

Article

Model for Reverse Logistic Problem of Recycling under Stochastic Demand

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Abstract: It has become obligatory for businesses to carry out recycling activities in the face of increasing environmental pollution and the danger of depletion of natural resources. The waste collection phase of the recycling process requires interactive transportation that uses a reverse logistics flow from customers to recycling facilities. Businesses need to create appropriate network structures to carry out these activities at minimum cost. This study has developed a model, based on reverse logistics, of collecting products from customers and sending them to warehouses and then to recycling facilities. The chance-constrained programming (CCP) approach was used to regulate the constraints involving stochastic demand in the model. Linearization was performed using the linear approximation method. The cost of transportation from Initial Collection Points (ICP) warehouses to recycling facilities is the most influential component on the objective function. This linearized model was solved by creating different scenarios by changing the standard deviation ratio, reliability level, and warehouse capacities within the scope of sensitivity analysis. In the sensitivity analysis, it was determined that the increase in confidence level and variance negatively affected the objective function. In addition, it has been concluded that the increase in demand has no effect on costs as long as the capacity of the facility is not exceeded.

Keywords: reverse logistics; recycling; chance-constrained programming; linear approximation method; mathematical model; logistic network



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1. Introduction

Technological developments and changing consumer behavior shorten product life. Taking into account consumer demands, a new product is added to durable and non-durable products every day. With this hedonic consumption behavior, the consumers' growing product and service usages also increase the number of used products and waste. In addition, the increasing world population also increases the demand for products, which increases the need for natural resources that lead to waste [1]. Causes such as raw material scarcity and environmental problems make it necessary to consider reverse logistics within the supply chain networks [2]. Many studies in recent years have addressed the reverse logistics applications used to minimize the damage of used products and scraps as a primary subject. Reverse logistics collects, cleans, disassembles, tests and sorts, transports, and recycles used products and wastes [3]. Reverse logistics is not just about garbage and scrap. Considering the amount of waste produced around the world, reverse logistics becomes more important than ever in order to reduce the waste rate and increase the return to the supply chain [4]. Reverse logistics covers issues including the return, repair,

recall, defect, damage during transportation, newly introduced products, and product replacement [5]. Any logistics activity carried out after delivering the product to the customer is also considered as reverse logistics. For example, if the product is defective, the customer sends it back to the factory. The factory, on the other hand, is required to collect the product, identify the malfunction by disassembling the product, and repair it. If repair is not possible, it recycles some or all of the product by separating it into parts.

The significance of reverse logistics practices is gradually increasing because they provide contributions, such as using resources more effectively, bringing recyclable wastes to the economy, energy savings, and increasing consumer satisfaction. At the same time, reverse logistics provides significant contributions to the economy due to the opening of new business fields, such as reproduction and recycling. Besides its contributions to the overall economy, firm-specific reverse logistics can increase a company's productivity and profitability by using low-cost, traditionally unused inputs or resources [6]. The economic effects of reverse logistics have become more visible as firms are constantly looking for elements that will give them a competitive advantage [7]. Within the scope of reverse logistics, determining and employing the most effective method to apply alternatives such as recycling, remanufacturing, repair, and disposal to products at the end of their useful lives is one of the considerable competitive weapons for firms. The reverse logistics process is, by its nature, a set of activities that adds value.

Reverse logistics has frequently been the topic of both business practices and academic studies in recent years. Reverse logistics applications have some application difficulties, along with the benefits they offer to businesses. In reverse logistics, there are various uncertainties, such as quality, price, quantity, and time of the returned product. These uncertainties cause a high degree of complexity in reverse logistics network design [8]. Therefore, having sufficient information about the parameters in the design and planning of the reverse supply chain procedure is the main issue that facilitates the solution [9]. In particular, planning the collection of the product from the end customers, distribution to the warehouses, considering the capacity and cost issues, and solving them most effectively and economically are among the primary objectives of the enterprises.

Recycling, one of the most frequently used reverse logistics methods, is a substantial field of study for the difficulties expressed above. Recycling has become a concept that has gained significance in recent years due to increased production; unconscious resource consumptions; and the need to reduce the wastes of plastic, glass, etc. Recycling includes the processes of collecting reusable wastes such as metal, plastic, glass, and paper/cardboard, bringing them into production with chemical and (or) physical processes, and reusing them [10]. Today, many firms have to turn to recycling activities due to both legal obligations and increasing environmental awareness.

Literature studies on reverse logistics have been examined in detail, and it has been determined that researchers have found this subject remarkable, especially in recent years. In the literature studies, however, it was determined that the reverse logistics model structure, in which product demands sent from customers for recycling are stochastic, was rarely before. It has been seen that the studies are mostly related to traditional business networks and distribution structures. In the few studies on e-commerce, it has been determined that deterministic demand [11] and stochastic demand that does not deal with recycling [12] are used. Therefore, this study has examined the stochastic-demand reverse logistics network problem, in which product amount sent by customers for recycling is unknown beforehand, and customer demands consist of random variables with a particular probability distribution. The study aims to transport the products sent by the customers for recycling to the warehouses and recycling facilities with minimum cost.

The rest of the paper is organized as follows: Section 2 provides an overview of the reverse logistics. Section 3 introduces the reverse logistics network design. Section 4 formulates a mathematical model. Modeling results and sensitivity analysis are presented in Section 5. Finally, the conclusion and suggestions for future work are summarized in Section 6.

2. Reverse Logistics

Reverse logistics has attracted the attention of researchers, especially within the last 20 years. Reverse logistics was previously seen as a part of logistics, and in later years it was defined as reverse distribution [13]. Today, the prevailing term “reverse logistics,” has begun to be used. Especially with the widespread use of supply chain applications, the scope, effectiveness, and limits of reverse logistics have become clear. The significance and economic return of reverse logistics differ according to the enterprise sector. Generally, reverse logistics gains more influence in products with high production value and return rates.

Economic and ecological reasons, increasing legal regulations for environmental protection, enterprises’ environmental awareness studies, and social responsibility perception lead businesses to implement reverse logistics activities [14]. Thus, the direction of the traditional forward flow from the consumer to the producer has reversed, which created the reverse logistics concept. This reverse flow is also called, in the literature, reverse logistics, reverse channel, reverse distribution, reverse flow logistics, return logistics, or reverse supply chain [13].

Reverse logistics refers to the material flow moving in the opposite direction to the main flow. Products in reverse logistics are transported from many points to central locations with lower levels of predictability and in smaller quantities, resulting in higher transportation and warehousing costs [7]. A reverse logistics system includes a supply chain designed to manage the flow of products or parts to be remanufactured, recycled, or disposed of and to reuse resources effectively [15]. Krajewski et al. [16] define reverse logistics activity as recovering unused or out-of-order products as an input for production or their more efficient use. Reverse logistics aims to carry out the logistics processes (the flow of products and materials from the end consumer to the supplier) in the most cost-effective, efficient way. In general, reverse logistics refers to the operations carried out to return products that have lost their original use value to manufacturers or special processing areas [17].

There is a close relationship between reverse logistics and sustainability. Because reverse logistics helps balance and implement sustainability, studies on this subject have gained intensity [18]. Sustainability is the social, economic, and environmental work for eliminating production-related damage to the environment and protecting the environment. With the expansion of supply chains, more network units are included in the chain, resulting in higher energy consumption and greenhouse gas emissions [19]. Reverse logistics operations play an important role in making supply chains greener, along with their contribution to reducing environmental pollution [20]. Reverse logistics is considered a prominent element of sustainability due to the backward movement of products from the consumer.

Sustainability is an umbrella concept associated with environmental protection and management approaches [21]. Sustainability is about creating long-term stakeholder value by managing risks and embracing opportunities from social, environmental, and economic factors. One of the most important issues that supply chain managers have to deal with today is sustainability, because companies are responsible for the environmental impact and social performance of the ecosystem they create [22]. Sustainability has become a strategic goal for all firms, and reverse logistics applications are the most important tools that serve this purpose [23]. One of the recent application areas of reverse logistics applications under the heading of sustainability is e-commerce. Few studies exist examining reverse logistics applications in e-commerce [24]. In the e-commerce environment, reverse logistics applications bring distinct features and priorities up and differ from traditional businesses. Furthermore, in the e-commerce environment, customers and businesses communicate at “zero distance” [25]. Das et al. emphasize that if the e-commerce delivery fails to comply with the contract terms, the return or replacement of the products is at a higher rate than traditional businesses [11]. Yanyan [24], on the other hand, gives suggestions for adapting four different reverse supply chain models to e-commerce: self-type reverse logistics model, third-party model, strategic alliance model, and integrated solution model. The design and application of models that will contribute to the development of e-commerce will increase

the efficiency of the process [24]. The current study has used the data of an e-commerce company, considering the frequency of use of e-commerce today.

3. Reverse Logistics Network Design and Modeling

As well as its economic contribution, reverse logistics network design affects other aspects of human life, such as the sustainability of the environment and natural resources [25,26]. For this reason, businesses that intend to engage in reverse logistics activities should consider more factors than those existing in current logistics practices. The reverse logistics network designs differ from traditional networks in three aspects [27]. These are centralization of testing and grading, deficient supply control and uncertainty, and integration of forwarding and backward flow.

Designing reverse logistics networks is more complex and challenging than forward logistics networks due to many variables and factors. The following features should be taken into account to create an effective reverse logistics network design due to the uncertainty about the quantities, return times, and quality of the products [13]:

- Who are the members of the reverse distribution channel?
- Which function will be fulfilled in which reverse distribution channel?
- What is the relationship between forward and reverse distribution channels?

One of the key points of reverse logistics network problems is the uncertainty in capacity, demand, and production quantity, which increases the complexity of the problem [1]. There are many models in the literature studies to solve this problem [25,28,29]. Employing advanced estimation techniques and information technologies facilitates product identification and product tracking over the network, and thus uncertainty regarding returned products reduces [25].

There are many studies on reverse logistics network design and modeling among reverse logistics studies. Shih [30] carried out reverse logistics system planning in Taiwan on the end-of-life household appliances required to be taken back by manufacturers. With the mixed-integer program, the study tried to minimize the total cost and presented the results by producing different scenarios [30]. Min [5] developed a nonlinear integer programming model that could solve the reverse logistics problem involving both initial collection points and return centers and solved the model with a genetic algorithm approach. Elwany et al. [25] examined and analyzed modeling and solution methodologies in reverse logistics network design. The authors classified the modeling techniques used in reverse logistics network design under four headings, according to flow type, model type, objective function, and uncertainty in reverse logistics and examined reverse logistics studies with sensitivity analysis, scenario-based approaches, robust optimization, and stochastic programming [25]. Lee and Dong [26] developed a two-stage stochastic model for a dynamic reverse logistics network design under uncertainty. Ramezani et al. [31] examined the multi-objective stochastic model work for forward and reverse logistics network design in terms of the speed of response and quality. Liu [32] has proposed a genetic algorithm-based model to solve the pickup location optimization of reverse logistics for e-commerce. Raghania and Pazhashfar [3] studied an optimization model for reverse logistics networks using a genetic algorithm under a stochastic environment. Yu and Solvang [33] tried to solve the reuse and recycling of products by considering environmental concerns, through real-world case analysis, with the multi-purpose mixed integer programming method. Gooran et al. [8] focused on designing and planning a reverse logistics network and proposed a model to maximize the return product amount and minimize the costs under risk and uncertainty. Liao [34] developed a mixed-integer nonlinear programming model for product improvement and reproduction in a reverse logistics network design. John et al. [35] has proposed a mixed integer linear programming model to multi-stage reverse logistics network design for used refrigerator product recovery. Oyola-Cervantes and Amaya-Mier [36] aimed to design a reverse logistics network for off-the-road tires discarded from mining sites by using mixed integer linear programming in their study. Kuşakçı et al. [37] has proposed a fuzzy mixed integer location-allocation model for end-of-life vehicles' reverse logistic network.

Azizi et al. [38] developed a two-stage stochastic programming model for a multi-period reverse logistics network design under return and demand uncertainty. Roudbari et al. [39] proposed a two-stage stochastic mixed integer programming model to design a reverse logistics network. They used a genetic algorithm and branch and cut algorithm to solve real world problems [39]. Sugimura and Murakami [40] developed a mixed integer linear programming model for an international reverse logistics network for cost minimization. Reddy et al. [41] proposed a mixed integer programming model for multi echelon, multi facility reverse logistics network design. An improved benders decomposition solution method was used in the study by developing classical benders compositions.

The studies in the literature have been examined, and it was found that the reverse logistics network problem, in which products are collected from customers for recycling and customer demands are stochastic, has rarely been investigated before. Therefore, this study is based on the model developed by Das et al. for the e-commerce business to collect products from customers and transport them to the intermediate warehouses and then to the central warehouses. Das et al. assume that customer demands are deterministic, considering that customer demands are a known certainty [11]. However, in the real world, the product demands that customers will send to the warehouses for recycling are uncertain. Das et al. also suggested the development of a stochastic network design for an e-commerce company in a future study. In this study, customer demands are assumed to be stochastic, so that uncertain demand can be taken into account. The stochastic model developed with this study will close the gap in the related field and contribute to the literature. In the following parts of the study, the sensitivity of the model was analyzed by changing the variables.

4. Materials and Methods

In recent years, due to rising production amounts, resources have started to run out, and reverse logistics and recycling practices have gained importance thanks to legal acts and an increasing consciousness about green policies. This study aimed to create a reverse logistics network model to send the products collected for recycling to the warehouses and recycling facilities of the e-commerce company serving in the men's, women's, and children's clothing; shoes; accessories; and home textile sectors in India. In the investigated problem, products are collected for recycling from customers in different locations and first sent to the initial collection point (ICP). Afterwards, all products collected in the ICP are sent to the recycling facility warehouses. In real world problems, the amount of product that customers will send for recycling cannot be predicted in advance. Assuming that the demands are stochastic because the demand for products collected for recycling varies unpredictably, the current study has addressed the deterministic mathematical model developed by Das et al. [11] and rearranged it for the case in which the demand is stochastic. It has been presumed that the products collected from the customers are first sent to warehouses and then to recycling facilities. Because the developed stochastic model contains radical expressions, the linear structure of the model is distorted. The nonlinear model was linearized and solved in the GAMS program. In addition, the sensitivity analyzes of the reference study were expanded and ICP capacities, variance, and confidence level changes were also examined within the scope of the study.

4.1. Mathematical Model

The assumptions, notations, and parameters discussed for the situation where the demand for the products collected for recycling is stochastic were explained, and then the mathematical model was presented.

Assumptions

1. This plant collects the products sent for recycling by customers in large neighborhoods in the northern part of the city [11].
2. The number of Initial Collection Points (ICP) and the locations of these facilities were predetermined. The number of products returned by customers cannot exceed the capacity of these facilities.

3. A customer is assigned to only one ICP. In other words, a customer's return request is sent to only one ICP.
4. Annual rental and maintenance costs of ICP facilities in the study area were estimated based on current cost figures.
5. The locations of the recycling facilities where the returned products are sent were predetermined.
6. Transport costs from customer locations to ICP and from ICP to recycling facilities were estimated using secondary sources [11].
7. A coefficient was calculated for the cost-difference in loading trucks at Full Truck Load (FTL) and loading Less than Truck Load (LTL). The longer the collected products stay at the ICPs, the more likely they are transported in FTL mode, from the ICPs to the recycling facilities. Thus, unit transportation cost shows a decreasing trend. Conversely, products will be transported in LTL mode when the waiting time of products reduces in ICPs. This situation increases the unit transportation cost of the returned products. The multiplication factor here is based on the changing unit transportation cost due to the changing waiting time of the returned products at the ICP.
8. As the work was limited to the Northern Capital Region (NCR), 80% of returns were assumed to be sent to the final warehouse in Gurugram (northern region). The remaining return products (20%) were sent equally to three recycling facilities [11].
9. The demands of the products sent back from the customers to the ICP were assumed to consist of random variables from the normal distribution.
10. The capacity of ICPs installed in different regions should not exceed 3500.

Sets:

I: Set of customers, $i \in I$

J: Set of initial collection points, $j \in J$

K: Set of recycling facilities, $k \in K$

Parameters:

C_j: Annual cost of renting and maintenance cost of the jth ICP

V_i: The amount of product returned from customer i per day

T: Total number of working days in a year

t: Waiting time of the return-product in the ICP

h: Daily warehouse cost of the return-product

u_{ij}: Unit transportation cost of the product returned from customer i to ICP j

u_{jk}: Unit transportation cost of the product returned from ICP j to recycling facility k

f: The coefficient to determine the effect of Full Truckload freight (FTL) or Less Than Truckload freight (LTL) on the transportation cost of the truck.

M: A very large number

g: Percentage of return-products

P: When an ICP is opened, the maximum amount of items that can be sent here.

Q: Minimum amount of return-product required to open an ICP

Decision Variables

$$Y_{ij} = \begin{cases} 1, & \text{if the ICP is opened at } j \\ 0, & \text{otherwise} \end{cases}$$

$$A_{ij} = \begin{cases} 1, & \text{if product is sent out of } i \text{ customer to ICP } j \\ 0, & \text{otherwise} \end{cases}$$

x_{jk}: Quantity of products returned from ICP to final warehouse k in one trip

Mathematical Model:

Objective Function

$$\text{Min } Z = C_j Y_j + hT \left(\frac{t+1}{2} \right) \sum_i \sum_j V_i A_{ij} + T \sum_i \sum_j V_i u_{ij} A_{ij} + f \frac{T}{t} \sum_j \sum_k u_{jk} x_{jk}$$

Subject to

$$\sum_j A_{ij} = 1 \quad \forall i \quad (1)$$

$$\sum_i A_{ij} \leq M Y_j \quad \forall j \quad (2)$$

$$gt \sum_i V_i A_{ij} \leq x_{jk} \quad \forall j \quad (3)$$

$$t \sum_i V_i A_{ij} \leq P Y_{ij} \quad \forall j \quad (4)$$

$$t \sum_i V_i A_{ij} \geq Q Y_{ij} \quad \forall j \quad (5)$$

$$\sum_j Y_j = 4 \quad (6)$$

$$A_{ij} = 0 \text{ or } 1 \quad \forall i, j \quad (7)$$

$$Y_j = 0 \text{ or } 1 \quad \forall j \quad (8)$$

$$X_{jk} \geq 0 \quad \forall j, k \quad (9)$$

The objective function consists of the costs of opening ICPs, transporting products from customers to ICPs, transporting products from ICPs to recycling facilities, and freights with full-capacity or under-capacity and aims to minimize the total cost. Constraint-1 ensures that each customer is assigned to an ICP. Constraint-2 multiplies the right side of the equation by M (a large number) and prevents the possibility of return products from customers to a closed ICP. Constraint-3 ensures flow balance between products sent from customers to ICPs for recycling and products forwarded from ICPs to recycling facilities. Once an ICP has been opened, constraint-4 shows the maximum item quantity to send there. Constraint-5 specifies the minimum reasonable product quantity to be recycled for an open ICP. Constraint-6 allows four ICPs to be opened. Constraints-7 and -8 indicate 0–1 decision variables, and constraint-9 is the sign constraint, ensuring the variable is positive.

The network created for the studied problem is given in Figure 1.

In this study, the deterministic reverse logistics model developed by Das et al. [11] was converted to the stochastic demand reverse logistics model. In this model, it is assumed that the demands are stochastic, considering that the amount of product that customers send to the initial collection point (ICP) for recycling will vary. In addition, in Das et al.'s model, constraint $gt \sum_i V_i A_{ij} = X_{jk}$ number 3, which was created to calculate the amount sent from the initial collection centers to the final warehouses, is not suitable for constraints containing stochastic variables; this constraint changed to $gt \sum_i V_i A_{ij} \leq X_{jk}$. In order to convert the demand to stochastic, constraints 3, 4, and 5 must be rearranged with the objective function, which includes the A_{ij} variable, which shows the amount of product sent by the customers to the initial collection point.

In the next section, the new objective function and new constraints created by chance-constrained programming are given.

The flow chart created for the calculations made in the study is given in Figure 2.

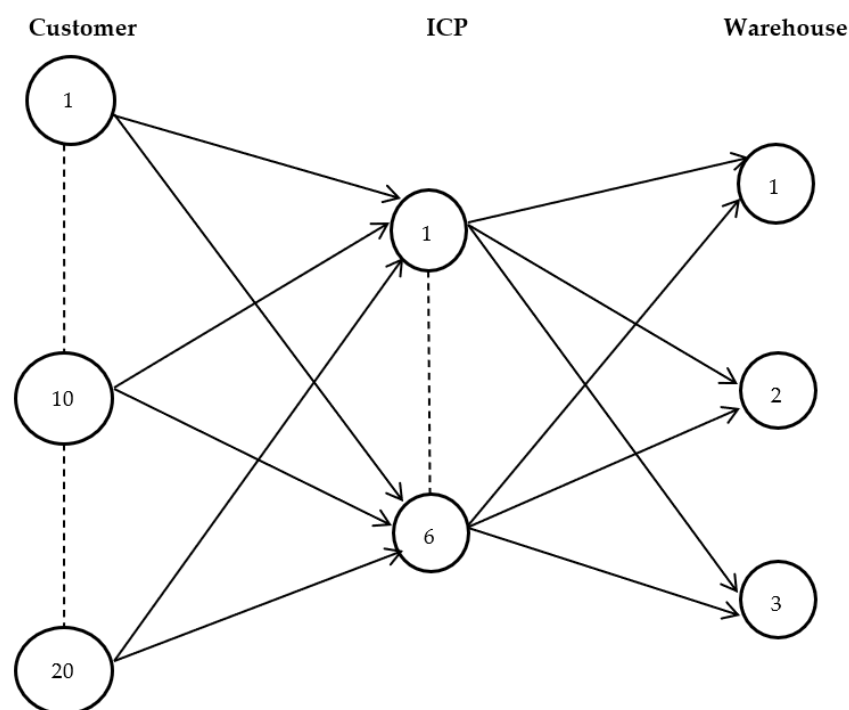


Figure 1. Demonstration of the studied problem on the network.

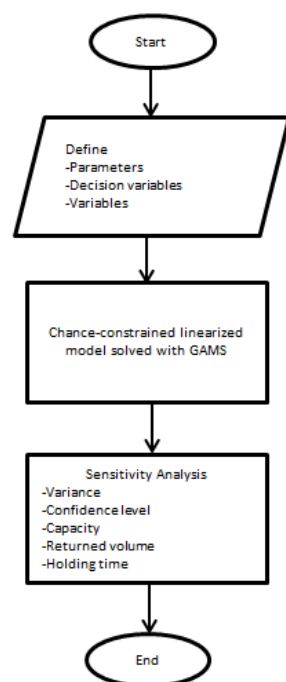


Figure 2. The flow chart created for the calculations made in the study.

4.2. Stochastic Programming with Recourse and Chance-Constrained Programming Approaches

Real-world problems generally contain random variables, and in order to create the mathematical model of these problems, stochastic programming approaches are utilized. The examination of the studies in which random variables are taken into account showed that the researchers used Chance Constraint Programming (CCP) and Stochastic Programming with Recourse (SPR) approaches in the mathematical model creation [42].

CCP is an approach used to construct constraint models containing stochastic variables [43,44]. The principal purpose of the CCP technique is to find the deterministic

equivalents of the probability constraints. This approach accepts that the probability of route failure is below a certain level, and the route failure-based costs are usually ignored [42]. The CCP approach can be expressed as $\Pr(Ax \leq b)$. This formulation states that the probability of realization of the $Ax \leq b$ constraint should be higher than the value of α , which indicates the probability value [45]. In the CCP approach, deterministic constraints with stochastic information are replaced with a stochastic constraint set formed through this information. At the probability level determined by this approach, some constraints containing stochastic information are allowed to be exceeded [43].

Route failure is allowed in applying the SPR approach to the model. However, after the route failure, the decision-maker should determine which auxiliary action should organize the route. This situation requires expert opinions or detailed research, which causes time-wasting [42].

Solving the model created with SPR is more challenging than solving the models produced with the CCP approach. In addition, because the determination of auxiliary actions in the SPR approach requires expert opinion or a detailed study, it takes longer to create the mathematical model. The literature studies examining the stochastic situation have stated that the researchers prefer the CCP approach because of its simple application to mathematical models and easy solutions [46]. Therefore, this study used the CCP approach to create constraints containing stochastic variables.

In stochastic models with stochastic variables in the literature, the chance constraints created by CCP are usually assumed to show a normal distribution [45,47,48]. Therefore, in this study, it has been assumed that the product demands sent from customers for recycling show a normal distribution.

V_i represents the random variable expressing the collection request that customer i sends back to the first collection point and is considered as $V_i \sim N(\mu_i, \sigma_i^2)$, $i \in I$. Because the collection demands were assumed to be stochastic and had a normal distribution in the problem, the following constraints have been created by arranging the objective function with the constraints 4, 5, and 6, which included the collection demands:

New objective function:

$$\text{Min}Z = \sum_j C_j Y_j + hT \left(\frac{t+1}{2} \right) \sum_i \sum_j A_{ij} \left(\mu_i + Z_{1-\alpha} \sqrt{\sigma_i^2} \right) + T \sum_i \sum_j \left(\mu_i + Z_{1-\alpha} \sqrt{\sigma_i^2} \right) u_{ij} A_{ij} + f \frac{T}{t} \sum_j \sum_k u_{jk} x_{jk} \quad (10)$$

Constraint #3:

$$gt \sum_i \mu_i A_{ij} + Z_{1-\alpha} \sqrt{gt \sum_i \sigma_i^2 A_{ij}} \leq x_{jk} \quad (11)$$

Constraint #4:

$$t \sum_i \mu_i A_{ij} + Z_{1-\alpha} \sqrt{t \sum_i \sigma_i^2 A_{ij}} \leq PY_{ij} \quad (12)$$

Constraint #5:

$$t \sum_i \mu_i A_{ij} + Z_{1-\alpha} \sqrt{t \sum_i \sigma_i^2 A_{ij}} \geq QY_{ij} \quad (13)$$

4.3. The Linearization of a Mathematical Model

The objective function created with the CCP approach and constraints 11, 12, and 13 were nonlinear because they contained rooted expressions. This situation complicated the solution of the model. Such problems are known as NP-hard problems in the literature. In order to solve the models with nonlinear constraints faster and easier, these constraints should be linearized. Investigating similar literature studies has revealed that the linear approach method is used among different approaches for transforming the constraints into linear [49]. The current study also used the linear approximation method to linearize the developed stochastic programming model. The Linear Approximation Method is a method used to transform nonlinear mathematical models into linear ones. The Linear Approach

Method finds a near-optimal solution to CCP models [48]. The Linear Approach Method was applied considering the following constraint:

$$\sqrt{\sum_{i=1}^n a_i^2} \leq \sum_{i=1}^n a_i \quad a_i \in R^+ \quad (14)$$

Applying this method to a nonlinear mathematical model makes the nonlinear components of the model linear. This approach can be used in simple mathematical inequalities and when no new variable or constraint is added to the model [48]. The constraints converted to linear using the linear approximation method are:

Objective Function:

$$\text{Min} Z = \sum_j C_j Y_j + hT \left(\frac{t+1}{2} \right) \sum_i \sum_j A_{ij} (\mu_i + Z_{1-\alpha} \sigma_i) + T \sum_i \sum_j (\mu_i + Z_{1-\alpha} \sigma_i) u_{ij} A_{ij} + f \frac{T}{t} \sum_j \sum_k u_{jk} x_{jk} \quad (15)$$

Constraint #11:

$$gt \sum_i \mu_i A_{ij} + Z_{1-\alpha} gt \sum_i \sigma_i A_{ij} \leq x_{jk} \quad (16)$$

Constraint #12:

$$t \sum_i \mu_i A_{ij} + Z_{1-\alpha} t \sum_i \sigma_i A_{ij} \leq PY_{ij} \quad (17)$$

Constraint #13:

$$t \sum_i \mu_i A_{ij} + Z_{1-\alpha} t \sum_i \sigma_i A_{ij} \geq QY_{ij} \quad (18)$$

5. Results

In this section, a stochastic model has been developed based on the mathematical model proposed by Das et al. The data used by Das et al. [11] has been utilized in the analysis of the developed model [16]. The sensitivity of the linearized stochastic model was analyzed by modifying the significant parameters of the model. In this section, firstly, the efficiency of the linearized model is examined. The effects of standard deviation ratio change, the confidence level change, the ICP capacity change, return volume change and holding time change on the objective function were also examined in this section.

5.1. Analyzing the Effectiveness of the Linearized Model

While analyzing the effectiveness of the developed model, the reliability level of the problem was 95%, and the ICP warehouse capacity was found to be 3000 items. In the reference article, the ICP capacity was 1652 for the situation allowing four ICP openings. For the reference study, the demands were also assumed to be stochastic, the standard deviation was 0.1, and the reliability level was 95%. Therefore, the ICP capacity in the root problem was increased according to these values and established as 3000. In the root problem, the warehouse holding cost was 1.5, the waiting time was four days, and the processing time in a year was 360 days. The study assumed that ICP warehouses sent 80% of the total product to the recycling facility in Gurugram, and the three facilities shared the remaining amount equally. Thus, the g ratio was 0.2. Because the product value of the four-day waiting time in the root problem was 1.2, f was appointed as 1.2 in the sample problem. Appendix A shows the annual rental costs of ICP warehouses, Appendix B, the daily products number sent from customers to ICPs, Appendix C, the unit transportation costs from customers to ICPs, and Appendix D, the unit transportation costs from ICPs to recycling facilities. These values were directly from Das et al.'s [11] study without changing.

The model was converted to linear form, and the problem was coded in the GAMS 24.1.3 program using the CPLEX 12.5.1.0 solver. The solution of the model was carried out on a computer running the "Windows Home Single Language" operating system, with an Intel Core i5-8265U CPU @ 1.60 GHz, 8 GB buffer. The problem with the 20 customers was solved within 0.12 s by using this data. The solution of the model has revealed that

ICPs should be opened in Central Delhi, South Delhi, West Delhi, and Noida, and which customer would be assigned to which warehouse was also determined. In addition, the number of products to be sent from ICP warehouses to recycling facilities has also been determined. According to the results obtained, the four cost items that make up the objective function were analyzed in detail, and these data formed Figure 3:

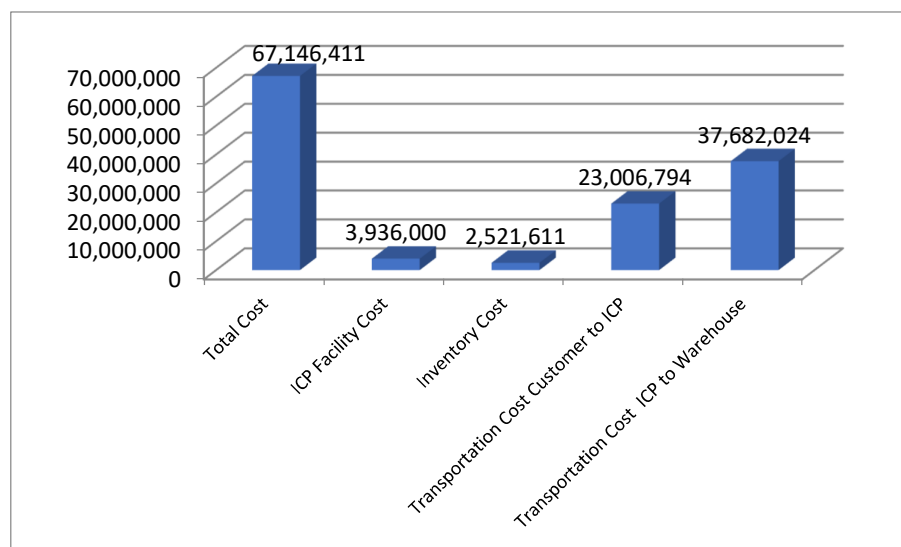


Figure 3. The elements of the total cost.

Figure 3 shows that the highest impact among the cost components constituting the objective function was the transportation cost from ICP warehouses to recycling facilities at a rate of 56.1%. While the transportation cost from customers to ICP warehouses constituted 34.3% of the total cost; the ICP Facility Cost was 5.9%, and the inventory cost was only 3.8% of the total cost.

5.2. Examination of the Effect of Variance Change on the Model

The literature studies considering the stochastic situation have taken a particular ratio of the average demand value and determined the standard deviation value for a customer. In the studies, usually, any of the 0.1, 0.15, or 0.20 of the demand value were assigned as that variable's standard deviation [46,48]. This study made calculations with increasing rates of average demand to determine the effect of standard deviation on the model. This study took 0.05, 0.10, 0.15, and 0.20 standard deviation ratios and examined the influence of change on the objective function. The results of the calculations for the problems with 0.05, 0.10, 0.15, and 0.20 standard deviations at the 95% confidence level are shown in Figure 4.

Figure 4 shows that, as the standard deviation rate increases, the total cost also increases.

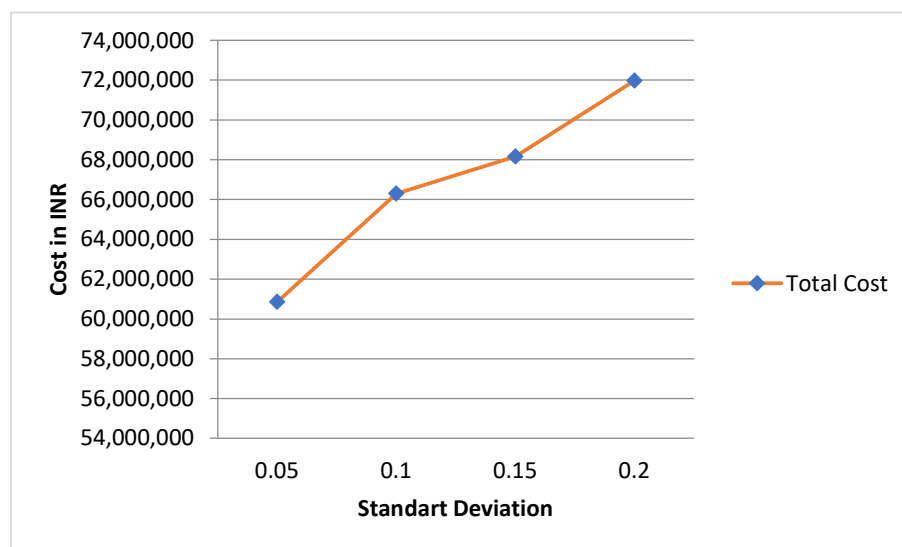


Figure 4. The examination of the effect of standard deviation changes on the model efficiency.

5.3. Examination of the Effect of Confidence Level Change on the Model Efficiency

The studies in the literature addressing stochastic variables have examined the effect of the change in the reliability level on the model performance. In these studies, it was determined that the increase in the reliability level generally affected the objective function negatively [31,33]. This study also solved the original problem using different confidence levels (90%, 95%, 97.5%, 99%) to determine the effect of the reliability level on the developed model. The results obtained as a result of the calculations are shown in Figure 4. Additionally, Lokesh et al. [50] found that, as the confidence level rises above 90%, the negative effect on the objective function increases. Figure 5 shows that the total cost tends to increase as the level of reliability increases.

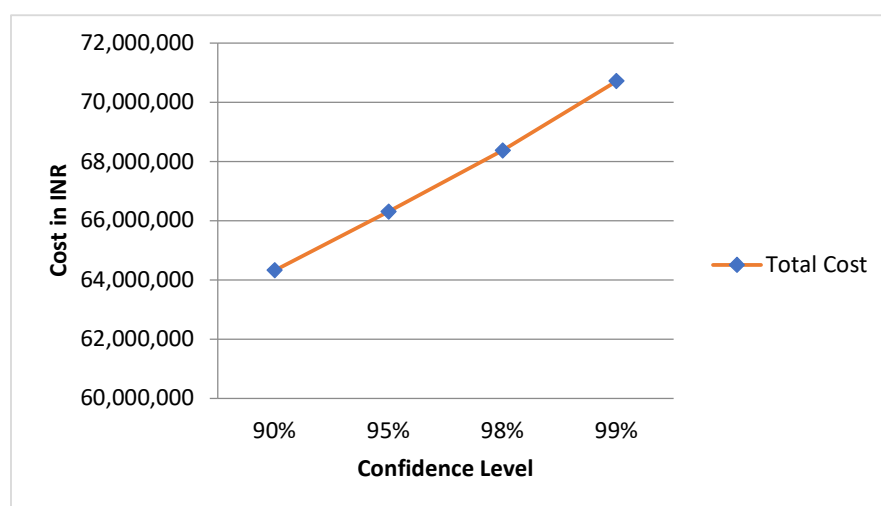


Figure 5. The examination of the effect of confidence level change on the model efficiency.

5.4. Examination of the Effect of the Changing ICP Capacity on the Model Effectiveness

In order to determine the effect of ICP capacity change on the model, the predetermined 3000-item capacity was increased or decreased by 5%, 10%, 15%, and 20%. Due to the assumption of the mathematical model specifying the capacity as a maximum of 3500 items, the warehouse capacity was designated as 3500 items. The problem was solved by changing warehouse capacities and sub-limits, and the total cost function was investi-

gated in detail. The item-costs forming the objective function were examined elaborately to determine the capacity change effect, and then Figure 6 was created.

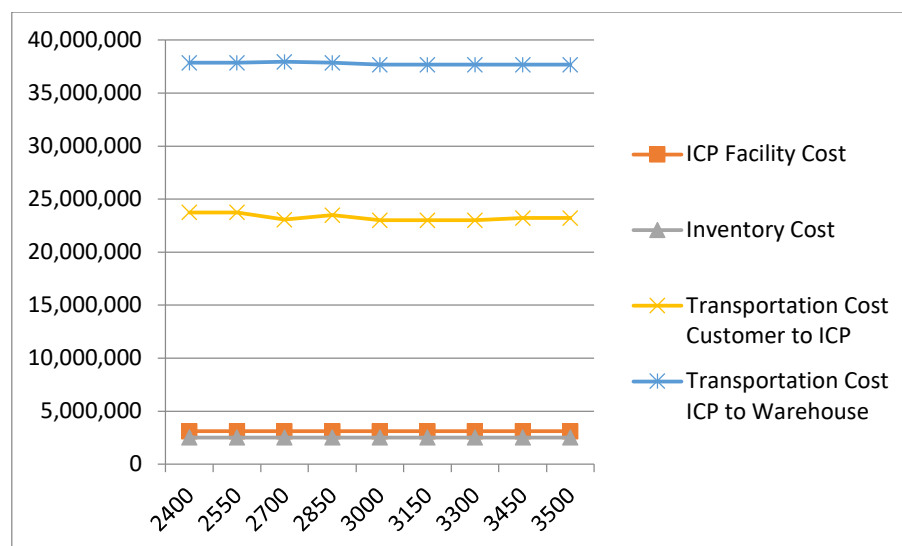


Figure 6. The examination of the effect of the capacity change on the element costs.

Figure 6 shows that the capacity change has never changed the ICP Facility Cost. Similarly, Li et al. [51] determined in the sensitivity analysis of their study on the multi-purpose reverse logistics network problem that the costs will not be affected as long as the increase in demand is met by the facility capacity. Because this cost is the warehouse's establishment cost and only occurs in the first setup, the subsequent changes will not affect this cost. Similarly, as there is no change in the holding time, the capacity change does not affect Inventory Cost. The other two cost items have been affected by the capacity change.

Figure 7 was created in order to examine the change in total cost with the change in capacity. Figure 7, created with capacity change costs, shows that the lowest cost emerged between 3000 and 3300 ICP capacity, and a higher cost emerged outside of this capacity range.

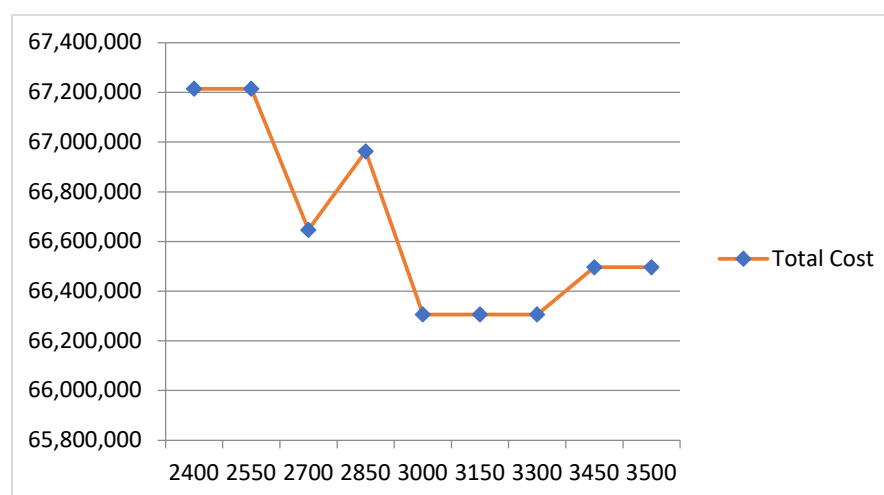


Figure 7. Examination of the effect of the capacity change on the total cost.

5.5. Examination of the Effect of the Changing Return Volume (V_i) on the Model Effectiveness

In order to examine the effect of the change in demand of the returned products on the change in the total cost, the volume for the returned product in the base problem has been changed. Sensitivity analyzes were performed by increasing or decreasing the return

volume in the basic problem by 5%, 10%, 15%, and 20%. The results obtained in order to determine the effect of the return product demand change on the total cost were shown in Figure 8.

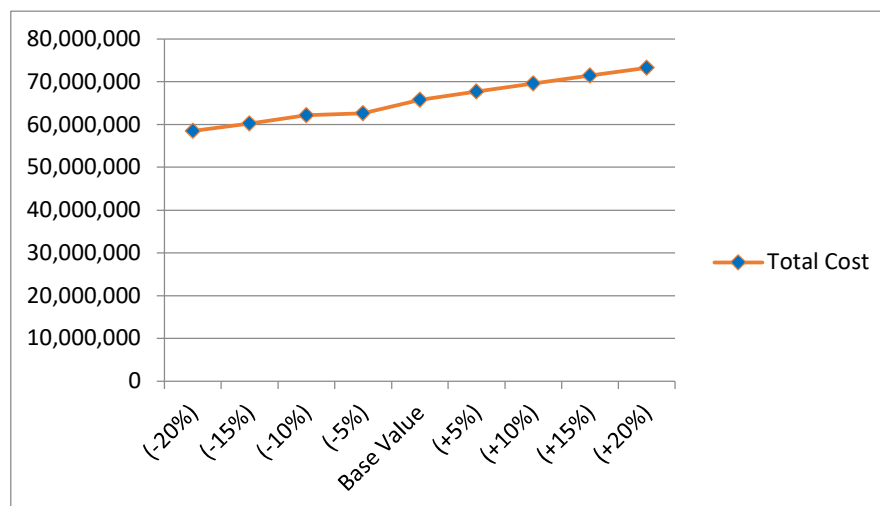


Figure 8. Examination of the effect of the return volume change on the total cost.

When Figure 8 is examined, it can be seen that, as the demand for the returned product increases, the total cost also increases. Accordingly, the lowest cost occurs when the demand amount is reduced by 20%, and the highest cost occurs when the demand amount is increased by 20%. As a result, the change in demand affects the total cost function in the same direction. An increase in the amount of demand increases the total cost, while a decrease in the amount of demand decreases the total cost.

5.6. Examination of the Effect of the Changing Holding Time on the Model Effectiveness

In this section, the relationship between the change on holding time and the change in total cost is examined. In order to determine the effect of the change, calculations were made by taking 3, 4, 5, and 6 holding times. Because the holding time will also affect the multiplication factor, the calculation has been made by taking into account the multiplication factors in the table given in Appendix D. Figure 9 was created using the results obtained.

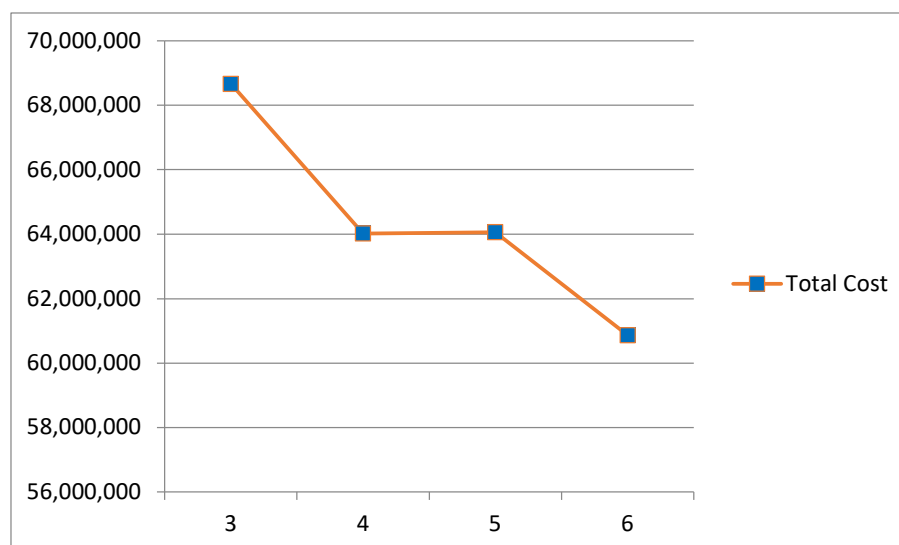


Figure 9. Examination of the effect of the holding time change on the total cost.

When Figure 9 is examined, it is seen that the total cost decreases as the holding time increases. The lowest cost occurs when the holding period is 6 days. It was thought that the cost would decrease further by increasing the waiting period and the calculation was made by determining the waiting time as 7 days. However, the solutions turned out to be infeasible when the holding period was taken more than 6 days. As a result, the lowest total cost is reached when the holding time is 6.

6. Conclusions

Under difficult competition conditions today, businesses have had to develop new environmental policies depending on their growing production because of the overconsumption of natural resources, high environmental pollution, and high global warming. On this subject, green procurement chain management and green approaches have started to gain importance, together with the increasing consciousness of enterprises and customers. Recycling activities are also one of the most significant green supply chain activities implemented in businesses. In recent years, the reverse logistics practices collecting the products from customers back and sending them to recycling facilities have also been gradually more widespread.

This study examined the reverse logistics network structure in which the products are transported from customers to central warehouses and then to recycling facilities. The literature study examination showed that customer demands are generally deterministic in reverse logistics. However, the number of products sent by customers for recycling is unpredictable. Therefore, the current study assumed that the product demands forwarded through the reverse logistics for recycling were stochastic. The study has converted the mathematical model recommended by Das et al. [11] to the chance constraint stochastic programming model, assuming that the collection demands comprised random variables. The linear structure of the model was broken down because the mathematical model generated by the CCP approach contained root expressions. Such problems are recognized as NP-hard problems in the literature, and they cannot be solved by the CPLEX solver due to the corruption in the model structure. Different methods were found in the literature for the linearization of non-linear constraints. Due to its easy application and fast, near-optimum solutions, this study used the linear approach method during linearizing. The problem obtained from Das et al.'s [11] study was solved by making it stochastic to analyze the model effectiveness.

In order to examine the effectiveness of the model in the study, sensitivity analysis was performed by changing some parameter values. The calculations showed that the objective function increased in parallel with the standard deviation ratio. As a result of the computations made to examine the effect of the reliability level, the total cost was found to increase with increasing reliability levels. Finally, the influence of the ICP capacity changes on the objective function was determined. The calculations revealed the total cost was the lowest when the ICP capacity was between 3000 and 3300. Furthermore, it was observed that changing the capacity did not influence ICP Facility Cost and Inventory Cost but only influenced the transportation costs from the customers and to the first warehouses and from the first warehouses to the last recycling facilities. The increase in the amount of returned product also increases the total cost. As a result, there is a same-way relationship between the objective function and the return volume. When the holding time was determined as 6, it reached the lowest total cost.

The current study examined the reverse logistics problem, in which the customer returns were transported to the initial warehouses and then to the last warehouses for recycling, and the customer demands were stochastic. The study determined a capacity constraint only for the ICP warehouse but not for vehicles and final warehouses. Future studies can set additional constraints on the capacities of trucks and final warehouses to the mathematical models. In addition, this study assumed that all warehouses had equal size. Future studies may consider warehouses in various capacities. Additionally, they may examine a multi-objective case where more than one purpose is taken into account.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Location of ICP	Annual Rental Cost of ICP
Y ₁ (Central Delhi)	C ₁ = 828,000
Y ₂ (South Delhi)	C ₂ = 792,000
Y ₃ (North Delhi)	C ₃ = 756,000
Y ₄ (West Delhi)	C ₄ = 756,000
Y ₅ (Gurugram)	C ₅ = 792,000
Y ₆ (Noida)	C ₆ = 720,000

Appendix B

Customer Index	Volume of Items Returned Daily	Customer Index	Volume of Items Returned Daily
1	V1 = 98	11	V11 = 74
2	V2 = 95	12	V12 = 70
3	V3 = 94	13	V13 = 66
4	V4 = 92	14	V14 = 80
5	V5 = 90	15	V15 = 75
6	V6 = 88	16	V16 = 78
7	V7 = 92	17	V17 = 64
8	V8 = 84	18	V18 = 62
9	V9 = 85	19	V19 = 65
10	V10 = 82	20	V20 = 70

Appendix C

Customer Index	ICPs (Y _j)					
1	28	32	32	33	40	39
2	26	31	32	34	41	38
3	26	30	31	32	42	37
4	27	31	30	31	43	36
5	30	26	33	31	37	38
6	31	27	34	32	39	36
7	32	25	35	33	38	37
8	32	33	25	30	45	38
9	31	34	26	31	44	37
10	30	35	27	32	43	36
11	33	32	31	27	37	43
12	34	31	30	28	38	42
13	32	33	30	26	39	41

Customer Index			ICPs (Yj)			
14	42	37	44	39	27	45
15	41	38	45	38	28	46
16	40	39	43	37	29	47
17	39	35	38	41	47	25
18	38	36	37	42	48	26
19	37	37	39	43	46	27
20	36	38	36	44	45	28

Appendix D

Yj	K1	K2	K3
Y1	53	97	83
Y2	52	96	82
Y3	55	98	84
Y4	51	95	81
Y5	50	96	82
Y6	58	100	85

Appendix E

Holding Time (t)	Multiplication Factor (f)
3	1.3
4	1.2
5	1.1
6	1.0

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