TWO-STAGE STOCHASTIC OPTIMIZATION MODEL FOR THE DESIGN OF A CAPACITATED, MULTI-PRODUCT, MULTI-ECHELON REVERSE LOGISTICS SYSTEM: A CASE STUDY IN TURKEY

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ABSTRACT

TWO-STAGE STOCHASTIC OPTIMIZATION MODEL FOR THE DESIGN OF A CAPACITATED, MULTI-PRODUCT, MULTI-ECHELON REVERSE LOGISTICS SYSTEM: A CASE STUDY IN TURKEY

Electrical and electronic equipment sector can be classified as one of the fastest growing industrial sectors in the world. Increase in customers' tendency to have latest technology resulting in an important increase in consumption of products and the reduction in useful product lifecycles. On the other hand, if the increase in waste electrical and electronic equipment (WEEE) cannot be managed properly, it may create a serious threat on human health and ecosystem due to several poisonous and chemical substances and cause important economic loss. By considering all these risks, European Union(EU) introduced a regulation in 2002 to take WEEE system under control. As a candidate for EU membership, Turkey enacted similar regulation by the year of 2012. It is aimed to minimize all possible threats and losses by giving responsibility to producers, distributors and municipalities for WEEE collecting and recycling activities. The regulation is relatively new in Turkey. In addition, customer awareness about the importance of WEEE system is not high enough. Thus, there is an important uncertainty in total return amounts. In this study, we aim to create an implementable and efficient reverse logistics(RL) network design tool for the WEEE collection system in Turkey with the presence of multiple product types, uncertain return quantities and capacity constraints for recycling activities. The methodology is based on RL network design using a two stage stochastic mixed integer linear programming with the objective of minimizing the total cost of the system for various return scenarios. The proposed model is tested by considering the collection and recycling system of a major white goods producer in Turkey. Since the proposed model is an NP hard problem, sample average approximation is used as a heuristic method for the proposed model under different number of return scenarios.

ÖZET

İKİ KADEMELİ STOKASTİK OPTİMİZASYON MODELİ İLE KAPASİTE KISITLI, ÇOK ÜRÜNLÜ, ÇOK AŞAMALI TERSİNE LOJİSTİK SİSTEMİ TASARIMI: TÜRKİYE'DE BİR VAKA ANALİZİ

Tüm dünyada teknolojide görülen hızlı değişimle beraber tüketicilerin daha yeniye olan eğilimlerinin arttığı görülmektedir. Bu eğilim ile ürünlerin kullanım ömürleri giderek azalmakta ve atıl duruma dönüşen ürün sayısı her geçen yıl daha da artmaktadır. Bu hızlı değişim içerisinde atıl olan ürünlerin kontrolsüz olarak doğaya salınması içerdikleri kimyasallar sebebiyle ekosistem için ciddi bir tehdit oluşturmakta ve beraberinde bazı değerli materyallerin tekrar kullanılamaması sebebiyle de ekonomik açıdan bir kayıp oluşmaktadır. Tüm bu nedenlerle atık elektrikli elektronik eşyaların (AEEE) geri dönüşüm süreçlerini kontrol altına almak amacıyla Avrupa Birliği 2002 yılında bir düzenleme yürürlüğe koymuştur. Benzer bir düzenleme aday ülke Türkiye'de de 2012 yılında devreye alınmıştır. Üreticiler, dağıtıcılar ve belediyeler dâhil birçok kurum geri dönüşüm sürecinden sorumlu tutularak olası tehdit ve kayıpların minimuma çekilmesi hedeflemiştir. Düzenlemenin Türkiye'de görece yeni olması ve tüketicilerin bilinç seviyesi sebebiyle sisteme dâhil olacak adetlerde ciddi bir belirsizlik söz konusudur. Bu çalışmada olası belirsizlikler de dikkate alınarak etkin bir AEEE süreç yönetimi için karar destek mekanizması geliştirilmesi hedeflenmiştir. İki kademeli stokastik optimizasyon modeli kurularak tek yönlü, çok kademeli, çok ürünlü ve kapasiteli bir tersine lojistik sistemi tasarımı amaçlanmıştır. Önerilen model, Türkiye'deki öncü bir beyaz eşya üreticisi ile yapılan vaka analizi ile test edilmiştir. Bağımsız bir pazar araştırma şirketinin geçmiş yıllar için verileri dikkate alınarak gelecek yıllar tahminleme yapılmış ve geliştirilen farklı senaryolarla nasıl bir AEEE sistemine ihtiyaç duyulacağı analiz edilmiştir. Çok sayıda senaryonun dikkate alındığı stokastik modelin çözümü içinse buluşsal bir yöntem olan örnek ortalama yaklaşım yönteminden faydalanılmıştır.

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A_{ijt}^{ps}	Amount of product type *p* sent from service location *i* to CC *j* in period *t*
B_{jkt}^{ps}	Amount of product type *p* sent from CC *j* to RF *k* in period *t*
C_{jt}^{ps}	Amount of product type *p* sent from CC *j* to third party recycler in period *t*
CC_{j}^{ps}	Binary variable of being CC *j* active for product type *p* under return scenario *s*
D_{ikt}^{ps}	Amount of product type *p* sent from service location *i* to RF *k* in period *t*
G_{kt}^{p}	Binary variable of being RF *k* active for product type *p* under in period *t*
GG_{k}^{p}	Binary variable for opening RF *k* for product type *p*
h^{p1}	Handling cost of product type *p* during shipment from service location to collection center
h^{p2}	Handling cost of product type *p* during shipment from collection center to recycling facility
i	Service Location
j	Collection Center
k	Recycling Facility
l	Shift
m_{ij}^{p1}	Unit transportation cost of product type *p* from service location *i* to collection center *j*
m_{jk}^{p2}	Unit transportation cost of product type *p* from collection center *j* to recycling facility *k*
m_{ik}^{p3}	Unit transportation cost of product type *p* from service location *i* to recycling facility *k*
o_{k}^{p}	Operation cost of recycling facility *k* for product type p in each shift
o_{c}^{p}	Fixed cost of opening collection center *j* for product type *p* (i.e. license cost)

p	Product
q_k^p	Capacity of recycling facility k for product p for one shift
r_{it}^{ps}	Amount of product p returned to service location i in period t
s	Return Scenarios
SS_{klt}^{ps}	Binary variable of being shift l active for RF k for product type p in period t under return scenario s
t	Period
U_{ikt}^{ps}	Binary variable for assignment of service i to RF k for product type p p in period t under return scenario s
w^p	Average weight of product type p
X_{ijt}^{ps}	Binary variable for assignment of service i to CC j for product type p in period t under return scenario s
Y_{jkt}^{ps}	Binary variable for assignment of CC j to RF k for product type p in period t under return scenario s
α_j	Rental cost per square meter for collection center j
β_k^p	Startup cost for recycling facility k
δ_t^p	Total capacity of third party recycler for product type p
θ_s	Probability of each alternative return scenario $s \in S$
π^{p1}	Unit sales revenue of product type p to third party recycler
π^{p2}	Unit sales revenue of recycled product type p
ϕ_t^p	Recycling target weight for product type p in period t

LIST OF ACRONYMS / ABBREVIATIONS

CC	Collection Center
CL	Closed Loop
CLSC	Closed Loop Supply Chain
EEE	Electrical and Electronic Equipment
EOL	End of Life
EOU	End of Use
EU	European Union
HA	Home Appliances
HH	Household
MILP	Mixed-integer Linear Programming
Min	Minimum
MO	Multi-objective
MPr	Multi-product
MPe	Multi-period
N	No
Nhh	Number of Household
RL	Reverse Logistics
RLN	Reverse Logistics Network
RF	Recycling Facility
SAA	Sample Average Approximation
SL	Service Location

SP	Stochastic Programming
SMILP	Stochastic Mixed Integer Linear Programming
WEEE	Waste Electrical and Electronic Equipment
Y	Yes

1. INTRODUCTION

In all over the world, there is rapid change in technology and consumers' behavior. In line with radical technological advances, consumers tend to increase the control of their lives through smart devices that can be used every time and everywhere. They look for the most innovative products instead of the most durable one. This situation causes an increase in consumption of high-tech products with the reduction in product lifecycles. As a result, the production of electrical and electronic equipment has emerged as one of the fastest growing industrial sectors in the world while the exhaustion of natural resources arises and waste accumulation reaches at critical levels. It is already known that electrical and electronic equipment waste, which is called e-waste, can create a serious threat on human health and ecosystem due to several poisonous and chemical substances. This fact pushes people and governments to act against these threats. In many European countries, especially European Union members, there are some regulations against these threats to ensure the proper collection and processing of e-waste. For example, the Waste Electrical and Electronic Equipment (WEEE) Directive is enacted by the EU in 2002. In this directive, WEEE is described as discarded, surplus, obsolete, or broken electrical and electronic devices (2002/96/EC). This waste is valuable as it contains up to 60% precious and useful materials such as gold, copper, and aluminum. (Widmer *et al.*, 2005) However, e-waste may also contain hazardous materials such as lead, cadmium, beryllium, mercury, and brominated flame-retardants. Thus, it is required to create formal e-waste management systems. EU WEEE Directive aims to protect the environment and human health by setting some regulations for e-waste management. In this context, the directive has an aim of improving WEEE recovery and reducing the environmental negative effects by increasing collection, reuse, recovery and recycling targets. WEEE directive states the responsibilities of producers and distributors with the aim of reaching targets related to reuse, recycling and recovery. Items covered by the directive are classified into 10 different product categories encompassing at least 100 products (European Union, 2003b).

According to the typical composition of WEEE collected in European countries, it is known that consumer electronics (including large household appliances, TVs and DVD players) is covering more than 70% of total WEEE. The average composition of collected WEEE in the EU can be checked in Table 1.1.

Table 1.1. Typical composition of WEEE collected in the EU according to the EU 10 WEEE categories. Sources: Huisman et al. (2008) and European Union (2003b)

No. EU WEEE Category (example appliances in parentheses)	**% of collected WEEE**
1. Large household appliances (refrigerators, ovens, washing machines, dishwashers)	49.07
2. Small household appliances (vacuum cleaners, toasters)	7.01
3. IT and telecommunications equipment (phones, laptops)	16.27
4. Consumer equipment (DVD players, televisions)	21.10
5. Lighting equipment (lamps)	2.40
6. Electrical and electronic tools (drills, saws)	3.52
7. Toys, leisure and sports equipment (game consoles)	0.11
8. Medical devices (pulmonary ventilators, dialysis)	0.12
9.Monitoring and control instruments (smoke detector, thermostats)	0.21
10.Automatic dispensers (Drink, Money dispensers)	0.18
Total WEEE (rounded)	100

As a candidate country for full membership to European Union since 1999, Turkey has embedded the WEEE directive into its own regulations in 2012. According to this directive, manufacturers, and distributors are responsible for the collection and processing of e-waste with predefined target rates for collection, recycling and recovery of each product category.

For recycling and recovery targets, there are minimum requirements with the percentage of total sales for each electrical and electronic equipment(EEE) product category.

In line with these targets, the directive emphasizes separate collection as a condition for ensuring specific treatment and recycling of WEEE. On the other hand, collection targets are specified with different considerations in the WEEE directive of Turkey and EU. In Turkey, collection targets are defined according to total sales quantities whereas EU WEEE directive defines these targets with the base of kg per person in population. The current collection, recovery and recycling targets specified with the WEEE Directive in Turkey can be seen in following tables.

Table 1.2. WEEE collection targets

	Yearly Based Collection Targets (%)											
EEE Categories	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**
1. Refrigerators/Coolers/ Air Conditioners	5.5	6	6.5	7	10	12.5	15	17.5	20	22.5	25	30
2.Home Appliances (Washing machine, Dishwasher, Oven, Hob, Dryer etc.)	4.5	5	5.5	6	8	10	12.5	15	17.5	20	25	30
3. Televisions and monitors	5.5	6	6.5	7	10	12.5	15	17.5	20	22.5	25	30
4. Informatics, telecommunication and consumer equipments (excluding Televisions and monitors)	4.5	5	5.5	6	8	10	12.5	15	17.5	20	25	30
5. Lighting Equipments	1	1.5	2	2.5	3	3.5	5	6	7	10	15	25
6. Small Home Appliances, Electrical and Electronical Devices, Toys, Sport and Entertainment Equipments, Tracking and Control Devices	3	3.5	4	4.5	5	8	10	15	17.5	20	25	30

Table 1.3. WEEE recycling targets

EEE Categories		Years	
		2013	2018
		% (weight-based)	
Big Home Appliances		65	75
Small Home Appliances		40	50
Informatics and Telecommunication Equipments		50	65
Consumer Equipments		50	65
	Lighting Devices	20	50
	Gas Discharge Lamps	55	80
Electrical and Electronic Devices		40	50
Toys, Sport and Entertainment Devices		40	50
Medical Devices		---	---
Tracking and Control Devices		40	50
Automat		65	75

Table 1.4. WEEE recovery targets

EEE Categories		Years	
		2013	2018
		% (weight-based)	
Big Home Appliances		75	80
Small Home Appliances		55	70
Informatics and Telecommunication Equipments		60	75
Consumer Equipments		60	75
	Lighting Devices	50	70
	Gas Discharge Lamps	70	80
Electrical and Electronics Devices		50	70
Toys, Sport and Entertainment Devices		50	70
Medical Devices		---	---
Tracking and Control Devices		50	70
Automats		70	80

It can be easily stated that current targets are not very assertive compared with the targets in EU countries. On the other hand, it is well known that there will be an increase in collection target rates in years and, producers and distributors need to assess the sufficiency of their related RL networks. In analyzing the requirements defined in the WEEE directive, numerous challenges arise since the responsibilities of stakeholders and their structural development for WEEE collection system are different from each other. Additionally, customer awareness has not reached enough saturation and this is an important reason under the current uncertainty in possible WEEE amount returned into the WEEE collection and recycling system of Turkey. Since Turkey can be considered as new in green activities, it is required to improve WEEE collection and recovery system by considering all related constituents.

It is known that Turkey has a similar structure with Europe in terms of the properties of electrical and electronic devices. Naturally, the same similarity is expected to observe in product types involved in WEEE systems. Therefore, with the help of the data shown in Table 1.1, it can be stated that large households and TVs have the majority in total amount of WEEE in Turkey. In line with this fact, the case study which is the subject of this thesis, is carried out with one of biggest white goods producers in Turkey. According to the search done by this producer, there is a significant number of old appliances are still in use. Among these products, 60-65% of refrigerators and 45-50% of washing machines have low energy rating (below A^{+}). Since consumers are more motivated to replace their appliances with the latest technology products, there is considerable need to develop a WEEE collection system in Turkey. Motivated by this fact, the mentioned producer has already initiated investments to establish a WEEE management system in line with its responsibility defined in the directive. On the other hand, there exist inefficiencies in terms of cost/revenue management of this system. RL is one of the most important issues in the management of WEEE, accounting for 50-70% of total cost of the WEEE collection and recovery system. (Xanthopoulos,2007). This percentage can be accepted as high while considering the percentage of the logistics cost as 10-15% in sales price of new product. Even though transportation cost is stated as the largest component of RL costs (Stock, 1996), there are other factors that have a direct impact on the management of RL systems such as regulations, product characteristics, return volumes, disposal costs, and applicable disposition alternatives. It is critical to control all costs in RL to generate an efficient value recovery system.

Since the transportation cost is one important factor affecting the total system efficiency, there are many studies in the literature focusing on this factor to make some improvements. It is also important to design a flexible system against continuously changing conditions.For example, the return rate of end-of-use (EOU) or end-of-life (EOL) cannot be known exactly at any time. Thus, capacity requirement may change continuously.

In this study, the problem about current reverse logistics network (RLN) of one white goods producers is examined and an optimization model is proposed for a multi-echelon, multi-product system with capacity constraint under return quantity uncertainty. Two stage stochastic mixed linear integer programming (SMILP) is used to minimize the total cost of the system for reverse logistics activities by determining the number of collection centers(CC) and recycling facilities(RF) with their locations as considering the uncertainty in various return scenarios. The sample average approximation(SAA) method is used as a solution approach for this stochastic optimization model. To examine the effectiveness of the proposed model, case study is carried out with the cooperation of one of the biggest white goods producers in Turkey. There are some special constraints in the proposed model to provide statements in the WEEE directive of Turkey. On the other hand, the model is designed as applicable in general by updating such special constraints according to the valid conditions in any new environment. As it stated before, the company has an operation in place for collecting and recycling activities of WEEE. Hence, this study is done to provide a tool for deciding requirements in the system according to the WEEE targets in Turkey. It is aimed to use the proposed model for improving the current system's efficiency. At the end of this case study, returned products are processed in their own RFs or directed to third party recyclers to minimize the total cost of the system with optimal assignments between service locations (SLs), CCs and RFs. Since the case study is conducted for largest white goods producer in Turkey, it will represent an important portion of the total WEEE collection and recycling system in Turkey. Additionally, we will examine the efficiency of the system by generating different scenarios about return quantities in coming years.

In next chapter, there is a review of studies in the literature related to the RLN optimization by using deterministic and stochastic modelling, case studies about that subject in global and especially in Turkey, and different estimation method for generating e-waste amounts in the future. In chapter 3, we define the problem and aim of this study.

After clarifying the problem considered in this study, we give the details of model development with assumptions, constraints and the mathematical model in Chapter 4. In this section, we also explain the method of sample average approximation (SAA) as a solution approach for the proposed two stage SMILP model.

In Chapter 5, we give the detail of a real life case study with the largest white goods producers in Turkey. Addition to the setting of parameter values based on a case study, there is also an explaination of estimation method for e-waste amounts in coming years. Since the model is designed as two-stage. In Chapter 6, computational results obtained by applying SAA to the the proposed two-stage SMILP model are presented. In Chapter 7, there are some sensitivity analyses by changing the initial conditions or constraints in the system.

The final chapter covers the main conclusions and comments related to the study and possible future study areas.

2. LITERATURE REVIEW

The importance of RL is continually increasing since it has many environmental, economic and social benefits for both manufacturing and service sectors. Thus, RL has been a popular research area with many studies carried out during the last wo decades. There are various definitions of RL in the literature. For example, Fleischmann *et al.* (2000) categorize the reverse logistics process into collection, inspection/separation, re-processing, re-distribution and disposal. On the other hand, Liu *et al.* (2002) and He *et al.* (2006) define this process as a combination of re-use, service, re-manufacture, recycle, and disposal, while Thierry *et al.* (1995) divide it into repair refurbishing, remanufacturing, cannibalizing, and recycling. Bereketli *et al.* (2011) show that reuse, recycling, and disposal are generally three different ways of treating WEEE. In this study, RL can be defined as including collection, recycling and disposal activities in line with the current WEEE system of the company.

While reviewing studies in the literature related with the optimization or design of RLN, it is possible to see many studies for various sectors in different countries. Even though there are some similarities between countries' product recovery policies for similar product types, each country may differentiate their policies with some special conditions according to their infrastructures. Ongondo *et al.* (2011) analyze about WEEE management practices in different countries and regions by examining global trends in the quantities and composition of WEEE. In this search, after analyzing current recovery systems in various countries, it is seen that many of them are not able to keep up with WEEE regulations. On the other hand, some European countries, such as Germany, Switzerland, United Kingdom, are successful to manage formal WEEE collection systems by distributing responsibilities for collection and recycling among stakeholders. There are some other countries involving in WEEE system without having any regulation. As an example, developing countries like China, India and some Asian countries are importing WEEE from other countries and they do not have any regulation regarding this issue.

As a result of this study, they underline four key issues as follow: there is an expectation to have continuously increase in global amounts of WEEE because of an emergence of new technologies and affordable electronics; informal recycling activities in developing countries should be changed to formal systems by setting strict safety standards under the potential valuable contributions; there is not enough legislative regulations about WEEE in global; and more accurate data about quantities and types of WEEE generated in the world is needed.

The implementation of WEEE management systems differs in each country and region. There are many studies related with the adaptation of these systems in changing conditions. It can be possible to classify them according to the type of supply chain design and modeling. In that mean, supply chain can be categorized into two as reverse supply chains without considering forward flows and a close loop supply chain dealing with forward flows of recovered/new products from upstream to downstream facilities addition to reverse logistics. In terms of modeling, stochastic or deterministic approaches are two main methods to classify studies in the literature.

During the review of studies in the literature, we firstly focus on studies using deterministic modelling to optimize RL systems. For this purpose, mixed linear integer programming(MILP) is one common method to search optimality in such systems. In these models, uncertainties are eliminated by some preliminary studies and the model optimizes the system under the introduced conditions. At second step, we review studies based on stochastic programming. Here, two-stage SMILP is one method to optimize the system by considering the uncertainties in various return scenarios. There are different heuristic approaches to solve such stochastic programming. Lastly, there is a review of modelling with multi-objective as deterministic and stochastics. In that case, the modelling is NP-hard and it is required to benefit some different approaches to reach a solution of the model. In further explanation, we classify studies with respect to these three issues and give some important examples respectively.

Fleischmann *et al.* (2001) propose one of the first studies on RL systems with deterministic modeling. The model is generated as adaptable to both closed loop supply chain (CLSC) and RLN. Then, it is examined for nine different sectors. It is explained in detail how different sectors affect the recovery systems according to customer profiles and product structures. The uncertainty is not involved in the modelling of this study, even though it is stated as one major characteristics of the product recovery system. Therefore, the proposed model is improved in various studies to obtain better accuracy in application by considering possible uncertainties in the system. Salema *et al.* (2007) study a generalized model for the design of a RLN. The model is based on the model proposed by Fleischman *et al.* (2001), but it is expanded by considering capacity limits, multi-product management and uncertainty in return quantities. As a result, they propose a capacitated multi-product RLN that considers uncertainty in demand and return flows. In another study, Salema *et al.* (2010) propose a multi-period and multi-product network model for simultaneous design and planning of supply chains with reverse flows. The proposed model is designed to determine the network structure, the production and storage levels, the flow amounts, and the non-satisfied demand and return volumes. It is designed for a four-echelon structure which means direct connection is not possible between customers and factories. Both strategic and tactical decisions are handled by dividing the time horizon according to strategic time units defined by management. The case study based on the Portuguese glass industry is solved to show models' applicability and adequacy. It is concluded that simultaneous design of forward and reverse chains increases model complexity and decreases model performance. Therefore, there is need to improve model performance by focusing alternative solution techniques.

Hong *et al.* (2006) study the design of infrastructure for e-scrap reverse production system based on collection of used electronic devices. The method is distinguished from previous studies by applying robust optimization to reverse production system design while considering the impact of uncertainty on parameters such as collected volume and prices. There is a robust problem formulation with enumeration of all scenarios by searching solution as being close to the optimal solution for each scenario. MILP model is used to maximize the system net profit for each specified scenario. Then a min–max robust optimization methodology finds a robust solution for all of the scenarios.

Achillas *et al.* (2010) develop an optimization model to determine optimal routes for WEEE within a RLN by taking into account existing infrastructure of CCs and RFs. The case study is carried out for the development of RLN in the Region of Central Macedonia to check the applicability of the proposed mathematical model.

Grunow and Gobbi (2009) contribute to the literature by considering the problem of assigning waste to collection schemes and the evaluation of different assignment strategies. There is an extension of MILP called as dynamic model to evaluate the proposed collection scheme against yearly changes in the market. In the proposed dynamic model, there is a choice between maintaining a stable solution or changing the assignment in every year to guarantee fair distribution of the volumes. In this way, it is possible to adapt RLN according to market share changes of stakeholders with the consideration of all related cost items in logistics operations in years.

Bennekrouf *et al.* (2011) present a MILP model by including costs of collection and treatment, and sales income from the second-hand market. Here the objective is to determine the best material flow between facilities that minimizes the cost under capacity constraints for multi period. The proposed model is solved in two levels. At the first level, the collection of several types of products from collection points to CCs within a defined period is considered. At the second level, a new flow from CC to last station for disposal or remanufacturing is determined within same time interval.

Alumur *et al.* (2012) study a profit-oriented RLN optimization model by taking into account a multi-period setting, modular expandable facility capacities, reverse bill of materials, minimum throughput constraint for each facility, variable operational costs and finite demands in the secondary market. The paper contributes to the literature by pointing out how an OEM needs to react to the trends in the return streams and secondary markets to increase its profitability.

Alshamsi and Diabat (2015) propose a MILP model to decide the optimal selection of sites, the capacities of inspection centers and remanufacturing facilities. They propose two transportation options for delivering the products across the reverse supply chain, in-house fleet or outsourced trucks. They also consider investment costs for in-house fleet or capacity expansion in inspection centers. The study contributes to the literature by introducing transportation options and investment considerations.

Qiang and Zhou (2016) generate a robust MILP model for RLN with the consideration of the uncertainty in RLN operations for WEEE. There are two coefficients as a risk preference for the uncertainty of recovery and penalty for the deviation from constraints in modeling. The study contributes to the literature by proposing the adjustment of robust level of the system by these coefficients.

John *et al.* (2017) conduct a study on RLN design for a multi-product, multi-echelon system. They consider remanufacturing, repairing and recycling as different recovery options. There is grading as the residual value of each returned product. It is used to decide appropriate recovery option. It is possible to determine the minimum percentage of high residual value of products required for setting a remanufacturing center with profit. The case study is done with the data provided by one of the India's largest third party service providers specializing in RL. The data is related with two commonly used consumer electronics: mobile phones and digital cameras. This study contributes to the literature by considering the product structure and the grading costs into the facility location problem.

In addition to deterministic approaches in modelling, there are various studies in the literature that apply the stochastic modelling to RLN systems. In this context, Jeihoonian *et al.* (2015) present a two-stage SMILP model for a closed loop supply chain by involving several recovery options in reverse logistics network. The uncertainty in the quality of returned products is considered by introducing a binary variable to the model.

As a heuristic approach, scenario clustering decomposition method was used to get a result for this large-scale optimization problem within reasonable execution time. There are clustered sub-models coordinated by a Lagrangean Progressive hedging-based method. Additionally, a Benders decomposition-based algorithm is used to solve each scenario cluster sub-model.

Chen *et al.* (2015) propose a two-stage stochastic closed-loop supply chain model considering the uncertainties in the market size, the return volume, and the quality of the returns. The proposed model is a stochastic mixed-integer quadratic program and it is not possible to get the solution by the help of available commercial software. Thus, they develop a heuristics method by integrating SAA and integer L-shaped method. They apply their model to a study based on BSH in Germany. They do several sensitivity analyses by changing the conditions for uncertain parameters such as disposal/recycling costs, remanufacturing cost, and customer's valuation on remanufactured products. By considering these uncertainties, they analyze the profitability for the product recovery options of firm and integrated network configuration for such operations. They design the model to incorporate a market clearing mechanism and profit maximization and this makes the study different than the others in the literature.

Yu and Solvang (2016) study the overall cost of the RL system for WEEE by taking into account the environmental impacts in terms of carbon emission. They propose a model that minimizes the overall costs of RL system for WEEE through location optimization and transportation planning, and the amount of WEEE generated at local collection sites while considering price of recycled products, and recycled materials as uncertain parameters. The proposed stochastic optimization model is solved by improved multi-criteria scenario-based solution methods to observe the effect of the change in uncertain factors.

Fattahi and Govindan (2017) deal with the design and planning of CLSC by considering the planning horizon with multiple tactical periods. In this model, the demand for new products and the number of returned products are probabilistic. Moreover, it is assumed that there is dependency between the quality level of return products and the related acquisition price from customers.

They apply the Latin Hypercube Sampling method to generate various scenarios by considering the uncertainties in demand and return amounts. They propose a MILP model by using the stochastic programming. Because of the complexity in the problem, they develop a novel simulation-based algorithm. The study is one important example of proposing a different solution approach for the solution of SMILP.

The scope of searches on RLN are enlarged by years and systems are designed with consideration of multi objectives. At that point, since the proposed models are getting hard to solve, researchers benefit from some heuristic approaches to reach reasonable solutions as in example studies discussed below.

Shokouhyar and Aalirezaei (2015) design a two-stage RLN based on sustainable development of economic, environmental and social objectives. A multi objective genetic algorithm is used to determine the locations for CCs and RFs. At the end of the study, it is aimed to help the decision makers for making the trade-off between environmental issues and economic and social impacts. The proposed model is tested on a real case study of current WEEE system in Iran.

Li *et al.* (2016) propose a bi-objective MILP model for a repair service in a multi-period setting to create flexibility in the facility capacities and RL network configuration gradually. It is aimed to minimize total RL cost and maximize customer satisfaction. To solve this NP-hard problem with two objectives, they develop a hybrid evolutionary algorithm. The proposed algorithm helps to decrease computation time of the model. The study contributes to the literature by considering the response time against customer requests and multiple decisions to design of RL network for repair service in together.

Kumar *et al.* (2016) study a forward-reverse logistics system by assuming that there are a fixed number of suppliers, facilities, distributors, customer zones, disassembly locations, re-distributors, and second customer zones. Under deterministic demand level at customer zones, the model is designed to maximize the profit and obtain an efficient vehicle routing at optimal or approximately optimal solution.

Since the proposed model is NP-hard, it is solved using Artificial Immune System (AIS) and Particle Swarm Optimization approaches. According to the results, AIS performs better. The paper contributes to the literature on RL by considering the cost profit addition to vehicle routing.

2.1. RLN Applications in Turkey

In this study, we consider a real-life problem in Turkey. Therefore, we review case studies designing RL networks. Even though there are many case studies for the design of RLN, few consider home appliances. Chen *et al.* (2013) and Qiang and Zhou *et al.* (2016) are two examples for the case studies about the design of RLN for home appliances in Hong Kong and China. Chen *et al.* (2015) further studies by considering a stochastic MILP to study the sufficiency of RLN in Germany for home appliances. It is possible to design RL systems by the help of other methods rather than linear programming. For this purpose, Queiruga *et al.* (2008) and Achillas *et al.* (2010) are two examples using multi-criteria decision making to propose the RLN for Spain and Greece. All these are some examples from the literature in the global. In further explanations, there are reviews of some studies about RLN design for Turkish market separately.

Ayvaz and Bolat (2014) propose a two stage SMILP to minimize total cost of the RLN. The RL is based on the network having multi-echelon, multi-product, capacity constraint under return quantity and quality uncertainties. They generate different scenarios from discrete exponential distribution which is obtained by historical product return data and used them in SP model to handle uncertainties. The proposed model is tested by a real case study of one third party recycler company for WEEE in Turkey. This study makes an important contribution to the literature by providing a generic multi-stage, multi-product recovery network that considers the uncertainty in return quality and quantity.

Ayvaz *et al.* (2015) study a two-stage stochastic profit maximization RLN design problem with the aim of proposing a generic algorithm under uncertainties of return quantity, quality ratio, and transportation cost. The location of collection, sorting and recycling centers and the flow quantity between facilities in the network are considered in the model. The proposed model is solved with SAA. The model is designed to be applicable to multiple or single echelon systems. It is aimed to propose a generic RLN for third party recycler companies. The generated model is examined for the case study of one big recycling company located in Kocaeli, Turkey. The study contributes to the literature by using SAA as a solution method for stochastic MILP to design RLN.

Kilic *et al.* (2015) consider a RLN in Turkey by creating ten different scenarios with different collection rates. A MILP model satisfying the minimum recycling rates stated in EU WEEE directive is used to provide solutions for each scenario to decide optimal locations of storage sites and recycling facilities. Although the proposed model has some similarities with the general purpose models in the literature, it mainly differs from the existing models by considering recycling rates for each product category defined in WEEE directive.

Aras *et al.* (2015) focus on RLN design problem by formulating a facility location-allocation model. In that model, there is a minimization of operating facility, capacity acquisition/expansion, labor, and transportation costs while determining the optimal location and capacity for RFs. As a case study application, real data of IT-based e-waste during past years is used to generate some scenarios about the number of used products that will be collected from the consumers in future.

Ozkir V. (2017) considers a decision support system and propose RLN design for the collection of small WEEE in Istanbul such as mobile phones. They construct a bi-objective spanning tree model and entropy embedded fuzzy AHP method to determine the location of nodes and get optimal routes for EOL product collections. The main contribution of this study is to provide a support for the construction of coordinated separate collection systems to decision makers.

In all explained studies at above, there is an analysis of different approaches to design RLN as being a part of CLSC or independent from forward flows. The MILP and SMILP are two possible methods to optimize the design of RL networks. If uncertainties are considered into the model with different scenarios, stochastic programming(SP) is used to solve the problem. In SP, it is difficult to reach a solution in a certain time. In that case, some heuristics approaches are used to ease the process. There is a classification of all reviewed studies in Table 2.1. Addition to the type of modelling and type of supply chain, some other properties such as number of periods, products and objectives, capacity constraint and possible uncertainty in total amount of returned products are used in this classification. Here, if there is any capacity limitation for any node namely SLs, CCs, RFs, and third party recyclers in RLN, the network is called as capacitated.

2.2. Literature Search in Estimation of E-Waste Generation

It is a clear fact that accurately estimating return quantity and timing are an important factor to manage RL systems successfully. The amount of generated e-waste determines the value of decision variables in RLN design problems. Therefore, there are many studies to estimate future return amounts. Methods used in these studies differentiate from each other with respect to availability of reliable data. These methods can be classified as estimations based on past return amounts and estimations based on life cycle of products in the market.

Jain and Sareen (2006) establish an approach to quantify e-waste in India for personal computers and televisions in Delhi. They benefit from the market supply method to estimate average e-waste amounts by changing average life cycle of each product for different scenarios. The method assumes EOL becoming obsolete with the rate of %100 at the end of their average life.

Table 2.1. Summary of literature review

Reference Articles	Modelling	Solution Method	Supply Chain	MO	MPe	MPr	Capacity	Uncertainty
Fleischmann *et al.* (2001)	MILP	Exact	Both	N	N	N	Infinite	N
Salema *et al.* (2007)	MILP	Exact	RLN	N	Y	Y	Finite	Y
Grunow and Gobbi (2009)	MILP	Exact	RLN	Y	N	Y	Infinite	N
Salema *et al.* (2010)	MILP	Exact	CLSC	N	Y	Y	Infinite	N
Achillas *et al.* (2010)	MILP	Exact	RLN	N	N	Y	Finite	N
Bennekrouf *et.al.* (2011)	SMILP	Exact	RLN	N	Y	Y	Finite	Y
Alumur *et.al.* (2012)	MILP	Exact	RLN	N	Y	Y	Infinite	N
Li *et al.* (May 2016)	MILP	Heuristic	RLN	Y	Y	Y	Infinite	N
Yu&Solvang (2016)	SMILP	Exact	RLN	Y	Y	Y	Finite	Y
Hong *et al.* (2006)	MILP	Exact	RLN	N	N	Y	Infinite	Y
Ayvaz and Bolat (2014)	SMILP	Exact	RLN	N	N	Y	Finite	Y
Kilic *et.al.* (2015)	MILP	Exact	RLN	N	N	Y	Infinite	N
Aras *et.al.* (2015)	MILP	Exact	RLN	N	Y	N	Infinite	N
Ozkir (2017)		Heuristic	RLN	Y	N	N	Infinite	Y
Saffari *et al.* (2015)	SMILP	Heuristic	RLN	Y	N	N	Finite	Y
Chen *et al.* (2015)	MILP	Heuristic	CLSC	N	Y	Y	Finite	N
Siri *et al.* (2015)	MILP	Exact	RLN	N	Y	Y	Finite	N
Alshamsi & Diabat (2015)	MILP	Exact	RLN	N	Y	Y	Infinite	N
Ayvaz *et al.* (2015)	SMILP	Heuristic	RLN	N	N	Y	Finite	Y
Qiang&Zhou (2016)	MILP	Exact	RLN	N	Y	Y	Finite	Y
Shokouhyar and Aalirezaei (2015)	MILP	Heuristic	RLN	Y	Y	Y	Finite	N
Queiruga *et.al.* (2007)		PROMETHEE	RLN	Y	Y	Y	Infinite	Y
Achillas *et al.* (2009)		ELECTRE III	RLN	N	Y	Y	Infinite	Y
Fattahi and Govindan (2017)	SMILP		CLSC	N	Y	Y	Infinite	Y
Kumar *et al.* (2016)	MILP	Heuristic	CLSC	Y	Y	Y	Infinite	N
John *et al.* (2017)	MILP	Exact	RLN	N	Y	Y	Finite	N
Shen *et al.* (2011)	SMILP	Heuristic	RLN	N	Y	N	Infinite	Y
Aydin and Murat (2013)	SMILP	Heuristic	RLN	N	Y	N	Finite	Y

Jang (2010) proposes the methodology for estimation of total return amount to the WEEE collection system by gathering data associated with annual domestic sales of home appliances and electronic devices, site visits, questionnaire surveys, interviews and conservations and a review of the available literature in Korea. In proposed estimation method, there is a consideration of the average life cycle for each product and the proportion of items reused, loaned or stored at households estimated by customer surveys.

Mmereki *et al.* (2012) use the Stanford method to forecast the e-waste amount by modeling the product life cycle with the variation in the distribution of life cycle and usage percentage. They benefit from the calculated average life cycle available in the literature and introduce the variance of the distribution with the help of the survey of the institution (National Co-ordinating Strategy Agency/Deutsche Gesellschaft für Technische Zusammenarbeit, NCSA/GZT, 1996.). The case study is done about computer waste in the city of Gaborone.

In case of having historical data, it is possible to apply forecasting methods for future e-waste estimations. By the help of all statistical studies about market figures such sales, penetration levels and installed bases, it is possible to generate different scenarios in forecasting return quantities. In the literature, to consider such scenarios, sampling methods are used. Fattahi and Govindan (2017) use Latin Hypercube Sampling method in their study to consider the impact of possible different return scenarios on the design and planning of an integrated forward/reverse logistics network. As stated previously, Chen *et al.* (2015) combine SAA and L-shaped methods for the consideration of different set of scenarios to reach a solution. These different set of scenarios were generated using the available historical data for return flows. SAA is a sampling method based on Monte Carlo simulation. The study of Ayvaz *et al.* (2015) is an example for benefiting from SAA to consider different set of return scenarios while solving the proposed two-stage stochastic MILP. They consider the uncertainties in return quality and quantity and generated large number of return scenarios. By the help of SAA method, all generated scenarios are regarded to reach a solution for the model.

From all reviewed studies at above, it is seen that this study contributes to the literature by proposing two-stage stochastic MILP for multi-product, multi-period, multi-echelon and capacitated RL system about WEEE collection and management system for large home appliances. This study will be the first study in Turkey focusing on all types of white goods defined in the WEEE directive of Turkey. The proposed model is used to optimize current RL network of one major white goods producer in Turkey. The case study is based on current WEEE collection and recycling activities of this major producer. Since the system of this company represents an important portion of the WEEE system in Turkey, the result of this study can highlight some main requirements to increase the efficiency of WEEE collection and management system in Turkey. It is aimed to present an indication about the future of WEEE systems in Turkey by proposing appropriate RL network as including collection, recovery and recycling activities.

As stated previously, accurately estimating return quantity is important factor to have better management of RL systems. From the current operations of the company, there is 2-year historical data about total amount of returned products to the current WEEE collection system of this company. Additionally, there is available historical data about sales amounts in Turkey for many years provided by one independent research and analysis company, Euromonitor. By the help of these available data, it is possible to decide appropriate method for the estimation of possible return amounts in coming years. Since the analysis is based on real data, it is possible to have better indication about the future and specify main requirements for WEEE management systems in Turkey.

3. PROBLEM DEFINITION AND AIM OF THE STUDY

3.1. Problem Definition

After the introduction of WEEE directive in Turkey, producers are given the responsibility of recycling their own products. Currently, while many producers are transferring their duties to third party recycler companies to reach targets in the directive, some producers are managing these operations by themselves. Since there is a wide range of dealer and aftersales service network for home appliances in Turkey, managing WEEE activities through this network is an option. As mentioned before, we focus on the current WEEE system of a major white goods producer in Turkey. Here, customers give their EOU or EOL products to services to receive rebates towards new products. These returned products are collected in each city and transferred to CCs or RFs. All these RL activities are conducted separately from the forward flow of new products. Since WEEE is relatively new concern in Turkey, customer awareness is evolving. Therefore, there is a high uncertainty in the total number of returned products to the WEEE collection and recycling system. Furthermore, the white goods market of Turkey is continuously growing and WEEE targets are increasing every year. Hence, capacity requirements for recycling activities will increase in the future. With all these concerns, the producer wants to know the sufficiency of their current system and check different collection and recycling options to manage this system efficiently. To this end, there is a need to optimize the WEEE collection and recycling system for this white goods producer in Turkey.

The general problem in this study can be defined as the optimization of a multi-echelon and multi-product RLN by considering capacity constraint and the uncertainty of return quantities. The model is developed as a two-stage stochastic MILP to determine the number and location of CCs and RFs that collect used products from service locations. The objective is to minimize the total cost of the system for different return scenarios. The proposed model considers CCs, RFs and third party recyclers.

As shown in Figure 3.1, returned products are collected from customer zones to SLs in each city and they are sent to CCs or RFs according to the type of product. In these CCs, returned products are classified according to the categories defined in the WEEE directive of Turkey. Finally, each of these categories is transported to the related RF or third party recycler for recycling operations. Different from some other applications, there is no resale option for collected EOU or EOL returned products after being repaired or remanufactured.

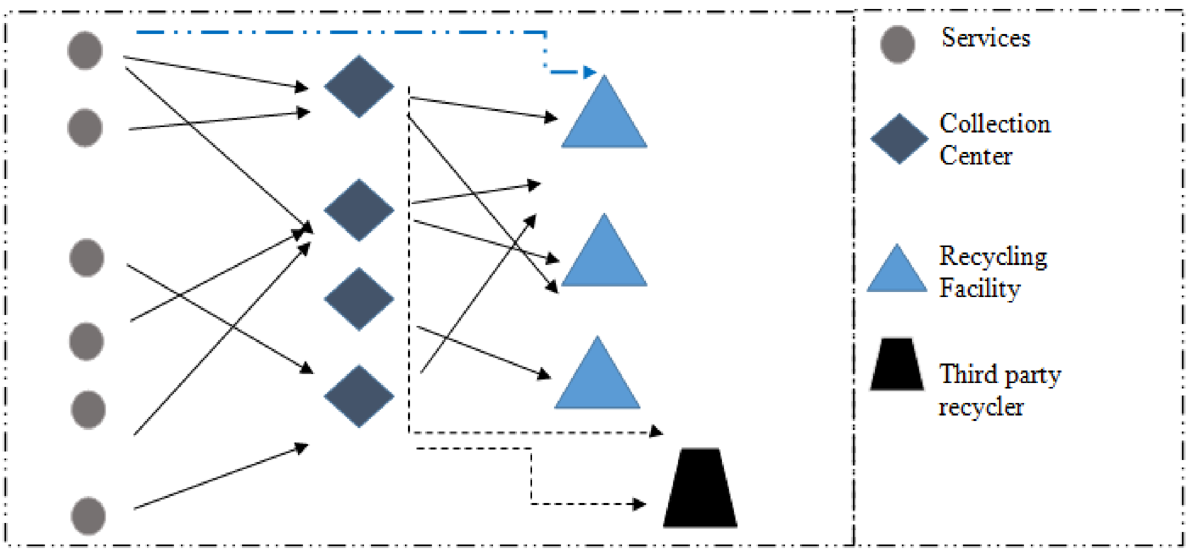

Figure 3.1. Schematic Representation of Reverse Logistics Network in Proposal

There are two important considerations in this study. One of them is to design RLN by deciding locations and capacities for each CC and RF. Another one is to optimize possible collection routes with appropriate assignments between SLs, CCs, RFs and third party recyclers. As a result, this study aims to examine the adequacy of current RFs and CCs for increase in WEEE recovery rate obligations and market size. To this end, multiple yearly return rate scenarios are generated.

3.2. Aim of the Study

This study aims to investigate an implementable and efficient RLN design for WEEE collection of a major white goods producer in Turkey with the presence of multi product types, uncertain return quantities and capacity constraints for RFs and third party recyclers. The methodology is based on a SMILP that minimizes the total cost of the system.

To examine the validity of the proposed model, the case study is done with the help of real data provided by the white goods producer. By considering the real data provided by this company and available data about sales quantities in last ten years on the website of one independent market search company, we develop the estimation method for e-waste amounts in coming years and generate different return scenarios. The model is designed as two stage SMILP to observe the effect of any change in return quantities as an uncontrollable factor. The proposed model is tested with various return scenarios and the resulting RLN design is presented. Furthermore, the system behavior is checked against any change in controllable factors such as capacity of RFs, fixed cost of opening new RFs or CCs. The motivation of this study can be summarized as contributing to the literature in RLN design by taking into consideration a multi-product, multi-period, multi-echelon system having ability of capacity adjustments with shift open/close decisions for RFs under return uncertainties, and to examine the performance of SAA as a solution approach for a two stage SMILP optimization model.

4. MODEL DEVELOPMENT

4.1. Model and Assumptions

The formulation given in this study is designed to decide the flow between the facilities in RLN by considering intermediate storages called as CC in the directive. In this context, two-stage SMILP is created to minimize the total cost of the system including variable transportation costs, capacity expansion cost with shift change in RFs, rental cost of CCs, fixed cost of opening new RFs and other related cost items. The principle of the model is to take some decisions at first stage like opening new RF and to search the optimal solution for whole of system at second stage with given first stage decisions and different possibilities for the realization of alternative return scenarios. The proposed model is considered the following assumptions:

- There is no capacity constraint at SLs for storing returned products temporarily.
- The capacity of a RF can be increased by changing the number of active shift.
- There is predefined unit transportation cost for each product type p while transferring between two cities.
- Each city is assumed as a SL in the network.
- The number of returned products at each SL is generated by the help of statistical analysis as creating a set of alternative return scenarios.
- Each SL can work with a CC or RF with consideration of possible restrictions for any product type.
- Each CC can work with the own RFs of the firm or third party recyclers depending on product type.
- There are three main product categories that are recycled at different facilities and each facility can recycle only one type.
- The candidate locations for CCs are known.
- The candidate locations for RFs are known.

- Direct transfer is not possible from a SL to a RF for some product categories. This situation depends on the regulation in Turkey.
- Since the investment for a new RF is relatively high, it cannot be closed once opened.
- Since CCs can be leased easily, they can be opened or closed dynamically.
- There is a capacity constraint associated with third party recyclers.

By considering the description of the model and assumptions stated at above, the proposed SP model under quantity uncertainty can be defined with the following sets, parameters, and decision variables as follow:

4.1.1. Sets

I: Set of SLs

J: Set of candidate locations for CCs

K: Set of candidate locations for RFs

L: Set of work shifts in a RF

P: Set of product types

S: Set of scenarios for returned products

4.1.2. Parameters

r_{it}^{ps}: Amount of product p returned to SL i in period t under scenario s

w^{p}: Average weight of product type p

ϕ_{t}^{p} : Target recycling weight for product type p in period t

q_{k}^{p} : Capacity of RF k for product p in one shift

δ_{t}^{p}: Total capacity of third party recycler for product type p

m_{ij}^{p1}: Unit transportation cost of product type p from SL i to CC j

m_{jk}^{p2}: Unit transportation cost of product type p from CC j to RF k

m_{ik}^{p3}: Unit transportation cost of product type p from SL i to RF k

α_j: Rental cost per square meter for CC j

f^p : Footprint for product type p

h^{p1}: Handling cost of product type p during shipment from SL to CC

h^{p2}: Handling cost of product type p during shipment from CC to RF

π_p^1 : Unit sales revenue of product type p to third party recycler

π_p^2 : Unit sales revenue of recycled product type p

o_k^p : Operation cost of recycling facility k for product type p in each shift

β_k^p : Startup cost for recycling facility k for product type p

o_c^p : Fixed cost of opening collection center for product type p (licensing cost etc.)

θ_s : Probability of each alternative scenario $s \in S$

4.1.3. Decision Variables

A_{ijt}^{ps} : Amount of product type p sent from SL i to CC j in period t

B_{jkt}^{ps} : Amount of product type p sent from CC j to RF k in period t

C_{jt}^{ps} : Amount of product type p sent from CC j to third party recycler in period t

D_{ikt}^{ps}: Amount of product type p sent from SL i to RF k in period t

$$CC_j^{ps} = \begin{cases} 1, \text{ if CC } j \text{ is active for product type } p \text{ in any period } t \text{ under scenario } s \\ 0, \text{ otherwise} \end{cases}$$

$$G_{kt}^{p} = \begin{cases} 1, \text{ if RF } k \text{ is active for product type } p \text{ in period } t \\ 0, \text{ otherwise} \end{cases}$$

$$GG_k^{p} = \begin{cases} 1, \text{ if RF } k \text{ is opened for product type } p \text{ in any period } t \text{ under scenario } s \\ 0, \text{ otherwise} \end{cases}$$

$$SS_{klt}^{ps} = \begin{cases} \text{1, if shift l is active for RF k in period t under scenario s} \\ \text{0, otherwise} \end{cases}$$

$$U_{ikt}^{ps} = \begin{cases} \text{1, if service i is assigned to RF k for product type p in period t under scenario s} \\ \text{0, otherwise} \end{cases}$$

$$X_{ijt}^{ps} = \begin{cases} \text{1, if service } i \text{ is assigned to CC } j \text{ in period } t \text{ for product type } p \text{ under scenario } s \\ \text{0, otherwise} \end{cases}$$

$$Y_{jkt}^{ps} = \begin{cases} \text{1, if CC } j \text{ is assigned to RF } k \text{ for product type } p \text{ at period } t \text{ under scenario } s \\ \text{0, otherwise} \end{cases}$$

4.1.4. Mathematical Model

min

$$z = \sum_{k\in K} \beta_k^p GG_k^p + \sum_{s\in S} \theta_s \Big(\sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} m_{ij}^{p1} A_{ijt}^{ps} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P}\sum_{t\in T} m_{jk}^{p2} B_{jkt}^{ps} +$$
$$\sum_{i\in I}\sum_{k\in K}\sum_{p\in P}\sum_{t\in T} m_{ik}^{p3} D_{ikt}^{ps} + \sum_{p\in P}\sum_{i\in I}\sum_{t\in T} h^{p1} r_{it}^{ps} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P}\sum_{t\in T} h^{p2} B_{jkt}^{ps} + \sum_{j\in J}\sum_{p\in P}\sum_{t\in T} h^{p2} C_{jt}^{ps}$$
$$+ \sum_{k\in K}\sum_{p\in P}\sum_{l\in L}\sum_{t\in T} o_k^p SS_{klt}^{ps} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} \alpha_j f^p A_{ijt}^{ps} + \sum_{j\in J}\sum_{p\in P} o_c^p CC_j^{ps} - \sum_{j\in J}\sum_{p\in P}\sum_{t\in T} \pi_p^1 C_{jt}^{ps}$$
$$- \sum_{j\in J}\sum_{p\in P}\sum_{t\in T} \pi_p^2 B_{jkt}^{ps} \Big) \tag{1}$$

subject to

$$\sum_{j\in J} X_{ijt}^{ps} + \sum_{k\in K} U_{ikt}^{ps} = 1 \qquad i\in I,\ p\in P,\ s\in S,\ t\in T \tag{2}$$

$$U_{ikt}^{ps} \le G_{kt}^{p} \qquad i\in I,\ k\in K,\ p\in P,\ t\in T \tag{3}$$

$$A_{ijt}^{ps} = r_{it}^{ps} X_{ijt}^{ps} \qquad i\in I,\ j\in J,\ p\in P,\ s\in S,\ t\in T \tag{4}$$

$$D_{ikt}^{ps} = r_{it}^{ps} U_{ikt}^{ps} \qquad i\in I,\ k\in K,\ p\in P,\ s\in S,\ t\in T \tag{5}$$

$$CC_j^{ps} \leq \sum_{j\in J}\sum_{p\in P} X_{ijt}^{ps} \qquad i\in I,\ p\in P,\ s\in S \tag{6}$$

$$X_{ijt}^{ps} \leq CC_j^{ps} \qquad i\in I,\ j\in J,\ p\in P,\ s\in S,\ t\in T \tag{7}$$

$$Y_{jkt}^{ps} \leq G_{kt}^{p} \qquad j\in J,\ k\in K,\ p\in P,\ s\in S,\ t\in T \tag{8}$$

$$\sum_{i\in I} A_{ijt}^{ps} = \sum_{k\in K} B_{jkt}^{ps} + C_{jt}^{ps} \qquad j\in J,\ p\in P,\ s\in S,\ t\in T \tag{9}$$

$$\sum_{k\in K} Y_{jkt}^{ps} \leq \sum_{i\in I} X_{ijt}^{ps} \qquad j\in J,\ p\in P,\ s\in S,\ t\in T \tag{10}$$

$$\sum_{k\in K} Y_{jkt}^{ps} \leq 1 \qquad j\in J,\ p\in P,\ s\in S,\ t\in T \tag{11}$$

$$B_{jkt}^{ps} \leq 3q_k^{p} Y_{jkt}^{ps} \qquad j\in J,\ k\in K,\ p\in P,\ s\in S,\ t\in T \tag{12}$$

$$\Big(\sum_{k\in K}\sum_{j\in J} B_{jkt}^{ps} + \sum_{k\in K}\sum_{i\in I} D_{ikt}^{ps} + \sum_{j\in J} C_{jt}^{ps}\Big)\, w^{p} \geq \phi_t^{p} \qquad p\in P,\ s\in S,\ t\in T \tag{13}$$

$$\sum_{j\in J} C_{jt}^{ps} \leq \delta_t^{p} \qquad p\in P,\ s\in S,\ t\in T \tag{14}$$

$$SS_{k1t}^{ps} \geq SS_{k2t}^{ps} \qquad k\in K,\ p\in P,\ s\in S,\ t\in T \tag{15}$$

$$SS_{k2t}^{ps} \geq SS_{k3t}^{ps} \qquad k\in K,\ p\in P,\ s\in S,\ t\in T \tag{16}$$

$$G_{kt}^{p} \leq SS_{klt}^{ps} \qquad k\in K,\ p\in P,\ s\in S,\ t\in T \tag{17}$$

$$\sum_{j\in J} B_{jkt}^{ps} + \sum_{i\in I} D_{ikt}^{ps} \leq \sum_{l\in L} SS_{klt}^{ps} q_p^{k} \qquad k\in K,\ p\in P,\ s\in S,\ t\in T \tag{18}$$

$$G_{kt}^{p} \leq GG_k^{p} \qquad k\in K,\ p\in P,\ t\in T \tag{19}$$

$$G_{kt}^{p} \leq \sum_{i\in I} U_{ikt}^{ps} + \sum_{j\in J} Y_{jkt}^{ps} \qquad k\in K,\ p\in P,\ s\in S,\ t\in T \tag{20}$$

Objective function (1) minimizes the total cost of a scenario consisting of the following components:

- $\sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} m_{ij}^{p1} A_{ijt}^{ps}$: Transportation cost of products from SLs to CCs in all periods.
- $\sum_{j \in J} \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} m_{jk}^{p2} B_{jkt}^{ps}$: Transportation cost of products from CCs to RFs in all periods.
- $\sum_{i \in I} \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} m_{ik}^{p3} D_{ikt}^{ps}$: Transportation cost of products from SLs to RFs in all periods.
- $\sum_{k \in K} \sum_{p \in P} \sum_{t \in T} \sum_{l \in L} o_k^p SS_{klt}^{ps}$: Fixed operating cost of RFs.
- $\sum_{p \in P} \sum_{i \in I} \sum_{t \in T} h^{p1} r_{it}^{ps} + \sum_{j \in J} \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} h^{p2} B_{jkt}^{ps} + \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} h^{p2} C_{jt}^{ps}$: Handling cost in CCs and in SLs.
- $\sum_{j \in J} \sum_{p \in P} o_c^p CC_j^{ps} + \sum_{k \in K} \beta_k^p GG_k^p$: Fixed cost of opening RFs and CCs like licensing cost.
- $\sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} \alpha_j f^p A_{ijt}^{ps}$: Rental cost of CCs
- $\sum_{j \in J} \sum_{p \in P} \sum_{t \in T} \pi_p^1 C_{jt}^{ps}$: Revenue from the sales of returned products to third party recyclers.
- $\sum_{j \in J} \sum_{p \in P} \sum_{t \in T} \pi_p^2 B_{jkt}^{ps}$: Revenue from the sales of recycled materials in RFs.

Constraints (2) ensure the assignment of each SL i to a CC j or RF k for each product type p in a given period t. Constraints (3) allow the assignment between SL i and RF k for product type p only if RF k is active for that product type. Constraints (4) prevent any product transfer from SL i to CC j if there is no assignment between them. Similarly, if there is no assignment between SL i and RF k, constraints (5) prevent any product transfer from SL i to RF k. Constraints (6) prevent opening of CC j if there are no SLs assigned to CC j. Constraints (7) make the assignment between SL i and CC j possible only if CC j is rented and active for product type p. Constraints (8) are used to allow the assignment of CC j to RF k only if RF k is active for product type p.

Constraints (9) are the balance equations for the flow in each CC j for any product type p. Constraints (10) prevent any assignment between CC j and RF k if there is no assigned SL i to CC j. Constraints (11) define the condition that each CC j can be assigned to only one RF k for each product type p. Constraints (12) allow the transfer from CC j to RF k for any product type p if the link between related CC j and RF k is active. Constraints (13) are used to meet the WEEE recycling targets related with each product type p. Constraints (14) check the total amount of product type p sent from CC j to third party recycler according to the established capacity of recyclers. Constraints (15) and (16) help to determine the active shifts of RFs constraints (15) control that the second shift can be active only if the first shift is active and constraint (16) control that the third shift can be active only if the second shift is active. Constraints (17) ensure that the first shift is active in period t whenever the RF k is open in that period. Constraints (18) control the total amount of product type p sent to each RF k in time period t according to the installed capacity of RF k. Constraints (19) check the status of each RF k for any product type p in time period t. Constraints (20) control the activation of RF k for product type p according to the links from SL i and CC j to RF k.

The proposed model is a stochastic location allocation model. Since the model is designed as a two-stage SMILP model, it is required that a large number of scenarios is taken into account. This is possible by using SAA which is a commonly used method in the literature.

The objective function of the problem considered in this study can be expressed as follows:

$$Z^* = \min_{\mathbf{a} \in A} c^T \mathbf{a} + \mathbb{E}[Q(\mathbf{a}, \varphi(s))] \tag{4.1}$$

where $\mathbf{a}$ denotes the first stage decisions and A is the feasible set for first stage decisions. The expected value function $\mathbb{E}[Q(\mathbf{a}, \varphi(s))]$ is approximated by sample average function $\sum_{n=1}^{N} Q\left(\mathbf{a}, \varphi(s^n)\right)/N$ where $Q\left(\mathbf{a}, \varphi(s^n)\right)$ represents the value of the second stage recourse problem corresponding to the first stage decisions $\mathbf{a}$ and parameter set $\varphi(s^n)$ including all other parameters.

The decision of opening new RF, GG_k^p is the only parameter specified as first stage decision. In summary, $Z^*$is equal to the minimum total cost occurred with the decisions at the first stage and expected value of the cost occurred at second stage for all scenarios $s \in S$.

4.2. Sample Average Approximation

There are various sampling-based approaches in the literature for stochastic programs with extremely large number of scenarios. They can be classified into two main groups as interior and exterior sampling methods (Verweij *et al*, 2003). Sample average approximation (SAA) is an exterior sampling method since the sampling is performed prior to the solution procedure. It can be defined as an approximation of the expected objective value of the optimization model by sample average estimates obtained with generated scenario sets. After solving the problem using these scenario sets, the first-stage solution of each scenario set is tested with a larger number of scenario set by solving only the second stage. The method continues by solving the following SAA problem repeatedly:

$$Z_N = \min c^T\mathbf{a} + \frac{1}{N}\sum_{n=1}^{N} Q(\mathbf{a}, \varphi(s^n)) \tag{4.2}$$

In scope of the methodology, there are *M* independent scenario sets denoted as *m*=1, 2, …, *M* each consisting of randomly generated scenarios. That are independently and identically distributed. The set of scenarios are called a *batch* in further explanations.

Let $Z_N^1, Z_N^2, \dots, Z_N^M$ denote the optimal objective values of each batch and $\hat{\mathbf{a}}^{\mathbf{1}}, \hat{\mathbf{a}}^{\mathbf{2}}, \dots, \hat{\mathbf{a}}^{\mathbf{M}}$ be the corresponding candidate solutions for the first stage decisions. The average of all these objective function values is denoted by

$$\bar{Z}_N = \frac{1}{M}\sum_{m=1}^{M} Z_N^m \tag{4.3}$$

Since $\mathbb{E}[Z] \leq Z^*$, $\bar{Z}_N$ provides a statistical lower bound on the the optimal value Z^* of the true problem (Ahmet and Shapiro, 2002). On the other hand, in the study of Shen *et al.* (2011), it is observed that $\bar{Z}_N$ is not always a lower bound because different sets of scenarios which may lead to different solution spaces of the problem. Nonetheless, $\bar{Z}_N$ is known as a good indicator for the quality of the solution obtained by the SAA method.

For any feasible first stage decision $\hat{\mathbf{a}} \in \boldsymbol{A}$, the upper bound for Z^* can be estimated by

$$\hat{Z}_{N'}(\hat{\mathbf{a}}) = c^T\hat{\mathbf{a}} + \frac{1}{N'} \sum_{n=1}^{N'} Q(\hat{\mathbf{a}}, \varphi(s^n)) \tag{4.4}$$

where $\{s^1, s^2, \ldots, s^{N'}\}$ is a scenario set of size N', where N' is chosen quite large and independent from the scenario sets used to generate $\hat{\mathbf{a}}$. This equation is solved M times and $Z^* = \min_{m=1,2,..,M} \hat{Z}^m$.

The variance of estimators $\bar{Z}_N$ and $\hat{Z}_{N'}(\hat{\mathbf{a}})$ can be calculated as follows:

$$\hat{\sigma}^2_{\bar{Z}_N} = \frac{1}{(M-1)M} \sum_{m=1}^{M} (Z_N^m - \bar{Z}_N)^2 \tag{4.5}$$

$$\hat{\sigma}^2_{\hat{Z}_{N'}(\hat{\mathbf{a}})} = \frac{1}{(N'-1)N'} \sum_{n=1}^{N'} \left(c^T\hat{\mathbf{a}} + Q\big(\hat{\mathbf{a}}, \varphi(s^n)\big) - \hat{Z}_{N'}(\hat{\mathbf{a}})\right)^2 \tag{4.6}$$

The quality of the solution is evaluated by means of percent gap defined as

$$\text{Gap} = 100 \text{ x } \frac{Z^* \text{-} \bar{Z}_N}{\bar{Z}_N} \tag{4.7}$$

In the literature, it is known that the effect of number of batches *(M)* and sample size *(N)* should be adjusted to improve the performance of the SAA method. From the study of Shen *et al*. (2011), it can be said that an increase in *M* does not affect the solution too much while an increase in *N* can improve the quality of the solution. The effect of these changes is analyzed in detail in the section titled as computational results.

5. SETTING PARAMETER VALUES BASED ON A CASE STUDY

As stated before, the company has an operation in place for WEEE collection and management according to the responsibility defined in the directive. Since current active CCs and RFs of the company will continue to exist in the network, they are introduced to the model as an initial condition. As it is defined before, capacity expansion is possible for RFs by increasing the number of active shifts and it is specified that two shifts can be available for any active RFs. In Table 5.1, there is a summary of current active CCs and RFs in different cities with corresponding product categories.

Table 5.1. The summary of current settlement of the company

Product Category	City 1	City 2	City 3
1	CC, RF	-	-
2	-	RF	CC
3	CC, RF	-	CC

As a white goods producer, the company is responsible for first three categories shown in Table 5.2. Hence, these three categories are included into the model while checking optimal condition for the current system. Additionally, there are recycling target rates specified in the Turkish WEEE directive. In this directive, recycling targets are given in terms of weight based on type of the product. In the current collection system, return quantities are known for each product type instead of total weights. Therefore, we use the average unit weight of each product type given in Table 5.2 to convert the quantities into weights.

Since the company has an operation in place for WEEE collection and recycling system for almost two years, data have been accumulated during this period. According to this data, there is a significant difference between the theoretical value shown in Table 5.2. and the realized value.

Table 5.2. Average unit weights for products groups

EEE Categories	Average Unit Weights (kg)
1. Refrigerators/Coolers/Air conditioner Devices	68.2
2. Home Appliances (Washing machine, Dishwasher, Oven, Hob, Dryer etc.)	55.2
3. TV and Monitors	31.7
4. Informatics and Telecommunication Equipments	2.5
6. Small Home Appliances, Electrical ve Electronical Devices	5.7

The realized values shown in Table 5.3. are calculated with respect to realized collected amounts per each product category during past two years. The reason of the difference can be explained that different types of product having different unit weights are classified into the same category and the distribution of these different products in total returned quantity directly affects the realized average unit weight. Therefore, we use realized average unit weights shown in Table 5.3 in our study instead of the values stated in the directive.

Table 5.3. Average unit weights for EEE products collected during last 2 years

EEE Categories	Realized Average Unit Weights (kg)
1. Refrigerators/Coolers/Air conditioner Devices	68.0
2. Home Appliances (Washing machine, Dishwasher, Oven, Hob, Dryer etc.)	35.0
3. TV and Monitors	32.0

According to the current directive, there are two options for used products after they are transported to a CC. They are either shipped to a RF or third party recycler. Therefore, candidate locations for CCs are determined by considering the existing sites of licensed third party recyclers. In Turkey, there are currently 49 licensed recyclers located in 17 different cities. 11 out of these 17 cities are selected for the set of candidate CCs as considering the density of the population. The list of available licensed firms in Turkey and their distribution at different cities can be seen in Table A.1 in Appendix A.

According to the WEEE directive, some product types need to be transported with special licensed trucks between CCs and RFs. This creates an additional cost for the system. To keep this cost at a minimum, candidate locations for RFs are also selected from candidate locations of CCs. Additionally, cities of current RFs of the company are also included within the set of these candidate locations. As a result, five cities out of these 11 cities are specified as the set of candidate RFs.

Transportation of WEEE is outsourced by the company to the logistics companies every year. The unit shipment cost is defined for each product type separately by considering the distance between cities. There are different cost figures for the transportation of three different product types from SLs in 81 cities to CCs located in eleven potential cities and RFs in five potential cities. This cost depends on the agreement the company makes with logistics companies. Because of the privacy policy, the company provide the masked data about this transportation cost values.

With the help of existing data during the past two years, the share of different cost items is summarized in the chart below. It can be easily seen that transportation cost has the biggest share in total cost of WEEE collection and recycling system.

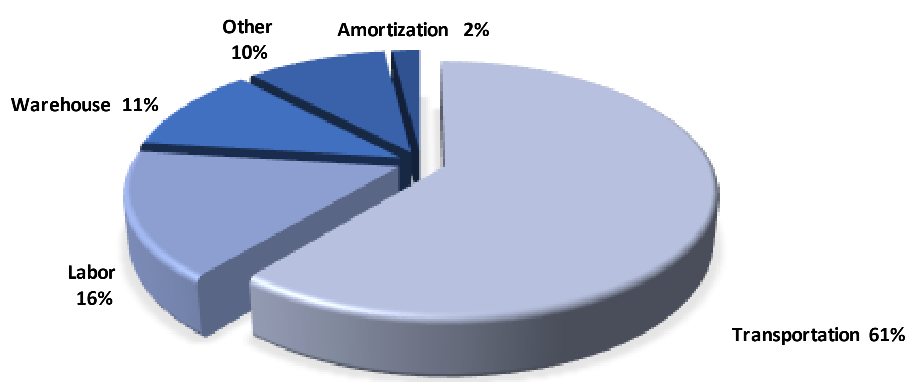

Figure.5.1. The share of cost components during the past two years.

The required capacity level for RFs is an important decision in the proposed model. Since there are installed capacities for open facilities, capacity expansion can be realized by increasing the number of shifts. In addition, it is also possible to open new facility in other candidate locations. At that point, the fixed cost of opening a new RF is defined by considering the product categories and defined capacity for each shift. Although it is assumed that there is no capacity constraint for a CC, there exist rental costs in each candidate city. All other cost items are calculated with the help of company experience in this field. (fixed operation costs, rental costs, shift change costs, fixed cost of opening a RF and so on)

5.1. Estimation of Return Quantities

Turkey has recently started to implement the WEEE directive and therefore there are limited data about the total return quantities till now. The current WEEE collection system of the company has been active for two years and the return quantities for each product type are known only for these years. In fact, two-year data is not enough to make any statically estimation for coming years and there is need to create another reasonable method to estimate return quantities in the future.

There are various methods developed in the literature for the estimation of the amount of used products returned. These methods can be classified into two groups: an estimation with the help of trend analysis in historical sales quantities and the consideration of lifetime for products available in the market. For example, Ling *et al.* (2012) study on the estimate of future obsolete streams in China. They firstly model the distribution of life cycle for home appliances (HA) and then generate the future stocks. Before developing a prediction model based on material flow analysis, the life cycle of HA is defined. Then per the distribution for the life cycle time of HA, they generate the future discarded amount of HA for coming years. Rather than focusing on the estimation of lifetime distribution of HAs, it is also possible to define estimation model with considering the sales amounts and average life period. As an example, Liu *et al.* (2006) roughly estimate the waste amount from the sales amount with some assumptions on the average length of use.

It is known that, consumers in Turkey traditionally prefer to give their EOU but workable EEEs to acquaintances in need. On the other hand, producers introduce campaigns like ‘bring the old one and get the new one’ to attract people for changing their white goods before the EOL. With the help of these campaigns, consumers are incorporated into WEEE collection system automatically. But there is again no accurate figure about the effect of such campaigns. Additionally, it is a fact that the economic condition of the country is critical to have enough power to lead the people changing their products before EOU. Consumers may be involved in WEEE collection system with changing their EOU or EOL products. Consumer awareness about recycling activities is a major factor to get them into collection system for used products. All these facts are enough to understand the level of uncertainty in the return rate of used products to the WEEE collection systems.

Since the producers are specified as the main responsible agent for recycling to meet WEEE targets in Turkey, it can be considered that producers will try to reach return quantities at least to meet these targets. On the other hand, these targets are specified with the rate in yearly sales quantities and there is no accurate data about sales in the future. But, there is enough historical data to get reasonable estimations for sales quantities in the future. Therefore, the prediction method of return amounts is developed as based on estimated sales quantities.

The penetration rate is calculated by the function of the number of people who buy a product category and the size of the relevant market. Installed base shows the total number of company’s products in the market or country at a period.

Since the producer has a responsibility for first three product categories listed in Table 5.1, we do all our analyses on these items. Here, there are different types of product included in each these categories. In detail, product category one includes refrigerators and coolers. In category two, there are white goods such as home laundry (washing machines, tumbler dryers), dishwashers, large cooking appliances (built-in or freestanding ovens, hobs) and vacuum cleaners. Lastly, product category three includes in-home consumer electronics like TVs and monitors. There are different penetration levels and market shares of the company for each of these product types.

Therefore, installed base and replacement sales are calculated for each product type and then combined according to the definition of product categories in the WEEE directive.

The information of market size, penetration rates and market shares of the company are obtained from historical data available at the website of one independent provider of strategic market research company, Euromonitor International. With the help of 10-year historical data, the number of households in Turkey for next five years is calculated by trend analysis shown in the following graph.

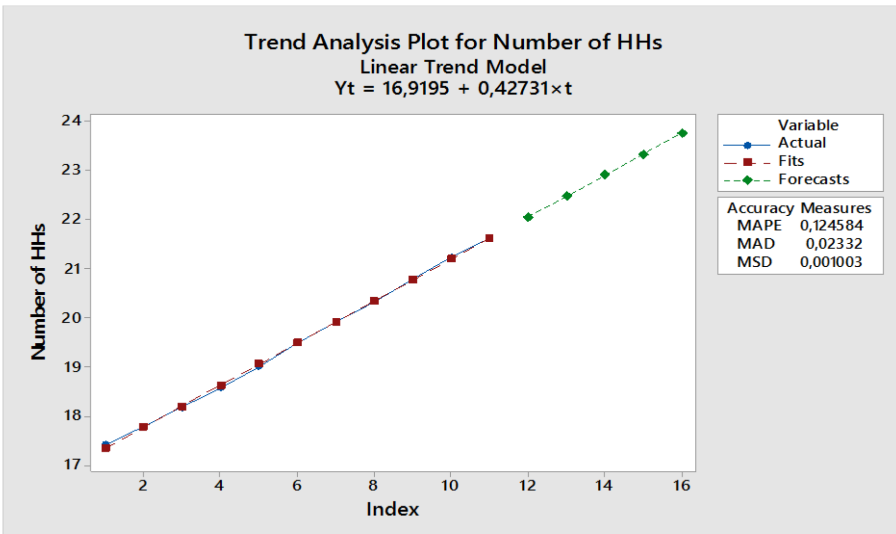

Figure 5.2. Trend analysis graph for number of HHs in Turkey

Data on the yearly sales volume for each product type are available. By the help of trend analyses, three different model possibilities are checked to decide the most convenient prediction model. These models can be listed as linear, quadratic and exponential trend models. With the comparison of the mean absolute percentage error (MAPE), median absolute deviation (MAD) and mean signed deviation (MSD) values in these plots, the suitable model is decided for each analyzed product type. MAPE, MAD and MSD values can be defined as statistics to compare the fits of different forecasting methods and smaller values usually indicate a better fit of the model. All trend analyses graphs are available in Appendix B.

After these analyses, penetration rates and market shares of the company for each product type are calculated as in following tables.

Table 5.4. Estimated penetration rates in years of 2017-2021

		Penetration rates (%)			
		2017	2018	2019	2020
Category 1	Refrigerator, Coolers	100.1	100.4	100.5	100.7
Category 2	Dishwasher	54.5	57.5	60.4	63.4
	Home Laundry	73.2	76.2	78.9	81.4
	Large Cooking Appliances	34.0	34.8	36.6	37.5
	Vacuum Cleaner	93.3	95.9	96.0	96.1
Catefory 3	In-home Consumer Electronics	97.0	97.7	98.3	98.5

Table 5.5. Estimation of company shares in years of 2017-2021

		Company Shares (%)			
		2017	2018	2019	2020
Category 1	Refrigerator, Coolers	39.4	39.6	39.8	40.3
Category 2	Dishwasher	42.1	43.4	45.3	48.0
	Home Laundry	65.0	64.3	63.0	62.0
	Large Cooking Appliances	28.2	28.5	28.8	29.0
	Vacuum Cleaner	16.1	15.5	14.9	14.3
Catefory 3	In-home Consumer Electronics	16.0	16.1	17.5	19.6

On the other hand, target collection rates are given in the WEEE directive of Turkey for each category and producers are responsible for reporting the collection of WEEE at least to meet these targets. But it is still uncertain how much these targets can be achievable in coming years. Therefore, it is required to observe system behavior with the change in return rates.

Additionally, as mentioned before, sales campaigns affect the consumers involved in WEEE collection systems. From the previous experiences of the company, it is known that the product mix, involved in WEEE collection system, can change according to the content of marketing activities. Sales campaigns are an incentive for consumers to change their white goods before coming to EOL.

By considering all these uncertainties, the proposed model is designed as SMILP. To solve the model by the help of SAA method, it is required to consider different number of scenario sets. These scenario sets considered in each run of SMILP are generated with the following calculation:

Return = WEEE target rate* Sales Volume* Random Number

where Sales Volume is estimated by the help of statistical analysis on historical data for past 10 years and WEEE target collection rates are taken from the directive for coming years. To generate random number, the uniform distribution with the range of [-1,1] is used and variation is differentiated with 1,2,3,4 sigma values. Estimated yearly sales volume for next four years is given in Table 5.6 at below.

Table 5.6. Estimated sales volume for each category during 2017-2020

	2017	2018	2019	2020
Category 1	1,256,123	1,314,835	1,370,224	1,424,392
Category 2	3,340,971	3,491,905	3,596,255	3,687,061
Category 3	607,743	626,805	712,846	810,972

We should generate various scenarios for different number of batches *(M)* and sample size *(N)* values. Each set of scenarios is generated as independent and identically distributed.

6. COMPUTATIONAL RESULTS

6.1. The Comparison of Single-Product and Multi-Product Modeling

The proposed model can be accepted as usable for both single and multi-product systems. Since all parameters related with product types are given as independent to each other, there is no condition to create any dependency between decisions for different product types. To demonstrate this independency, the optimization model is separately run for each category and the combination of 3 WEEE categories. The study is done with the available data about return amounts for the years of 2015-2016. Since we use available realized data, there is no uncertainty into the model. Thus, the optimization model can be deterministically run. After comparing the result of each run, it is seen that results are totally same for both cases. The comparison table for objectives values that can be checked as at below Table 5.7.

Table 6.1. The comparison of Single-Product and Multi-Product Models

		Objective Value
Single-Product Model	p_1	-170,158.14
	p_2	-19,650,200.00
	p_3	108,097.32
Total		-19,712,260.82
Multi - product Model		-19,712,260.82

The detail comparison with decision parameters such as CCs and RFs for each run can be checked in Appendix C. The only difference between these two models is ease of application to get same results. Multi-product modelling has an advantage to present the results for all product categories in together. Additionally, even though the company is currently able to provide all parameters for each product type separately, all activities in RLN cannot be done separately. In case of having such dependency, single-product model will not be efficient tool for users.

Since one main target of this study is to provide a support tool for decision makers, it is important to consider the model efficiency in changing conditions. By considering all these options, we continue with multi-product model in our further studies.

6.2. Solution for Multi-Product Modelling with SAA

The model is designed as two-stage SMILP and SAA is used as a solution method for this proposed model. The model is taking the decision of opening new RFs at first stage and searching the solution for the rest of decision variables at second stage by considering the first stage decisions. After determining the parameter values, the defined model is solved with the help of the GAMS 24.8.5 by using Gurobi 7.0.2 as a solver.

In the literature, there are some studies to check the impact of replication number*(M)* and number of scenario*(N)* on the performance and solution of the SAA. As an example, Shen *et al.* (2011) has one important study to examine the effect of the M and N. As a result of their study, it is shown that increasing number of batches does not affect the solution quality too much while increasing the CPU time in each run. Therefore, it is not easy to apply SAA for large number of batches. Similarly, Aydin and Murat (2013) has a comparison of SAA results for different M and N values in their study. According to their experiments, it is stated that increasing number of scenarios improve the quality of the solution and there is remarkable relation between them. The gap value calculated by (27) is used as performance indicator in all comparison. By considering these studies, SAA is performed with M=10 and N= {10,20,30} for base case. In all these designed experimental study, it is aimed to search computational and solution quality performance of the proposed SAA method to solve the proposed SMILP.

By considering all possibilities of sample size N, after the solution of ten different batches, the result in each run can be summarized with the optimal value and first stage decisions shown in Table 6.1 as follow:

Table 6.2. Runs from SAA for different number of scenarios

	N=30		*N*=20		*N*=10	
Batch	Objective Value	First Stage Decision	Objective Value	First Stage Decision	Objective Value	First Stage Decision
m		$\{p_1;p_2\}$		$\{p_1;p_2\}$		$\{p_1;p_2\}$
1	-17,544,033	{1;2}	-15,484,586	{1;2}	-17,884,971	{1;2}
2	-17,818,558	{1;2,10}	-19,111,914	{1;2}	-17,290,742	{1;2,7}
3	-15,983,755	{1;2}	-16,885,774	{1;2,5}	-14,945,031	{1;2,10}
4	-16,222,519	{1;2}	-18,317,294	{1;2,10}	-18,264,859	{1;2}
5	-15,645,839	{1;2,5}	-18,402,267	{1;2,10}	-17,472,633	{1;2}
6	-17,282,048	{1;2}	-16,780,932	{1;2}	-17,629,238	{1;2,5}
7	-14,934,708	{1;2,7}	-17,747,195	{1;2}	-15,936,930	{1;2,5}
8	-18,544,442	{1;2,7}	-16,983,695	{1;2}	-18,642,091	{1;2}
9	-16,312,194	{1;2}	-15,527,883	{1;2}	-15,889,049	{1;2}
10	-18,561,460	{1;2,10}	-16,555,889	{1;2,7}	-17,591,447	{1;2}
Average	-16,884,956		-17,179,743		-17,154,699	

In these results, there are only 4 possible sets for first stage decision as $\{p_1,p_2\}=\{1;2\}$,$\{p_1,p_2\}=\{1;2,5\}$, $\{p_1,p_2\}=\{1;2,7\}$ and $\{p_1,p_2\}=\{1;2,10\}$. By generating a large number of scenarios N'=60, second-stage decisions and the optimal value of each batch are computed corresponding to each first-stage decision. This operation is repeated for ten different replications and the replication with the best optimal value is taken to give the best first-stage decision configuration. In the last step of the SAA procedure, the problem is solved with this configuration and a large number of scenarios as N''=120. Optimal values for each possible set of first stage decision are resulted as in Table 6.2 for N' and N'' scenarios.

Table 6.3. Runs of different set of first stage decision for large number of scenarios

First Stage Decision	The optimal value	
$\{p_1;p_2\}$	$N' = 60$	$N'' = 120$
{1;2}	NA	
{1;2,10}	-16,252,990	-15,916,751
{1;2,5}	-16,252,615	
{1;2,7}	-16,247,813	

At the end, the gap between the optimal value Z^* for N''=120 and the average of optimal values obtained for ten batches at first step is calculated to assess the quality of the solution. It is computed by100x($(Z^*$-$\bar{Z}_N)/\bar{Z}_N$). All gap values are summarized in Table 6.3.

Table 6.4. Percent values GAP different N values

First Stage Decision	N'=60			N''=120
$\{p_1;p_2\}$	N=10	N=20	N=30	N=30
{1;2,10}	5.26%	5.39%	3.74%	5.73%
{1;2,5}	5.26%	5.40%	3.74%	
{1;2,7}	5.29%	5.42%	3.77%	

Recall that $\bar{Z}_N$ provides a lower statistical bound for the optimal value Z^* and therefore all gap values are positive. In this study, the gap, less than 10%, is showing that the obtained objective value is close to the optimal value. Since the first stage decision set of $\{p_1$-City 1; p_2-City 2,5$\}$ has minimum gap value with N'=60 and N''=120, the objective value obtained for this case is closest one to the optimal value.

In addition to the first-stage decision of opening RFs, there are many second-stage decisions in the problem and it is not possible to get one result. On the other hand, there are some system behaviors that can be observed in each run in compliance with the change in input parameters. Observations:

- Under base case conditions, the system tends to work with the closest third party recyclers to CCs instead of working with RFs since logistics cost has an important effect in system efficiency. For the same reason, even though there is free capacity in open RFs, return products might be sent to third party recyclers to minimize total cost of the system.

- As stated before, direct shipment from SLs to RFs is possible for some type of products. This means having less transportation cost for these items. It is seen from the results that the system naturally benefits from this advantage instead of using CCs as transfer node.

- In the light of statistical analysis for return amounts, there is an expectation to have continuously increase in total return amounts. Therefore, there is a need to increase total recycling capacity of the system. This is possible by opening new shifts at RFs and starting to work with new third party recyclers in different cities in coming years.

- It is required to increase active number of CCs in the system. Their locations are chosen according to the distribution of return amounts in regions. Since there is an additional logistics cost after the transportation from CCs, CCs are mostly chosen in cities where third party recyclers are available.

- By considering all possible increase in total return amount by years, there is no need to increase the number of current available RFs. Instead of this, it is better to have third party recyclers options as widely spread among Turkey. It is also possible to expand the available capacities of RFs by opening new shifts.

7. SENSITIVITY ANALYSIS

7.1. Sensitivity to the Change of Available Capacity in RFs and Third Party Recyclers

Since the system is designed as two stage SMILP and the first stage decision is a decision of opening RFs, it is clearly known that possible capacity levels for RFs and third party recyclers will directly affect this decision. Therefore, the system performance is firstly examined against the change in available capacities for any RFs and third party recyclers. To this end, the number of shifts is increased from two to three, and the total capacity of third party recyclers is assumed to be infinite. After these changes, SAA is applied to get the solution of SMILP under new capacity conditions. After applying SAA, the results can be compared with those of the base case. They are given in Table 7.1.

Table 7.1. The comparison of the result of new defined case with base case

	Base Case (M=10, N=30)		3 shifts in RFs & Infinite capacity in third party recyclers (M=10, N=30)	
	Objective Value	First Stage Decision $\{p_1;p_2\}$	Objective Value	First Stage Decision $\{p_1;p_2\}$
Best	-18,561,460	{1;2,10}	-20,944,718	{1;2}
Average	-16,884,956		-18,543,396	
N=60	-16,252,990	{1;2,10}	-18,454,666	{1;2}
N=120	-15,916,751	{1;2,10}	-18,063,646	{1;2}
GAP (%)	5.73%		2.59%	

After removing the capacity limitation into the model, the required time to reach any solution is decreased. As it is observed in the base case, the system has a tendency to work with closest third party recyclers to CCs. Enhancing third parties' capacity infinitely helps to increase total return amounts sent to these recyclers instead of RFs. This leads to decrease in total transportation cost and therefore there is clear increase in objective value of the problem for different number of scenarios.

7.2. Sensitivity to the Changes in the Set-up Costs and Rental Costs

The proposed model is designed to minimize total cost of the system and there are several cost items addition to transportation cost. In this section, we check the sensitivity of the network design against any change in the fixed cost of setting new RFs and CCs. For this purpose, two scenarios are applied separately to observe changes in the system. Firstly, the rental cost for CCs is increased with 25% and SAA is applied for the new case. Secondly, the fixed cost of opening new RFs is decreased with 25% and the results at the end of SAA for both case are compared with their objective values and shown in Table 7.2.

Table 7.2. The results after changing rental cost for CCs and open cost for RFs

Case: 25% increase in rental cost of CCs (M=10, N=30)			
	Objective Value	First Stage Decision $\{p_1;p_2\}$	GAP(%)
Lower bound	-17,254,695	{1;2,5}	8.47%
N=60	-16,123,589	{1;2,5}	
N=120	-15,792,718	{1;2,5}	
Case: 25% decrease in fixed opening cost of RF (M=10, N=30)			
	Objective Value	First Stage Decision $\{p_1;p_2\}$	GAP(%)
Lower bound	-17,760,267	{1;2,7}	7.61%
N=60	-16,753,402	{1;2,7}	
N=120	-16,409,224	{1;2,7}	

From the results for both cases, it can be stated that fix cost occurring with opening new RFs or CCs influences the decision parameters of the proposed model. After such a big change in different cost parameters, there is a change in the location of second RF in an optimal solution. In general mean, in any case, there is a need to increase the total capacity of RFs for product category 2 while having enough capacity in RF for product category 1.

7.3. The Analysis of the Effect of the Discount Factor

Note that the base case model is decomposable into product types since cost parameters of one product category do not affect those of other categories. According to the current agreement of the company with the logistics firm, unit transportation costs are defined separately for each product. But it is known that the delivery for different kind of products can be done together. With the consideration of real life conditions, it is nearly impossible to manage the transportation of each product category separately and therefore RL system per each category should not be assumed fully independent from each other. It is known that there are many studies in logistics sector to increase the system efficiency with the combined transportation of different materials such as milk run systems. Similarly, logistics companies can benefit from the co-transportation to decrease the total cost of the system. Such possible relation between different product categories may influence decision parameters defined in the proposed model and also change the result relatively. To this end, discount factor is incorporated into the proposed model as motivating the system for the combined transportation of different product categories from SLs to CCs. Denoting the discount factor by μ, the following constraints are added to the model:

$$nDF_{ijt}^{ps} \leq \sum_{p \in P} X_{ijt}^{ps} \tag{7.1}$$

$$\beta_{ijt}^{ps} = 1 - \mu DF_{ijt}^{ps} \tag{7.2}$$

where n is equal to the number of product types considered in the modeling and DF_{ijt}^{ps} is a binary variable which is equal to one if any CC j is active for all types of products under scenario s in year t.

β_{ijt}^{ps} is the factor that affect total transportation cost from SL i to CC j for all returns. The new objective function for the proposed model is by adding this factor as follow.

$$\beta_{ijt}^{ps} \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} m_{ij}^{p1} A_{ijt}^{ps} \tag{7.3}$$

The stochastic optimization model is solved again with discount factor by using the SAA. Since the best performance is seen with M=10 and N=30 for base case, the new defined case is solved for same M and N values. Additionally, same generated batch of return scenarios are used to have correct comparison with the result of base case.

At first step, it is observed that the required time to reach any solution is increased considerably. Additionally, there are some replications with no solution within the defined maximum time as execution time of the model. In summary, it is getting hard to reach a solution in this new situation. The reason behind this change can be stated that the complexity of the model is increased by adding new binary variable with five indices and some additional constraints relatedly. For the replication with any results at first step, the second step is tried to apply with N'=60. This operation is repeated for ten times with different batches and it is not possible to reach any result within defined execution time for the model. Therefore, the performance of SAA is checked with the calculation of gap between the best optimal value and the average of optimal values resulted in ten batches at first step.

There is a comparison of objective values in each batch with their average and therefore there are naturally some negative gap values as seen in Table 7.3. The important issue in that calculation is the magnitude of these gaps and it is seen that all of them are less than +/- 10% except one case. When the situation in that batch is analyzed, it is seen that the objective value at the end of the defined running time is not enough close to the optimal solution and there is big relative gap at the end of the run within the defined execution time, 15,000 seconds. Therefore, the objective value of batch 10 is not included in any calculation or comparison in this evaluation.

Table 7.3. The summary of the results for the model with discount factor

M=10, N=30			
Batch m	Objective Value	First Stage Decision $\{p_1;p_2\}$	Gap(%)
1	-18,107,833	{1;2}	-4.35%
2	NA	NA	
3	-16,488,821	{1;2}	4.98%
4	-17,036,748	{1;2}	1.82%
5	NA	NA	
6	-18,292,951	{1;2}	-5.42%
7	NA	NA	
8	NA	NA	
9	-16,836,268	{1;2}	2.98%
10	-12,596,601	{1;2}	27.41%
Average	-17,352,524		

In general mean, since the gap values are at about 5% at most and SAA is still enough good solution approach for the stochastic model with the discount factor. To understand the effect of the discount factor, the result in each batch can be compared with the related result get in base case. To this end, as it is shown in Table 7.4, the optimal value is getting better in case of considering common transportation for different type of products.

Table 7.4. The comparison of the results for base case and discount factor

	Base Case		Discount Factor	
Batch m	Objective Value	First Stage Decision $\{p_1;p_2\}$	Objective Value	First Stage Decision $\{p_1;p_2\}$
1	-17,544,033	{1;2}	-18,107,833	{1;2}
2	-17,818,558	{1;2,10}	NA	NA
3	-15,983,755	{1;2}	-16,488,821	{1;2}
4	-16,222,519	{1;2}	-17,036,748	{1;2}
5	-15,645,839	{1;2,5}	NA	NA
6	-17,282,048	{1;2}	-18,292,951	{1;2}
7	-14,934,708	{1;2,7}	NA	NA
8	-18,544,442	{1;2,7}	NA	NA
9	-16,312,194	{1;2}	-16,836,268	{1;2}
10	-18,561,460	{1;2,10}	-12,596,601	{1;2}
Average	-16,884,956		-17,352,524	

After all analyses, having any additional dependency between different type of products increase the complexity of the model. It increases the required time to get any solution. On the other hand, it is required to open less number of RFs for the case of doing common transportation for different type of products.

8. CONCLUSION AND FUTURE RESEARCHES

In this study, RLN as open loop, capacitated, multi-echelon, multi-product with uncertain return quantity is discussed and two-stage SMILP is used to take decisions for the number of CCs and RFs with their locations to collect used products from services as minimizing the total cost of the system in case of observing different return scenarios. SAA method is used as a heuristic method to reach a solution for this defined stochastic model. The proposed model is examined with the help of the case study done with the cooperation of one major white goods producer in Turkey. This company is also implementer of some recycling activities with its own settlement to provide WEEE targets of the directive in Turkey valid by the year of 2012. Therefore, the proposed system is designed as decision support system for the company and all decision parameters are shaped accordingly. With the aim of improving the current efficiency of RLN, the model is set to minimize total cost of the system while setting links between SLs, CCs, and RFs. Additionally, there is an appropriate allocation of returned products to RFs and third party recyclers. The current collection and recycling operations of the company is checked whether if it is enough to meet requirements against any remarkable change in possible return quantities. By using two stage SMILP as an optimization approach, the system is examined for a wide range of different return scenarios. As a solution method for defined stochastic model, SAA is used and “GAP (%)” value is defined to check the performance and the quality of the solution getting by this method. Addition to the base case defined at the beginning of the experimental study, different cases are generated to observe the change in the system’s behavior and the performance of SAA for various cases. Since we can get gap values less than 10% in each generated case, SAA is an appropriate method to provide enough good solution for the proposed model. With the experiments with large number of return scenarios for next 4 years, it is seen that current settlement of the company for RFs is enough but there is certain need to increase number of CCs with possible third party recyclers relatively. To have reasonable computation time in each run, this study is done by multi-product system for multi-period on yearly basis. In real life, all possible operations in such WEEE collection and recycling system may not work in annual period.

Therefore, further analyses in the scope of this study can be done by decreasing the length of the period. It is possible to apply same optimization model in quarterly or monthly basis to accommodate the features of real life better. Even though the proposed model is designed for multi-product systems, by the help of scenario analysis, it is seen that possible dependency between different type of products increase the length of required time in SAA considerably. For the case of having such increase in the complexity level of the model, one possible search area can be about adaptation of the SAA procedure to get the result within reasonable execution time.

Addition to these improvements, there are several avenues for future research. Firstly, other possible heuristic approaches to solve such stochastic optimization models can be investigated. Secondly, addition to the method for searching the optimal value of the model, the simulation model can be developed to provide better traceability of each decision parameters defined in the model. Lastly, the proposed model can be improved to be used for rolling horizon time period and thereby it is possible to continuously query the decision parameters of the system for coming years.

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APPENDIX A: SUMMARY OF RECYCLING SYSTEM IN TURKEY

Table A.1. The distribution of licensed third party recyclers among different cities

City	Number of Third Party Recyclers
ANKARA	10
ANTALYA	1
BALIKESİR	1
BOLU	1
BURSA	5
DENİZLİ	2
ESKİŞEHİR	4
HATAY	1
İSTANBUL	8
KIRIKKALE	1
KOCAELİ	7
MANİSA	2
MARDİN	1
NEVŞEHİR	2
NİĞDE	1
SAKARYA	1
TOKAT	1
TOTAL	**49**

Table A.2. Enumeration of cities for potential collection centers

Set of potential Collection Centers	
City	**Index**
ESKİŞEHİR	1
BOLU	2
İSTANBUL	3
KOCAELİ	4
BURSA	5
DENİZLİ	6
ANKARA	7
TOKAT	8
MARDİN	9
MANİSA	10
ANTALYA	11

Table A.3. Enumeration of cities for potential recycling facilities

Set of potential Recycling Facilities	
City	**Index**
ESKİŞEHİR	1
BOLU	2
BURSA	5
MANİSA	10
ANKARA	7

APPENDIX B: TREND ANALYSES

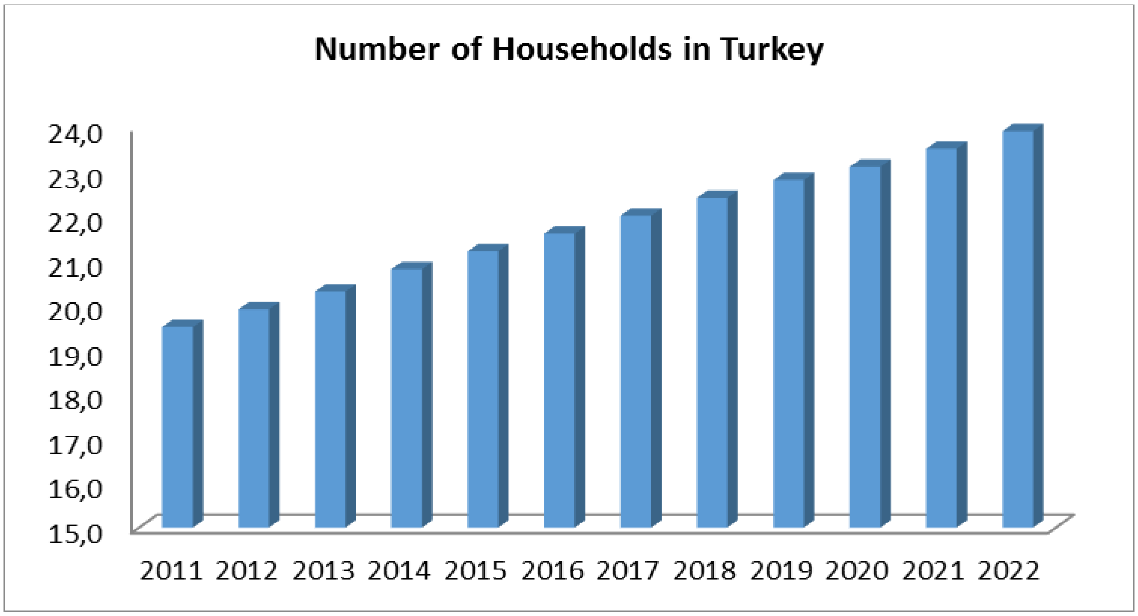


Figure B.1. Estimation for Number of Households in Turkey

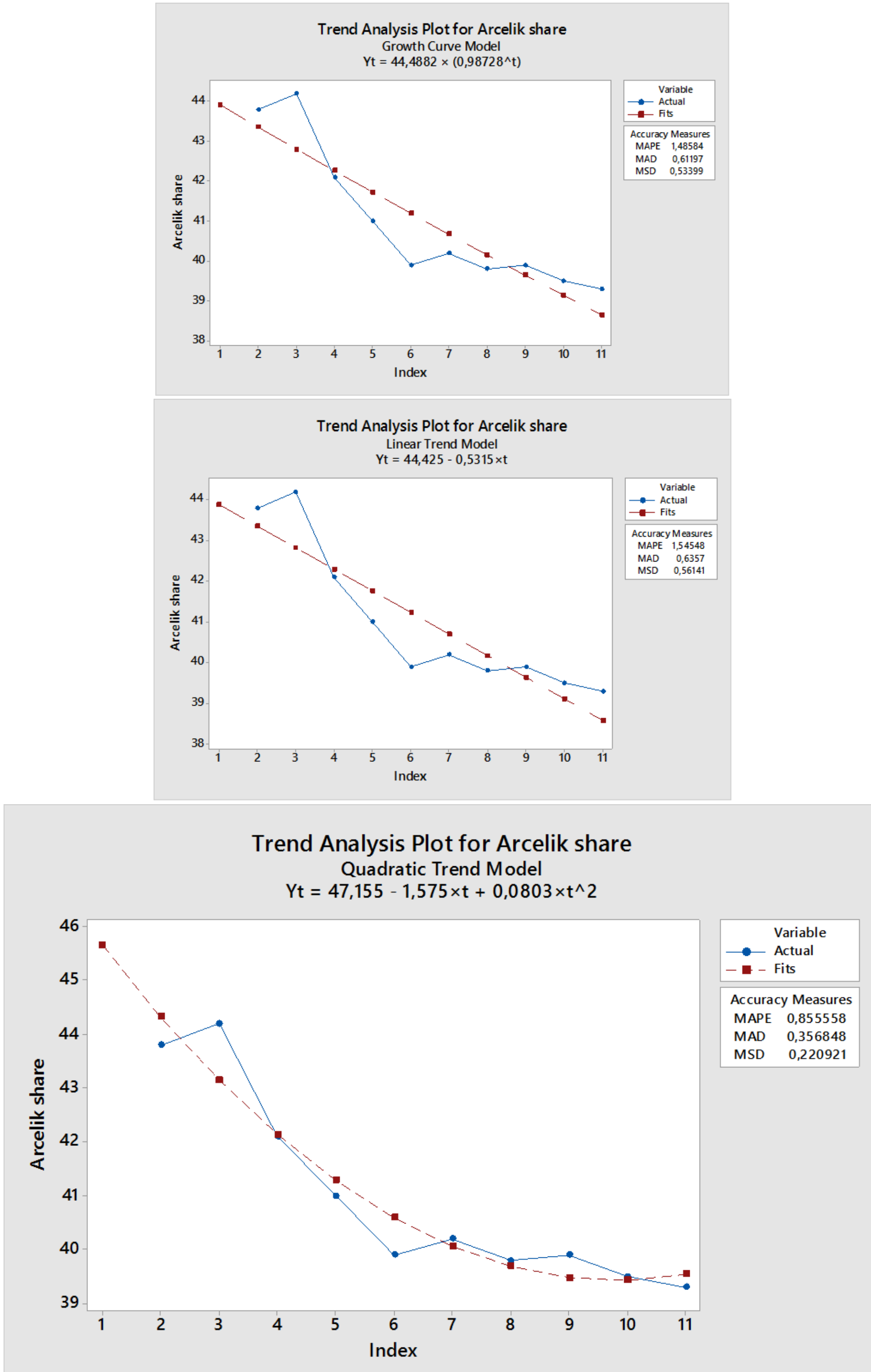


Figure B.2. The company's market share in cooling business

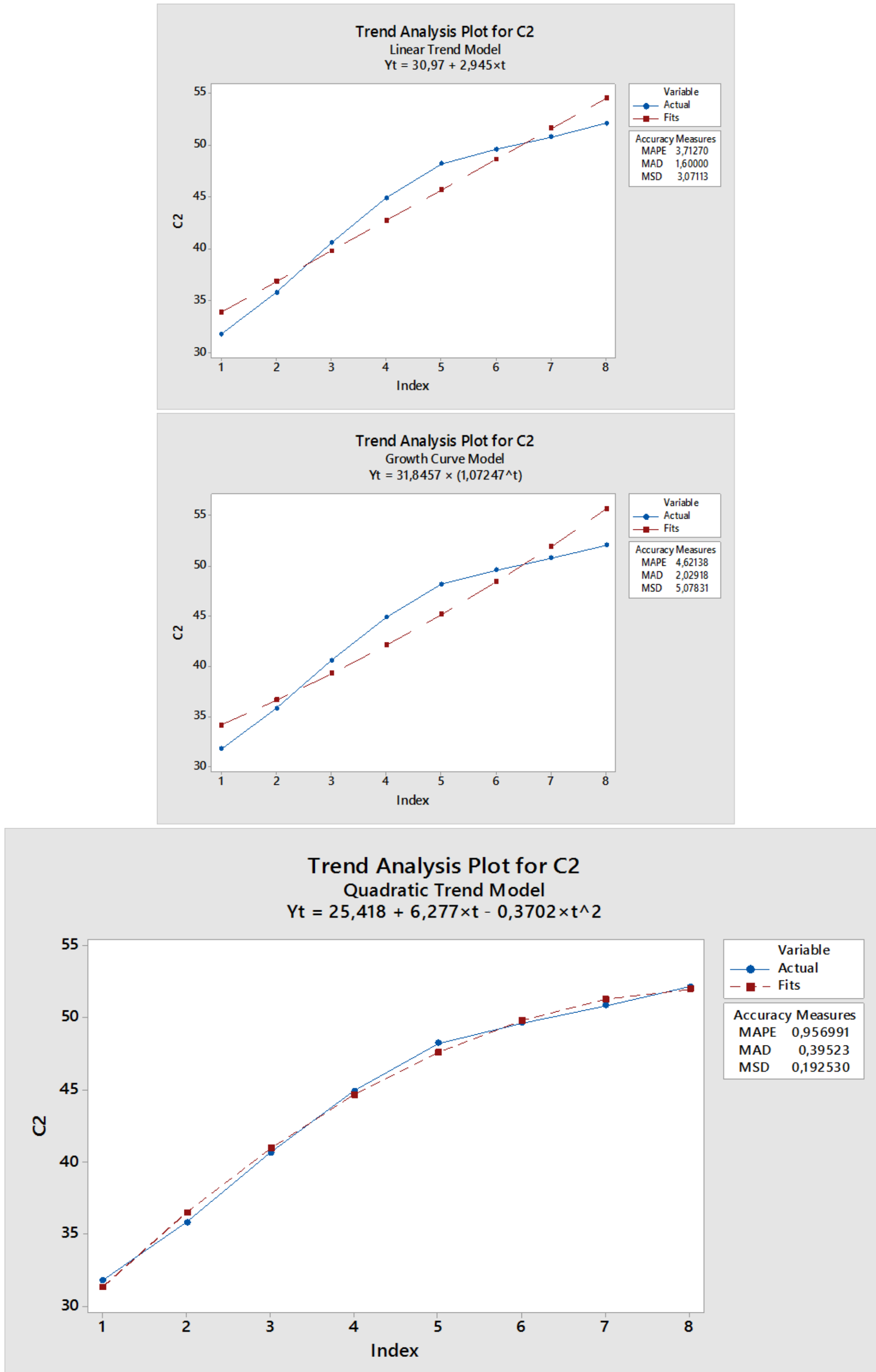


Figure B.3. The penetration level change in dishwasher business

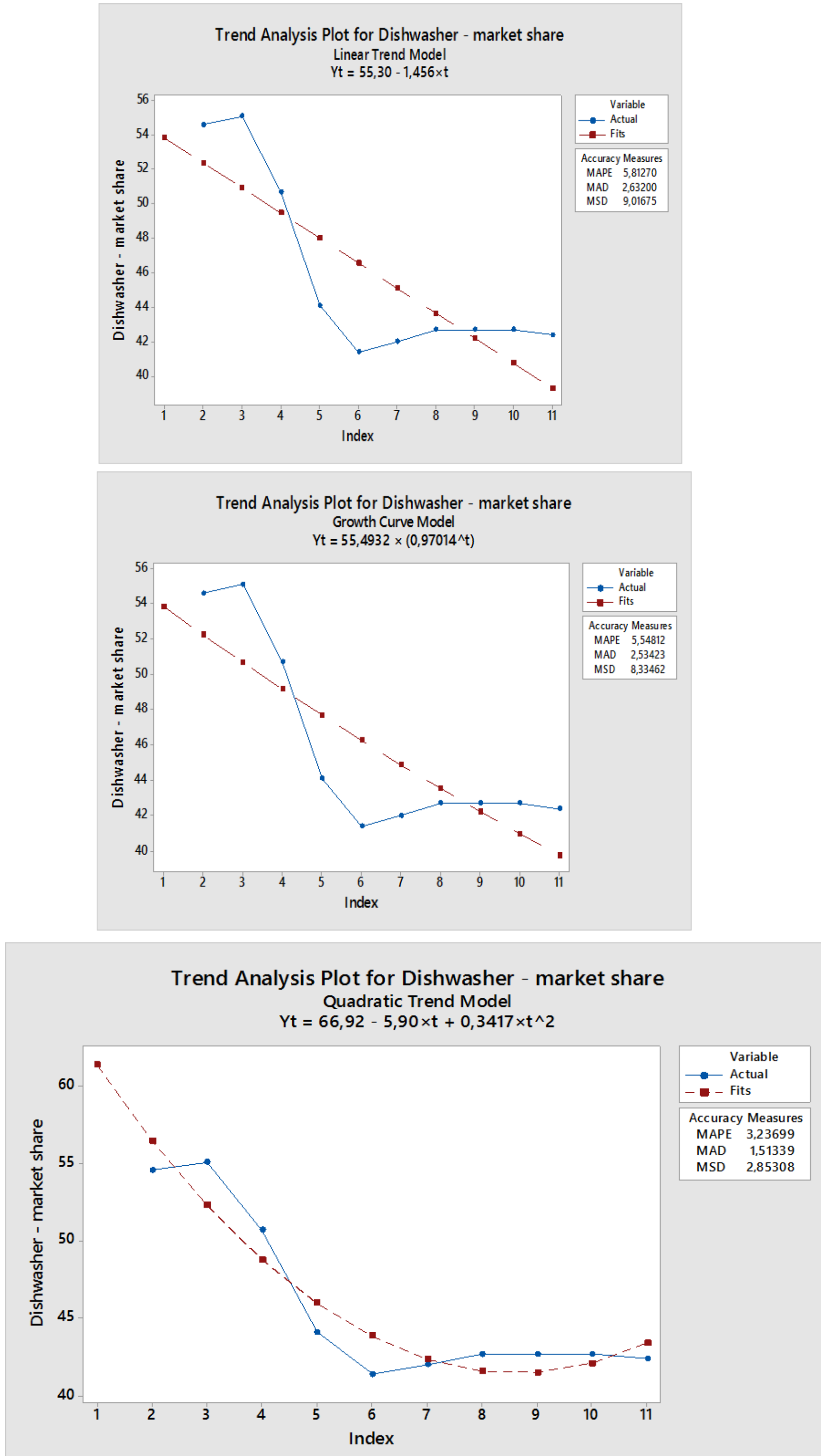


Figure B.4. The company’s market share in dishwasher business

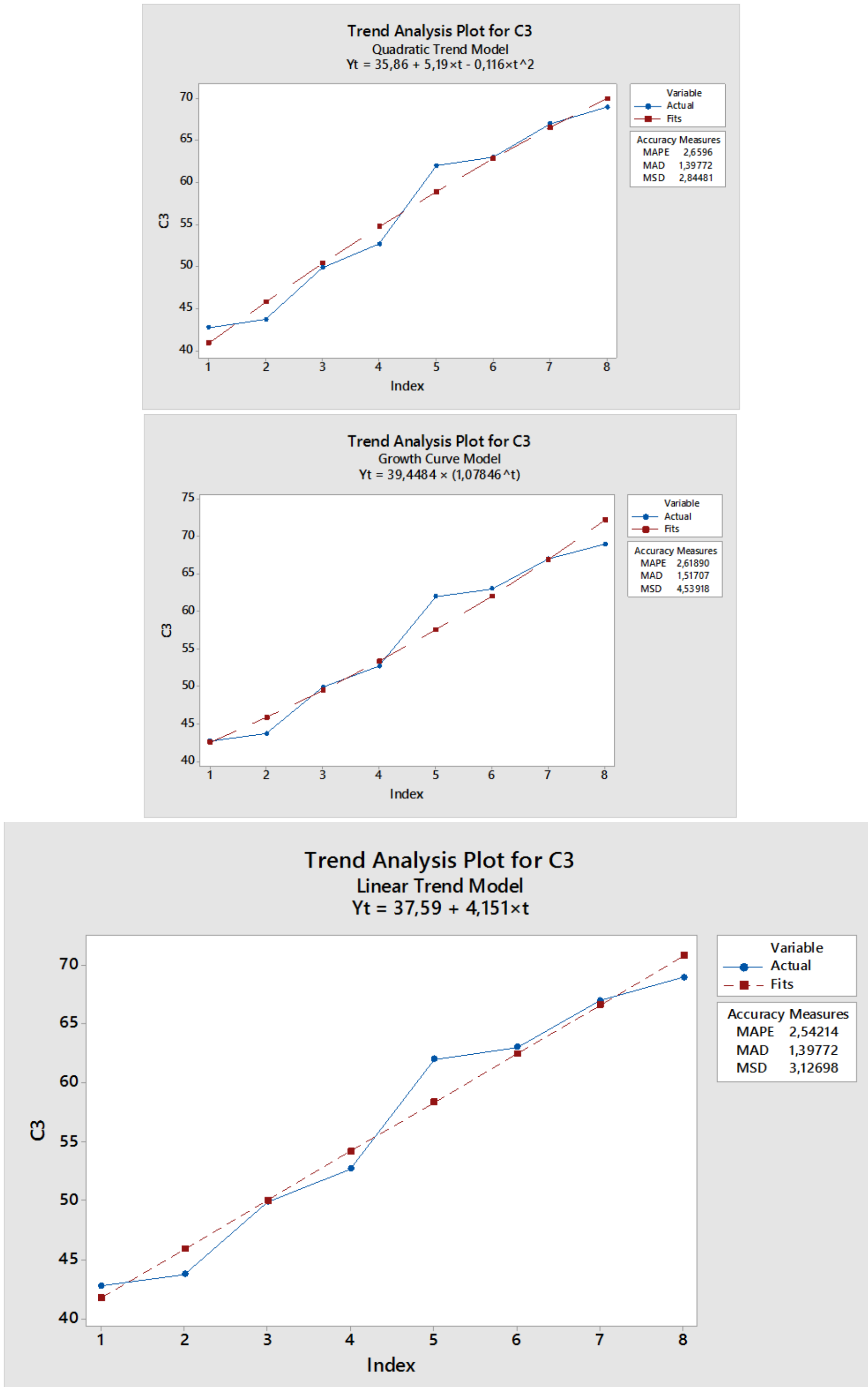


Figure B.5. The penetration level change in home laundry business

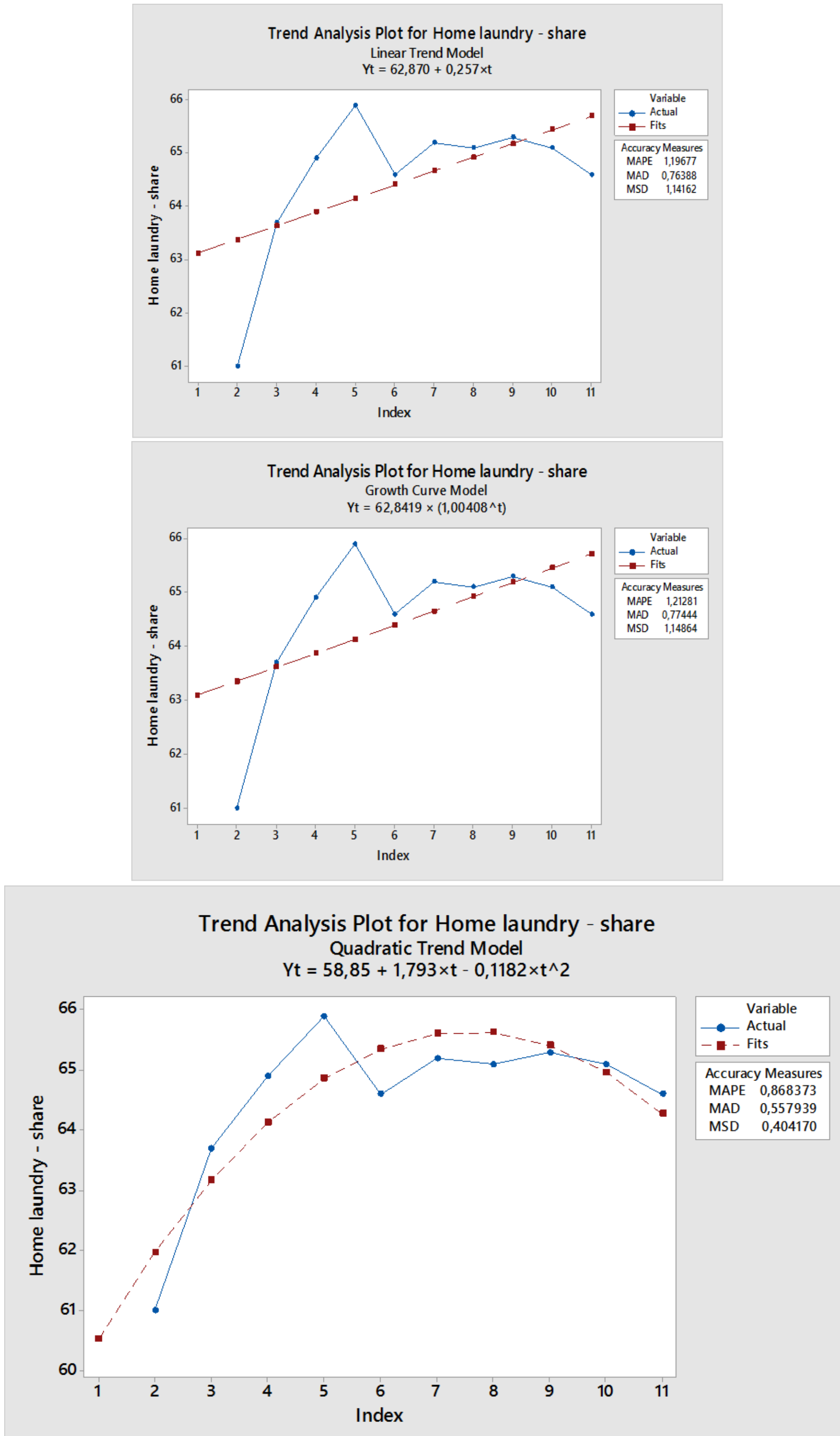


Figure B.6. The company’s market share in home laundry business

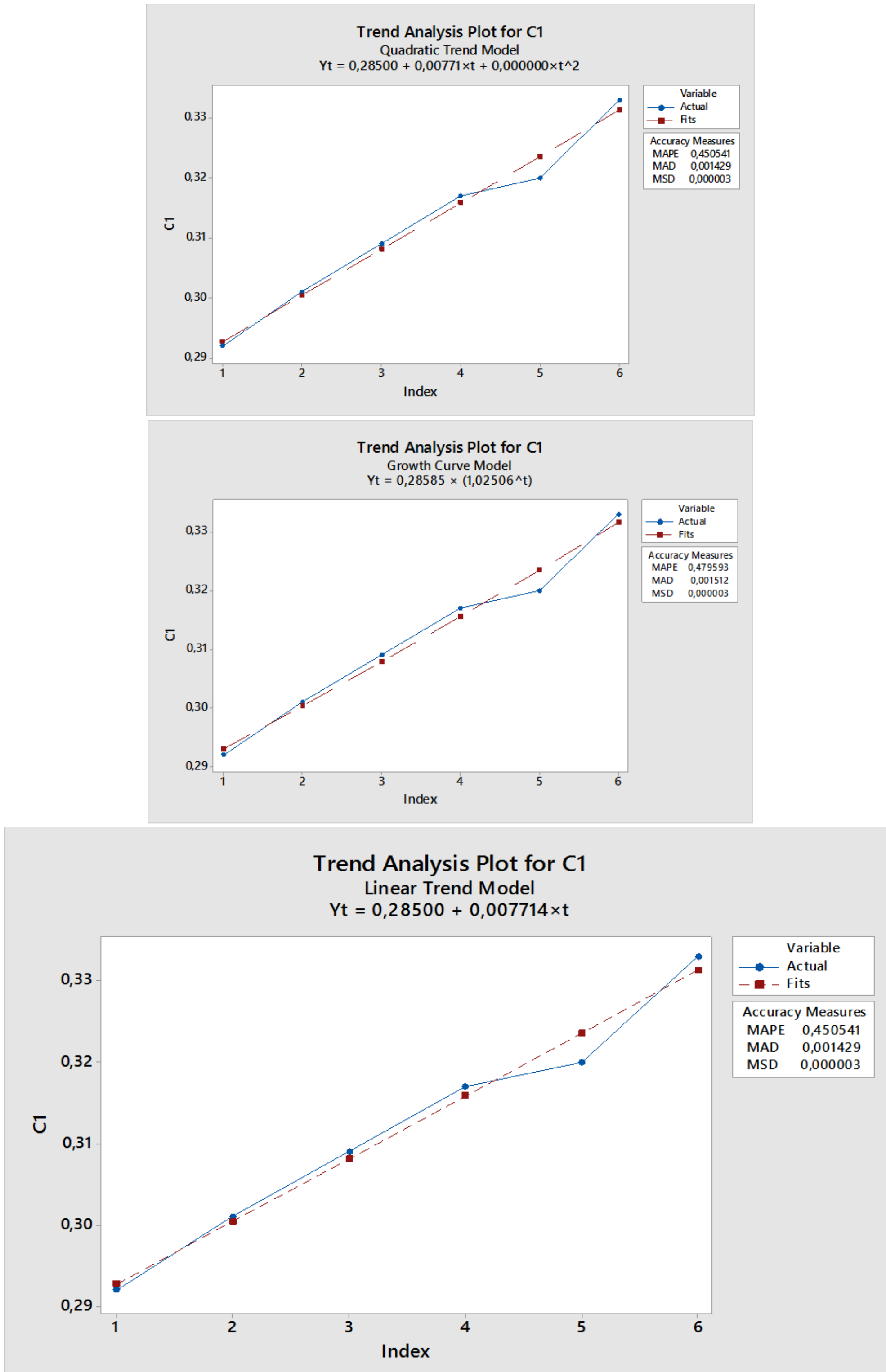
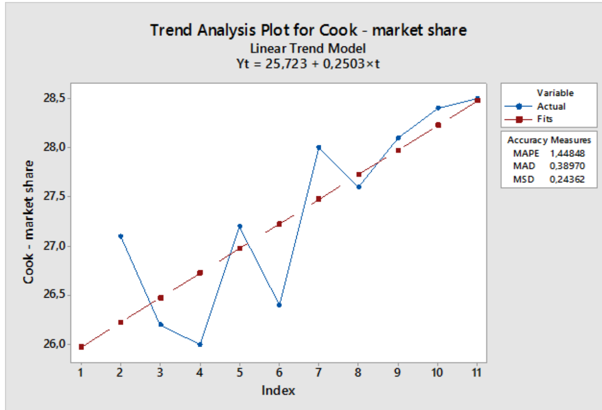
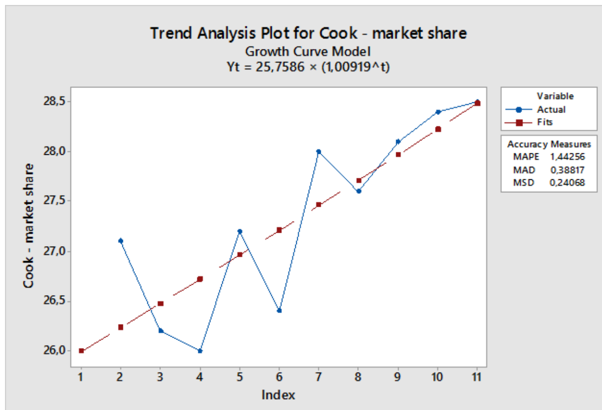


Figure B.7. The penetration level change in large cooking appliances





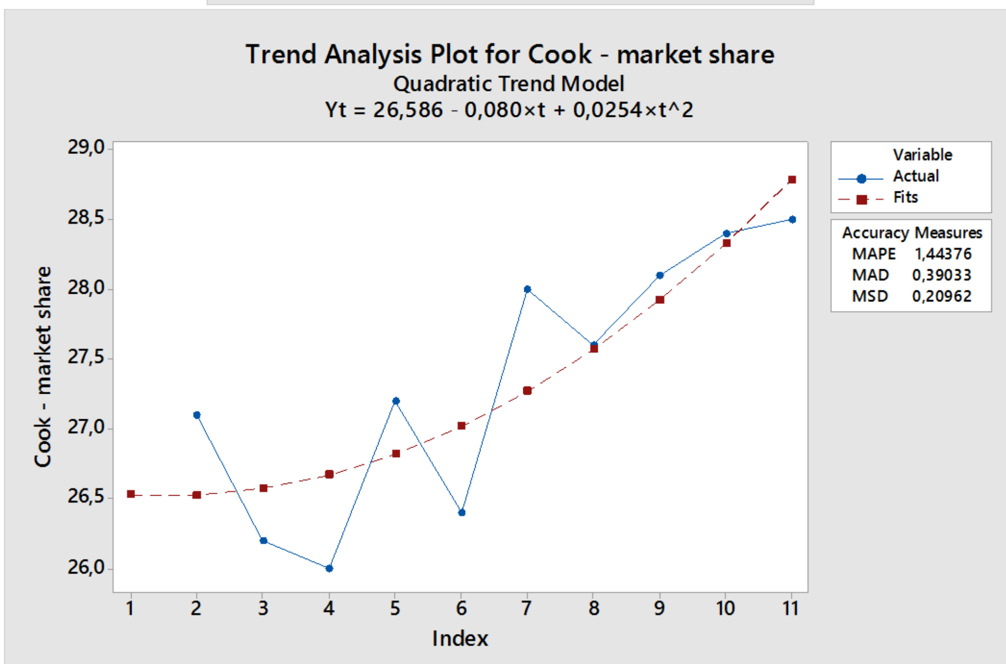
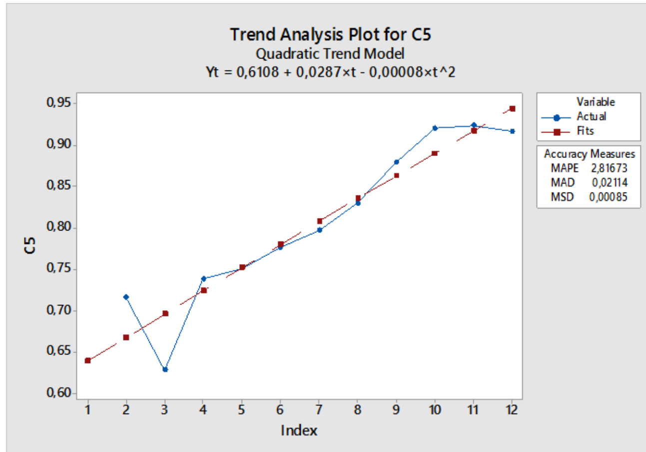
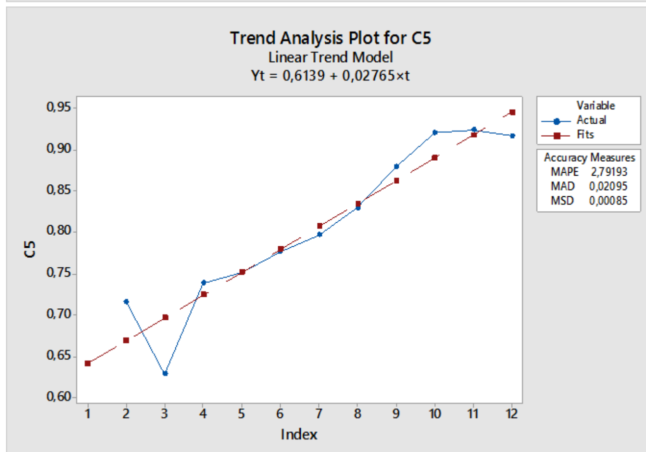


Figure B.8. The company's market share in large cooking appliances





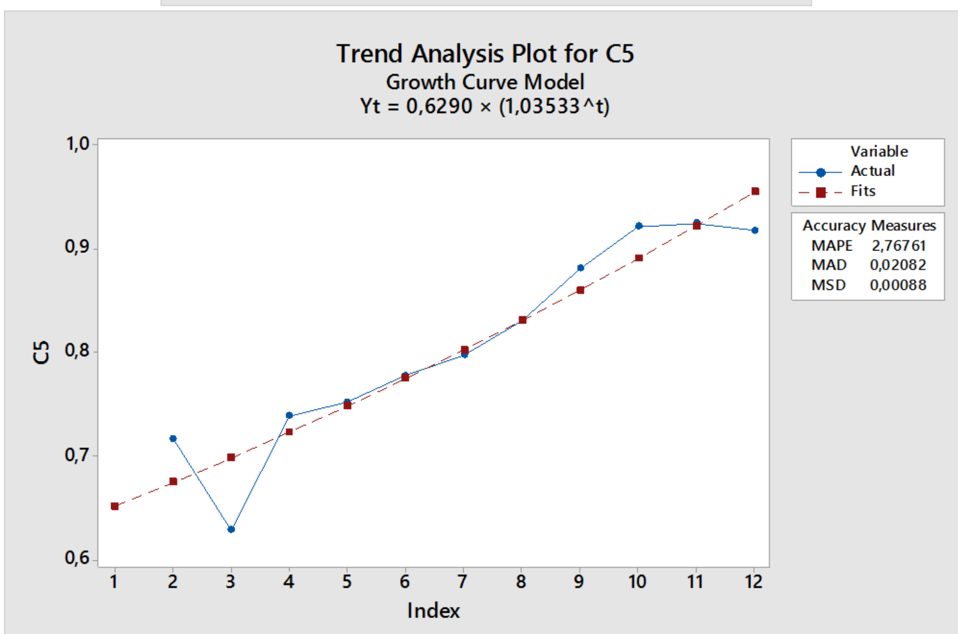


Figure B.9. The penetration level change in vacuum cleaners

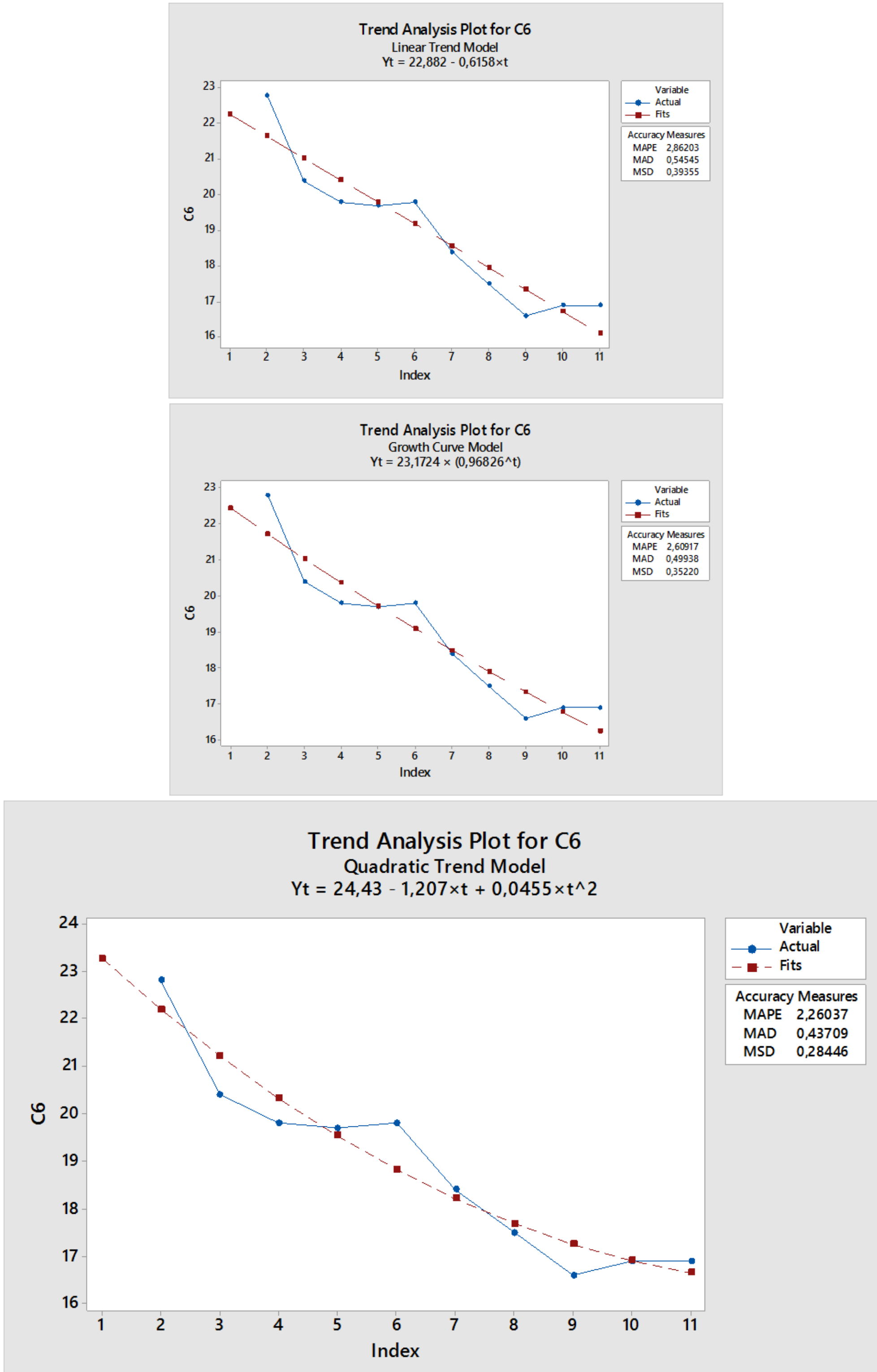
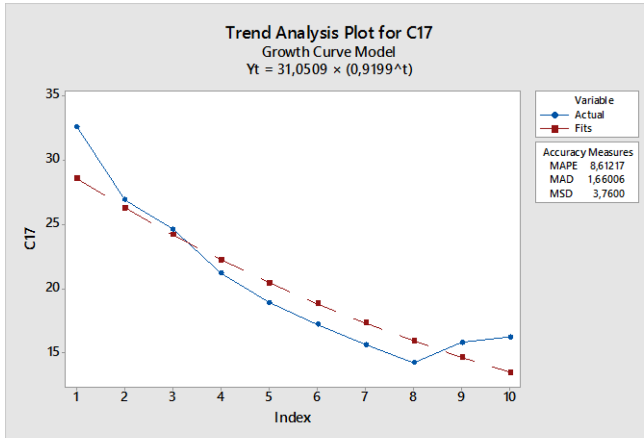
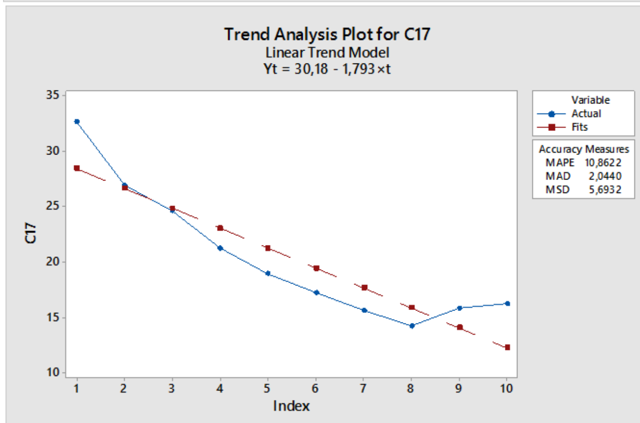


Figure B.10. The company's market share in vacuum cleaners





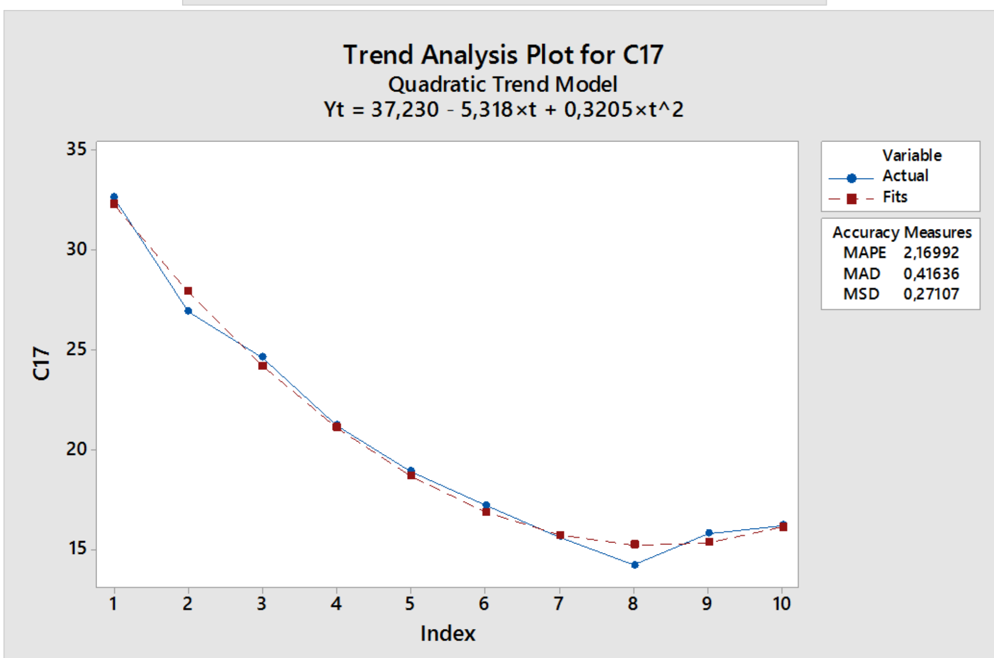


Figure B.11. The company's market share in consumer electronics

APPENDIX C: SCENARIO AND SENSITIVITY ANALYSES

Table C.1. The comparison of single and multi-product modelling

		Objective Value
Single Product Model	p_1	-170.158,14
	p_2	-19.650.200,00
	p_3	108.097,32
Total		***-19.712.260,82***
Multi - product Model		***-19.712.260,82***

		Collection Centers
Single Product Model	p_1	Ankara, Antalya,Bursa,Denizli, Eskişehir, Kocaeli, Manisa, Mardin, Tokat
	p_2	Bolu, İstanbul
	p_3	Ankara, Antalya,Bursa,Denizli, Eskişehir, İstanbul, Kocaeli, Manisa, Mardin, Tokat
Multi Product Model	p_1	Ankara, Antalya,Bursa,Denizli, Eskişehir, Kocaeli, Manisa, Mardin, Tokat
	p_2	Bolu, İstanbul
	p_3	Ankara, Antalya,Bursa,Denizli, Eskişehir, İstanbul, Kocaeli, Manisa, Mardin, Tokat

		Recycling Facilities
Single Product Model	p_1	Eskişehir
	p_2	Bolu
	p_3	x
Multi - product Model		Eskişehir, Bolu

*** performed for 2015-2016 with real return amounts