A PROMOTION-AWARE PURCHASE DECISION AID FOR CONSUMERS

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF INFORMATICS

OF

THE MIDDLE EAST TECHNICAL UNIVERSITY

BY

KAMİL AKHÜSEYİNOĞLU

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

THE DEPARTMENT OF INFORMATION SYSTEMS

JANUARY 2016

A PROMOTION-AWARE PURCHASE DECISION AID FOR CONSUMERS

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ABSTRACT

A PROMOTION-AWARE PURCHASE DECISION AID FOR CONSUMERS

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January 2016, 110 pages

Grocery shopping has become more complicated in recent years, since savings related concerns have made it harder to select what to buy and where to buy, which in turn results in consumers fulfilling their grocery needs by visiting more than one store. Moreover, consumers are exposed to numerous promotions of different types such as in-store and credit card promotions. Therefore, consumers are in need of help regarding promotion-aware purchase decision making. The main purpose of this research is to aid consumers in satisfying their needs. The proposed solution is designed to be used by consumers in the pre-purchase planning phase. A novel contribution of the study is the inclusion of credit card promotions into the purchase decision process. The proposed solution is customer centric, and provides shopping alternatives to the consumers by using their preferences and pre-defined shopping lists. The model proposes a purchase prediction model to predict the frequency of shopping and the average shopping amount using the past purchases of a consumer. The goal of the model is not to identify the best alternative, but instead to provide a ranked list of alternatives by using the PROMETHEE II outranking method, in order to aid the decision. The model also helps consumers to follow-up on promotions effortlessly by using a workflow engine. A mobile prototype application is developed to demonstrate the applicability of the proposed model. Then, the promotion based purchase problem is defined as an Integer Linear Programming (ILP) problem and the model is evaluated against the optimum results on a given real-life test data set. The results indicate that the model helps consumers obtain 62.22% of the optimum total credit card promotion bonuses available in the test data set.

Keywords: Consumer decision process, mobile information system, recommendation system, PROMETHEE

ÖZ

TÜKETİCİLER İÇİN PROMOSYONA DUYARLI SATIN ALMA YARDIMCISI

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Ocak 2016, 110 sayfa

Son yıllarda market alışverişleri daha karmaşık bir hal almıştır. Tasarruf kaygısı neyin satın alınması gerektiğinin belirlenmesini ve nereden alınacağını daha da güçleştirdi. Tüketiciler market ihtiyaçlarını birden çok markete uğrayarak tamamlamaya başladı. Dahası, tüketiciler birbirinden farklı sayısız tipte promosyona maruz kalıyor. Tüketicilerin promosyonlara duyarlı satın alma karar sürecinde yardıma ihtiyaçları var. Bu çalışmanın esas amacı da tüketicilerin yardım ihtiyacını karşılayabilmek. Önerilen çözüm tüketiciler tarafından ön satın alma sürecinde kullanılabilmesi için tasarlandı. Çalışmanın özgün katkısı kredi kartı promosyonlarının da tüketim karar destek sürecine eklenmesidir. Önerilen çözüm tüketici odaklıdır. Alışveriş alternatifleri, tüketicilere onların tercihlerini ve konumları kullanılarak önceden tanımlı alışveriş listesine göre tavsiye edilir. Çalışma, tüketicinin geçmiş satın alma bilgisini kullanarak gelecekteki harcama sıklığını ve ortalama alışveriş tutarını tahmin eden bir satın alma tahmin modeli önerir. Önerilen çözüm en iyi alternatifi önermez fakat PROMETHEE II kullanarak alternatifleri sıralar ve bu sıralanmış listeyi verir. Bu model, iş akış motoru kullanılarak müşterilerin çaba harcamadan promosyonları takip edebilmesine yardımcı olur. Önerilen modelin uygulanabilirliğini göstermek için bir mobil prototip uygulama geliştirildi. Daha sonra, promosyon bazlı satın alma problemi bir tamsayı doğrusal programlama kullanılarak tanımlandı ve model optimal sonuçlara göre değerlendirildi. Elde edilen sonuçlar modelin tüketicilere optimal toplam kredi kartı kampanya puanlarının %62,22’sini kazanmasına yardım ettiğini gösterdi.

Anahtar Kelimeler: Tüketici karar süreci, mobil bilgi sistemi, tavsiye sistemi, PROMETHEE

dedicated to my wife and family

ACKNOWLEDGMENTS

First and foremost I am grateful to my thesis supervisor Assist. Prof. Dr. P. Erhan Eren for his endless support, motivation and endurance throughout my study.

I owe a great debt of gratitude to Assoc. Prof. Dr. Altan Koçyiğit for his invaluable guidance, comments and discussions about the research. I am grateful to Dr. Süleyman Özarslan for his constructive comments throughout my study. I am indebted to my colleague Alptuğ Dilek for his encouragement and support.

It gives me great pleasure in acknowledging the participation in my defense and valuable feedbacks of my examining committee members, Assoc. Prof. Dr. Altan Koçyiğit, Assoc. Prof. Dr. Banu Günel Kılıç, Assist. Prof. Dr. Ayça Tarhan, and Assoc. Prof. Dr. Tuğba Taşkaya Temizel.

My thesis would not have been completed without my wife Nuray. She guided me in my research study by sharing her experiences and helped me to figure out and to conduct statistical analyses. Most importantly, I cannot find the words to show my deepest and uttermost appreciativeness to her because of her generous support and presence in my life with her eternal love.

Finally, this thesis would not have been possible without the love and support of my family. Without unlimited support and love of my mother Meryem Akhüseyinoğlu, I could not achieve any success in my life. I would like to express my gratitude to my father Mahir Akhüseyinoğlu for his inestimable endeavor and love. I would like to show my indebtedness to my enviable sister Meltem Tulğar and my protective brother Fırat Akhüseyinoğlu for always being nearby me.

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LIST OF ABBREVIATIONS

AHP: Analytic Hierarchy Process

ANFEL: The National Federation of Household Appliance Manufacturers

ANOVA: Analysis of VAriance

CCP: Credit Card Promotion

CCPCS: Credit Card Promotion Completion Score

CRM: Customer Relationship Management

DM: Decision Maker

ELECTRE: ELimination and Choice Translating Reality

EWMA: Exponentially Weighted Moving Average

GIS: Geographical Information System

HTML: Hypertext Markup Language

HTTP: Hypertext Transfer Protocol

ILP: Integer Linear Programming

LINMAP: The Linear Programming Technique for Multidimensional Analysis of Preference

MADM: Multi Attribute Decision Making

MAUT: Multi Attribute Utility Theory

MCDA: Multi-Criteria Decision Analysis

MCDM: Multi-Criteria Decision Making

Mdn: Median

MDS: Multidimensional Scaling

MODM: Multiple Objective Decision Making

NISO: The National Information Standards Organization

PPDSS: Personalized Promotion Decision Support System

PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluations

PSA: Personal Shopping Assistant

PSC: Potential Step Count

PTA: Potential Transaction Amount

PVIKOR: Extended Multiple Criteria Compromise Ranking

REST: Representational State Transfer

RFID: Radio Frequency Identification

RRSC: Remaining Required Step Count

RRTA: Remaining Required Transaction Amount

RS: Recommendation System

SC: Step Count

$\widetilde{\mathbf{SC}}$**:** Estimated Average Step Count

SDSS: Spatial Decision Support System

S.E.: Standard Error

SMS: Short Message Service

TA: Transaction Amount

$\widetilde{\mathbf{TA}}$**:** Estimated Average Transaction Amount

TL: Turkish Lira

TOPSIS: The Technique for Order of Preference by Similarity to Ideal Solution

TP: Total Price

VIKOR: Multiple Criteria Compromise Ranking

WEEE: Waste Electrical and Electronic Equipment

YAWL: Yet Another Workflow Language

CHAPTER 1

INTRODUCTION

Consumer buying decision making is a process of purchasing a product or service. It covers all the steps before, during and after the purchase action. In consumer behavior research, it is assumed that purchases are made after a decision process [1]. In literature, consumer decision process is modelled by a flow of action steps. Consumers determine their need for a product or service (1), gather information about possible alternatives (2), evaluate those alternatives based on some criteria (3), and make the intended purchase (4). Post-purchase evaluation (5) and disposition of the product (6) are other steps in this process [1, 2, 3, 4].

Buying decisions should not be thought as standalone decisions. Buying decisions are remade frequently and influenced by previous purchase decisions. Thus, they are rather connected [5]. Grocery market visits are good examples of connected and repetitive buying decisions [6]. According to Einhorn and Hogarth [7], the main objective in repetitive decisions is to select a satisfactory alternative rather than the optimal one in order to minimize the decision effort. They claim that consumers try to minimize the time and effort required to reach a final decision. Consumers do not want to put extensive emphasis on each decision since they make numerous decisions in a single shopping trip [8]. In grocery shopping, this is the case. Consumers do not buy a single product, but a bunch of products out of plenty of available products. Even if grocery shopping is routine, pre-visit planning is required [6] such as writing down shopping list, which increases the required cognitive effort by the consumers [9].

Grocery shopping has become complicated. Consumers spend more and more time in stores but have less and less time for grocery shopping [9]. As indicated in [10], the average grocery store trip is about 41 minutes. It is also noticeable that, consumers with lower-income stay longer in grocery stores than consumers with higher income do [10]. This is because they try to compare all the possible alternatives based on price more strictly. Economists argue that consumers always make rational decisions by calculating all the possible alternatives perfectly, valuing them according to their criteria and selecting the best one that suits most [11]. In contrast, Guitouni and Martel [12] state that a decision cannot be rational, irrational or non-rational, but can be within the area of 'decision domain' encapsulated by these three points. Thus, consumers are not rational since they do not have enough processing capacity and time [11, 12]. As a human being, consumers do not have an unlimited capacity of processing [13]. Therefore, with increase of the alternatives, the decision process becomes harder due to this limited capacity [12, 14].

Due to the lack of time and process capacity, consumers build heuristics for repetitive decisions such as grocery shopping decisions [8, 13]. To select a product from a product group or to select a brand, consumers use simple and also fast decision models such as choosing the lowest price product, choosing the one on sale, choosing the brand that worked best in the past, choosing the one that close relatives are also using etc. [8]. These generated heuristics are not stable, but evolving over time. After the purchase decision, consumers do evaluation about the products they select until the disposal of the product. These evaluations affect and change the tactics used in the decision process [8]. Moreover, Hoyer finds out in [8] that for specific kind of product such as laundry detergent, consumers' evaluation process in the store does not exist. It is also clear that choosing grocery products is not as difficult as buying an automobile or a house [8]. This shows that consumers easily select the single product brand inside the store. However, single product selection is not the situation in a regular shopping transaction. Thus, as stated in [9], in a grocery transaction 18 items are bought on average from a possible 30 to 40 thousand products. Moreover, grocery shopping is time consuming since consumers spend time to collect information, compare options and select where to shop [15] which are the steps of the consumer decision process mentioned above.

The emerging trends in store visits make grocery shopping more complicated. As stated in Deloitte's American Pantry 2013 Study [16], on average consumers visit five different grocery stores to complete their regular grocery needs. In addition, customers want to narrow the set of products in the stores, which in return overlaps with the upcoming plans of huge grocery store chains [17]. The intended plans may result in increase of average store visits by customers. Increase in number of stops in grocery shopping increases the necessity of pre-purchase planning.

Promotions play a critical role in shopping business [18, 19]. As stated in Deloitte's American Pantry 2014 Study [20], consumers do not complete their grocery shopping at a single store. They plan their store visits according to the sales and the promotions. Consumers tend to use promotions, price cuts, coupons for budget planning [18]. This makes consumer buying decision harder. More than 40% of purchase decisions depend on the price of the products and the promotions related to them [21]. Customers' shopping list preparation is also affected by the norm of promotions. 46.8% of the products in the shopping lists are included due to available promotions [9]. Above this, 44.8% of the products are actually bought because they are on sale [9]. Unplanned purchases are enlightened by a study conducted in Turkey. In that study [22], 49% of unplanned purchases at the store are due to available price cuts. In the study by Gupta [23], customers change their intended coffee brand because of a related promotion. In addition, grocery store promotions are mostly rewarded if the customers use grocery store loyalty cards in their transactions. According to Deloitte's American Pantry 2014 Study [20], half of the grocery shoppers use their loyalty cards at grocery stores regularly. This situation introduces additional obligations to consumers. Knowing that there is a promotion at a store is not enough. They have to consider loyalty cards they have before grocery shopping planning.

Consumers are not the only actor in purchasing. Marketing is a set of actions to produce, communicate, deliver and exchange goods that are valuable to the customers [2]. The components of the marketing are *Product, Promotion, Place* and *Price,* which are known as the 4Ps of marketing [2]. Promotion component is used by the marketers to establish communications with customers. Thus, promotions are one of the vital parts of the marketing. One of the main goals of the marketing is to increase sales by promoting promotions, increase profits and gain new customers [18, 24, 25, 26, 27]. Due to increase in return from promotions, marketers start to spend more on promotions rather than advertisements [19]. Effective promotions have positive effects on retailers, but the opposite is also possible. Ineffective promotions lead to decrease in market share. 90% of the brands are affected negatively due to ineffective promotions [28]. In addition, customers regard unrelated promotions as junk, which affects their opinion against the advertising company [18]. In total, promotions have both positive and negative outcomes to the customers and to the retailers.

Promotion centric grocery shopping started to be strengthened after the global economic crisis in 2007. Consumers changed their habits in shopping by selecting cheaper products after the global financial crisis [19]. U.S. Grocery Shopper Trends 2012 [29] shows that customers started to place more emphasis on products' value. The report underlines these findings from surveys. The consumers select their primary grocery store because of the lower prices. The quality of the store and the product variety in the store come after the pricing reasons. The Shoppers' search rate for discounts permanently increased 17% over the recession period [29]. The search for discounts results in increase in product sales from 25% to 38% due to promotions [19]. Marketers also adjusted their plans after the economic crisis. They started to offer more promotions. Average total promotional period in a year increased by four weeks after the global crisis [19].

1.1. Motivation

Consumers may want to do shopping in the near stores or in the cheapest store. Thus, selecting the grocery store is one of the main problem for consumers. Introducing grocery store promotions bring in additional difficulties. Consumers have to follow promotions at each store to learn which product is on sale or to learn which store is cheaper. Consumers may be informed of sales and promotions through conventional methods such as brochures, point-of-purchase promotional displays, TV and newspaper advertisement, in-store radio, and through websites. Moreover, email and social media started to be used for notifying customers about promotions [30]. Nevertheless, the drawback is that individuals are prone to many sales and promotions and most of them are ignored. As mentioned earlier, the customers make poor decisions in case of a huge amount of information. Even if they are able to process each promotion, it is hard for them to select the most suitable one among others. Increase in the number of the promotions is going to make consumers ignore more promotions even if they are valuable and beneficial.

Besides grocery store promotions, payment options such as debit and credit cards should also be considered in the consumer decision process. Banks and financial institutions that issue debit and credit cards also offer different kinds of card-based reward programs to impose their customers to use their cards in shopping. Airline rewards or frequent flyer programs, hotel rewards, cashback rewards, point rewards, and gas rebate rewards cards are some of the main rewards-based credit cards. Cardholders can earn different types of reward points for each transaction and/or by reaching a total amount of payment within specific time limits. To maximize their earnings, customers have to follow each card reward program and select the most suitable card for a specific transaction. If the consumer has a credit card that gives cash back for each grocery store transaction, it is plausible for him to use that card at grocery stores. If the customer wants to earn airline reward points to buy cheap or free airline tickets, he needs to use that card frequently to fulfill his goal. Thus, it is hard to select the payment method by customers.

Furthermore, banks offer ‘conditional promotions’ or credit card promotions where consumers have to complete predefined conditions to earn discount, points, or cash-back. For instance, one has to spend X TL to get Y TL points as a reward in a specific time frame. Banks in Turkey promote numerous credit card promotions to attract credit card holders to use their cards. Cardholders also seek this kind of promotions to lower their expenditures. Seeking credit card promotions as well as the product promotions causes consumers to be overloaded. Assume that the consumers are informed about the promotions and they are able to earn rewards from these promotions. They have to follow the rewards/points they earned and use them before the expiration date. Unfortunately, like in grocery store promotions, credit card conditional promotions and reward programs become another burden for consumers even for non-promotion seekers or busy ones. According to Laroche et al. [25], busy consumers also love to save money along with saving time, even if they do not have enough time to search promotions.

In the lights of the things mentioned above, the consumer decision process now requires more time by consumers. Increase in promotions, increase in number of available stores, and increase in number of products in grocery stores require more time to compare and analyze the alternatives. Therefore, consumers need a purchase decision aid, which is promotion-aware.

1.2. Purpose of the Study

In this study, the research goal is to propose a promotion-aware model to aid consumers in overcoming problems and difficulties mentioned above in the consumer decision process. This research is focused on the information gathering and the alternative evaluation steps of the decision process.

The generated model is planned to serve customers to ease store selection, grocery promotion selection and credit card promotion selection by using predefined shopping list. Therefore, the model is not restricted to a single store. It is to be used in pre-purchase planning.

The proposed model should eliminate the difficulties of the credit card promotion follow-up. This way, consumers may start to benefit from these promotions and decrease their expenses. Moreover, the model should aid consumers while conforming to their choices. The model should evaluate the shopping options based on consumer preferences. Thus, it should be a consumer-based model.

1.3. Contributions

The major contribution of the study is the promotion-aware decision aid model and its conceptual design. As described in Section 2.2.1, there are studies related to shopping and promotions. However, to the best of our knowledge, none of them has similar objectives and solutions as the current study. The closest work to our study is PromotionRank [18]. Simply, PromotionRank combines grocery store promotions according to the categories of the products in the shopping list. Thus, the notion of the combination of grocery store promotions according to the shopping list is similar to our study. However, there are critical differences. First, PromotionRank is used within a grocery store. Second, it considers only one grocery store. Third, credit card promotions and payment options are not covered. Nevertheless, in our study, the proposed model targets pre-purchase planning since consumers need help at deciding which grocery store to do shopping. Therefore, it also covers the reality of visiting more than one store by consumers. Moreover, a novel contribution of the study is to consider credit card promotions along with grocery promotions in aiding purchase decisions.

Another contribution of the study is the proposed purchase estimation model. The purchase estimation model is used to predict consumer purchase pattern to measure the properness of a credit card promotion for a consumer.

Besides the proposed model, a mobile prototype is developed to realize the applicability of the model. It is an example of client-server architecture. The model results are obtained by using the server-side implementation of the prototype. To evaluate the performance of the proposed model, the shopping alternative selection problem is formally defined as an Integer Linear Programming (ILP) problem and the optimum results gathered by ILP are compared with the model's results. This implemented artifact is another contribution of the thesis research.

1.4. Thesis Outline

This thesis is comprised of six chapters. The remaining chapters are organized as follows:

In Chapter 2, the literature review is presented. It presents background information about Recommendation Systems and Multi Criteria Decision Making (MCDM) methods and it explores the related work in the literature.

Chapter 3 represents the proposed solution. First, terminology descriptions are given. Second, the conceptual design is explained.

Chapter 4 describes the implemented mobile prototype application, which is based on the conceptual design.

Chapter 5 evaluates the proposed model results. The dataset used for the evaluations is explained and data preparation processes are described. Then, the evaluation of the model results and the statistical analyses are given.

Chapter 6 concludes the study and provides suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the literature review and introduces background information about Recommendation Systems in general and Multi Criteria Decision Making (MCDM) methods in particular. In the second part, it explores the related work in the literature. The related work sub-section is divided into shopping and promotion recommendation related studies, workflow related studies and PROMETHEE related studies.

2.1. Background Information

2.1.1. Recommendation Systems

Recommendation Systems (RSs) have become a separate research area in mid-1990s [31]. Due to plenty of information people have been exposed recently, they have been confounded about how to manage the information in order to reach their purposes. When people face with such excessive amount of information, they may be lack of judging which significant aspects of the information to use. Hence, to guide the people looking for meaningful information to use in an effective manner, recommendation systems have been considered essential and this research area has arisen [32]. The core mission of the studies in this area is to solve the recommendation problem. The recommendation problem can be thought of finding the most suitable items, actions or information for people according to their needs [33]. The definition of recommendation systems has been shifted since the late 1980s. Rudimental recommender systems, known as *text-based filtering systems*, were handled from the cognitive aspect. They were thought as the systems that consider the characteristics of the items preferred by users and suggest appropriate items in compliance with keywords. The later version of the recommender systems has been addressed as considering the relations between users and institutions, so classified as sociological filtering systems. This second type of recommender systems underpins the recent ones, which emphasizes the individualized and useful matches to the needs of information seekers [32].

In order to rank many possible items properly, the usefulness of recommendable items is calculated by ‘utility functions’. These functions are used to set a utility value for every possible item that is not already rated by the user. Thus, the problem of recommendation becomes recommending the item or set of items that maximizes the utility for that particular user [34].

In order to represent the utility function formally, there needs to be two sets as *Users* and *Items*. The utility function *R* maps the elements belong to the Cartesian product of User and

Item sets to real or integer number values R_0 that are greater than zero. Then this relation represents how appropriate a recommendation of item $i \in Items$ to user u ∈ Users [34].

$$R: Users \times Items \rightarrow R_0$$

Here the assumption is that the utility values for all user and item pairs are not known, instead the subset of pairs can be matched to R_0 values. Hence, the utility function for each user on an item $R(u, i)$ is an approximation or estimation and the recommended item is selected in a way that will maximize the utility of users:

$$i = \arg\max i \in Items\ R(u, i), \forall u \in Users$$

To make recommendations, RSs have to estimate individuals' preferences based on some sort of information. The category of the system is determined by the information used to make an estimation.

2.1.2. Types of Recommendation Systems

Recommendation systems are grouped into two main categories in most studies in the literature as *content based* and *collaborative* recommender systems [32, 35]. Early research in this domain starts with the papers handling the collaborative filtering [31]. Content-based systems use textual representations of the item features in order to make predictions on the user preferences. They utilize the past choices of the users, the ones watched, visited, read and advised by them, to recommend new items. As an example, if a user has ordered home design magazines before, s/he will be recommended home design magazines that s/he has not ordered yet [36]. Collaborative systems utilize the preferences of the similar users (in terms of taste) to recommend items rather than content analysis. Items are recommended based on the reviews of the similar users who have been used the items before. Beside these, *demographic*, *utility-based* and *knowledge-based* recommendation systems have been proposed as the types of the recommendation systems [32]. In demographic recommendation systems, users are recommended items according to their personal attributes and classifications are made according to their demographics like their ages, gender, and social status. Utility-based ones make recommendations by calculating the utility functions for each user as the name implies. To suggest items in a knowledge-based system, rules are defined and logical inferences are made on the preferences of the users. Finally, *hybrid recommender systems* can be thought as another type of recommender systems. Rather than a single recommender system type, this category implies the integration of the aforementioned recommender system types. The aim of the use of a hybrid system is to overcome the drawback of a standalone system and to obtain a more robust one. As the Web 3.0 and Internet of Things technologies have been started to be ubiquitous, the recommender systems will be on the rise by incorporating the context information like location, weather, mobile device usage, and personal habits obtained via smart technology facilities to the information utilized by traditional recommender systems mentioned above [36].

Another broadly recognized classification of the recommender systems groups them as *model-based* and *memory-based* considering the methods used for obtaining recommendations [36]. As its name implies, model-based approach aims to fit a model to the data, handled as a matrix consisting of ratings by users for each item. Those models may belong to optimization problem solving, artificial intelligence or machine learning domains so that every new input to this matrix causes the need for the update of the model. Similar to model-based methodologies, memory-based methods also apply to item-rating matrix and keep it up-to-date for producing accurate results. Differently, they utilize distance metrics of the user preferences in order to find the close and distant items or user preferences [36].

Items in question and the preferences of users are shown in assorted forms in recommendation systems like using single or multi features to define an item [32]. Majority of the recommender systems use a single criterion value for the utility function such as comprehensive assessment or rating of an item by a user. The recent studies in the literature considers this single criterion value assumption for the utility function as limited due to the fact that users may look for more than one factor when making decisions. Hence, the appropriateness of an item recommendation for a specific user does not depend solely upon a single criterion. Especially the performance of the systems, which recommend items according to the opinion of other users, may be improved by the inclusion of multiple criteria [34]. As noted by [32], in most of the systems user models are constructed manually. To give an example, some systems ask for the weights of all criteria from users. Multi-criteria systems could utilize from the existing techniques as from MCDM and single criterion recommender systems. Present recommender systems make use of several methodologies like machine learning that generate user profiles by training the sample set [32]. In [37], authors draw an attention to the issue that recommendation is a new kind of MCDM problem that have need for new modeling techniques different from traditional ones. Traditional decision making models could be divided into two categories as individual and group decision making. Individual decision making handles the decision problem of a single user over various possible solutions. On the other hand, group decision making process includes several users and the same decision problem. The final solution is obtained among the alternative solutions by the consensus among the users. However, for the recommender systems, the preferences and experiences should be shared between users to solve similar decision making problems.

2.1.3. Multi Criteria Decision Making Methods & Examples of Multi Criteria Problems

As defined by [38] (p. 1) "MCDM stands for Multiple Criteria Decision Making and deals with the (mathematical) theory, methods and methodological issues and case studies (applications) for decision processes where multiple criteria (objectives, goals, attributes) have to be (or should be) considered." MCDM should be considered as decision making process to evaluate multiple criteria which can be qualitative and quantitative and which contradict each other [39] [40]. MCDM is a sub research field of operations research models [41, 42]. In classical optimization models, decisions are made by optimizing an objective value among candidate feasible solutions subject to defined constraints. However, since the criteria of the MCDM problems, which contradict each other, are tackled at the same time, the solution is not optimal but a fair one. Hence, the awareness of the organizational decision making characteristics have given rise to multi-criteria decision analysis (MCDA) [12].

MCDM problems can be found in daily life in many areas. For example, a consumer may pay attention to various characteristics of a car including but not limited to the price, safety, comfort, and gas mileage. Hence, car manufacturers would aim to optimize those characteristics, i.e. to minimize the costs and maximize the safety and riding comfort. As another example, water supply service for the public could be thought. Water resources should be developed by preparing plans and those plans should be assessed considering several factors such as water shortage, cost, energy etc. [39]

Despite the assortment of MCDM problems, they share some common characteristics. The main characteristics of the MCDM problems are given below [39]:

- Multiple objectives/attributes: Every MCDM problems have multiple objectives and attributes, so for each problem, objectives and attributes should be generated by people who make decision.
- Conflict among criteria: The criteria used to make decisions in MCDM problems are usually conflict with each other. For example in case of the car design problem, the production cost may increase due to additional safety measures.
- Incommensurable units: The criteria used in MCDM problems have usually different units of measure. Again, if we tackle the car design problem, we see that cost is represented in dollars while efficiency is represented by gallons per kilometer and safety has nonnumeric representation and so on.
- Design/selection: MCDM problems try to design a best alternative or select the best one among the previously defined options by using all the criteria.

2.1.4. What is MCDM/MADM/MODM/MAUT?

People are incompetent about analyzing multiple flow of diversified information in an effective manner. The MCDM methods appeared because of this. A broad definition of MCDM is given in Section 2.1.3 Multi Criteria Decision Making Methods. As a widely accepted categorization [39], MCDM methods can be divided into two broad categories as Multi Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM) [42, 43, 44]. This categorization is made according to the settings of the decision making problem. When the number of alternatives is finite, MADM is used [45]; conversely, for the infinite number of alternatives MODM is applied. This classification of the MCDM methods can also be based on the way of problem solving. In MADM, a *selection* among the finite number of alternatives is made according to explicit or implicit tradeoffs whereas the MODM solves the *design* problem according to a set of constraints and finds the best solution considering multi objectives. In other words, MODM methods deal with mathematical optimization problems that have multiple objective functions. MADM can be considered as a decision aid to a decision maker to select the best option in a way that s/he obtains maximum satisfaction regarding multiple attributes [39].

As pointed out by [41, 46, 47] MCDM methods can also be grouped into two main categories as MAUT and outranking methods. MAUT stands for multi-attribute utility theory and handles the decision making problems having multiple objectives from the aspect of utility theory. The aim of utility theory is to quantify the preferences of individuals in a way that the attributes having different scales can be brought to the same measurable interval. In other words, MAUT performs a numerical evaluation on each alternative [46] and calculates the utility function for decision makers. Then the MAUT solves an optimization problem by maximizing the utility function [48] and the result is a rank, which orders the evaluation of alternatives. MAUT does not compare the alternatives in a pairwise manner, as it is the case in outranking methods [46].

On the other hand, outranking methods, of which philosophy was first proposed by [49]; do not apply for a utility function. Outranking methods are built upon the idea that the alternatives to be compared are assumed to have different levels of supremacy on the other ones. Hence, in outranking methods, alternatives are compared to each other in a pairwise manner from the point of each criterion in order to see which alternative dominates the performance of the other one. To establish the outranking relations, preferences are settled for each criterion and two distinct thresholds are obtained which are indifference and preference levels. The indifference threshold is the value that a decision maker (DM) would ignore this amount of difference on a criterion for two different alternatives. The preference threshold implies such a point that when it is surpassed for an alternative, the DM would tend to prefer this option. The area between these two levels is named as indifference zone. Thereby, the ranking process is completed by aggregating the information for all pairs of alternatives and all criteria to compare the overall performances of the alternatives [48].

2.1.5. Classification of MADM Methods According to Additional Information Required From DMs

MADM problems are briefly represented by decision matrix, which comprises of alternatives to be selected / ranked in the rows and criteria in the columns of it. All of the types of MADM methods have the need for extra information from decision makers in addition to the information included in decision matrix to select / rank alternatives. To give an example, decision matrix does not include criteria weight or preference / indifference values of decision makers [50]. Hwang and Yoon [39] provide a classification for MADM methods from this aspect, i.e. based on the additional information required from decision makers about alternatives and attributes [50]. Figure 1 below demonstrates the simplified version of the classification schema provided by [39] again in a later study of the authors [51]. For example, if additional information is not required from decision makers, then the dominance method should be used. If and additional information is required, then the classification of the methods is based on the type of information required: either about attributes or about environment. To give an example, Simple Additive Weighting, Weighted Product, TOPSIS, ELECTRE, Median Ranking Method, and Analytic Hierarchy Process (AHP) methods require cardinal importance of the attributes, weights, from the decision maker [50]. In addition, if the ordinal importance of the attributes is provided by the decision makers, then lexicographic method and elimination by aspect method can be used as explained by [50]. However, the taxonomy proposed by [50] with slight adjustments on the one proposed by [51], groups Maximin and Maximax methods under the type of methods that require no additional information. To the best of our knowledge, there is no other current study proposing the classification of MADM methods. Since the PROMETHEE II method used in this study was derived from ELECTRE [41], it can be said that the method used in this study is a type of multi attribute decision making method requiring cardinal values for attribute importance, i.e. weights of the attributes.

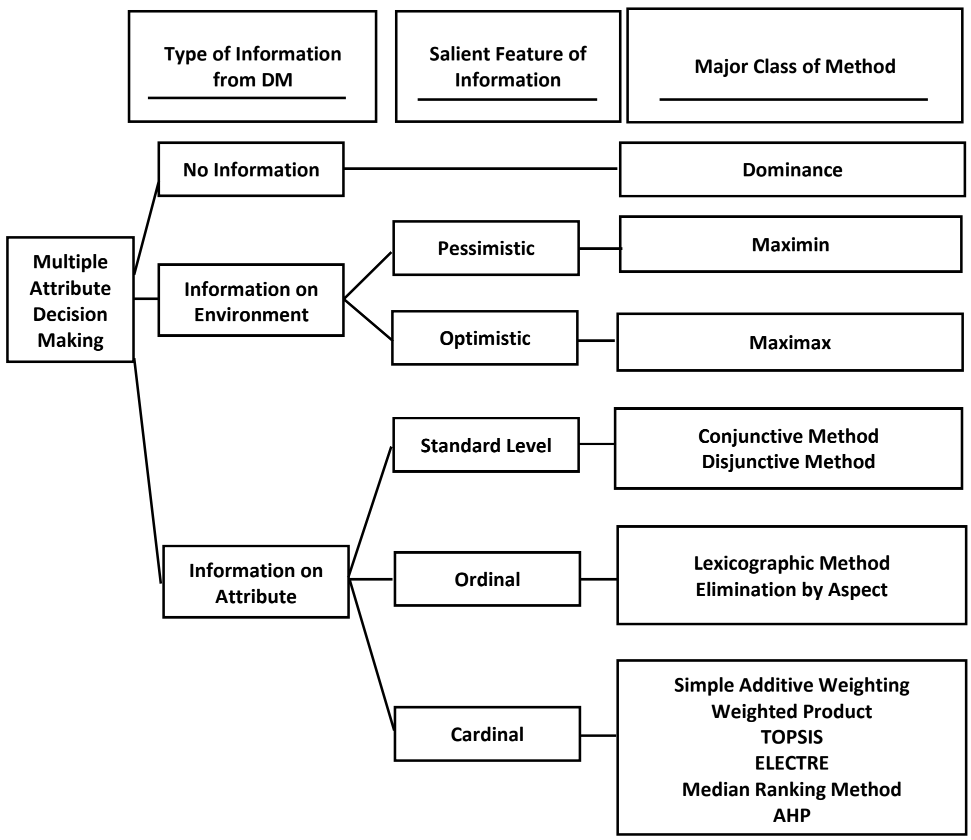


Figure 1 – Classification of MADM methods

2.1.6. Classification of MADM Methods According to Compensation Behavior

MADM methods can also be classified according to their compensation behavior against the aggregation of the criteria. Hwang and Yoon [39] define MADM methods as the procedure to process the attribute information, so tackles the classification of MADM methods from the aspect of attribute information processing. De Boer et al. [52] approach to this division by considering the type of the decision rule applied by decision models. Overall, they group the MADM methods as having two types of models, which are *compensatory* and *non-compensatory* models, from different aspects. In compensatory models, there exists a balance between competing attributes such that the poor performance of a criterion for an attribute can be tolerated by the satisfactory performance of another attribute for the same alternative [12, 39]. Compensatory models can further be grouped into subtypes depending on the calculation of the score, which is assigned to each alternative combining the effects of multi criteria for each alternative. Those types are *concordance*, *compromising*, and *scoring* models. In scoring models, the decision is made by evaluating the convenience of the utility function since the selection of the best alternative is based on the score calculated for each alternative, utility, which is to be maximized. The members of this group are hierarchical additive weighting, simple additive weighting, and interactive simple additive weighting. However, in compromising models, the option nearest to best solution is selected. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the Linear Programming Technique for Multidimensional Analysis of Preference (LINMAP) and nonmetric Multidimensional Scaling (MDS) methods can be given as examples to compromising models. Finally, concordance models rank the alternatives by evaluating the candidate rankings and selecting the one meeting concordance measure. ELECTRE, linear assignment, and permutation methods fall into this class of compensatory methods. For compensatory methods to be able to compensate the poor and good performance, the units of measure for all attributes should be the same either the normalization techniques should be used by those methods [50].

On the other hand, non-compensatory methods do not include the trade-off mechanism among conflicting criteria, i.e. an attribute underperforming cannot be counterpoised by the satisfactory performance of another attribute [12, 39]. Lexicographic, maximin, maximax, conjunctive constraint, and disjunctive constraint methods reside in this type [39, 50].

An intermediary third type of methods is named as partially compensatory methods, which can be thought as somewhat compensatory and somewhat non-compensatory. To be more precise, trade-off is allowed in case of small difference between the attribute performance of two different alternatives whereas the large differences could not be tolerated [12, 53].

2.1.7. Outranking Methods

Outranking relations was emerged as a response to the need of circumventing difficulties posed by the aggregation features of MAUT methods. MAUT methodologies assume the presence of a best solution, which has full dominance over other alternatives whereas the partial dominance is allowed in outranking methods [54, 55]. Hence, the outranking methods can cope with incomparable type of relations between alternatives whereas MAUT methods cannot [55]. In addition, because of the partial dominance is allowed, outranking models are mentioned as to be type of partially compensatory methods. The backbone of the outranking models is the pairwise comparison of alternatives for each criterion in order to find out whether there exists a preference for the concerned alternative over other ones and if so, to define the degree of the preference. Then the overall performances of alternatives are evaluated considering all the criteria together with the weights assigned to each of them. An outranking model should be seen as a top prior method when the attributes used for the decision making problem have *incommensurate* or incomparable unit of measures, wide range of measurement scales, and are difficult to be aggregated [54]. Furthermore, while applying MAUT models users have difficulty with ordinal attributes but outranking models makes the use of ordinal attributes easy [55]. There are numerous outranking methods proposed and proved in the literature, but the PROMETHEE and ELECTRE methods will be elaborated here. The reason for explaining these two methods is that the PROMETHEE is the selected method for ranking the alternatives in this study and the PROMETHEE was asserted as a response to the drawbacks of its ancestor, the ELECTRE method [41].

2.1.7.1. ELECTRE

ELECTRE (ELimination Et Choix Traduisant la RÉalité) [56] is mentioned to be a popular and the most commonly used method among other outranking methods. The ELECTRE was developed in order to rank the alternatives regarding several criteria representing the factors that decision makers consider [55, 57]. The method, of which roots back to late 1960s, was then enhanced to incorporate solutions to handle different type of situations/problems, which are ELECTRE II, ELECTRE III, and ELECTRE V. The goal of all these ELECTRE methods is to solve ranking problem and the idea of the methods is based on the Roy's decision aid phenomenon [58]. ELECTRE uses outranking approach which it compares the alternatives in a pairwise manner. This method is compensatory just like PROMETHEE method, which means that it regards the relative importance of the criteria [57]. Below the succinct information on the ELECTRE models is given, the one who is concerned about getting more detailed information about the models can refer to referenced articles:

- **ELECTRE I** [56]**:** It is the ancestor of the next generation of the ELECTRE methods. It concentrates on the solution of choice problems by reducing the set of possible alternatives by eliminating the improper ones and obtaining a set of best alternatives [55].
- **ELECTRE II** [59]**:** This method is the extended version of ELECTRE I from theoretical aspect which also investigates the outranking relationships between alternatives. This method introduces the *concordance* and *discordance* concepts [58] to arrange the alternatives that are not dominated by other alternatives in a complete way [55].
- **ELECTRE III** [60]**:** This version of the ELECTRE model is suitable for stochastic decision making problems [57] because of incorporating fuzzy approach to define thresholds for criteria [55, 58]. In other words, it uses intervals for each criterion instead of deterministic single values for determining preference and indifference thresholds [57].
- **ELECTRE IV** [61]**:** It is the adjusted version of the ELECTRE used when the relative importance of the criteria, i.e. the weights, cannot be obtained from the decision makers [55, 58].

2.1.7.2. PROMETHEE

The PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) method, which falls into outranking category of MCDM methods, was first asserted by [62] and then enhanced by [63]. Since PROMETHEE is adverted among MCDM methods, it is used as a tool for decision making by taking into account multiple conflicting criteria. In addition, because of belonging to MADM category, the subtype of MCDM, PROMETHEE handles finite number of alternatives to rank or select the subset of them considering the defined criteria [57, 64, 65]. PROMETHEE has several versions that are PROMETHEE I, PROMETHEE II, PROMETHEE III, PROMETHEE IV, PROMETHEE V, PROMETHEE VI, PROMETHEE GDSS, PROMETHEE GAIA, PROMETHEE TRI, and PROMETHEE CLUSTER [57]. PROMETHEE I can produce partial rankings by taking into account incomparability between alternatives whereas PROMETHEE II produce complete rankings [64].

As all other MCDM methods, PROMETHEE uses a decision matrix, which is also called as evaluation/ payoff matrix or evaluation table [41]. This matrix includes alternatives for being ranked in the rows and the criteria (attributes) in its columns as shown in Table 1. The value in a cell shows the performance of the interested alternative on the interested criterion. For example, PV_{ij} is the performance value of i^{th} alternative (A_i) on the j^{th} criterion (Cj).

Table 1 - Decision matrix

	w_1	w_2	...	w_j
	C_1	C_2	...	C_j
A_1	PV_{11}	PV_{12}	...	PV_{1j}
A_2	PV_{21}	PV_{22}	...	PV_{2j}
...	...	...	...	...
A_i	PV_{i1}	PV_{i2}	...	PV_{ij}

If the process of applying PROMETHEE as an MCDM method is considered, then the below steps should be followed [66]:

- Decision makers, actors and stakeholders should be identified. Decision makers are the ones who give the final decision about the problem. Actors participate in the analysis step and the stakeholders can be anyone affected by the final decision.
- Criteria (C_1, C_2, ..., C_j) used for evaluating the alternatives should be chosen.
- Alternatives (A_1, A_2, ..., A_i) to be evaluated in the decision process should be collected.
- Evaluation of alternatives against each criterion is required. In this step, the performance values of the alternatives for all the criteria (PV_{11}, PV_{12}, ..., PV_{ij}) are determined.
- The cardinal (quantifiable) relative importance of the criterion, aka known as weight, against other criteria is needed in PROMETHEE method as needed in most of the multi criteria methods [48, 67]. Hence, the weights of each criterion (w_1, w_2, ..., w_j) should be determined. Weights of the criteria are quantitative and on a ratio scale. Hence, if one of the criteria has a weight, which is as double of another criterion, then the first criterion is twice as important as the second criterion [68]. PROMETHEE does not present a guideline for assigning the weights, but presumes that decision makers can distribute the weights in a reasonable fashion in case small number of criteria exist [67].
- A preference function P (criterion function) should be selected. This function maps the difference of performance values (PV) between each pair of alternatives to a value between zero and one. The preference function represents the degree of preference attributed to the better alternative in pairs. Decision maker applies to preference function to compare the contribution of the alternatives to each attribute [64]. In other words, if we tackle two alternatives a and b, then the value of preference function P(a, b) shows the degree of preference of alternative *a* over alternative *b* on a specific criterion.

In order to implement PROMETHEE, two additional types of information are needed besides the evaluation matrix. That additional information includes weights of the criteria and preference function [64, 67] as explained above. Decision makers are assumed able to assign the quantitative weights with acceptable accuracy [68] especially when the number of criteria is small [67]. However, in this study, since the customers who have made market transactions in the dataset are impossible to be reached, weights are assigned in a way to test many different possibilities. They are increased properly from starting zero up to reaching one. The details of this process are explained in Section 5.4.2. The most important difference of PROMETHEE and other outranking approaches is that PROMETHEE uses preference functions. Here the aim is to incorporate the uncertainty existing in the PVs of the criteria, as the nature of the decision making problem [66]. As stated above, preference function translates the difference of performance values (PVs) between two alternatives, a and b, into a value from interval 0 and 1:

$$P_j(a,b) = G_j\left[f_j(a) - f_j(b)\right] \tag{2.1}$$

$$0 \le P_j(a,b) \le 1 \tag{2.2}$$

fj represents the performance value of an alternative on attribute (criterion) j which is represented as PV_{ij} in the decision matrix above. Gj is a non-decreasing function of the difference of $f_j(a)$ and $f_j(b)$. The possible preference relations between two alternatives can be shown as follows [69]:

$$\begin{gathered} P_j(a,b) = 0, no\ preference\ (indifference) \\ P_j(a,b) \approx 0, weak\ preference \\ P_j(a,b) \approx 1, strong\ preference \\ P_j(a,b) = 1, strict\ preference \end{gathered}$$

Brans and Vincke proposed [63] six different preference functions which are usual criterion, u-shape criterion, V-shape criterion, level criterion, V-shape with indifference criterion and Gaussian criterion. In order to calculate the value of preference function, preference (p) and indifference (q) values should be known. Preference value p is the minimum deviation that is sufficient for a decision maker to make strong preference of one alternative over another. Indifference value q can be considered as the largest deviation, which is neglected by the decision maker while comparing the alternatives. An intermediate value between preference and indifference values (s) is needed for only Gaussian preference function [57, 64]. Figure 2 shows those preference functions proposed by [63]. The graphs are adopted from the study of Balali et al. [57]. H(d) maps to Pj (a,b) which is explained above. dj is equivalent of the difference between the performance values of the alternatives: $f_j(a) - f_j(b)$.

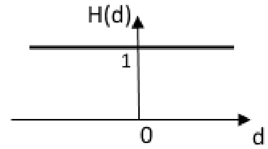
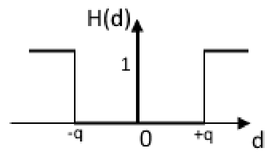
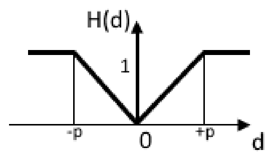
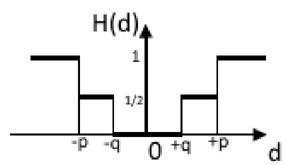
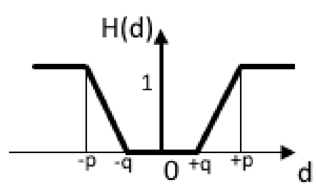
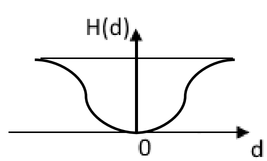
Type of Function	Preference Function	Definition
Usual Criterion		$\boldsymbol{H(d) = \begin{cases} 0, & d = 0 \\ 1, & d \neq 0 \end{cases}}$
U-Shape Criterion		$\boldsymbol{H(d) = \begin{cases} 0, & -q \leq d \leq q \\ 1, & d < -q \text{ or } d > q \end{cases}}$
V-Shape Criterion		$\boldsymbol{H(d) = \begin{cases} d/p, & -p \leq d \leq p \\ 1, & d < -p \text{ or } d > p \end{cases}}$
Level Criterion		$\boldsymbol{H(d) = \begin{cases} 0 & , & \lvert d \rvert \leq q \\ \frac{1}{2} & , & q < \lvert d \rvert \leq p \\ 1 & , & p < \lvert d \rvert \end{cases}}$
V-Shape with Linear preference and indifference area		$\boldsymbol{H(d) = \begin{cases} 0 & , & \lvert d \rvert \leq q \\ \frac{(\lvert d \rvert - q)}{(p - q)} & , & q < \lvert d \rvert \leq p \\ 1 & , & p < \lvert d \rvert \end{cases}}$
Gaussian Criterion		$\boldsymbol{H(d) = 1 - e^{-d^2/2\sigma^2}}$

Figure 2 – Preference functions as proposed by [63]

The process of decision making by PROMETHEE then continues with the calculation of overall preference index of each alternative. Preference index of an alternative “a” over alternative b is represented as π(a,b). The preference index expresses that if the outperforming alternative of a pair wins a value for a criterion with lower weight, it is less worthwhile than winning the value for a criterion with higher weight [48].

$$\pi(a,b) = \left(\sum_{j=1}^{n} wj\ P_j(a,b)\right) / \left(\sum_{j=1}^{n} wj\right) \tag{2.3}$$

After the calculation of the overall preference index of alternative “a” over alternative b, then the positive (leaving) and negative (entering) flow of alternative “a” should be calculated. Positive flow indicates the degree of how much alternative “a” outperforms all the remaining alternatives and is depicted as ϕ^+ (a). Conversely, negative flow indicates the degree of how much alternative “a” is outperformed by other alternatives and is depicted as ϕ^-(a). Those positive and negative flows are calculated for alternative “a” considering all of the remaining alternatives, not just only alternative “b”. Hence, “x” in the formula below represents all of the remaining alternatives in the set of alternatives “A” when we exclude alternative “a”. ϕ (a) is the net outranking flow of alternative “a” and a higher value of it means the higher attraction of the alternative “a” [64].

$$\phi^+(a) = \sum_{x \epsilon A} \pi(x,a) \tag{2.4}$$

$$\phi^-(a) = \sum_{x \epsilon A} \pi(a,x) \tag{2.5}$$

$$\phi(a) = \phi^+(a) - \phi^-(a) \tag{2.6}$$

As indicated before, PROMETHEE I presents a partial ordering of the alternatives whereas PROMETHEE II presents complete ranking. PROMETHEE I utilizes leaving and entering flows separately to find three types of outranking relations: preference (aPb) , indifference (aIb) and incomparability (aRb). On the other hand, PROMETHEE II considers the net outranking flow to rank the alternatives. As a result, PROMETHEE I guarantees the indifference and incomparability relations different than PROMETHE II [64]. Figure 3 demonstrates the procedure explained above for PROMETHEE II application.

The apparent feature of PROMETHEE III is its use of intervals for the calculation of flow values rather than just using single real values [65]. PROMETHEE IV handles the decision making problems where the set of alternatives is continuous, rather than a discrete set [70]. PROMETHEE V was developed for tackling portfolio management problems and solves an optimization problem with subject to some constraints in order to select subset of the alternatives [71]. Brans and Mareschal [72] proposed PROMETHEE VI for representing human brain. The PROMETHEE GDSS was suggested to aid in-group decision making cases. For more complex decision making problems, [73] came up with PROMETHEE GAIA with its capability to graphically represent the problem via interactive visual component [65].

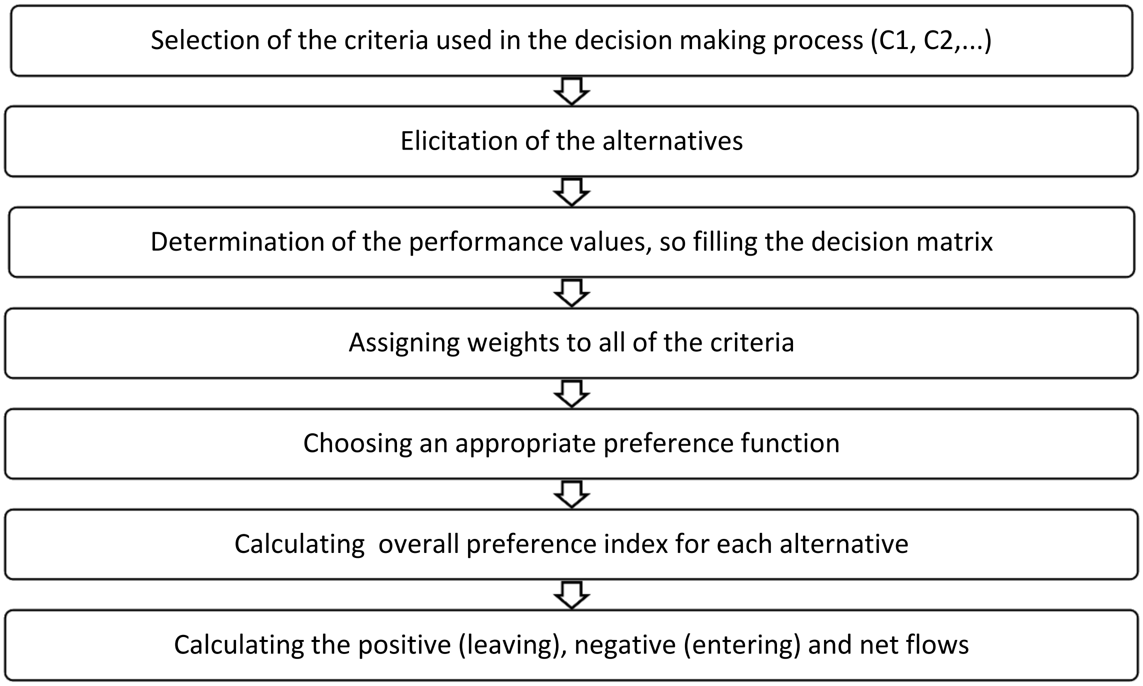


Figure 3 – Procedures of PROMETHE II

2.2. Related Work

This section summarizes the related work in the literature. First, studies that targeted shopping and promotional recommendation are given. Second, studies in which cost aware workflow engines are used or proposed are listed. At the end, researches that use PROMETHEE as a MCDM method are presented.

2.2.1. Shopping and Promotional Recommendation Related Studies

Mobile technology changes the way of shopping. 52% of consumers use technology in grocery shopping [29]. According to Digital Commerce's white paper in September 2014 [74], 53% of customers use smartphones to plan their shopping. The technology is being used before and at the shopping time. Mobile technology enhancements help customers to use technology commonly. Customers use it to check prices, search products, prepare shopping lists, read product reviews etc. One of third consumers uses technology for online coupons. During shopping, top two mobile contents that influence customers are coupon and sales promotions [74]. Grocery firms started to adapt mobile marketing to influence customers before and during the shopping [21]. Thus, technological improvements mostly mobile solutions improvements would shape the future shopping habits of customers.

In this section, researches related to recommendation systems in customer buying process especially related to promotions are exemplified. To our best knowledge, no research proposed a model or a system that addresses both grocery store promotions and credit card promotions.

Here, studies mostly related to promotions including grocery store promotions are listed. The findings are not narrowed by mobile solutions.

Nurmi et al. presents PromotionRank [18] to rank grocery store promotions with the help of personal shopping list. PromotionRank targets recommending personalized promotions. It is a recommender system with the capability of information retrieval methods. The products in the shopping list are linked to the categories in that store by using information retrieval methods. After the linking phase, the system examines and recommends additional product category based on the products in the shopping list by collaborative filtering technique. Then, each possible product category is scored and available store promotions are ranked according to calculated scores. PromotionRank is both evaluated with offline history of grocery market transactions as well as with real customers at shopping. The prototype demonstrated in this study is developed on Nokia N900 smartphone, which is attached to a shopping cart.

The results based on observations shows that PromotionRank is able to combine accurate promotions with customers' shopping list without affected by the number of items in shopping list. In reality, PromotionRank is capable of enhancing sales in grocery stores by promoting personalized promotions. The main contribution of this paper can be summarized as personal shopping list has enough information to rank promotions that are appraised as relative and interesting by the customers.

PromotionRank uses shopping lists instead of consumer shopping history. Nurmi et al. states that shopping history is sensitive since it has information about purchased product of customers. It is hard to access to this sensitive data. Moreover, even if past purchases may have clues about periodic needs of the customers, shopping lists are constructed for the upcoming purchase event, which shows customers' current needs directly.

PromotionRank is designed to serve and is evaluated for a single grocery store. The customers start to use it while visiting the grocery store. Customers are willing to visit more than one store to complete their ordinary grocery shopping. It is important to note that the pre-purchase planning is not mentioned in PromotionRank. In our research, the fact of visiting more than one store is targeted by including stores into the shopping alternatives.

Massive [75], is a mobile grocery shopping assistant to help customers in buying process. The shopping list is entered textually by the users. Natural language entries are linked to actual products. Massive uses PromotionRank to show personalized promotions to the customers according to the indoor location in the store. The system is to be used within the store. It has not any pre-store visit aiding.

Yang et al. [76] proposed a location-aware system to recommend websites of merchants. The website has information about offers and promotions. The system is a combination of both content and location aware recommendation systems. The system analyses the web access history of a customer to generate personal profile and combines it with the current location information with the help of mobile devices. The system recommends vendors' website that are closer to the customer and is related to the customer's interests. It shows top-n related websites. The customer is indirectly exposed to vendors' promotions. The proposed system is evaluated for one and half year time with 136 graduate and undergraduate students. The system is provided on laptops or PDAs. Each participant uses it for 3-month time. The results show that the proposed system is statistically better than only location and only content based recommendation systems.

Chan et al. [27] suggest pricing and promotion strategy to raise profit of online shops. The purposed system permits customers to bargain over the list prices. When a customer wants to buy a product, the system shows the list price of the product. If the customer is satisfied by the price, the purchase transaction is completed. If not, the system asks the customer to state the maximum and acceptable price for the product. Then the system presents newly generated reduced price of the product to persuade the customer to complete the transaction. If this reduces price is also not accepted by the customer, different types of promotions are combined to satisfy the customer expectation. The system is tested on an online shop for 14 weeks and the performance of the online shop is statistically analyzed. The results suggest that purchase performance of the online shop is increased but the profit of the shop is not affected.

Shop-bots are websites that enable customers to compare prices of products and get information about the retailers. In this study [77], the next generation shop-bots are proposed namely Shopbot 2.0. Instead of just comparing prices, Shopbot 2.0 is capable of searching sales promotions and recommends products to shoppers related with the currently searched item. In order to justify this system, top selling books and their recommendations in Amazon.com and Buy.com is used. In the proposed system, recommendations are chosen according to the promotion sales. Instead of selecting the most related book, one of the top-n related books is selected with the help of integer programming. Authors state that since shopbots users are price oriented customers, rearranging the recommendations according to sales promotion would be more appropriate.

Ozarslan and Eren [4] proposed a mobile framework, MobileCDP, to cover all the five steps in customer buying process. It combines problem realization including personal promotions, product information research, shopping alternative evaluation, purchase and after purchase review steps into single framework. Previous studies only target one or two steps of this decision process. The framework has a module that is responsible from matching and showing promotion information to the user. Statistical results show that the proposed model decreases the required time, and the cognitive effort of the customers and reduces purchase cost.

The authors developed a prototype [78] of personalized promotion decision support system (PPDSS) to be used for electronic commerce. They used Java and PHP to implement the system with an experimental dataset consisting of 50 products, 1500 customers and 10000 transactions. Their system consisted of three modules, namely marketing strategies, promotions patterns model, and personalized promotional products. Marketing strategies module lets the decision maker, marketing manager, to define different promotions according to different pricing strategies like product life-cycle pricing strategy .The module for promotions patterns model does statistical analyses and utilize data mining approaches for producing promotions addressing the need of different customer groups. They discover the associations among products bought together and make analysis for discovering the products to be trend. The third module, personalized promotional products module, puts all the promotions generated for customers together and rank them to assist the customer. They apply Weighted Sum Model as the MCDM method and used profit, customer satisfaction in promotion, and success ratio of promotion as the criteria for ranking. In their application, decision makers are allowed to set the weights of the criteria. In order to evaluate the performance of the system, they simulate the costs and prices for 10 different products. They compare the total sales and gross profit of the cases when their system is used and when not used. Their personalized promotion system outperforms the traditional promotion methodology (with a lower discount rate than PPDSS) in most cases (for different amount of promoted sales).

In order to enhance the shopping experience of the customers in retail stores, Ngai et al. [79] proposed utilizing RFID technology to develop a Personal Shopping Assistant (PSA) system in conjunction with Customer Relationship Management (CRM) system. They selected a branch of a supermarket chain in Hong Kong and developed a prototype system by collecting requirements negotiating with managers and customers. RFID tags embedded in customers' shopping carts and tag readers on several locations in the retail store were used to track the shopping behavior of the customers. By using the current data flowing to database from RFID tags, they provided cross-selling promotions to customers. In other words, tag readers detect the items added to the shopping cart and the related products to the ones in the basket are recommended using association-mining technique. By using the historic data from the shopping carts, they provide more personalized promotion recommendations by displaying discounted items accordingly. Within the layered architecture of their system, they also used workflow, as used in this study, to control the flow of the data and the processes in the system. In addition, they applied k-means clustering algorithm based on the demographics of the customers to generate recommendations proper to different customer groups. They evaluated the system by interviewing managers of the retail store and conducting a survey among the users of their system. They applied one-sample t-test on the answers of the users and found that the users' thoughts have statistically significant difference than being neutral to the system. In other words, they have positive attitude towards the system having mean values of effectiveness and usability greater than 3 points on a 5 point-scale.

2.2.2. Cost Aware Workflow Design Related Studies

Workflow engines are software systems to define complex and frequently changing business processes. In this study, a workflow engine is used in order to define numerous different types of promotional conditions. Promotions are defined as processes. It serves in the decomposition of the promotional logic from the rest of the system. Newly introduced promotion type can be added to the system without any logical change. The detailed explanation of the reasons behind the workflow engine usage is given in Section 3.2.1. Moreover, the cost information, which is the price of the shopping, is embedded to the workflow steps. The inclusion of the cost information into the workflow is not newly introduced concept. In this section, the concept of cost-aware workflows presented in the literature is summarized.

Wynn et al. [80] introduces an approach to link cost information to each business process structurally. In general, businesses concentrate on time and resource based process management and manage cost-based judgments separately. The study points out that these two approaches are combined to enhance efficiency in process management. Managers would be able to make decisions by considering cost results of operations. To demonstrate the concepts, Wynn et al. gives an illustrative example of home loan process. They used Yet

Another Workflow Language (YAWL) [81] workflow engine to realize proposed concepts. They implemented a cost manager component to set cost information to appropriate processes. In another study, Wynn et al. [82] state the benefits of not holding the cost information directly in the workflow steps but combining them explicitly to be able to reuse the business process model in the change of cost data. Adams et al. [83] extended the YAWL implementation details that are briefly mentioned in in [80]. The main idea of these correlated studies is given by the Wynn et al. in [84] and is developed over time. In our study, there is no need to have a separate cost manager component. The cost of promotional steps is not changed after the promotion is declared. Thus, the cost data is embedded into workflow definitions.

The cost-aware workflow-modelling notion is also mentioned in other studies [85, 86]. In these studies, the scientific calculation applications that are modelled as workflows are redesigned with price-awareness in order to be price effective. Deploying on grids or on cloud system, the scheduling of tasks is necessary. The completion time and the price required to complete a computationally intensive application should be planned. For example, on cloud resources are paid per use. The scheduling algorithms are developed to limit the total resources used, which results in reduction in price demand. There is no business process concept. The relatedness of these studies is due to the usage of price data along with the scientific process steps. These studies show us the conceptual base to import price data to promotion steps explicitly.

2.2.3. PROMETHEE Related Studies

PROMETHEE is a widely accepted and applied method by the researchers and the practitioners in the industry for making decisions in diversified areas. Behzadian et al. [65] conducted a review study and scanned the papers written of which the authors utilized PROMETHEE method. They made a detailed study to investigate the relatedness of the 195 papers and to categorize them according to their topics. They reported a classification which divides the papers using PROMETHEE into nine application domains, namely “environment management, hydrology and water management, business and financial management, chemistry, logistics and transportation, manufacturing and assembly, energy management, social, and other topics”. This last category includes the papers, which could not be grouped under any of the remaining category, and those papers were related to medicine, agriculture, education, design, government, and sport domains. Brans and Mareschal [87] also mention banking, investments, medicine, and health care, chemistry, and water resources as the fields PROMETHEE has been applied as an MADM method in prospering implementations. They add the tourism, ethics in operations research, industrial location selection, and labor planning as other application areas on to the ones mentioned by [65].

In the light of main research, areas of PROMETHEE mentioned above, some of the studies are outlined below. PROMETHEE related studies are selected by searching different combinations of ‘promotion’, ‘PROMETHEE’, ‘recommendation’ and ‘multi-criteria’ words in keywords, title and abstract section. Scopus, ISI Web of Science and Science Direct databases are searched. Mostly related ones are selected and summarized.

In their study [88], Niknafs, Charkari, and Niknafs proposes a new method for recommending items in online stores utilizing PROMETHEE II, one kind of MCDM (Multi-Criteria Decision Making) method grouped under outranking type. They use four criteria, which are reviewer rankings, price, brand and interests of customer, defined by negotiating with experts and applying literature. They gathered data from epinions.com and preprocessed to avoid biased ratings. In order to validate their model, they develop a prototype recommender system, and then measure its performance by using precision and recall rate metrics. At the time of this paper published, there was not so many works, which use PROMETHEE in recommender system. As a result, they proposed a novel approach and showed that their model is feasible and even vying. In addition, they claimed that cold-start problem, the case when there is no sufficient information about new customers or items could be defeated by their model because of not requiring any initial information about users.

In another study [89], the authors present multi-criteria decision process for choosing doors in tunnels used for safety in highways. Those doors are crucial in case of emergencies like fire or accidents in highway tunnels to let people move away and come to safe place. There are international standards and requirements for tunnel doors and the authors define criteria applying to them including but not limited to door width, door closure speed, lifetime and cost. Three different MCDM methods are chosen which are VIKOR, PVIKOR and PROMETHEE. Data were obtained from three companies of tunnel door production. Results showed that the three selected MCDM methods all of which recommends the same door as optimal choice produce the similar results. Consequently, the authors justify the use of MCDM models in the selection of tunnel doors and suggest the use of those methods for public procurement procedures.

In the study about an evaluation mechanism for the internet presence of Greek National Forest Parks [90], the authors apply PROMETHEE II to rank website by using their web presence as the criteria. They collect the data via search engines and yellow pages for local foundations. They defined 30 criteria for the evaluation of the presence of those websites (like providing more than one language support, FAQ part, search engine, site map and so on) and weighted all the criteria equally, i.e. 1/30. They provide the whole ranking results based on the total net flow measure used in PROMETHEE II method. They discuss the results of top ten and worst ten websites and conclude that the best ones belong to the hotels generally and worst ones belong to public organizations. In addition, they apply t-test for those two groups (top ten and worst ten) and find statistically significant difference between group averages. They also note that there is a huge gap between the best and the worst internet presence in terms of total net flow. They emphasize most important three criteria contributing to the “high superiority” of the websites are language support, use of Google map and provision of search engines.

In their study [91], Walther, Spengler, and Queiruga carry out study for selecting the locations of WEEE (waste electrical and electronic equipment) handling facilities in Spain. They adopt a two-step approach for the solution of the problem. As the first step, they apply multi criteria decision making method to eliminate candidate locations to establish such facilities. Authors prefer PROMETHEE among other methods because of its being easy and giving interpretable results to decision makers. They decided to the criteria used as input for PROMETHEE by sending surveys to the experts in this domain. Those criteria included nine different parameters, called as “location factors” by the authors which are thought to be required for the proper operation of WEEE facilities. In addition, the weights of the criteria were decided based upon the answers of the experts to the survey questions. They grouped the criteria under three main groups: economical, infrastructural and legal. As the result of the first step, they eliminated first candidate 100 locations and reduced to 40 locations. Then since ANFEL, the national federation of household appliance manufacturers in Spain, desires to establish national waste treatment system, as it will include several facilities, they apply warehouse location problem solving as second method on those 40 final candidate locations. Finally, they conducted a case study for processing the waste of large household appliances in Spain.

Marinoni proposes the use of stochastic approach for decision making process in conjunction with GIS (geographical information system), known as SDSS (spatial decision support system) [92]. The author prefers PROMETHEE as the outranking method because of its being mathematically simple and letting stakeholders to involve in decision process. Different from ordinary use of PROMETHEE, author proposes to fit the values of alternatives for each criterion to a statistical distribution. Then Monte Carlo simulation is applied to construct the population, which those distributions come from. In order to validate the proposed model, he carried out a ranking study on an example problem, which is about the selection of land parcels for residential housing construction. The results of this study showed that the use of mean values as input to PROMETHEE and the use of stochastic distributions produced close results. However, the stochastic approach provides more insight about the decision process.

CHAPTER 3

PROPOSED SOLUTION

This chapter explains the proposed solution in detail starting by describing key terminology descriptions that are used in the study. It continues by providing explanatory information about the conceptual design, which includes the proposed model decomposition and some major processes used in the proposed model.

3.1. Definitions

Before presenting the solution in Section 3.2, the terminology related to grocery market and credit card promotions is provided first.

3.1.1. Description of Grocery Market Promotions

Grocery market promotions or simply market promotions are promotions that are defined for grocery markets. These promotions are mainly available to customers with store loyalty cards. They are managed by the store itself.

Store promotions can be declared for specific products for product categories or for whole grocery store. 'Buy one get two' type promotions are good examples of product based promotions. Stores can also promote discounts based on total purchase amount in a particular product group. For example, if customers spend 25 TL for cleaning products, 5 TL bonuses will be awarded for the next visit. The discount may be defined as percentages. In addition, there are storewide promotions based on transaction total, in which case there is no product or product group restrictions.

Store promotions are typically valid for a limited time only. The bonus earned with these promotions may include a product, discount, money back bonus, loyalty bonus.

3.1.2. Description of Credit Card Promotions

These promotions are defined by different banks. The credit card promotions are declared by the banks in order to promote the usage of their credit cards and to make the consumers oblige to use in the future. The credit card promotions could be thought as a task or a process for each customer in order to get an extra bonus after its completion. In this study, we do not deal with promotions, which are about installments because they do not have any bonus or reward declaration.

An example of credit card promotion can be defined as:

> *Do 5 times grocery market shopping of amount of 100 TL between 31 October 2012 and 20 November 2012 in order to get 50 TL bonus.*

Let us decompose the information stated in this promotion.

3.1.2.1. Bonus Amount

The bonus amount is the monetary gain of a credit card holder in the case of promotion completion. Bonuses are gained by doing shopping and can be used again in shopping which creates a shopping spiral for customers. It could be a direct deduction from the credit card statement or could be a bonus. Bonuses are given to the credit card holder, but only be used in another purchase by using the same credit card. We define bonus as all types of monetary gain from credit card promotions. As in the given example, the bonus amount of the promotion is 50 TL bonuses.

3.1.2.2. Restrictions: Minimum Shopping Amount Limit & Required Number of Purchase

The limit of the amount of the shopping and the required number of purchases are two correlated restrictions of the promotions. Customers have to make purchases of 'minimum shopping amount' of 'required number of purchase' times. Thus, as stated in the example, customers have to spend a minimum of 100 TL in grocery markets for five times.

3.1.2.3. Time Period

Promotions are set for a period. The start and the end dates of the promotion define the availability period for the credit card holders. As in the given example, this promotion is available from 31 October 2012 to 20 November 2012.

Credit card promotions are completed when customers satisfy restrictions in the defined period. In return, they are awarded the defined bonus amount.

Another example of credit card promotion can be defined as:

> *Consume 500 TL in a grocery store between 31 October 2012 and 20 November 2012 in order to get 50 TL bonuses.*

In this example, the period and the bonus amount definitions same with the previous one. The difference is in the restrictions.

3.1.2.4. Restrictions: Required Total Purchase Amount

Some promotions may have restrictions based on the total purchase amount. The difference from the previous example is that there is no restriction of the minimum transaction amount or required number of purchases. The customer can do shopping in different transaction amounts many times or make a single purchase of the total purchase amount. As in the given example, customers need to do shopping for 500 TL. It does not matter if they reach or pass this limit in 5 or 10 transactions. The only restriction is to spend 500 TL or more.

In our study, credit card promotions are categorized based on the restriction type. We defined promotions with the number of purchase restriction as '*Step Promotions*'. We defined promotions with the total purchase amount restriction as '*Total Promotions'.*

There is another sub-type of credit card promotions, which can be sampled as follows:

> *Do 5 times grocery market shopping of amount of 100 TL between 31 October 2012 and 20 November 2012 in order to get 10 TL bonuses for each transaction.*

This promotion type is similar to the Step Promotions but the bonus amount is awarded for each transaction. In Step Promotion, customers are qualified for the bonus amount after completing all purchase steps. However, in this type, customers gain bonus amount after each step. Thus, we categorize this type as a sub-type of Step Promotions. We defined this type as *'Bonus per Step Promotions'.* The categorization of the promotions is given in Figure 4.

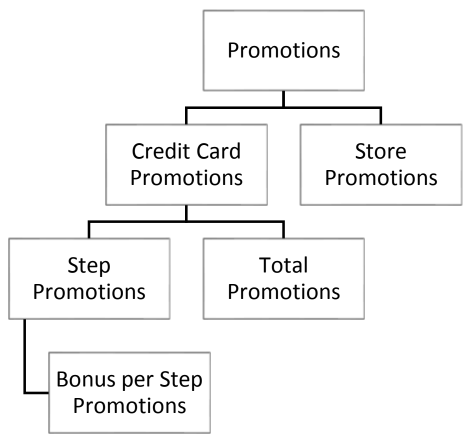


Figure 4 – Promotion Categorization

The credit card promotions are not restricted only to the grocery markets, but in this study, we concentrate on the promotions for the grocery markets. Moreover, credit card promotions may not be available in all the grocery markets. The promotions can be defined for specific grocery market chains or local markets. If a promotion were not restricted to any grocery market, the promotion would be available in all the grocery stores.

The above descriptions are just for the bonus amount gathering part. However, the definitions of the credit card promotions do not only consist of the bonus amount gathering part. The registration part and the bonus usage part are also important.

Besides the restriction and the period declarations, the credit card holders have to register for newly available promotions by following the instructions given by the promotion issuer, namely the banks. The banks present different types of registration methods such as using SMS, website, mobile applications, social networks, etc. The registration is required to obtain the bonus amount at successful completion of the promotions. Moreover, the customers have to use gathered bonuses within the other specific period. If they forget to use these bonuses, the banks withdraw these bonuses.

3.1.3. Description of Credit Card Promotion Metadata

In this study, the metadata definition of the credit card promotions is used instead of verbal definitions. Metadata lets us declare the credit card promotions more formally. Metadata, which is called 'data about data', describes the data and enables easy management. It is mostly used for formal descriptions [93]. There are three main categories of metadata as defined by the National Information Standards Organization (NISO): These are descriptive metadata, structural metadata and administrative metadata [93]. For the credit card promotions, descriptive metadata is used. It describes the important data about the promotions, and it becomes readable by information systems and understandable for humans. The metadata structure and example values are given in Table 2.

Table 2 – Credit Card Promotion Metadata Structure

Shopping Sector	Grocery Sector
Bonus Amount	50 TL
Bonus per Step	10 TL
Required Number of Purchase	5 times
Minimum Purchase Amount	100 TL
Required Total Purchase Amount	500 TL
Promotion Time Period	September 1-30
Bonus Usage Time Period	October 5-10
Applicable Markets	$Market_A$
Applicable Credit Cards	$CreditCard_A$

The given metadata structure is used for all the credit card promotion types. Common fields and promotion specific fields are grouped in Table 3.

Table 3 – Fields Used by Credit Card Promotion Types

Common Fields	*Shopping Sector, Bonus Amount, Promotion Time Period, Bonus Usage Time Period, Applicable Markets, Applicable Credit Cards*
Step Promotion Fields	*Required Number of Purchase, Minimum Purchase Amount*
Total Promotion Fields	*Required Total Purchase Amount*
Bonus per Step Promotion Fields	*Bonus per Step, Number of Purchase*

The metadata definition is used to convert the credit card promotion rules and the restrictions to Work-Flow Engine based specifications, which are explained in Section 3.3.2.

3.2. Conceptual Design Description

This section starts with the description of the proposed model and then continues by showing the data flow of the system. Functionalities of decomposed parts are also described. By giving functionalities, justification of each part is also given indirectly.

3.2.1. Decomposition of the Proposed Model

An overview of the proposed system and a data flow diagram is given in Figure 5, showing the flow of data between modules of the system. It could be also interpreted as the system decomposition diagram since it also visualizes the modules of the system.

Figure 5 – System Dataflow Diagram

As shown in Figure 5, the Shopping Alternative Generator module takes the customer shopping list as an input and takes price of products in the shopping list, available market promotions and available credit card promotions to generate shopping alternatives. Then, the Outranking Method module ranks the generated alternatives according to customer preferences. The generation of the shopping alternatives and the ranking process are the main parts of the system. After the selection of a shopping alternative by the DM, the system updates customer shopping history and credit card promotion states through the Customer Manager module. The

Customer Manager module uses the Workflow Engine module to hold and update credit card promotion states.

Deciding which products to purchase in the next grocery market visit is another research topic. Recommendation of the products to the consumers based on their purchase history or periodical needs are not the scope of this study. Current study is focused on proposing a model to rank shopping store alternatives based on price, location and available promotions. It is assumed that the shopping list is already defined by the consumer.

The system is composed of a product price module, a market promotion module, a credit card promotion module, a customer manager module, a workflow engine module, a shopping alternative generator module, and an outranking method module. These modules are described next.

3.2.1.1. Product Price Module

As the name implies, this module searches and returns the prices of the given products in consumer shopping list. It finds product prices at each grocery market. In this study, it is assumed that the price of each product is known. This module is just used to feed *Shopping Alternative Generator* with the individual product prices. As stated in [94], consumers have problems in being sure about the individual product prices even if they know overall price levels of different stores. The existence of this module eliminates this problem.

3.2.1.2. Market Promotion Module

This module searches and then returns available market promotions at a given grocery market. The search is made based on the products in the given shopping list and the store options. It is assumed that the promotions are defined.

3.2.1.3. Credit Card Promotion Module

This module creates the metadata of the credit card promotions that feed the *Workflow Engine Module*. It is assumed that the credit card promotions are already defined and this module converts them to the metadata definitions as described in Section 3.1.3. This module enables the users not to search for newly introduced promotions, which destroys the overhead of the promotion search process.

3.2.1.4. Customer Manager Module

This module manages the customer related data, stores the customer preferences, and serves information to the Shopping Alternative Generator and the Outranking Method Module. It coordinates the Workflow Engine Module. It provides location, credit cards and loyalty cards of the consumer to the Shopping Alternative Generator, and it provides consumer preferences such as the criteria weights and the threshold values to the Outranking Method Module. It is a controller between the Shopping Alternative Generator and the Workflow Engine Module. The Shopping Alternative Generator retrieves customer specific credit card promotion states from the Workflow Engine Module through the Customer Manager Module.

It also keeps track of consumer shopping history information, calculates Credit Card Promotion Completion Score (CCPCS) and delivers it to the Shopping Alternative Generator. The details of managing the customer shopping history information and the calculation of CCPCS are described later in this section.

3.2.1.5. Workflow Engine Module

It has a workflow engine to manage the states of the credit card promotion. It uses metadata definition of the credit card promotions and creates instances of a workflow engine specification per customer. Thus, having the metadata of the promotion, the module reuses it for every customer whenever needed. For example, Customer_A and Customer_B could have started to pursue a promotion at the same time. Each customer should have their own state for the same promotion, but the rules and the restrictions on the promotion are identical for both. The promotion rules and restrictions are defined in the promotion metadata and it is used to generate customer-specific instances.

The proposed model has the workflow engine module since the credit card promotions are kinds of process definitions as defined in Section 3.1.2. Modeling them by using the workflow engine is straightforward. A typical promotion has a registration step, one or more purchase steps, one or more bonus gathering steps and a bonus usage step. The consumer has to register for the promotion, has to make purchases that are matched with promotion's restrictions and the consumer has to use that bonus within a period. The nature of credit card promotions requires that the consumers have to follow them attentively since the periods are so strict and it is very common for a cardholder to forget them. The complexity of following a credit card promotion reveals the need of a system to aid consumers to follow them easily. The workflow engine module is also serves for this purpose. It serves as a guideline to complete a promotion successfully. The customers can be informed about the required steps to complete the promotion with the help of using a workflow engine.

In this study, *Yet Another Workflow Language, YAWL* is selected as a workflow system [81]. The selection of YAWL is necessary for the evaluation of the model and the realization of the model. A different workflow system could be selected for the proposed model. However, YAWL is selected since it is an open source workflow system. In addition, Java based libraries are provided. The workflow specifications are easily modelled by built-in editors.

The workflow specifications are execution flow declarations [81]. In our case, it is the definition of the steps to complete a promotion from the registration step to the bonus usage section. To create specifications, the metadata declarations are used. The conversion process is explained in Section 3.3.2.

3.2.1.6. Shopping Alternative Generator

This module communicates with other modules to create shopping alternatives according to the shopping list for a specific customer. It gets available grocery market promotions, product prices, credit card promotion states, etc., to create alternatives. The alternative generation process is explained systematically later in this section. The generated alternatives are inputs of Outranking Method Module.

3.2.1.7. Outranking Method Module

This module takes the generated shopping alternatives and ranks them according to the criteria weights and the threshold values given by the consumers, and outputs ranked alternatives to the consumers for the final decision. Customers could select any of the ranked alternatives. The selected alternative is used to update the shopping history of the customer as well as the state of the credit card promotion stored in workflow engine, if the selected alternative has a credit card promotion.

In the model decomposition, the module name is kept as *Outranking Method Module* since the proposed model does not depend on a specific outranking method. Just a ranking process is needed for the proposed model. It can be done by any outranking method. However, for the evaluation process and the realization of the model, the PROMETHEE II method is selected from PROMETHEE method family as the outranking method.

Before giving justification of selecting PROMETHEE, it is plausible to state the need for an outranking method in our model. In the proposed model, there is no need to find the best alternative among possible alternatives. Sorting of the alternatives based on the customer preferences is sufficient. The purpose of this model is not to select the best shopping alternative for customers, but to rank all the alternatives to support the decision making process. This way, PROMETHEE is selected from other outranking method alternatives.

As it is stated in Section 2.1.4, one of the classifications of MCDM methods comprises MAUT and outranking methods. In this study, PROMETHEE II is preferred as an outranking method rather than a MAUT methodology. The reason lying behind this choice is that MAUT models require the calculation of the utility function, whereas in many of the real world problems a mathematical representation of the DM's utility function is not easily obtained [58]. In addition, because of providing flexibility due to the integration of the information obtained from decision makers like preference thresholds, outranking methods are preferable over MADM or MAUT methods.

A counter argument for the preference of outranking methods to other ones states that decision makers become more satisfied when they apply to non-compensatory methods [12]. As stated before, the outranking methods are types of the compensatory methods. Hence, both of PROMETHEE and ELECTRE methods are compensatory methods that the relative importance of the criteria is considered [57]. What makes the decision makers dissatisfy with outranking approach are the low accuracy results that they obtain [95]. They put a considerable amount of effort on examining the reasons for the low accuracy results. However, the reason lying behind this is not the due to the weakness of the outranking approach. The actual reason is the use of outranking methods for complex decision making problems that are hard to interpret by decision makers.

PROMETHEE and ELECTRE are pair wise comparison methods in which the alternatives are compared in pairs for each single criterion. Moreover, in these methods, the decision makers can set the criteria weights and the preference thresholds [57]. Hence, the decision makers are easily involved in the decision making process and Guitouni and Martel [12] suggest using pair wise comparison methods.

Selection of an MCDA method among the current methods and justifying the reason for the selection is a troublesome task and many of the researchers are incapable of doing this [12]. However, a method can be selected by considering the advantages of it and the appropriateness of it to the problem settings. In this study, the family of PROMETHEE methods is selected among other outranking approaches because of its being rather simple to comprehend and to apply [64, 65] even for the decision makers which are not familiar with MADM methods [96]. In addition, PROMETHEE is known to be one of the most popular and commonly used outranking methods because it is a quite transparent method with computations [66, 96]. Another reason for choosing the PROMETHEE family is that it requires fewer inputs compared to other families [67]. For example, there is no veto threshold in PROMETHEE methods (The veto threshold means that if it is passed, the alternative under evaluation should be directly eliminated) [57]. As stated in [63] by Brans et al. even if the ELECTRE method is well known and one of the mostly used outranking method, it is a bit complex because of the extra parameters required from the decision maker. Parameters with no economic meaning like concordance values, discordance values, and discrimination thresholds are hard to be understood by the decision maker. It is not clear to combine the outranking results with these parameters. The primary purpose of the PROMETHEE methods is creating an understandable MCDA by decision makers. Moreover, as also stated, the count of the parameters that is to be set by the decision makers is at most two, namely preference and indifference thresholds, and these parameters have economic meanings.

Martin et al. [97] preferred PROMETHEE approach and stated their justification as it is being fully adequate for the applications they care about (environmental impact assessment) because of having a flexible modelling procedure. They also indicate the perfectness of the PROMETHEE in terms of being one of the most intuitive methods from the decision makers' point of view.

The PROMETHEE I method provides the decision makers with partial rankings letting the incomparable results. However, it requires extra effort of the decision makers to evaluate the results. In contrast, PROMETHEE II presents a complete rank of all the alternatives by ordering them from the best to the worst [67]. Furthermore, as [65] found out in their broad literature review on PROMETHEE methods, PROMETHEE II is the most preferred version of the PROMETHEE family. Hence, in this study the PROMETHEE II is preferred over other methods.

In practice, the additional information required by PROMETHEE, namely the weights, the preference and the indifference thresholds, and the preference functions should be obtained from the decision makers [96]. However, Brans and Vincke [63] propose six different preference functions and claim that those functions fit for most of the practical situations. Those functions are explained in more detail in Section 2.1.7.2. Routroy and Kodali [98] present a guideline for the selection of a preference function among the ones proposed by Brans and Vincke [63]. In addition, a concise form of the guideline can be found in their later study [99]. According to their guideline, type I (usual criterion) and type VI (Gaussian criterion) are seldom used functions. Among the remaining functions, type III (V-shape criterion) and type V (V-shape criterion with the indifference threshold) are the suitable ones for the decision making problem in this study because they include quantitative criteria. Type II and type IV preference functions are used for the decision making problems including qualitative criteria. The preference function of type III only considers the preference threshold in calculations. However, the consumers would tend to neglect the returns of credit card or market promotions under a certain amount in their minds, so there would be an indifference threshold. Hence, type V preference function, V-shape with linear preference and indifference area, will be a plausible assumption for the comparison of alternatives representing different promotions. As a result, V-shape with the linear preference and the indifference area is selected as the preference function in this study.

3.3. Description of Essential Processes in the Proposed Model

Some of the important processes are going to be defined next. First, how the shopping alternatives are generated by the Shopping Alternative Generator is explained. Second, the creation of a workflow system specification from a metadata of a credit card promotion is defined.

3.3.1. Generation of Shopping Alternatives Process

The generation of the shopping alternatives is one of the main processes of the proposed system. Before ranking the alternatives, we need to generate those alternatives. Before going further, what a shopping alternative is should be defined.

A shopping alternative is a combination of different data that is used for the comparison by the outranking method. As described earlier, outranking methods rank a set of alternatives based on a set of criteria. Therefore, we need to define the set of criteria, calculate values of those criteria and sort them accordingly.

Any shopping activity has its own value that is obtained by the consumer. The value that is obtained after each purchase is defined as [2]:

$$Value = benefits - (price + hassle) \qquad (3.1)$$

The hassle is the consumption time and the required effort of the consumer to complete the purchase [2]. The benefits obtained by the consumer are personal, but we know that the consumers evaluate the value of each purchase by considering the price, the time and the effort of the purchase. Therefore, we have three criteria:

I. **Price:** It is the price of the shopping list at a grocery market. Deductions based on both grocery market promotions and credit card promotions are applied to this criterion. For example, the total price of a product list at $Market_A$ is 100 TL and the calculated deduction is 10 TL. This makes the price of the shopping list at $Market_A$ as 90 TL. As stated in [100], price is one of the traditional criteria, which is intuitively used in our model as a criterion.

II. **Distance:** This is another criterion, which is calculated based on the distance of the customer to a market. As mentioned in [94], selecting a grocery market decision is influenced by the distance to that market. Therefore, this criterion is also added to the proposed model.

III. **Credit Card Promotion Completion Score (CCPCS):** This criterion is used to score different credit card promotions based on their terminality. Since the consumers are tend to avoid uncertainty in the shopping [24], the uncertainty should be modelled. Assume that $Customer_A$ has two credit cards and each card has a promotion at the same grocery market. Therefore, the customer decides which credit card to use at the shopping. To simulate the consumer decision behavior, we proposed this criterion. It is a numerical score. It models how easy to complete a credit card promotion by the consumer. It is used to specify the required effort of the consumer to complete the promotion, which is the indirect effort of the purchase. Higher score means easier completion of the promotion. It changes by the time of the purchase, by the customer's shopping history and by the promotion itself. This score is calculated when there is an available credit card promotion at the purchase time at the selected grocery market.

We defined the set of criteria that as a whole creates the shopping alternative. Each alternative is a grocery market based. For each grocery market, one shopping alternative is generated. The selection of an alternative by the consumer means that the consumer selects to do shopping at a specific market. Moreover, it is the selection of available promotions at that market as well. Nevertheless, the selection of the alternative not always encapsulates the selection of a credit card promotion. One may not want to use a credit card or even does not have any credit card. Therefore, the shopping alternative may not have a credit card promotion.

A credit card promotion is 'suitable' for the shopping alternative if:

1. It is defined for one of the customer's credit cards and for the specific grocery market,
2. It is not already completed by the customer,
3. If its type is *Step Promotions,* then the price of the shopping list has to be greater than the minimum transaction amount restriction of the promotion.

Assume that there are three grocery markets with available grocery promotions. $Customer_A$ has a credit card and two credit card promotions are available at the shopping time. The Shopping Alternative Generator checks the suitability of the available credit card promotions (CCPs). Both of the promotions are labelled as suitable in this scenario. Then the Shopping Alternative Generator generates three shopping alternatives. One of the shopping alternatives stands for doing shopping without using a credit card promotion. Other two alternatives stand for doing shopping by using the credit card promotions. Thus, the number of alternatives generated can be calculated by:

$$\#\ of\ alternatives = n + \sum_{i=1}^{n} \#\ of\ suitable\ CCPs\ at\ Market_i\ , n\ is\ \#\ of\ markets \qquad (3.2)$$

The exploration of the generation of a shopping alternative is given in the upcoming section. The generation of the shopping alternative can be broken up into three small processes: Calculating ‘Price’, ‘Distance’ and ‘Credit Card Promotion Completion Score’.

3.3.1.1. Calculation of the Price Value

The price value is calculated by adding the product prices in the shopping list and by reducing deductions of both the market promotions and the credit card promotions. Since the unit of price is Turkish Lira (TL), it is required to convert deductions defined by each promotion to a monetary value. This enables our model to compare different markets with different types of promotions.

Some promotions may require the pre-mentioned conversion. For instance, customers pay one for two products in a grocery market promotion. This promotion is converted to a monetary value. The monetary value of this promotion equals to the price of the single product. This is valid since the customer pays only for one product. If there were no such promotion, the customer would pay for both of the products. As another example, assume that the customers pay 10 percent less for a product. The monetary value of this promotion is the sum of 10 percent of the price of the product in the shopping list.

Monetary value of the credit card promotions are also calculated based on the promotion types.

The monetary value of a *Step Promotion* is calculated by:

$$Monetary\,Value = \; Bonus/Required\ Number\ of\ Purchase \tag{3.3}$$

The monetary value of a *Total Promotion* is calculated by:

$$Monetary\,Value = \frac{Bonus * \; Shopping\ Price}{Required\ Total\ Purchase\ Amount} \tag{3.4}$$

The bonus, the required number of purchases and the required total purchase amount are defined in the metadata of a credit card promotion. The shopping price is the sum of the prices of all products in the shopping list at the grocery market.

The conversion of the promotion to the monetary value makes the term ‘price’ a calculated value and may cause it not to represent the actual transaction amount of the customer at the point of sale. Thus, the calculated price value is not always the real purchase amount.

Price value calculation is analyzed for the generation of a single shopping alternative. Assume that, we have a shopping list and the shopping alternative is being generated for the $Market_A$ and for the $Customer_A$. The intended time of purchase is September 10 and the $Customer_A$ has the $CreditCard_A$.

1. The total price of the shopping list is calculated. The price of each product is taken from the *Product Price Module*. Each product could have a different price at the different

grocery market. Therefore, the Product Price Module returns the total price of the products at the $Market_A$. This way, the total price of the shopping list at the $Market_A$ is calculated. For example, in the $Market_A$ the total price is 110 TL (referred as TP_A).

2. The grocery market promotions are handled next. It is required to make deductions to the total price based on the available promotions at $Market_A$. However, grocery promotions may be defined for a product or for a product group. The promotions may be only available to the loyalty cardholders. Thus, the available promotions at the $Market_A$ are limited based on the shopping list and loyalty cards of the customer. If there is no product in the shopping list with a promotion, none of the promotions is going to be applied.

   Applicable promotions are requested from the Market Promotion Module. Assume that the $Customer_A$ has three of $Product_A$ in his shopping list and there is 10 percent discount for the $Product_A$ in the $Market_A$. The discount is going to be deduced from the TP_A. Assume that the price of the $Product_A$ is 20 TL. Thus, with this promotion, the price of the $Product_A$ becomes 18 TL. In total, 6 TL discount is applied to TP_A, which makes the total price 104 TL.

3. The credit card promotions are handled lastly. Assume that the Credit Card $Promotion_A$ (CCP_A) has a metadata of:

Table 4 – A *Step Promotion* metadata

Shopping Sector	Grocery
Bonus Amount	50 TL
Required # of purchase	5 times
Min. purchase amount	100 TL
Promotion Period	September 1-30
Bonus Usage Period	October 5-10
Available Market	$Market_A$
Credit Card	$CreditCard_A$

As explained earlier, we know how to interpret Table 4. Since our purchase amount is 104 TL, which is greater than the minimum purchase amount, and the promotion is available on September 10, this promotion is suitable for this purchase. This promotion need to be transformed to a monetary value. To obtain the bonus amount, a customer has to make five different purchases of minimum amount of 100 TL. In our model, we converted this promotion to the monetary value by using the Equation 3.3. Thus, assuming that the customer is going to complete this promotion, it is plausible to say that the customer would gain 50/5 = 10 TL discount at each purchase. Therefore, the price value becomes 104 - 10 = 94 TL.

One may argue that there should not be such an assumption about customer's future purchases. It is impossible to be sure about the completion of a promotion beforehand. This is correct. However, we eliminated this uncertainty from price calculation and put it to the third criterion, the Credit Card Promotion Completion Score. How this uncertainty covered by the third criterion is explained later in this section.

By completing the third step, the price calculation process is completed.

3.3.1.2. Calculation of the Distance Value

The calculation of the distance value is relatively easy and straightforward process compared to the previous one. The unit of the distance value is minutes. This value is the time required for the consumer to reach the market from his current location.

3.3.1.3. Calculation of the Credit Card Promotion Completion Score

As mentioned before, this score represents the effort of the customer to complete a credit card promotion. Higher score means that a promotion is more likely to be completed by the customer. To complete the promotion defined in Table 4, the customer has to do shopping with the amount of 100 TL or more for at least five times in September. Some customers may not go to the shopping five times in a month. Some customers may often do shopping with smaller amounts. Thus, we model customer shopping habits to calculate this score accurately. We need to predict whether the customer can complete the promotion. More strictly, we need to produce a score of completion of the promotion. This score is used to compare the credit card promotions. First, we need to identify which features of the credit card promotion could be estimated and try to generate a model to make estimations.

The credit card promotions have two specific requirements that are more closely related to the customer shopping routines. These are the 'Required number of purchase' and the 'Minimum Purchase Amount'. To satisfy that restriction, customers frequently need to do shopping. The customers with lower shopping frequency would select promotions with lower required number of purchases, but higher minimum purchase amount limit. The customers who do shopping together may spend more per transaction. On the other hand, single shoppers may prefer visiting stores more. Thus, they would spend less on each transaction. These are some examples of the different characteristics of the customers. Therefore, the proposed model has to deal with these differences. In the proposed solution, the customer behavior is estimated based on these two fields. Besides the pre-mentioned requirements, another crucial requirement is the period of the promotion. It defines the time limitation in which the promotion has to be completed. Therefore, we need to consider time limitations in our estimations.

The customer shopping habits change over time. Thus, it is not constant but it evolves. Customers change their home location, which changes their distance to grocery markets for example. They may start to use their cars instead of walking which enables them to purchase more items. This increases their average transaction amount and may reduce the frequency of shopping. Therefore, we need to propose a purchase estimation model, which handles these changes in the shopping habits.

The Customer Manager Module explained in Section 3.2.1.4 calculates the Credit Card Promotion Completion Score (CCPCS) by using the purchase estimation model. The purchase estimation model estimates the average number of transactions and the average transaction amount of a customer for a period and the Customer Manager Module uses these estimations to calculate CCPCS.

To calculate the estimated values, we use the Exponentially Weighted Moving Average (EWMA) estimation from statistics. In the EWMA, most recent data is weighted higher. It applies to non-uniform weighting to the time series data. It includes all the previous data into the estimation, but assigning exponentially decreasing weights to the older ones. With the EWMA, the older values become sufficiently small to be ignored.

$$S_t = \lambda * x_t + (1 - \lambda) * S_{t-1} \tag{3.5}$$

In Equation 3.5, S_t is calculated by averaging latest X_t value with all the previous S values. The 'λ' is used as a decay factor. It takes values between zero and one. The higher λ means that the previous values are discounted faster.

Before explaining the usage of the EWMA in the estimation process, the term *time frame* should be declared. The time frame is the time range that is used to calculate the estimations. For example, when the time frame is 10 day, the total transaction amount of the customer is calculated by looking transactions in the last 10 days. Similarly, the step count is the number of store visits in the last 10 days. The time frame is used to define the length of the transaction history. The higher the time frame is the more the proposed model remembers the previous transactions.

Assume that we have customer transactions of T_1 to T_n. Also, assume that the time frame is 30 days. Then, the time frame starts from 30 days before T_n. The 30-day period covers transactions from T_2 to T_n.

T_1 … T_2 … T_3 …. …. T_n

Time Frame

By the transaction T_{n+1}, the time frame window is shifted to the right.

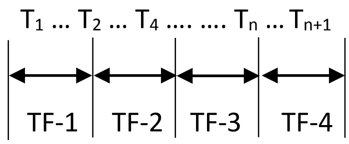
T_1 … T_2 … T_4 …. …. T_n … T_{n+1}

Time Frame

The updated time frame covers the transactions from T_4 to T_{n+1}. Then, the estimated values are also updated. Since the time frame is moved with every new transaction, we named this approach as the *Moving Time Frame*.

We could choose not to move time frame at every transaction, but divide the customer transaction history into the fixed time-frame chunks. Assume that the time frame is 1 week.

Then, the transaction history is divided into chunks of 1-week. The demonstration of time frame of 1-week time is given below. The time frame is denoted by *TF-#*.



We named this approach as the *Fixed Time Frame* approach since the time-frame window is not moved with each transaction. If this approach were used in the proposed model, the previous time-frame chunk would be used to estimate values of the transaction in the following chunk. For example, T_n resides in the chunk TF-3. Then, TF-2 is used to calculate the estimated values. For T_{n+1}, TF-3 chunk would be used since T_{n+1} resides in TF-4.

In the proposed model, we used the moving time-frame approach. In Section 5.7.1, the statistical analyses are conducted to see if our selection is plausible or not. In the upcoming sections, the explanations are made based on the moving time-frame approach.

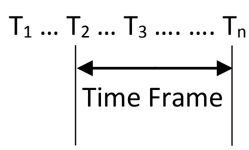
Estimated Average Step Count per Time Frame

This estimated average value indicates the customer average number of purchases in the time frame. To estimate average step count per month, EWMA is used. Assume that the time frame is 30 days.

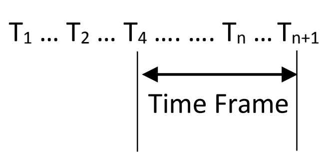
$$\widetilde{\mathrm{SC}}_{\mathrm{n}} = \lambda * \mathrm{SC}_{\mathrm{n}} + \left((1 - \lambda) * \widetilde{\mathrm{SC}}_{\mathrm{n-1}}\right) \tag{3.6}$$

Let T_n is the purchase date of n^{th} transaction and SC_n is the number of transactions (step count) between T_n and T_n – 30 days (both inclusive).

SC_n is calculated each time by moving time frame of 30 days.



The time frame starts from 30 days before T_n. The 30 days period covers transactions from T_2 to T_n. SC_n equals to the number of purchases within the time frame. By the transaction T_{n+1}, the time frame is updated accordingly and SC_{n+1} is calculated similarly.



The updated time frame now covers transactions from T_4 to T_{n+1}.

If the customer does not make any purchase for 30 days, SC_n equals to one since the only purchase within 30 days will be upcoming n^{th} transaction. This turns out that $SC_1 = 1$ and $\widetilde{SC_0} = 0$. These are initial values used in our model.

Estimated Average Transaction Amount per Time Frame

This estimated average transaction amount value indicates customer average total purchase amount in the time frame. Similar to $\widetilde{SC_n}$ it is calculated by using EWMA. Assume that the time frame is 30 days.

$$\widetilde{TA_n} = \lambda * TA_n + ((1-\lambda) * \widetilde{TA_{n-1}}) \tag{3.7}$$

Let T_n is the purchase date of n^{th} transaction and TA_n is the total transaction amount between T_n and T_n – 30 days (both inclusive).

The update process of the time frame and the recalculation of TA_n are completely same with SC_n.

If the customer does not make any purchase for 30 days TA_n equals to transaction amount of n^{th} transaction since the only purchase within 30 days will be upcoming n^{th} transaction. This turns out that $TA_1 = T_1$ and $\widetilde{TA_0} = 0$ where T_1 is the first purchase amount of the customer. These are initial values used in our model.

As stated earlier, these estimates are used to calculate CCPCS. This score is calculated differently for different types of credit card promotions. The type of the promotion determines the usage of TA_n and SC_n. There are two main promotion type. One of them is *total promotion* type and the other one is the *step promotion* type.

Calculation of CCPCS for *Total Promotion* Type

To finish total promotion type promotions, customers are required to make certain total amount of purchases in the promotion period. The proposed model has to estimate the total purchase amount capacity of the customer in the promotion period. $\widetilde{TA_n}$ is used for the estimation as explained before.

Assume that there is a credit card promotion CCP_A that starts at T_s and ends at T_f. Let the current transaction is at T_n where $T_s < T_n < T_f$. We can estimate future grocery expenses of $Customer_A$ between T_n and T_f. First, $\widetilde{TA_n}$ value is calculated by current transaction and potential transaction amount (PTA) is calculated as follows:

$$PTA = (\widetilde{TA_n}/30) * (T_f - T_n) \tag{3.8}$$

$\widetilde{TA_n}$ is divided by 30 since the time frame is 30 days. Dividing by the time-frame size, we calculated the transaction amount per day. Then daily transaction amount is multiplied by number of remaining days of the promotion, T_f - T_n. This way, PTA is calculated for the remaining of the promotion period.

Next step is to calculate CCPCS as follows:

$$\mathrm{CCPCS} = (\mathrm{PTA}/\mathrm{RRTA}) * 100 \tag{3.9}$$

RRTA is the remaining required transaction amount to complete CCP_A by $Customer_A$. Initially, RRTA equals to the required transaction amount for CCP_A. Then, RRTA is reduced by the transaction amount of every purchase made by using CCP_A.

Calculation of CCPCS for *Step Promotion* Type

To finish step promotion type promotions, customers are required to fulfill two different restrictions. One of them is the step count and the other is the minimum transaction amount. This means that customers have to make purchases of minimum transaction amount for 'step count' times. This is why we need to calculate CCPCS based on our two estimates: $\widetilde{\mathrm{TA}_\mathrm{n}}$ and $\widetilde{\mathrm{SC}_\mathrm{n}}$. By using $\widetilde{\mathrm{SC}_\mathrm{n}}$, the model ensures that the step count restriction is taken into consideration. The shopping frequency of the customers is estimated by this value. By using $\widetilde{\mathrm{TA}_\mathrm{n}}$, the model ensures that total transaction amount is also taken into consideration.

PTA value is calculated exactly the same way as in the Equation 3.8.

Assume that there is CCP_A, which starts at T_s and ends at T_f. Let the current transaction is at T_n where $T_s < T_n < T_f$. We can estimate number of grocery market visits of $Customer_A$ between T_n and T_f. First, $\widetilde{\mathrm{SC}_\mathrm{n}}$ value is calculated and then potential step count (PSC) is calculated as follows:

$$\mathrm{PSC} = \widetilde{(\mathrm{SC}_\mathrm{n}}/30) * (\mathrm{T_f} - \mathrm{T_n}) \tag{3.10}$$

$\widetilde{\mathrm{SC}_\mathrm{n}}$ is divided by 30 since the time frame is 30 days. Dividing by the time-frame size, we calculated the number of store visits per day. Then the daily store visit count is multiplied by number of remaining days of the promotion, T_f - T_n. This way, PSC is calculated for the remaining of the promotion period.

Next step is to calculate CCPCS for *Step Promotions:*

$$\mathrm{CCPCS} = [((\mathrm{PSC}/\mathrm{RRSC}) + (\mathrm{PTA}/\mathrm{RRTA}))/2] * 100 \tag{3.11}$$

RRTA is the remaining transaction amount and RRSC is the remaining required step count to complete CCP_A by $Customer_A$. RRTA is explained earlier. RRSC is similar to RRTA. This time the required step count is decremented one by one after every purchase and RRSC equals to this decremented value.

As seen from the both calculation of CCPCS, 'one hundred' is multiplied as a constant. As we mentioned earlier, some of the generated shopping alternatives may not have any credit card promotions. Thus, to simulate shopping alternatives without any credit card promotion, we set CCPCS to a default value 100, which indicates that there is certainty of completing a promotion. In order to make all generated shopping alternatives comparable with each other, CCPSs are calculated based on this constant value. This way, the uncertainty level becomes comparable and easy to understand. By introducing CCPCS, the uncertainty of completing a promotion is successfully modelled.

3.3.1.4. Sample Purchase Scenario to Calculate CCPCS

In this section, a sample scenario is provided to demonstrate the calculation of CCPCS. The calculation of CCPCS is a part of Shopping Alternative Generation process. To make it simple to understand, only the calculation of CCPCS is demonstrated.

In Table 5, four different purchases of $Customer_A$ are listed. The price and the date of purchases are given. Suppose that $Customer_A$ does not have any previous purchases. Assume that $Customer_A$ prefers $Market_A$ in grocery shopping and $Customer_A$ has $CreditCard_A$ and $CreditCard_B$.

Table 5 – Purchase list of the sample scenario

Purchase No	Price (TL)	Date
Purchase #1	107.25	September 2
Purchase #2	95.5	September 14
Purchase #3	125	September 20
Purchase #4	110	October 9

The CCPCS is calculated one by one for each purchase. Assume that there are two credit card promotions, which are available for purchases in Table 5. The type of $Promotion_A$ is *Step Promotion* and the type of $Promotion_B$ is *Total Promotion.* The metadata definitions are given in Table 6 and Table 7 respectively.

Table 6 – Metadata definition of $Promotion_A$ of sample scenario

Shopping Sector	Grocery
Bonus Amount	50 TL
Required # of purchase	5 times
Min. purchase amount	100 TL
Promotion Period	September 1- October 15 (45 days)
Available Market	$Market_A$
Credit Card	$CreditCard_A$

Table 7 – Metadata definition of $Promotion_B$ of sample scenario

Shopping Sector	Grocery
Bonus Amount	25 TL
Required Total Purchase Amount	250 TL
Promotion Period	September 5-25 (21 Days)
Available Market	$Market_A$
Credit Card	$CreditCard_B$

CCPCS is calculated if there is suitable credit card promotion. If there is no suitable promotion, then it is set to 100. So, the scenario is pursued over purchases. The value ‘λ’ is set to *0.9* for this scenario and the time frame is set to 30 days.

1. Purchase #1

The date of first purchase is at September 2. Promotion_B is not suitable since it is not available at September 2. Promotion_A is the only available at that time. In addition, the minimum purchase amount required by Promotion_A is satisfied by Purchase #1 since 107.25 is greater than 100.

The type of Promotion_A is *Step Promotions* so the calculation routine described for this type is going to be applied. The calculation steps can be summarized as:

1. Calculation of step count in last 30 days (SC_n)
2. Calculation of total transaction amount in last 30 days (TA_n)
3. Calculation of Estimated Average Step Count ($\widetilde{SC_n}$)
4. Calculation of Estimated Average Transaction Amount ($\widetilde{TA_n}$)
5. Calculation of Potential Step Count (PSC)
6. Calculation of Potential Transaction Amount, (PTA)
7. Calculation of CCPCS

Since this is the first purchase, the only purchase in 30 days is Purchase #1 thus $SC_1 = 1$ and $TA_1 = 107.25$. Then $\widetilde{SC_1}$ is calculated:

$$\begin{aligned} \widetilde{SC_1} &= \lambda * SC_1 + \left((1-\lambda) * \widetilde{SC_0}\right) \\ &= 0.9 * 1 + 0.1 * 0 \\ &= 0.9 \end{aligned} \tag{3.12}$$

Then $\widetilde{TA_1}$ is calculated:

$$\begin{aligned} \widetilde{TA_1} &= \lambda * TA_1 + \left((1-\lambda) * \widetilde{TA_0}\right) \\ &= 0.9 * 107.25 + 0.1 * 0 \\ &= 96.525 \end{aligned} \tag{3.13}$$

The Promotion_A is available for 44 days from September 2. Then PSC of Promotion_A is calculated:

$$\begin{aligned} PSC &= \widetilde{(SC_1/30)} * (T_f - T_n) \\ &= (0.9/30) * 44 \\ &= 1.32 \end{aligned} \tag{3.14}$$

Then PTA is calculated:

$$\begin{aligned}\mathrm{PTA} &= (\widetilde{\mathrm{TA}_1}/30) * (\mathrm{T_f} - \mathrm{T_n}) \\ &= (96.525/30) * 44 \\ &= 141.57\end{aligned} \tag{3.15}$$

PSC value means that Customer$_A$ is going to visit grocery stores for 1.32 times in 44 days. PTA value means that Customer$_A$ is going to spend 141.57 TL in 44 days. At last, CCPCS of Promotion$_A$ is calculated:

$$\begin{aligned}\mathrm{CCPCS} &= [((\mathrm{PSC}/\mathrm{RRSC}) + (\mathrm{PTA}/\mathrm{RRTA}))/2] * 100 \\ &= [((1.32/4) + (141.57/400))/2] * 100 \\ &= 34.197\end{aligned} \tag{3.16}$$

RRSC and RRTA are calculated as if Purchase #1 is already done. The type of Promotion$_A$ is not *Total* Promotion. Therefore, there is no remaining required transaction amount (RRTA). However, RRTA is calculated by multiplying remaining required step count (RRSC) with the minimum transaction amount of Promotion$_A$. CCPCS is a score to simulate the uncertainty of completing a promotion in upcoming days. The score of completing Promotion$_A$ by Customer$_A$ is 72.497.

2. Purchase #2

The date of Purchase #2 is September 14. Promotion$_A$ and Promotion$_B$ are available at that time. However, the minimum purchase amount required by Promotion$_A$ is not satisfied by Purchase #2 since 95.5 is smaller than 100. Thus, only Promotion$_B$ is suitable for Purchase #2 and CCPCS is calculated just for the shopping alternative that has Promotion$_B$. CCPCS of the shopping alternative that has Promotion$_A$ is 100 as stated earlier.

The type of PromotionB is *Total Promotion* so the calculation routine described for this type is going to be applied. The calculation steps can be summarized as:

1. Calculation of total transaction amount in last 30 days (TA_n)
2. Calculation of Estimated Average Transaction Amount ($\widetilde{\mathrm{TA}_n}$)
3. Calculation of Potential Transaction Amount (PTA)
4. Calculation of CCPCS

Since this is the second purchase, total purchase amount within 30 days is sum of transaction amount of Purchase #1 and Purchase #2. Thus, TA_2 = 202.75. Then $\widetilde{\mathrm{TA}_2}$ is calculated as follows:

$$\begin{aligned}\widetilde{\mathrm{TA}_2} &= \lambda * \mathrm{TA}_2 + \left((1-\lambda) * \widetilde{\mathrm{TA}_1}\right) \\ &= 0.9 * 202.75 + 0.1 * 96.525 \\ &= 192.128\end{aligned} \tag{3.17}$$

The $Promotion_B$ is available for 12 days from September 14. Then PTA is calculated:

$$\begin{aligned} \mathrm{PTA} &= (\widetilde{\mathrm{TA}_2}/30) * (\mathrm{T_f} - \mathrm{T_n}) \\ &= (192.128/30) * 12 \\ &= 76.851 \end{aligned} \tag{3.18}$$

At last, CCPCS of $Promotion_B$ is calculated:

$$\begin{aligned} \mathrm{CCPCS} &= (\mathrm{PTA}/\mathrm{RRTA}) * 100 \\ &= (76.851/154.5) * 100 \\ &= 49.741 \end{aligned} \tag{3.19}$$

The score of completing $Promotion_B$ by $Customer_A$ at September 14 is 49.741. $\widetilde{\mathrm{SC}_2}$ is not required to calculate CCPCS since $Promotion_B$ is type of total promotion. However, it is required for future calculations. The number of purchases within 30 days is two so $SC_2 = 2$ and $\widetilde{\mathrm{SC}_2}$ is also calculated:

$$\begin{aligned} \widetilde{\mathrm{SC}_2} &= \lambda * \mathrm{SC}_2 + \left((1 - \lambda) * \widetilde{\mathrm{SC}_1}\right) \\ &= 0.9 * 2 + 0.1 * 0.9 \\ &= 1.89 \end{aligned} \tag{3.20}$$

3. Purchase #3

The date of Purchase #3 is September 20. $Promotion_A$ and $Promotion_B$ are available at that time. Moreover, both promotions are suitable for Purchase #3. Thus, CCPCS is calculated for both shopping alternatives.

By the third purchase, the purchases within 30 days are Purchase #1, Purchase #2 and Purchase #3 thus $SC_3 = 3$ and $TA_3 = 327.75$. Then $\widetilde{\mathrm{SC}_3}$ and $\widetilde{\mathrm{TA}_3}$ is calculated:

$$\begin{aligned} \widetilde{\mathrm{SC}_3} &= \lambda * \mathrm{SC}_3 + \left((1 - \lambda) * \widetilde{\mathrm{SC}_2}\right) \\ &= 0.9 * 3 + 0.1 * 1.89 \\ &= 2.889 \end{aligned} \tag{3.21}$$

$$\begin{aligned} \widetilde{\mathrm{TA}_3} &= \lambda * \mathrm{TA}_3 + \left((1 - \lambda) * \widetilde{\mathrm{TA}_2}\right) \\ &= 0.9 * 327.75 + 0.1 * 192.128 \\ &= 314.188 \end{aligned} \tag{3.22}$$

$$\begin{aligned} \mathrm{PTA} &= (\widetilde{\mathrm{TA}_3}/30) * (\mathrm{T_f} - \mathrm{T_n}) \\ &= (314.188/30) * 27 \\ &= 282.769 \end{aligned} \tag{3.23}$$

These values are common for both $Promotion_A$ and $Promotion_B$. PSC is only calculated for $Promotion_A$. CCPCS is calculated for both alternatives. By the time September 20, 27 days are left for $Promotion_A$ and 6 days left for $Promotion_B$. Here are the calculations for $Promotion_A$:

$$\begin{aligned}\text{PSC} &= (\widetilde{\text{SC}_3}/30) * (\text{T}_\text{f} - \text{T}_\text{n}) \\ &= (2.889/30) * 27 \\ &= 2.60\end{aligned} \tag{3.24}$$

$$\begin{aligned}\text{CCPCS} &= [((\text{PSC}/\text{RRSC}) + (\text{PTA}/\text{RRTA}))/2] * 100 \\ &= [((2.60/3) + (282.769/300))/2] * 100 \\ &= 90.461\end{aligned} \tag{3.25}$$

Here are the calculations for $\text{Promotion}_\text{B}$:

$$\begin{aligned}\text{CCPCS} &= (\text{PTA}/\text{RRTA}) * 100 \\ &= (282.769/29.5) * 100 \\ &= 958.54\end{aligned} \tag{3.26}$$

For Purchase #3, it is clear that $\text{Promotion}_\text{B}$ is more likely to be completed by Customer_A compared to $\text{Promotion}_\text{A}$.

4. Purchase #4

The date of Purchase #4 is October 9. $\text{Promotion}_\text{B}$ is not available at that time. $\text{Promotion}_\text{A}$ is available. $\text{Promotion}_\text{A}$ is suitable for Purchase #4 since the minimum required transaction amount is satisfied. Thus, CCPCS is calculated just for the shopping alternative generated for $\text{Promotion}_\text{A}$.

By the fourth purchase, the purchases within 30 days are Purchase #2, Purchase #3 and Purchase #4 thus $\text{SC}_4 = 3$ and $\text{TA}_4 = 330.5$. Then $\widetilde{\text{SC}_4}$ and $\widetilde{\text{TA}_4}$ is calculated:

$$\begin{aligned}\widetilde{\text{SC}_4} &= \lambda * \text{SC}_4 + \left((1-\lambda) * \widetilde{\text{SC}_3}\right) \\ &= 0.9 * 3 + 0.1 * 2.889 \\ &= 2.989\end{aligned} \tag{3.27}$$

$$\begin{aligned}\widetilde{\text{TA}_4} &= \lambda * \text{TA}_4 + \left((1-\lambda) * \widetilde{\text{TA}_3}\right) \\ &= 0.9 * 330.5 + 0.1 * 314.118 \\ &= 328.862\end{aligned} \tag{3.28}$$

By the time October 9, $\text{Promotion}_\text{A}$ is available for 7 days more. Then PTA, PSC and CCPCS are calculated accordingly:

$$\begin{aligned}\text{PTA} &= (\widetilde{\text{TA}_4}/30) * (\text{T}_\text{f} - \text{T}_\text{n}) \\ &= (328.862/30) * 7 \\ &= 76.734\end{aligned} \tag{3.29}$$

$$\begin{aligned}\text{PSC} &= (\widetilde{\text{SC}_4}/30) * (\text{T}_\text{f} - \text{T}_\text{n}) \\ &= (2.989/30) * 7 \\ &= 0.697\end{aligned} \tag{3.30}$$

$$
\begin{aligned}
\mathrm{CCPCS} &= [((\mathrm{PSC}/\mathrm{RRSC}) + (\mathrm{PTA}/\mathrm{RRTA}))/2] * 100 \\
&= [((0.697/2) + (76.734/200))/2] * 100 \\
&= 36.608
\end{aligned}
\tag{3.31}
$$

Since only 7 days left for Promotion_A, the completion score is diminished compared to calculations for Purchase #3.

CCPCS calculation is demonstrated for four consecutive purchases. In the next section, the creation of the workflow specifications is described.

3.3.2. Creation of Workflow System Specifications from Promotion Metadata

In YAWL, the specifications are defined using a built-in specification editor visually. In this study, an automatic specification creation from the metadata is not implemented. However, the manual conversion process is explained and an example is provided.

Suppose that there is a credit card promotion with the metadata declaration given in Table 4. To model this promotion, it is required to have a registration step, 5 purchase steps since the required number of purchases is 5 and a bonus usage step. The visualization of the promotion specification is given in Figure 6.

Cost-based step notification is adopted in the specification modelling. Each step has its own cost data. In this study, the price value is used as the cost of a step. For this promotion for example, the purchase steps have the cost of 100 TL which is the minimum purchase amount defined in the metadata. Thus, steps from Purchase #1 to Purchase #5 equal in cost.

The registration step has also a cost data. For example, if the registration step is made by using SMS, then sending an SMS cost is associated with this step.

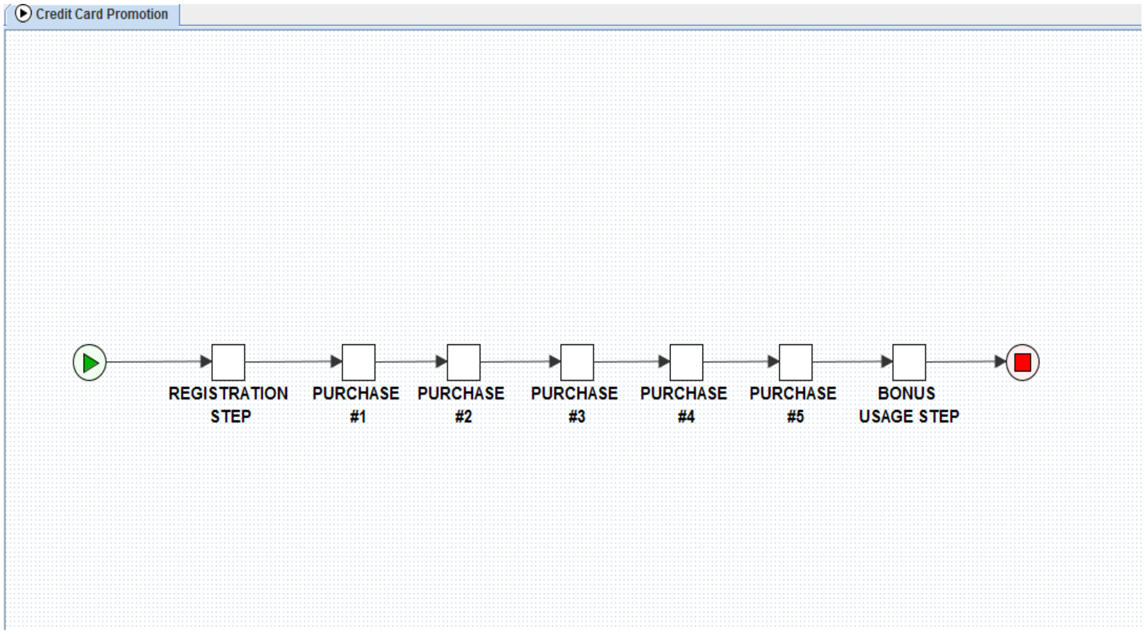


Figure 6 – A credit card promotion specification visualization

The bonus usage step is the last step for this promotion process. If the customer reached to this step, this means that he completed all required purchases and gained the predefined bonus amount, which is 50 TL. However, this means that the customer has to spend 50 TL more. The cost of the bonus usage step is set to the bonus amount.

The benefit of cost-based modelling is that the remaining cost to complete a promotion can be interpreted. The remaining required transaction amount (RRTA) value is calculated using the workflow engine. The workflow holds the state of the promotion and tracks the remaining steps to calculate RRTA. Assume that the customer is completed the steps until Purchase #4. This means that Purchase #4, #5 and bonus usage step are left. By going over the remaining steps, the RRTA is calculated which is 200 TL because of two purchase steps. Only the cost of purchase steps is used in calculating RRTA. However, the cost of the other steps can be used to inform DMs for the notification purposes.

CHAPTER 4

PROTOTYPE

In this study, the proposed model is realized as a prototype to show the applicability of it. The application is one of the examples of client-server architecture. The client side is developed as an Android mobile application while the server side is implemented on Spring Framework [101]. The Android application is developed on Ionic-Framework [102]. Ionic-Framework enables developers to create mobile applications by using HTML5 technologies. An Android application can be implemented by coding in JavaScript. For this prototype, the client application is developed by coding in JavaScript and converted to an Android application. The prototype is used and tested on Samsung Galaxy S5 smartphone. MySQL is selected as the relational database management system.

The mobile client communicates with the server side through REST calls, which are done by using HTTP requests. The Spring-based server application provides services based on Representational State Transfer (REST), which is known as RESTful Services. The shopping alternative generation process and the ranking process are performed at the server side. The mobile application does not perform any calculation. The users define their preference and threshold values through the mobile application. The server side is independent from the client side in this prototype. The client side application could be replaced easily without changing the server side in the future.

In order to generalize the conceptual design, it is required to select an outranking method and a workflow engine. As described earlier, the PROMETHEE II method is selected as the outranking method and it is implemented in server side to rank generated alternatives. YAWL [81] is used as the workflow engine. The server application uses YAWL to hold promotion states. It helps customers to identify what the requirements are to complete the promotion. YAWL specifications are manually generated based on the defined promotions as described in Section 3.3.2.

Since this is a prototype, static data are used. The product list, the product prices, the grocery stores, the credit cards, the grocery market promotions and the credit card promotions are manually defined in the database and used. No automatic search mechanism is implemented. Therefore, Product Price Module, Market Promotion Module and Credit Card Promotion Module are not implemented. The implemented modules of the conceptual design are given in Figure 7. The dotted region represents the system. It takes a pre-defined shopping list and generates ranked shopping alternatives. Then, the system is feed by the selected shopping alternative.

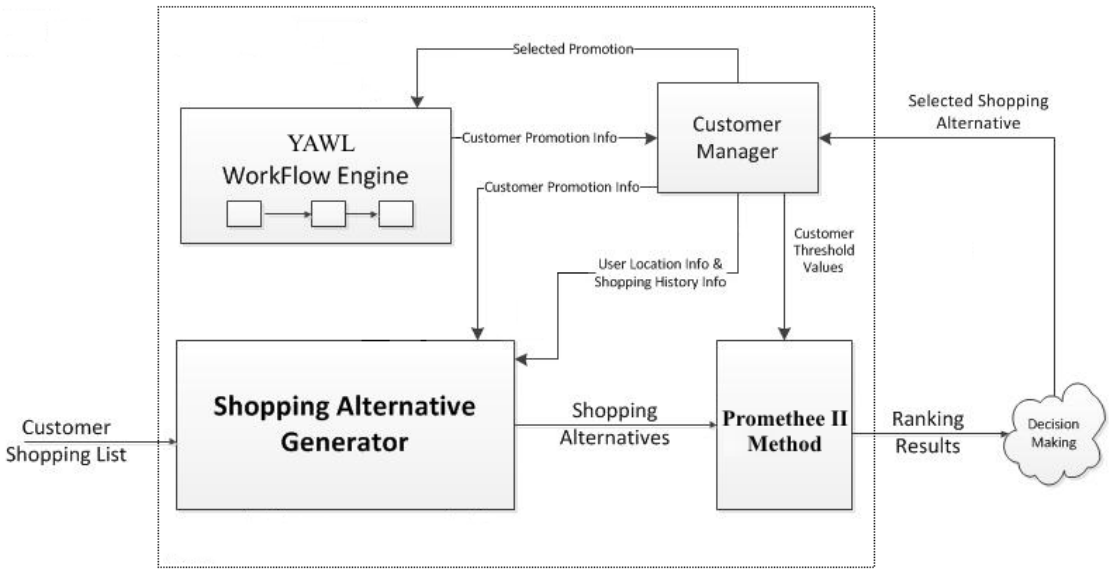


Figure 7 – The implemented modules in the prototype

In the prototype, users follow a flow of actions through the mobile application. The first step is login phase. Then, the user selects or deselects products listed in their next purchase. Since it is a prototype, product list is static. Then the user is requested to select from possible predefined grocery stores. The stores are listed with the total price of products listed in the previous step. The available grocery promotions are applied and the total price is calculated accordingly. After the selection of one or more stores, the application requests from the user to select credit cards. The credit cards are predefined credit cards of the user. The user may not use a credit card for this purchase. Then, the user can skip this step. The generation of shopping alternatives is made based on these selections. Credit card promotions that are defined for the selected cards are taken into account for the shopping alternative ranking process. Next, the program lists a set of shopping alternatives that are ranked by the PROMETHEE II method based on the defined criteria weights and threshold values of the user. This process is explained in detail in Section 3.3.1. At the end, the user has the flexibility to select any of the ranked alternatives. This is the Decision Making step also shown in Figure 7. After the selection of one of the listed options, the model updates the user's shopping history and promotion states that are handled by the YAWL workflow engine. The screenshots of the prototype are given in Figure 8. The steps are represented in sequence starting from the login screen and ending with the selection of the shopping alternative.

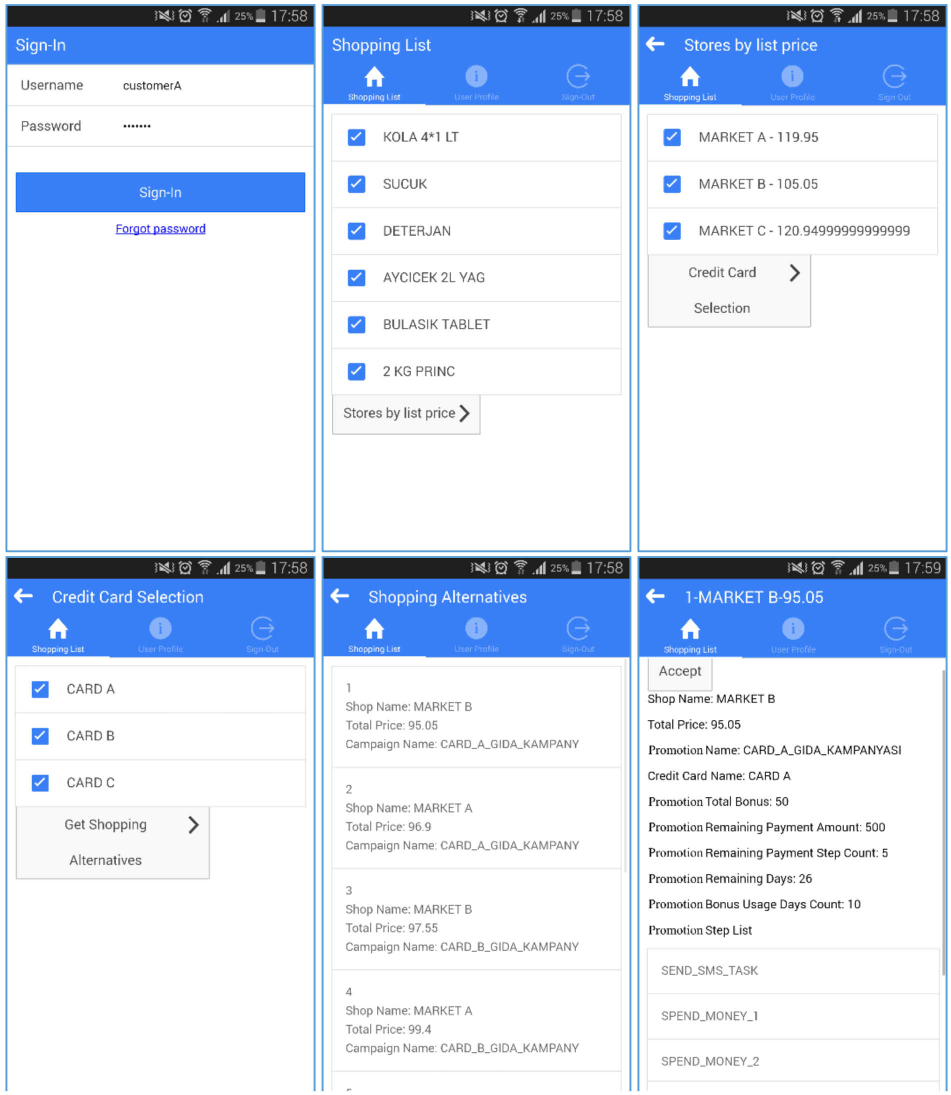


Figure 8 – The screenshots taken from prototype implementation

As seen in the last screenshot, the user is informed by detailed information about the credit card promotion. The remaining step count and the name of the steps can be seen. The user can do further analysis on given information and select the best alternative for himself.

As mentioned earlier, the PROMETHE II method is selected as the outranking method. Therefore, the users have to define their criteria weights and threshold values to feed the PROMETHEE II method in ranking process. To address this requirement, we designed a screen for user profiles where the criteria weights and the threshold values are defined. The screenshot of that screen is given in Figure 9. The PROTMETHEE method uses these defined values in its calculations. The user profiles are saved in the database.

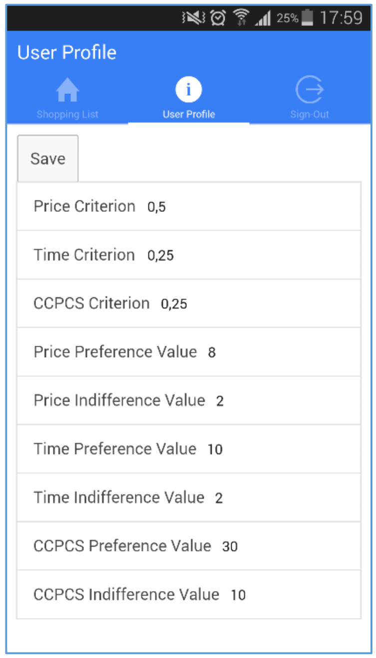


Figure 9 – The screenshot of the user profile

In order to clarify the usability of the prototype, some usage metrics are collected. The prototype is analyzed from the login page to the shopping alternative selection and the time required to reach to the end of the action flow is measured. Moreover, the time required to generate the shopping alternatives is measured. The prototype is run for 10 times and the average process time is calculated. The user reached to the last step in 6.8 seconds on average. The generation of the shopping alternatives took 679 milliseconds on average. This is the time required for the server to response to the shopping alternative generation request from the client.

CHAPTER 5

RESULTS

In this chapter, the evaluation of the proposed model results is presented which is based on the generated dataset explained in Section 5.1. The evaluation process is explained in Section 5.2. Optimum results of Integer Linear Programming are listed in Section 5.3. Results gained by the proposed solution are described in Section 5.4. The effectiveness of the proposed model is given in Section 5.5 and Section 5.6. Lastly, the statistical analyses are given in Section 5.7.

5.1. Dataset Description

5.1.1. Grocery Market Dataset Description

In order to validate our proposed model, we use grocery market shopping dataset provided by a local Turkish grocery market. The dataset has all the shopping transactions between October 2012 and August 2014. It is a period of 699 days. The raw data contains 1.7 million individual product purchase transactions of 21275 different products. These individual product transactions create 254807 shopping lists, which belong to 15665 distinct customers. Every transaction contains a customer identification number, product group hierarchy, product name, product unit count, price and transaction date and time. Product hierarchy contains 23 main group, 99 first level sub-group and 712 second-level sub-group. The transaction history is collected via a loyalty card of each customer. At each transaction, the loyalty card is scanned and the product purchases are stored in the store database.

5.1.2. Preprocess of Raw Dataset

To eliminate improper data in raw dataset, data preprocessing is done to make dataset usable for validation. First, transactions with price equals to zero or below zero are eliminated. According to [22] since only 10% of the consumers do daily grocery shopping, shopping data of customers with three transactions per day is highly inconceivable. These customers are possible to be corporate customers. Thus, customers with daily transaction count greater than or equal to three are eliminated.

As the second step of the data preprocess, outlier analysis is conducted. Outlier values are the ones reside far from the rest and cause the model and the descriptive statistics, like mean, median and standard deviation of the data to be biased. Hence, they should be detected and dealt with. There are two ways to detect outliers [103]:

- Consulting visual tools: Histograms and boxplots can be drawn.
- Using z-scores of the data points to see the deviation of them from a standard normal distribution

For this study, second option is preferred because the statistical distribution of the data is not known precisely, but at least known as not to be a normal distribution. The normality of the data can be checked again by utilizing histograms, Q-Q or P-P plots and skewness and kurtosis values [103]. As it is seen in Figure 10, the data obviously do not have a normal distribution because the histogram is skewed to left side and the dark line on the P-P plot does not lie on the diagonal line. If the distribution were normal, then the line would reside on the diagonal line meaning that the calculated z-scores of the data match up with normal distribution values.

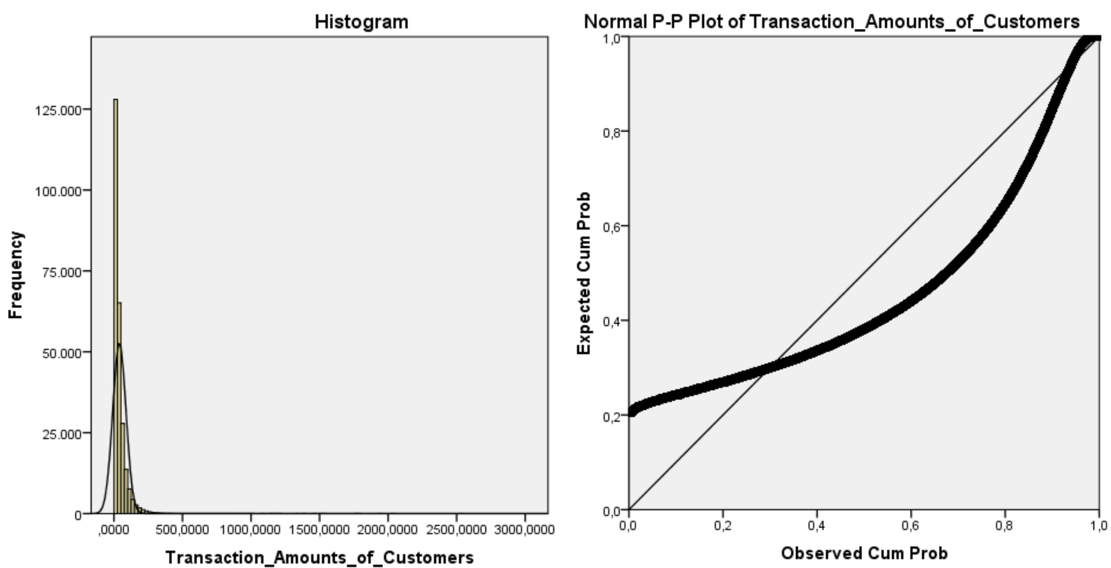


Figure 10 – Histogram (left) and P-P Plot (right) for transaction amounts of customers

The rationale of the second option for outlier analysis is to bring the data points to the interval of the values belonging to a normal distribution by standardizing them. To calculate the z-scores of the samples, the mean of the data is subtracted from every data point and divided by the standard deviation of the data.

$$z = \frac{X - \bar{X}}{S} \tag{5.1}$$

After the calculation of z-scores, they are compared to the normal distribution. In normal distribution, 95% of the data should have absolute values that are less than 1.95, and 99% should have absolute values that are less than 2.58. All cases should have absolute values smaller than 3.29 [103]. Hence, the transaction amounts of the customers, which have z-scores greater than 3.29, can be seen as outliers. As the result of this analysis, 4838 of the observations are found to be outliers and omitted from the dataset. Boxplots of the dataset before and after the outlier analysis can be seen in Figure 11. Outlier analysis removes the ones, which are shown with asterisk, extreme outliers that are greater than 3 times of interquartile range (IQR). Outliers indicated by circle sign are not eliminated but this does not cause a problem since these outliers are mild outliers, which are greater than 1.5 times of the IQR [104].

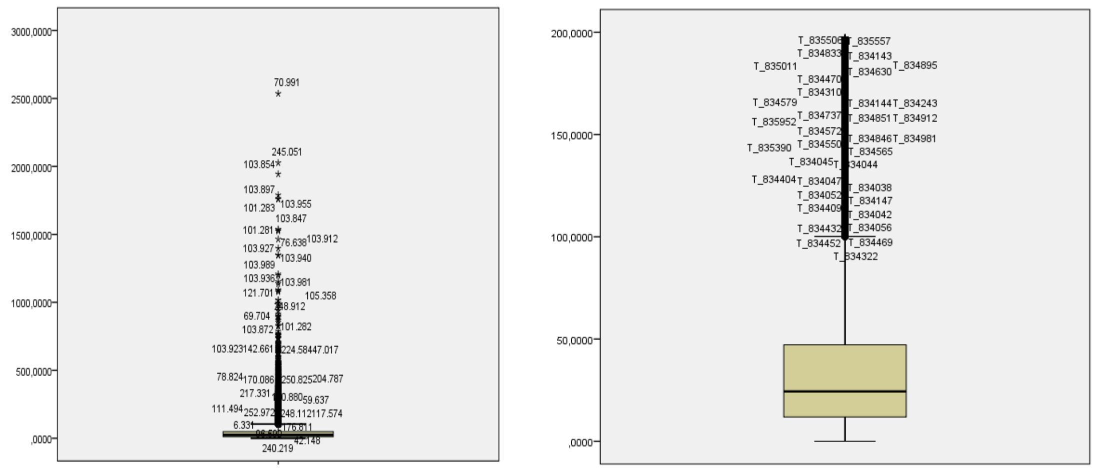


Figure 11 – Boxplot of transaction amounts before (left) and after (right) outlier analysis

After elimination of improper data, 220659 purchase transaction of 9946 customers left. More precisely, 34148 transactions and 5719 customers are removed from the dataset.

5.1.3. Data Preparation

The dataset is not complete without defining credit card promotions and grocery market promotions available at the period of the given data set. We implemented crawling applications in order to crawl grocery market promotions and credit card promotions between October 2012 and August 2014. Publicly available data of credit card promotions and grocery market promotions are used as announced on the internet. Crawled data is not simulated data but actual promotions provided by grocery markets and national banks. We select a subset of available credit cards based on promotions count. As a result, four credit cards with highest credit card promotion count for store markets are selected for our study.

The crawled credit card promotion data consists of credit card brand name, grocery market name, promotion period, bonus amount, and number of required shopping steps and required minimum shopping amount. As explained in 3.1 Definitions, we collected fields required to define a credit card promotion. Number of promotions by each credit card is listed in Table 8.

Table 8 – Number of credit card promotions by credit card

Credit Card Brand Name	# of promotions	Total Bonus Amount (TL)
Card 1	15	663
Card 2	31	690
Card 3	27	1207
Card 4	14	510
TOTAL	87	3070

In addition to credit card promotions, we need to define grocery market promotions. Similarly, we found out the number of promotions by grocery markets on the internet. We chose five top grocery markets that have maximum number of promotions. However, the publicly available data has some data deficiency. As explained in Section 3.1.1, market promotions mostly declare discounts on products. Without having the actual price and discounted price at the time of the promotion, it becomes unusable in our study. The effect of the promotion remains unknown by just having promotional prices. In the provided dataset, product prices are known at the purchase time. If the discount percentage or the price of the products listed in a promotion were available, we would be able to apply those promotions to our dataset. However, most of the crawled promotions do not have price information and almost none of the promotions listed have discount amount or percentage. Therefore, we decided to generate grocery market promotions randomly. To minimize the effect of this randomization, we created promotions based on the number of promotions in each store given in Table 9. The selected stores are nationwide store chains in Turkey.

Table 9 – Number of grocery market promotions by grocery market

Store	# of promotions
Store 1	101
Store 2	112
Store 3	110
Store 4	86
Store 5	111
Total	520

We collected the number of promotions at each store and the period of each promotion. We generate promotions based on mostly purchased 100 products in the provided dataset. Five to 30 products are selected randomly from 100 products for each promotion. Promotions are defined as discounts on products. Discount percentages are randomly selected from 2% to 10% (inclusively).

As we mentioned previously, there may be fluctuations in product prices and same products may be sold in different prices at different stores. In order to simulate this fact, we define five different stores as listed in Table 9. One of the five stores is the store that we take the raw dataset. That store is used as a reference store. Then, product prices are randomly generated for other four different stores. Random prices are obtained by adding ±10 percent to the prices at the reference store. The percentage rate is again determined randomly.

Another required data in this research is the proposed model is the distance of the customers to the grocery stores. The distance is represented in minutes. It is the required time to travel to a store. Distance values are generated randomly. The values are selected from zero to 30 minutes randomly.

The generated data is stored in a database to be used in the model evaluation. If the data were regenerated, randomness in the generation process would affect the outcomes. Storing in the database enables us to do analysis from scratch whenever needed.

5.2. Proposed Solution Evaluation

After the data preparation step, the dataset is ready for detailed analysis. Since we know purchase history of the customers for approximately 24 months period and the promotions are declared, it is possible for us to evaluate the proposed model. Customer shopping history gives us the time, the total amount of the purchases as well as the products bought in each transaction. Thus, by traversing customer transactions one by one, *Net Expense* can be calculated as:

$$Net\ Expense = Expense\ Amount - Promotion\ Saving \tag{5.2}$$

Expense Amount is total expense of a customer in all transactions. *Promotion Saving* is defined as the sum of deductions of grocery market promotions and completed credit card promotion bonuses amount. *Total Net Expense* for all customers calculated as:

$$Total\ Net\ Expense = \sum_{i=1}^{n} Net\ Expense_i\,, n = \#\ of\ customers \tag{5.3}$$

In the evaluation process, the proposed model is tested according to the *Total Net Expense*. The optimum minimum *Total Net Expense* is calculated by Integer Linear Programming (ILP). Then, *Total Net Expense* is calculated by using the model. These findings are compared to find the performance of the proposed solution.

In the evaluation process, the distance values are ignored. Just price-based evaluation is done. It is possible to convert distance information to a monetary value and add this value to expense amount. However, this addition would be same for both optimum calculations and proposed model based calculations because it is assumed that the location of the grocery stores in the generated dataset equals to each other. Thus, increasing or decreasing the *Total Net Expense* with constant values would not affect comparison results.

5.2.1 Calculating Optimum Total Net Expense

To find optimum minimum total net expense, Integer Linear Programming (ILP) is used. As defined in Equation 5.3, to minimize total net expense, it is required to minimize total expense amount and/or maximize total promotional savings.

In the dataset, a customer has option of shopping at five different grocery stores for a given shopping list. In addition, each grocery store has its own grocery market promotions. Besides this, the customer can pay by credit card. There would be available credit card promotions (CCPs) which have different restrictions and different bonus rewards. Thus, it is required to select the 'best' combination in order to gain the maximum bonus.

At a given time, there would be only one CCP available but in upcoming days there would be newly announced CCPs. The selection of a CCP is affected by previously selected CCPs and it affects the upcoming transactions. This is why ILP is needed in our case. With ILP, it is possible to be sure about the selection of the best shopping alternative, which results in minimum payment amount. The shopping alternative is the selection of the store, the store promotions, and the credit card promotions.

Examine the Figure 12 to understand the difficulties in the shopping alternative selection better. In the figure, transactions of a customer are shown as blue lines defined from T_1 to T_7. T_1 represents the first transaction and T_7 represents the last transaction. As in the dataset, there are five different grocery stores shown as green vertical lines represented by K_1 to K_5. In addition, credit card promotions available for a specific time period which are defined by red lines represented by C_1 to C_5. The length of the red lines shows the start and end time of the CCP. It is possible to draw such diagram for each customer since transactions of them are already defined in the dataset and the upcoming promotions are known beforehand. Assume that the customer has the required credit cards for the defined CCPs. The grocery store promotions are not shown separately in the diagram. The selection of the store covers the selection of the promotions available at that store.

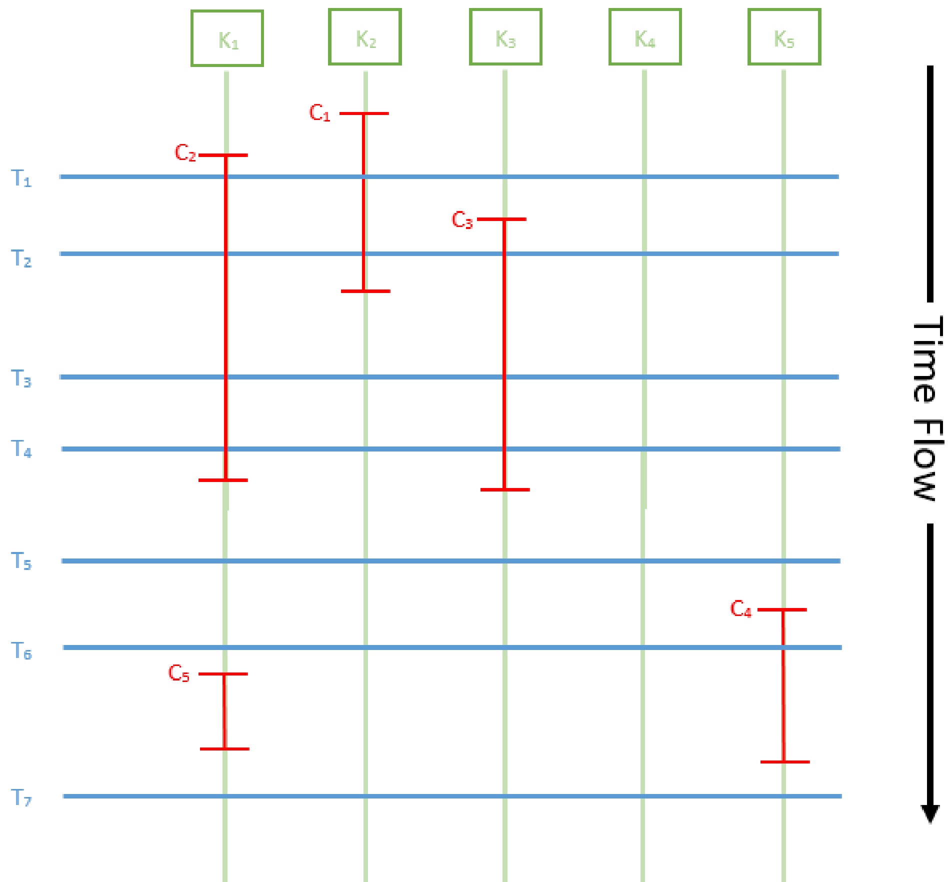


Figure 12 – Visualization of customer transactions (blue horizontal lines) with grocery stores (green vertical lines) and available credit card promotions (red lines)

For transaction T_1, customer may select to do shopping at one of the five grocery stores. C_2 is available at K_1 while C_1 is available at K_2. For T_1, only these two CCPs are available. There is no CCP defined at K_3, K_4 or K_5. Therefore, the customer has to decide where to shop. He may do shopping at K_1 with, without C2, or at K_2 with, without C1, or at K_3, K_4 and K_5 without any CCP. For transaction T_2, it is even more complicated. There are three CCPs (C_1, C_2 and C_3) available at different stores and two stores (K_4 and K_5) have no CCP. For T_3 and T_4, similarly two CPPs are available. For T_5 and T_7, there is no CPP defined and for T_6 only C_4 is defined. C_5 has no intersection with given transactions so it is not usable by this customer.

The problem is to select the best shopping location and best promotion combination to minimize net expense of the customer. To be sure, it is necessary to use a mathematical optimization, which is ILP. We can state the problem formally as:

$$Minimize \sum_{i=1}^{m}\sum_{k=1}^{p}\left(T_{ik} * \sum_{j=1}^{n} X_{ijk}\right) - \left(\sum_{a=1}^{d} W_a * \rho_a + \sum_{b>d}^{e} Y_b * \rho_b + \sum_{c>e}^{n} Z_c * \rho_c\right)$$

$T_{ik} =$
$Purchase\ amount\ of\ purchase\ i\ at\ market\ k\ after\ store\ promotions\ deducted$

Subject to:

$$X_{ijk} = \begin{cases} 1, & purchase\ i\ is\ made\ at\ store\ k\ and\ credit\ card\ promotion\ j\ is\ used \\ 0, & otherwise \end{cases}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{p} X_{ijk} = 1\ (i = 1,2,\dots,\mathrm{m};\ \mathrm{k} = 1,2,\dots,\mathrm{p};\ \mathrm{j} = 1,2,\dots,\mathrm{n})$$

$$W_a = \begin{cases} 1, & \sum X_{iak} \geq \theta_a \quad (a = 1,2,\dots,d) \\ 0, & otherwise \end{cases}$$, for *step promotions*

$$Y_b = \begin{cases} 1, & \sum T_{ik} * X_{ibk} \geq \beta_b \ (b = d+1, d+2, \dots, e) \\ 0, & otherwise \end{cases}$$, for *total promotions*

$$Z_c = \begin{cases} \sum X_{ick}, & 0 \leq \sum X_{ick} < \alpha_c \\ \alpha_c, & \sum X_{ick} \geq \alpha_c \end{cases} \quad (c = e+1, e+2, \dots, n)$$, for *per step promotions*

Credit card promotion constraints are:
θ_a = Required number of purchases to complete '*step promotions'*
β_b = Required total purchase amount to complete '*total promotions'*
α_c = Maximum number of purchases that '*per step promotions' can be used*

Credit card promotion bonuses are:
$\rho_a = Bonus\ amount\ of$ '$step\ promotions$'
$\rho_b = Bonus\ amount\ of$ '$total\ promotions$'
$\rho_c = Bonus\ amount\ for\ single\ suitable\ purchase\ of$ '$per\ step\ promotions$'

ILP problem stated above is just for a single customer. In dataset, there are 9946 customers. Therefore, the ILP problem is modelled and solved for each customer separately and the optimum results are sum up to calculate total net expense. ILP problems are constructed based on the generated dataset. That is, grocery market promotions and credit card promotions are all defined for 2 years period. The ILP does not have explicit variables or constraints for grocery market promotions. These promotions are injected into transaction amount, which is represented as T_{ik}.

To solve ILP problem stated above, optimization software CPLEX is used [105]. CPLEX Studio Community Edition is used in this study. The problem size is limited to 1000 decision variables and 1000 constraints. CPLEX Studio accepts models written in Optimization Programming Language (OPL). To generate models in OPL, a Java program is implemented. The program iterates over each customer and the transactions in the dataset to set up OPL models. ILP problem is generated for 9946 customers. By using CPLEX Studio, these models run consecutively and optimum results are obtained automatically.

5.2.1 Calculating the Total Net Expense by the Proposed Model

To gather the proposed model outcomes, it is required to implement the proposed model. The developed prototype is used in calculations. The prototype development explained in Chapter 4. The implemented server side Spring-based application is used.

As shown in Figure 5, shopping list is required as an input to the Shopping Alternative Generator module. For each customer, customer transactions defined in the dataset are used as input to the program. The outranking method ranks alternatives based on customer's criteria weights and threshold values. Customers, as decision makers, can select any alternatives from ranked ones. Nevertheless, in order to evaluate the proposed model, a systematic way is required to select one of the alternatives. Since our model is compared to optimum results, it is plausible to select the alternative that is ranked at the top. It is required to note that since the proposed model uses MCDM, we cannot talk about best result but rather a satisfactory one from DM perspective [12]. The proposed model suggests the one as more satisfactory alternative. For each purchase, the ranking of the alternatives and the alternative at the top is selected. This repetitive process simulates the usage of the model for two years by 9946 customers.

Outranking methods need criteria weights and threshold values in order to rank the alternatives. However, in this study, the required inputs are unknown. As described in Section 5.1, we have the purchase history of a local grocery market and the evaluation process is based on this dataset. Without knowing the exact preferences of each customer of that local market, there would be no relevance of selecting a predefined value for criteria weights and threshold values. To overcome this drawback, the proposed model is observed with numerous different weights and threshold values. This way, it could be said that the 'best' performance of the model on the dataset is find. The 'best' performance means that the combination of the criteria and threshold values that gives the lowest total net expense. The model is compared to the optimal values by using lowest total net expense value. The details about the comparison results are given in Section 5.5.

5.3. The Optimum Results Obtained By Integer Linear Programming

As explained in Section 5.2.1, ILP problem is defined for each customer in the dataset. For 9946 customer, ILP model is generated and solved by using CPLEX Optimizer [105]. The optimization results are summarized in Table 10. Total expense, total credit card promotion bonus gain and total net expense are listed.

Table 10 – Summary of the optimum findings

Name	Optimum Result
Total Expense	7,864,295.54 TL
Total Credit Card Promotion Bonus Gain	191,776 TL
Total Net Expense	7,672,519.54 TL

As defined by the Equation 5.3, Total Net Expense is calculated by subtracting total promotion bonus gain from total expense. Total expense of the customers is 7,864,295.54 TL. Total credit card promotion bonus gain is 191,776 TL. The optimum Total Net Expense is 7,672,519.54 TL.

Optimum findings are separated into three parts as shown in Table 10. This separation enables us to compare the optimum results with the proposed model findings more clearly. The grocery store promotions are also considered as the promotion bonus gain. It is not separately listed here since the store promotions are deduced from each transaction while the ILP models are constructed. Thus, the grocery store promotion gains are already deduced from the total expense.

5.4. The Results Obtained By the Proposed Model

As stated in Section 5.1, there are missing data in the dataset to test the proposed model with full functionality. The missing data is the customer preferences, which consist of the criteria weights, and threshold values that feed PROMETHEE II.

As stated in [67], DMs who have no expertise in the problem domain or has little understanding of the defined criteria could have difficulties to assign those weights properly. In PROMETHEE, like other outranking methods, a method to select the right criteria weights is not defined. AHP could be used to categorize criteria into sub-criteria and help to assign the weights accordingly [67]. However, in the proposed model, only three criteria are used and there is no hierarchical relation between them which makes using AHP not an applicable option to determine criteria weights. The same problem is valid for the decision of the threshold values.

Threshold values of the outranking methods are defined for each criterion by the DMs like as the criteria weights. In literature, most of the PROMETHEE applications do not provide any guidance to select criteria weights and threshold values. Rather, they choose to ask directly to the DMs to determine those values [106]. PROMETHEE makes easier to understand the criteria and threshold values by the DMs. However, in our case it is completely impossible to reach out the customers in the provided dataset. To determine criteria and threshold values, a survey method is proposed in [106]. It can be stated that, survey could be conducted with small number of participants to determine customer preferences and the proposed model could be tested based on those values. However, since we have real grocery market transactions for about 2 years of time and for 9946 customers, any data obtained by surveys could not be advantageous over the real data. The survey results would be only for small set of customers. On the other hand, we have the ability to test the proposed model with numerous different criteria weights and threshold values instead of collecting values via surveys.

To overcome drawbacks of not having customer preferences beforehand, we set up a pre-evaluation procedure in order to obtain criteria weights and threshold values for each criterion. In the proposed model, there are four variables, which have direct effect on the model outcomes. These are:

1. Time Frame declared in Section 3.3.1
2. Lambda value of EWMA
3. Weights of the price, the time and the CCPCS criterion
4. Preference and indifference thresholds of each criterion

Variable #1 and #2 are the values that are declared for the proposed model itself. #3 and #4 are inputs of the PROMETHEE method, which should be selected by the DMs. The time criterion is set to zero not to include it in to the comparison process as stated in Section 5.2. The effect of the time criterion on the outcome of the proposed model is evaluated separately later in this section.

5.4.1. Selection of the Criteria Weights and the Threshold Values

To find the 'best' combination of the criteria weights and the threshold values of each customer, the time frame and the lambda values are left constant at first. The proposed model is then tested by walking values within a predefined range for each criterion. The best combination is the one that minimizes the net purchase amount of that customer. Table 11 shows the constant values for the time frame and the lambda value. Table 12 gives the predefined ranges for weights, and thresholds. Incremental values used within those ranges are also listed.

Table 11 – Constant values selected for the process of adjusting customer preferences

Variable Name	**Constant Value**
Time Frame	30 days
Lambda	0.9

Table 12 – Range of walking values defined for variables

Variable Name	Range of Walking Values	Incremental Value
Price Criterion Weight	0 – 1	0.1
CCPCS Criterion Weight	0 – 1	0.1
Price Criterion Preference Threshold	0 – 10 TL	2 TL
Price Criterion Indifference Threshold	0 – 5 TL	1 TL
CCPCS Preference Threshold	0 – 100	10
CCPCS Indifference Threshold	0 – 50	5

CCPCS is a score, which have values from zero to 100. That is why the range of CCPCS preference threshold is from zero to 100. For the price-criterion preference threshold, 10 TL is selected as the endpoint of the range. The range space is set after numerous trial runs of the evaluation process. After 10 TL, increasing the price-criterion preference threshold has no positive effect on the outcomes. Intuitively, indifference thresholds should be less than preference thresholds since a value that is negligible for a customer cannot be important as well. Thus, endpoint of the indifference threshold ranges are set to the half of the preference thresholds. To decrease the number of trials the incremental values are set to 2TL for preference thresholds.

The number of the different combinations according to the given values in Table 12 turns out to be 13750. Each possible combination is tested for each customer which makes the number of runs to 9946 X 13750 ~= 137 Million. The combinations, which minimize the net payment amount for each customer, are selected and stored.

5.4.2. Time-frame and Lambda Based Model Results for All Customers

The criteria weights and the threshold values are already selected. The next step is to figure out the effects of the time frame and the lambda values on the proposed model results. To isolate the influence of the criteria weights and the threshold values, they are kept constant.

The range of the lambda and the time frame values and incremental values used within those ranges are given in Table 13.

Table 13 - Range of walking values defined for time frame and lambda variables

Variable Name	Range of Walking Values	Incremental Value
Time Frame	1 – 105 weeks	1 Week
Lambda	0 – 1	0.1

Time frame is changed from 1 week to 105 weeks by 1 week of intervals. 105 weeks is the maximum time length of the dataset. Lambda values are adjusted from zero to one exclusively.

Figure 13 illustrates the effects of both lambda values and the time-frame values on the total net expense. The colors in the diagram represent a range of total net expense amount as can be seen in the figure legend. Each colored surface demonstrates range of 100 TL. Two expense amounts, which are in the same range, are represented by the same color. This diagram shows actual total net payment amount. The figure is limited to the time frame from 45 to 65 weeks.

The minimum total net payment amount is reached at the time frame of 55 weeks and lambda value of 0.6. The net expense at this point is 7,852,508 TL. In the next section, the effect of the time frame is highlighted by fixing the lambda at 0.6 and then the effect of the lambda is highlighted by fixing the time frame at 55 weeks.

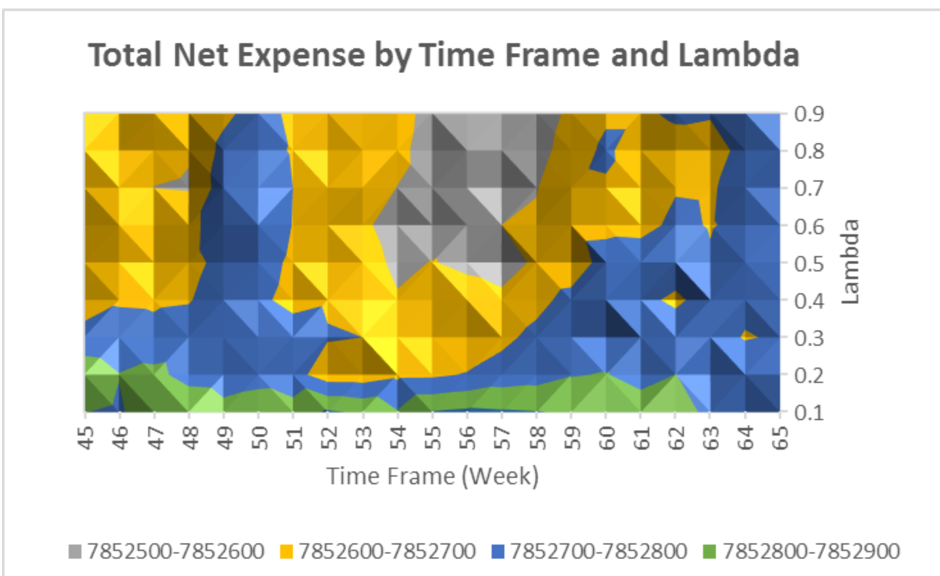


Figure 13 – Surface diagram to illustrate the effect of lambda & time frame on the total net expense

At lambda 0.6 and time frame 55 weeks, the customers earned 119,340 TL bonuses. The total payment of the customers is 7,971,848 TL. The model results are obtained for 9946 customers in the dataset.

We have two different approaches to use the time frame in the proposed model. One of them is the fixed time frame and the other one is the moving time frame. The details of the two approaches are given in Section 3.3.1.3. Statistical analysis is conducted to see if there is any significant difference between these two approaches and the results are given in Section 5.7.1. Since the moving time-frame approach has statistically significant difference compared to the fixed time-frame approach, in the current section, the results of the proposed model is given based on the moving time-frame approach. Moreover, statistical analyses are also conducted to see if there is significant effect of changing the time frame and the lambda values in Section 5.7.2 and Section 5.7.3 respectively.

5.4.2.1. The Comparison of the Moving Time-Frame Approach and Fixed Time-Frame Approach

The comparison of the moving and the fixed time frame approaches is done by comparing the total net expense amounts of each approach at different time-frame sizes. In Figure 14, top graph shows the total net expenses by lambda values. The time frame is set to 55 weeks. It is clear that the moving time-frame approach is always gives the smaller total net expense compared to the fixed time-frame approach.

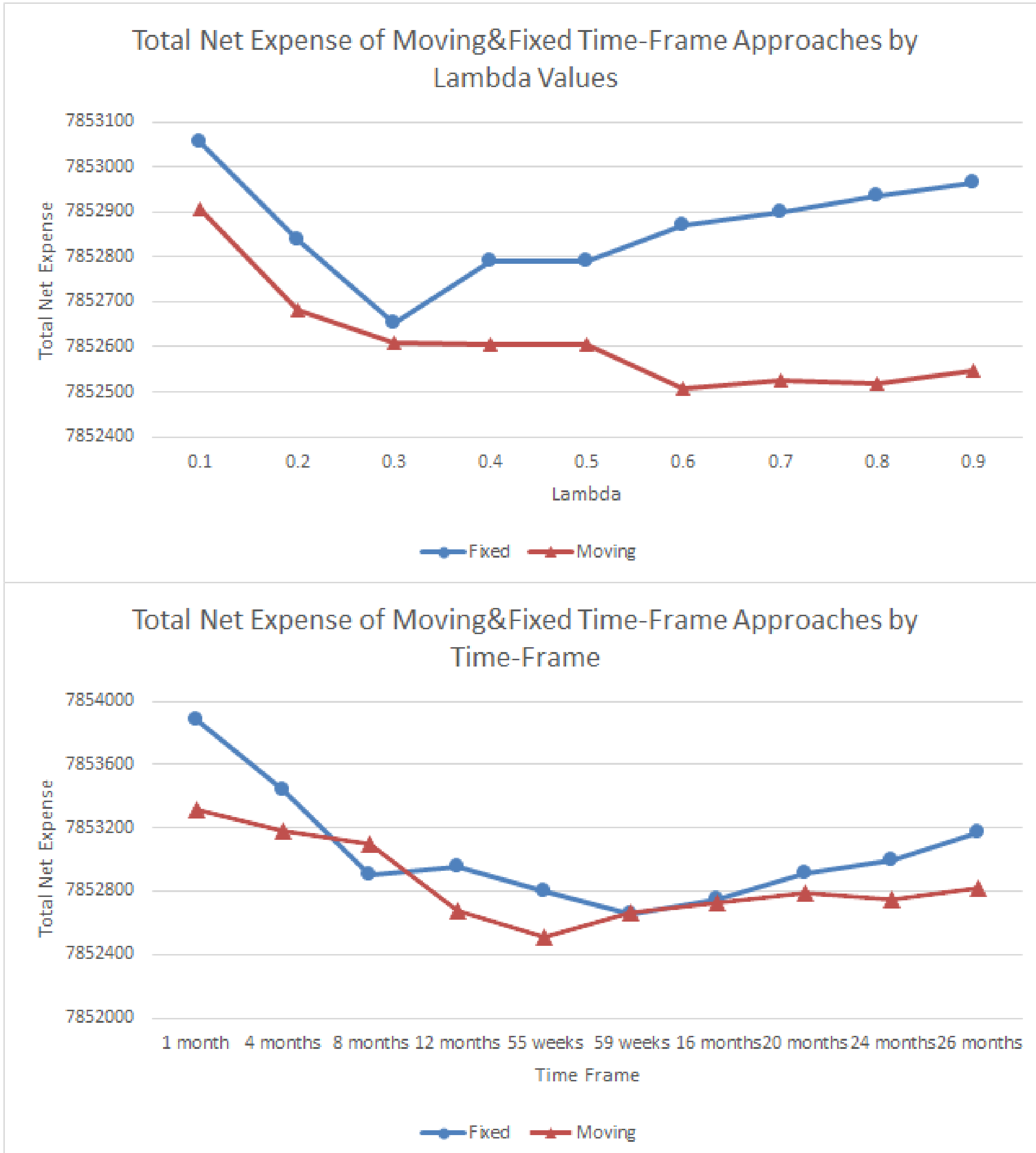


Figure 14 – Total Net Expense of moving and fixed time frame approaches by time frame and lambda values

The bottom graph in Figure 14 shows the total net expenses by time-frame size. The lambda is fixed at 0.6 for moving-time frame and 0.3 for the fixed time-frame approach. The minimum total net expense is obtained at 55 weeks by the moving time frame. For the fixed time-frame approach, the minimum amount is obtained at 59 weeks. It is clear that in most time-frame sizes the moving time-frame approach performs better. As stated earlier, the statistical analyze is also conducted to show the differences between these approaches in Section 5.7.1.

5.4.2.2. The Effect of the Time-frame (Lambda=0.6)

In this sub-section, the effect of the time frame on the model outcomes is listed. The results are given by graphs. There are three different graph-pairs. The first one is for total net expense, the second one is for total bonus gain and the third one is for total expense. The lambda value is fixed at 0.6.

In Figure 15, the change of the total net expense by time frame is shown. The total net expense is calculated by Equation 5.3. The graph at the top shows the total net expense amount obtained by the proposed model with the optimum minimum expense amount and the actual expense amount. The model outcome is closer to the optimum expense amount than actual expense amount. The graph at the bottom is a closer look to the effect of the time frame on the total net expense. It is clear that the minimum total net expense is obtained at 55 weeks.

Figure 15 – Total Net Expense by time-frame (lambda=0.6)

In Figure 16, the change of the total bonus earnings is shown. At the top graph, the model based earnings and the optimum maximum bonus earning are shown. At the bottom graph, the model results are shown alone. It is clear that the maximum gain is captured at time frame 55 weeks. After 55 weeks, the expansion of the time frame decreases total earnings.

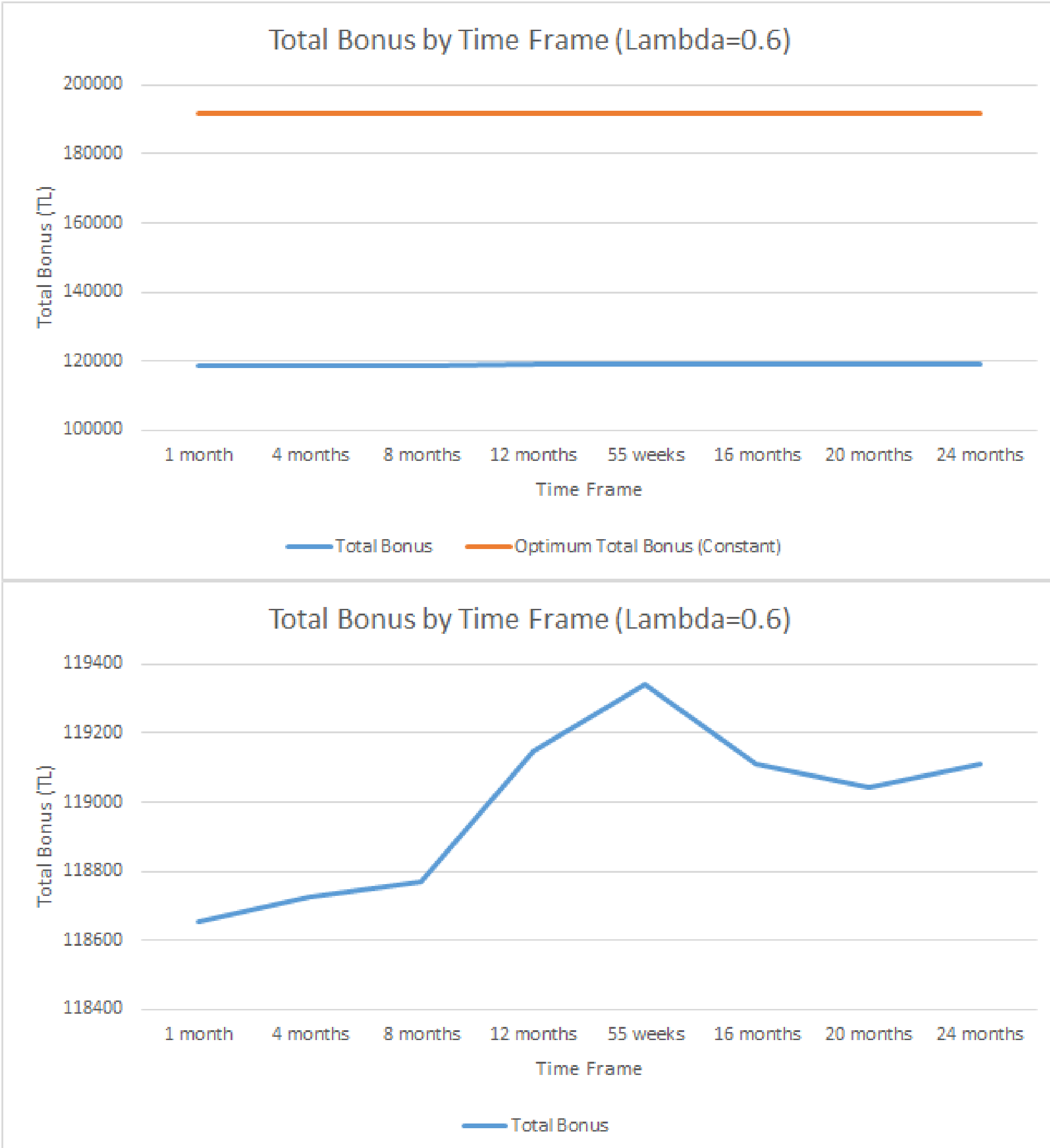


Figure 16 –Total bonus amount by time-frame (lambda=0.6)

In Figure 17 shows the change of the total expense by time frame. The total expense is total payment of all of the customers. The minimum total expense is obtained at 12 months. Intuitively, it would be expected that the minimum total net expense be also obtained at 12 months. However, it is not the case. The minimum total net expense is at 55 weeks. This shows that the model guides the customers to pay more. However, this helps them to earn more bonuses. That is why the minimum total expense is at 55 weeks but not at 12 months.

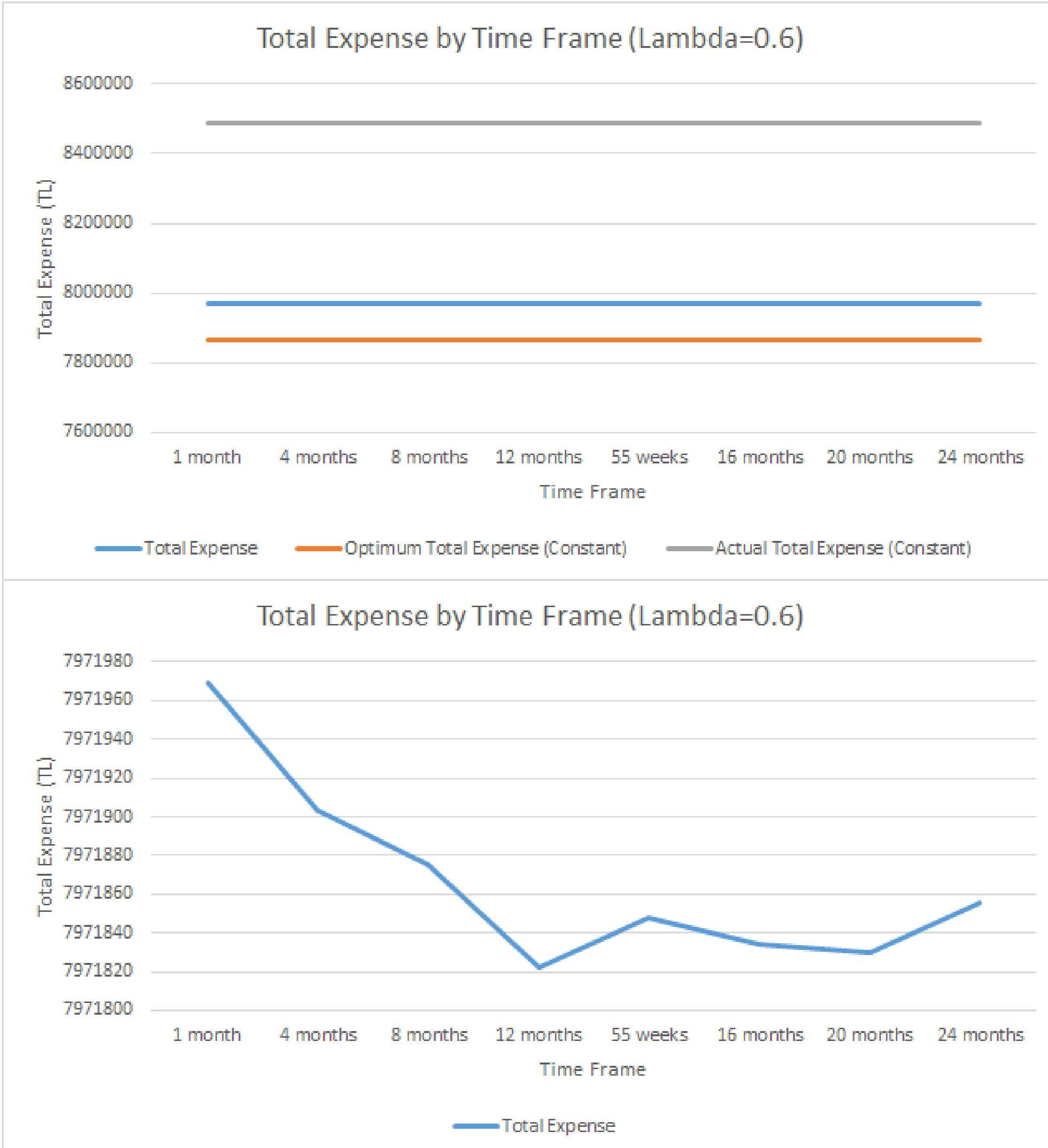


Figure 17 – Total expense by time-frame (lambda=0.6)

5.4.2.3. The Effect of the Lambda (Time-frame=55 Weeks)

In this sub-section, the effect of the lambda on the model results is listed. The results are given by graphs. There are three different graph-pairs. The first one is for total net expense, the second one is for total bonus gain and the third one is for total expense. The time frame is fixed at 55 weeks.

In Figure 18, the total net expense variations due to the lambda values are shown. The total net expense is decreased sharply from 0.01 to 0.1. Then, the rate of decrement is slowed down. At 0.6, the minimum total net expense is obtained. After 0.2, the lambda effect is weakened.

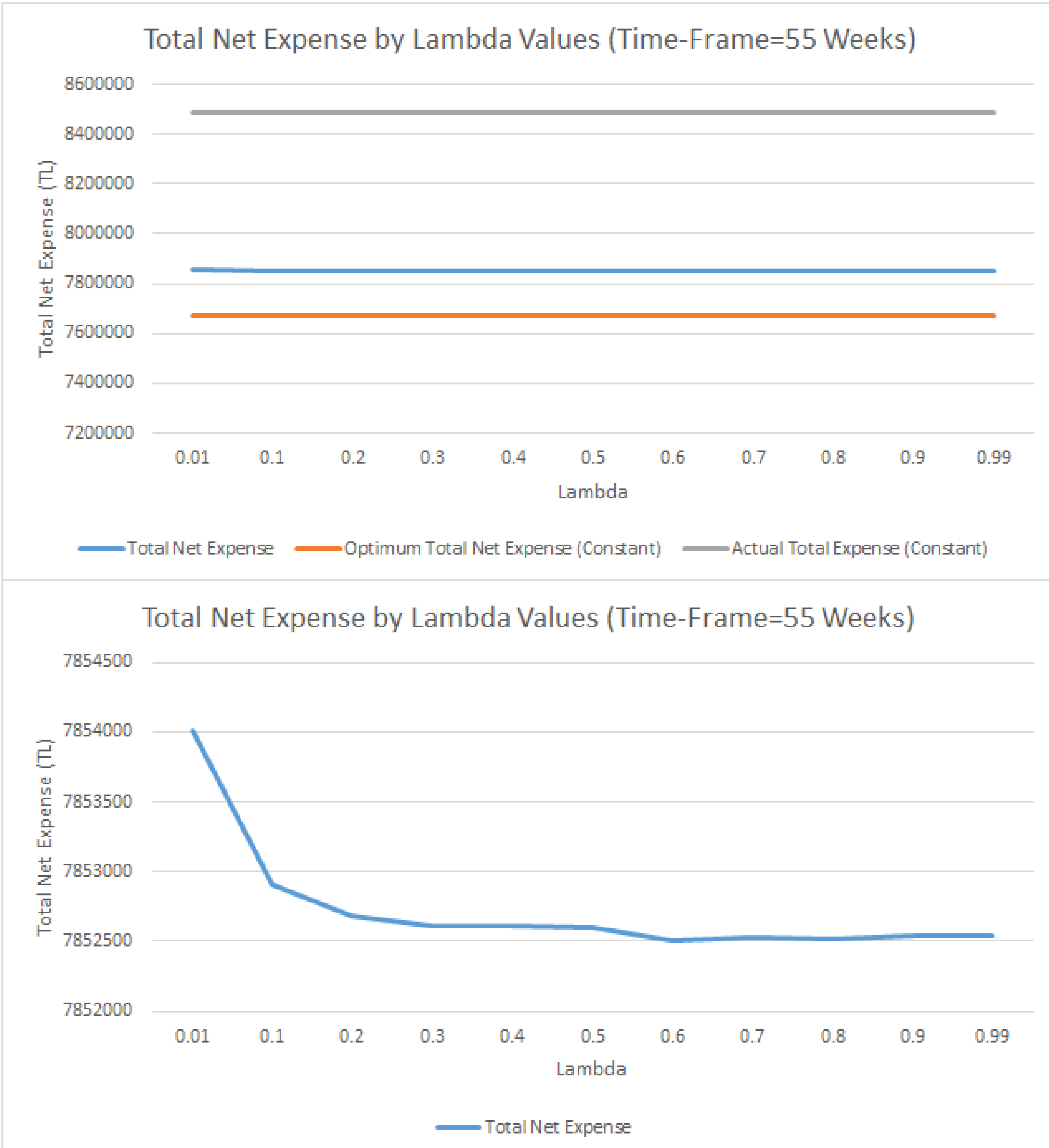


Figure 18 – Total net expense by lambda values (time-frame=55 weeks)

Figure 19 shows the effect of the lambda values on total bonus earnings. The maximum total bonus gain is gathered at lambda 0.6. However, the effect of the lambda becomes almost stable after 0.6. Increasing the value of the lambda after 0.2 seems not so effective.

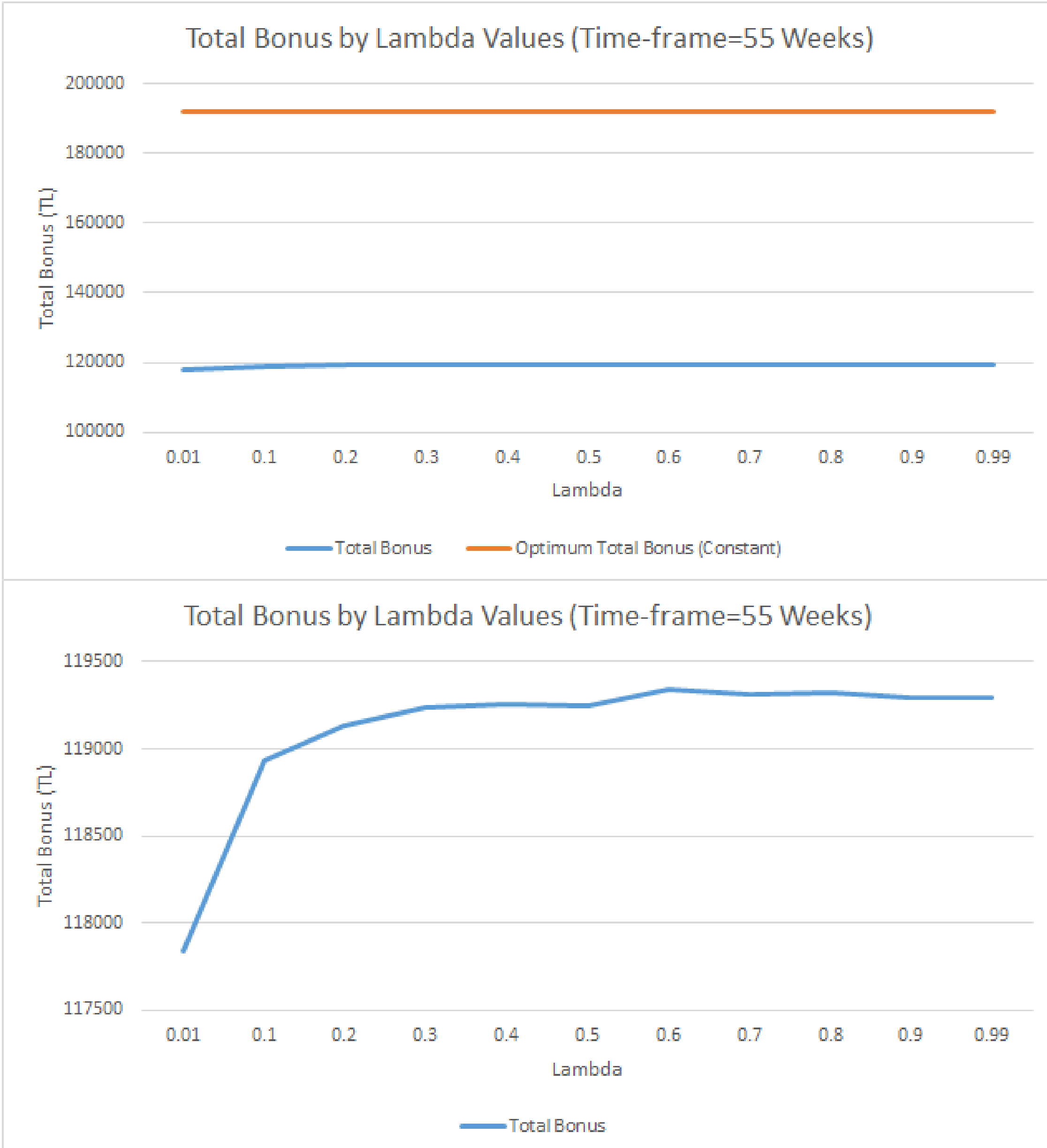


Figure 19 – Total bonus amount by lambda values (time-frame=55 weeks)

Similarly, Figure 20 highlights the variation of the total expense by the lambda values. The minimum payment amount is obtained at 0.2 but the minimum total net expense is at 0.6. This again shows that the model makes the customers to pay in order to gain more.

Figure 20 – Total expense by lambda values (time-frame=55 weeks)

The lambda value has effects on model results but increasing the lambda value from 0.2 to 0.99 seems ineffective. The statistical analyses are listed in Section 5.7.2.

5.4.3. The Effect of the Time Criterion Weight

In the previous sections, the weight of the time criterion was zero. In this section, time criterion is put into consideration.

In Figure 21, the effect of the time criterion weight is visualized. As shown in the top graph, the total time required to travel to the shopping stores is decreasing by the increase in time criterion weight. This means that the model recommends shopping stores, which are closer to the customers. However, putting more importance to the time criterion reduces the importance of price and the CCPCS criterion. Thus, shopping in closer stores makes customers to spend more which is shown in the bottom graph. This is common tradeoff between time and price.

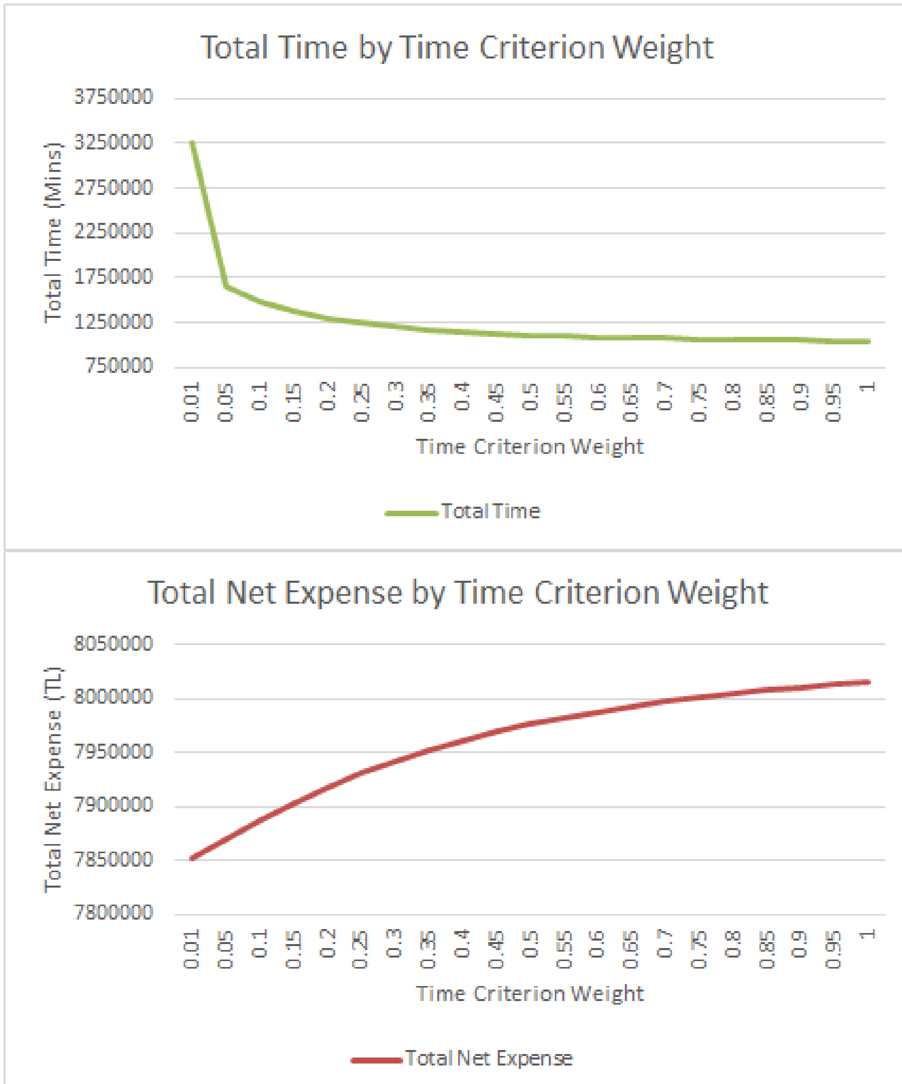


Figure 21 – Total Net Expense by time criterion weight

5.4.4. Time-frame and Lambda Based Model Results for Top 100 Customers

In this section, the top 100 customers that have most purchase count are focused. In Figure 22, the change in total net expense of top 100 customers is given. The graphs show that increasing the time-frame size decreases the total net payment amount steadily. The effect of lambda is ignorable from 0.6 to 0.9 but from 0.1 to 0.5, the effect is noticeable.

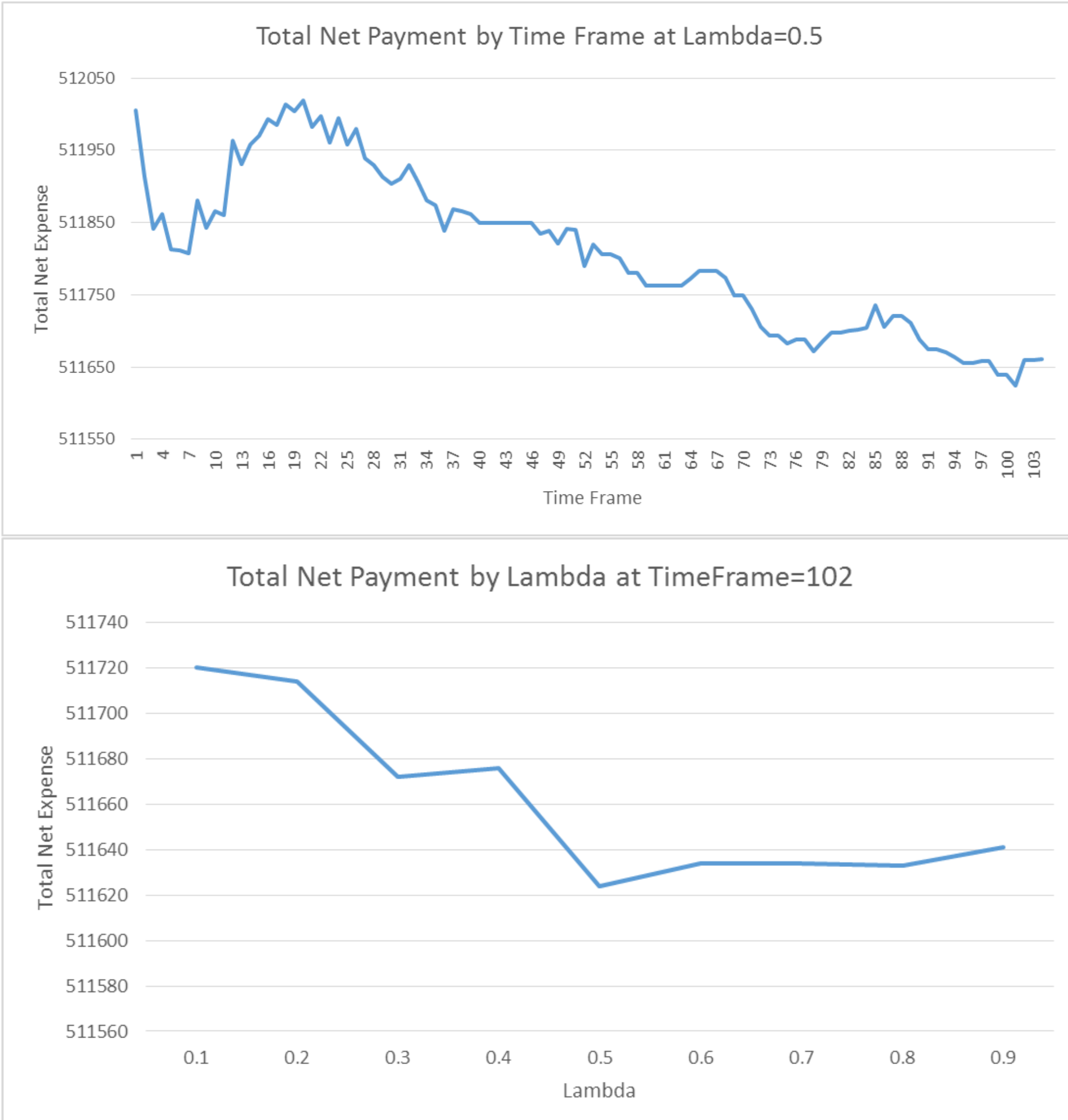


Figure 22 – Total Net Payment by Time Frame and Lambda Values of Top 100 Customers

5.5. Evaluation of the Proposed Model Results by Optimum Findings

As stated in Section 5.2, the evaluation process is based on the minimum total net expense amount. The minimum total net expense amount is compared to the optimum minimum expense amount. The purpose of this comparison is to locate the position of the proposed model with respect to the optimum findings.

The optimum findings are listed in Section 5.3 and the results obtained by the proposed model are listed in Section 5.4. The performance of the proposed model with respect to total net payment is calculated by:

$$Performance_{Net\ Expense} = \left(NetExpense_{Model}/NetExpense_{Optimum}\right) * 100 \quad (5.4)$$
$$= (7852508/7672519.54) * 100$$
$$= 102.34\ \%$$

The performance of the proposed model according to the total net payment is given above. If the proposed model were used as a shopping assistant by 9946 customers for more than 2 years, the total net payment of them would be higher by 2.34% compared to the optimum findings. This means that each customer approx. spend 18 TL more. It is important to note that this comparison is done with respect to the optimum finding. In ILP modelling, transactions are known beforehand. However, in the proposed model, the system just knows the latest transaction history within the time frame value and the currently available promotions.

The second comparison is made on the total credit card promotion bonus gain. Similarly, the performance of the proposed model is calculated by:

$$Performance_{Bonus} = \left(Bonus_{Model}/Bonus_{Optimum}\right) * 100 \quad (5.5)$$
$$= (119339.8/191776) * 100$$
$$= 62.22\ \%$$

The proposed model helps the customers to earn 119,339.8 TL credit card promotion bonuses, which are 62.22% of the optimum earned bonus. This outcome is also promising since the proposed model is compared to the optimum results. In optimum results, all credit card promotions are predefined, so there is certainty. However, in the proposed model case, the model tries to find the best available shopping alternative. No information about the future credit card promotion is present. To calculate the completion score of a credit card promotion (CCPCS), the current state of the customer in that credit card promotion is taken into account. For example, think of a credit card promotion with requirement of five transactions to complete it. If the customer has already made three transactions with that promotion, it is highly probable that the shopping alternative with that promotion would be ranked high by the model. However, it may not be completed by the customer in upcoming transactions. This example is one of the natural hardness of the decision problem that affects the performance of the model.

To conclude, the obtained results suggest that the proposed model helps customers to reduce their grocery market expenditure. To reduce expenditure, the model uses grocery store promotions and credit card promotions. Furthermore, it also considers prices at different stores to rank possible shopping alternatives. The ranking process is done by using customer preferences.

5.6. Further Evaluation of the Results

In addition to the evaluation of the results according to the optimum results in the previous section, the further evaluations of the results are given in this section.

As described in Section 5.1, the number of customers in the generated dataset is 9946. However, when the optimum results are also explored for each customer, it is realized that

4521 customer do not gain any bonus from credit card promotions. Hence, only 5425 customers of the all customers have credit card promotion gain, which is greater than zero TL. In this section, the performance of the proposed model is evaluated for the customers who have credit card promotion gain. The performance of the model is calculated by the Equation 5.5.

The model results are explored for each customer. It is found out that the proposed model helps 2142 customers to gain the optimum bonus gain from credit card promotions. Thus, the performance of the proposed model is 100% for those customers. Thus, the proposed model performs at maximum for 39.48% of the rest of the customers. Moreover, the performance of the model is between 50% and 99% for 1406, which correspond to 26% of the customers. The proposed model performs between 1% and 49% for 597 customers, which corresponds to 11% of the customers. Unfortunately, the performance of the model is 0% for 1280 customers, which corresponds to 23% of the customers.

The performance of the model is at the maximum or at the minimum for 62.48% of the customers. It would be expected that the model cover more customers in the middle performance levels. However, it is not the case because of the structure of the credit card promotions. A customer gains the total bonus amount or the customer does not gain any bonus. Thus, it is plausible that the model performance is grouped at opposite poles, 100% and 0%.

The top 100 customers, who have the maximum number of purchase, are selected from 2142 customers who gained the optimum bonus. The purchase statistics are analyzed for top-100 customers. The average number of weekly grocery shopping is 1.05 and the average weekly purchase amount is 30 TL.

5.7. Statistical Analyses

In this section, the explanatory statistical analyses results are given. First, the time-frame approaches are statistically analyzed. Second, the effect of the time frame is analyzed. Third, the effect of the lambda values on the model results is analyzed.

5.7.1. Statistical Analyses of the Two Time-Frame Approaches

The aim of this analysis is to compare the mean of net expense amounts belonging two different approaches, fixed time frame and moving time frame. By doing so, we will be able to see whether two methods cause consumers to pay different amount in total in a statistically significant manner or not. In order to decide which statistical test to apply, the distribution of the two different dataset should be examined. If they are normally distributed, a parametric test can be applied. Otherwise, a non-parametric test should be preferred. Beforehand, some descriptive statistics are given at Appendix A, which are also used in statistical tests further. First, the histogram and one of frequency plots, P-P or Q-Q plot, can be used to examine the distribution of the data visually. Hence, those graphs for the two datasets, one for fixed and one for moving time frame, are given at Appendix B. It is obvious that none of the datasets has a normal distribution when their histograms are observed. Both look skewed to the left and both have grouped data samples. Moreover, the P-P plots approve the non-normality of the datasets because the curves formed by dots do not reside on the diagonal lines. It means that, observed cumulative probability of the samples does not comply with the expected cumulative probability, which belongs to a normal distribution.

Another way of checking non-normality is to inspect skewness and kurtosis values of the datasets. According to descriptive statistics at Appendix A, the two datasets have skewness and kurtosis values, which are not equal to zero, as it should be for normally distributed data. Hence, we can say that they do not have normal distribution. Furthermore, standardized skewness and kurtosis values should be compared to standard normal distribution to see whether the difference of those values is statistically significant or not.

$$Z_{\text{skewness}} = \frac{Skewness}{Standard\ error\ of\ skewness} \tag{5.6}$$

$$Z_{\text{kurtosis}} = \frac{Kurtosis}{Standard\ error\ of\ kurtosis} \tag{5.7}$$

For small samples including less than 200 data points and for $p<0.05$, absolute values greater than 1.96 are accepted to have significant skewness and kurtosis. [107]. Regarding this, fixed time-frame dataset has significant skewness and kurtosis values, so is not normally distributed ($Z_{\text{skewness}}=8.57$, $Z_{\text{skewness}}=8.79$). Moving time-frame dataset is also non-normal because of having significant skewness and kurtosis values ($Z_{\text{skewness}}=7.70$, $Z_{\text{skewness}}=5.45$).

After finding out that the datasets are not normally distributed, non-parametric test can be applied to compare the means of them. Wilcoxon signed-ranked test is the proper test because the same set of transactions are used to calculate net expense values, so the two dataset (one for fixed and the other for moving time frame) are not independent. According to the test result, total net expenses obtained by using fixed time frame (Mdn=7,853,404 TL) are significantly higher than the ones obtained by using moving time frame (Mdn=7,853,009 TL), $T=671.50$, $p<0.05$, $r = -0.41$. Here, the medians of the two datasets are compared because the data are not normally distributed. T represents the test statistic calculated for Wilcoxon signed-ranked test. Significance value is less than 0.05 that is denoted by p. The effect size r is 0.41 that represents the effect of the method used on total net expenses and expresses a medium to large effect [107]. The statistical analyze results state that the moving time-frame approach is more effective one.

5.7.2. Statistical Analyses of Lambda

In order to examine the effect of lambda values on the total net expense values, the total net expense values are grouped according to corresponding lambda values. In calculations, the exact total net expense values are used. However, to make the total net expense values in Table 14 to be more readable, the minimum total net expense amount, which is 7,852,508, is subtracted from each cell.

Table 14 – Total Net Expense Values Grouped by Lambda Values

Time frame (in weeks)	Total Net Expense Values (7,852,508 is subtracted)								
	λ=0.1	λ=0.2	λ=0.3	λ=0.4	λ=0.5	λ=0.6	λ=0.7	λ=0.8	λ=0.9
1	3337	4183	4530	4818	4832	4898	5047	4957	4703
2	1425	1853	2024	2323	2490	2439	2514	2743	2770
3	723	872	1026	1057	1183	1327	1451	1435	1395
4	757	840	650	535	464	503	448	606	816
5	720	629	471	283	178	273	288	370	316
6	653	476	457	257	278	308	282	292	386
7	499	609	492	507	491	337	182	186	177
8	467	595	550	475	493	479	333	360	284
9	515	560	576	273	257	181	270	255	271
10	445	544	402	179	191	217	176	233	196

Each of these nine groups was inspected to see whether they are normally distributed or not. As it is explained before, the normality of data can be checked by referring to histograms, P-P or Q-Q plots, and by comparing standardized skewness and kurtosis values to the ones belonging to normal distribution. The graphs at Appendix C show that none of the expense groups has normal distribution because the shapes of the histograms are far different from the normal curve. In addition, dotted curves are not close to the diagonal lines on P-P plots meaning that observed cumulative probability of the data is not the same with the expected cumulative probability of normal distribution.

Moreover, all of the groups have non-zero skewness and kurtosis values, a case that should not be observed for normally distributed data. The standard values of those skewness and kurtosis values were calculated as shown in Table 15. All of them have greater absolute values than 1.96, so we can say that they have significantly different skewness and kurtosis values compared to normal distribution. As a result, a nonparametric statistical test should be chosen for understanding the effect of lambda values on the total net expense values. Since the same transaction-data are used for all lambda values (expense groups are related, not independent) and there are more than two conditions for lambda values, i.e. 9 different lambda values, Friedman's ANOVA test was chosen [103]. According to test results, selecting different lambda values did not change the total net expense amounts significantly, $\lambda^2(8) = 8.347, p > 0.05$.

The test results state that the change in lambda values from 0.1 to 0.9 does not have significant effect on the total net expense obtained by the proposed model. However, this does not mean that the lambda is not required totally. It is a decay rate of the transaction history. It is required to be non-zero value for EWMA calculations. However, for the selected subset data, there is no effect of the value change.

Table 15 – Skewness and Kurtosis Information about Net Expense Groups according to Lambda Values

λ	Skewness	S.E.skewness*	Kurtosis	S.E.kurtosis*	Zskewness	Zkurtosis
0.10	2.64	0.69	7.28	1.33	3.85	5.46
0.20	2.58	0.69	6.82	1.33	3.75	5.11
0.30	2.49	0.69	6.35	1.33	3.63	4.76
0.40	2.29	0.69	5.25	1.33	3.34	3.94
0.50	2.17	0.69	4.59	1.33	3.16	3.44
0.60	2.18	0.69	4.68	1.33	3.17	3.50
0.70	2.14	0.69	4.46	1.33	3.11	3.34
0.80	2.02	0.69	3.79	1.33	2.95	2.84
0.90	1.92	0.69	3.27	1.33	2.79	2.45
*S.E.=Standard error						

We conducted another statistical analyze to check if there is a significant difference in lambda values for top 100 customers who have highest purchase count. Friedman's ANOVA test was chosen [103]. According to test results, selecting different lambda values changes the total net expense amounts significantly, $\lambda^2(7) = 13.114, p < 0.05$.

5.7.3. Statistical Analyses of the Time-Frame

A similar procedure to the one described above was followed to inspect the effect of the time frame on the total net expense values. The total net expense values are grouped according to corresponding time frame values. In calculations, the exact total net expense values are used. However, to make the total net expense values in Table 16 to be more readable, the minimum total net expense amount, which is 7,852,508, is subtracted from each cell.

Table 16 – Total Net Expense Values Grouped by Time Frame

	Total Net Expense Values (7,852,508 is subtracted)									
λ	tf=1	tf=2	tf=3	tf=4	tf=5	tf=6	tf=7	tf=8	tf=9	tf=10
0.1	3337	1425	723	757	720	653	499	467	515	445
0.2	4183	1853	872	840	629	476	609	595	560	544
0.3	4530	2024	1026	650	471	457	492	550	576	402
0.4	4818	2323	1057	535	283	257	507	475	273	179
0.5	4832	2490	1183	464	178	278	491	493	257	191
0.6	4898	2439	1327	503	273	308	337	479	181	217
0.7	5047	2514	1451	448	288	282	182	333	270	176
0.8	4957	2743	1435	606	370	292	186	360	255	233
0.9	4703	2770	1395	816	316	386	177	284	271	196
tf=time-frame in weeks										

Ten groups of time-frame values were inspected to see if they are normally distributed or not. As explained earlier, histograms, P-P or Q-Q plots and comparison of standardized skewness and kurtosis values can be used to check the normality of the data. The graphs at Appendix D show that none of the expense groups has normal distribution because the shapes of the histograms are far different from the normal curve. In addition, dotted curves are not close to the diagonal lines on P-P plots meaning that observed cumulative probability of the data is not same with the expected cumulative probability of normal distribution.

Moreover, all of the groups have non-zero skewness and kurtosis values, a case that should not be observed for normally distributed data. The standard values of those skewness and kurtosis values were calculated as shown in Table 17. Time Frame #1 has greater absolute value than 1.96, so we can say that it has significantly different skewness and kurtosis values compared to normal distribution. As a result, a nonparametric statistical test should be chosen for understanding the effect of time frame on the total net expense values. Since the same transaction-data are used for all lambda values (expense groups are related, not independent) and there are more than two conditions for lambda values, i.e. 10 different time frame groups, Friedman's ANOVA test was chosen [103]. According to test results, time frame values change the total net expense amounts significantly, $\lambda^2(9) = 68.491, p < 0.05$.

Table 17 – Skewness and Kurtosis Information of Net Expense Groups according to time frame

Time Frame	Skewness	S.E.skewness*	Kurtosis	S.E.kurtosis*	Zskewness	Zkurtosis
1	-1.91	0.72	3.73	1.4	-2.66	2.67
2	-0.95	0.72	0.33	1.4	-1.32	0.23
3	-0.48	0.72	-1.06	1.4	-0.67	-0.76
4	0.34	0.72	-1.58	1.4	0.48	-1.13
5	0.96	0.72	-0.13	1.4	1.34	-0.09
6	1.3	0.72	1.25	1.4	1.81	0.89
7	-0.32	0.72	-1.79	1.4	-0.45	-1.28
8	-0.35	0.72	-0.82	1.4	-0.49	-0.58
9	0.76	0.72	-1.48	1.4	1.05	-1.06
10	1.07	0.72	-0.47	1.4	1.49	-0.34
*S.E.=Standard error						

The result of the Friedman's ANOVA test is significant so we need to make further test, which is called post hoc test. Since non-parametric test was applied, the post hoc test is also non-parametric. The notion behind making post hoc test is to find actually, which groups of data have significant differences. It is not enough to say that 10 groups of data have significant differences. To do the post hoc test, the differences between mean ranks of the groups are compared to a value called critical difference [103] and calculated by:

$$critical\ difference = Z_{\alpha/k(k-1)}\sqrt{\frac{k(k+1)}{6N}} \quad (5.8)$$

Where N is the sample size which is 9 in this case (9 different lambda values), k is the number of conditions which is 10 (number of different time-frame groups) and α is the 0.05. Then:

$$\alpha/k(k-1) = .05/10(9) \cong 0.00056 \quad (5.9)$$

The result above is used to find the corresponding Z value that is equals to 3.25. Therefore, the critical difference is:

$$critical\ difference = 3.25\sqrt{\frac{10(11)}{54}} \cong 4.64 \quad (5.10)$$

So, the difference between the mean ranks of two different groups is required to be equal to or greater than 4.64 [103]. The mean ranks of time-frame groups are given in Table 18. For example, the mean rank difference between Time-frame-1 and Time-frame-10 is 8.44. The difference is greater than 4.64 so there is a significant difference between time frames of 1-week and of 10-weeks. Time-frame-5 to Time-frame-10 have significantly different than Time-frame-1. However, there is no significant difference between Time-frame-1 and Time-frame-2. The post hoc test results show that increasing the time-frame range from 1 week to 2 weeks is not important, but increasing it to 5 weeks results in a significant difference. To conclude, the time-frame value is statistically important value, which affects the total net expense.

Table 18 – Mean ranks of 10 time-frame data groups.

Mean Ranks

	Mean Rank
Time-frame-1	10.00
Time-frame-2	9.00
Time-frame-3	7.89
Time-frame-4	6.89
Time-frame-5	4.33
Time-frame-6	3.56
Time-frame-7	3.67
Time-frame-8	4.89
Time-frame-9	3.22
Time-frame-10	1.56

CHAPTER 6

DISCUSSION AND CONCLUSION

This chapter concludes the study by summarizing the motivation behind conducting such research and the key contributions of this study. The results and the performance of the proposed solution are mentioned and discussed. In addition, the limitations in the study are indicated. The feasible further research areas are proposed which are not in the scope of the current research study.

6.1. Discussion and Conclusion

Consumers have to make plenty of decisions before, during or after the purchase action. All of these decisions are called the consumer buying decision making process. Consumers define their needs, consider options to fulfill their needs, make the purchase and do a review about the purchased items. The process is not a standalone action. Buying decisions are influenced by previous buying experiences and in return influences future decisions. Thus, purchase decisions are continuous actions and consumers do purchase planning so frequently. This frequency enables them to develop heuristics in the shopping especially in grocery shopping. To select individual product brand, a customer may use heuristics such as buying the cheapest brand or buying the best quality product. However, the developed heuristics are not enough to decrease the cognitive efforts required in the purchase planning.

The grocery shopping statistics show that grocery shoppers spend approx. 41 minutes in stores. Low-income shoppers spend even more time. This indicates that pricing concerns play an important role and make it hard to select what to buy. This is just in store time spending values. There is also the pre-purchase planning process. On average, consumers complete their grocery needs by visiting more than one store. Before visiting a store, they need to select the store first. To select the store, they make product price comparisons for example. The price comparison may include promotions, sales, price-offs, coupons etc. Moreover, payment options put additional burden to consumers. The credit card promotions may affect their store selection at the pre-purchase planning or they need to make that decision at the store. Thus, the grocery shopping becomes more complicated.

Promotion based shopping, and promotion-based marketing are strengthened after the global economic crisis in 2007. This shows that promotion centric planning by consumers would increase in the future. Consumers need aiding in the promotion-based purchase decision making process. This is where the current research is focused on. The proposed solution is designed for the customers at the pre-purchase planning phase.

The proposed model helps customers to select a shopping option based on their preferences. The shopping alternative is the combination of the grocery store, the grocery store promotions, and the credit card promotions if any. The model does not provide the 'best' alternative, but a ranked list of alternatives. It uses the outranking method to rank those alternatives. It aids customers to compare different stores according to the price and the relative distance. The model also considers the complexity of the completing the credit card promotion while ranking these alternatives. The ranking process highly depends on the customer preferences such as the criteria weights and the threshold values, which feed the outranking method. The model requires a predefined shopping list from the customer and ranks the alternatives based on this shopping list. The proposed solution is a purchase decision aid that uses an MCDM method. It is not restricted to a single store and it is not designed for using within the store. It helps to select the shopping store based on the currently available product prices and the promotions before even starting the purchase process. Thus, the proposed model addresses the goal of aiding consumers in purchase decisions.

Customer purchasing capacity is estimated by using the Exponentially Weighted Moving Average (EWMA). The purchasing capacity is defined as the daily average amount of purchase and the average count of daily store visits. The purchase history is used to estimate the purchasing capacity. Only the purchase prices are used. No product-based history is needed by the proposed model.

The model considers credit cards and their intent of use. The model also considers credit card promotions if the customer has that credit card. Moreover, there are different kinds of credit card reward programs. For example, there are frequent flyer reward programs. Frequent flyer credit card promotions help the customers to collect bonuses or 'miles' to buy cheap or free flight tickets. The customers may select credit card type based on their intention. If they want to travel with cheap flights, they would use credit cards with flyer reward programs. A customer who has a car may decide to use credit cards that possess gas reward programs. The model adjusts its ranking process according to the customer profiles. The shopping alternatives that match the customer intention ranked higher.

Another benefit of the proposed solution is the simplification of following the credit card promotions with the help of the workflow engine. The consumers would be aware of both grocery store promotions and credit card promotions effortlessly by using such a system. Moreover, since the model helps the customers to find where to buy by using which credit card promotion, they do not deal with rules and restrictions of the promotions. It provides guidance to pursue promotions. In addition, the conceptual model is location-aware. The customer location is used to determine the distance to the stores.

The proposed solution is implemented and a mobile application is developed as a prototype. The prototype is another contribution of the study. The PROMETHEE II method is selected as the outranking method and YAWL is used as the workflow engine. The application is used in the model evaluation process. The model results are collected over the implemented system. The problem of purchase alternative selection is defined as an ILP problem. The optimum results are compared to the outcomes of the model. The model helps customers gain 62.22% of credit card promotion bonuses defined in the test dataset compared to the optimum results. The model makes customers pay less for the same set of products by combining promotions effortlessly. Thus, it aids consumers in purchase decision process successfully. Only 2.34% net expense increase is obtained after the use of the system. The statistical analyses reveal that the time-frame value is statistically significant, $\lambda^2(9) = 68.491, p < 0.05$ whereas the change in lambda values is insignificant.

6.2. Limitations and Further Research

The research study does not provide any product price finding mechanism. It is assumed that the product prices are already available and the model uses that price information through its related module. It is possible to integrate price-sharing systems like MobiShop [108] and LiveCompare [109]. In addition, the conceptual design can be served as an online shopping website to aid consumers. Moreover, the model requires a pre-defined shopping list as an input. The determination of the shopping list is out of the current research scope.

The dataset used in the study is taken from a local store. In the study, other store prices are generated randomly. The model would be evaluated by obtaining price information at different stores without random generation. Moreover, the model can be evaluated with longer historical data. The purchase data period is limited to two years. Another limitation of the study is the declaration of the grocery store promotions. The store promotions are randomly generated. The number of promotions at each store and the availability period of the promotions are known. However, the exact details of the promotions are unknown such as the products on sale, the discount amount etc. The exact promotional details would be gathered and evaluations could be reprocessed. In addition, in the study, only four main credit card brands are used. The number of the credit card brands can be increased in the further studies.

Increase in promotional awareness by such a system would require further research that recommends shopping list changes according to available grocery stores and credit card promotions. This way the customers can earn more bonuses and reduce their expenses while buying more products.

The model is explained over grocery shopping. However, the conceptual design is not restricted to grocery shopping. Grocery shopping is selected because the promotions are mainly used in stores and in literature, promotion-based studies are conducted on grocery purchase data. The conceptual design could be applied to other sectors such as car fuel consumption. Credit card promotions are defined for fuel transactions as well and car owners have plenty of options to select which gas station to use with which credit card and which promotion.

PROMETHEE II is selected as the outranking method in the study. Besides the justification of the selection, other outranking methods such as ELECTRE could also be used in the further studies and the results would be compared. Moreover, in PROMETHEE II, there is no guideline for the selection of preference function. Thus, the preference function used in the study could be different. The change in the results can be observed.

The customer preferences are not collected from the customers. The criteria weights and threshold values can be obtained from the customers via surveys and the customers can try the prototype for their purchase decisions. The general satisfaction level of the customers can be obtained again via surveys.

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APPENDICES

Appendix A: Descriptive Statistics of the Fixed Time-Frame Dataset and the Moving Time Frame Dataset

Table 19 – Descriptive statistics of the two datasets:
Fixed time-frame (Type A) and moving time-frame (Type B)

Time Frame Type / Statistic	Type A	Type B
N (no missing value)	90	90
Mean	7853889.98	7853598.53
Median	7853404.00	7853009.00
Mode	7853070	7852765
Standard deviation	1066.37	1334.854
Variance	1137140.38	1781836.274
Skewness	2.176	1.956
Std. error of skewness	0.254	0.254
Kurtosis	4.419	2.739
Std. error of kurtosis	0.503	0.503
Range	5055	4871
Minimum	7853057.00	7852684.00
Maximum	7858112.00	7857555.00
25 Percentile	7853281.00	7852795.00
50 Percentile	7853404.00	7853009.00
75 Percentile	7854069.00	7853727.00

Appendix B: Histogram and P-P Plot Graphs of Fixed Time-Frame Dataset and Moving Time-Frame Dataset

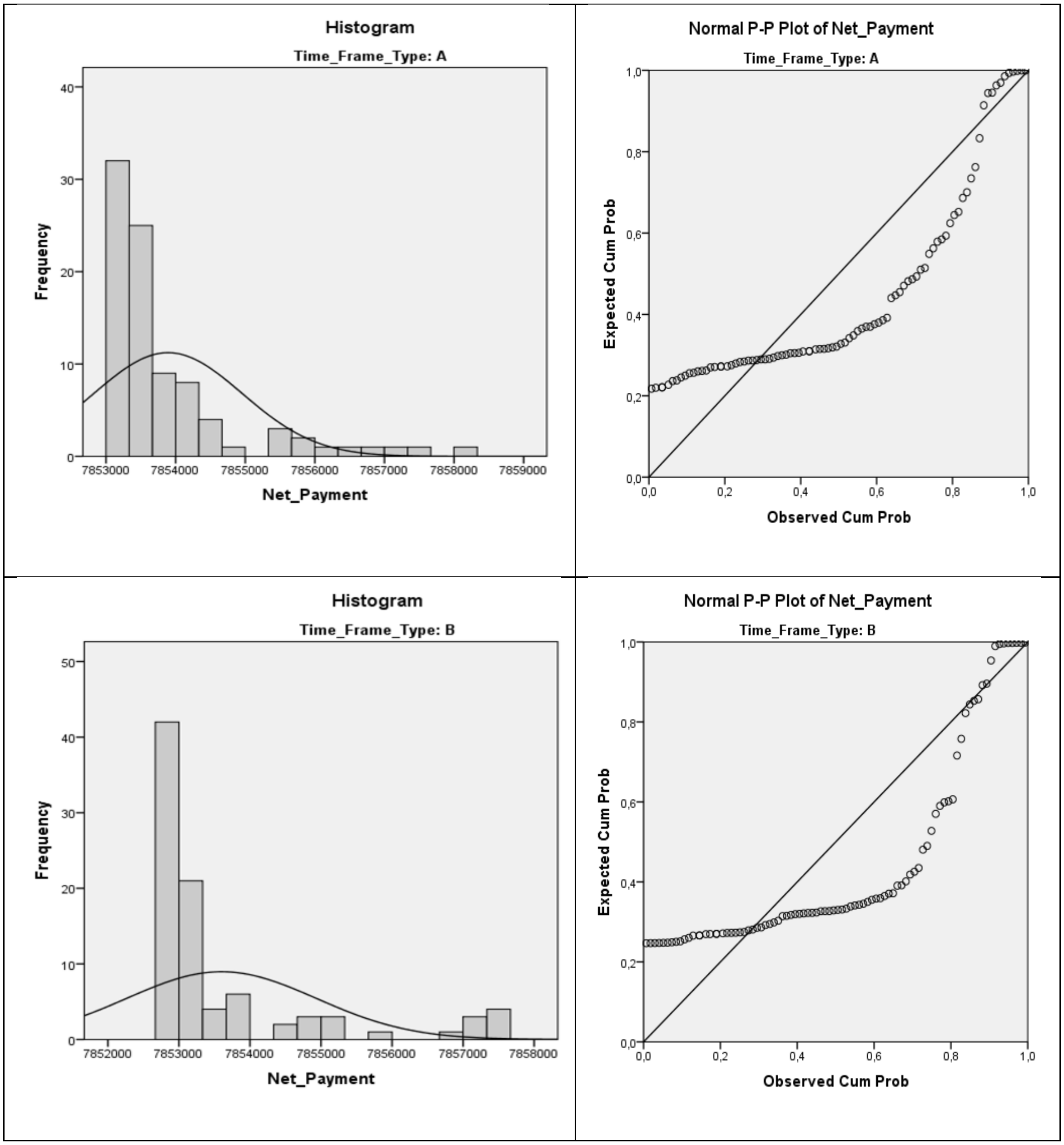
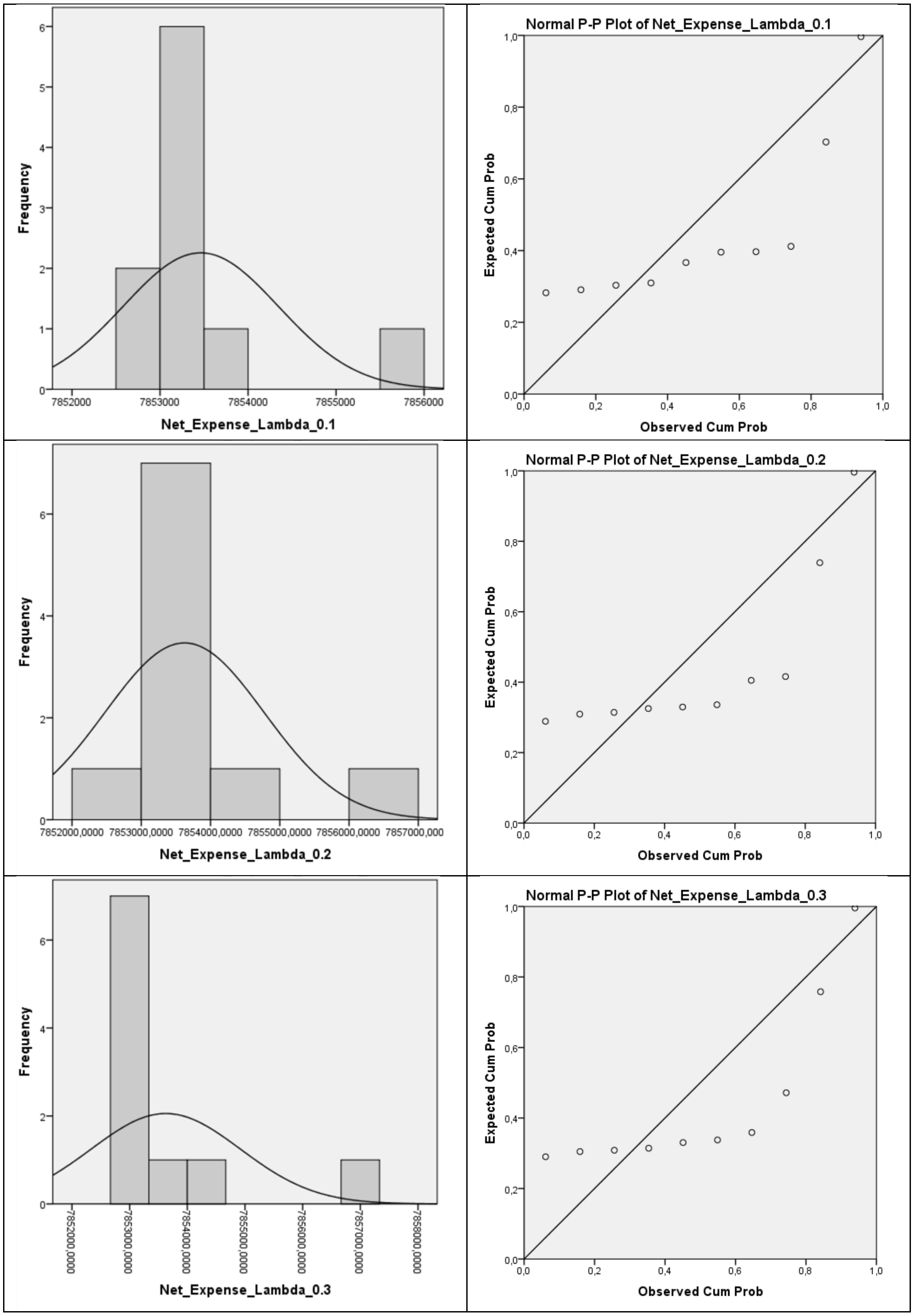
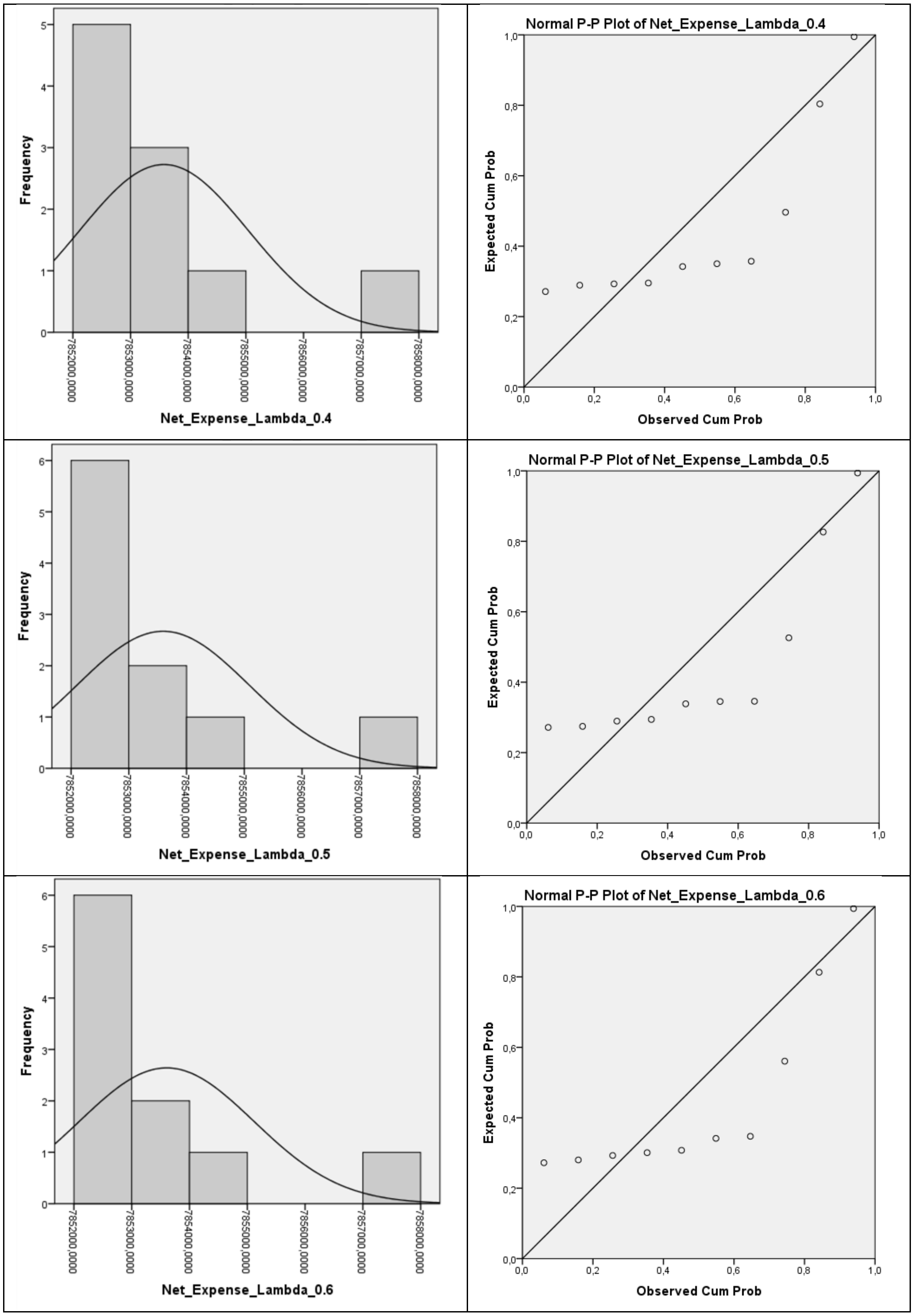


Figure 23 – Histogram and P-P Plot graphs of fixed time-frame dataset (Type A) and moving time-frame dataset (Type B)

Appendix C: Histogram and P-P Plot Graphs of Expense Groups of Different Lambda Values




Frequency
Net_Expense_Lambda_0.4
Normal P-P Plot of Net_Expense_Lambda_0.4
Expected Cum Prob
Observed Cum Prob
Frequency
Net_Expense_Lambda_0.5
Normal P-P Plot of Net_Expense_Lambda_0.5
Expected Cum Prob
Observed Cum Prob
Frequency
Net_Expense_Lambda_0.6
Normal P-P Plot of Net_Expense_Lambda_0.6
Expected Cum Prob
Observed Cum Prob

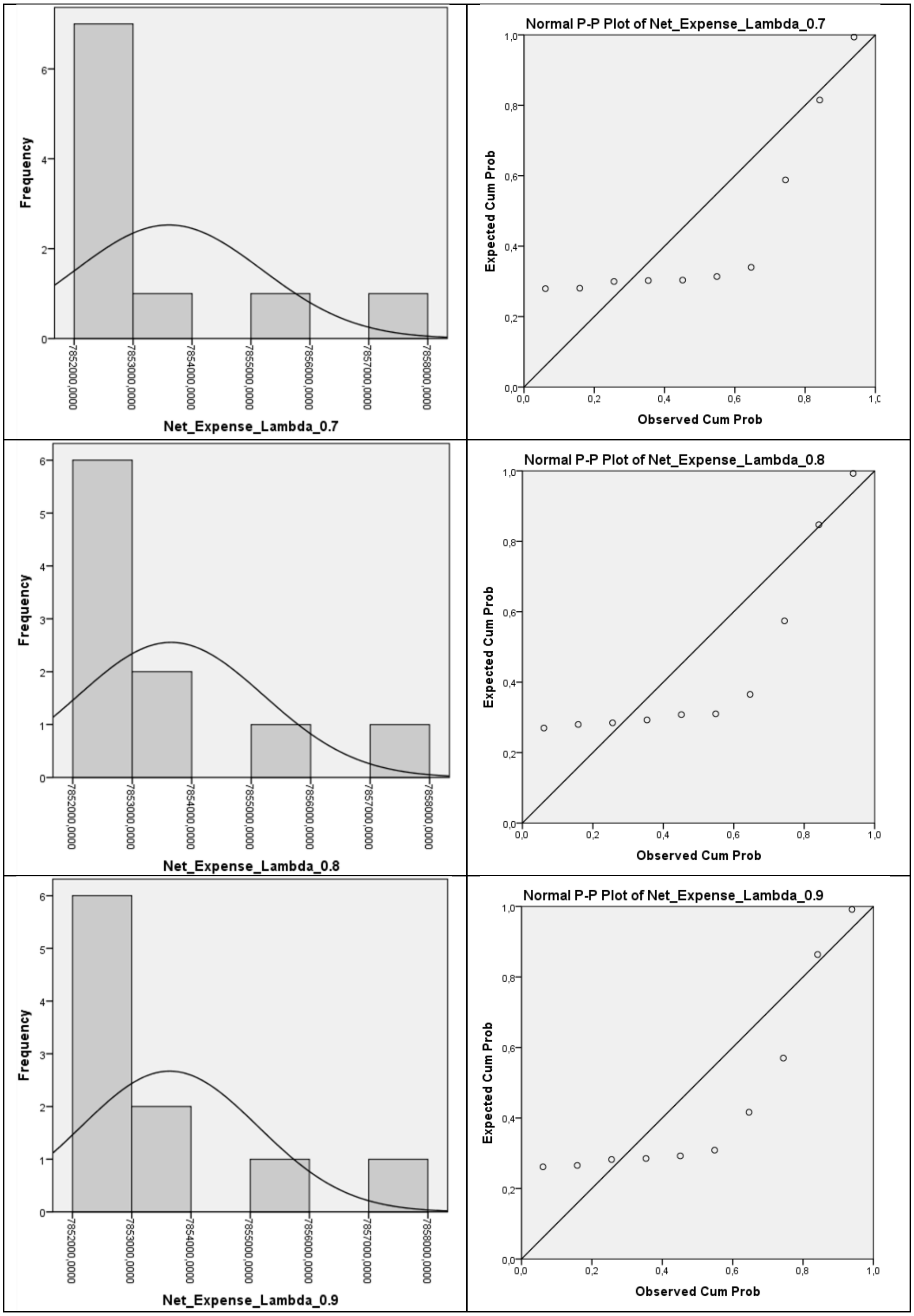
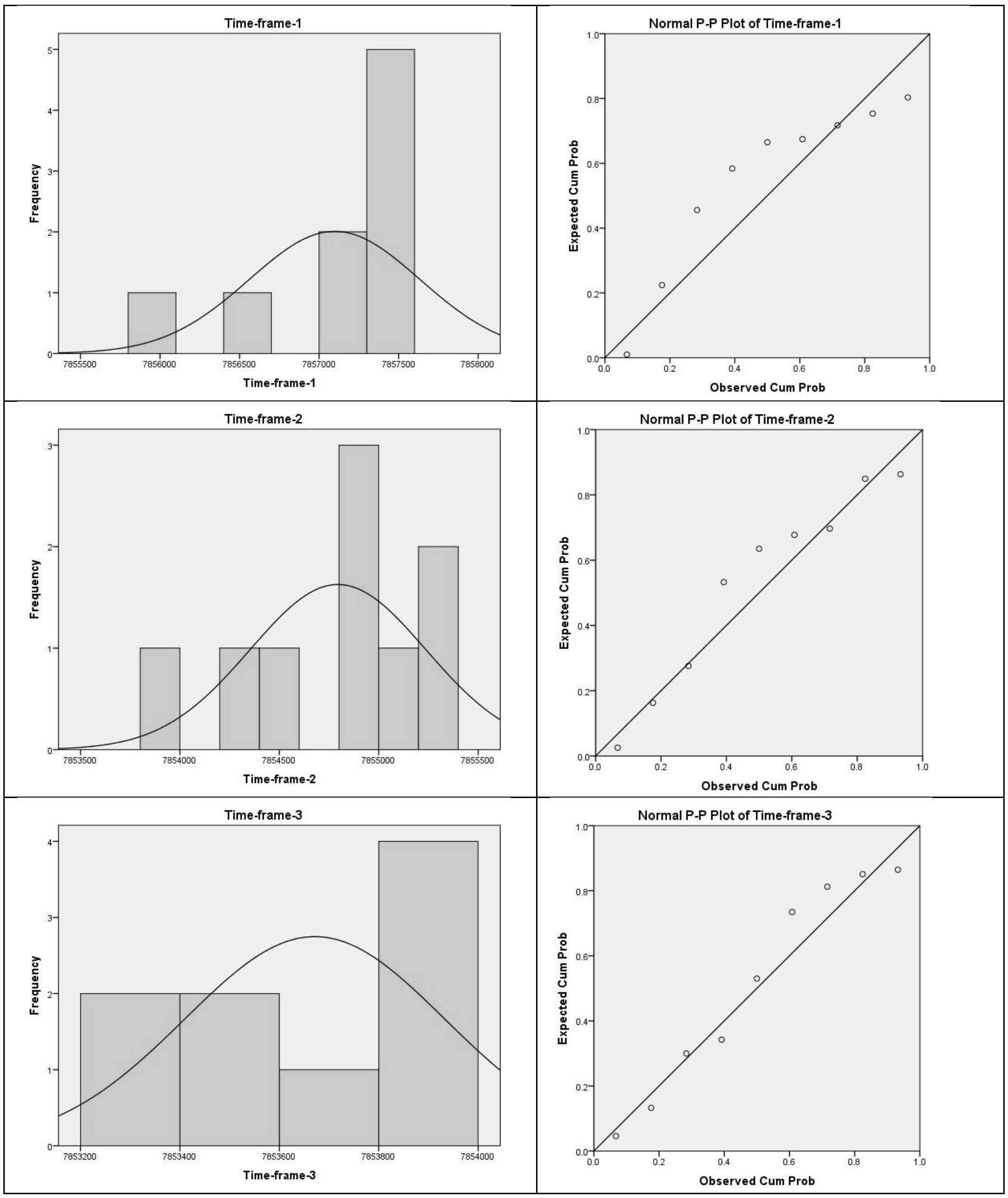
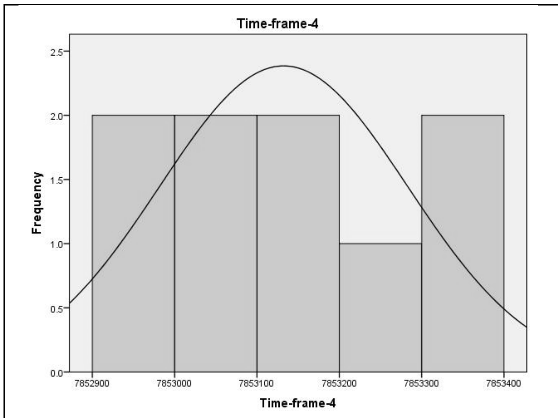
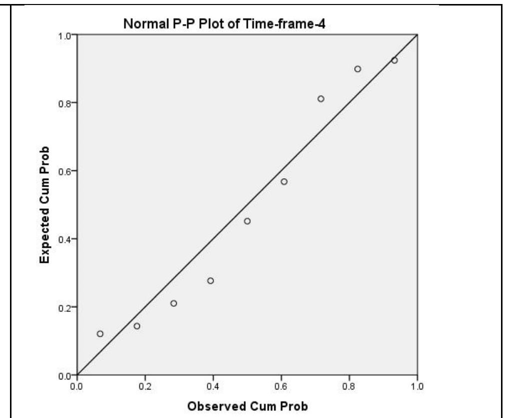


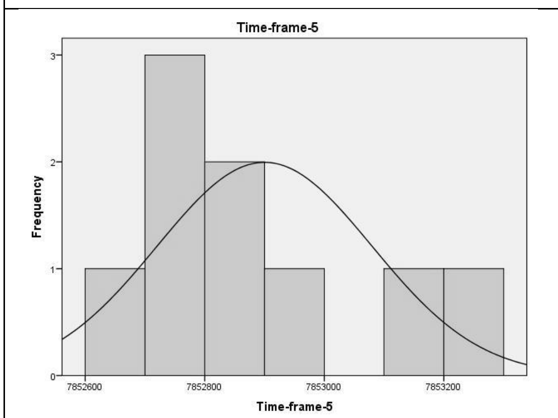
Figure 24 – Histograms and P-P plots for expense groups according to different lambda values

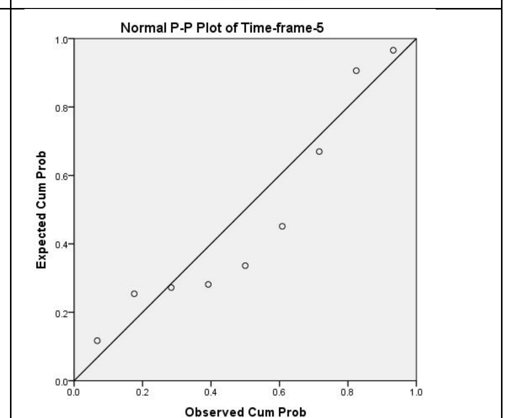
Appendix D: Histogram and P-P Plot Graphs of Expense Groups of Different Time-Frame Values

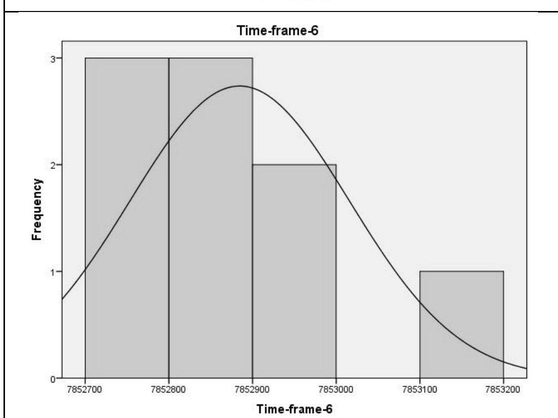


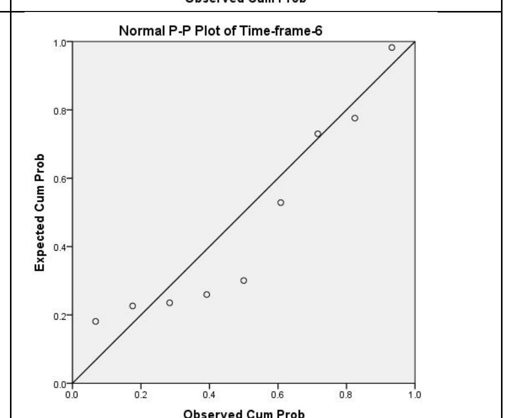

Time-frame-4
Frequency
Time-frame-4
7852900
7853000
7853100
7853200
7853300
7853400

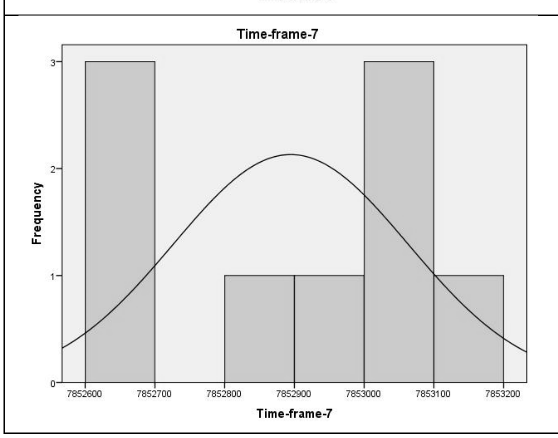

Normal P-P Plot of Time-frame-4
Expected Cum Prob
Observed Cum Prob

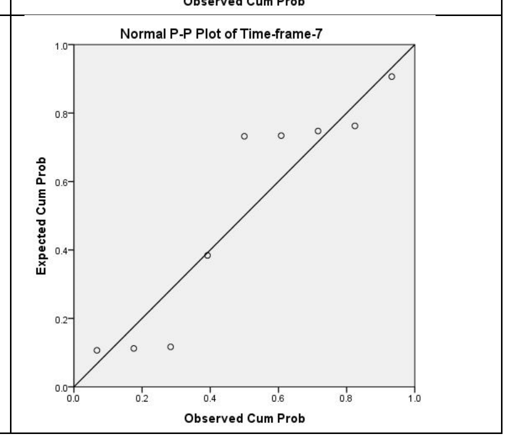

Time-frame-5
Frequency
Time-frame-5
7852600
7852800
7853000
7853200


Normal P-P Plot of Time-frame-5
Expected Cum Prob
Observed Cum Prob


Time-frame-6
Frequency
Time-frame-6
7852700
7852800
7852900
7853000
7853100
7853200


Normal P-P Plot of Time-frame-6
Expected Cum Prob
Observed Cum Prob


Time-frame-7
Frequency
Time-frame-7
7852600
7852700
7852800
7852900
7853000
7853100
7853200


Normal P-P Plot of Time-frame-7
Expected Cum Prob
Observed Cum Prob

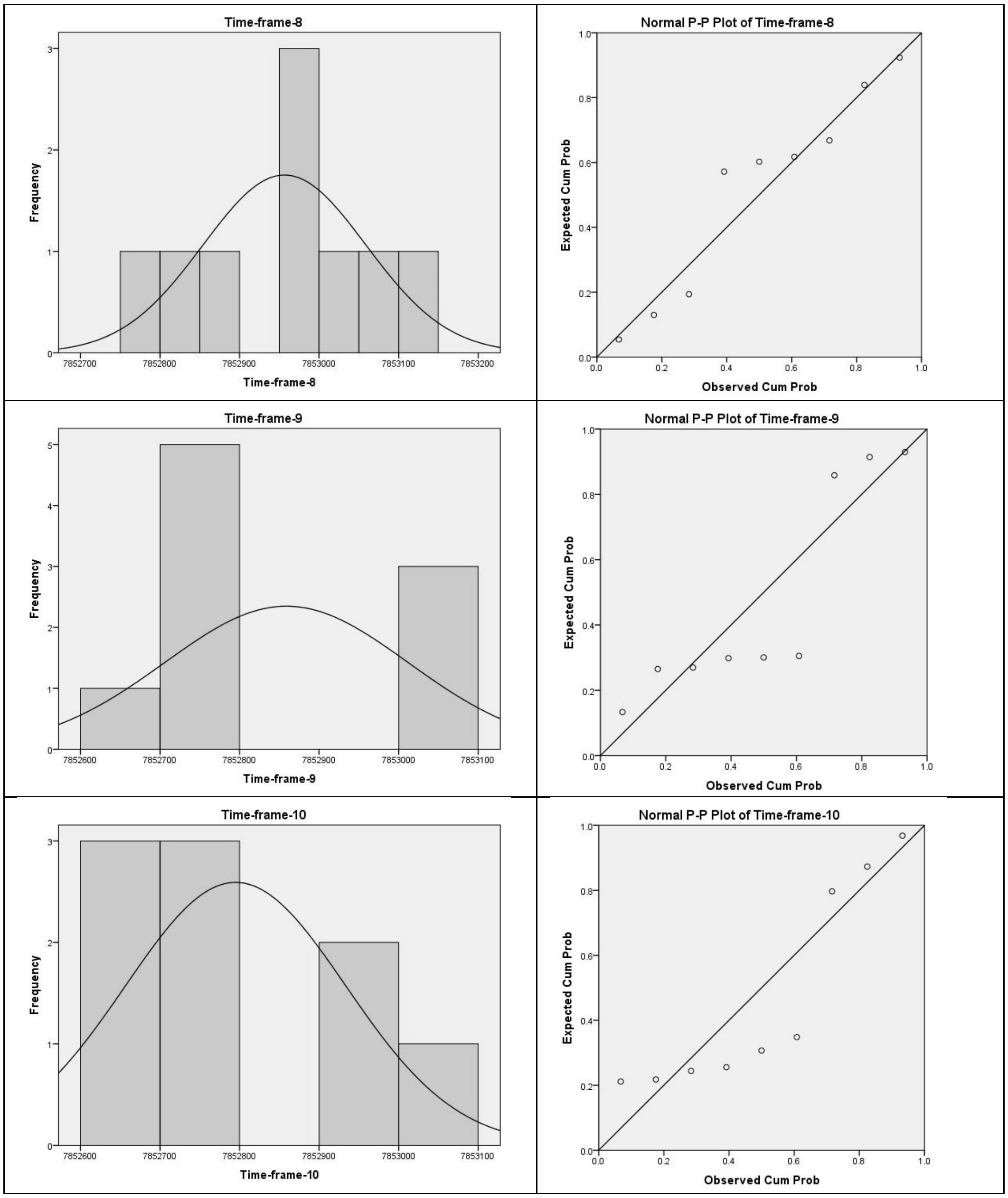


Figure 25 – Histograms and P-P plots for expense groups according to different time frames

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Uygulamalı Matematik Enstitüsü ☐

Enformatik Enstitüsü X

Deniz Bilimleri Enstitüsü ☐

YAZARIN

Soyadı : AKHÜSEYİNOĞLU
Adı : KAMİL
Bölümü : BİLİŞİM SİSTEMLERİ

TEZİN ADI (İngilizce) : A PROMOTION-AWARE PURCHASE DECISION AID FOR CONSUMERS

TEZİN TÜRÜ : Yüksek Lisans X Doktora ☐

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. ☐
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. ☐
3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. X

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