have relatively high prices.
- "Exterior part" column includes the sales volume of parts like traffic set, fire extinguisher, etc.

- "Mako" column gives the total sales of spare parts that originated from Mako Elektrik Sanayi ve Ticaret A.Ş. as the supplier for the distributor of the DMU.
- "Otoyol" column gives information about the sales of spare parts that are supplied from Otoyol.
- "Tofas" column is the sales volume of spare parts supplied from Tofas.
- "Trendy" is the sales volume of the Trendy motorcycles' spare parts.
- "Motor oil" column depicts the total sales of motor oil in each DMU for the given period.
- "Sales" are the volume of the total sales to the relevant dealer by the distributor during the given period.

Data refinement steps are as follows;

- All attributes which are introduced in TL unit are converted into YTL.
- Rows which have null value/values are deleted after calculating "Market share" of each row (dealer/DMU), because it is decided that all dealers that compose the market should be taken into consideration while calculating the market size, even though some of them do not have enough information for performance evaluation.

After that, data preparation steps are performed. As it is mentioned, clustering is needed for this study; because it is not logical to evaluate the dealers that concentrate on different sales distributions. For that purpose, we evaluate "Accessory ratio", "Accumulator ratio", "Epidemic-Tofas ratio", "Mako ratio", "Otoyol ratio", "Tofas ratio" and "Motor-oil ratio" for all DMUs. These ratios are calculated by dividing relevant sales amount of the dealer to the total sales of the dealer. The ratio values change between 0 and 1, in other words, ratios vary from 0% to 100%. For example, 80% of "Tofas ratio" means that the "Tofas" sales of the dealer at hand compose 80% of its total sales amount. Ratios allow us to construct the clusters in future steps.

Then the market share of each DMU is calculated. "Market share" is another derived attribute which is used as one of the output variables in the input-output model. $\text{TotalSales}_{location}$ is the total sales of "Location" in which the relevant DMU is included during the given period. TotalSales$_{DMUi}$ is the sales amount of the ith DMU during that period. Market shares of all DMUs are calculated by;

$$MarketShare = \frac{TotalSales_{DMU_i}}{TotalSales_{location}}$$

There are 12 different locations that make it easier for the distributor to classify the dealers. The number of dealers differs for all locations.

Table 4.2. Attributes, units, range and number of non-blank rows in the refined data set

Attributes	Unit	Min. Value	Max. Value	Number of non-blank rows
Location	-	2	13	10624
Debt cost	YTL	0.0	11134.9	6622
Invoice term	Days	1	152	6609
Number of orders	Times	1	2903	10624
Invoice cost	YTL	3.0	877876.8	10614
Discount	YTL	-12.0	225197.1	2671
Accessory	YTL	0.8	225197.1	8320
Accumulator	YTL	20.0	98736.0	854
Epidemic-Tofas	YTL	169.2	48550.4	65
Exterior part	YTL	48.6	1107.5	6
Mako	YTL	1.3	679703.9	1488
Otoyol	YTL	0.6	349757.6	672
Tofas	YTL	1.8	793049.1	4337
Trendy	YTL	863.5	863.5	1
Motor oil	YTL	2.7	299573.7	846
Sales	YTL	3.1	922632.7	10624
Market share	Percentage	0	100	10624
Accessory ratio	Percentage	0.0027	100	8320
Accumulator ratio	Percentage	0.019	100	854
Epidemic-Tofas ratio	Percentage	0.025	100	65
Mako ratio	Percentage	0.0097	100	1488
Otoyol ratio	Percentage	0.0002	100	672
Tofas ratio	Percentage	0.0079	100	4377
Motor oil ratio	Percentage	0.0028	100	846

In Table 4.2 attributes after data refinement and data preparation steps are presented. “Exterior-part ratio” and “Trendy ratio” are not calculated; because there are only six dealers for the exterior parts and one dealer for trendy motorcycle parts.

After some experimental trials on DEA-Solver Software, it is decided to choose the data clusters that we will work on according to these steps;

1. Choose DMUs that “Motor oil ratio” < 10 % and “Accessory ratio” < 50%
2. Market shares are calculated.
3. Null valued units which have null values for one of the inputs “Location”, “Debt cost”, “Invoice term”, “Number of orders”, “Invoice cost” are removed by applying MS Access queries.
4. The DMUs that have total sales of more than 10000 YTL are chosen.

After applying proper queries in MS Access, we get 3778 DMUs that satisfy the requirements of the first step. The rationale behind this step is that some dealers are specialized in Motor oil sales and we do not want to analyze these dealers. Also, dealers which have “Accessory ratio” more than 50 % are not in the scope of our study. We make a decision to evaluate the accessory dealers (which have “Accessory ratio” > 50 %) in a different step.

The second step is another key point in this evaluation. In the original data, we have only one output which is “Sales”. However, it is also necessary to take into account the effect of location in the model. For that reason, “Market share” is calculated for each DMU. The value is determined by dividing “Sales” of the DMU by the total sales of all DMUs in the same location. Note that all the DMUs in the same location are chosen out of 3778 DMUs. The process is shown in the Figure 4.1.

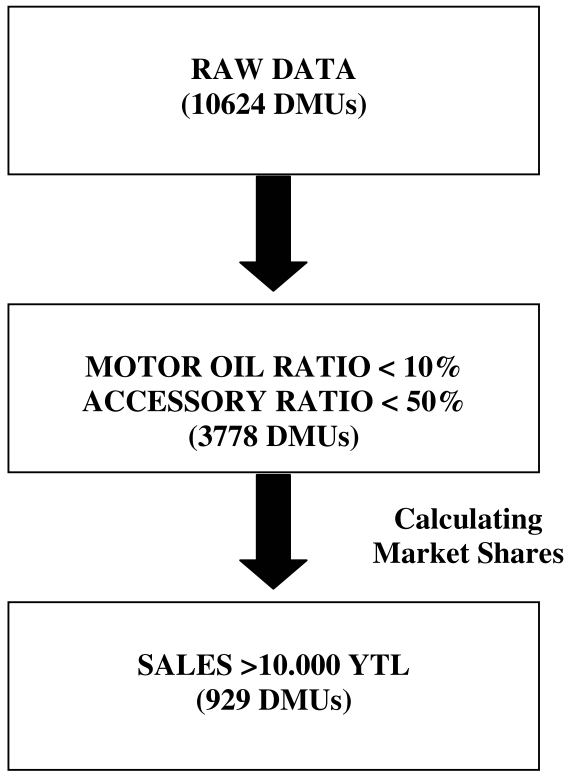

Figure 4.1. Elimination steps of the raw data

In the third step, it is decided to eliminate small dealers, and simplify the analysis. Small dealers may tend to be over-rated in the efficiency assessment (Dyson et al., 2001). This fact may cause the results of DEA evaluation to be biased. Taking all these facts into account, DMUs that have “Sales” amount less than 10000 YTL are selected. Note that the value 10000 YTL is only chosen to eliminate the small sized dealers which can cause bias in evaluations. In other words, 10000 YTL is not a result of an experimental study and that value can be chosen as some other value such as 12000 YTL which can help us about eluding small dealers from performance evaluation. We perform sensitivity of results to 10000 YTL in Chapter 5.

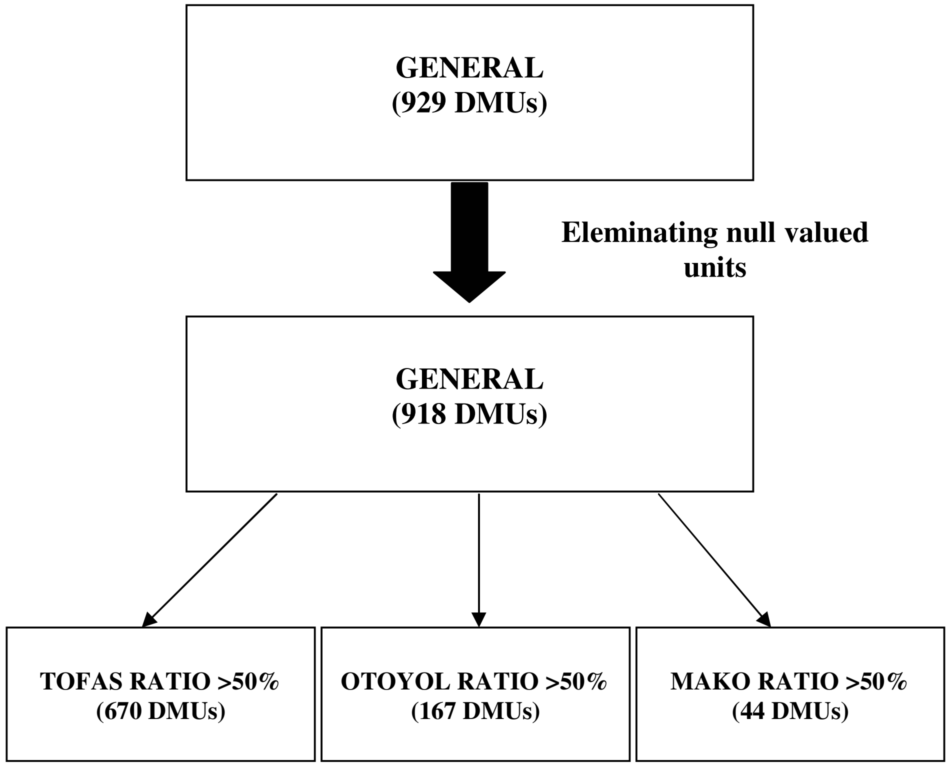

Figure 4.2. The illustration of obtaining the clusters

After these simplifications, a data pool composed of 929 dealers is obtained, decision units that have null values in any input or output variable are eliminated. The number of DMUs that go through all these steps is 918 and we call this group as "General".

However, the units within General Model have different specifications. For example, some of them are concentrated on selling Tofas based spare parts; another group of dealers are selling Mako based spare parts at most, etc. For that reason, we go one step further and apply a query that chooses dealers which have "Tofas ratio" over 50%. Then, same query is carried out for "Otoyol" and "Mako". As a result, four different clusters are defined. The clusters are extracted as shown in the Figure 4.2.

Table 4.3 shows the clusters obtained and the number of DMUs for the corresponding cluster.

Table 4.3. Number of dealers in the clusters

Cluster Name	Number of DMUs before null values	Number of DMUs
General	929	918
Tofas	678	670
Otoyol	167	167
Mako	46	44

Accessory dealers are examined in a different process:

1. We have chosen DMUs which are having "Accessory ratio" > 50% out of 10624 DMUs (6304 DMUs)
2. 6304 DMUs are taken into consideration and total market size of each location is calculated.
3. In the light of market size of locations, the "market share" of each DMU is obtained.
4. DMUs which have null value/values in their any attribute are eliminated.
5. DMUs which have "Sales" volume more than 10000 YTL are chosen (33 DMUs)

The Accessory cluster is obtained as shown in the Figure 4.3.

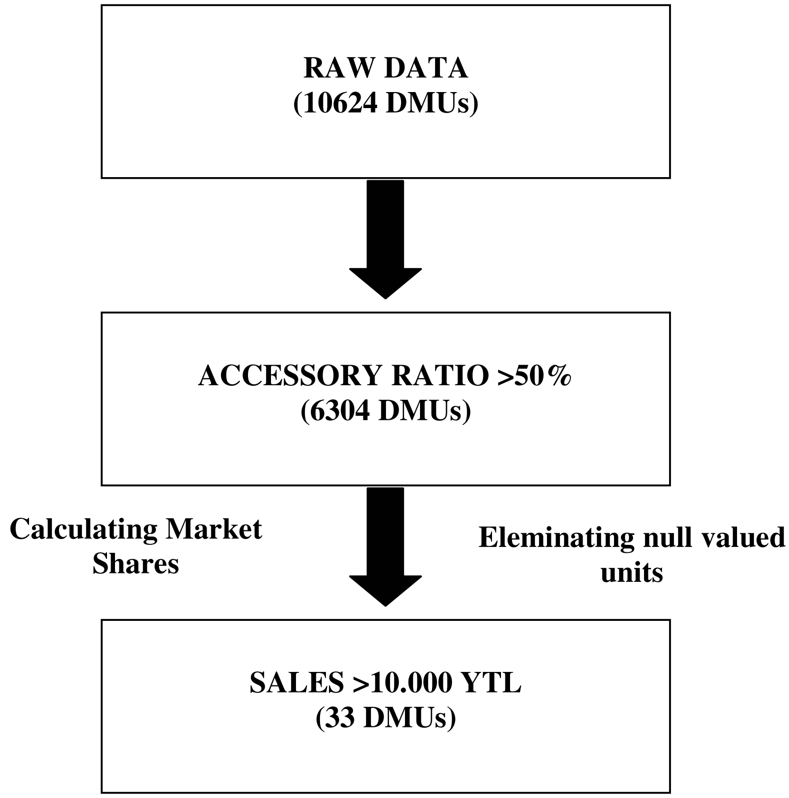

Figure 4.3. The illustration of obtaining the Accessory cluster

Finally, five data clusters are obtained. Now, there are two steps remaining before starting experimental study; one is composing an input-output model, the other is choosing a DEA model.

An input-output model which is given in Table 4.4 is composed to depict the business policy of the distributor. In other words, input and output variables are chosen by taking into account that the variables should meet the goals and objectives of the distributor. The model has four input variables (“Invoice term”, “Number of orders”, “Cost”, and “Discount”) and two output variables (“Sales” and “Market share”).

Choosing the input-output variables procedure is based on two basic points. First, basically what the performance criteria of a dealer are from the distributor’s perspective. Secondly, the variables should have as minimum correlation as possible. The point is, the correlation between the input and output variables is disregarded, but the correlation between input variables (“Invoice term”, “Number of orders”, “Cost”, and “Discount”) and output variables ("Sales" and "Market share") should be within an acceptable range. To clarify, while the high correlation between "Invoice term" and "Cost" is under consideration, the correlation between "Invoice term" (input variable) and "Sales" (output variable) is negligible.

Table 4.4. Input and output variables for the models

Inputs	Outputs
Invoice Term (days)	Sales (YTL)
Number of Orders (times)	Market Share (percentage)
Cost (YTL)	
Discount (YTL)	

In the light of two points mentioned above and some input-output model trials on the DEA-Solver software, it is decided that "Sales" and "Market share" are the outputs and "Invoice term", "Number of orders", "Cost", and "Discount" are the inputs of our model (Table 4.4). The descriptions of the input-output variables are given below.

INVOICE TERM is one of our input variables and is highly correlated with DEBT COST. Because of high correlation between these two variables, it is decided that the model should include at most one of two variables INVOICE TERM and DEBT COST. INVOICE TERM which is the number of days remaining for the payment day is chosen as one of the input variables.

NUMBER OF ORDERS shows that how many times the distributor makes delivery to the relevant dealer. Notice that the more the NUMBER OF ORDERS, the higher the cost of the transportation and operational problems for the distributor. So, this is assigned as another input variable that we want to minimize. Furthermore, since we are performing this analysis from the distributor's point of view, lower number of orders means that the dealer is bearing the inventory holding cost.

COST is the cost of all goods sold to the dealer by the distributor. This input should be as low as possible. However, note that this variable is not under the control of dealers;

even it is not fully under control of distributor. The analysis is done under the assumption that a lower COST value indicates higher profit for the distributor. Therefore, lower costs indicate more efficient dealers.

DISCOUNT is an input variable that gives information about the distributor's total price cut provided to each dealer. This variable is mostly under the control of distributor. Also, it is considered that, the lower the *discount*, the more efficient the dealer.

Turning to the output variables, there are two output variables; SALES and MARKET SHARE. SALES is the sales volume of the distributor to relevant dealer for the given period. It is considered that the higher SALES amounts indicate higher profits and therefore indicate more efficient dealers.

MARKET SHARE gives us an idea about how successful the dealer is beyond the SALES volume, because we calculate the MARKET SHARE of each dealer with respect to its location's total sales volume. It is preferable for a dealer to have a high MARKET SHARE. The input variables are not fully under control of neither the distributor nor the dealers, but the output variables, "Sales" and "Market share", depend on the dealers' performance. So, it is decided to apply the output oriented models, namely CCR-O and BCC-O. However; note that, with multiple inputs and multiple outputs, the piecewise linear segments defining the efficiency frontier are replaced with efficient "facets" due to the multi-dimensional nature of the example (Blose and Tankersley, 2004).

CCR-Output (CCR-O) and BCC-O models are chosen for the performance evaluation of the clusters. As a result, ten different models which are given in Table 4.5 are taken into consideration in the analysis which is reported in Chapter 5.

Table 4.5. DEA application models

Cluster Name	Type of DEA Model	Number of DMUs
General	CCR-O BCC-O	918
Tofas	CCR-O BCC-O	670
Otoyol	CCR-O BCC-O	167
Mako	CCR-O BCC-O	44
Accessory	CCR-O BCC-O	33

5. EXPERIMENTAL STUDY

In this chapter, the results of (5 clusters x 2 DEA approaches) 10 models are introduced. The samples from DEA-Solver-PRO's excel sheet results are presented and commented for these 10 models. In the General Model, it is preferred to give examples of results as much as possible. The remaining models are discussed only by presenting the most important excel sheet results.

Sensitivity analysis regarding sales amount limit (10000YTL) is added at the end of the chapter. The efficiency results of 10 clusters which are obtained according to 5000YTL criterion are introduced and are compared with the current results. After that sensitivity analysis, an approach related to determining the sources of inefficiency is discussed.

5.1. General Model

General Model is the biggest model with 918 dealers, in the study. Results are presented for both General CCR-O and BCC-O Models.

5.1.1. General CCR-Output Oriented Model

There are 918 DMUs in this data set and the basic statistics on these data are given in Table 5.1.

Table 5.1. Statistics on input/output variables of the General CCR-O Model

	Invoice term(days)	Number of Orders (times)	Cost (YTL)	Discount (YTL)	Sales (YTL)	Market Share (percent)
Max	143,00	2903,00	1129058,89	228086,24	1223753,00	23,78
Min	3,00	1,00	8484,24	10,00	10000,56	0,09
Average	59,21	190,51	59538,74	12828,40	65826,78	1,11
SD	18,75	283,95	102326,73	24973,48	111681,70	2,01

The correlation between variables in DEA analysis is a crucial point in the selection of the inputs and outputs. High correlation between two inputs or two outputs means that both variables direct towards the same result. Using two highly correlated variables in the model may bias the results. For that reason, attention is paid to this point and highly correlated variables are excluded from the input-output model. Although there is a high correlation between COST and SALES, it is not taken into consideration, since one of the variables is input and the other is output. The highest correlation is observed between SALES and DISCOUNT variables. It is logical for a DMU to take high amount of discount while having high sales volume. The other correlation values can be seen from Table 5.2.

Table 5.2. Correlation between input/output variables of the General CCR-O Model

	Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
Invoice term	1,0000	-0,1437	-0,0506	-0,0555	-0,0462	-0,0929
Number of Orders	-0,1437	1,0000	0,7149	0,8058	0,7223	0,5783
Cost	-0,0506	0,7149	1,0000	0,8949	0,9993	0,8494
Discount	-0,0555	0,8058	0,8949	1,0000	0,8917	0,7976
Sales	-0,0462	0,7223	0,9993	0,8917	1,0000	0,8473
Market Share	-0,0929	0,5783	0,8494	0,7976	0,8473	1,0000

Table 5.3 gives some information about the efficiency scores of the model. As stated at the beginning of this chapter, the General Model includes 918 DMUs and 32 of them are found to be CCR-efficient DMUs. In other words, it is not possible to increase any output of these DMUs without increasing any input or without decreasing any other output value. However, 886 DMUs are determined as CCR-inefficient DMUs. These DMUs can increase their outputs radially and they also may have input excesses or output shortfalls. The average efficiency score of all 918 DMUs is calculated to be 0,8823 and the minimum efficiency score of a DMU is found to be 0,6357. Standard deviation of the efficiency scores is found as 0,0495.

The efficient DMUs are also used as reference set elements by inefficient units. We call these DMUs as *efficient peers* or *efficient referents*. The efficient peers to DMU_0 are those DMUs which correspond to positive (λ^{*})s. All inefficient DMUs include two ore more efficient DMUs in their reference set. The more an efficient DMU is used in reference set the more it is a good role model to inefficient DMUs in terms of input/output mix.

Table 5.3. Basic results of the General CCR-O Model

Number of DMUs	918
Average of Scores	0,8823
SD	0,0495
Maximum	1
Minimum	0,6357
Number of Efficient DMUs	32
Number of Inefficient DMUs	886

Table 5.4. Efficient DMUs and reference set frequencies for the General CCR-O Model

Peer Set	**Frequency to Other DMUs**	**Peer Set**	**Frequency to Other DMUs**
78	1	6305	28
374	9	6307	0
375	24	6535	94
377	30	6543	0
390	49	6582	430
481	183	6596	0
488	498	7089	4
608	0	7259	264
1139	20	7308	12
1349	3	7516	623
3768	30	7728	0
3808	2	7927	3
4837	6	8042	0
4933	0	8367	485
5094	19	8784	4
6288	88	8787	57

Table 5.4 shows the peer set which includes the IDs of the dealers and the second column depicts the usage frequency of each efficient DMU as an efficient peer by

inefficient DMUs. According to Table 5.4, it can be concluded that the dealers 481, 488, 6582 7259, 7516, and 8367 are outstanding role models for inefficient dealers. Especially DMU 7516 is the most used DMU as an efficient peer. Whereas, some DMUs are never used as efficient referents despite being efficient like the other referent DMUs. This can be described as their input/output mixes are not suitable for any inefficient unit.

Before investigating more about the General CCR-O Model, Figure 5.1 gives a visual illustration of information given in Table 5.4. Here it is shown that 6 DMUs dominate the other efficient units in terms of reference set frequency as it is shown in Table 5.4.

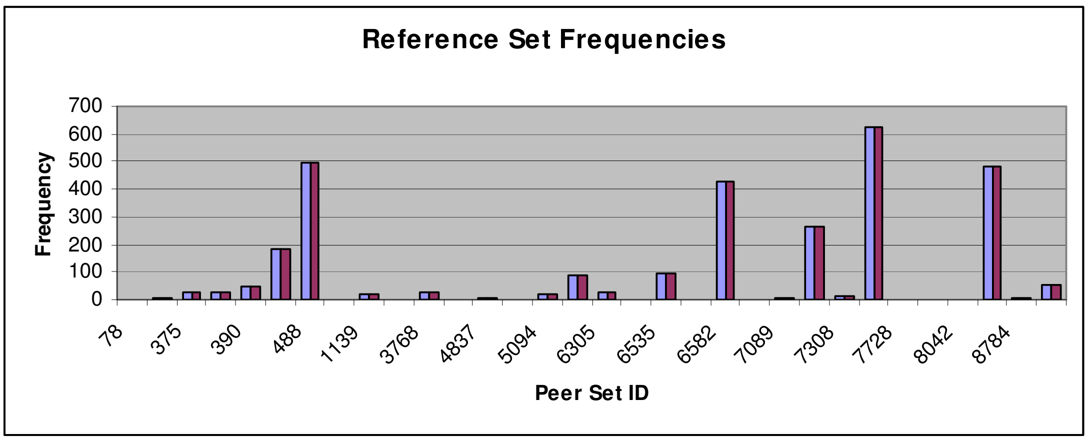

Figure 5.1. Reference set frequencies for the General CCR-O Model

The DEA-Solver software presents more information regarding the performance evaluation of the DMUs. Such as;

- Slack values
- Weighted data
- Weights
- Projection
- Efficiency score graphs
- Efficiency scores

The full results of the models are given in the accompanying CD to the thesis. Some sample results of *slack values*, *weighted data*, *weights*, and *efficiency scores tables* for the General Models are given in Appendix A.

Projected values can be calculated for CCR-O model by the formulas below. Here $\hat{x}_0$ and $\hat{y}_0$ are the projected input and output values, respectively. t^{-*} and t^{+*} are the input excesses and output shortfalls, respectively.

Table 5.5. Projected values for the General CCR-O Model

No.	DMU	Score	Projection	Difference	%
	I/O	Data			
1	1	0,8831			
	Invoice term	46	46	0	0,00%
	Number of Orders	144	144	0	0,00%
	Cost	27410,29	27410,29	0	0,00%
	Discount	5252,22	4644,73	-607,49	-11,57%
	Sales	30844,66	34925,73	4081,07	13,23%
	Market Share	0,98	1,11	0,13	13,23%
2	2	0,8904			
	Invoice term	46	46	0	0,00%
	Number of Orders	129	129	0	0,00%
	Cost	25592,92	25592,92	0	0,00%
	Discount	4516,31	3754,81	-761,50	-16,86%
	Sales	29176,25	32767,02	3590,78	12,31%
	Market Share	0,93	1,04	0,11	12,31%

Finally, $\eta^* = 1/\theta^*$ and η^* is the radial augmentation potential of the output variables. The projected values of the first two DMUs are given in Table 5.5. The calculations are done according to formulas below:

$$\hat{x}_0 = x_0 - t^{-*}$$

$$\hat{y}_0 = \eta^* y_0 + t^{+*}$$

5.1.2. General BCC-Output Oriented Model

General BCC-O Model is obtained by applying BCC-O oriented model to the General data set. BCC is a variable returns to scale based model, while CCR is a constant returns to scale based model. Therefore, a higher number of efficient units is expected in BCC-O model in comparison with CCR-O model.

The data set is same in both CCR-O and BCC-O models. For that reason, statistical results and correlation values are as in Table 5.1 and Table 5.2, respectively.

Table 5.6. Basic results of the General BCC-O Model

Number of DMUs	918
Average of Scores	0,9045
SD	0,0499
Maximum	1
Minimum	0,6472
Number of Efficient DMUs	64
Number of Inefficient DMUs	854

Table 5.6 includes some differences from the Table 5.3. Average of efficiency scores is slightly larger in BCC-O model than that of CCR-O model. The reason is that the variable returns to scale model forms a tighter region that envelops the units. As a result, the efficiency levels of BCC models exceed those of the CCR models. The minimum efficiency level of BCC-O model is also slightly larger than that of CCR-O model. Also, the number of efficient units increases in the BCC-O model. This is an expected result, because VRS models give flexibility to the DMUs and the number of efficient units goes up.

Reference set frequencies given in Table 5.7 differ from those of CCR-O model, but in both models a few units provide superiority over the other DMUs. These units are DMU 435, DMU 488, DMU 6288, DMU 6535, DMU 6582, DMU 7259, DMU 7516, and DMU 8367. More discussion is introduced during the comparison of the models.

Table 5.7. Efficient DMUs and reference set frequencies for the General BCC-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
38	31		743	7		3957	2		6543	1
78	1		1139	19		4780	19		6582	185
210	3		1287	0		4837	4		6596	0
374	4		1349	1		4846	93		7089	120
375	14		1379	0		4933	0		7259	413
377	19		1380	0		5031	2		7308	5
390	37		1985	1		5094	12		7319	0
392	3		2066	2		5132	3		7516	477
405	6		2240	65		5183	6		7654	16
416	4		3717	0		5552	0		7728	0
418	13		3768	22		6288	212		7927	3
435	158		3769	1		6305	29		8042	0
481	83		3808	1		6307	0		8367	527
488	367		3844	29		6390	51		8784	11
530	5		3884	0		6519	0		8787	40
608	0		3952	6		6535	349		9029	97

Figure 5.2 depicts the Table 5.7 graphically.

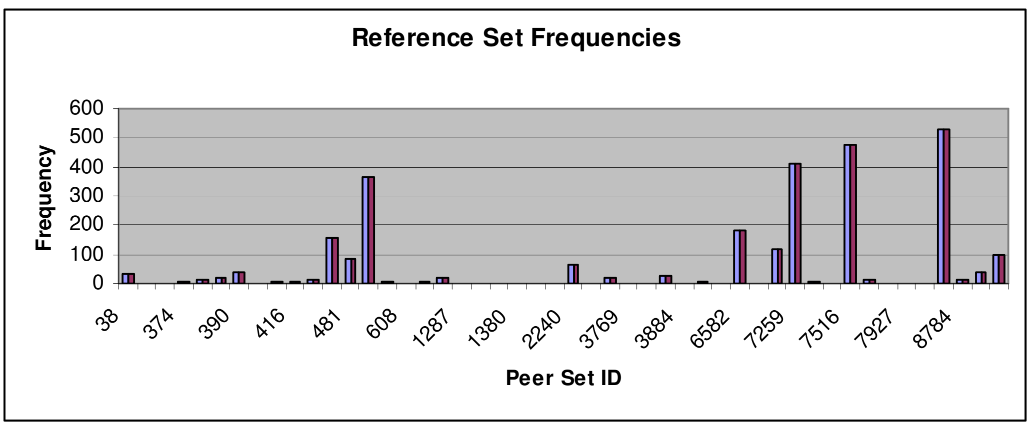

Figure 5.2. Reference set frequencies for the General BCC-O Model

The projections of the first two units are given in Table 5.8. Since the BCC-O model envelops a tighter region, the projection values are smaller than those of CCR-O model. In other words, BCC-O model's projection values are more attainable.

Table 5.8. Projected values for the General BCC-O Model

No.	DMU I/O	Score Data	Projection	Difference	%
1	1	0,8842			
	Invoice term	46	46	0	0,00%
	Number of Orders	144	144	0	0,00%
	Cost	27410,29	27410,29	0	0,00%
	Discount	5252,22	4850,80	-401,42	-7,64%
	Sales	30844,66	34885,25	4040,59	13,10%
	Market Share	0,98	1,11	0,13	13,10%
2	2	0,8910			
	Invoice term	46	46	0	0,00%
	Number of Orders	129	129	0	0,00%
	Cost	25592,92	25592,92	0	0,00%
	Discount	4516,31	3864,87	-651,44	-14,42%
	Sales	29176,25	32745,40	3569,15	12,23%
	Market Share	0,93	1,04	0,11	12,23%

Table 5.9. Returns to scale properties of the General BCC-O Model

DMU	Score	RTS	RTS of Projected DMU
1	0,884174749		Constant
2	0,89100289		Constant
5	0,930575201		Constant
6	0,99617016		Constant
8	0,984201299		Constant
9	0,964856303		Constant
12	0,886854016		Constant
16	0,920016814		Increasing
20	0,876050277		Increasing
22	0,91128604		Increasing
29	0,929413885		Constant
31	0,883859746		Increasing
38	1	Increasing	
39	0,894810389		Increasing
40	0,93191627		Increasing
43	0,867449536		Constant
49	0,902406634		Increasing
58	0,894732599		Constant
61	0,90046177		Increasing
62	0,915564318		Constant

RTS notion is another characteristic of BCC-O model. Three basic RTS features are available; increasing, decreasing or constant returns to scale. Table 5.9 shows the RTS characteristics of the first twenty DMUs of General BCC-O Model.

According to Table 5.10 IRS and CRS are the two dominant characteristics of this data set. CRS has the highest frequency.

Table 5.10. Summary of RTS for the General BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	28	307	335
Number of CRS	32	480	512
Number of DRS	4	67	71
Total	64	854	918

5.2. Tofas Model

Tofas cluster is composed of the dealers that have “Tofas ratio” higher than 50%. In other words, performance evaluation assessment is applied to the dealers that perform more than half of their sales by the spare parts supplied from Tofas.

While describing the General Model, it is aimed to depict the DEA-Solver’s result sheets as well as possible. Since these descriptions are done in the General Model, beginning from the Tofas Model, we will give only key points about the results.

5.2.1. Tofas CCR-Output Oriented Model

In Tofas Model “Invoice term” and “Number of orders” variables have smaller average values than those of the General Model. In contrast, “Cost” and “Discount” variables are greater than those of the General Model. “Sales” and “Market share” variables are also greater than those of the General Model. The values are shown in Table 5.11.

Table 5.11. Statistics on input/output variables of the Tofas CCR-O Model

	Invoice term(days)	Number of Orders (times)	Cost (YTL)	Discount (YTL)	Sales (YTL)	Market Share (percent)
Max	68,00	2903,00	1129058,89	228086,24	1223753,32	23,78
Min	3,00	1,00	8484,24	10,00	10000,56	0,09
Average	51,20	218,02	61123,26	13562,04	67252,08	1,20
SD	9,01	317,62	108483,28	27204,03	117546,83	2,24

Table 5.12 shows the correlations between input/output variables of Tofas CCR-O.

Table 5.12. Correlation between input/output variables of the Tofas CCR-O Model

	Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
Invoice term	1,0000	-0,1105	-0,1090	-0,1641	-0,1061	-0,1277
Number of Orders	-0,1105	1,0000	0,7566	0,8205	0,7692	0,5809
Cost	-0,1090	0,7566	1,0000	0,9656	0,9994	0,8511
Discount	-0,1641	0,8205	0,9656	1,0000	0,9674	0,8330
Sales	-0,1061	0,7692	0,9994	0,9674	1,0000	0,8510
Market Share	-0,1277	0,5809	0,8511	0,8330	0,8510	1,0000

Although the number of assessed units decreases, the number of efficient units rises in comparison to General CCR-O Model.

Another point is that some efficient units of General CCR-O Model, such as; DMU 6582, 481, 390, 3768, 6535 are not included in Tofas cluster. That may cause a change in the shape of efficiency frontier. As a result, some new decision units may become efficient units.

The basic results of the Tofas CCR-O Model are given in Table 5.13.

Table 5.13. Basic results of the Tofas CCR-O Model

Number of DMUs	670
Average of Scores	0,8958
SD	0,0551
Maximum	1
Minimum	0,6606
Number of Efficient DMUs	40
Number of Inefficient DMUs	630

Table 5.14. Efficient DMUs and reference set frequencies for the Tofas CCR-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
6	41		4933	2
210	1		6288	134
374	4		6305	19
375	4		6307	0
377	11		6543	14
417	11		6596	0
435	18		7089	61
484	47		7259	261
486	4		7476	1
488	350		7516	401
530	68		7728	0
608	2		7927	20
743	0		7929	41
1139	57		8119	8
1189	228		8218	15
1349	2		8367	424
1380	0		8784	46
1985	1		8787	9
3836	37		8811	0
4780	9		9029	12

The efficient units and their frequencies in the reference sets are given in Table 5.14. There are some efficient units that have high reference set frequencies. Some of these efficient units are common with General CCR-O Model, such as; DMU 488, DMU 6288, DMU 7259, DMU 7516, DMU 8367.

The Figure 5.3 gives an idea about the general appearance of the reference set frequencies of the efficient units.

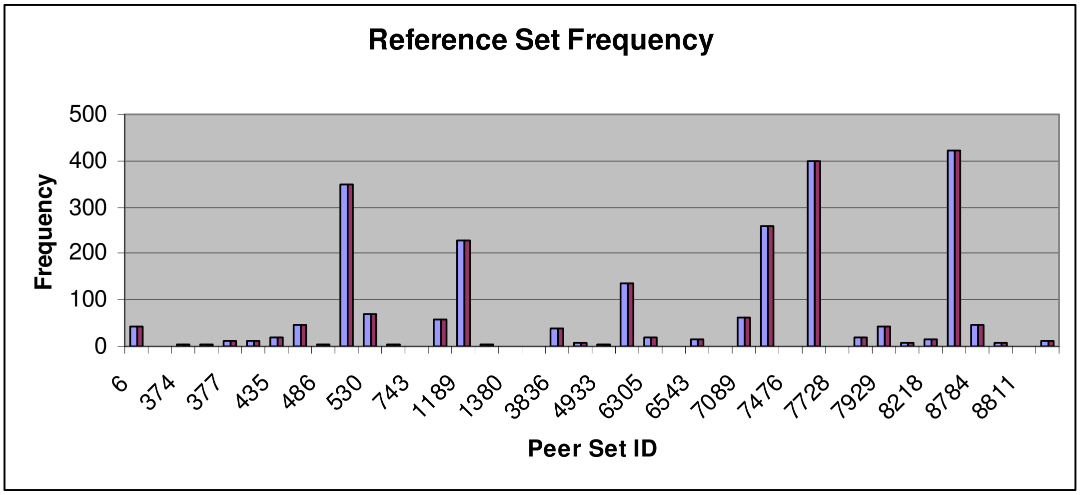

Figure 5.3. Reference set frequencies for the Tofas CCR-O Model

5.2.2. Tofas BCC-Output Oriented Model

As it is shown in Table 5.15, the average efficiency score of Tofas BCC-O Model exceeds that of Tofas CCR-O Model. That point is an expected result.

Table 5.15. Basic results of the Tofas BCC-O Model

Number of DMUs	670
Average of Scores	0,9135
SD	0,0517
Maximum	1
Minimum	0,6697
Number of Efficient DMUs	55
Number of Inefficient DMUs	615

The minimum efficiency score and the number of efficient DMUs rise in comparison to Tofas CCR-O Model, as well.

Table 5.16. Efficient DMUs and reference set frequencies for the Tofas BCC-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
6	84		1189	208		6543	12
38	25		1287	7		6596	0
210	2		1349	1		7089	110
374	4		1379	2		7259	273
375	7		1380	2		7469	15
377	11		1985	1		7476	1
392	3		3717	0		7516	356
405	6		3749	2		7654	17
416	2		3769	1		7728	0
417	8		3836	56		7927	21
418	6		4780	19		7929	16
435	120		4846	78		8119	45
484	23		4933	4		8218	15
486	2		6288	181		8367	348
488	201		6305	22		8784	71
530	64		6307	0		8787	8
608	7		6390	31		8811	1
743	7		6393	0		9029	113
1139	34						

Since the BCC-O is a VRS based model, the efficient units and their reference set frequencies are quite different from those of Tofas CCR-O Model. For example, DMU 6, DMU 435, DMU 8119, DMU 8784, DMU 9029 have shown an improvement in setting a good model for inefficient units. Furthermore, DMU 4846 reaches to a quite well frequency level although it is not an efficient unit in Tofas CCR-O Model. The full data is given in Table 5.16.

The reference set frequencies of efficient units are given in Figure 5.4 as a chart illustration of the data in Table 5.16.

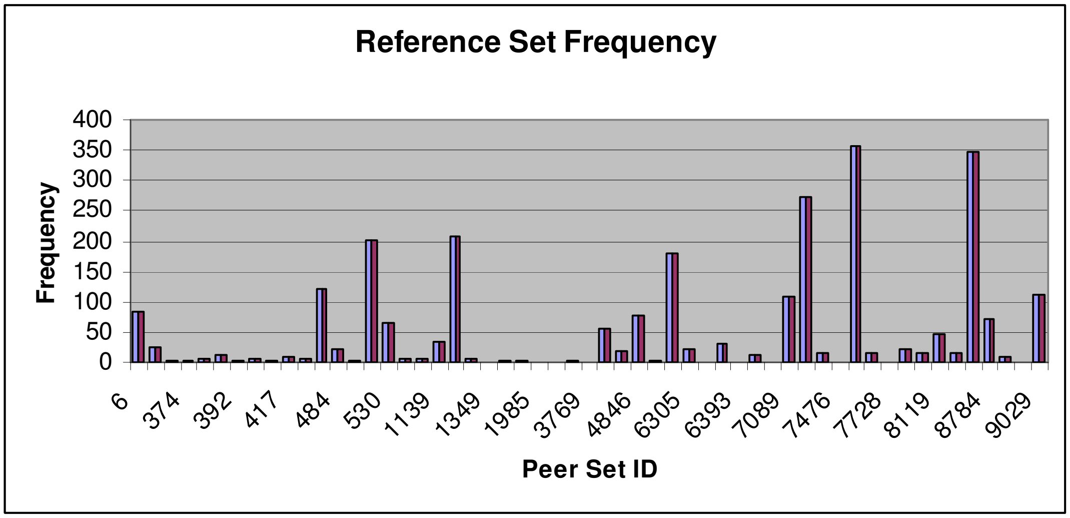

Figure 5.4. Reference set frequencies for the Tofas BCC-O Model

Table 5.17. Summary of RTS for the Tofas BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	12	116	128
Number of CRS	40	490	530
Number of DRS	3	9	12
Total	55	615	670

According to Table 5.17, CRS characteristic of Tofas data set is really dominant by 530 units out of 670 units. It is possible to conclude that dealers in Tofas Model display CRS characteristics.

5.3. Otoyol Model

Otoyol cluster is composed of the units that have “Otoyol ratio” over 50%. There are 167 dealers in this cluster. Otoyol CCR-O and Otoyol BCC-O Models are introduced in this section.

5.3.1. Otoyol CCR-Output Oriented Model

Table 5.18 shows the related statistics and Table 5.19 shows the correlations between the input/output variables of the Otoyol CCR-O Model.

Table 5.18. Statistics on input/output variables of the Otoyol CCR-O Model

	Invoice term(days)	Number of Orders (times)	Cost (YTL)	Discount (YTL)	Sales (YTL)	Market Share (percent)
Max	143,00	938,00	315808,15	113563,53	354104,04	7,52
Min	53,00	5,00	8892,22	2028,72	10106,24	0,10
Average	89,80	140,83	46564,69	15099,92	52123,40	0,74
SD	16,05	153,31	58898,30	19784,82	65525,08	0,96

Table 5.19. Correlation between input/output variables of the Otoyol CCR-O Model

	Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
Invoice term	1,0000	-0,1105	-0,1090	-0,1641	-0,1061	-0,1277
Number of Orders	-0,1105	1,0000	0,7566	0,8205	0,7692	0,5809
Cost	-0,1090	0,7566	1,0000	0,9656	0,9994	0,8511
Discount	-0,1641	0,8205	0,9656	1,0000	0,9674	0,8330
Sales	-0,1061	0,7692	0,9994	0,9674	1,0000	0,8510
Market Share	-0,1277	0,5809	0,8511	0,8330	0,8510	1,0000

Table 5.20. Basic results of the Otoyol CCR-O Model

Number of DMUs	167
Average of Scores	0,9365
SD	0,0402
Maximum	1
Minimum	0,7701
Number of Efficient DMUs	19
Number of Inefficient DMUs	148

The average efficiency score of the Otoyol CCR-O Model that is shown in Table 5.20 is higher than those of both General CCR-O and Tofas CCR-O Models.

Table 5.21 shows the efficient units and their usage frequencies for the Otoyol CCR-O Model. There is a noteworthy result regarding this model. None of the efficient units of the Otoyol CCR-O Model is efficient in the General CCR-O Model. In other words, all the efficient DMUs above are inefficient when they are evaluated within the General cluster.

Table 5.21. Efficient DMUs and reference set frequencies for the Otoyol CCR-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
97	3		6585	22
432	0		7215	0
2132	5		7360	41
2200	5		7452	3
2240	143		7475	2
2261	1		7960	10
3743	74		8053	4
4007	3		8767	0
4472	1		9037	14
4847	9			

Figure 5.5 tells us about the information in Table 5.21 more clearly.

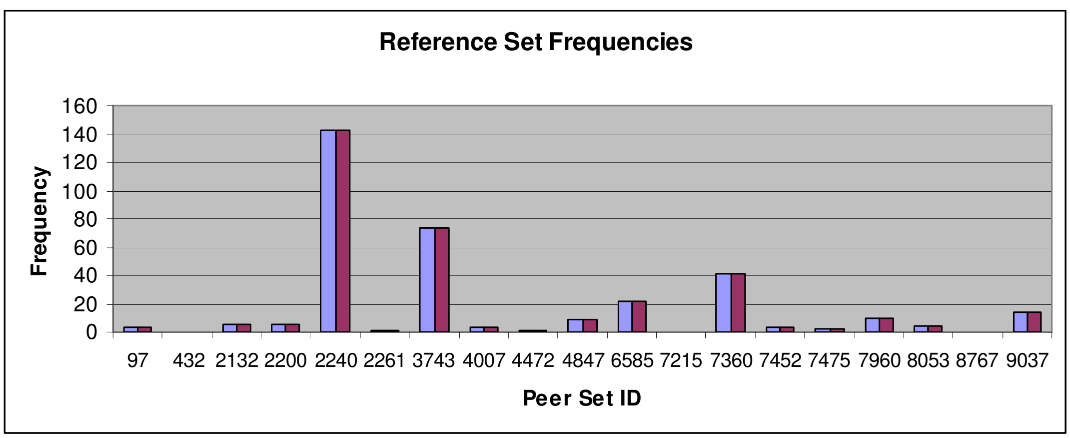

Figure 5.5. Reference frequencies for the Otoyol CCR-O Model

5.3.2. Otoyol BCC-Output Oriented Model

Table 5.22 introduces basic results of the Otoyol BCC-O Model. The average efficiency score of the model is greater than that of Otoyol CCR-O Model. Since the efficiency scores of BCC models are generally higher than CCR models, this increase is anticipated.

Table 5.22. Basic results of the Otoyol BCC-O Model

Number of DMUs	167
Average of Scores	0,9542
SD	0,0355
Maximum	1
Minimum	0,7721
Number of Efficient DMUs	31
Number of Inefficient DMUs	136

Table 5.23. Efficient DMUs and reference set frequencies for the Otoyol BCC-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
97	6		5441	25
369	0		5552	11
432	1		5698	1
2132	8		6429	3
2200	3		6585	32
2226	25		7215	0
2240	114		7360	42
2261	5		7452	3
2374	0		7475	3
2537	1		7701	18
3689	1		7960	13
3743	36		8053	7
4007	0		8136	37
4472	0		8767	0
4847	9		9037	16
5018	44			

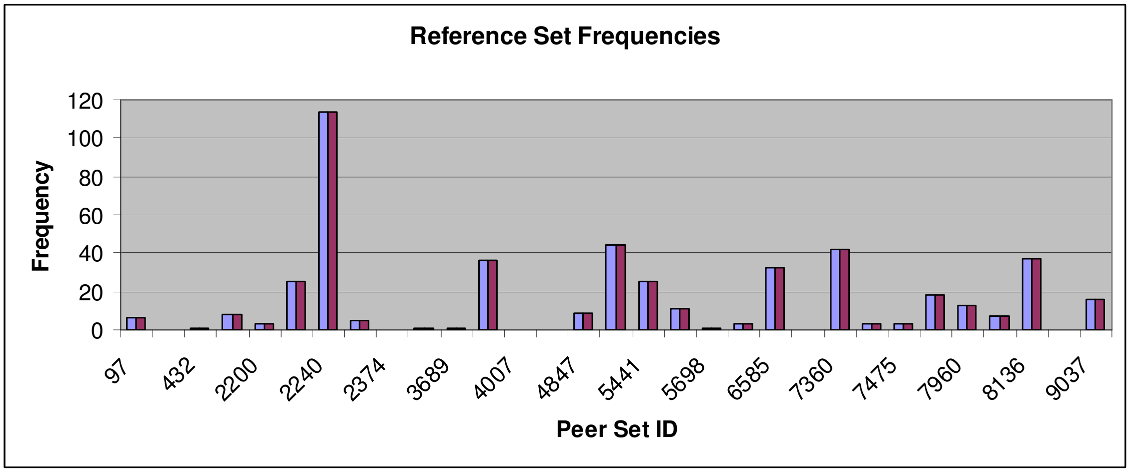

Figure 5.6. Reference set frequencies for the Otoyol BCC-O Model

Note that, according to Table 5.23, there are some extra efficient units that are not available in Otoyol CCR-O Model but efficient in Otoyol BCC-O Model. For example, DMU 369, DMU 2226, DMU 5018, DMU 5441, DMU 7701, DMU 8136 are some units that show high performance in reference set frequency, although they are not included in peer set of Otoyol CCR-O Model. Figure 5.6 depicts the reference set frequencies of the efficient units.

As it is shown in Table 5.24, there are 103 dealers that have IRS properties. IRS can be assumed as the dominant character in this model.

Table 5.24. Summary of RTS for the Otoyol BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	12	91	103
Number of CRS	19	45	64
Number of DRS	0	0	0
Total	31	136	167

5.4. Mako Model

Mako cluster is obtained by choosing the units that have “Mako ratio” over 50%. There are 44 dealers in this cluster and in this part we discuss the Mako CCR-O and Mako BCC-O Models.

5.4.1. Mako CCR-Output Oriented Model

Statistics and correlation levels of the Mako CCR-O Model are given in Table 5.25 and Table 5.26, respectively.

Table 5.25. Statistics on input/output variables of the Mako CCR-O Model

	Invoice term(days)	Number of Orders (times)	Cost (YTL)	Discount (YTL)	Sales (YTL)	Market Share (percent)
Max	94,00	380,00	622293,96	20534,42	707300,47	7,46
Min	13,00	13,00	10532,37	10,00	11783,39	0,14
Average	71,68	73,25	108065,94	2055,48	121757,16	1,67
SD	15,84	72,18	144738,95	3533,52	164922,06	1,88

Table 5.26. Correlation between input/output variables of the Mako CCR-O Model

	Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
Invoice term	1,0000	-0,1966	-0,0098	-0,0430	-0,0138	-0,0304
Number of Orders	-0,1966	1,0000	0,7542	0,7570	0,7665	0,7279
Cost	-0,0098	0,7542	1,0000	0,9866	0,9995	0,9017
Discount	-0,0430	0,7570	0,9866	1,0000	0,9868	0,8871
Sales	-0,0138	0,7665	0,9995	0,9868	1,0000	0,9056
Market Share	-0,0304	0,7279	0,9017	0,8871	0,9056	1,0000

A really high efficiency average of DMUs is obtained in Mako CCR-O Model in comparison to previous models. As it is illustrated in Table 5.27, the minimum efficiency level is also quite high.

Table 5.27. Basic results of the Mako CCR-O Model

Number of DMUs	44
Average of Scores	0,9598
SD	0,0372
Maximum	1
Minimum	0,8704
Number of Efficient DMUs	9
Number of Inefficient DMUs	35

Table 5.28. Efficient DMUs and reference set frequencies for the Mako CCR-O Model

Peer set	Frequency to other DMUs
78	1
390	3
481	31
3768	2
3808	2
4837	2
6535	24
7308	5
8042	0

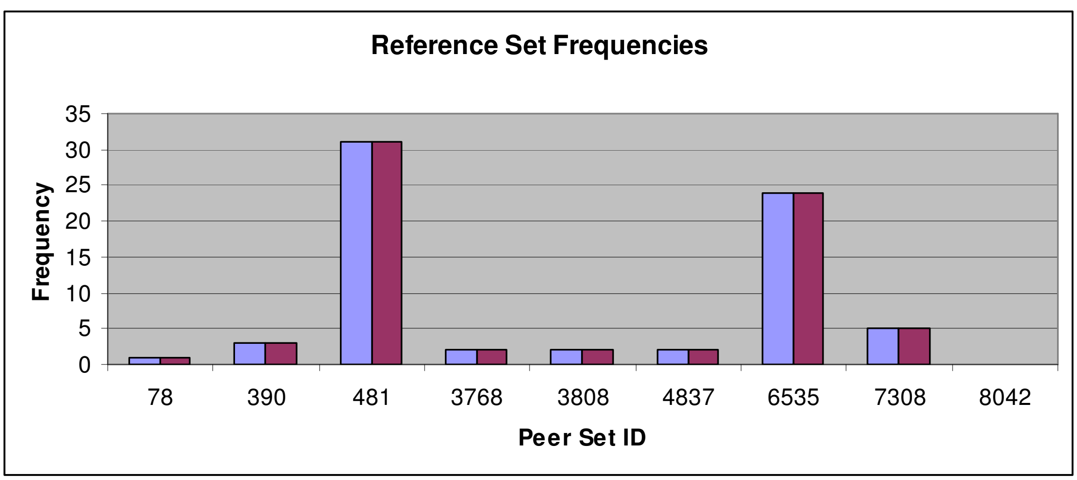

Figure 5.7. Reference set frequencies for the Mako CCR-O Model

Table 5.28 shows the efficient units and their usage frequencies as efficient peers. As it is given in Figure 5.7, there are only 9 efficient units in the Mako CCR-O Model.

However, note that contrary to the Otoyol Model, all the efficient units in Mako CCR-O Model are also efficient in the General Model. Figure 5.7 depicts the reference set frequencies.

5.4.2. Mako BCC-Output Oriented Model

As it is shown in Table 5.29, the average efficiency scores of the DMUs are greater than those of the Mako CCR-O Model. The number of efficient DMUs is also increases in comparison to Mako CCR-O Model, as it is expected.

Table 5.29. Basic results of the Mako BCC-O Model

Number of DMUs	44
Average of Scores	0,9738
SD	0,0338
Maximum	1
Minimum	0,8709
Number of Efficient DMUs	20
Number of Inefficient DMUs	24

Table 5.30 includes interesting results. Nine efficient units out of 20 are not used as efficient peers by any of the inefficient units.

Table 5.30. Efficient DMUs and reference set frequencies for the Mako BCC-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
31	0		4837	0
78	0		4874	0
390	2		5019	1
481	23		5031	0
2066	4		6535	19
2755	0		7308	2
3768	1		7319	0
3808	1		7603	17
3957	0		8042	0
4460	0		8207	3

The Figure 5.8 shows the frequencies given in Table 5.30 in a graphical form. It is shown that the most of the efficient units do not serve as a reference unit more than one time. In other words, there are some other efficient units that are more suitable models for inefficient units

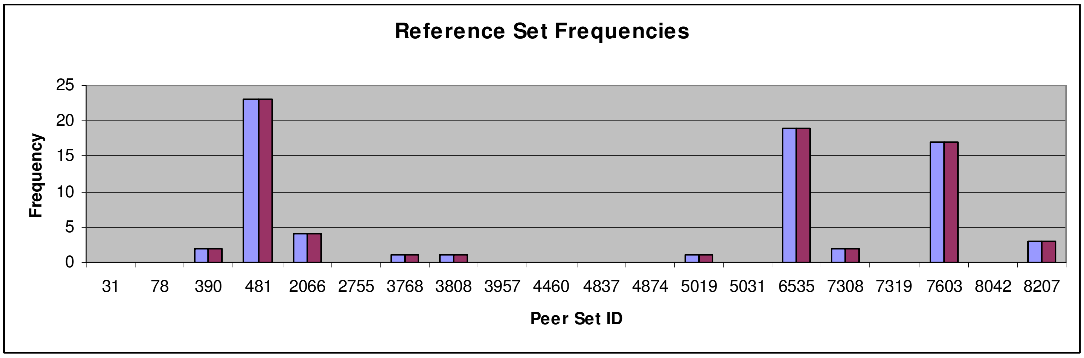

Figure 5.8. Reference set frequencies for the Mako BCC-O Model

Table 5.31. Summary of RTS for the Mako BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	10	19	29
Number of CRS	9	5	14
Number of DRS	1	0	1
Total	20	24	44

Table 5.31 illustrates the RTS characteristics of the Mako BCC-O Model. IRS is also a dominant attribute in this model.

5.5. Accessory Model

Dealers in this group are chosen out of 10624 DMUs. These dealers have “Accessory ratio” value over 50% and “Sales” amount more than 10000 YTL. 33 units satisfy these conditions. In this section, we analyze the Accessory CCR-O and Accessory BCC-O Models.

5.5.1. Accessory CCR-Output Oriented Model

Accessory units are quite different from the clusters we have discussed so far. Because all clusters that we have investigated are the subgroups of the General data set. However, all decision units of Accessory cluster are out of General data set. In other words, there is no common DMU in the Accessory and General Models.

Table 5.32 illustrates the basic statistics of the Accessory CCR-O Model.

Table 5.32. Statistics on input/output variables of the Accessory CCR-O Model

	Invoice term(days)	Number of Orders (times)	Cost (YTL)	Discount (YTL)	Sales (YTL)	Market Share (percent)
Max	61,00	252,00	796025,58	25541,79	859539,40	70,37
Min	2,00	3,00	9111,70	35,67	10884,92	1,86
Average	46,00	39,94	79760,75	6144,85	86406,77	13,34
SD	12,07	52,80	134321,48	6639,20	144979,30	12,98

The correlation degrees for the Accessory cluster are very low, which is preferable. Similar to the previous models, there is a high correlation between “Cost” and “Sales” variables. However, since one of them is input and the other is output variable, that fact does not cause any problem. Table 5.33 shows the all correlation levels for input/output variables of the Accessory cluster.

Table 5.33. Correlation between input/output variables of the Accessory CCR-O Model

	Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
Invoice term	1,0000	-0,7204	-0,0378	0,0418	-0,0365	-0,0821
Number of Orders	-0,7204	1,0000	0,2339	-0,0358	0,2364	0,2005
Cost	-0,0378	0,2339	1,0000	0,1042	1,0000	0,9038
Discount	0,0418	-0,0358	0,1042	1,0000	0,1048	0,2486
Sales	-0,0365	0,2364	1,0000	0,1048	1,0000	0,9037
Market Share	-0,0821	0,2005	0,9038	0,2486	0,9037	1,0000

Table 5.34. Basic results of the Accessory CCR-O Model

Number of DMUs	33
Average of Scores	0,9826
SD	0,0285
Maximum	1
Minimum	0,8618
Number of Efficient DMUs	15
Number of Inefficient DMUs	18

The basic information about the results of the Accessory CCR-O Model is illustrated in Table 5.34. The efficiency score average is the highest average out of 9 models that are presented so far. The minimum efficiency score is also so high. Furthermore, almost half of the units are efficient.

Table 5.35. Efficient DMUs and reference set freq. for the Accessory CCR-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
1182	2		5149	2
2042	4		6591	0
2186	5		6872	0
2718	7		7748	8
2764	15		7956	7
4023	0		8940	0
4396	0		9035	1
4864	0			

The reference set frequencies of the Accessory CCR-O Model are given in Table 5.35.

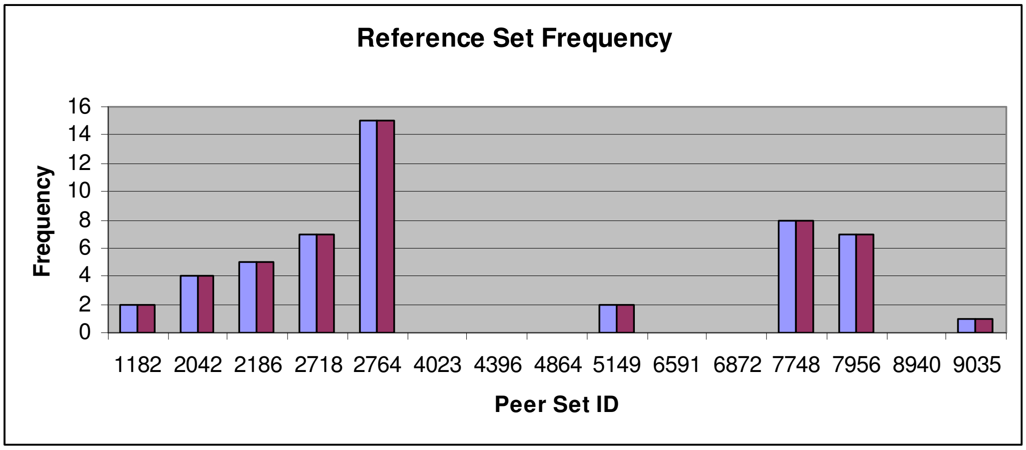

Figure 5.9. Reference set frequencies for the Accessory CCR-O Model

DMU 2764 and DMU 7748 are the best model DMUs for inefficient units. On the other hand, there are 6 DMUs that are never used as efficient referents. The reference set frequencies for the Accessory CCR-O Model are displayed in Figure 5.9

5.5.2. Accessory BCC-Output Oriented Model

Table 5.36 introduces the basic results of the Accessory BCC-O Model. Average efficiency score and the number of efficient DMUs are greater than those of the Accessory CCR-O Model.

Table 5.36. Basic results of the Accessory BCC-O Model

Number of DMUs	33
Average of Scores	0,9876
SD	0,0262
Maximum	1
Minimum	0,8625
Number of Efficient DMUs	20
Number of Inefficient DMUs	13

Table 5.37 gives information about the reference set frequencies of the Accessory BCC-O Model.

Table 5.37. Efficient DMUs and reference set freq. for the Accessory BCC-O Model

Peer set	Frequency to other DMUs		Peer set	Frequency to other DMUs
17	0		4864	0
1182	3		5149	2
2042	8		6591	0
2186	2		6872	0
2371	0		7597	7
2372	0		7607	0
2718	2		7748	3
2764	12		7956	6
4023	2		8940	0
4396	0		9035	2

In the light of Figure 5.10, four units differentiate from the others. These units can be described as the best models for inefficient units. DMU 2042, DMU 2764, DMU 7597, DMU 7956 are the most preferred efficient units by the inefficient units.

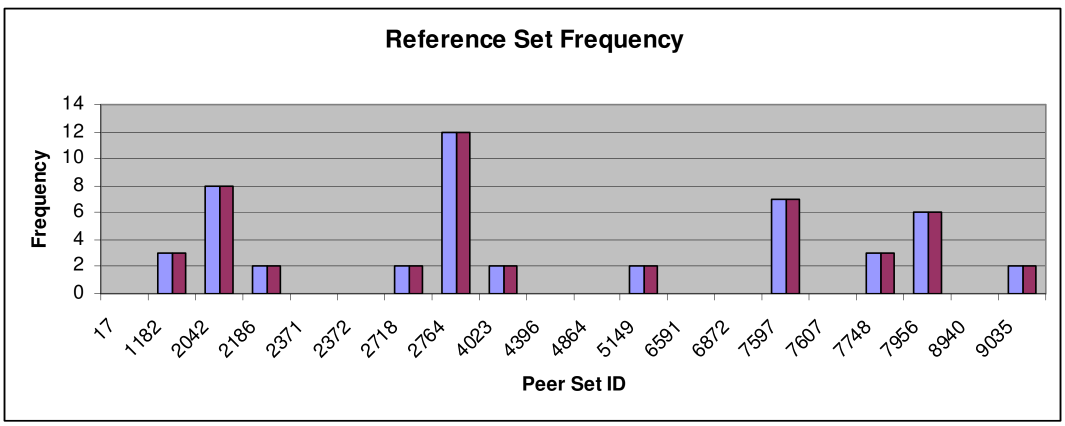

Figure 5.10. Reference set frequencies for the Accessory BCC-O Model

Table 5.38. Summary of RTS for the Accessory BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	4	7	11
Number of CRS	15	6	21
Number of DRS	1	0	1
Total	20	13	33

According to Table 5.38, CRS is the dominant characteristic of the Accessory BCC-O Model.

5.6. Discussion of the Results

In this section, the model results are discussed one by one. As it is described in the problem definition chapter, all models, except Accessory Model, are derived from the General Model's data set. For that reason, General Model's results are compared with each other as BCC-O and CCR-O models. After that, Tofas, Otoyol and Mako results are compared with the results of the General Model. Finally, the Accessory Models are interpreted independently, because the data set of that cluster is different from the others.

5.6.1. General Model

In this part, we focus on efficient units in both General Models. Then we compare the basic results of the General Models. RTS results are also covered.

Table 5.39. Efficient units' comparison for the General Models

Peer Set	CCR Frequency	BCC Frequency		Peer Set	CCR Frequency	BCC Frequency		Peer Set	CCR Frequency	BCC Frequency
38		31		1985		1		6307	0	0
78	1	1		2066		2		6390		51
210		3		2240		65		6519		0
374	9	4		3717		0		6535	94	349
375	24	14		3768	30	22		6543	0	1
377	30	19		3769		1		6582	430	185
390	49	37		3808	2	1		6596	0	0
392		3		3844		29		7089	4	120
405		6		3884		0		7259	264	413
416		4		3952		6		7308	12	5
418		13		3957		2		7319		0
435		158		4780		19		7516	623	477
481	183	83		4837	6	4		7654		16

Table 5.39. Efficient units' comparison for the General Models (Continued)

488	498	367		4846		93		7728	0	0
530		5		4933	0	0		7927	3	3
608	0	0		5031		2		8042	0	0
743		7		5094	19	12		8367	485	527
1139	20	19		5132		3		8784	4	11
1287		0		5183		6		8787	57	40
1349	3	1		5552		0		9029		97
1379		0		6288	88	212				
1380		0		6305	28	29				

Efficient units of both models are presented in Table 5.39. When we analyze the units, we observe that all CCR-efficient units achieve to be efficient in BCC-O model, as well. All BCC-efficient (only BCC-efficient) units display IRS or DRS characteristics. That may be rephrased as; General BCC-O Model adds new efficient units to the model from the IRS or DRS region of efficient frontier.

Table 5.40. Comparison of basic results for the General Models

	General CCR-O	General BCC-O
Number of DMUs	918	918
Average of Scores	0,8823	0,9045
SD	0,0495	0,0499
Maximum	1	1
Minimum	0,6357	0,6472
Number of Efficient DMUs	32	64
Number of Inefficient DMUs	886	854

According to Table 5.40, average efficiency score of General BCC-O Model exceeds that of General CCR-O Model. The number of efficient units increases in BCC-O model in comparison to CCR-O model.

Table 5.41. Summary of RTS for the General BCC-O

RTS	Efficient	Projected	Total
Number of IRS	28	307	335
Number of CRS	32	480	512
Number of DRS	4	67	71
Total	64	854	918

As it is shown in Table 5.41, the number of CRS and IRS units are close to each other. It seems viable to use BCC model in such a data set, because VRS characteristic is remarkable.

5.6.2. Tofas Model

5.6.2.1. Comparison of the General CCR-O and Tofas CCR-O Models. In Table 5.42 there are three types of units; 1) Efficient only in the Tofas CCR-O Model, 2) Efficient only in the General CCR-O, and 3) Efficient in both models. The units that are efficient only in the Tofas CCR-O may be considered as the units that cannot be efficient in the General data set. However, only General-efficient ones should be analyzed if they exist in the Tofas cluster as a decision unit or not. In fact, none of the only General-efficient units are included in Tofas cluster. That is, these units do not pass the "Tofas ratio" > 50% criterion and are not included in the performance assessment of the Tofas Models.

Table 5.42. Efficient units' comparison for the Tofas CCR-O Model

Peer Set	Tofas CCR-O	General CCR-O		Peer Set	Tofas CCR-O	General CCR-O
6	41			4933	2	0
78		1		5094		19
210	1			6288	134	88
374	4	9		6305	19	28
375	4	24		6307	0	0
377	11	30		6535		94
390		390		6543	14	0
417	11			6582		430
435	18			6596	0	0
481		183		7089	61	4
484	47			7259	261	264
486	4			7308		12
488	350	498		7476	1	
530	68			7516	401	623
608	2	0		7728	0	0
743	0			7927	20	3
1139	57	20		7929	41	
1189	228			8042		0
1349	2	3		8119	8	
1380	0			8218	15	
1985	1			8367	424	485
3768		30		8784	46	4
3808		2		8787	9	57
3836	37			8811	0	
4780	9			9029	12	
4837		6				

Table 5.43. Comparison of basic results for the Tofas CCR-O Model

	Tofas CCR-O	General CCR-O
Number of DMUs	670	918
Average of Scores	0,8958	0,8823
SD	0,0551	0,0495
Maximum	1	1
Minimum	0,6606	0,6357
Number of Efficient DMUs	40	32
Number of Inefficient DMUs	630	886

The average efficiency score of the Tofas CCR-O Model is higher in comparison to the General CCR-O Model. Generally, average efficiency scores increase as the number of DMUs in the model decrease. Table 5.43 supports this observation.

5.6.2.2. Comparison of the General BCC-O and Tofas BCC-O Models.

Table 5.44. Efficient units' comparison for the Tofas BCC-O Model

Peer Set	Tofas BCC-O	General BCC-O	Peer Set	Tofas BCC-O	General BCC-O	Peer Set	Tofas BCC-O	General BCC-O	Peer Set	Tofas BCC-O	General BCC-O
6	84		743	7	7	4780	19	19	7259	273	413
78		1	1139	34	19	4837		4	7308		5
38	25	31	1189	208		4846	78		7319		0
210	2	3	1287	7	0	4933	4	0	7469	15	
374	4	4	1349	1	1	5031		2	7476	1	
375	7	14	1379	2	0	5094		12	7516	356	477
377	11	19	1380	2	0	5132		3	7654	17	16
390		37	1985	1	1	5183		6	7728	0	0
392	3	3	2066		2	5552		0	7927	21	3
405	6	6	2240		65	6288	181	212	7929	16	
416	2	4	3717	0	0	6305	22	29	8042		0
417	8		3768		22	6307	0	0	8119	45	
418	6	13	3749	2		6390	31	51	8218	15	
435	120	158	3769	1	1	6393	0		8367	348	527
481		83	3808		1	6519		0	8784	71	11
484	23		3836	56		6535		349	8787	8	40
486	2		3844		29	6543	12	1	8811	1	
488	201	367	3884		0	6582		185	9029	113	97
530	64	5	3952		6	6596	0	0			
608	7	0	3957		2	7089	110	120			

In Table 5.44 efficient units and their reference set frequencies in the Tofas BCC-O and General BCC-O Models are illustrated. Note that a DMU that is efficient in General Model is also efficient in Tofas Model if it is present in the Tofas cluster.

Table 5.45 presents the comparison of the basic results of the Tofas and General BCC-O Models. Tofas BCC-O Model's results are better than those of the General BCC-O Model.

Table 5.45. Comparison of basic results for the Tofas BCC-O Model

	Tofas BCC-O	General BCC-O
Number of DMUs	670	918
Average of Scores	0,9135	0,9045
SD	0,0517	0,0499
Maximum	1	1
Minimum	0,6697	0,6472
Number of Efficient DMUs	55	64
Number of Inefficient DMUs	615	854

Tofas BCC-O Model differs from the other models in RTS perspective, because CRS characteristic is obviously dominant in this data set. Table 5.46 shows the RTS results of the Tofas BCC-O Model.

Table 5.46. Summary of RTS for the Tofas BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	12	116	128
Number of CRS	40	490	530
Number of DRS	3	9	12
Total	55	615	670

5.6.3. Otoyol Model

5.6.3.1. Comparison of the General CCR-O and Otoyol CCR-O Models. According to Table 5.47, there is not any unit that is efficient both in the Otoyol CCR-O and General

CCR-O Models. Namely, all efficient units in the Otoyol CCR-O Model actually are inefficient in the General CCR-O Model. We also observe that none of the only General-efficient units is included in the Otoyol data set.

Table 5.47. Efficient units' comparison for the Otoyol CCR-O Model

Peer Set	Otoyol CCR-O	General CCR-O		Peer Set	Otoyol CCR-O	General CCR-O
78		1		6305		28
97	3			6307		0
374		9		6535		94
375		24		6543		0
377		30		6582		430
390		49		6585	22	
432	0			6596		0
481		183		7089		4
488		498		7215	0	
608		0		7259		264
1139		20		7308		12
1349		3		7360	41	
2132	5			7452	3	
2200	5			7475	2	
2240	143			7516		623
2261	1			7728		0
3743	74			7927		3
3768		30		7960	10	
3808		2		8042		0
4007	3			8053	4	
4472	1			8367		485
4837		6		8767	0	
4847	9			8784		4
4933		0		8787		57
5094		19		9037	14	
6288		88				

Furthermore, we study on the only Otoyol-efficient units. For example; DMU 4472 has taken efficiency score of (0,8063) in the General CCR-O Model which makes it rank 897th out of 918 DMUs. Also DMU 7475 is ranked as 841st and DMU 4007 is ranked as 685th out of 918 DMUs. It is interesting that these dealers are being evaluated as efficient units in the Otoyol cluster.

Results that are introduced in Table 5.48 become more comprehensible after the explanations above. It is clear that, the data set of the Otoyol cluster is more suitable for getting high efficiency scores, because there are weakly performing DMUs in the cluster in comparison to the General cluster.

Table 5.48. Comparison of basic results for the Otoyol CCR-O Model

	Otoyol CCR-O	General CCR-O
Number of DMUs	167	918
Average of Scores	0,9365	0,8823
SD	0,0402	0,0495
Maximum	1	1
Minimum	0,7701	0,6357
Number of Efficient DMUs	19	32
Number of Inefficient DMUs	148	886

5.6.3.2. Comparison of the General BCC-O and Otoyol BCC-O Models.

Table 5.49. Efficient units' comparison for the Otoyol BCC-O Model

Peer Set	Otoyol BCC-O	General BCC-O	Peer Set	Otoyol BCC-O	General BCC-O	Peer Set	Otoyol BCC-O	General BCC-O	Peer Set	Otoyol BCC-O	General BCC-O
38		31	1380		0	4846		93	7259		413
78		1	1985		1	4847	9		7308		5
97	6		2066		2	4933		0	7319		0
210		3	2132	8		5018	44		7360	42	
369	0		2200	3		5031		2	7452	3	
374		4	2226	25		5094		12	7475	3	
375		14	2240	114	65	5132		3	7516		477
377		19	2261	5		5183		6	7654		16
390		37	2374	0		5441	25		7701	18	
392		3	2537	1		5552	11	0	7728		0
405		6	3689	1		5698	1		7927		3
416		4	3717		0	6288		212	7960	13	
418		13	3743	36		6305		29	8042		0
432	1		3768		22	6307		0	8053	7	
435		158	3769		1	6390		51	8136	37	
481		83	3808		1	6429	3		8367		527
488		367	3844		29	6519		0	8767	0	
530		5	3884		0	6535		349	8784		11
608		0	3952		6	6543		1	8787		40
743		7	3957		2	6582		185	9029		97
1139		19	4007	0		6585	32		9037	16	
1287		0	4472	0		6596		0			
1349		1	4780		19	7089		120			
1379		0	4837		4	7215	0				

Table 5.49 can be summarized like the previous ones. General-efficient units are efficient only in the General Model. We determine that none of the only General-efficient units is included in the Otoyol data set. The only Otoyol-efficient units are inefficient in the General BCC-O Model.

Average efficiency score in Otoyol BCC-O Model is fairly higher than that of the General BCC-O Model. Minimum efficiency score of the Otoyol BCC-O Model, on the other hand, is much higher than that of the General BCC-O Model. Table 5.50 shows the basic results for the two models.

Table 5.50. Comparison of basic results for the Otoyol BCC-O Model

	Otoyol BCC-O	General BCC-O
Number of DMUs	167	918
Average of Scores	0,9542	0,9045
SD	0,0355	0,0499
Maximum	1	1
Minimum	0,7721	0,6472
Number of Efficient DMUs	31	64
Number of Inefficient DMUs	136	854

Otoyol data set shows IRS characteristic as it is shown in Table 5.51. Note that there are not any units that show DRS characteristic. That may be interpreted as; this data set really displays the retail store behavior that has been indicated in the Chapter 3. (Barros et. al, 2003) presents similar results in the study.

Table 5.51. Summary of RTS for the Otoyol BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	12	91	103
Number of CRS	19	45	64
Number of DRS	0	0	0
Total	31	136	167

5.6.4. Mako Model

5.6.4.1. Comparison of the General CCR-O and Mako CCR-O Models. All efficient units of the Mako CCR-O Model are also efficient in the General CCR-O Model. That means Mako CCR-O Model does not have any specific efficient unit. Table 5.52 shows the results.

Table 5.52. Efficient units' comparison for the Mako CCR-O Model

Peer Set	Mako CCR-O	General CCR-O		Peer Set	Mako CCR-O	General CCR-O
78	1	1		6305		28
374		9		6307		0
375		24		6535	24	94
377		30		6543		0
390	3	49		6582		430
481	31	183		6596		0
488		498		7089		4
608		0		7259		264
1139		20		7308	5	12
1349		3		7516		623
3768	2	30		7728		0
3808	2	2		7927		3
4837	2	6		8042	0	0
4933		0		8367		485
5094		19		8784		4
6288		88		8787		57

Table 5.53. Comparison of basic results for the Mako CCR-O Model

	Mako CCR-O	General CCR-O
Number of DMUs	44	918
Average of Scores	0,9598	0,8823
SD	0,0372	0,0495
Maximum	1	1
Minimum	0,8704	0,6357
Number of Efficient DMUs	9	32
Number of Inefficient DMUs	35	886

Table 5.53 introduces the basic results of the Mako CCR-O and General CCR-O Models. The average efficiency score and the number of efficient units in Mako CCR-O Model are greater than that of the General CCR-O Model, as it is expected.

5.6.4.2. Comparison of the General BCC-O and Mako BCC-O Models.

Table 5.54. Efficient units' comparison for the Mako BCC-O Model

Peer Set	Mako BCC-O	General BCC-O		Peer Set	Mako BCC-O	General BCC-O		Peer Set	Mako BCC-O	General BCC-O		Peer Set	Mako BCC-O	General BCC-O
31	0			1139		19		4780		19		6582		185
38		31		1287		0		4837	0	4		6596		0
78	0	1		1349		1		4846		93		7089		120
210		3		1379		0		4874	0			7259		413
374		4		1380		0		4933		0		7308	2	5
375		14		1985		1		5019	1			7319	0	0
377		19		2066	4	2		5031	0	2		7516		477
390	2	37		2240		65		5094		12		7603	17	
392		3		2755	0			5132		3		7654		16
405		6		3717		0		5183		6		7728		0
416		4		3768	1	22		5552		0		7927		3
418		13		3769		1		6288		212		8042	0	0
435		158		3808	1	1		6305		29		8207	3	
481	23	83		3844		29		6307		0		8367		527
488		367		3884		0		6390		51		8784		11
530		5		3952		6		6519		0		8787		40
608		0		3957	0	2		6535	19	349		9029		97
743		7		4460	0			6543		1				

Table 5.54 shows the efficient DMUs and reference set frequencies for the Mako BCC-O and General BCC-O Models.

According to Table 5.55 the average efficiency score of the Mako BCC-O Model is really high. The effect of being a small data set and the effect of having a VRS frontier create these results for the model. As a result, efficiency score average of 0,9738 is obtained. Another point is that the almost 50 % of DMUs are efficient in this model. That may be interpreted as; all units have performances close to each other.

Table 5.55. Comparison of basic results for the Mako BCC-O Model

	Mako BCC-O	General BCC-O
Number of DMUs	44	918
Average of Scores	0,9738	0,9045
SD	0,0338	0,0499
Maximum	1	1
Minimum	0,8709	0,6472
Number of Efficient DMUs	20	64
Number of Inefficient DMUs	24	854

Table 5.56 describes that the Mako BCC-O Model shows IRS characteristic like the Otoyol BCC-O Model.

Table 5.56. Summary of RTS for the Mako BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	10	19	29
Number of CRS	9	5	14
Number of DRS	1	0	1
Total	20	24	44

5.6.5. Accessory Model

Accessory cluster is derived in a different way from the other clusters as it is illustrated in Figure 4.3. Accessory data set has 33 dealers; there is no common dealer with the General data set. The CRS and IRS are the two characteristics of the Accessory BCC-O Model.

In the Accessory cluster, models within the cluster are compared, because this data set is obtained in a different way from the General data set. It is shown in Table 5.57 that there are five efficient units which are efficient in the Accessory BCC-O Model but not in Accessory CCR-O Model.

Table 5.57. Efficient units' comparison for the Accessory Models

Peer Set	CCR Frequency	BCC Frequency
17		0
1182	2	3
2042	4	8
2186	5	2
2371		0
2372		0
2718	7	2
2764	15	12
4023	0	2
4396	0	0
4864	0	0
5149	2	2
6591	0	0
6872	0	0
7597		7
7607		0
7748	8	3
7956	7	6
8940	0	0
9035	1	2

Table 5.58. Comparison of basic results for the Accessory Models

	Accessory CCR-O	Accessory BCC-O
Number of DMUs	33	33
Average of Scores	0,9826	0,9876
SD	0,0285	0,0262
Maximum	1	1
Minimum	0,8618	0,8625
Number of Efficient DMUs	15	20
Number of Inefficient DMUs	18	13

Both Accessory Models in Table 5.58 have high efficiency score averages and low standard deviations. According to Table 5.59, the Accessory BCC-O Model shows CRS and IRS characteristics.

Table 5.59. Summary of RTS for the Accessory BCC-O Model

RTS	Efficient	Projected	Total
Number of IRS	4	7	11
Number of CRS	15	6	21
Number of DRS	1	0	1
Total	20	13	33

5.7. Sensitivity Analysis for the Sales Threshold Levels

Sensitivity analysis is performed for examining the effect of the threshold level of the sales volume on the efficiency scores. For that reason, it is decided to change the threshold level from 10000YTL to 5000YTL (The value 5000YTL is not a specifically chosen point, it is only a reasonable value that is decided for the execution).

The average efficiency results and the number of efficient DMUs for the 20 models are given in the Table 5.60. Naturally, the number of dealers in the clusters increases as the threshold level decreases. For example, General cluster is composed of 1228 dealers under 5000YTL criterion while it has 918 dealers under 10000 YTL criterion. Similar results are valid for the other clusters. Number of efficient units increases or remains same, as the number of dealers increases in the cluster.

As the cluster size increases, the average efficiency scores generally decrease. Accordingly, average efficiency scores in 5000 YTL clusters are smaller than those of the 10000YTL clusters. Mako CCR-O Model is the only exception for the above expression, efficiency score average of the Mako CCR-O (5000 YTL) is higher than that of Mako CCR-O (10000 YTL).

As a result, average efficiency scores are affected by the change of threshold level. However, the efficiency changes actualize in a reasonable range.

Table 5.60. Efficiency results for the different threshold levels

Model	Number of DMU	Number of Efficient Units	Average Efficiency Score
General CCR-O (10000YTL)	918	32	0,8823
General CCR-O (5000YTL)	1228	37	0.8635
General BCC-O (10000YTL)	918	64	0,9045
General BCC-O (5000YTL)	1228	67	0.8824
Tofas CCR-O (10000YTL)	670	40	0,8958
Tofas CCR-O (5000YTL)	883	40	0.8709
Tofas BCC-O (10000YTL)	670	55	0,9135
Tofas BCC-O (5000YTL)	883	66	0.8910
Otoyol CCR-O (10000YTL)	167	19	0,9365
Otoyol CCR-O (5000YTL)	214	24	0.9352
Otoyol BCC-O (10000YTL)	167	31	0,9542
Otoyol BCC-O (5000YTL)	214	37	0.9450
Mako CCR-O (10000YTL)	44	9	0,9598
Mako CCR-O (5000YTL)	64	14	0.9623
Mako BCC-O (10000YTL)	44	20	0,9738
Mako BCC-O (5000YTL)	64	24	0.9693
Accessory CCR-O (10000YTL)	33	15	0,9826
Accessory CCR-O (5000YTL)	58	22	0.9762
Accessory BCC-O (10000YTL)	33	20	0,9876
Accessory BCC-O (5000YTL)	58	31	0.9799

5.8. Sources of Inefficiency for the Models

In this section, it is aimed to present an overall picture regarding the inefficiency sources of the dealers. Table 5.61 depicts the number of slack values in each model. For example, in General CCR-O (10000 YTL) there are 918 dealers, 393 of the dealers have slack values for “Invoice term”, 132 dealers have slack values for “Number of orders”, one dealer has a slack value for “Cost”, and 621 dealers have slack values for “Discount” variable. Accordingly, slack values for the output variables are introduced. Number of slack values for each model is given, as well.

The number of total slack values reveals the source of inefficiency for the dealers. “Invoice term” and “Discount” are the two input variables that have high slack value frequencies. These two variables are under the control of the distributor. It can be concluded that the distributor should decrease the “Invoice term” and the “Discount” rate for the related dealers, to make them more efficient. “Number of orders” is also another source of inefficiency, but this input variable is not as dominant as the "Invoice term" and "Discount" variables. *Cost* (cost of goods sold) seems not to be a source of inefficiency.

Table 5.61. Number of positive slack values

Model	Number of positive slack values					
	Invoice Term	Number of Orders	Cost	Discount	Sales	Market Share
General CCR-O (10000YTL)	393	132	1	621	0	280
General CCR-O (5000YTL)	290	362	1	799	0	417
General BCC-O (10000YTL)	554	155	0	521	21	285
General BCC-O (5000YTL)	810	296	1	728	10	367
Tofas CCR-O (10000YTL)	221	111	0	238	2	188
Tofas CCR-O (5000YTL)	188	288	0	526	2	284
Tofas BCC-O (10000YTL)	406	136	0	245	12	225
Tofas BCC-O (5000YTL)	558	234	0	400	9	282
Otoyol CCR-O (10000YTL)	109	112	0	52	1	116
Otoyol CCR-O (5000YTL)	131	127	1	61	0	146
Otoyol BCC-O (10000YTL)	111	85	0	56	0	96
Otoyol BCC-O (5000YTL)	150	121	1	62	0	128
Mako CCR-O (10000YTL)	13	29	0	32	0	31
Mako CCR-O (5000YTL)	36	0	44	1	0	45
Mako BCC-O (10000YTL)	10	19	0	20	0	22
Mako BCC-O (5000YTL)	26	0	35	0	0	36
Accessory CCR-O (10000YTL)	9	3	1	15	0	11
Accessory CCR-O (5000YTL)	4	11	1	27	1	20
Accessory BCC-O (10000YTL)	9	1	0	10	0	9
Accessory BCC-O (5000YTL)	13	6	0	22	0	14
Total	**4041**	**2228**	**86**	**4436**	**58**	**3002**

As for the output variables, there is a crucial point to be noted. The slack values that are shown in Table 5.61 are not the only output improvements for inefficient units. Please note that, a radial improvement (increase) is available in all output variables regarding inefficient units. Here, we present the further improvement possibilities for output variables. For that reason, it is not possible to say that the *"Sales"* volume is not a source of inefficiency. However, it is possible to say that the Market Share is a more important source of inefficiency, due to its high slack value frequency, as it is shown in Table 5.61.

6. CONCLUSION

Competitive economic conditions force the managers to improve the performance of their organizations. Improving performance requires evaluating operations or processes, related to production, providing services, and marketing, systematically. Benchmarking and performance evaluation are widely used to improve performance and to increase productivity all over the world. Although performance issues have not been on the agenda of the Turkish business world until recently, changes in the economic environment of Turkey in the last a few years pushed Turkish companies to revise their way of doing business and they began to search for new ways of improving their efficiency.

This thesis analyses the comparative dealer efficiency of a spare part distributor, employing data envelopment analysis (DEA). At the beginning of the study, we have a data set of dealers and a set of potential input-output variables given in the data set.

First, some data clusters are extracted from the raw data for the analysis. Obtained data clusters are General, Tofas, Otoyol, Mako, and Accessory. After that, an input-output model is formed. Two different models, CCR-Output Oriented and BCC-Output Oriented, are applied to each data cluster. The results of the models are compared within the cluster and with the other clusters.

General Model is the largest data set in our study. There are 918 dealers in this model. Tofas, Otoyol and Mako clusters are derived from the General Model's data set. As for the results, 32 dealers are efficient according to the General CCR-O Model and 64 dealers are efficient according to the General BCC-O Model. BCC-efficiency generally exceeds the CCR-efficiency (Cooper et al., 2000). Accordingly, average efficiency scores of the dealers are 0,8823 and 0,9045 in CCR-O and BCC-O models, respectively.

For further discussion about the General Model, all CCR-O efficient units are also efficient in the BCC-O model which shows the results are in accordance with the theory. DMU 481, DMU 498, DMU 6288, DMU 6582, DMU 7259, DMU 7516, and DMU 8367 are the dealers which have high reference set frequencies in both CCR-O and BCC-O models. This can be interpreted as; these dealers are good examples in terms of input-output mix for inefficient units. In contrast, efficient units, which appear few times in reference sets, are likely to have unusual combination of inputs and outputs. Those types of efficient units are not suitable for offering best operating practices for inefficient units to emulate. DMU 608, DMU 4933, DMU 6307, DMU 7728, and DMU 8042 are efficient units, but they have zero reference set frequencies in both CCR-O and BCC-O models. In other words, there is not any inefficient unit that emulates these efficient dealers.

Table B.1 shows the data of these five DMUs. Note that DMU 608 has a symbolic discount amount of 10 YTL which is the minimum value in the cluster. That kind of discount amount makes the DMU's input-output mix unusual.

Table 6.1. Outliers of the General Model

DMU	Location	(I)Invoice term	(I)Number of Orders	(I)Cost	(I)Discount	(O)Sales	(O)Market Share
608	11	42	37	15.668	10	15.693	0,8140
4933	4	59	2274	1.129.059	228.086	1.223.753	20,0607
6307	5	14	2793	547.439	157.872	588.507	7,5872
7728	7	27	3	37.600	8.252	39.884	0,5054
8042	8	71	75	138.439	65	157.448	1,6314

DMU 4933 is a real outlier, because the dealer has the maximum "Sales" amount of the cluster and it has a really high "Market share" of 20 %. Also, it has a "Number of orders" value of 2274, which is more than ten times the average value. DMU 6307 is also an outlier with the high values of "Number of orders", "Sales" and "Market share". DMU 7728 has a "Number of orders" value of 3, which is the minimum value in the cluster and that makes the input-output mix of the DMU 7728 an inappropriate example for inefficient units. DMU 8042 has a symbolic discount amount of 65YTL and possibly this is the reason of having zero reference set frequency. Similar cases are available in the other models.

In the light of the comparisons, it can be concluded that the efficiency results of small data sets may be biased. The Otoyol cluster is a good example for such a case. None of the efficient units of the Otoyol CCR-O Model is efficient in the General CRR-O Model.

RTS character is another issue of the study. The retail store studies generally use the VRS models and IRS is the characteristic of several studies such as; Keh and Chu (2002), Barros and Alves (2003). In our study IRS and the CRS attributes are balanced. In Tofas and Accessory clusters the CRS is dominant, but in Mako cluster IRS is dominant. Additionally, it is common for all models that DRS is a very unusual property.

As aforementioned, if any General-efficient unit is included in a cluster, it is also efficient in that cluster. In other words, there is no unit that is inefficient in any model, while it is efficient in the General Model. This also proves that being efficient in a large data set is harder than being efficient in a small data set.

Tofas BCC model's VRS characteristic is an interesting result of the study, it is clear that CRS is dominant in that cluster. In other words, the scale sizes of the Tofas dealers do not affect the dealers' productivity as much as other clusters. Tofas is a common and well-known brand in Turkey, and the dealers probably do not need any specialized service quality for selling the relatively inexpensive spare parts. For that reason, it is reasonable that Tofas dealers display CRS characteristics.

Companies that have many dealers or retailers can use DEA as a guideline for improving their overall efficiency, but there are some key points that should be taken into account.

First of all, input or output oriented models should be chosen considering the control capability of units on input-output variables. It is obvious that, the model should be assigned on that basis.

Secondly, clustering is the right method to use when there is not any homogeneity within the DMUs. However, one must note that each cluster should be evaluated individually and strategic decisions should be given according to the conditions within the clusters.

Another point related to our case is that the comparison must be done in a strategic way. For example, if strategically, Otoyol cluster is important for the distributor, the

DMUs in this cluster should be the concern. If it is not a must to sell Otoyol spare parts, it can be concluded that there is no need to work with such a group of dealers none of which is efficient in the General Model.

RTS selection is also a key issue, in cases like dealer network or retailer chain, BCC is most suitable efficient frontier type. However CCR should be used to make comparison and more sensitive judgments about the units.

As an overall conclusion, in a comparative efficiency study, the data set and the DEA model selections are crucial points for a proper performance assessment study. Data set should be composed of homogeneous decision making units. Choosing the right RTS model is also important. As it is derived from the results, efficiency scores can change substantially in CCR and BCC models. Therefore, input-output model selection is one of the main decision points. Finally, it can be concluded that there is no single and perfect method for the performance evaluation process. All the evaluations should be based on the strategic perspectives and the targets of the companies to survive and to remain competitive.

APPENDIX A: SAMPLE RESULTS

Some partial examples from the results of DEA-Solver software are given in this part. In Table A.1 first column shows the DMU IDs while the second column gives the efficiency scores of the DMUs. The following four columns inform us about the input excesses, t^{-*} values, for each DMU. The last two columns present the output shortages, t^{+*} values, for the same DMUs.

Table A.1. Slack value examples of the General CCR-O Model

DMU	Score	Excess	Excess	Excess	Excess	Shortage	Shortage
		Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
		S-(1)	S-(2)	S-(3)	S-(4)	S+(1)	S+(2)
1	0,8831	0	0	0	607,49	0	0
2	0,8904	0	0	0	761,50	0	0
5	0,9284	0	41	0	0,00	0	0
6	0,9905	0	0	0	7260,00	0	0
8	0,9803	0	0	0	0,00	0	0
29	0,9278	0	1	0	0,00	0	0
74	0,8795	25	0	0	0,00	0	0
77	0,8805	0	0	0	0,00	0	0
78	1,0000	0	0	0	0,00	0	0
82	0,9089	0	0	0	1271,71	0	0
83	0,8775	25	20	0	0,00	0	0
84	0,9492	0	0	0	31,97	0	0
86	0,9358	0	0	0	9025,70	0	0
4095	0,8372	14	0	0	2046,40	0	0,0679
4116	0,9001	17	0	0	8581,14	0	0,0705
4187	0,8405	4	0	0	1164,55	0	0,0586
4302	0,8570	0	124	0	4325,35	0	0,1854
4328	0,7913	36	0	0	0,00	0	0,0274
4331	0,9301	0	0	0	17980,22	0	0,9896
4350	0,8750	23	0	0	380,89	0	0,0515

For example, DMU 5 has an efficiency score of (0,9284) which means that the output values of DMU 5 can be augmented by a multiplier equals to $(0{,}9284^{-1})$ radially. DMU 5 does not have any input excess for "Invoice term", but it has an input excess value of (41) for the “Number of orders”. The input excesses and output shortfalls for remaining variables are zero.

DMU 4302 has an efficiency score of (0,8570) and has both input excesses and output shortfalls. From the Table A.1 we can conclude that, this DMU 4302 must decrease its “Number of orders” by 124 days. Furthermore, the value of discount applied to the relevant DMU must be decreased by 4325,35 YTL to get an efficient DMU. Also, the “Market share” of the DMU should be raised by (0,1854) for reaching the efficient frontier. However; if we observe an efficient DMU such as DMU 78, we cannot see any input excesses or output shortfalls. That fact is the requirement of the CCR-efficiency definition.

Table A.2. Weighted data for the input/output variables of the General CCR-O Model

DMU	Score		VX(1)	VX(2)	VX(3)	VX(4)		UY(1)	UY(2)
1	0,8832		0,0840	0,0128	1,0355	0		0,9716	0,0284
2	0,8904		0,0888	0,0121	1,0221	0		0,9716	0,0284
5	0,9284		0,0758	0	0,9809	0,0204		0,9244	0,0756
6	0,9905		0,0298	0,0173	0,9624	0		0,9173	0,0827
8	0,9803		0,0341	0,0047	0,9713	0,0100		0,9249	0,0751
9	0,9627		0,0493	0,0060	0,9728	0,0107		0,9249	0,0751
12	0,8858		0,0852	0,0120	1,0316	0		0,9716	0,0284
16	0,8609		0	0	1,1174	0,0442		0,8865	0,1135
20	0,8757		0,0378	0,0260	1,0546	0,0235		0,9451	0,0549
22	0,8750		0	0,0380	1,1049	0		0,9544	0,0456
29	0,9278		0,0735	0	0,9884	0,0159		0,9591	0,0409
31	0,8435		0	0,0192	1,1481	0,0183		0,9454	0,0546
38	0,8820		0	0	1,1338	0		0,9317	0,0683
39	0,8871		0	0,0475	1,0526	0,0272		0,9454	0,0546
40	0,8525		0	0,0627	1,0867	0,0237		0,9454	0,0546
43	0,8666		0	0,0477	1,0834	0,0228		0,9454	0,0546
49	0,8551		0	0	1,1694	0		0,9317	0,0683
58	0,8871		0,0361	0,0195	1,0327	0,0389		0,9451	0,0549
61	0,8703		0	0,0418	1,1073	0		0,9544	0,0456
62	0,9026		0,0230	0,0282	1,0237	0,0330		0,9451	0,0549

The weighted data values are given in Table A.2. These values are calculated by multiplying weights obtained from LP models and the given input/output values.

Note that, the efficiency score of each DMU equals to the ratio between total weighted output and total weighted input.

Table A.3 is a sample of input/output weights of the first twenty DMUs out of 918 DMUs in the General cluster. All these weights which maximize the unit's efficiency score while do not permit any other DMU's efficiency score exceed one are unique for each DMU.

Table A.3. Weights for the input /output variables of the General CCR-O Model

DMU	Score		V(1)	V(2)	V(3)	V(4)		U(1)	U(2)
1	0,8832		0,001830	0,000089	0,000038	0		0,000032	0,0290
2	0,8904		0,001930	0,000094	0,000040	0		0,000033	0,0306
5	0,9284		0,001580	0	0,000017	0,000002		0,000015	0,0372
6	0,9905		0,000663	0,000087	0,000008	0		0,000007	0,0193
8	0,9803		0,000757	0,000017	0,000008	0,000000		0,000007	0,0176
9	0,9627		0,001120	0,000026	0,000012	0,000001		0,000010	0,0260
12	0,8858		0,001890	0,000092	0,000039	0		0,000033	0,0301
16	0,8609		0	0	0,000099	0,000028		0,000069	0,2780
20	0,8757		0,000651	0,000509	0,000048	0,000011		0,000040	0,0724
22	0,8750		0	0,000521	0,000087	0		0,000065	0,0984
29	0,9278		0,001600	0	0,000027	0,000002		0,000023	0,0307
31	0,8435		0	0,000872	0,000095	0,000012		0,000074	0,1338
38	0,8820		0	0	0,000130	0		0,000092	0,2117
39	0,8871		0	0,000511	0,000056	0,000007		0,000043	0,0785
40	0,8525		0	0,001030	0,000112	0,000014		0,000087	0,1577
43	0,8666		0	0,000472	0,000051	0,000007		0,000040	0,0725
49	0,8551		0	0	0,000099	0		0,000070	0,1604
58	0,8871		0,000555	0,000434	0,000041	0,000009		0,000034	0,0617
61	0,8703		0	0,000504	0,000084	0		0,000063	0,0952
62	0,9026		0,000384	0,000300	0,000029	0,000006		0,000023	0,0427

Table A.4 is a part of the efficiency score sheet from the General CCR-O Model results. From the table below we can learn about the reference set of each DMU and efficiency ranks of all DMUs out of 918 units. For example, DMU 20 has an efficiency score of (0,8757) and ranks 453rd . The reference set of the DMU 20 is composed of DMU 481, DMU 488, DMU 6582, DMU 7516, and DMU 8367.

Table A.4. Efficiency score data for the General CCR-O Model

DMU	Score	Rank	Reference set (lambda)									
1	0,8831	395	488	0,4784	6582	0,1895	7259	0,0239	7516	0,2649		
2	0,8904	348	488	0,4486	6582	0,2199	7259	0,0043	7516	0,3042		
5	0,9284	161	377	0,3749	488	0,2635	6582	0,4991	7259	0,0947		
6	0,9905	38	375	0,0361	488	0,0865	6582	1,3085	8787	0,2037		
8	0,9803	50	377	0,0586	488	0,0991	6582	1,0601	7259	0,0521	8787	0,2224
9	0,9627	69	377	0,0264	488	0,3404	6582	0,6318	7259	0,0766	8787	0,1202
12	0,8858	379	488	0,4598	6582	0,2218	7259	0,0123	7516	0,2639		
16	0,8609	565	481	0,0118	488	0,1966	7516	0,3119				
20	0,8757	453	481	0,4123	488	0,0931	6582	0,0907	7516	0,1410	8367	0,2531
22	0,8750	461	488	0,2341	7516	0,2169	8367	0,1174				
29	0,9278	165	488	0,6191	6582	0,1399	7259	0,0976	7516	0,0592		
31	0,8435	719	481	0,2658	488	0,0309	7516	0,0611	8367	0,2293		
38	0,8820	408	488	0,1582	7516	0,2408						
39	0,8871	370	481	0,0183	488	0,3368	7516	0,2416	8367	0,2448		
40	0,8525	641	481	0,0099	488	0,1712	7516	0,2002	8367	0,0598		
43	0,8666	523	481	0,1397	488	0,2871	7516	0,3112	8367	0,2326		
49	0,8551	623	488	0,2153	7516	0,3277						
58	0,8871	369	481	0,3599	488	0,2024	6582	0,0137	7516	0,0332	8367	0,5396
61	0,8703	496	488	0,2417	7516	0,2670	8367	0,0849				
62	0,9026	282	481	0,1374	488	0,5259	6582	0,4208	7516	0,0202	8367	0,2182

Table A.5. Slack value examples of the General BCC-O Model

DMU	Score	Excess	Excess	Excess	Excess	Shortage	Shortage
		Invoice term	Number of Orders	Cost	Discount	Sales	Market Share
		S-(1)	S-(2)	S-(3)	S-(4)	S+(1)	S+(2)
1	0,8842	0	0	0	401,42	0	0
2	0,8910	0	0	0	651,44	0	0
5	0,9306	0	37	0	0	0	0
6	0,9962	0	0	0	10593,74	0	0
8	0,9842	0	0	0	1378,12	0	0
9	0,9649	0	0	0	523,07	0	0
12	0,8869	0	2	0	0	0	0
16	0,9200	0	34	0	330,52	0	0
20	0,8761	0	0	0	0	0	0
22	0,9113	0	0	0	2155,60	0	0
413	0,9735	0	22	0	0	966,62	0
416	1	0	0	0	0	0	0
417	0,9579	0	0	0	0	588,06	0
418	1	0	0	0	0	0	0
420	0,9259	0	18	0	0	193,34	0
421	0,9681	0	0	0	871,35	672,00	0
432	0,9108	48	0	0	2813,64	0	0
435	1	0	0	0	0	0	0
456	0,9952	4	33	0	1008,94	0	0
459	0,9467	0	0	0	3225,44	558,44	0

The DMUs in Table A.5 are chosen according to having slack values in different input and output variables. For that reason the units are not same with the units in the Table A.1. But it is possible to say that, an increase in efficiency scores can be observed in the General BCC-O Model in comparison to the General CCR-O Model. Accordingly, the slack values of General BCC-O Model are smaller than those of the General CCR-O Model.

Weighted data of the first twenty units are presented in Table A.6.

Table A.6. Weighted data for the input/output variables of the General BCC-O Model

DMU	Score	VX(0)	VX(1)	VX(2)	VX(3)	VX(4)		UY(1)	UY(2)
1	0,8842	-0,0303	0,1153	0,0006	1,0454	0		0,9639	0,0361
2	0,8910	-0,0320	0,1219	0,0006	1,0319	0		0,9639	0,0361
5	0,9306	0,0108	0,0673	0	0,9671	0,0294		0,9247	0,0753
6	0,9962	0,0093	0,0204	0,0193	0,9549	0		0,9339	0,0661
8	0,9842	0,0091	0,0226	0,0159	0,9685	0		0,9432	0,0568
9	0,9649	0,0134	0,0327	0,0203	0,9700	0		0,9432	0,0568
12	0,8869	-0,0319	0,1179	0	1,0411	0,0004		0,9634	0,0366
16	0,9200	-0,2525	0,0217	0	1,3178	0		0,9471	0,0529
20	0,8761	-0,0412	0,0606	0,0266	1,0704	0,0251		0,9368	0,0632
22	0,9113	-0,1238	0,0238	0,0408	1,1566	0		0,9378	0,0622
29	0,9294	-0,0226	0,0856	0	1,0124	0,0005		0,9634	0,0366
31	0,8839	-0,1870	0	0,0537	1,2451	0,0196		0,9307	0,0693
38	1	-0,2805	0	0	1,2805	0		0,9449	0,0551
39	0,8948	-0,0653	0	0,0362	1,1466	0		0,9392	0,0608
40	0,9319	-0,2763	0	0,0035	1,3418	0,0040		0,9505	0,0495
43	0,8675	-0,0395	0	0,0466	1,1285	0,0173		0,9377	0,0623
49	0,9024	-0,2126	0	0	1,3207	0		0,9449	0,0551
58	0,8947	0,0720	0	0,0251	0,9931	0,0274		0,9497	0,0503
61	0,9005	-0,0948	0	0,0470	1,1584	0		0,9392	0,0608
62	0,9156	0,0525	0	0,0264	0,9893	0,0241		0,9635	0,0365

Weights of the input/output variables of the General BCC-O Model are given in Table A.7. Data of the first twenty units are presented in this table, as well.

Table A.7. Weights for the input/output variables of the General BCC-O Model

DMU	Score	V(0)	V(1)	V(2)	V(3)	V(4)		U(1)	U(2)
1	0,8842	-0,0303	0,0025	0,000004	0,000038	0		0,000031	0,0368
2	0,8910	-0,0320	0,0027	0,000004	0,000040	0		0,000033	0,0389
5	0,9306	0,0108	0,0014	0	0,000017	2,72E-06		0,000015	0,0371
6	0,9962	0,0093	0,0005	0,000097	0,000008	0		0,000007	0,0154
8	0,9842	0,0091	0,0005	0,000059	0,000008	0		0,000007	0,0133
9	0,9649	0,0134	0,0007	0,000087	0,000012	0		0,000010	0,0197
12	0,8869	-0,0319	0,0026	0	0,000040	9,18E-08		0,000032	0,0387
16	0,9200	-0,2525	0,0005	0	0,000117	0		0,000074	0,1296
20	0,8761	-0,0412	0,0011	0,000522	0,000049	1,12E-05		0,000039	0,0833
22	0,9113	-0,1238	0,0005	0,000559	0,000091	0		0,000064	0,1341
29	0,9294	-0,0226	0,0019	0	0,000028	6,52E-08		0,000023	0,0275
31	0,8839	-0,1870	0	0,002440	0,000103	1,30E-05		0,000072	0,1698
38	1	-0,2805	0	0	0,000147	0		0,000093	0,1707
39	0,8948	-0,0653	0	0,000389	0,000061	0		0,000043	0,0873
40	0,9319	-0,2763	0	0,000058	0,000138	2,44E-06		0,000087	0,1429
43	0,8675	-0,0395	0	0,000461	0,000053	4,97E-06		0,000040	0,0827
49	0,9024	-0,2126	0	0	0,000112	0		0,000071	0,1293
58	0,8947	0,0720	0	0,000557	0,000040	6,30E-06		0,000034	0,0565
61	0,9005	-0,0948	0	0,000566	0,000088	0		0,000062	0,1268
62	0,9156	0,0525	0	0,000280	0,000028	4,52E-06		0,000024	0,0283

Reference set data and the efficiency scores of DMUs are shown in the table below. Likewise, Table A.8 is including only the first twenty units' data.

Table A.8. Efficiency score data for the General BCC-O Model

DMU	Score	Rank	Reference set (lambda)											
1	0,8842	571	488	0,4779	6582	0,1683	7089	0,0628	7259	0,0241	7516	0,2670		
2	0,8910	523	488	0,4483	6582	0,2085	7089	0,0335	7259	0,0044	7516	0,3053		
5	0,9306	267	377	0,2846	488	0,4252	6535	0,0243	6582	0,1601	7259	0,1059		
6	0,9962	66	488	0,3808	6535	0,0818	6582	0,3421	8784	0,0501	8787	0,1452		
8	0,9842	87	488	0,3611	6535	0,0651	6582	0,3195	7259	0,0537	8787	0,2006		
9	0,9649	123	488	0,4463	6535	0,0256	6582	0,3385	7259	0,0776	8787	0,1120		
12	0,8869	554	488	0,4592	6582	0,2160	7089	0,0514	7259	0,0100	7516	0,2634		
16	0,9200	324	435	0,3878	4846	0,2080	7516	0,1775	9029	0,2268				
20	0,8761	631	481	0,4118	488	0,0898	6582	0,0884	7516	0,1405	8367	0,2551	9029	0,01
22	0,9113	385	435	0,5096	488	0,0097	7516	0,2452	8367	0,0604	9029	0,1750		
29	0,9294	275	488	0,6178	6582	0,1512	7089	0,0875	7259	0,0893	7516	0,0542		
31	0,8839	574	405	0,1060	435	0,3353	481	0,0784	4780	0,3188	8367	0,1614		
38	1,0000	1	38	1										
39	0,8948	487	435	0,2546	488	0,2621	7516	0,2492	8367	0,2341				
40	0,9319	259	38	0,2568	435	0,3465	4846	0,3318	6288	0,0363	7516	0,0286		
43	0,8675	693	481	0,1149	488	0,3032	6288	0,1041	7516	0,2631	8367	0,2147		
49	0,9024	439	38	0,2001	435	0,5319	7516	0,2680						
58	0,8947	489	390	0,0253	481	0,1749	488	0,2654	5094	0,1218	8367	0,4126		
61	0,9005	453	435	0,6323	488	0,0223	7516	0,3074	8367	0,0380				
62	0,9156	350	488	0,5959	5094	0,1365	6535	0,0199	6582	0,1092	8367	0,1386		

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