

**A COMPREHENSIVE DECISION-MAKING APPROACH TO THE ATM CASH
FLOW MANAGEMENT**

(BANKAMATİKLERDEKİ NAKİT AKIŞINA YÖNELİK BÜTÜNSEL KARAR
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FLOW MANAGEMENT**

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LIST OF SYMBOLS

ACF	: Autocorrelation Function
AHP	: Analytic Hierarchy Process
AHW	: Holt-Winters Additive Model
ANP	: Analytic Network Process
ANN	: Artificial Neural Network
AR	: Auto-Regressive
ARIMA	: Auto-Regressive Integrated Moving Average
ARMA	: Auto-Regressive Moving Average
ATM	: Automated Teller Machine
ATMIA	: ATM Industry Association
BOFLA	: Bi-Objective Model for Facility Location-Allocation
B&C	: Branch-and-Cut
CC	: Compact Chromosome
CI	: Computational Intelligence
CFS	: Correlation-Based Feature Selection
CIT	: Cash in Transit
CNN	: Convolutional Neural Network
CRN	: Cross Removal Method
CRP	: Cash Replenishment Planning
CRPS	: Continuous Ranked Probability Score
DEA	: Data Envelopment Analysis
DQN	: Deep Q-Network
DM	: Decision Maker
DSS	: Decision Support System
EC	: Extended Chromosome
EDA	: Exploratory Data Analysis
ESN	: Echo State Network
ETS	: Exponential Triple Smoothing Model
GA	: Genetic Algorithm
GDO	: Gradient Descent Optimization
GIS	: Geographical Information System
GMDH	: Group Method of Data Handling
GP	: Goal Programming
GPR	: Gaussian Process Regression
GRNN	: General Regression Neural Network
HWM	: Holt-Winter Method
IA	: Index of Agreement
IT2FNN	: Interval Type-2 Fuzzy Neural Network
LASSO	: Least Absolute Shrinkage and Selection Operator
LS-SVM	: Least Square Support Vector Machine
LSTM	: Long Short-Term Memory
MA	: Moving Average

MAD	: Mean Absolute Deviation
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MSE	: Mean Squared Error
MCD	: Markov Chain-Based Model per Day
MCDM	: Multi-Criteria Decision-Making
MCW	: Markov Chain-Based Model per Week
MCES	: Monte Carlo Evaluation Selection
MFE	: Mean Forecast Error
MLP	: Multi-layer Perceptron
MILP	: Mixed Integer Linear Programming
MLFF	: Multi-Layer Feed Forward Neural Network
MPO	: Model Predictive Output
NARX	: Nonlinear Autoregressive Exogeneous Inputs
NARMAX	: Nonlinear ARMA with Exogeneous Inputs
NMI	: Neighborhood Mutual Information
NNS	: Near Neighbor cSearch
NRGA	: Non-Dominated Ranked Genetic Algorithm
NSGA-II	: Non-Dominates Sorted Genetic Algorithm
NTM	: Nearest Trajectory Model
OECD	: Organization for Economic Co-operation and Development
OSA	: One-Step-Ahead
PACF	: Partial Autocorrelation Function
PNs	: Petri Nets
POS	: Point of Service
PSECMAC	: Pseudo Self-Evolving Cerebellar Model Articulation Controller
PSO	: Particle Swarm Optimization
RBF	: Radial Basis Function
REMM	: Random Effect Multinomial Model
RMSE	: Root Mean Square Error
RNN	: Recurrent Neural Network
ROA	: Return on Asset
RGAC	: Rank Based Genetic Algorithm
SA	: Simulated Annealing
SAM	: Sequence Alignment Method
SMAPE	: Symmetric Mean Absolute Percent Error
SVM	: Support Vector Machine
SVR	: Support Vector Regression
TBB	: Turkiye Bankalar Birliği
TSA	: Time Series Analysis
VMND	: Variable Mixed-Integer Programming Neighborhood Search
VPT	: Virtual Pre-Transaction
VRP	: Vehicle Routing Problems
VTP	: Vehicle Tour Problem
WNN	: Wavelet Neural Network
WRS	: Wavelet Reconstructed Signals
WT	: Wavelet Transform

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ABSTRACT

Automated Teller Machines (ATMs) are self service cash collection and distribution points of the banks serving as point of service (PoS) locations. Their history dates back to 1967 to the first machine installed by Barclays Bank in London and since then financial service providers all around the world employ them as a tool for simple and efficient access to money. According the World Bank 2020 statistics, worldwide there were 41.24 ATMs per 100.000 adults, and this number continues to increase and for Turkey this ratio is 82.31¹.

Banks have many ATMs distributed in their country, and each ATM hold enormous amount of cash stock within; therefore, their cash flow management is an arising problem in the financial sector. There are two conflicting objectives in the optimization problem in the ATM cash circulation problem. The first objective is to minimize the costs, therefore controlling better inventory levels and ideally replenishing these machines considering the logistic costs. The cash stocked in ATMs is deprived from the overnight interest, therefore all the cash inside these machines have an important opportunity or holding cost. On the other hand, if these machines are not replenished sufficiently, the customers may not withdraw money that will result directly as customer dissatisfaction. Therefore, finding a balance between these beared costs and satisfaction of clients is necessary.

The literature focus on this problem over three bases; where to locate these ATMs, how to forecast cash demand of these machines, and how to replenish these machines cost efficiently without compromising service levels. The ATM deployment problem, has a multi-criteria decision making (MCDM) problem characteristic, where criteria such as accessibility, security and population coverage are considered along with efficiency analysis of the selected locations. MCDM methods such as AHP, ANP, TOPSIS or Genetic Algorithm (GA) are some common methodologies used in this problem

¹ <https://data.worldbank.org/indicator/FB.ATM.TOTL.P5>

literature. Demand forecasting problem is the most interested part of the ATM literature by academics. Basically, forecasted values are the primary inputs of the replenishment problem, therefore better forecasting results would yield to better management opportunities. Each ATM acts like a time series, and to forecast this time series, literature used fuzzy approaches, statistical techniques and machine learning models. The ATM replenishment literature mainly consists of finding the best routes that minimizes total traveled time while replenishing ATMs. Simulation, GA and vehicle routing problem (VRP) models are the frequently used methodologies in this problem.

In this thesis, all the literature related on ATMs are deeply reviewed. The employed models, used data sets and the aim of the study is summarized for each article. Forecasting literature on the ATM cash demand problem is intensely examined. The articles are classified according to their employed methodologies (with details), used data characteristics and employed error metrics. A common time series data (NN5 Competition) is found and the accuracy results of the literature employing this data set are tabulated. As the first target, non-utilised forecasting models in ATM demand problem are detected as recurrent neural networks (RNN) and long-short term memory (LSTM), and it is aimed to outperform the existing literature accuracy results.

In the application part, the daily ATM cash demand data belonging to NN5 competition data set is used. Firstly, the data is prepared or preprocessed using Box-Plot approach to replace the outliers and median for missing value replacement. Statistical analysis are performed such as Augmented Dickey-Fuller Test (ADF) for checking the stationarity of the series, autocorrelation and partial autocorrelation function (ACF) and (PACF) to detect the correlated series and error lags that will be used as parameter.

In the forecasting part, firstly, statistical forecasting techniques autoregressive moving average (ARIMA) and its' seasonal version (SARIMA) is employed for the reduced data set of NN5 series consisted of 11 ATMs, and the obtained satisfactory results compared with the literature that used the same reduced data set. Then machine learning (ML) techniques like deep neural network (DNN), recurrent neural network (RNN) and long short term-memory (LSTM) are employed for the complete data set of NN5 series,

and the outcomes are compared with the existing literature that employed same complete data set of 111 series obtaining outperforming results. As far as it is known this is also the first study, that employs RNN and LSTM models in the ATM cash demand problem using NN5 series. In addition, results are evaluated considering alternative error metrics (MAE, MAPE, SMAPE) and the best performing forecasting model for each ATM is selected individually. In general, the literature approach to the forecasting problem selecting the best performing forecasting model in average, this thesis differs from the literature because it proposes optimizing the ATMs individually.

The forecasted values for each ATM considered as the input for the replenishment problem. Firstly, the average forecasted demand is calculated, and using the optimum order quantity formula, the optimal replenishment period is calculated for each ATM. Two static inventory control mechanisms are used in the calculation process. First one is the optimum order quantity (with four adapted alternatives) where ATMs are replenished with fixed amounts in each visit. The second mechanism is the lot for lot strategy where ATMs are replenished according to the next days demand. For instance, ATMs may be replenished each end of the day with the next day demand or every two days with the next two days demand. Maximum replenishment period is considered as seven days or one week, therefore a total of seven alternatives are tested for lot for lot strategy.

For each replenishment alternative, costs like holding and back-out costs and replenishment costs are calculated. In the same time, service levels for each ATM are tracked. Two service levels are identified for this problem, the first one counts the cash out days which is directly linked with the unsatisfied customer numbers, the second service level corresponds to the ratio of successfully withdrawn money to the total withdrawal demand.

All these calculation steps result with the necessary data table for the ideal replenishment period and strategy selection problem. Therefore, best replenishment decision is selected among eleven alternatives using alternative factors.

For the replenishment decision problem three approaches are identified, namely; cost-oriented, customer oriented and integrated approaches. The cost-oriented approach selects the replenishment strategy that gives the minimum total cost, where total cost is sum of the holding, back-out and replenishment costs. The consumer-oriented approach selects the refilling strategy that maximizes the average service level, where daily service level and amount service level is averaged. The integrated approach selects the replenishment period and amount, considering both total cost and average service level. A penalty cost is identified for every missed centesimal of the service level and a hypothetical cost is calculated for each alternative. The minimum hypothetical cost giving strategy is selected as the replenishment decision.

For each ATM, the best replenishment period and amount is selected for each three approaches using the first 28 days of the forecasting horizon (which is equivalent to four weeks or one month). Then for all the three approaches, the selected replenishment strategy is tested again for the further 28 days, following the variations in the total costs and service levels.

The decision-making approach developed in this thesis dissociates from the existing literature with its comprehensive nature. This study integrates the forecasting and replenishment problem of the ATMs and proposes pareto-optimal solutions for alternative scenarios. It considers the best forecasting model for each ATM, and use the forecasting outcomes as the input of the replenishment process. Then, calculates costs and service levels for alternative replenishment decisions and selects bests of them, finding a balance between costs and service levels. In addition, it tests the decision for a further replenishment horizon with equal length, and preserve its robust nature.

The proposed decision support system (DSS) in this thesis, is easy to implement for the banks in their ATM network management optimization procedures. All the outcomes of this study are reproducible and does not require any additional computer sytem or program. In this study the proposed DSS is employed for the ATMs, but according to its nature it may be used in all the point of service (PoS) location problems like vending machines, gas stations.

The followed methodology not only focus with better forecasting performances but also examines the outcomes of the results for two conflicting objectives (minimizing costs and maximizing service levels). The decision-making procedure is realized for each machine and can be easily adapted by the banks or other self-service point locations like gas stations, vending machines or corner markets.



RÉSUMÉ

Les guichets automatiques ou les ATMs sont des points de collecte et de distribution d'espèces en libre-service des banques. Leur histoire remonte à 1967 avec la première machine installée par la Barclays Bank à Londres et depuis lors, les prestataires de services financiers du monde entier les utilisent comme un outil pour un accès simple et efficace à l'argent. Selon les statistiques de la Banque Mondiale, en 2020, il y avait dans le monde 41.24 distributeurs automatiques de billets pour 100 000 adultes, et ce nombre continue d'augmenter et pour la Turquie, ce ratio est de 82.31.

Les banques ont de nombreux ATM répartis dans leur pays, et chaque guichet automatique détient une énorme quantité de liquidités à l'intérieur; par conséquent, leur gestion des flux de trésorerie est un problème récurrent dans le secteur financier. Il y a deux objectifs contradictoires dans le problème d'optimisation dans le problème de la circulation des espèces aux guichets automatiques. Le premier objectif est de minimiser les coûts, donc de mieux contrôler les niveaux de stocks et idéalement de réapprovisionner ces machines compte tenu des coûts logistiques. Les espèces stockées dans les guichets automatiques sont privées de l'intérêt au jour le jour, par conséquent, toutes les espèces à l'intérieur de ces machines ont une opportunité ou un coût de détention important. D'autre part, si ces machines ne sont pas suffisamment réapprovisionnées, les clients peuvent ne pas retirer d'argent, ce qui entraînera directement l'insatisfaction des clients. Il est donc nécessaire de trouver un équilibre entre ces coûts supportés et la satisfaction des clients.

La littérature se concentre sur ce problème sur trois bases; où localiser ces guichets automatiques, comment prévoir la demande de liquidités de ces machines et comment réapprovisionner ces machines de manière rentable sans compromettre les niveaux de service. Le problème de déploiement de l'ATM a une caractéristique de problème de prise de décision multicritères (MCDM), où des critères tels que l'accessibilité, la sécurité et la couverture de la population sont pris en compte avec l'analyse de

l'efficacité des emplacements sélectionnés. Les méthodes MCDM telles que AHP, ANP, TOPSIS ou Genetic Algorithm (GA) sont des méthodologies courantes utilisées dans cette littérature sur les problèmes. Le problème de la prévision de la demande est la partie la plus intéressante de la littérature ATM par les universitaires. Fondamentalement, les valeurs prévues sont les principales entrées du problème de réapprovisionnement, donc de meilleurs résultats de prévision donneraient de meilleures opportunités de gestion. Chaque ATM agit comme une série temporelle, et pour prévoir cette série temporelle, la littérature a utilisé des approches floues, des techniques statistiques et des modèles d'apprentissage automatique. La littérature sur le réapprovisionnement des ATM consiste principalement à trouver les meilleurs itinéraires qui minimisent le temps total parcouru lors du réapprovisionnement des ATM. Les modèles de simulation, algorithme génétique, et de problèmes de routage de véhicules (VRP) sont les méthodologies fréquemment utilisées dans ce problème.

Dans cette thèse, toute la littérature relative aux guichets automatiques est examinée en profondeur. Les modèles employés, les ensembles de données utilisés et le but de l'étude sont résumés pour chaque article. La littérature prévisionnelle sur le problème de la demande de liquidités aux guichets automatiques est examinée de manière approfondie. Les articles sont classés en fonction de leurs méthodologies employées (avec des détails), des caractéristiques des données utilisées et des mesures d'erreur employées. Une série de données chronologiques communes (Compétition NN5) est trouvée et les résultats de précision de la littérature utilisant cet ensemble de données sont tabulés. En tant que première cible, les modèles de prévision non utilisés dans le problème de la demande ATM sont détectés en tant que réseaux de neurones récurrents (RNN) et mémoire à long terme (LSTM), et il vise à surpasser les résultats de précision de la littérature existante.

Dans la partie application, les données quotidiennes de demande de liquidités des guichets automatiques appartenant à l'ensemble de données de concurrence NN5 sont utilisées. Premièrement, les données sont préparées ou prétraitées à l'aide de l'approche Box-Plot pour remplacer les valeurs aberrantes et la médiane pour le remplacement des valeurs manquantes. Des analyses statistiques sont effectuées telles que le test Dickey-

Fuller augmenté (ADF) pour vérifier la stationnarité de la série, l'autocorrélation et la fonction d'autocorrélation partielle (ACF) et (PACF) pour détecter les séries corrélées et les retards d'erreur qui seront utilisés comme paramètre.

Dans la partie prévision, premièrement, les techniques de prévision statistique moyenne mobile autorégressive (ARIMA) et sa version saisonnière (SARIMA) sont employées pour l'ensemble de données réduit de la série NN5 composée de 11 ATM, et les résultats satisfaisants obtenus par rapport à la littérature qui a utilisé le même jeu de données réduit. Ensuite, des techniques d'apprentissage automatique (ML) telles que le réseau neuronal profond (DNN), le réseau neuronal récurrent (RNN) et la mémoire à court terme (LSTM) sont utilisées pour l'ensemble de données complet de la série NN5, et les résultats sont comparés à la littérature existante qui utilisaient le même ensemble de données complet de 111 séries obtenant des résultats supérieurs. Pour autant que l'on sache, il s'agit également de la première étude qui utilise les modèles RNN et LSTM dans le problème de la demande de liquidités des guichets automatiques utilisant la série NN5. De plus, les résultats sont évalués en tenant compte des métriques d'erreur alternatives (MAE, MAPE, SMAPE) et le modèle de prévision le plus performant pour chaque ATM est sélectionné individuellement. En général, l'approche de la littérature au problème de prévision sélectionnant le modèle de prévision le plus performant en moyenne, cette thèse diffère de la littérature car elle propose d'optimiser les ATM individuellement.

Les valeurs prévues pour chaque guichet automatique considéré comme l'entrée pour le problème de réapprovisionnement. Tout d'abord, la demande moyenne prévue est calculée et, à l'aide de la formule de quantité de commande optimale, la période de réapprovisionnement optimale est calculée pour chaque guichet automatique. Deux mécanismes de contrôle des stocks statiques sont utilisés dans le processus de calcul. Le premier est la quantité de commande optimale (avec quatre alternatives adaptées) où les distributeurs automatiques de billets sont réapprovisionnés avec des quantités fixes à chaque visite. Le deuxième mécanisme est la stratégie lot pour lot où les guichets automatiques sont réapprovisionnés en fonction de la demande des jours suivants. Par exemple, les guichets automatiques peuvent être réapprovisionnés chaque fin de journée

avec la demande du lendemain ou tous les deux jours avec la demande des deux jours suivants. La période maximale de réapprovisionnement est considérée comme sept jours ou une semaine, donc un total de sept alternatives sont testées pour la stratégie lot pour lot.

Pour chaque alternative de réapprovisionnement, les coûts tels que les coûts de maintien et de retrait et les coûts de réapprovisionnement sont calculés. Dans le même temps, les niveaux de service de chaque guichet automatique sont suivis. Deux niveaux de service sont identifiés pour ce problème, le premier compte les jours d'encaissement qui est directement lié au nombre de clients insatisfaits, le deuxième niveau de service correspond au rapport entre l'argent retiré avec succès et la demande totale de retrait.

Toutes ces étapes de calcul aboutissent au tableau de données nécessaire pour la période de réapprovisionnement idéale et le problème de sélection de stratégie. Par conséquent, la meilleure décision de réapprovisionnement est sélectionnée parmi onze alternatives en utilisant des facteurs alternatifs.

Pour le problème de décision de réapprovisionnement, trois approches sont identifiées, à savoir; approches axées sur les coûts, axées sur le client et intégrées. L'approche axée sur les coûts sélectionne la stratégie de réapprovisionnement qui donne le coût total minimum, où le coût total est la somme des coûts de détention, de retrait et de réapprovisionnement. L'approche axée sur le consommateur sélectionne la stratégie de remplissage qui maximise le niveau de service moyen, où le niveau de service quotidien et le niveau de service sont moyennés. L'approche intégrée sélectionne la période et le montant de réapprovisionnement, en tenant compte à la fois du coût total et du niveau de service moyen. Un coût de pénalité est identifié pour chaque centésimal manqué du niveau de service et un coût hypothétique est calculé pour chaque alternative. La stratégie d'attribution des coûts hypothétiques minimum est sélectionnée comme décision de réapprovisionnement.

Pour chaque ATM, la meilleure période et le meilleur montant de réapprovisionnement sont sélectionnés pour chacune des trois approches en utilisant les 28 premiers jours de

l'horizon de prévision (ce qui équivaut à quatre semaines ou un mois). Ensuite, pour les trois approches, la stratégie de réapprovisionnement sélectionnée est à nouveau testée pendant les 28 jours supplémentaires, en suivant les variations des coûts totaux et des niveaux de service.

L'approche décisionnelle développée dans cette thèse se démarque de la littérature existante par son caractère compréhensif. Cette étude intègre le problème de prévision et de réapprovisionnement des GAB et propose des solutions optimales de Pareto pour des scénarios alternatifs. Il considère le meilleur modèle de prévision pour chaque GAB et utilise les résultats des prévisions comme données d'entrée du processus de réapprovisionnement. Ensuite, calcule les coûts et les niveaux de service pour les décisions de réapprovisionnement alternatives et sélectionne les meilleures d'entre elles, en trouvant un équilibre entre les coûts et les niveaux de service. De plus, il teste la décision pour un nouvel horizon de réapprovisionnement d'égale longueur, et préserve son caractère robuste.

Le système d'aide à la décision (DSS) proposé dans cette thèse est facile à mettre en œuvre pour les banques dans leurs procédures d'optimisation de la gestion du réseau ATM. Tous les résultats de cette étude sont reproductibles et ne nécessitent aucun système ou programme informatique supplémentaire. Dans cette étude, le DSS proposé est utilisé pour les guichets automatiques, mais selon sa nature, il peut être utilisé dans tous les problèmes de localisation des points de service (PoS) comme les distributeurs automatiques, les stations-service.

La méthodologie suivie non seulement se concentre sur de meilleures performances de prévision, mais examine également les résultats des résultats pour deux objectifs contradictoires (minimisation des coûts et maximisation des niveaux de service). La procédure de prise de décision est réalisée pour chaque machine et peut être facilement adaptée par les banques ou d'autres points de libre-service comme les stations-service, les distributeurs automatiques ou les marchés du coin.

ÖZET

Bankamatikler (ATM'ler), bankalar tarafından self servis nakit toplama ve dağıtım aracı olarak kullanılan otomatik cihazlardır. İlk ATM, 1967 yılında Barclays Bank tarafından Londra'da kurulmuş olup, bu tarihten beri ATM'ler dünyanın her yerindeki finansal hizmet sağlayıcıları tarafından nakit paraya hızlı ve verimli erişim aracı olarak kullanılmaktadırlar. Dünya Bankası'nın 2020 istatistiklerine göre dünya genelinde 100.000 yetişkine 41.24 ATM düşerken bu oran artmaya devam etmekte, Türkiye'de ise aynı oran ortalamanın üzerine çıkmakta, 100.000 yetişkine 82.31 ATM olarak hesaplanmaktadır.

Bankaların kendi ülkelerinde geniş bir coğrafyaya yayılmış çok fazla sayıda ATM'si bulunmaktadır. Her bir ATM'nin içinde ise muazzam miktarda nakit stoğu mevcuttur. Bu stok, nakit akışı yönetimini finans sektörünün önemli bir sorunu haline getirmektedir. ATM nakit akışı optimizasyon probleminde birbiriyle çelişen iki amaç ortaya çıkmaktadır. İlk amaç, makineleri doldurma ve makinelerde para bulundurma maliyetlerini içerir. Bu maliyetlerin enküçüklenmesi istenir. Burada, bankalar ATM'lerindeki stoklanan nakit para için gecelik faizden faydalanamamakta, dolayısıyla bu makinelerde stoklanmış tüm nakit para aynı zamanda önemli bir fırsat maliyeti veya elde tutma maliyetine dönüşmektedir. Öte yandan, makineler yeterince doldurulmazsa, müşteriler istedikleri anda istedikleri miktarda nakit çekimi yapamayacak, dolayısıyla müşteri memnuniyeti düşecektir. Oysaki nakit akışı optimizasyon probleminin ikinci amacı müşteri memnuniyetinin enbüyüklenmesi olmalıdır. Bu nedenle, katlanılan maliyetler ile müşterilerin memnuniyeti arasında bir denge bulmak gerekmektedir.

Mevcut yazın bu sorunsala üç temel eksen üzerinden odaklanmaktadır; bu temeller sırasıyla, ATM'lerin nereye yerleştirileceği, bu makinelerin nakit talebinin nasıl tahmin edileceği ve bu makinelerin hizmet seviyelerinden ödün vermeden maliyet etkin bir şekilde nasıl doldurulacağıdır. ATM yerleşim problemi, seçilen yerleşim yerlerinin verimlilik analizi ile birlikte erişilebilirlik, güvenlik ve nüfus kapsamı gibi kriterlerin

dikkate alındığı çok kriterli karar verme (ÇKKV) problem özelliğine sahiptir. AHP, ANP, TOPSIS veya Genetik Algoritma (GA) gibi ÇKKV yöntemleri, bu problem yazınında kullanılan bazı yaygın metodolojilerdir. Talep tahmini problemi, ATM literatürünün araştırmacılar tarafından en çok ilgi gören kısmıdır. Temel olarak, tahmin edilen değerler, yenileme probleminin birincil girdileridir, bu nedenle daha iyi tahmin sonuçları, daha iyi yönetim fırsatlarına yol açacaktır. Her ATM bir zaman serisi gibi davranır ve bu zaman serisini tahmin etmek için yazında bulanık yaklaşımlar, istatistiksel teknikler ve makine öğrenimi modelleri sıklıkla kullanılmaktadır. Son olarak ATM ikmal literatürü, temel olarak ATM'leri doldururken toplam seyahat süresini en aza indiren en iyi rotaları bulmaktan oluşur. Simülasyon, GA ve araç rotalama problemi (VRP) modelleri bu problemde sıklıkla kullanılan metodolojilerdir.

Bu tezde, ATM'lerle ilgili tüm yazın derinlemesine gözden geçirilmiştir. Kullanılan modeller, kullanılan veri setleri ve çalışmanın amacı her makale için özetlenmiştir. Bununla birlikte, ATM nakit talebi problemine ilişkin tahmin literatürü yoğun bir şekilde incelenmektedir. Makaleler, kullanılan metodolojilere, veri özelliklerine ve hata ölçütlerine göre sınıflandırılmıştır. Yapılacak analiz ve çalışmalar doğrultusunda yazında ortak olarak kullanılan bir zaman serisi verisi (NN5 Yarışması) bulunmuş ve bu veri setini kullanan literatürün doğruluk sonuçları, yapılacak çalışmaların sonuçlarıyla karşılaştırmak amacı ile analiz edilerek tablolastırılmıştır. Tahminleme çalışmalarında ilk olarak, ATM talep probleminde daha evvel kullanılmamış ama iyi sonuçlar vereceği hipotetik olarak beklenen çeşitli tahmin modelleri kullanarak ki, tekrarlayan sinir ağları (RNN) ve uzun kısa süreli bellek (LSTM) modelleri bunların arasında sayılabilir, mevcut yazındaki doğruluk sonuçlarından daha iyi performanslara erişim hedeflenmiştir.

Çalışmanın uygulama bölümünde, NN5 rekabet veri setine ait günlük ATM nakit talebi verileri kullanılmıştır. İlk olarak, veriler, aykırı değerlerin değiştirilmesi için Box-Plot yaklaşımı ve eksik değer ikamesi için medyan kullanılarak hazırlanmış veya ön işleme tabi tutulmuştur. Serilerin durağanlığını kontrol etmek için Artırılmış Dickey-Fuller Testi (ADF), korelasyonlu serileri ve parametre olarak kullanılacak hata gecikmelerini

tespit etmek için otokorelasyon ve kısmi otokorelasyon fonksiyonu (ACF) ve (PACF) gibi istatistiksel analizler yapılmıştır.

Hazırlanmış verilerle tahmin aşamasına geçilmiş, ilk olarak 11 ATM'den oluşan NN5 serisinin indirgenmiş veri seti için, istatistiksel tahmin teknikleri otoregresif hareketli ortalama (ARIMA) ve mevsimsel versiyonu (SARIMA) kullanılmış ve aynı indirgenmiş veri seti kullanılan literatür ile karşılaştırıldığında tatmin edici sonuçlar elde edilmiştir. Daha sonra NN5 serisinin tüm veri seti için derin sinir ağı (DNN), tekrarlayan sinir ağı (RNN) ve uzun kısa süreli bellek (LSTM) gibi makine öğrenmesi (ML) teknikleri kullanılmış ve sonuçlar mevcut literatürle karşılaştırılmıştır. Yapılan tahminlama çalışmaları sonucunda, 111 zaman serisinin aynı eksiksiz veri setini kullanan literature göre daha iyi performans gösteren sonuçlar elde edilmiştir. Bildiğimiz kadarıyla çalışmamız ATM nakit talebi probleminde RNN ve LSTM modellerini NN5 serisi kullanarak yaklaşan ilk çalışmadır. Ulaşılan sonuçlar alternatif hata metrikleri (MAE, MAPE, SMAPE) dikkate alınarak değerlendirilmiş ve her ATM için en iyi performans gösteren tahmin modeli ayrı ayrı seçilmiştir. Bu çalışmanın tahminleme metodolojisi, ortalama olarak en iyi performans gösteren tahmin modelini seçen tahmin problemi literatür yaklaşımından ATM'leri ayrı ayrı optimize etmeyi öneren doğası ile ayrılmaktadır.

Çalışmanın ikinci aşamasında ikmal problemi üzerine yoğunlaşmıştır. Önerilen metodolojide her bir ATM için tahmin edilen talep değerleri, ikmal probleminin girdisi olarak kabul edilmektedir. İlk aşamada ortalama tahmini talep hesaplanmakta ve ekonomik sipariş miktarı formülü kullanılarak her bir ATM için optimal yenileme süresi ortaya konulmaktadır. Hesaplama sürecinde iki statik stok kontrol mekanizması kullanılmaktadır. Birincisi, ATM'lerin her ziyarette sabit miktarlarla doldurulduğu ekonomik sipariş miktarıdır. İkinci mekanizma, ATM'lerin sonraki gün talebine göre doldurulduğu talebe göre ikmal stratejisidir. Örneğin, ATM'ler bir sonraki günün talebiyle günün sonunda veya sonraki iki günün talebiyle iki günde bir doldurulabilir. En uzun ikmal süresi yedi gün veya bir hafta olarak kabul edilir, bu nedenle talebe göre dolum stratejisi için toplam yedi alternatif test edilmiştir.

Her bir ikmal alternatifi için elde tutma ve elde bulundurmama maliyetleri ile lojistik maliyetleri hesaplanmış, aynı zamanda her bir ATM'nin hizmet seviyeleri takip edilmiştir. Hizmet seviyeleri takibi için iki hizmet düzeyi belirlenmiş olup, bunlardan birincisi, memnun olmayan müşteri sayılarıyla doğrudan bağlantılı olan başarısız para çekme günlerinin sayılması, ikinci ise hizmet düzeyi yani başarıyla çekilen paranın toplam çekme talebine oranı olarak saptanmıştır. Tüm bu hesaplama adımları, ideal ikmal periyodu ve dolum miktarı için gerekli veri tablosunu oluşturmaktadır. Bu şekilde alternatif faktörler kullanılarak on bir alternatif arasından en iyi ikmal kararı seçilektedir.

İkmal kararı problemi için üç yaklaşım tanımlanmıştır. Bu yaklaşımlar sırasıyla; maliyet odaklı, müşteri odaklı ve entegre yaklaşımlardır. Maliyet odaklı yaklaşım, toplam maliyetin elde tutma, elde bulundurmama ve lojistik maliyetlerinin toplamı olduğu, minimum toplam maliyeti veren ikmal stratejisini; müşteri odaklı yaklaşım, günlük hizmet düzeyi ve miktar hizmet düzeyi ortalamasının alındığı, ortalama hizmet düzeyini eniyileyen yeniden doldurma stratejisini; entegre yaklaşım ise, hem toplam maliyeti hem de ortalama hizmet düzeyini aynı anda iyileyecek ikmal süresini ve miktarını seçer. Hizmet düzeyinin kaçırılan her bir yüzdesi için bir ceza maliyeti belirlenmiş ve her alternatif için varsayımsal bir maliyet hesaplanmıştır. Sonuçta, ikmal kararı olarak en düşük varsayımsal maliyeti veren strateji seçilmektedir.

Önerilen metodolojinin son bölümünde, her ATM için, tahmin ufkunun ilk 28 günü (dört haftaya veya bir ay) kullanılarak her üç yaklaşım için en iyi ikmal süresi ve miktarı seçilmekte; ardından, üç yaklaşımın tümü için, seçilen ikmal stratejisi, toplam maliyetler ve hizmet düzeylerindeki değişiklikleri takip ederek devam eden 28 gün boyunca tekrar test edilmektedir.

Bu çalışmada geliştirilen karar verme yaklaşımı, kapsamlı doğası ile mevcut literatürden ayrılmaktadır. Çalışma, ATM'lerin tahmin ve ikmal problemini entegre etmekte ve alternatif senaryolar için pareto-optimal çözümler önermektedir. Birinci adımda, her bir ATM için en iyi tahmin modelini dikkate almakta ve tahmin sonuçlarını ikmal sürecinin girdisi olarak kullanmaktadır. İkinci adımda, alternatif dolum kararları için maliyetleri

ve hizmet düzeylerini hesaplamakta ve bunların arasından en iyisini seçerek maliyetler ve hizmet düzeyleri arasında bir denge kurmaktadır. Son olarak, bu kararı aynı uzunluktaki talep ufku için test etmekte ve maliyet-hizmet düzeyi üzerindeki değişimin azlığıyla sağlam yapısını korumaktadır.

Bu tezde önerilen karar destek sistemi (KDS), bankaların ATM nakit akışı yönetimi prosedürlerinde uygulanması kolay bir yaklaşımdır. Bu çalışmanın tüm sonuçları tekrarlanabilir niteliktedir ve herhangi bir ek bilgisayar sistemi veya programı gerektirmez. Çalışmada önerilen KDS, ATM'ler için kullanılmış olmakla birlikte çalışmanın doğası gereği otomatlar, benzin istasyonları gibi tüm hizmet noktası konum problemlerinde kullanılabilir niteliktedir.

İzlenen metodoloji yalnızca daha iyi tahmin performanslarına odaklanmakla kalmaz, aynı zamanda iki çelişen hedef için sonuçları irdeler (maliyetleri en aza indirmek ve hizmet seviyelerini en üst düzeye çıkarmak). Karar verme prosedürü her makine ayrı ayrı için gerçekleştirilir ve bankalar veya benzin istasyonları, otomatlar veya köşe marketler gibi diğer self servis noktaları tarafından da kolayca uyarlanabilir.

1. INTRODUCTION

In the total cash circulation, Automated Teller Machines (ATMs) play a crucial role. World Bank 2020 statistics show that globally there were 41.24 ATMs per 100.000 adults, and this number continues to increase year by year and for Turkey this ratio is 82.31 which is relatively high². According to the Türkiye Bankalar Birliği (TBB) report, there are 52798 ATMs in Turkey³. ATMs are computerized telecommunications devices that provide clients of a financial institution with access to financial transactions in a public place. ATMs are one of the most important key touch-points to reach the customers and they are considered as the time independent point of sale (PoS) and service locations of the finance industry. Due to their multi-task nature such as obtaining account information, withdrawals, fund transfer, deposits, cash investment, payment tool etc. they can be also characterized as a point of purchase. The history review of the ATMs may be found on Batiz-Lazo (2009) who studied the emergence and evolution of ATM networks. Similarly, Konheim (2016), summarized the literature the encountered problems and the necessary technical enhancements on ATM inventory achievement.

ATMs are expected to sustain their operability and profitability for an extended period of time after they start to operate. Therefore, designing the optimum ATM network with right locations, right number and right services that are provided to the customers can enable considerable amount of reduction in cost and increase in revenue, thus increase in profit margins. ATMs play a crucial role by making cash easily available to the customers without any time constraint. However, ATM management is a complex process those financial institutions, consulting firms and academics continually dealing with it. Mainly they are focusing to lower costs, reduce inventory and boost productivity for optimizing the retail bank supply chain. ATM management is an important part of the overall cash demand management, they are directly linked by deposits, withdrawals and orders with the

² <https://data.worldbank.org/indicator/FB.ATM.TOTL.P5>

³ https://www.tbb.org.tr/Content/Upload/istatistikraporlar/ekler/1598/Bankalarimiz_2020.pdf

branches, retail customers, and central bank. Armored carriers of the correspondent bank, and cash routing process, is another important part of the management process, always considering the risk criterion, and ensuring the needed security. Accessibility is another criterion that banks consider for customer satisfaction and brand image.

Especially, ATM management deals with two conflicting objectives. ATMs should contain enough cash to meet customer demand which is highly hard to forecast, at the same time, the cash that is in the stock (in the machine) is devoid of the overnight interest profit, which can be very expensive, considering the excessive network of ATMs that a bank holds. By taking into consideration mainly these two goals, banks have to plan their operations, forecasting demand and planning inventory for maintaining and improving service levels while reducing inventory, they should also lower their supplier spend and reduce waste and excess in operation. When they accomplish these steps, they may focus also on optimizing the delivery and routing network in order to reduce the logistics and transportation costs.

In this thesis it is focused on developing a decision support system (DSS) for banks, to optimize individually their ATMs. It is started to compare results of the alternative forecasting models over machines, then selecting the best performing forecasting model for each machine. Next step is based on selecting the replenishment frequency and cash amount for ATMs, calculating costs and tracking service levels. The ultimate step is based on testing the selected replenishment strategy over a further period, tracking the changes in the costs and service levels.

The rest of this study is organized as follows: the next section presents the literature review. The review classifies ATM literature on four parts; deployment, replenishment, forecasting and related literature. It deeply examines the literature on the forecasting problem. Section three is the methodologic background of the proposed DSS. Section four is consisted of forecasting part of the case study, which presents the data and shows the forecasting results over alternative metrics. Fifth section gives the outcomes of the ATMs over selected performance metrics, comparing the results, and validating the selected replenishment strategy. The final section is the concluding and discussion part of the thesis. All the data, codes and calculation sheets employed in this thesis are accessible in the appendices.

2. LITERATURE REVIEW

The first studies on the ATMs dates back to Zilberfarb (1989) which concentrated on the effect of ATMs on demand deposits and McAndrews (1991) who investigated the evolution of the shared ATM networks. In this thesis, the literature on the ATMs is categorized in four classes. The ATM deployment problem, the forecasting problem, the replenishment problem and “related”. The “related” class is consisted of works like security of the machines, ATM IT infrastructures and the economic impact of the ATMs.

2.1. ATM DEPLOYMENT PROBLEM

Location selection decision has a substantial effect on long-term profitability and sustainability of an ATM network. Therefore, the first step of the ATM management is the deployment of the new ATMs, and analyzing the efficiencies of the existing ATM locations. For this reason, ATM location problem is a popular topic that arises in ATM management literature.

Location management is generally viewed as one of the critical topics for its cost reduction and profit increase potential in every single line of business. Therefore, firms need to establish location strategies for their business units such as stores, plants and distribution centers in accordance with their overall business strategy. Accordingly, ATM location problem is one of the research areas that took part in literature. Optimum location selection affects directly the customer satisfaction (accessibility), and vehicle routing costs. In the literature there are several articles that examine ATM location problem by different approaches such as mathematical formulations, genetic algorithms (GA) and geographic information systems (GIS).

Adams (1991) defined the right location as the difference between a costly service and a bottom-line benefit. The components that must be considered listed as school district(s), work sites, future expansion/ building plans, propert values, road quality, accessibility to

metropolitan hubs, population density, traffic flow, safety, visibility and demographics. In this study it is emphasized that the greatest percentage of the existing customers is an important criterion still, it should be focused on attract every card-carrying consumer in a given place.

Wilson (1999), in his primary study on ATM placement, underlined the role of the ATMs changing the face of banking even in that time and concentrated on their location problem. Even if this study is a pioneer work that does not include any mathematical solution to this specific problem, reader may hopefully understand that examining this study, including interviews with professionals and sector tips, to observe the factors and numbers that changed in twenty years may be quite insightful for progress of this study. Visibility and fee income are taken into account as objectives of the bank while the factors that can be assessed with decision process are safety, display of the logo, rental payments, revenue sharing and ancillary cost of providing service. In general, the right locations are considered as grocery or drug stores, workplaces, supermarkets that has enough traffic and ensure the security. Beside those sports facilities, theme parks, highway rest stops that are high traffic locations with non-local customers may be other alternatives ATM placement locations.

Zhang and Rushton (2008), introduced a multi-site location-allocation model, which is described in the context of locating bank branches. They aimed to assist multi-site facility owner for locating new sites or closing current sites in the presence of one or more competitors and suggested Genetic Algorithm (GA) for solving the model.

Aldajani and Alfares (2009), formulated a mathematical model for determining optimum number and location of ATMs. They implemented a novel heuristic solution based on convolutional networks with predetermined service level, and applied the model to the different problems such as mesh of roads, high priority centers and an actual map of a city, observing the total percentage coverage.

Cinar (2009), considering a case study in Turkey, aimed to provide a decision support model (DSS) for bank branch location selection. It is believed that this deployment problem is highly correlated with the ATM deployment problem, therefore it is included in the survey. The employed model is based on five main criteria, namely, demographic,

socio-economic, sectoral employment, banking and trade potential with twenty-one subcriteria and fuzzy AHP is solved weighting the factors while TOPSIS is used for ranking the alternatives.

Li et al. (2009) studied the site selection and layout of ATMs, employing Particle Swarm Optimization (PSO) to geographical information system (GIS). They conducted the experiment in China, Tianjin, choosing randomly 50 ATMs, located in different sites, viz. bank branches, commercial districts, schools, enterprises and taking into account 12652 transactions of a ten-day period.

Qadrei and Habib (2009), formulated the ATM deployment problem as an optimization problem and they tried to minimize deployment and operational costs subject to the customers' satisfaction and the bank's requirements and they proposed a Genetic Algorithm (GA) to search possible placement of ATMs.

Alhaffa et al. (2011), presented a Rank Based Genetic Algorithm using convolution (RGAC) for ATMs location problem. Their study is the only one, which considers different types of ATMs and the maximum number of ATMs to be deployed per location in our knowledge.

Rahmati et al. (2014), developed a bi-objective model for facility location-allocation (BOFLA) problem with immobile servers and stochastic demand, which is related to ATMs. Since it is a NP-Hard class problem they employed two algorithms; non-dominated sorted genetic algorithm (NSGA-II) and non-dominated ranked genetic algorithm (NRGA), respectively.

Erol Genevois et al. (2015), focused on ATM location selection problem, and throughout a deep literature survey, they determined the relevant criteria for deployment problem. They clustered criteria and considering the interrelationship among them, employed Analytic Network Process (ANP) to detect importance level of criteria and built a general framework for further researches.

Bilginol et al. (2015), approached to the ATM location selection problem, by canonical correlation analysis to determine the criteria affecting the ATM site selection decisions, and ordinary least square analysis to analyze results, and find the optimum ATM location and their predictive efficiencies. They choose a sample bank located in Istanbul, and predicted the ATM transactions using linear regression based on residents, social media, POI and competitor figures, using the geographical data.

Zupanovic et al. (2015), tried to determine the customer behavior toward using ATM by the technology acceptance model. They employed Analytic Hierarchy Process (AHP) model for ranking the location criteria of an ATM. They categorized the criteria as technical, socioeconomic and competition, and provided all the subcriteria, with their explanations. They conducted a real-world application in their study.

Celik Turkoglu and Erol Genevois (2017), identified seventeen criteria and clustered them into five groups for ATM deployment problem, then collaborating with experts they obtained the interrelationship between the factors and throughout the fuzzy ANP process, they obtained the weights and rankings of them.

Celik Turkoglu et al. (2018), proposed an integrated approach combining Analytic Network Process (ANP) and Goal Programming (GP) model for determining the required number of ATMs and their locations, in a real case study. They tested their model under different approaches, and compared the results.

Adane et al. (2021), evaluated the determinants of ATM deployment in commercial banks of Ethiopia. They employed descriptive statistics and econometric regression model to analyze data and they used random effect model to fit the data.

Goker and Dursun (2021), proposed an MCDM approach for locating ATMs, in Turkish banking sector. They employed ELECTRE II and PROMETHEE II for the case study and identified three sustainable concepts.

As can be observed from this section, although the extensive location selection literature, the studies on the ATM deployment problem are still limited. Starting with 2008, it has been only a decade and main studies that are concentrated on the ATM deployment problem, employs different methods, yet most of the studies utilize genetic algorithm-based models, while there are some articles that consider the multicriteria and multiobjective nature of the ATM deployment problem.

2.2. ATM REPLENISHMENT PROBLEM

Another important part of the ATM business consisted of the inventory level control and the armoured vehicle routing problem (VRP). Therefore, minimizing the total rented armoured vehicles and reducing the total traveled distance are essential in the ATM management process. In the literature there are several articles that are mainly focusing on this problem.

Miranda and Munoz (2005), built a simulation-based decision support system (DSS) that considers both regular and emergency orders of ATMs in inventory control management. The DSS requires the data namely; capacity, costs, forecasts of demand and customer arrivals, capacity and returns reorder point, periodic reorder point, reorder size and lot size.

Castro (2009), focused on cash management in ATMs, obtaining discrete probability distribution of cash demand and applying three stochastic programming models to the two short-term and one mid-term problem respectively. The short-term model with fixed costs is solved by an Integer Problem, while the short-term model with fixed and staircase costs is solved by Mixed Integer Linear Programming (MILP) equivalent deterministic formulation. The mid-term model with fixed and staircase costs of the nature multi-stage stochastic problem is solved by its MILP deterministic equivalent.

Armenise et al. (2010), applied genetic algorithms (GA) for looking out optimal ATM replenishment strategies which minimize the cash stock and assure cash dispensing service. They experimented 30 ATMs of Poste Italiane S.p.A. in different cities, location types, cash capacity and transaction volume, and differently from the literature, their approach is not based on forecast of cash demand, but on conditions. They

employed Extended Chromosome (EC) and Compact Chromosome (CC), and reached a lower average of daily cash stock than company does by human interactions.

Silva and Raposo (2010), investigated the joint replenishment problem of an ATM network. They proposed an economic inventory management problem to detect the ideal replenishment frequency of each ATM, and conducted a case study in Portugal ATMs.

Gubar et al. (2011) employed modified algorithms for Vehicle Routing Problem (VRP) and statistical methods to optimize cash flow in case of the encashment process in the ATM network with prediction of ATM refusal. The main factors considered in this study are ATM location and opening hours, irregular number of operations per week and increasing of operation number in holidays and salary days.

Armenise et al. (2012), employed GA, EC and CC for optimizing cash management of an Italian Bank. They realized eight experiments on two years data of 30 ATMs in different location, capacity and usage features, from which 20 ATMs are used as training set, and the remaining ten ATMs are used as testing set. Comparing to bank existent strategy, they succeeded to lower residual stock, and eliminating the cash-out days in individual ATM, clustered ATMs and whole network problem.

Anbuudayasankar et al. (2012), were interested in ATM replenishment problem, and developed three heuristics to solve bi-objective vehicle routing problems with forced backhauls, namely minimizing the total routing cost and minimizing the span of travel tour. They applied, the models to standard data sets of vehicle routing problems (VRPB), and generated datasets, and resulted that the third model which is based on genetic algorithm (GA) yields to better results.

Yan et al. (2012), focused on the security of the Cash in Transit (CIT) problem which is directly related to ATMs. They formulated the potential movements of vehicles, and incorporated similarity of time and space for routing and scheduling concept into the problem, constructing an integer multiple-commodity network problem which is solved by decomposition/collapsing technique.

Capkovic (2012), modelled the ATMs by means of place/transition Petri nets (PNs). In their approach they pointed out travelling salesmans problem by means of PNs, and solved the money replenishment problem of an ATM network, founding the shortest path of the cash in transit.

Kurdel and Sebestyénova (2012) employed GA to deal with rich vehicle routing problem for generating periodic routes for each day reducing cash-related cost without run-out situation. Their results showed that some ATMs may need two replenishments in a day, while some others may be filled every two days.

Van Anholt and Vis (2012), designed a performance measuremet system for the ATM inventory management problem and conducted several simulations for demonstrating the improvement on the costs and service. They also employed data of a commercial bank, and with the conducted sensitivity analysis, resulted with higher fill rates and cost reduction in the same time.

Zelenka et al. (2012), addressed the cash deployment problem for an ATM network, combining as the exact approach, All Nearest Neighbors (ANN) method with Near Neighbor cSearch (NNS) supported by the Brute-Force Method or the Cross Removal Method (CRN) and as the heuristic approach Ant Colony Optimization algorithm.

Ghodrati et al. (2013), approached to ATM replenishment problem as a traditional inventory problem and used simulation for determining the required cash amount. They categorized ATM based on their average daily transactions, and throughout a conducted survey, they suggested different replenishment strategies for different banks and ATM types, employing a GA based model.

Scholtz et al. (2013), approached the ATMs cash management problem as a multi-objective optimization model, and they integrated the VRP, continuous review policy of inventory management, the knapsack problem and stochastic discrete-event simulation. They conducted a case study in South Africa with 90 different scenarios, and highlighted the importance of VRP methods on cost saving.

Broda et al. (2013), prepared a report for optimization of ATMs replenishment, with a Serbia Bank, considering yearly data of 40 ATMs. Their study is based on time series analysis and regression models, and they incorporated three costs into formulation; replenishment cost, insurance cost and opportunity cost.

Someya (2014), in her technical review, defined the cash replenishment planning as a formulation of an optimized plan to maintain adequate amount of cash in ATMs by monitoring the amount of remaining cash, forecasting future demand and appropriately timing replenishment. She overviewed the cash replenishment planning service, explained the steps of them, and showed some figures validating her approach.

Ekinci et al. (2015), have been the first-ones who are employed their forecast results for the replenishment decisions of the ATMs. They included location and time dependent variables in the forecasting models. Basically, they aggregated data of the closer ATMs, considering them as a cluster. They employed their forecast model on two and half year's withdrawal data of 152 ATMs located in Istanbul, attaining an average Mean Absolute Percentage Error (MAPE) of 20%. Then they calculated related replenishment policy cost both with the actual ATM, clustered ATMs and individual ATMs data, and concluded that a clustered ATM approach yields to better results.

Talarico et al. (2015), introduced a risk constraint to the capacitated VRP for Cash in Transit (CIT) sector. They developed constructive heuristics and local search block of local search operators and combined them with multistart heuristic and a perturband-improve structure for obtaining worthy results in a significant computation time.

van Anholt et al. (2016), formulated the ATM replenishment problem as a mixed-integer linear programming (MILP) problem, and developed an exact Branch-and-Cut (B&C) algorithm. They proposed a flexible clustering heuristic, for reducing the size of the problem, and applied their model to a real data set of 6377 ATMs of Netherland, obtaining good upper and lower bounds which may yield to important cost savings.

Diao et al. (2016), proposed an optimization framework for managing the ATM cash flow management, including interactions among various constraints and cost factors into their model. They demonstrated the effectiveness of their cash refill amount of schedule proposal, by employing a sample data of a commercial bank.

Agoston et al. (2016), outlined that the replenishment problem for banks and the third-party cash suppliers, should be optimized as a whole. In their study, they determined possible Pareto-improvement re-contracting schemes for joint cash management strategies based on a Baumol-type cash demand forecast.

Bati and Gozupek (2017), aimed to optimize the cash related costs of an ATM network, by formulating a linear program that jointly decides ATM visit time, delivered cash amount and the road that should be followed. They proposed also polynomial-time heuristic algorithm and compared it with the results of the optimization model.

Larrain et al. (2017), solved an ATM management and replenishment problem in Chile, with cassettes of predefined cash amount size, and stockouts. They took information of a random sample of 60 locations, including geographical data, period-related replenishment restrictions, number of ATMs, expected daily demand distributed to three daily shifts, namely, morning, afternoon and night and employed a variable mixed-integer programming neighborhood search (VMND) to the inventory-routing problem (IRP). They compared their results with B&C algorithm, and obtained a significantly reduced computational time and improved lower bounds.

Serengil and Ozpinar (2019) proposed an algorithm that tries to find optimum loading days of 41 Turkish ATMs. They considered out of service time, time pay for employees and transportation expenses in the algorithm and used fixed logistic costs.

Ekinici et al. (2021) tried to find an optimal ATM replenishment policy for 98 ATMs located in Istanbul. They focused on weekly demand of ATMs, and adapted a location related clustering approach. They gave the replenishment costs under alternative dissatisfaction rates (cash-out situation).

Kiyaei and Kiaee (2021) employed Double Deep Q-Network (DQN) algorithm to reduce replenishment costs of two ATMs of NN5 series. Their cash replenishment planning (CRP) system target decreasing ATM downtime without increasing operational costs.

Chiussi et al. (2022) introduced a vehicle tour problem (VTP) with minimum coverage requirements for seven Netherland cities with 338 ATMs. Their proposed metaheuristic showed that population coverage significantly increases the replenishment costs.

Tang et al. (2022) combined GA, PSO and Simulated Annealing (SA) for the ATM replenishment problem as banknote addition planning model of 72 Chinese ATMs. They evaluated their model with total cost, number of shortages, number of full banknotes and usage rates.

Studies concentrating on the ATM replenishment problem, dates back to 2005, and continue to arise in the literature. Especially after 2012, the studies on this specific topic are intensified, and protect its contemporary nature with the recent researches. In general, academics tried to approach this problem by vehicle routing problem tools and network optimization, by classifying and clustering the existing ATMs. Some papers, also integrated their demand forecast results with the replenishment problem investigations.

2.3. ATM RELATED PROBLEM

In the literature, there exist some articles that are not interested in the cash management process of the ATMs, but instead of this, they try to find effects of the ATMs in the economy, and the bank performance. Some of them are provided below.

Zilberfarb (1989), studied the effect of the ATMs on demand deposits, using an empirical Israeli data, constructing a theoretical model, including monthly averages of real demand deposits and explanatory variable, namely; macroeconomic indicators such as GNP, GNPPC and index of industrial production, opportunity cost (interest rate), and the intensity of ATMs usage.

McAndrews (1991), presented a paper about the evolution of shared ATM Networks, providing a glossary about ATM terminology, discussing the abilities of shared networks, advantages and main risks.

Prager (2001), investigated the effects of ATM surcharges (usage fees) which started in 1996 by the Cirrus and Plus national ATM networks, on small banking organizations deposit market shares and profitability by experimentally comparing different banks.

McAndrews (2003) reviewed the ATM network pricing literature such as wholesale fees (switch fees and interchange fees) and retail fees (usage fees and surcharge fees), involving three main participants; card holders, cardholder's bank and ATM owner. He concluded that prices directly affect the number of ATMs that banks deploy, and related with deposit interest rate, distances traveled by depositors and non-depositors, profit of banks and welfare of bank clients.

Bjorndal et al. (2004), presented a cooperative game with transferable utility, for a group of banks that consider to connect their ATMs. In the first place, they divided game into two parts, namely, single location games with single bank and multiple banks in the location, and two allocations games; aggregation allocations and transaction-based allocation.

Rajamani et al. (2005), built a framework to analyze cash supply chains as a closed-loop, describing also the cash flow management system that utilized by financial institutions of the United States and discussing the effects of the FED policies on cash supply chain.

Dilijonas and Bastina (2007) presented an approach to cash management and support system for ATM network based on agent-oriented technologies, analyzing optimization scopes if electronic systems involved in retail banking. They mentioned nineteen different roles in ATM network service, and influencers of optimization process.

Takala and Viren (2007) investigated the impact of ATMs on the use of cash scrutinizing using European data. Their research shows that the distribution of cash has

been moving from bank branches into ATMs and demand for cash continues to growing. They also indicated that anonymity, speed and security are crucial factors examining the future of the cash usage.

Snellman and Viren (2009), studied the relationship between ATM networks and cash usage. They tested the data of 20 Organization for Economic Co-operation and Development (OECD) countries over 1984-2003, and concluded that number of ATMs depends on competitiveness in the banking sector and is highly related to the population density.

Yarlikas (2009), proposed a new ATM interface design, analyzing three existing ATM types of different banks operating in Turkey. He conducted a transaction performance analysis and a questionnaire collaborating with 30 experts, for determining the strong parts of the existing ATMs and merged these proprieties in the features of the new proposed ATM.

Ou et al. (2009), realized an empirical evaluation in Taiwan, researching the impact of the ATM intensity on the cost efficiency. They employed actual ATM numbers, bank operating and financial data to measure the extent of ATM investment, concluding that ATM investments are associated with the positive cost efficiency.

Paik and Subramanian (2009), presented a protocol designed to provide ATM services to the world's rural poor and described strategies to reduce the microdeposits costs of ATMs. They employed a simulation of ATM usage patterns and distributions and obtained successful results in cost optimization without compromising customer satisfaction.

Kondo (2010), investigated the role of ATMs on bank profitability in Japan. He concluded that although ATMs do not have any significant effect on Return on Asset (RoA), showed positive impacts on profitability between 2000 and 2003 thanks to fees and commissions and interest income.

Thodenius et al. (2011), described the first ten years progress of the Swedish ATMs, which was the one of the pionner countries in ATM usage, starting from 1967. They explored the first steps in the emergence of self-service technology in banking, concentrating mainly on the saving bankings, researching technology and corporate strategies in their socio-historical context. They defined ATM technology as the modernization process in the saving banks thanks to the intense competiton and rising transaction costs.

Ling et al. (2011), investigated effects of the upper and lower withdrawals limits on ATM queue length. They concluded that increasing ATM withdrawal limit shorten the queue. As far as it is known, this is the unique study in the literature, considered the withdrawal limit as a determinant factor to cluster ATMs or forecasting variable.

Kamfiroozie and Ahmadzadeh (2011), focused on the efficiency and simplicity of the ATM usage. They defended that customization on the ATM screen, employing customer information and records of activities may yield for customers to a better ATM usage satisfaction.

Hamidi et al. (2012), argued that the long queue in front of the ATMs results with client dissatisfaction and proposed a linear approximation for non linear queuing model that try to minimizes customer waiting time and percentage of idle time for ATM. They presented their goal programming model results under 13 different data set, yielding to a more optimized and computationally more effective solutions comparing with the non-linear model suggested by Passandieh and Niaki (2010).

Kumar et al. (2012), focused to propose a concept of Virtual Pre-Transaction (VPT) via smartphones, for reducing the service time of an ATM that yields to a reduction in queue time and queue length and they provided an experimental analysis on that.

Mahmood and Shaikh (2013), focused on minimizing ATM usage time, for reducing the queue length and waiting time of the customers. Analyzing the transaction data set of an

international bank, they proposed different adaptive ATM interfaces, and they implemented their results to an actual bank ATM network.

Carbó-Valverde and Rodríguez-Fernández (2014), investigated the determinants of debit card transaction volumes at ATM and PoS, and explored the relationship between them and impact on the demand currency. They detected that, ATM and PoS transactions have opposite effects and have large economic impact one on another.

Madhavi et al. (2014) addressed the downtime problem in the ATM management via a predictive data mining tool called Weka. They described predictive analysis as extracting information from database for predicting trends and behavior patterns of the system.

Narteh (2015), examined the dimensions of ATM service quality and their relationship with customer satisfaction in the retail banking sector by a structured questionnaire collected from the literature, founding the convenience, reliability, ease of use, privacy and security, responsiveness and fulfillment as the major priorities of a perceived ATM service quality.

Sathye and Sathye (2017), employed bootstrap Data Envelopment Analysis (DEA), to investigate the impact of the ATMs, on the bank's performance efficiency besides the factors such as ownership, soundness, size and risk. They found that, in India, oppositely to the developed countries, ATM intensity had a negative impact on the technical efficiency.

Hasheminejad and Reisjafari (2017), discussed ATM management related problems such as forecasting cash demand, fraud detection, ATM failure, user interface and replenishment strategy. They also reviewed the use of the Artificial Intelligence techniques on the ATM management topic, providing comparisons and all the relevant available data set for further researches.

Cedolin and Genevois (2019), employed Data Envelopment Analysis (DEA) in order to measure the the performances of the ATMs, employing metrics like paid comission, comission revenue, client and total transaction numbers.

Ilagan et al. (2019), proposed a scheduling model for the maintenance of the ATMs that maximizes the working time. Their proposed model proposed considered assumptions for constraints regarding the operating hours of armored vehicles, proactive service, service warranty, and replenishment.

Ogata et al. (2019), proposed a security measure based on secure peripheral devices. The secure dispenser verifies the authenticity of a received dispensing command with the transaction evidence.

Velivassaki et al. (2019), presented an ATM cash management system application named as “uCash”, which identify both expected and unexpected changes in external factors affecting ATM cash withdrawals.

Ogata et al. (2020), proposed a security measure employing peripheral devices in an ATM to prevent “unauthorized cash wihdrawals” of logical attacks. The measure protects multiple transaction sub-process in a deposit transaction and harmonizes with existing system and operations.

Balakrishnan and Kalaierasi (2021), reviewed the ATM cash forecasting studies. They classified literature over the employed method, and presented studies with additional key notes.

Reddy et al. (2021), presented a protection framework for ATM robbery that analyzes the different phsyical assaults on ATMs using a wireless sensor network along with tilt and vibration sensors.

Thirumoorthy et al. (2021), outlined the importance of security of ATMs. They embedded a system in the machines taht uses Internet of Things (IoT) to report the damage directly to the authorities.

Excluding the first two studies, it can be said that ATM literature has been growing approximately since a decade, and from the progress, the researches will continue to create solutions for different segments of the ATM cash management problems.

2.4. ATM FORECASTING PROBLEM

Most of the ATM management research studies, are concentrated on the forecasting studies. Being in a highly dynamic stochastic demand environment, an accurate forecasting model would yield to better inventory levels and replenishment policies. Clearly, being of a point of service (PoS) location, all transactions that are realized in the ATMs, provides large amount of data (in general online feedback), that includes time window, client details, withdrawal or deposit amount etc. Therefore, ATM management becomes a subject of the big data analytics. In the literature, we can conclude that the main part of the ATM management studies is concentrated in this specific area, applying different techniques such as genetic algorithms, regression models, simulation techniques or neural networks structures.

Kumar and Walia (2006) presented two neural network model (daily and weekly) addressing to cash forecasting problem of a bank branch. In addition, they classified existing cash forecasting approaches into four categories, namely; time series method, factor analysis method, expert systems approach and neural networks approach.

Simutis et al. (2007), employed Artificial Neural Network (ANN) to forecast daily cash demand of 1225 ATMs, simulated by integrating weekly and monthly seasonality along with long-term trends over two years, and proposed an optimization procedure to estimate optimal cash load for each ATM, considering cost of cash, uploading cost and daily services costs. They evaluated their models under two scenarios with different interest rates and uploading costs and resulted with an error of less than 10%.

Simutis et al. (2008), used a flexible Artificial Neural Network (ANN) with a special adaptive regularization term, obtained by cross-validation technique, and Support Vector Regression (SVR) algorithm for testing forecasting accuracy of simulated data and experimental data of real 15 ATMs over two years. They estimated MAPE of daily cash demand forecasting for 50 following days, and obtained results ranging between 15-28% for the first model and 17-40% for the SVR model.

Laukaitis (2008), proposed a linear wavelet model, to predict cash flow and intensity of transactions in ATMs, by using data of Lithuania cards payment market data belonging to November 2013 – March 2014. His study aimed to analyze data functionally without losing its ultra-high frequency nature, and used Ex-poste prediction to check the validity of continuous-time stochastic process models, by Hilbert-valued autoregressive process.

Brentnall et al. (2008), developed a statistical model called as random-effects point process model, for estimating the ATMs withdrawal times. Their study is based on the four months transactions of 1000 accounts of a UK Bank, observing the data they found out variation in overall rate, cyclical pattern, constant long-term rate of withdrawal and consecutive withdrawals in quick succession. Their model provided promising results for predicting customers' behaviors individually.

Zapranis and Alexandridis (2009), employed aimed to describe describe a unique non supervising method for the NN5 data set competition. They used wavelet analysis to extract the dynamics of the process and used wavelet NN, for a forecasting horizon of 56 days.

Brentnall et al. (2010a), developed a predictive-sequential forecasting system for cash machine stocking, preferring density forecasts over point forecasts, and considering seasonal structure, first-order autocorrelation and cash-out days of data taken from 190 ATMs of UK over two years. They compared linear models, autoregressive models, structural time series models and Markov-switching models, taking as error measure logarithmic score and continuous ranked probability score (CRPS), and resulted that the appropriate model should be chosen for each ATM.

Brentnall et al. (2010b), tried to predict individual withdrawal amount on a single ATM visit, using data of the 5000 UK high-street bank accounts over a four-month period. They employed a multinomial model with Dirichlet distribution to model random effects and empirical distribution of individual maximum likelihood fits.

Garcia-Pedrero and Gomez-Gil (2010), inspired from hybrid complex NN model, and using the information obtained by wavelet decomposition, they predicted the reduced NN5 series with a SMAPE score of 27%.

Paul (2010), studied the data of the two comercial banks, for understanding the cash flow between bank and ATM, in order to confirm an optimum utilization of cash without causing a stock-out position. They argued that the main drivers of the ATM demand are location of the ATM, number of current and salary accounts and seasonal factors.

Rodrigues and Esteves (2010) analyzed calendar effects in daily ATM withdrawals, and outlined the importance of adjusting data for seasonality and working day effects. In their study, the number of working days and seasonal effects are strongly correlated, apart from that the day of the week, the week of the month, public and religious holidays, paydays are other factors that affect time series, and must be considered as anomalies related to the date.

VanAnholt and Vis (2010) presented an integrative analytical online forecasting and replenishment model targeting a predefined fill rate for ATMs, and calculated efficient ordering quantities and moments. They realized a trade-off between ordering cost (preparation, sorting cash, transportation and replenishment costs), and inventory holding cost which is missed interest rate of the inventory. The model characteristics are hourly demand with a trend overlay, variable lead times, capacitated inventory and real time track of ATM inventory. They compared their decomposition forecasting model with ANN, via numerical simulation experiments and demonstrated that proposed model yield to better solution unders different circumstances.

Ramirez and Acuna (2011), employed two dynamic models, namely, Nonlinear Autoregressive Exogeneous inputs (NARX) and Nonlinear Autoregressive Moving Average with Exogeneous Inputs (NARMAX) performed by Neural Networks (NN) and Least Square Support Vector Machine (LS-SVM) to forecast daily ATM cash demand, using NN5 competition data set and compared the results of the two models.

Teddy and Ng (2011), proposed a pseudo self-evolving cerebellar model articulation controller (PSECMAC) model to forecast ATM cash demand. They employed the model on NN5 competition dataset of 111 empirical daily ATM cash withdrawal series, firstly data preprocessing and then employing Monte Carlo Evaluation Selection (MCES) technique for feature selection. They provided results of both one-steps ahead prediction and recurrent prediction, using as error measure the Symmetric Mean Absolute Percent Error (SMAPE), and reached an average SMAPE of 27.25% and 27.60%, respectively, which outperforms the other global and local learning models.

Andrawis et al. (2011), selected nine final models among 140 preprocessing combinations, and combined them to forecast ATMs demand of NN5 competition data set. The employed models are namely; standard multilayer neural network, Gaussian process regression, Echo state network, Echo state network ensemble, ARMA, AR, multiple regression, Holt's exponential smoothing and simple moving average. They firstly performed a time aggregation, and converted the time series from daily to weekly, then they practiced a seasonality analysis, and applied median-based deseasonalization method. They obtained SMAPE errors ranging between 18.94% and 23.77% with a combined value of 18.95% which procured the championship in NN5 competition among the computational intelligence models and second prize among both statistical benchmarks and computational intelligence models.

Atsalaki et al. (2011), employed Neural Networks models with different parameters such as alternative inputs (one to five) and hidden layers (one to ten), to forecast 100 ATMs daily cash withdrawal. They feed the network with a time series of 735 day (two years), and calculated the root mean square error (RMSE) for each ATM, obtaining the lowest score as 4.69.

Wichard et al. (2011), combined alternative forecasting method by taking weighted average of the forecast. They used this hybrid model on the NN5 data set with seven-day cycle, one-year cycle and Easter correction, and obtained SMAPE results around 21%.

Acuna et al. (2012), realized a comparative study between nonlinear autoregressive (NARX) and nonlinear autoregressive with exogenous variables (NARX) models, employing Artificial Neural Networks (ANN) and Support Vector Machine (SVM) for classification and regression in order to forecast 30 ATMs withdrawal series of the NN5 competition data set. They employed index of agreement (IA) of Willmott (1981) as the performance indices, and reached similar results for both models that ranging between 0.7 and 0.95.

Cardona and Moreno (2012), presented a two-step model that aims to reduce cash management costs of a bank branch. They employed ARMA-ARCH model with a neural network (a data mining technique), for forecasting daily cash demand, and then solved a linear programming model for the optimal allocation of the results.

Gurgul and Suder (2013), examined the daily withdrawals of 293 ATMs in Poland, considering location of them, such as bank branch, shopping center, gas station. They employed ARIMA and SARIMA models with seasonal dummies into data set, and obtained a MAPE of 17%. The main diversity of their model, is to consider seasonality as stochastic nature and not deterministic.

Darwish (2013), employed an Interval Type-2 Fuzzy Neural Network (IT2FNN) with an online structure and parameter learning abilities to forecast 25 ATMs demand in a simulated environment. In his study, he reached a mean forecast error (MFE) of 6.57% and withdrawal forecast accuracy of 97.72% per week, which is highest of the literature, still not really comparable with other studies who employs different data sets, and perform weekly forecasts, which is obviously easy than daily-one.

Wagner (2013), concentrated competing techniques of daily cash demand in supply chains. He proposed a joint forecasting approach, namely, vector time series and SARIMA, using MAPE for European banks.

Arora et al. (2014) proposed a fuzzy ARTMAP methodology for predicting the ATM cash requirement. They selected parameters employing mutual information algorithm, and conducted a sensitivity analysis, revealing that training size is important while number of input parameters does not change the ultimate results.

Zandevakili and Javanmard (2014) in order to deal with the cash management optimization in ATMs, focused on forecasting cash demand at specific time intervals as daily, weekly or monthly, and examined the papers that dealt with this problem using soft computing techniques like fuzzy logic and neural networks.

Kamini et al. (2014), employed ARIMA, MLP, WNN, GRNN to forecast NN5 data et. They, then reconstructed the phase space using chaotic parameters, embedding dimension and delay time, and resulted with a SMAPE of 14.71%.

Venkatesh et al. (2014), concentrated on similar day-of-the week cash demand pattern of ATMs to cluster them, in order to realize a group forecast. They built a time series model for each ATM, discretized the seven continuous daily withdrawal seasonality parameters, and measured it by sequence alignment method (SAM). Then, via four different neural network models, namely; general regression neural network (GRNN), multi-layer feed forward neural network (MLFF), group method of data handling (GMDH) and wavelet neural network (WNN), estimated the cash demand of ATM centers of NN5 competition dataset. The obtained SMAPEs for all models ranged between 18.44% and 21.10% which is promising, and among the best results in the literature.

Catal et al. (2015), advocated the the enhancement of the data set in order to improve accuracy. They preprocessed the NN5 data set and using exponential smoothing model reached an average SMAPE score of 21.57%.

Nemeshaev and Tsyganov (2016), focused on pre-processing data in time series forecasting. They selected a NN architecture, and reached an average MAPE score of 32% for Russian ATMs.

Khanarsa and Sinapiromsaran (2017), used multiple ARIMA subsequences, SARIMA and exponential smoothing model in order to increase forecasting accuracy on the ATM cash demand problem of NN5 data set.

Rajwani et al. (2017), employed two years transaction record data set of an ATM network in order to forecast the cash demand. They presented their results obtained by regression, and showed the ability of the model both for increasing the customer satisfaction and cost efficiency.

Perera et al. (2018), tried to find most suitable forecasting technique for Sri Lankan ATMs. They tried regression and time series analysis technique, and selected ARIMA as the best operating model.

Jadwal et al. (2019), dealt with NN5 cash demand problem using NN, but for individual ATMs and clustered ATMs. They employed RMSE as the error metric which is difficult to compare the efficiency of the proposed algorithm with the existing literature on the same data set.

Arabani and Komleh (2019), employed DNN to predict cash demand of 1056 ATMs in Iran. They obtained a RMSE of 7.45% for test data (RMSE should not be in percentage, the authors misinterpreted the results).

Asad et al. (2020), employed DNN and LSTM to predict replenishment amount of 2241 Pakistans' ATMs. They clustered their ATMs in nine groups and showed the results for high demand cluster in RMSE.

Rafi et al. (2020), built a Vector Auto Regressive Moving Average with Exogenous Variable model (VAR-MAX) for seven ATMs located in Pakistan. They employed RMSE and SMAPE metrics and compared their results with Rajvani (2018).

Vangala and Vandalani (2020), employed nine alternative forecasting models to forecast cash demand of 40 Indian ATMs including DNN. The average SMAPE score obtained in the study is 23.69%.

Cedolin and Genevois (2021), reviewed and classified articles on ATM forecasting problem, and outlined the important aspect of the problem. They also, compared the error metrics and results of the alternative approach on the same data set.

Cedolin and Genevois (2021), built aggregated time series employing NN5 data, and proposed a decision framework, where ARIMA and SARIMA results of the aggregated series may be used on the individual ATMs forecasting problem.

Gorodetskaya et al. (2021), developed a scenario for solving specific banking tasks to optimize demand for ATMs. Their proposed machine learning pipeline, aims to help researchers that deal with forecasting econometric time series.

Fallahtafi et al. (2022), categorized ATMs on the accessibility and surrounding environmental factors. Then, they employed several statistical and machine learning models to accurately forecast the ATM cash demand before and during COVID-19.

Thanks to the technological development of the computer's components, and reduced computational time, the use of the artificial intelligence methods and models gain importance in the literature. This progress also reflected to the ATM cash demand forecasting studies commencing with 2007. In general studies preferred to employ different learning models and neural network structures to forecast the stochastic demand, considering different error measures. As can be observed from the part above, the NN5 competition data set helped researchers to develop and improve their methodologies, and provided a comparison platform.

2.5. CLASSIFICATION OF ATM FORECASTING LITERATURE

ATM cash forecasting literature, has been a trend research topic for ten years. In order to extend the survey, first it is cross checked the references of the existing studies than it is used additional keywords on Web of Science such as “Cash Management”, “Demand Forecasting” and “ATM Management”. 39 articles or proceeding papers that are related to the topic are found. The reviewed articles are enlisted in Table 2.1, and here upon will be referred with their reference numbers. Table 2.1 is in chronological order, including the author(s), year and title of the studies.



Table 2.1 ATM Forecasting Literature

Ref.	Author(s)	Year	Title
[1]	Kumar and Walia	2006	Cash Forecasting: An Application of ANN in Finance
[2]	Simutis et al.	2007	Optimization of Cash Management for ATM Network
[3]	Simutis et al.	2008	Cash Demand Forecasting for ATMs using NN and SVR Algorithms
[4]	Brentnall et al.	2008	A Statistical Model for the Temporal Pattern of Individuals ATM Withdrawals
[5]	Zapranis and Alexandridis	2009	Forecasting Cash Money Withdrawals Using Wavelet Analysis and Wavelet Neural Networks
[6]	Brentnall et al.	2010	Predicting the Amount Individuals at ATMs using REMM
[7]	Brentnall et al.	2010	Predictive-Sequential forecasting System Development for ATM Stocking
[8]	Garcia-Pedrero and Gomez-Gil	2010	Time Series Forecasting Using RNN and WRS
[9]	Paul and Mukherjee	2010	ATMs and Cash Demand Forecasting: A Study of Two Commercial Banks
[10]	Rodrigues and Esteves	2010	Calendar Effects in Daily ATM withdrawals
[11]	Van Anholt and Vis	2010	An Integrative Online ATM Forecasting Replenishment Model with A Target Fill Rate
[12]	Wichard et al.	2011	Forecasting the NN5 Time Series with Hybrid Models
[13]	Andrawis et al.	2011	Forecast Combinations of CI and Linear Models for the NN5 Time Series Competition
[14]	Atsalaki et al.	2011	Cash Withdrawals Forecasting by NN
[15]	Ramirez and Acuna	2011	Forecasting Cash Demand in ATM Using NN and Least Square SVM
[16]	Teddy and Ng	2011	Forecasting ATM Cash Demands Using PSECMAC
[17]	Dilijonas and Sakalauskas	2011	Self-Service Systems Performance Evaluation and Improvement Model
[18]	Acuna et al.	2012	Comparing NARX and NARMAX models using ANN and SVM for cash demand forecasting for ATMs
[19]	Darwish	2013	A Methodology to Improve Cash Demand Forecasting for ATM Network
[20]	Gurgul and Suder	2013	Modelling of Withdrawals from Selected ATMs of the "Euro net" Network
[21]	Wagner	2013	Forecasting Daily Demand in Cash Supply Chains
[22]	Arora et al.	2014	Approximating Methodology: Managing Cash in ATMs Using Fuzzy ARTMAP Network
[23]	Kamini and Ravi	2014	Chaotic TSA with NN to Forecast Cash Demand in ATMs
[24]	Venkatesh et al.	2014	Cash Demand Forecasting in ATMs by Clustering and NN
[25]	Catal et al.	2015	Improvement of Demand Forecasting Models with Special Days
[26]	Aseev et al.	2016	Forecasting Cash Withdrawals in the ATM Network Using a Combined Model based on the HWM and Markov Chains
[27]	Nemeshaev and Tsyganov	2016	Model of the Forecasting Cash Withdrawals in the ATM Network
[28]	Khanarsa and Sinapiromsaran	2017	Multiple ARIMA Subsequences Aggregate TSM to Forecast Cash in ATM
[29]	Rajwani et al.	2017	Regression Analysis for ATM Cash Flow Prediction

Table 2.1 continues

[30]	Perera and Hewage	2018	Determinants of ATM Loading Requirements in Sri Lankan Cash Supply Chains
[31]	Jadwal et al.	2019	K-Means Clustering with NN for ATM Cash Repository Prediction
[32]	Arabani and Komleh	2019	The Improvement of Forecasting ATMs Cash Demand of Iran Banking Network Using CNN
[33]	Asad et al.	2020	A LSTM Based Model for Predicting ATM Replenishment Amount
[34]	Rafi et al.	2020	ATM Cash Prediction Using Time Series Approach
[35]	Vangala and Vandalani	2020	ATM Cash Demand Forecasting in an Indian Bank with Chaos and Deep Learning
[36]	Cedolin and Erol Genevois	2021	An averaging approach to individual time series employing econometric models: a case study on NN5 data
[37]	Cedolin and Erol Genevois	2021	ATM'lerdeki Nakite Yönelik Talep Tahmini Üzerine SistematiK Yazın Analizi
[38]	Gorodetskaya et al.	2021	Forecasting Time Series in the Banking Sector Using a Machine Learning Pipeline
[39]	Fallahtafti et al.	2022	ATM cash demand before and during the COVID-19 using an extensive evaluation of statistical and ML models

The techniques and methodologies, employed data characteristics, the utilized error metrics, the inputs and outputs of the system, the source and the size of the data, the length of the forecasting horizon, the consideration of anomalies with the solution provided for these anomalies, the programs that are often utilized for solving the forecasting problems are some of the research focus of the study.

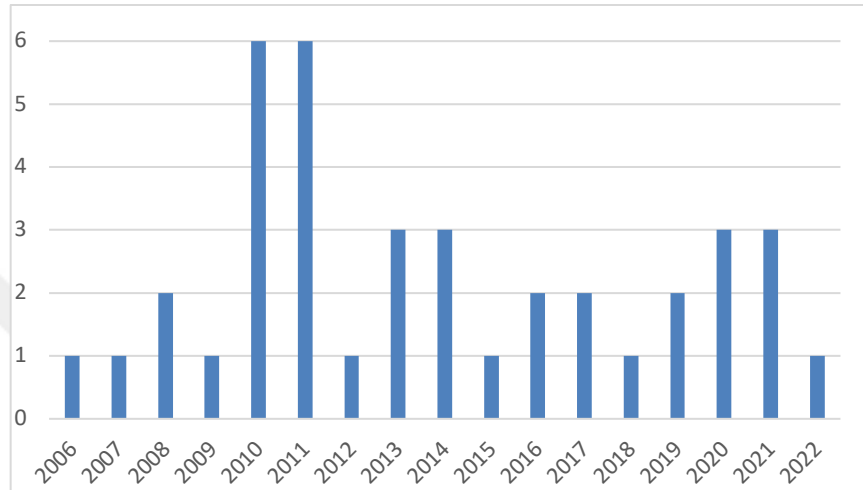


Figure 2.1 Yearly Distribution of ATM Cash Forecasting Studies

As can be observed from Figure 2.1 since 2006, the researchers continue to put their efforts on this specific topic. 2010 and 2011 are the most popular years, respectively, of this specific literature and that can be explained by the announcement of Neural Network Competition data set belonging to 111 ATMs of The United Kingdom, from here called as “NN5”.

In the literature there are many alternative methodologies that applied into forecasting problem. However, the ATM forecasting techniques can be dichotomized as Statistical Techniques and Artificial Intelligence Techniques. Another special category might be the hybrid approaches that not only compare the results of alternative techniques but apply them integrating. The main statistical techniques that are utilized in the literature are linear models such as ARMA, ARIMA, SARIMA, the regression models including different parameters, point process and interval search methodologies. Exponential Smoothing tool and correlation test are the other powerful statistical tools that are used. On the other hand, applied AI Techniques are general different neural network models

as convolutional NN, wavelet NN, general regression NN, recurrent NN and fuzzy NN. MASA and SVR are the other powerful tools that are employed in the research. The proportion of the techniques is as in the Figure 2.2.

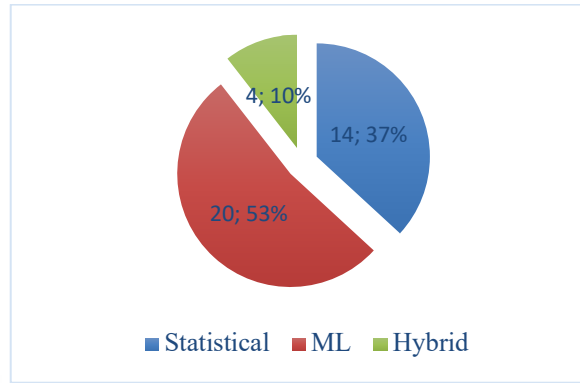


Figure 2.2 Technical Distribution of ATM Forecasting Studies

One can interpret the Figure 2.2 as the equilibrium between the statistical and ML techniques. However, such approach would be misleading considering the content of the selected articles. In most of these studies, the statistical techniques occupy a benchmark role for the proposed ML technique. In other words, the results of the statistical models are utilized for the comparison and are outperformed generally. The proportion of the hybrid articles can be taken into account as one of the further research directions of the literature concentrating to hybrid models which generally yield to better solutions.

The data properties of the selected articles are investigated in four major categories, namely; the source of the data, the data length, the output value or the forecasting horizon, and the ATM number where each ATM represents a single time series-model. Table 2.2 summarizes these characteristics.

Table 2.2 The Data Characteristics

Reference	Data Source	Data Length	Output	ATM Number
[1]	Bank of India	3 months	Daily / Weekly	1 Branch
[2]	Experimental	2 years	Next Day Demand	1225
[3]	Experimental	2 years	Next Day Demand	15
[4]	Experimental	4 months	Timing of Withdrawal	1000 accounts
[5]	NN5	2 years	56 Days Demand	11
[6]	Experimental	4 months	Amount of Withdrawal	5000 accounts
[7]	Experimental	2 years	ATM Scores	190
[8]	NN5	2 years	56 Days Demand	11
[9]	Bharath Bank	3 months	Monthly Demand	120
	Global Bank	monthly	Monthly Demand	33
[10]	Portugal Bank	7 years	Calendar Effects	1
[11]	Dutch Bank	1.5 years	4 Months	1
[12]	NN5	2 years	56 Days Demand	111
[13]	NN5	2 years	56 Days Demand	30
[14]	Experimental	2 years	110 Days Demand	100
[15]	NN5	2 years	100 Days Demand	30
[16]	NN5	2 years	56 Days Demand	30
[17]	India Bank	3 months	Weekly Demand	5500
	Lithuanian Bank	6 months	Weekly Demand	21
[18]	NN5	2 years	100 Days Demand	30
[19]	Experimental	1 year	Weekly Demand	25
[20]	Experimental	4 years	60 Days Demand	293
[21]	European Bank	759 days	28 Days Demand	20
[22]	X Bank	2 years	Next Day Demand	1
[23]	NN5	2 years	56 Days Demand	111
[24]	NN5	2 years	Weekly Demand	30
[25]	NN5	2 years	56 Days Demand	111
[26]	Ekaterinburg Bank	8 months	21 Days	11
[27]	Russian Bank	7 months	Weekly Demand	1
[28]	NN5	2 years	2 Years Fitting	111
[29]	Pakistan Bank	2.5 years	Transaction Amount	1
[30]	NN5	2 years	56 Days Demand	11
[31]	Iran Bank	1 year	73 Days	1056
[32]	Sri Lankan Bank	2 years	Monthly Demand	1
[33]	Pakistan Bank	22 months	Replenishment Amount	2241
[34]	Pakistan Bank	2.5 years	56 Days Demand	7
[35]	Indian Bank	2 years	Next Day Demand	100
[36]	NN5	2 years	56 Days Demand	11
[39]	Iran Bank	3 years	Monthly Demand	3

The NN5 competition data set is the main data source of the literature, followed by experimental (simulated) data. In general, financial institutions do not prefer to share their data, and this is one of the major problems that researcher encounter and mention in their articles. The simulation of the data is in general realized in special software's such as ARENA, Simulink or ROCKWELL Simulation. However, there are also some countries private banks that shared their transaction data with researchers, like Portugal, Germany, India, Pakistan, Russia etc. The data source types are depicted with their proportion in the following Figure 2.3.

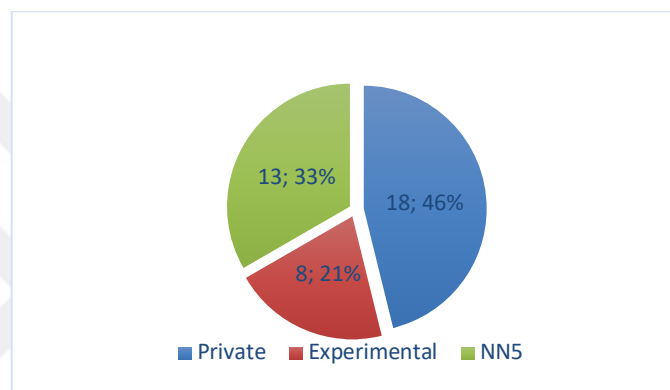


Figure 2.3 The Data Source Distribution

Figure 2.3 shows that 46% of the articles employed different private banks data set, while 33% of them employed NN5 competition data set. Eighth out 31 articles generated their data via simulation techniques. The main advantage of using real-data is having a time series including all the characteristics that are definable and undefinable. This cannot be generated via simulation techniques although an error-term can be included. However, comparing the forecasting accuracies of different time series can be interpreted as meaningless. Still, [9] and [17] employed transaction data of two different ATM Network. Therefore, the NN5 competition data set appears in most of the articles which includes two years of daily withdrawals of United Kingdom ATMs. The whole data set is consisted of 111 time series, while some of the researchers preferred to work with restricted version of the data set belonging to 11 ATMs.

The data length is also an important characteristic of the studies, while the data length increases, the chance of a better forecasting accuracy increases too. The minimum time

series length is three months [1] - [9] and [17], while the maximum length is seven years [9]. We categorized the data length column of the Table 2.2 as; up to two years, two years, and more than two years.

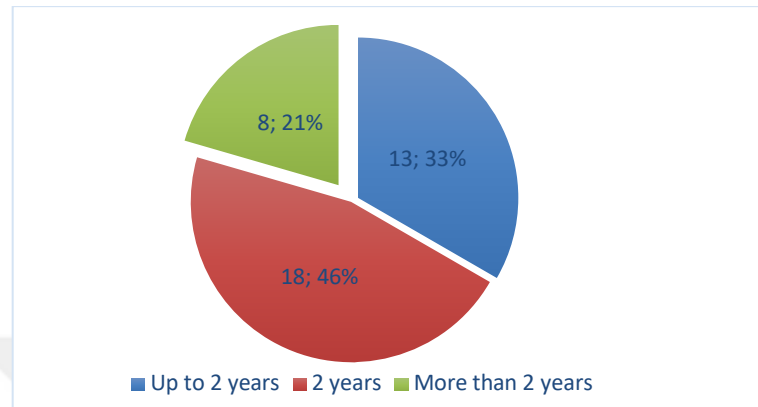


Figure 2.4 The Data Length Classification

In Figure 2.4, 8 articles based on a data length that is more than two years, the 46% of the papers uses two years' data, 13 studies utilize a data length that is less than two years like three months or four months. Considering the trend or seasonality components of the data the short-term based studies have some training drawbacks. For instance, many articles like [13], [17] or [19] outline the effect of the special calendar days on the withdrawal characteristic of the clients. When the training period does not contain this calendar days, miss a very valuable input to interpret for forecasting. Even more only the articles that have twice of these days, in other words, articles of two years' data length can make evidence of such an effect. Therefore, we strictly believe that for such a difficult forecasting task, the minimum requirement of data length should be two years as in the 67% of the related articles. Rodrigues and Esteves (2010), in their paper focused the seven years' data of a Portugal Bank, only to examine the correlation of the calendar days with daily withdrawal amount [10].

The forecasting horizon is another important characteristic of the studies. In principle, when the forecasting horizon increases the increase of the error term is expected. On the other hand, when the forecasting horizon shorten, the forecasting accuracy increase. However, the added-value of a meaningful range of forecasting cannot be denied. In addition, the literature about replenishment studies on the ATM, mention the excessive

costs of the armored vehicles of Cash in Transit (CIT), thus a daily replenishment of the ATMs is out of question.

The minimum forecasting horizon is the “next day” like in [2], [3] or [22], while the lengthiest horizon is four months [11]. The majority of the articles preferred septuplets like weekly demand, 28 days demand or 56 days demand considering the strongest seasonality index “day of the week”. [4] and [6] differ from other researches because they try to forecast timing of withdrawal of 1000 accounts and amount of withdrawal of 5000 accounts, respectively. Similarly, [29] tries to predict transaction amount of a single Pakistan Bank branch. Only the [1], focused on two different forecasting time horizon, namely daily and weekly, still their prediction model is for an Indian Bank Branch, but not on an ATM. [7] focus on trying the best working machine among 190 simulated ATMs, and its output is the ATM scores. [10] gives as output the correlation of the calendar effects with withdrawal series. The frequency of the forecasting horizon of the remaining articles is depicted in Figure 2.5.

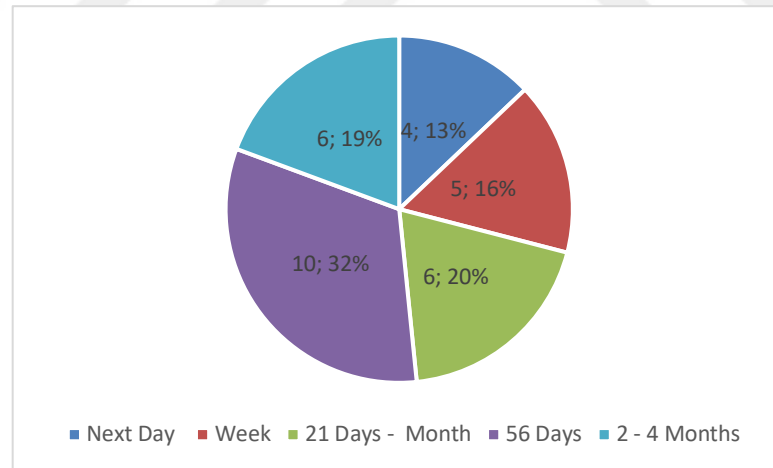


Figure 2.5 The Forecasting Horizon

In the Figure 2.5, the most preferred forecasting horizon is 56 days with 32%. Most of these articles employ NN5 competition data set, and compare their results, and as a base for comparison they necessitate the same length of forecasting horizon. The two months, 73 days, 100 days (2), 110 days and four months are consolidated in two - four months' category with 19%. Only four out 27 of the forecasting horizons is next day,

while weekly estimation models consist 16% of the studies. The percentage of forecasting horizon “21 days up to a month” is 20%.

The last category that is to be investigated about data properties on ATM cash management studies is the number of the time series. Each ATM stands for a single time series. While the study bases on a single ATM or a single bank branch, this the single time-series model. However, when the study employs data of alternative ATMs this is a multiple time-series model. The main difference of these two models is that the first-one does not have a comparison opportunity, their model can over fit to the selected ATM, still may be not working as well as on the other machines. When there are alternative machines, the much better, the model most provide satisfactory solution for all the time series, therefore a more difficult task occurred where the real-life problem is approached. In the articles where multiple time series taken into account, the average error term is given to indicate the model accuracy. A single time-series model would be only choosing the best fitting machine, and marketing it. In the following figure the ATM (time series) numbers are classified, the [1], [4] and [6] that employs one branch, 1000 accounts and 5000 accounts data, respectively, are excluded.

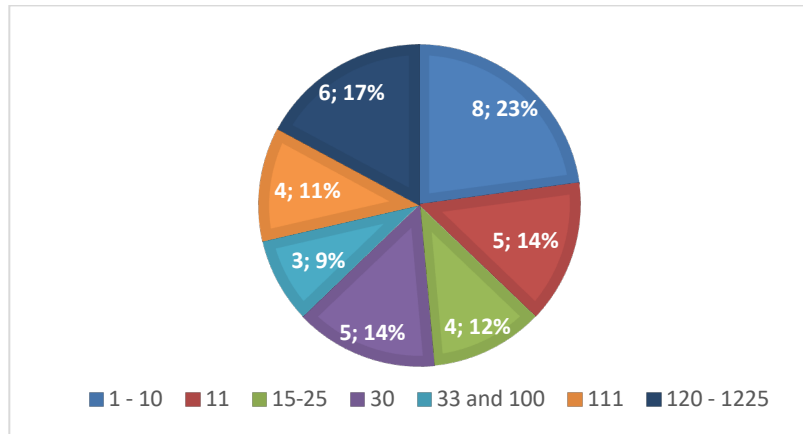


Figure 2.6 The ATM Number

As in Figure 2.6, the 11 ATMs are the restricted version of NN5, as of 30 ATMs. Only four articles dealt with the whole NN5 competition data set. The selection of optimum ATM number is out of question, because it is up to the data provider. However, in Figure 2.6, the importance of having at least 11 ATMs is outlined, in order to have better results with better models. In addition, classifying the ATMs, detecting the

similar characteristics, would be a plus. As far as we know, clustering ATMs in order to forecasting the cash demand is only taken into account by [24]. In other words, instead of developing the same model for each ATM, researchers can first classify the ATM groups, then build several models for each group testing their model robustness.

Another important review step, is the investigation of the specific methods, and the training algorithms that employed in the literature. In general, the articles employed alternative methods into same data set and compared results. In Table 2.3, these details including the utilized error measure with the average forecast accuracy can be found. The reading of abbreviation section is necessary to understand the Table 2.3.

Table 2.3 The Methodological Properties of the Literature and Accuracy

Ref.	Forecasting Technique(s)	Method Details	Training Method / Configuration	Error Measure	Average Error
[1]	AI	ANN	Hidden Layers (7-12)	MFE - weekly MFE - daily	6.32% 5.41%
[2]	AI	three-layer feed forward ANN	Levensberg-Marquardt	RMSE	10.00
[3]	AI	three-layer feed forward ANN SVR	Cross-Validation	MAPE	0.76% 4.10%
[4]	Statistical	Random-effects point process model		Kolmogorov-Smirnov Test	95.00%
[5]	AI	WNN ARMA	Differ for Each ATM	SMAPE	27.92% 33.20%
[6]	Statistical Point Forecast	Dirichlet and Empirical Distribution		MSE	
[7]	Statistical Density Forecast	Linear Models Autoregressive Models Structural Time Series Models Markov-Switching Models		Logarithmic Scoring CRPS	
[8]	AI	ANN	Feed-Forward Fully Recurrent RNN + WRS	SMAPE	12.40% 13.00% 8.30%
[9]	Statistical	Linear Models			
[10]	Statistical	Correlation Test			

Table 2.3 continues

[11]	Statistical	Decomposition (Modified Linear Regression)	Time Based Coefficients	MAPE	37.79%
	AI	ANN	Decomposition 1 Hidden Layer GDO		42.42%
[12]	Hybrid	Easter Correction			22.87%
		State Space Reconstruction and NTM			24.19%
		ANN	1 or 2 Hidden Layers Rprop Algorithm Cross Validation	SMAPE	25.61%
		Hybrid	Weighted Average		19.38%
[13]	Hybrid	GPR-ITER			19.90%
		GPR-DIR			21.20%
		GPR-LEV			20.20%
		NN-ITER		SMAPE	21.10%
		NN-LEV			19.80%
		MULT-REGR			19.00%
		MOV-AVG			19.50%
[14]	AI	ANN	5 input 7 hidden layers	RMSE best	4.69
				RMSE worst	14.60
[15]	AI	MLP	9 input - 4 hidden		22%
		LS-SVM	Cross-Validation	SMAPE & IA	27%
		RBF	9 input - auto hidden by runtime		26%
[16]	AI	PSECMAC	MCES		27%
			RreliefF	SMAPE	29%
			CFS		27.5%
[17]	AI	ANN	1 Hidden Layer	Performance Increase	24%
[18]	AI	NARX-ANN	9 input 4 hidden layers		20.05%
		NARMAX-ANN	10 input 4 hidden layers	SMAPE & IA	24.09%
		NARX-SVM	9 input 4 hidden layers		25.83%
		NARMAX-SVM	10 input 4 hidden layers		24%
[19]	AI	IT2FNN	4 layers	MFE	6.5%
[20]	Statistical	SARIMA	switch models	MAPE	16.71%

Table 2.3 continues

[21]	Statistical	SARIMA Vector Time Series	Box-Jenkins	MAPE	19.14% 20.50%
[22]	AI	fuzzy ARTMAP NN	NMI (best parameter selection)	MFE	5.10%
[23]	Statistical	ARIMA		SMAPE	27.76%
		MLFF			23.87%
	AI	WNN			23.33%
		GRNN			23.16%
[24]	AI	GRNN MLFF GMDH WNN	Clustering	SMAPE	18.44% 21.10% 20.32% 20.60%
[25]	Statistical	Exponential Smoothing	Special Days Integration	SMAPE	21.57%
[26]	Hybrid	AHW MCD MCW Hybrid	Trend + Seasonal Variations Peaks and Holes Peaks and Holes	MAPE	40.45% 51.64% 57.28% 35.72%
[27]	AI	ANN		MAPE	32.00%
[28]	Statistical	MASA SARIMA ETS		SMAPE	19.75% 29.36% 21.15%
[29]	Statistical	Regression	Linear Ridge Linear LASSO Bayesian Ridge	MSE	5.00 3.00 3.00
	AI		Recurrent NN LSTM		3.00 2.80 2.90
[30]	AI	ANN ANN to Clustered Time Series	1 Hidden Layer (8 neurons) 10-fold Cross Validation		RMSE
[31]	Statistical	ARMA Regression		Systematic Error	1.70% 13.28%
[32]	AI (2 hidden layers)	CNN CNN SVM SVM ANN ANN	Cross Validation Cross Validation	RMSE	9.38 4.74 10.35 13.66 7.45 5.01

Table 2.3 continues

[33]	AI	LSTM	Look Back 7	RMSE	179
		LSTM			132.53
		DNN			196.5
		DNN			177
[34]	Statistical	ARIMA		SMAPE	22.5%
		VARMAX			31.4%
[35]	AI	Statistical		SMAPE	24.35%
		ARIMA			23.69%
		MLP			23.89%
		XGBOOST			22.39%
		RF			23.63%
		SVR			24.61%
		GRNN			24.64%
		GMDH			23.09%
[36]	Statistical	1D CNN			23.14%
		LSTM			23.89%
[39]	AI	ARIMA		MSE	21.89%
		SARIMA			0.005
		Statistical			0.011
		ARIMA			0.015
		SARIMA			0.017
		SVM			
		KNN			

In Table 2.3, the ATM cash management literature categorized as forecasting technique(s), method details, training method and configuration(s), employed forecasting measures and their values. The AI techniques are the most common techniques that are employed to approach forecasting problem, followed by statistical techniques and hybrid techniques. The most common AI Techniques is the ANN [1] - [2] - [8] - [11] etc. followed by other special NN structures such as WNN [5] - [23] - [24] or CNN [32]. SVM is another powerful tool that employed in the problem [3] - [18] - [32] - [39]. Therefore, there is no consensus on the most adapted algorithm to this specific problem, however there is an ongoing competition among the models with their accuracy performances. Similarly, to the studies that employ AI techniques, statistical techniques does not share also a common methodology. SARIMA [20] - [21] - [28] - [39], ARIMA [23] - [39] and regression models [11] - [29] - [31] are some of the popular methods that are employed to prediction of the cash management problem. The other approaches that are used in the problem are linear models [9], correlation tests [10], decomposition [11], exponential smoothing [25], MASA [28] and ARMA [31].

In addition to the articles that concentrate on simple type technique, there are also articles that employ both statistical and AI techniques, and compare their results as in [11] - [23] - [29] - [39]. In [11] modified linear regression model with time-based coefficients yield to a better forecast accuracy comparing to ANN. This is the only study where a statistical technique outperforms an AI technique. In [23] ARIMA models appear which does not take into account the seasonality of the time series. Considering the seasonality emphasis of almost of the articles on such kind of time series, our intuition is that the use of the SARIMA would yield to better results may even outperform some of the MLFF, WNN or GRNN methods employed in the same article.

Last category is the articles who used a hybrid approach, using both statistical and AI techniques [12] - [13] - [26]. [12] with the nearest trajectory model and state space reconstruction with Easter correction, merge the ANN model, and improve the forecasting accuracy by approximately 5%. On the other hand, [13] tries to find the most suitable methods with each other and provides seven alternative combinations. [26] shows how a hybrid model outperforms significantly the methods such as AHW, MCD or MCW.

The employ of the fuzzy logic into problem appears only in two articles [19] and [22]. [19] incorporates interval type-two fuzzy numbers into the NN structure, while [22] uses neighborhood mutual information for best parameter selection and use fuzzy ARTMAP as methodology. Configuration of NNs differ or each article in manner of the employed hidden layers and the existing neurons in each layer. Cross-validation and sigmoid gradient descent optimization are the fundamental algorithms that are used.

The error measures employed to test the robustness of the models have different alternatives. SMAPE [8] - [13] - [28] etc. and MAPE [3] - [11] etc. are the most common error measures that are employed and they are followed by measures such as RMSE [14] - [30] - [32], MSE [6] - [29] or MFE [1] - [19] - [22]. Other than these common measures, [4] employed Kolmogorov-Smirnov test to random-effects point process model, [7] used logarithmic scoring rules to evaluate the ATMs and [17]

concentrates on the performance increase measure. The percentage of the common error measures met in the studies is given in the Figure 2.7.

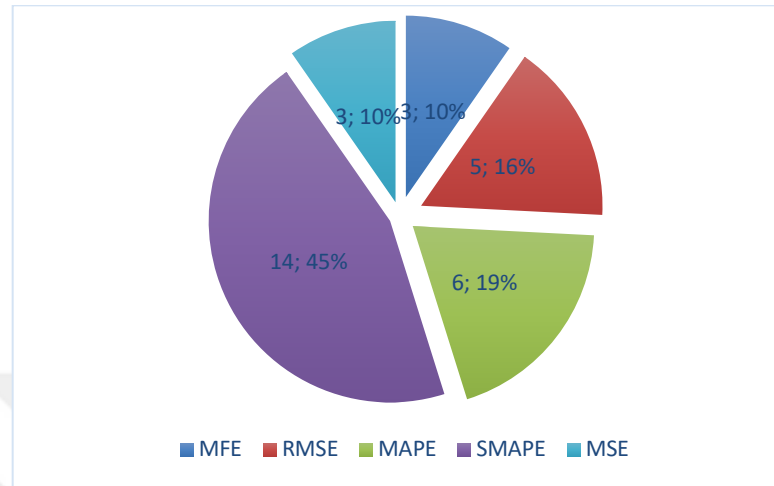


Figure 2.7 The Employed Error Metric

As is observed from the Figure 2.7, SMAPE is the leader error metric with 14 articles indicating 45% of the studies. This error measure followed by MAPE (19%) and RMSE (16%).

The inputs or parameters that should be taken into account in cash management time-series is an open to argument subject. The literature stress on some several main inputs of the system. However, there are some inputs that are only used in one or two articles. [4] and [6] are not included in the context for focusing to a different objective. [7] differ from the other studies scoring the ATMs and its' inputs are seasonal structure, first-order autocorrelation, cash-out days, zero withdrawals, spikes, strong day of the week and seasonality factors. [8] - [14] and [28] do not mention the inputs of their systems, [16] employs a best parameter selection algorithm itself. [23] employs the delay time and embedding dimension as chaotic parameters in the model, [27] does not detail the inputs and just say "daily withdrawals" while [29] consider all the transaction details up to 60 parameters in the model. The remaining articles are enlisted with their inputs in Table 2.4.

Table 2.4 Employed Inputs

	Day of the Week	Month of the Year	Week of the Month	Holidays	Special Dates	Day of the Month	Average Daily Cash Demand of the Last Week	ATM Location
[1]	*							
[2]	*	*		*			*	
[3]	*	*		*		*	*	
[5]	*							
[9]								*
[10]	*	*	*	*				
[11]	*	*				*		
[12]	*	*	*	*				
[13]	*	*	*		*	*		
[15]	*	*	*		*	*		
[17]	*	*				*	*	
[18]	*	*	*		*	*		
[19]		*			*		*	*
[20]					*			*
[21]	*	*		*				
[22]								*
[24]	*							
[25]	*	*	*		*			
[26]	*							
[30]	*	*	*	*				
[31]	*			*				*
[32]	*	*	*	*				
[35]	*			*				
[39]	*			*		*		*

Table 2.4 shows that “day of the week” is the most common parameter and 20 articles employed it. This is also an alternative way of proof of the strong weekly seasonality claim of the researchers. Month of the year (14) and week of the month (8) are the following common inputs. A week monthly seasonality is a mentioned issue also in the articles. Although holidays (8) category with special dates (6) are not merged in this study, there is no article that employs both of them in the same time. This may be interpreted as that the only difference is linguistic and researchers indicated the same input with different names. Therefore, they have cited totally 16 times. The remaining inputs such as day of the month, average daily cash demand of the last week, ATM location, salary day can be observed from Table 2.4. There are also inputs that are not

mentioned due to their low frequencies, such as working day [1], day before holidays [17], customer properties [9], [22] and weather [31]. Figure 2.8 summarizes the inputs employ of the articles.

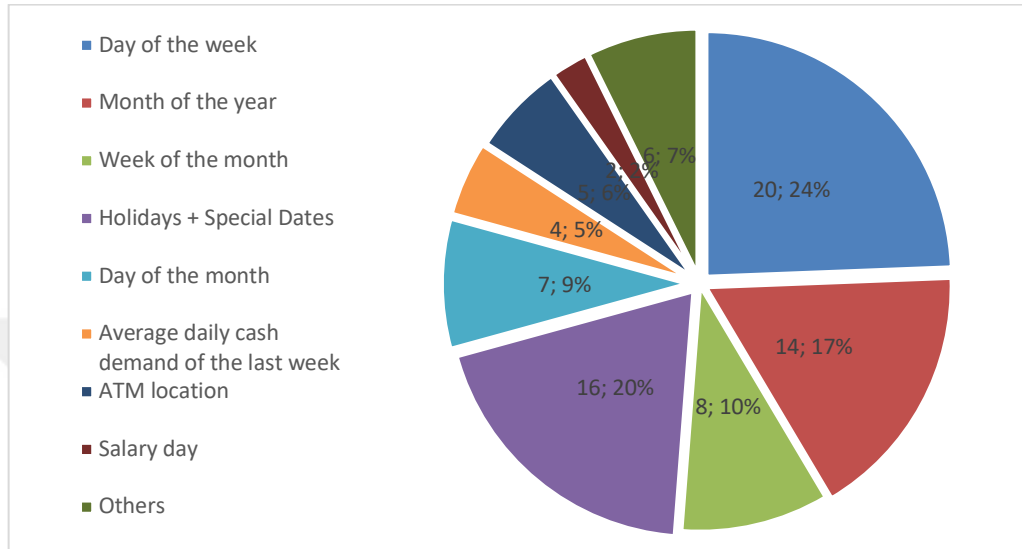


Figure 2.8 The Employed Inputs Frequency

Trend and seasonality are the main elements of the time series, however in the literature the strongest element is undoubtedly the seasonality especially 7 days' cyclical attitude of the time series mentioned in 14 different articles. Weekly seasonality is evaluated as the most important characteristic of ATM cash demand time series. Monthly seasonality appears to be relatively weak factor as in [2] - [12] - [19] and [21]. [20] mentions to an annual cycle pattern while [25] mentions the quarter of the year seasonality. Trend is only mentioned in [31] in Sri Lankan Bank problem and dealt with the inflation-adjustment technique.

Another specific problem that occurs in cash demand time series is the missing values, that can be occurred by the data corruption or the machine break down time. When the machine is out of cash, cash demand reflects to the time series as "0" while this does not reflect at all the real situation. The researchers for dealing this problem employed different techniques such as mean of two neighbors [8], median interpolation [12] - [23], cubic spline interpolation [15] - [18] and mean of time series [25] - [30].

In this thesis all the literature articles on the ATM cash demand forecasting studies are deeply examined. These articles are enlisted with their chronological orders, then categorized with different perspectives.

The focus of all these studies is about improving the ATM demand prediction accuracy of the time series, using alternative forecasting techniques and comparing their results. However, the major drawbacks of these papers, they do not clearly compare their results in alternative error metrics, in other words they are limited with a single error metric. Secondly, they are not clear about their selected parameters in the used forecasting models, therefore they present irreproducible results. Thirdly, the forecasting outcome of their study is not reflected to the real-life. More specifically, the forecasted values are not used in the replenishment process. Ultimately, some ML methods that are especially developed for forecasting problem like RNN and LSTM are not used in the literature. In addition, the studies focus on improving average accuracy of multiple ATMs, and selects the same forecasting model for each ATM.

This thesis compares the accuracy results in alternative error metrics, and find the best forecasting model in alternative error metrics. All the parameter and application details are given in the study and results are reproducible. The forecasting outcomes of the models are then employed as the input of the replenishment problem. Costs and service levels for each ATM is found using the forecasted series in the next periods. This thesis is the first study that employs RNN and LSTM forecasting model in the ATM cash demand forecasting problem. It aims and succeeds to outperform all the related literature on the same data set with increased accuracy results. Differently, in this study, the forecasting task is exercised for each ATM individually and best forecasting model for each ATM is found.

3. METHODOLOGIC BACKGROUND

3.1. PRELIMINARIES ON FORECASTING

Forecasting is a planning tool relying to the historical data to determine or more correctly estimate-predict the direction of future trends. However, in finance industry, due to the highly dynamic environment, and excessive factors that affect the business, forecasting has been always challenging. Especially when the time horizons get longer, forecasts return to be less effective, and conventional forecasting methods, both qualitative and quantitative ones (weighted moving average, exponential smoothing...) may become useless.

The ultimate purpose of a forecast is to minimize the error, and this is generally done by selecting the model that gives the lowest forecast error according to different measures, namely; Mean absolute deviation (MAD), mean squared error (MSE), mean absolute percent error (MAPE), symmetric mean absolute percent error. Where A_t is the actual value and F_t is the forecasted value at time t .

$$MAD = \frac{\sum |A_t - F_t|}{n} \quad (3.1)$$

$$MSE = \frac{\sum (A_t - F_t)^2}{n} \quad (3.2)$$

$$MAPE = \frac{1}{n} \sum_t \left| \frac{A_t - F_t}{A_t} \right| \quad (3.3)$$

$$SMAPE = \frac{1}{n} \sum_t \frac{|A_t - F_t|}{(|A_t| + |F_t|)/2} \quad (3.4)$$

Time-series analysis and trend projections are the most common approaches that are used for economic forecasting. In trend projections, historical data is used to compute the trend line, using the least squares technique, which will be employed to predict the future estimations. The equation is as:

$$\hat{y} = a + bx \quad (3.5)$$

Where $\hat{y}$ is the computed value of the variable to be predicted, a is the y-axis intercept, b is the slope of the regression line and x is the independent variable. The equations to calculate the regression variables are

$$b = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} \quad (3.6)$$

Another step to predict correctly the future is to examine the seasonal variations in data. The seasonal model may be used to adjust the trend data for seasonal variations in demand. Cyclical variations are patterns in the data that occur every several time units, they are difficult to forecast, because they are dependent to a wide variety of factors. Associative forecasting is used when changes in one or more independent variables can be used to predict the changes in the dependent variable. Multiple-regression analysis deals with that kind of forecasting problems.

3.2. STATISTICAL FORECASTING TECHNIQUES

3.2.1. Moving Average

The first moving average models are introduced by Wold (1938). When in the general linear processes, there are only a finite number of nonzero weights θ , a **moving average series of order q** , abbreviated as $MA(q)$, can be notated as

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (3.7)$$

The first-order moving average process, $MA(1)$, is the simplest one where $E(Y_t) = 0$ and there is no correlation beyond lag 1 or $k \geq 2$. The other characteristics of $MA(1)$ can be summarized as below

$$\gamma_0 = Var(Y_t) = \sigma_e^2(1 + \theta^2) \text{ and } \gamma_1 = -\theta\sigma_e^2 \quad (3.8)$$

$$\rho_1 = (-\theta)/(1 + \theta^2) \text{ and } \gamma_k = \rho_k = 0 \text{ for } k \geq 2 \quad (3.9)$$

The general $MA(q)$ process, has the auto covariance and autocorrelation functions as

$$\gamma_0 = (1 + \theta_1^2 + \theta_2^2 + \dots + \theta_q^2)\sigma_e^2 \quad (3.10)$$

$$\rho_k = \begin{cases} \frac{-\theta_k + \theta_1\theta_{k+1} + \theta_2\theta_{k+2} + \dots + \theta_{q-k}\theta_q}{1 + \theta_1^2 + \theta_2^2 + \dots + \theta_q^2} & \text{for } k = 1, 2, \dots, q \\ 0 & \text{for } k > q \end{cases} \quad (3.11)$$

3.2.2. Autoregressive Process

The first autoregressive processes are presented by Yule (1926), that says the actual value of the series Y_t is linear combination of the p most recent past values of itself plus an independent “innovation” term e_t that incorporates everything not explained by past values into the series at time t . The first-order autoregressive process AR (1) is as

$$Y_t = \Phi Y_{t-1} + e_t \quad (3.12)$$

By taking the variance of both sides, and taking the expected values, assuming the stationarity condition, and independency of innovation term,

$$\gamma_k = \phi\gamma_{k-1} \quad (3.13)$$

and for $k = 1$, $\gamma_1 = \phi\gamma_0 = \phi\sigma_e^2/(1 - \phi^2)$, the general expression becomes

$$\gamma_k = \phi^k \frac{\sigma_e^2}{1 - \phi^2} \quad (3.14)$$

and thus

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \phi^k \quad (3.15)$$

The magnitude of autocorrelation function decreases exponentially as the number of lags k increases.

When $0 < \phi < 1$, correlations are positive. When $-1 < \phi < 0$, the lag 1 autocorrelation is negative and the signs of successive autocorrelations alternate signs with exponentially decreasing magnitudes.

The second-order autoregressive process AR (2) is as

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + e_t \quad (3.16)$$

By solving the quadratic equations, and taking partially derivatives, Yule-Walker equations:

$$\gamma_k = \phi_1 \gamma_{k-1} + \phi_2 \gamma_{k-2} \quad (3.17)$$

$$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} \quad (3.18)$$

3.2.3. Autoregressive Moving Average Model

When the time series is partly autoregressive and partly moving average of order p and q , respectively, we talk about ARMA (p, q) models. The related time series model is as with autocovariance and autocorrelation functions.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (3.19)$$

$$\gamma_0 = \frac{1 - 2\phi\theta + \theta^2}{1 - \phi^2} \sigma_e^2 \quad (3.20)$$

$$\rho_k = \frac{(1 - \theta\phi)(\phi - \theta)}{1 - 2\theta\phi + \theta^2} \phi^{k-1} \quad (3.21)$$

3.2.4. Integrated Autoregressive Moving Average Model

When the time series do not have a constant mean over time, the stationarity assumption drops, and nonstationary models appear as $Y_t = \mu_t + X_t$, which often called trend factor. In general, the first difference of the series gives the detrended series, in which non stationary nature returns to be stationary. In some of the cases only the second difference of the series yield to be stationary.

Therefore, an ARIMA(p,d,q) model is d degree stationary version of an ARMA(p,q) model. In practical, this degree is either 1 or 2. When we have an ARIMA(p,1,q) process with $W_t = Y_t + Y_{t-1}$, the difference equation form of the model can be written as

$$Y_t = (1 + \phi_1)Y_{t-1} + (\phi_2 - \phi_1)Y_{t-2} + \dots + (\phi_p - \phi_{p-1})Y_{t-p} - \phi_p Y_{t-p-1} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (3.22)$$

and can be represented as, where m is an earlier time than $t = 1$

$$Y_t = \sum_{j=-m}^t W_j \quad (3.23)$$

The ARIMA(p,2,q) process is simply obtained by summing twice, and represented as

$$Y_t = \sum_{j=-m}^t \sum_{i=-m}^j W_i = \sum_{j=0}^{t+m} (j+1)W_{t-j} \quad (3.24)$$

The differencing is not the only way to induce stationarity. Percentage changes and logarithm, power transitions and Box-Cox are other mathematical transformation tools for obtaining stationarity and normality (Jonathand and Kung-Sik, 2008).

3.2.4. Seasonal ARIMA Model

When the series have common cyclical tendencies, that cannot be modelled with seasonal deterministic trends, stochastic seasonal models are preferred in the forecasting problems. A seasonal $MA(Q)$ model of order Q with seasonal period s can be expressed as

$$Y_t = e_t - \Theta_1 e_{t-s} - \Theta_2 e_{t-2s} - \dots - \Theta_Q e_{t-Qs} \quad (3.25)$$

Similarly, a seasonal $AR(P)$ model of order P with seasonal period s can be expressed:

$$Y_t = \Phi_1 Y_{t-s} + \Phi_2 Y_{t-2s} + \dots + \Phi_P Y_{t-Ps} + e_t \quad (3.26)$$

which are co-employed to deal with the series. When seasonal process is non stationary, the seasonal difference is employed,

$$\nabla_s Y_t = Y_t - Y_{t-s} \quad (3.27)$$

A multiplicative seasonal ARIMA model with non-seasonal orders p, d, q and seasonal orders P, D, Q with seasonal period, is expressed by

$$W_t = \nabla^d \nabla_s^D Y_t \quad (3.28)$$

3.3. ARTIFICIAL INTELLIGENCE - MACHINE LEARNING TECHNIQUES

3.3.1. Chronology

Intelligence may be defined as the ability to understand and learn things and concepts for solving the problems or making decisions and it is the contrary of doing things automatically or by instinct. Artificial Intelligence (AI) is a science that investigates the machine thinking ability. The idea pioneered by famous mathematician Alan Turing (1950) with the Turing Imitation Game where a machine replaces human and tries to

deceive the interrogator. The first AI model, is proposed by McCulloch and Pitts (1943) and based on neural computing by Artificial Neural Networks (ANN).

In 1970s Stanford University with the support of NASA, formed a team to determine molecular structure of Martian soil. The problem was to incorporate the expertise of Lederberg (Nobel prized in Genetics) into computer to perform at human expert level. These studies than named as “Expert Systems”. After the project “DENDRAL”, AI that had been seen as general-purpose, knowledge-sparse weak methods, transformed to a domain-specific, knowledge-intensive techniques. This was the start of the knowledge engineering which is constituted of capturing, analyzing and expressing in rules an expert’s “know-how”. Especially in the chemistry, geology, medicine and military science, remarkable expert system applications appeared, these studies reflected also to the manufacturing and business area, and reviewed by (Durkin 1994).

In 1980s, with the advances in computer technology and neuroscience, the Neural Networks field came into prominence. Hopfield (1982) introduced his own NN with feedback ability. Kohonen (1982) introduced self-organizing maps and Barto et al. (1983) explained the reinforcement learning. The keystone was the back-propagation learning algorithm invented by McClelland and Rumelhart (1986).

Neural Networks can learn, adapt to the changes and establish patterns in problems where rules are unknown and deal with fuzzy or incomplete information. However, there are several drawbacks of them. The most criticized part, usually is the black box acting structure, the lack of explanation and the slowness of the training process.

3.3.2. Artificial Neural Networks

One of the most popular Machine Learning approaches is Artificial Neural Networks (ANN). ANN is the analogy of human brain which is consisted from billions of neurons (basic information processing units) and trillions of connections. Neurons have a simple structure but together they build a huge processing power.

Human brain is a highly complex, non-linear and parallel information-processing system. Information is stored and processed in a NN simultaneously throughout the whole network, rather than at specific locations, which means that data and process are not local but global. ANN tries to emulate the biological NN, learning is fundamental and the processors are analogous to the neurons. These neurons are connected by weighted links to transmit the signals with each other. A basic ANN architecture is in Figure 3.1.

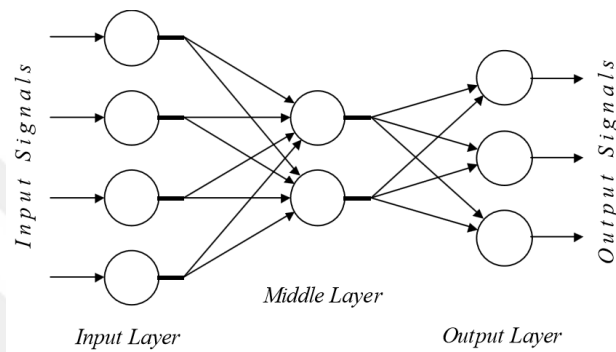


Figure 3.1 Basic ANN Structure

The neuron is the simple computing element, it computes the weighted sum of the input signals, compares it with a threshold value " Θ ". If the input is greater than or equal to threshold, the neuron is activated, and output value attains +1, if the input is less than the Θ the neuron output becomes -1. An example diagram and the activation function called as sign function is given in Figure 3.2.

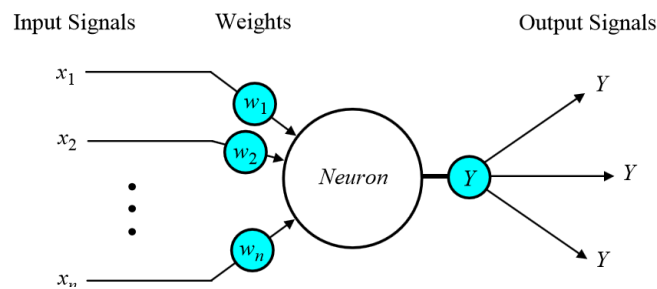


Figure 3.2 Schematization of a Neuron Working Structure

Where neuron employs the transfer or activation function:

$$X = \sum_{i=1}^n x_i w_i \text{ and } Y = \begin{cases} +1, & \text{if } X \geq \theta \\ -1, & \text{if } X < \theta \end{cases} \quad (3.29)$$

The commonly used activation functions of NN are given in the Figure 3.3.

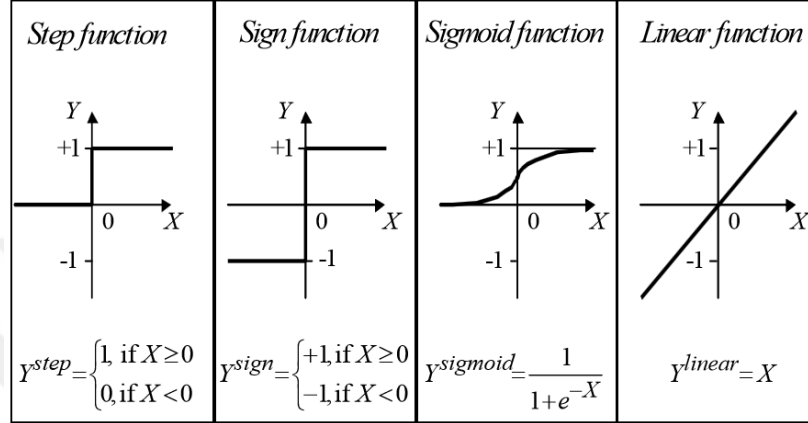


Figure 3.3 Common Activation Functions

3.3.2.1. Perceptron

The first and simplest form of a NN, consisted of a single neuron with adjustable synaptic weights, introduced by Rosenblatt (1958) as “perceptron”. In the model, weighted sum of the inputs is applied to the hard limiter, which classifies outputs as +1 and -1 respect to the inputs. An illustration is given in Figure 3.4.

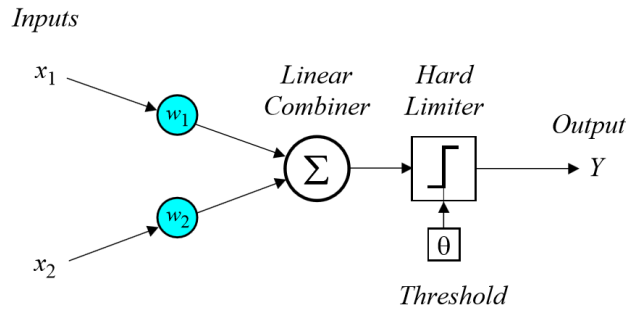


Figure 3.4 Single-layer two-input perceptron

The initial weights are randomly assigned between [-0.5, 0.5] and continuously updated for obtaining consistent outputs with the training examples. This is done by small adjustments in the weights to reduce the difference between the actual and desired

outputs. This error term is expressed as $e(p)$ calculated at each iteration p , where $Y(p)$ is the actual output and $Y_d(p)$ is the desired output.

$$e(p) = Y_d(p) - Y(p) \quad (3.30)$$

If $e(p) \geq 0$, the output $Y(p)$ should be increased, if $e(p) \leq 0$, $Y(p)$ should be decreased. The basic learning rule of the algorithm, where learning rate α is a positive constant less than 1 is as follow:

$$w_i(p+1) = w_i(p) + \alpha x_i(p) e(p) \quad (3.31)$$

This weight training step is repeated until the convergence. This perceptron model can learn the basic logical operations *AND* and *OR*, however is not capable to learn *Exclusive-OR*.

3.3.2.2. Multilayer Neural Networks

Due to the limitations of a single layer NN structure, the multilayer perceptron models; with one or more hidden layers (called as computation layers) in which input signals are propagated in a forward direction layer by layer, are emerged. These hidden layers hide the layers' desired outputs, and cannot be observed through the input/output behavior, this is the most criticized part of NN which is quite a black-box that difficult to understand. In sector, the commercial ANN platforms employ one or two hidden layers, with each layer up to 1000 neurons. The experimental NN can reach up to six layers (four of them are hidden layers), and employ millions of neurons. The presentation of multilayer perceptron model is in Figure 3.5.

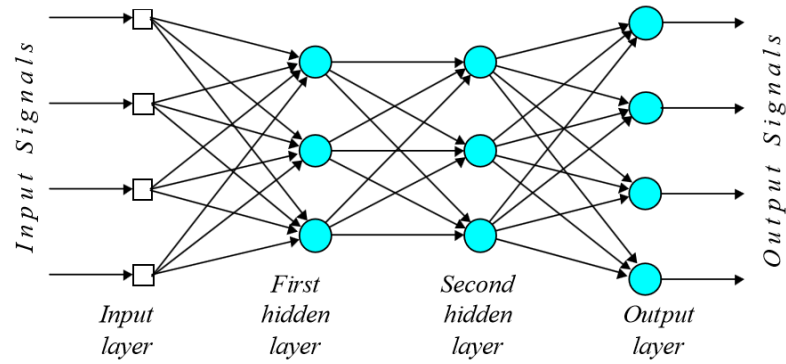


Figure 3.5 Multilayer perceptron with two hidden layers

In back-propagation NN, the network computes the outputs, adjusting the weights to reduce the error, in the first part of the learning algorithm training input pattern is presented to the input layer, and it is propagated until the generation of the output layer. The second-phase is consisted of the error calculation and backwards propagation from the output layer to the input layer with the weight modification. This repeating process can be schematized as in Figure 3.6.

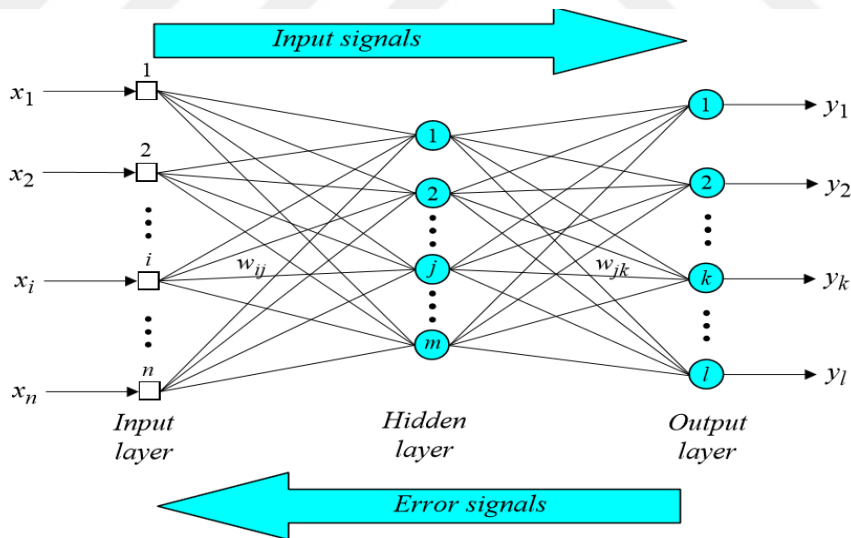


Figure 3.6 Back-propagation Neural Network with three layers

In the initialization step of the algorithm, the weights and threshold levels set uniformly distributed random numbers with a small range. In the activation step actual outputs of the neurons in the hidden layer are calculated with:

$$y_j(p) = \text{sigmoid} \left[\sum_{i=1}^n x_i(p) \cdot w_{ij}(p) - \theta_j \right] \quad (3.32)$$

where n is the number of inputs of neuron j in the hidden layer, and *sigmoid* is the sigmoid activation function. Activation process continue with following formula where m is the number of inputs of neuron k in the output layer.

$$y_k(p) = \text{sigmoid} \left[\sum_{j=1}^n x_{jk}(p) \cdot w_{jk}(p) - \theta_k \right] \quad (3.33)$$

Then the errors associated with output neurons propagated backwards, updating the weights. This step is done by calculating the error gradient for the neurons belonging to the output layer.

$$\delta_k(p) = y_k(p) \cdot [1 - y_k(p)] \cdot e_k(p) \quad (3.34)$$

where

$$e_k(p) = y_{d,k}(p) - y_k(p) \quad (3.35)$$

The weights corrections are calculated by (3.34) and the weights are updated as (3.35).

$$\Delta w_{jk}(p) = \alpha \cdot y_j(p) \cdot \delta_k(p) \quad (3.36)$$

$$w_{jk}(p+1) = w_{jk}(p) + \Delta w_{jk}(p) \quad (3.37)$$

The process continues with the calculation of error gradient in the hidden layer

$$\delta_j(p) = y_j(p) \cdot [1 - y_j(p)] \cdot \sum_{k=1}^l \delta_k(p) \cdot w_{jk}(p) \quad (3.38)$$

The weights corrections are calculated by (3.39) and updated by (3.40).

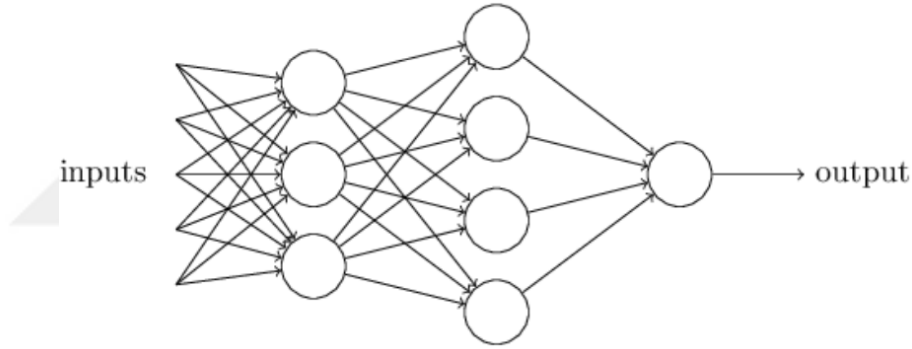
$$\Delta w_{ij}(p) = \alpha \cdot x_i(p) \cdot \delta_j(p) \quad (3.39)$$

$$w_{ij}(p+1) = w_{ij}(p) + \Delta w_{ij}(p) \quad (3.40)$$

In the iteration step, p is increased by one and returned to the activation step, repeating the process until the error term remains under the predefined threshold level.

3.3.3. Deep Neural Networks (DNN)

When the problem is complex enough to be captured with a basic ANN, hidden layers are added in the NN structure to capture the complex relations between inputs and outputs. An ANN structure with one or more hidden layers is called Deep Neural Network (DNN).



More number of layers => Deeper network => More complex relationships

Figure 3.7 DNN Structure

Figure 3.7 indicates a 5-3-4-1 DNN where there are five inputs and a single output. Two hidden layers have three and four neurons, respectively. Increasing the hidden layers, may increase the accuracy, however it can cause problems like overfitting (memorizing instead of learning) and would be computationally time-consuming process. In this study, Keras and Tensorflow are used to implement DNN to the forecasting problem. Keras is a model-level library that provides high-level building blocks in order to develop ML models, and Tensorflow is a special lower-level part of Keras library.

3.3.3. Recurrent Neural Networks (RNN)

RNN is a special class of neural networks that employs temporal sequence of the data and shows a dynamic behavior (Rumelhart et al. 1986). It employs same function for every input, while the output depends on the recent computation. The computed output is copied and sent to the RNN. Briefly, the inputs are the inputs and the previous outputs of the system. Differently from the general ANN structure, this additional internal state memory, relates all the inputs to each other. The RNNs are generally used in unsegmented tasks such as handwriting or speech recognition or time series forecasting. An illustrative RNN is given as.

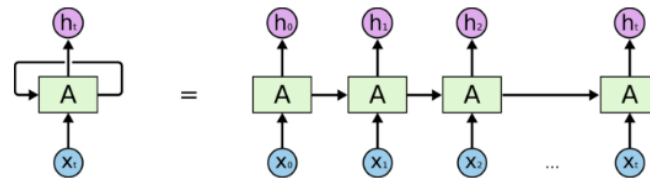


Figure 3.8 RNN Structure

In the Figure 3.8, x_t represents the input at time t and h_t is the output at time t . Then the inputs of step $t+1$ becomes x_{t+1} together with h_t .

However, training a RNN is a difficult task. In problems with long sequences, RNNs face with vanishing or exploding gradient problems. The vanishing gradient problem is based on the extremely small gradient values that prevent the weight changing. The exploding gradient problem is based on having large gradient values that yield to large updates in NN weights. This situation, create an unstable model which is unable to learn from training data. LSTM is a modified RNN which deals with these problems.

3.3.4. Long Short-Term Memory (LSTM)

LSTM is an updated version of RNNs that is suitable for time series prediction with unknown duration and lags (Hochreiter and Schmidhuber, 1997). Differently from the RNNs, LSTMs have three gates in the propagation process. The Input Gate selects the inputs that should be employed to modify the memory. In this gate, sigmoid function

decides the inputs that will let be through by 0 or 1, and tanh function weight these values from -1 to 1. The Forget Gate looks the previous state and the current input. Then uses sigmoid function to discard the unnecessary inputs. In the Output Gate, the memory block and the input are used to decide the final output. Figure 3.9 illustrates an illustrative LSTM network.

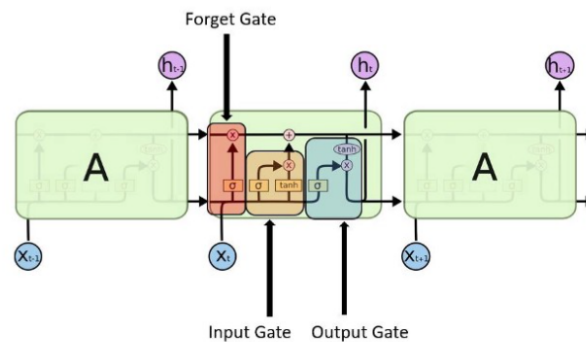


Figure 3.9 LSTM Structure

LSTM, which is basically an adaptive RNN with multiple gates, developed for specifically time series forecasting problem, is a robust forecasting model that requires heavy computational time.

In the Methodologic Background section, the employed forecasting methods in this study are given in their utilisation order. The forecasting study starts with statistical models; ARIMA and SARIMA. Then Machine Learning models namely; DNN, RNN and LSTM are employed for 111 time-series. The error metrics tracked in this thesis are MAE, MAPE and SMAPE, and the best forecasting model for each ATM is selected according to the SMAPE. The forecasting results of the selected model is applied on the replenishment process of the ATMs. All the methodologies mentionned here, are applicable in Python, with existing libraries on KERAS. The application of this thesis is performed using a MacBook Air (M1) with a memory of 8GB, in Google Collaboratory Environment supported by GPU and TPU.

4. PROPOSED METHODOLOGY and APPLICATION

The proposed methodology in this thesis, is based on an integrated approach. Firstly, for each ATM alternative forecasting models are tested and the best prediction model is selected, and employing the outcomes of the selected model, best replenishment frequency and amount per ATM is found. The selected replenishment strategy again tested for a further replenishment horizon. As it is mentioned in the literature review part, in general the articles focus on a specific part of the ATM problem, for instance increasing accuracy of their forecasting model, however they do not interpret this accuracy as a cost. The aim of this thesis is to show the outcomes of the forecasts in terms of selected performance criteria. Figure 4.1, shows the proposed decision support system (DSS) outlining the general application steps.

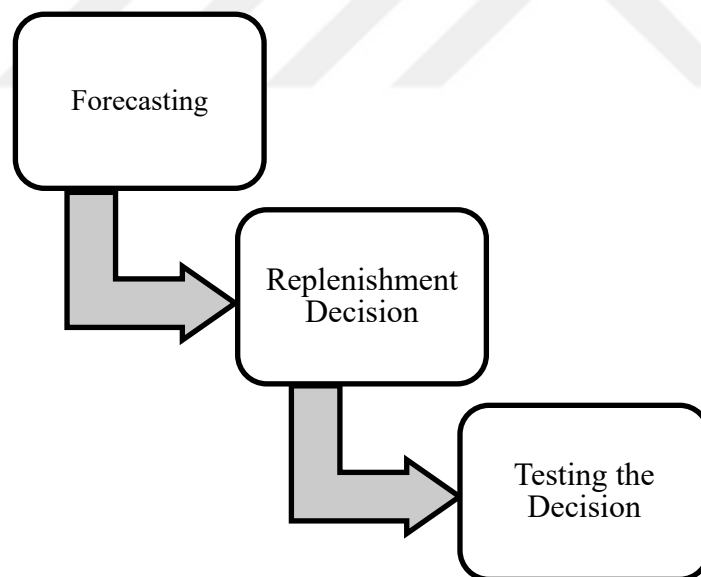


Figure 4.1 Proposed DSS

The first thing to do is to prepare the data to realize efficient forecasting models. When the data is pre-processed and cleaned, it is ready to be part of the forecasting problem. Then statistical tools will be used in order to find parameters of the statistical forecasting models. These models are namely, ARIMA and SARIMA which will be used as benchmark models.

Next step is selecting the hyperparameters of the ML forecasting models. This process is done by a limited grid search algorithm, and presented within the study. When the complexity of the problem increases the computational time necessitated for forecasting increases too. Therefore, tracking the computational time of each model, and finding adequate parameters are really important concepts in machine learning studies. Hyperparameters like learning rate, epochs or window size should be selected carefully. Figure 4.2, outlines the followed application steps for the forecasting process.

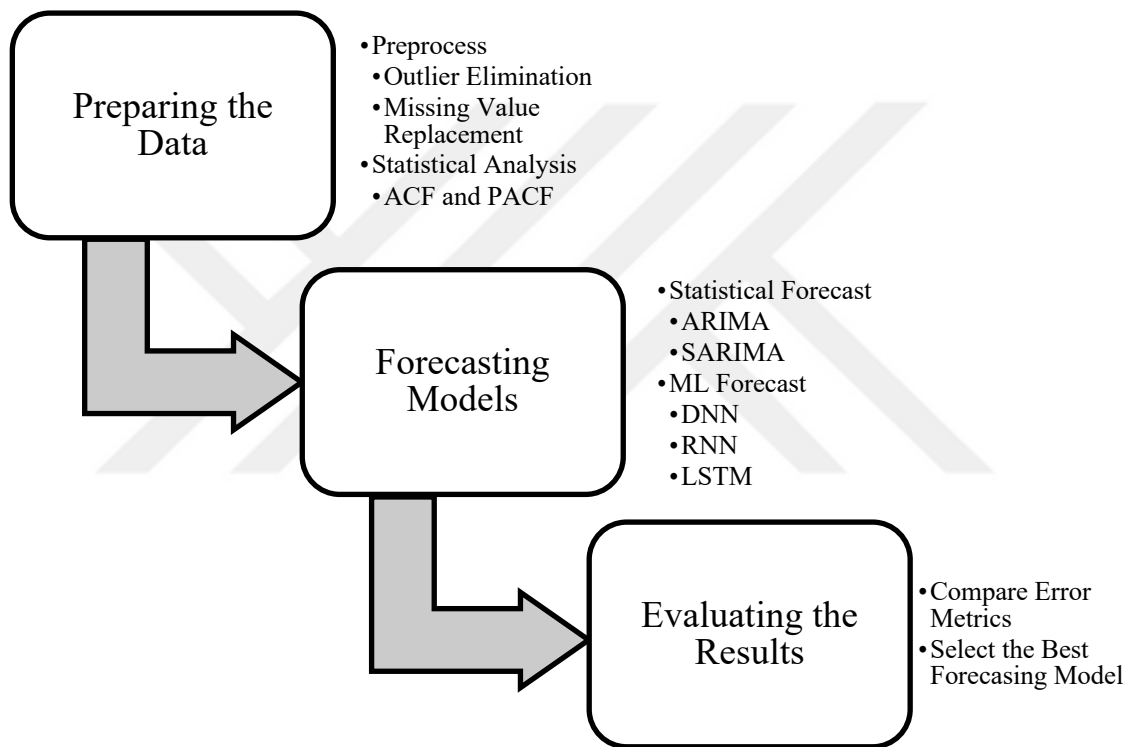


Figure 4.2 DSS for Forecasting

In Figure 4.2, the best forecasting model for each ATM is selected to continue to the individual replenishment decisions of the ATMs, which is schematized in Figure 4.3. The two stock control policies are employed to perform this replenishment alternatives. The first policy is called as Lot for Lot where ATMs are replenished according to the estimated demand and the time span is selected one to seven days. For instance, ATMs may be replenished daily or each 3 days with the estimated demand of the coming three days. The maximum replenishment period is seven days due to the weekly seasonality of the system. The second policy is to find pseudo-optimal replenishment period of the system. Considering, the holding cost and replenishment cost of the system, for each

ATM, the optimal replenishment period is calculated. However, this number is never integer, therefore the roundup and rounddown values are tested within the system, with a special Q value and adapted Q value. Therefore, a total of four alternatives are tested in second policy, while seven alternatives are tested in first policy.

To test these alternatives, multiple Excel Sheets are prepared. Performance criteria like costs (holding, back-out, replenishment and total), and service levels (day-based, amount-based) are calculated. For each ATM, these steps are repeated and the outputs are collected.

Then three approaches are designed for decision-making. The first approach is the cost-oriented approach, where for each ATM the replenishment strategy that gives the minimum cost is selected. The second approach is the customer-oriented approach, where for each machine the replenishment strategy that gives the maximum service level is selected. Third approach is the equilibrium approach between the costs and service levels. To find this balance each missing percentile of the service level is penalized and transformed into a cost. The outcomes of these approaches are presented and compared, and the final decision is up to the bank decision makers. Figure 4.3 shows the adapted DSS for the replenishment stage.

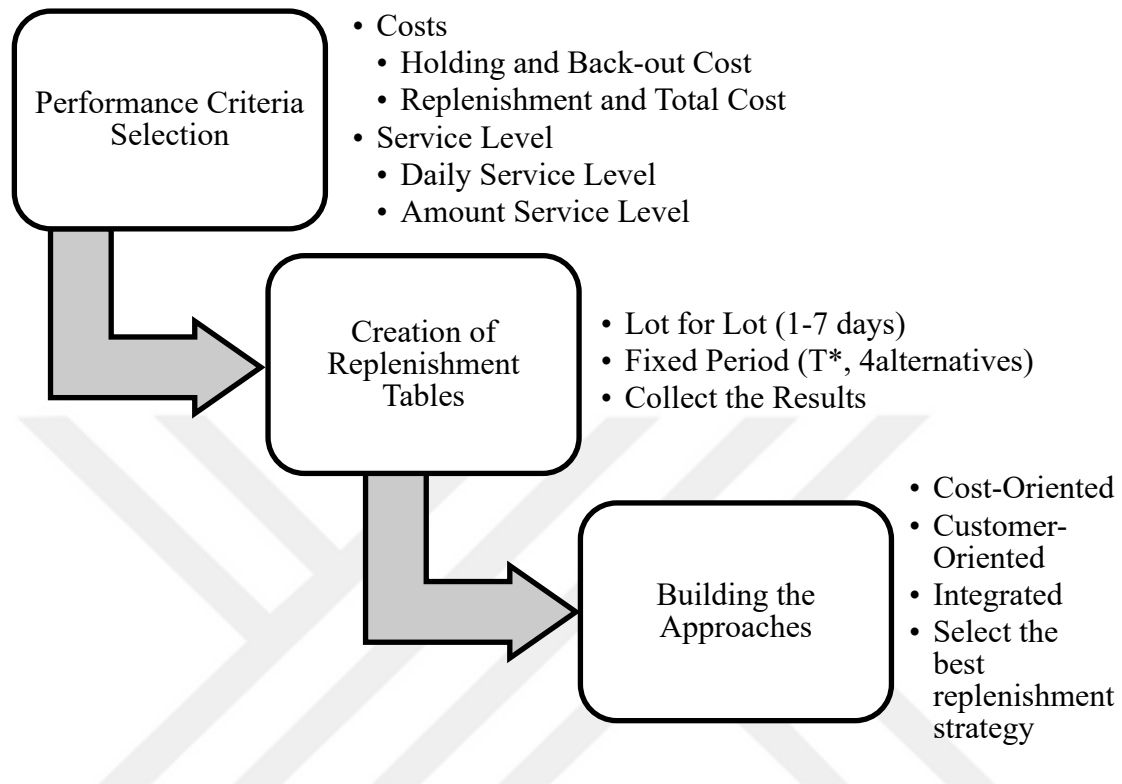


Figure 4.3 DSS for Replenishment

4.1 DSS FOR FORECASTING

4.1.1 Preparing the Data

In the application the data set provided by NN5 competition is employed. This data can be provided at competition web-site⁴ or accessed from the authors' github account⁵. The objective of this academic competition is to evaluate the accuracy of the computational intelligence (CI) methods in time series forecasting, where participants can use alternative CI methods. The participants of this competition presented their studies at the 2008 International Symposium on Forecasting ISF'07 AND 2008 IEEE held in Hong-Kong and Las-Vegas. The training data consists of two years (735 days) of daily

⁴ <http://www.neural-forecasting-competition.com/NN5/>

⁵ <https://github.com/MicheleCedolin/ATMs/blob/main/NN5temiz.xlsx>

cash demand at various ATMs at different locations in England beginning at 18 March 1996 ending at 22 March 1998. The competition results are compared over a fixed horizon of 56 days test data with SMAPE. Cash machines are considered as miniature retail outlets with cash money as product. The data may contain several time series patterns including multiple overlying seasonality, local trends, structural breaks, outliers, zero and missing values. These are often driven by a combination of unknown and unobserved causal forces driven by the underlying yearly calendar, such as recurring seasonal periods, bank holidays, or special events of different length and magnitude of impact, with different lead and lag effects. Unfortunately, the data is linearly scaled to ensure the anonymity of the machines.

In order to ensure the clarity and brevity of the study, the detailed charts and calculations are given only for some ATMs. All the calculations and python codes employed in this study are done in Google Colaboratory, and the results are reproducible. The following library and codes should be downloaded before the application process (Figure 4.4).

```
import numpy as np
import pandas as pd
import seaborn as sns
import tensorflow as tf
import time
from matplotlib import pyplot as plt
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM
import math
from sklearn.metrics import mean_squared_error, r2_score
NN5 = pd.read_excel("https://github.com/MicheleCedolin/ATMs/blob/main/NN5temiz.xlsx?raw=true")

from numpy.random import seed
seed(1)
tf.random.set_seed(
    1
)
```

Figure 4.4 Necessary Libraries

The data preprocessing is an important step for time series forecasting. Outliers may affect the standard variation or mean of the data. They may cause bias in the estimation accuracy of forecasting models. While exercising preprocessing the trend and seasonality of the data should be observed. When the data is stationary, missing value

replacement may be done with arithmetic mean of the whole series, when there is trend, median and mod are alternative statistical tools to do the replacement. The outlier elimination is generally done by using quartile values (Figure 4.5).

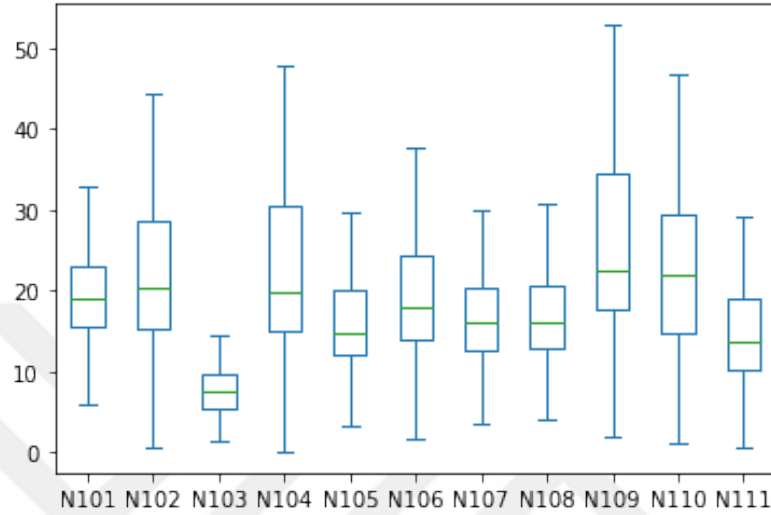


Figure 4.5 Box Plot for first 11 ATMs

Downquantiles and upquantiles are calculated, respectively by 0.25 and 0.75, then following codes are exercised to prepare the series (Figure 4.6). The mean and missing values of the first eleven series are given in Table 4.1.

```
df = NN5.iloc[:,1:]
median = df.median()
std = df.std()
down_quantiles = df.quantile(0.25)
up_quantiles = df.quantile(0.75)
IQR = up_quantiles - down_quantiles
outliers_low = (df < down_quantiles - 1.5*IQR)
outliers_up = (df > up_quantiles + 1.5*IQR)
df[outliers_low] = np.nan
df[outliers_up] = np.nan
df.fillna(median, inplace=True)
df.describe()
```

Figure 4.6 Outlier Elimination Code

Table 4.1 Missing Values and Mean

	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
Missing Values	23	18	10	22	10	16	15	10	13	15	19
Mean	19320	22426	7743	23311	16149	19509	16806	17531	26554	22797	15178

As can be observed from Table 4.1, the time series data may be corrupted due to the technical problem for machine breakdown situations, therefore before starting the forecasting process a detailed analysis on the time series should be exercised and the source of this missing values should be detected. The purer data would result better forecasting accuracies. Data visualization may be done following the code given in Figure 4.7.

```
from matplotlib import pyplot
values = NN5.values
groups = [58,23,32]
i = 1
# plot each column
pyplot.figure()
for group in groups:
    pyplot.subplot(len(groups), 1, i)
    pyplot.plot(values[:, group])
    pyplot.title(NN5.columns[group], y=0.5, loc='right')
    i += 1
pyplot.show()
```

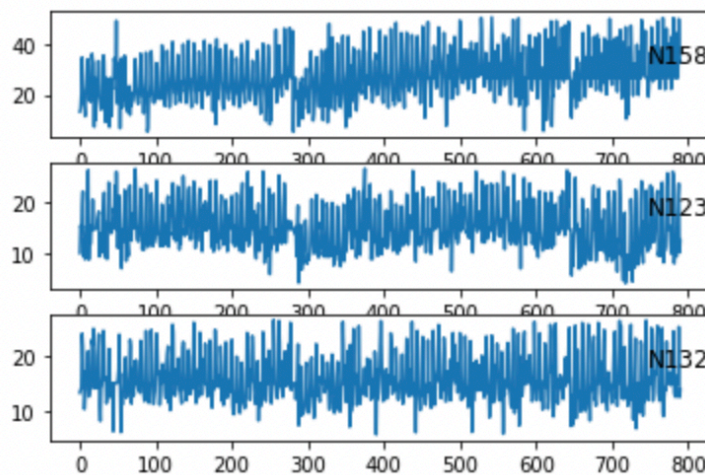


Figure 4.7 Plotting the Series

Figure 4.7 depicts the 58th, 23th and 32th ATMs, respectively. When the Figure 4.7 are observed, the strong weekly seasonality and stationarity of the series may be observed.

The first step of the forecasting phase is to calculate the autocorrelation (serial correlation) and partial auto correlation of the series. Autocorrelation estimates past

observed values effect on the current value, differing from partial autocorrelation in which only the recent observation is measured for influence on the current value. Lag is the number of previous observations measured during autocorrelation. The order of the autoregressive and moving average process are defined according to the autocorrelation (ACF) and partial autocorrelation (PACF) function. Figure 4.8 shows the ACF and PACF charts of the first ATM.

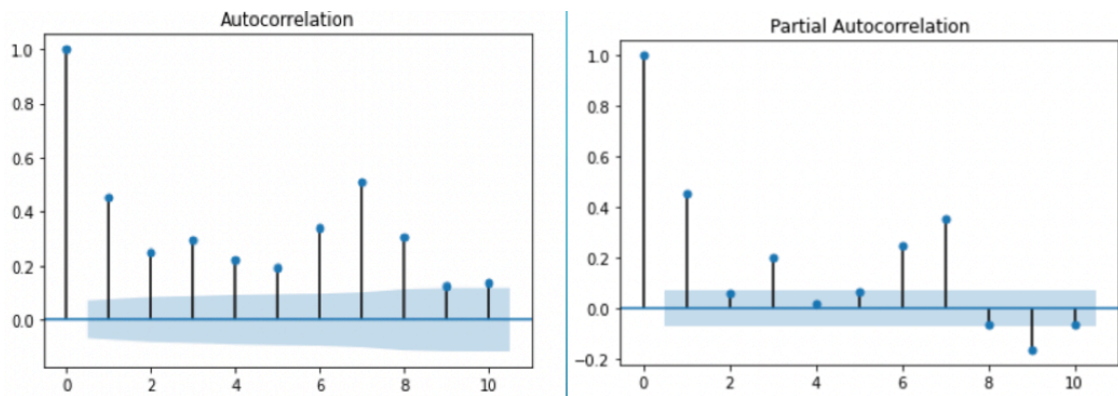


Figure 4.8 ACF and PACF Charts for ATM#1

The strongest correlations for both functions are at lag seven, which is linked directly the strong weekly seasonality of the series. In other words, the day of the week is a really important feature on the calculation process, mondays' demand and next monday demand will have similar attitudes. The same calculations are done for each series and lag-seven had the highest correlation value.

4.1.2 Statistical Forecasting Models

4.1.2.1 ARIMA Process

ARIMA is a statistical model that interpret a time series and predict future values. It is the combination of AR and MA processes. In the applicaton, ARIMA is employed for the first eleven series as a benchmark model to compare the results with the sophisticated machine learning forecasting models. The seleceted parameters of the ARIMA model is as follows, the lag order p is seven, the differencing order d is zero (no trend detected) and the order of the moving average q is seven. The python code employed for ARIMA is in Figure 4.9.

```

from statsmodels.tsa.arima_model import ARIMA
model = ARIMA(series, order = (7,0,7))
model_fit = model.fit()
residuals = model_fit.resid
output = model_fit.forecast()

```

Figure 4.9 ARIMA Code

The SMAPE scores of the ARIMA model for the first 11 series are in Table 4.2.

Table 4.2 ARIMA Scores (SMAPE)

N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
16.92	35.09	21.39	24.95	21.61	15.29	33.5	20.44	16.61	33.39	18.41

The ARIMA scores for the first 11 series range between 15.29% and 35.09%. The best forecasted machine with ARIMA is the first ATM, while the second ATM is the worst forecasted machine. The SMAPE scores are in general around 20% which is similar to the related literature on the same data set. The average SMAPE for the 11 machines is 23.42%. This situation is a clue that there are no extreme accuracy differences between forecasting models used in NN5 competition.

4.1.2.2 SARIMA Process

SARIMA is an extension of ARIMA which incorporates seasonality in the forecasting process. It is a strong widely used statistical forecasting technique. In the application p , d , q values are not changed, however P , D , Q values are selected as (7,0,7) for 12 weeks. Where P is the seasonal autoregressive order, D is the seasonal difference order, Q is the seasonal moving average order and m is the number of time steps for a single seasonal period. The python code employed for SARIMA is as in Figure 4.10.

```

from statsmodels.tsa.statespace.sarimax import SARIMAX
model = SARIMAX([series], order=(7,0,7), seasonal_order=(7,0,7,12))
model_fit = model.fit()
residuals = model_fit.resid
output = model_fit.forecast()

```

Figure 4.10 SARIMA Code

The SMAPE scores of the SARIMA model for the first 11 series are in Table 4.3.

Table 4.3 SARIMA Scores (SMAPE)

N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
15.63	27.06	21.79	16.93	23.47	17.59	28.65	23.47	12.80	34.38	18.96

The SARIMA scores for the first 11 series range between 12.80% (ATM#9) and 34.38% (ATM#10). The average SMAPE is 21.88%, integrating seasonality contributed to the average accuracy by 1.53%. However, SARIMA does not outperform ARIMA model for each ATM, therefore employing a single forecasting model for all the ATMs remains debatable. Figure 4.11 shows the forecasting results for the first ATM.

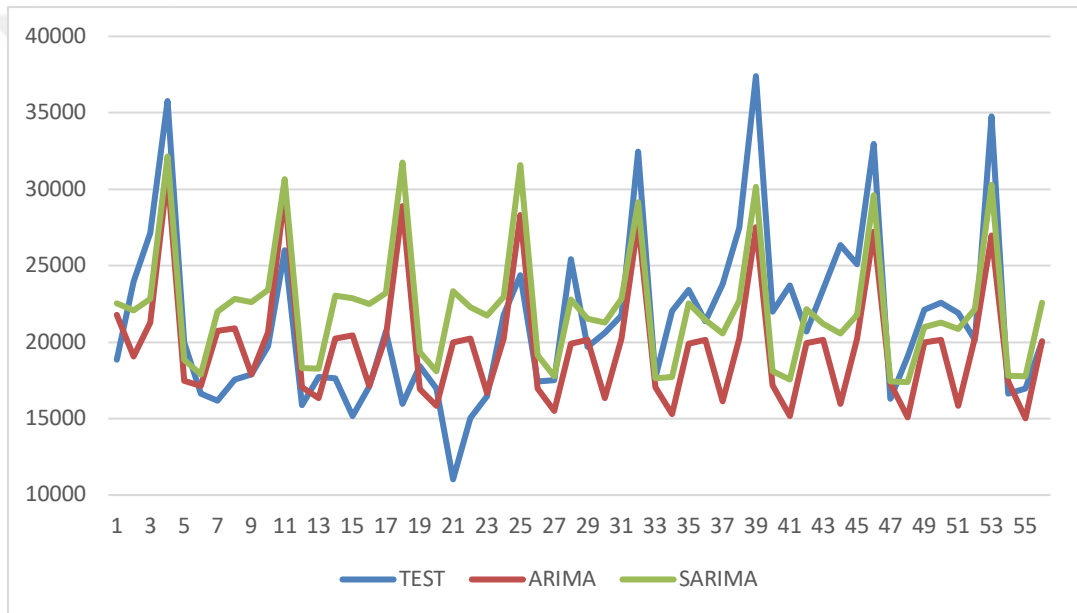


Figure 4.11 Forecasting Results for ARIMA and SARIMA (ATM#1)

4.1.3 Machine Learning Forecasting Models

Machine learning (ML) is basically the employ of computer systems that may learn and adapt without explicit instructions, by employing algorithms and statistical models to analyze and draw inferences from data patterns. Time series forecasting is an important part of the ML problems. In this application, three main time series forecasting ML models are employed; DNN, RNN and LSTM, respectively.

4.1.3.1 Hyperparameter Selection

Model parameter and hyperparameter selection is the initial phase of building machine learning algorithms. Model parameters are determined using the training data set, learned in the application process like weight in the artificial neural network or regression coefficients. Hyperparameters are adjustable parameters that are tuned to obtain optimal learning conditions such as model architecture (number of hidden layers) learning rate, number of epochs.

Training a ML process is a computationally time-consuming and difficult process. Especially hyperparameter tuning of the algorithms, require expert opinions and search algorithms like random search or grid search algorithm. In this thesis, grid search algorithm is used that searches exhaustively through a manually specified subset of the hyperparameter space of the targeted algorithm.

The model architecture is defined, allowing to a maximum three hidden layers. In neural networks, a hidden layer is located between the input and output of the algorithm, in which the function applies weights to the inputs and directs them through an activation function as the output. In short, the hidden layers perform nonlinear transformations of the inputs entered into the network. An extremely large number of hidden layers can increase the training time to the point that it is impossible to adequately train the neural network, and may yield to overfitting situations where the data is not learned but memorized, and does not respond well to the test data.

Number of epochs is another important hyperparameter of the ML system. In this thesis, the number of epochs are limited in the subset of [100, 500, 1000], where the computational time required for the training phase significantly increased, and variation in the error metrics are tracked. For the learning rate selection, adaptive learning rate algorithm is used and suitable learning rate is selected for each model. Window size is another important hyperparameter belonging to time series forecasting problem. In this thesis, due to the strong weekly seasonality of the data, optimum window size selection

is performed in multiple of sevens subset [7, 28, 56] and best window size is selected within the limited grid search.

For the optimizer, the Stochastic Gradient Descent (SGD) with momentum is used, it requires less memory compared to the classical GD algorithm, as the derivative is computed taking only one point at once, and it converges faster with momentum. The momentum class is selected between [0.1, 0.5, 0.9] subset. The generic loss function of the Keras library is MSE, in this study alternative error metrics are added in the calculation system. Table 4.4, shows the results for the first ATM for alternative hyperparameters.

Table 4.4 Hyperparameter Selection (ATM#1)

LSTM 2 Layers	Window Size:28, Epochs: 100		
	Momentum: 0.1	Momentum: 0.5	Momentum: 0.9
MAE	3.60	3.54	3.41
SMAPE	16.51	16.30	15.73
MAPE	17.83	17.77	16.96
MSE	20.75	20.51	19.36
LSTM 2 Layers	Window Size:56, Epochs: 100		
	Momentum: 0.1	Momentum: 0.5	Momentum: 0.9
MAE	3.52	3.56	3.62
SMAPE	16.16	16.46	17.14
MAPE	17.54	18.54	16.43
MSE	20.02	20.02	20.84
LSTM 2 Layers	Momentum: 0.9, Epochs: 500		
	Window Size: 7	Window Size: 28	LSTM 3 Layers
MAE	2.78	3.13	3.79
SMAPE	13.22	14.61	18.04
MAPE	13.58	15.74	16.86
MSE	13.23	17.32	24.50

For instance, ATM#1 best accuracies are obtained when window Size is seven. Though, when all the other parameters are same, there is not a significant accuracy difference between window sizes 28 and 56. When LSTM algorithm has three layers, ATM#1 obtains the worst SMAPE score with 18.04%. Two hidden layers are selected as best network architecture, the momentum increase is reflected to the computational time directly, with slightly changes in the error metrics.

4.1.3.2 Deep Neural Network (DNN)

A Deep Neural Network (DNN) is an ANN structure with at least one hidden layer. In time series forecasting this hidden layer, in general finds the secret relation between time lags and engineered features.

In ATM cash demand forecasting domain, the employ of DNN starts with Simutis et al. (2007). They simulated 1225 ATMs and used three-layer feed-forward NN (FFNN) to forecast next day cash demand. Simutis et al. (2008) continued to use FFNN with 15 neurons in each layer for 15 real ATMs. They trained NN with Levenberg-Marquardt optimization, minimizing the RMSE and reached to an average MAPE of 20.6% forecasting the next-day demand.

Andrawis et al. (2011) proposed a hybrid forecasting algorithm in which they used DNN models. They aggregated NN5 daily series into weekly series and reached an average SMAPE 19.83% for NN model. Atsalaki et al. (2011), tested 5000 alternative FFNN structures for 100 ATM daily cash withdrawals, minimizing the RMSE. They found that for one-step ahead forecast the best score obtained when the network has seven hidden layers and five inputs. Acuna et al. (2012) developed ANN architectures for NARX and NARMAX models for 30 ATMs of NN5 data set with a 100 days of forecasting horizon. They reached a SMAPE average of 20.05% for NARX and 24.09% for NARMAX. Venkatesh et al. (2014) employed multi-layer feed forward NN (MLFFN) to the NN5 data clustered series and reached an average SMAPE of 21.10%.

Arabani and Komleh (2019), employed DNN to predict cash demand of 1056 ATMs in Iran. They used two hidden layers with 1500 and 902 neurons, respectively. They obtained a RMSE of 7.45% for test data (RMSE should not be in percentage, the authors misinterpreted the results). Vangala and Vandalani (2020), employed nine alternative forecasting models to forecast cash demand of 40 Indian ATMs including DNN. Their adapted DNN structure has one hidden layer, learning rate of 0.1 and a momentum of 0.9. The average SMAPE score obtained in the study is 23.69%.

In this study, the proposed DNN model has two layers with a momentum 0.9. By an adaptive learning rate algorithm, learning rate is selected as 10^{-6} . Figure 4.12 shows the loss vs learning rate values for the first ATM.

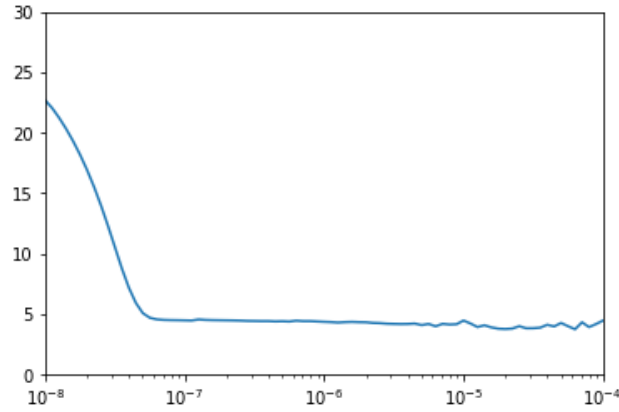


Figure 4.12 Learning Rate vs Loss

All the ML codes are exercised in Google Colaboratory environment using MacBook Air M1, selecting hardware accelerator TPU. In average, for a single ATM a DNN model with 500 epochs ran in 66 seconds, while this computational time increased to 135 seconds when DNN is executed for 1000 epochs. A RNN model with 500 epochs is ran on average in 246 seconds while this computational time is 555 seconds for a LSTM model with 500 epochs. Figure 4.13 shows the common definitions necessary for each machine learning model. Figures 4.14 shows the python code of the employed DNN model.

```

def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
    dataset = dataset.shuffle(shuffle_buffer).map(lambda window: (window[:-1], window[-1]))
    dataset = dataset.batch(batch_size).prefetch(1)
    return dataset

def smape(x_valid, results):
    return np.mean((2* np.abs(results - x_valid))/ ((np.abs(x_valid) + np.abs(results))))

def mape(x_valid, results):
    return np.mean(np.abs(x_valid - results)/np.abs(x_valid))

time = np.arange(2*395+1, dtype="float32")
results = []
valids = []
for i in range(1,112):
    print("Step {} has started.".format(i))
    series=NN5.iloc[:,i].values
    split_time = 735
    time = np.arange(2*395+1, dtype="float32")
    time_train = time[:split_time]
    x_train = series[:split_time]
    time_valid = time[split_time:]
    x_valid = series[split_time:]
    valids.append(x_valid)
    window_size = 28
    batch_size = 30
    shuffle_buffer_size = 100
    dataset = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)

```

Figure 4.13 Necessary Definitions

```

model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(10, activation="relu", input_shape=[window_size]),
    tf.keras.layers.Dense(10, activation="relu"),
    tf.keras.layers.Dense(1)
])

optimizer = tf.keras.optimizers.SGD(lr=1e-6, momentum=0.9)
model.compile(loss="mse", optimizer=optimizer)
history = model.fit(dataset, epochs=500, verbose=0)
forecast = []
for time in range(len(series) - window_size):
    forecast.append(model.predict(series[time:time + window_size][np.newaxis]))
forecast = forecast[split_time-window_size:]
results.append(np.array(forecast)[:, 0, 0])
print("Step {} has finished, results shape is {} mean is {}".format(i, (np.array(forecast)[:, 0, 0]).shape, np.mean(results))

```

Figure 4.14 DNN500 Code

SMAPE and MAPE metrics are defined in the system along with windowed dataset properties. A loop is constructed, and with Sigmoid Gradient Descent (SGD) Optimizer, using “RELU” as an activation function, with just one hidden layer of ten neurons the model is compiled. The results are printed along with SMAPE, MAPE and MAE error metrics using following code in Figure 4.15.

```

column_names = NN5.columns[1:112]

mae_list = []
smape_list = []
mape_list = []
for i in range(len(results)):
    mae_list.append(tf.keras.metrics.mean_absolute_error(valids[i], results[i]).numpy())
    smape_list.append(smape(valids[i], results[i]))
    mape_list.append(mape(valids[i], results[i]))
    name = [column_names[i] + "_preds"]
    if i == 0:
        df = pd.DataFrame(results[i], columns = name)
    else:
        df[name] = pd.DataFrame(results[i])

df_metric = pd.DataFrame(columns = column_names[:112], index = ["SMAPE", "MAPE", "MAE"])

df_metric.iloc[0] = smape_list
df_metric.iloc[1] = mape_list
df_metric.iloc[2] = mae_list
df_metric

writer = pd.ExcelWriter('DNN.xlsx')
df.to_excel(writer)
writer.save()

writer2 = pd.ExcelWriter('DNNError.xlsx')
df_metric.to_excel(writer2)
writer2.save()

```

Figure 4.15 Printing the Results

The forecasting results of the first eleven series are given in Table 4.5. All the remaining results may be found in the Appendix A. The SMAPE scores of all the series for DNN500 are between 11.82% and 32.24%, with an average of 21.56%. For DNN1000 the SMAPE range is between 11.67% and 32.26% with an average of 21.22%. The increase of the epochs is slightly contributed to the average forecasting accuracy of the problem. However, in the same time is doubled the necessitated computational time. When the DNN is performed with the 2000 epochs, no contribution on the accuracy is detected plus necessitated time is increased heavily.

Table 4.5 DNN Scores

DNN500	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
SMAPE	0.14	0.26	0.21	0.23	0.24	0.15	0.26	0.23	0.13	0.21	0.23
MAPE	0.14	0.41	0.21	0.27	0.27	0.15	0.32	0.29	0.13	0.25	0.25
MAE	2.86	4.15	1.82	5.59	3.61	2.63	4.13	3.35	3.69	5.52	3.46
DNN1000	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
SMAPE	0.14	0.25	0.20	0.23	0.24	0.15	0.26	0.22	0.13	0.21	0.22
MAPE	0.14	0.38	0.20	0.27	0.27	0.16	0.31	0.27	0.14	0.25	0.24
MAE	2.82	3.92	1.75	5.61	3.62	2.75	4.09	3.17	3.76	5.56	3.42

The average SMAPE for the first 11 machines is 20.81% for DNN500 and 20.45% for DNN1000. The average accuracy difference for SMAPE between DNN500 and DNN1000 in the first eleven ATMs is only 0.3%, which is quite low. However, there is a significant performance improvement comparing to ARIMA (23.42%) and SARIMA (21.88%). As the complexity of the model nature increase, the accuracy increase also as is expected.

4.1.3.3 Recurrent Neural Network (RNN)

RNN is an improved version of DNN with temporal sequences. In the literature, there is no RNN model dealing with ATM cash demand problem and this is the first study that applies RNN for NN5 series. The proposed RNN model has two layers, a momentum of 0.9 and a learning rate of 10^{-6} . The employed python code is in Figure 4.16.

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[None]),
    tf.keras.layers.SimpleRNN(40, return_sequences=True),
    tf.keras.layers.SimpleRNN(40),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

optimizer = tf.keras.optimizers.SGD(lr=1e-6, momentum=0.9)
model.compile(loss="mse", optimizer=optimizer)
history = model.fit(dataset, epochs=500, verbose=0)
forecast = []
for time in range(len(series) - window_size):
    forecast.append(model.predict(series[time:time + window_size][np.newaxis]))
forecast = forecast[split_time-window_size:]
results.append(np.array(forecast)[:, 0, 0])
print("Step {} has finished, results shape is {} mean is {}".format(i, (np.array(forecast)[:, 0, 0]).shape, np.mean(results)))
```

Figure 4.16 RNN Code

In Figure 4.16, the model is alterned with RNN structure. It is added two hidden layers of simple RNN with 40 neurons and a transformative dense layer. Table 4.6 gives the RNN results for 500 epochs for the first 11 ATMs. The remaining outcomes may be found in the Appendix A.

Table 4.6 RNN Scores

RNN	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
SMAPE	0.15	0.26	0.20	0.21	0.26	0.17	0.29	0.25	0.13	0.21	0.25
MAPE	0.15	0.39	0.20	0.24	0.24	0.19	0.34	0.36	0.13	0.27	0.30
MAE	3.09	4.16	1.71	5.30	3.76	2.99	4.50	3.71	3.74	5.62	3.85

The SMAPE scores of all the series for RNN are between 13.02% and 46.24%, with an average of 23.33%. The average SMAPE for the first eleven series is 21.63%, which is better than statistical models; (ARIMA 23.41%, SARIMA 21.88%), however worst then DNN models; (DNN500 20.82%, DNN1000 20.45%). The recurrent structure of the NN is quite strong within self but do not neccesarly reflects to the accuracy outcomes.

4.1.3.4 Long Short-Term Memory (LSTM)

LSTM is an updated version of RNN model for time series prediction. Rajwani et al. (2017) proposed the first LSTM model to approach cash demand forecasting problem. They used data set of Pakistan ATMs transaction records over two and half years and obtained a MSE of 0.029 (which is hard to interpret). Sadly, they did not give any detail about the model parameters. Recently, Vangala and Vandalani (2020) trained a LSTM model to forecast ATM cash demands, using “Adam” optimizer with a learning rate of 1%. Using a memory block of two to ten, and 300 to 1000 epochs, they reached an average SMAPE of 23.13% for 40 Indian ATMs. The python code constructed for LSTM is in Figure 4.17.

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[None]),
    tf.keras.layers.SimpleRNN(40, return_sequences=True),
    tf.keras.layers.SimpleRNN(40),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

optimizer = tf.keras.optimizers.SGD(lr=1e-6, momentum=0.9)
model.compile(loss="mse", optimizer=optimizer)
history = model.fit(dataset, epochs=500, verbose=0)
forecast = []
for time in range(len(series) - window_size):
    forecast.append(model.predict(series[time:time + window_size][np.newaxis]))
forecast = forecast[split_time-window_size:]
results.append(np.array(forecast)[:, 0, 0])
print("Step {} has finished, results shape is {} mean is {}".format(i, (np.array(forecast)[:, 0, 0]).shape, np.mean(results)))
```

Figure 4.17 LSTM Code

In Figure 4.17, LSTM model have two bidirectional layers of 32 neurons that are used with a transformative dense layer. LSTM is run for 500 epochs with a learning rate of 10^{-6} , and momentum of 0.9 using SGD optimizer. Table 4.7 gives the LSTM results for the first 11 ATMs, the remaining outcomes may be found in the Appendix A.

Table 4.7 LSTM Scores

LSTM	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
SMAPE	0.16	0.32	0.21	0.27	0.23	0.21	0.26	0.27	0.18	0.23	0.24
MAPE	0.16	0.50	0.20	0.29	0.23	0.25	0.30	0.32	0.17	0.26	0.28
MAE	3.24	5.25	1.84	6.15	3.39	3.91	3.87	3.72	5.38	6.10	3.73

The LSTM SMAPE scores of all the 111 series are between 13.22% and 35.40%, with an average of 22.83%. The average SMAPE for the first eleven series is 23.45%, which is quite the same with ARIMA 23.41%, but worst than SARIMA 21.88%. The ML models; DNN500 20.82%, DNN1000 20.45% and RNN 21.63% outperform the LSTM model for the first eleven series. The Figure 4.18 shows the ML forecasting results for the first ATM.

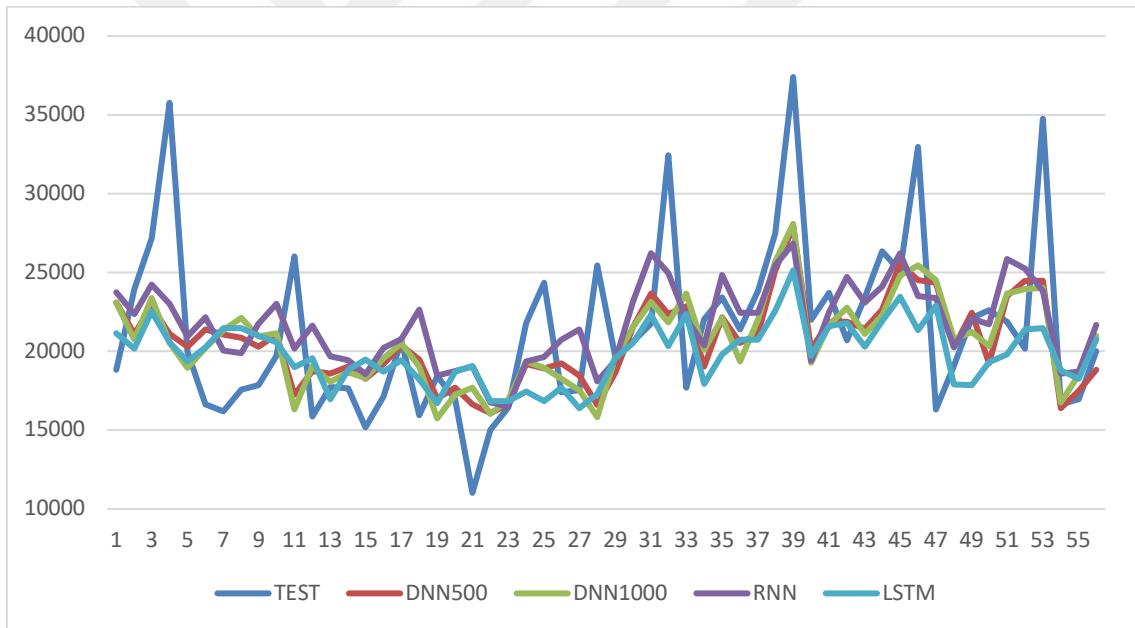


Figure 4.18 ML Forecasting Results (ATM#1)

4.1.4 Evaluating the Results

In the previous sub-sections, the forecasting errors are calculated for four alternative ML models. In this study the best performing forecasting model for each machine (111 series) is found for three alternative metrics. The forecasting model selection for the first 11 ATMs are in the Table 4.8, the remaining selections may be found in the Appendix B.

Table 4.8 Forecasting Model Selection

	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
SMAPE	0.14	0.25	0.20	0.21	0.23	0.15	0.26	0.22	0.13	0.21	0.22
MAPE	0.14	0.38	0.20	0.24	0.23	0.15	0.30	0.27	0.13	0.25	0.24
MAE	2.82	3.92	1.71	5.30	3.39	2.63	3.87	3.17	3.69	5.52	3.42
SMAPE	DNN1000	DNN1000	RNN	RNN	LSTM	DNN500	LSTM	DNN1000	DNN500	DNN500	DNN1000
MAPE	DNN1000	DNN1000	LSTM	RNN	LSTM	DNN500	LSTM	DNN1000	DNN500	DNN1000	DNN1000
MAE	DNN1000	DNN1000	RNN	RNN	LSTM	DNN500	LSTM	DNN1000	DNN500	DNN500	DNN1000

The distribution of the selected models according to alternative error measures are in Table 4.9 and Figure 4.17.

Table 4.9 Selected Model Numbers

	DNN500	DNN1000	RNN	LSTM
SMAPE	20	44	21	26
MAPE	22	35	22	32
MAE	20	43	20	28

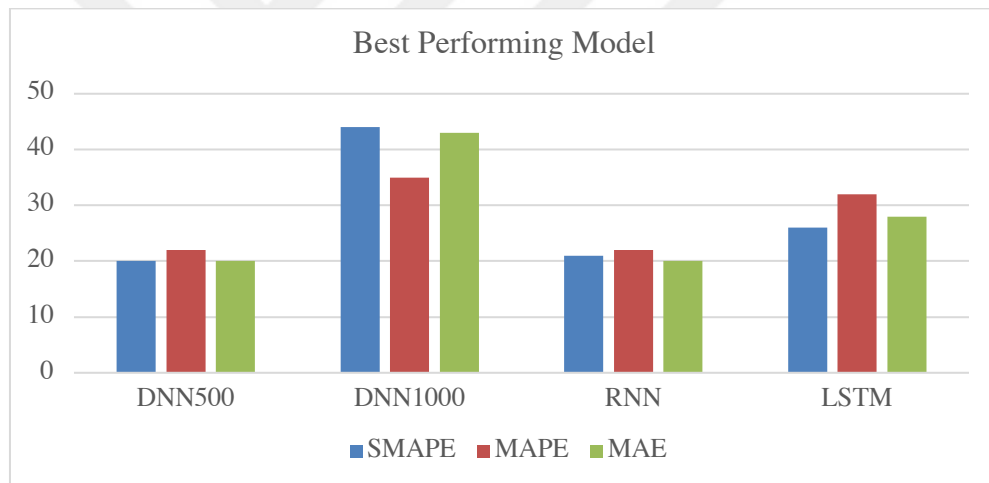


Figure 4.19 Selected Model Numbers

In general, DNN1000 is the best performing model for each metric, followed by LSTM. According to SMAPE, 44 out of 111 ATM demands respond better to DNN1000, 26 of them is better forecasted with LSTM, 21 ATM demands is suitable for RNN and DNN500 may be used to forecast demand of 20 ATMs. These numbers slightly change, when alternative error metrics (MAPE, MAE) are selected. There is no domination between models, therefore each series should be examined separately, and for each ATM the best performing forecasting model should be selected.

The error metrics have advantages and disadvantages among them, for instance MAPE is very sensitive to the small values, while SMAPE symmetrically punish the two-way deviations. MAE is a scale-based error metric, and difficult to interpret when there are multiple time series with different magnitude. In this thesis, SMAPE is selected because is the common metric of the literature using data set NN5.

In addition, according to the selected error metric, the selected forecasting model may be changed. However, there is a strong correlation between error metrics on the forecasting model selection. For instance, for 84 series, SMAPE and MAPE select the same forecasting model which is a quite good ratio (75.68%). For 88 series minimum MAPE and MAE scores, select the same model (79.28%). This number increase up to 100 series considering SMAPE and MAE (90.09%). In other words, in multiple time series forecasting the selected error metric would change slightly the rest of the decision.

In this chapter, the focus was to increase the forecasting accuracy, and finding the best forecasting model for each ATM. The next section describes the replenishment decision basing on the selected forecast model. The cost and service level outcomes of the selected forecasting model over a fixed forecasting horizon of 28 days (four week is considered as one month) is calculated.

4.2 DSS FOR REPLENISHMENT

4.2.1 Performance Criteria Selection

The replenishment frequency and filling amount of the ATMs are really important decisions for banks considering all the excessive ATM networks that a bank holds. The optimization of this frequency and fill-rate with result significant cost decrease for a bank. However, when this cost decrease is targeted, the service level of the ATMs should be tracked also.

In this study, the optimal replenishment frequency T^* is calculated basing on periodic inventory replenishment method over 28 days. Firstly, the average of the forecasted

series is calculated. Then optimal replenishment quantity is calculated using following formula

$$Q = \sqrt{2 * \bar{D} * C_s / C_h} \quad (4.1)$$

Where $\bar{D}$ is the average of the forecasted series, C_s is the ordering cost and C_h is the holding cost. In this study the ordering cost is considered as the replenishment cost of an ATM and fixed to 100 TL per replenishment (Ekinici et al. 2015). The holding cost of an ATM is the overnight interest rate of the Central Bank of the country, this rate is calculated by dividing 18% to 365. Then by dividing the calculated Q to the average demand T* values are calculated. All these calculations are made in MS Excel. An example Excel Sheet is in Table 4.10, where the first 28 days of the test data of some series are employed.

Table 4.10 T* Calculation

Day	N109 preds	N110 preds	N112 preds	N130 preds	N135 preds	N145 preds	N149 preds	N158 preds
1	14598	15306	19940	12613	20876	24646	21287	19940
2	20380	18268	28614	15972	26857	25751	23115	28614
3	36154	17234	37046	36536	29904	37684	35672	37046
4	51885	30768	26630	51162	54039	27353	45762	26630
5	39895	42446	49405	36593	48597	27353	36763	49405
6	20196	21287	30655	17134	17829	34977	8078	30655
7	23200	20493	27693	17120	21344	28189	17149	27693
8	21981	36210	26290	18254	32313	32412	21740	26290
	*	*	*	*	*	*	*	*
	*	*	*	*	*	*	*	*
	*	*	*	*	*	*	*	*
24	29974	35913	39371	30003	30924	38279	30967	39371
25	45564	40986	26630	48994	36395	27353	35587	26630
26	35629	22031	49008	35813	37174	27353	36777	49008
27	19430	33121	31392	15859	10062	28784	15264	31392
28	24221	20536	28855	15788	15320	22931	17673	28855
Average	29469	28581	31671	26281	29183	30193	27060	31671
Total	825128	800255	886791	735856	817120	845408	757667	886791
EOQ	109322	107661	113333	103239	108790	110657	104758	113333
T*	3,71	3,77	3,58	3,93	3,73	3,66	3,87	3,58
Tmin	3	3	3	3	3	3	3	3
EOQ'	88407	85742	95013	78842	87549	90579	81179	95013
Tmax	4	4	4	4	4	4	4	4
EOQ''	117875	114322	126684	105122	116731	120773	108238	126684

As in the Table 4.10, T^* values are round up and round down adapting the Q values. To sum up there are four alternative ways to replenish the ATMs with a fixed fill amount. Employing T^- and filling ATMs more frequently which presumed to increase service level, but will increase the replenishment costs or employing T^+ which may yield to decreased service level. In this thesis, the optimal replenishment period is calculated for each machine in each forecasting model. For the first eleven series the results are in Table 4.11. The remaining results may be found in Appendix B.

Table 4.11 Optimal T^* Values

	NN5-101	NN5-102	NN5-103	NN5-104	NN5-105	NN5-106	NN5-107	NN5-108	NN5-109	NN5-110	NN5-111
TEST	4.57	4.34	6.72	3.94	4.99	4.67	4.82	5.05	3.71	3.47	4.81
DNN1000	4.61	4.40	7.12	4.00	5.08	4.57	4.96	5.15	3.74	3.95	5.21
DNN500	4.60	4.39	7.22	3.98	5.06	4.62	4.96	5.15	3.75	3.93	5.21
RNN	4.71	4.38	6.89	4.10	5.44	4.45	5.16	4.81	3.76	3.75	4.86
LSTM	4.50	4.57	7.34	4.31	5.19	4.53	5.19	5.31	3.99	4.01	4.94

As in the Table 4.10, T^* values tend to be between four and five days, and this range does not change among the selected forecasting model. These results mean that banks should replenish these ATMs every four or five days. The third ATM may be replenished every 6 day or once a week, while the ninth and tenth ATMs should be replenished more frequently; every three days. The classification of the ATMs over the optimal replenishment period is a new perspective on the literature, proposed on this thesis. The distribution of the T^* values for test data and alternative forecasting models are in Table 4.12.

Table 4.12 T^* Distribution

	1<T<2	2<T<3	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	8<T<9
TEST	0	0	13	67	20	6	5	0
DNN1000	0	0	13	59	26	7	6	0
DNN500	0	0	13	59	26	8	5	0
RNN	0	0	15	57	29	7	3	0
LSTM	0	0	8	55	36	6	6	0

Table 4.12 shows that replenishment of the ATMs every day or every two days is out of question according to the optimal T^* strategy. For test data, 13 ATMs' T^* values are between three and four, 67 ATMs' T^* values are between four and five and 20 ATMs' T^* values are between five and six. Figures 4.19 and 4.20 show the numbers and percentage of T^* values according to the alternative forecasting models.

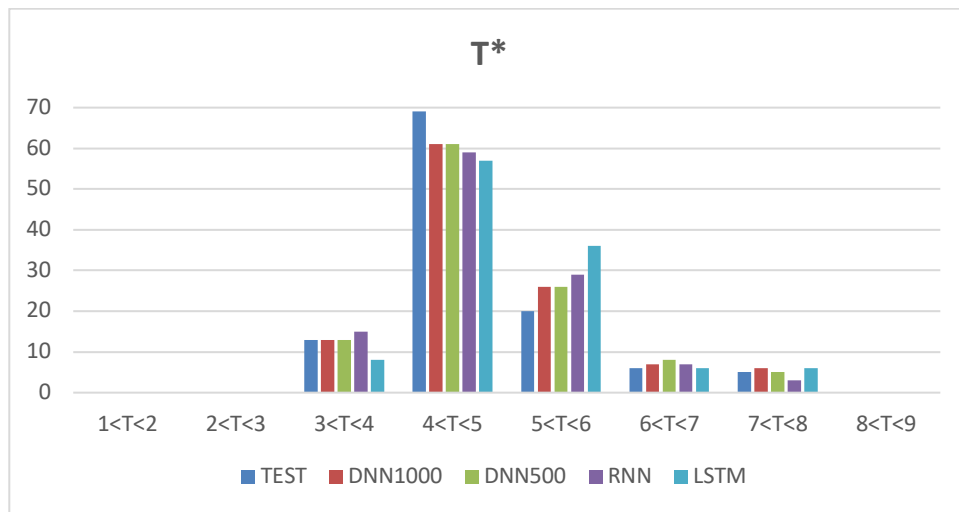


Figure 4.20 T* Numbers

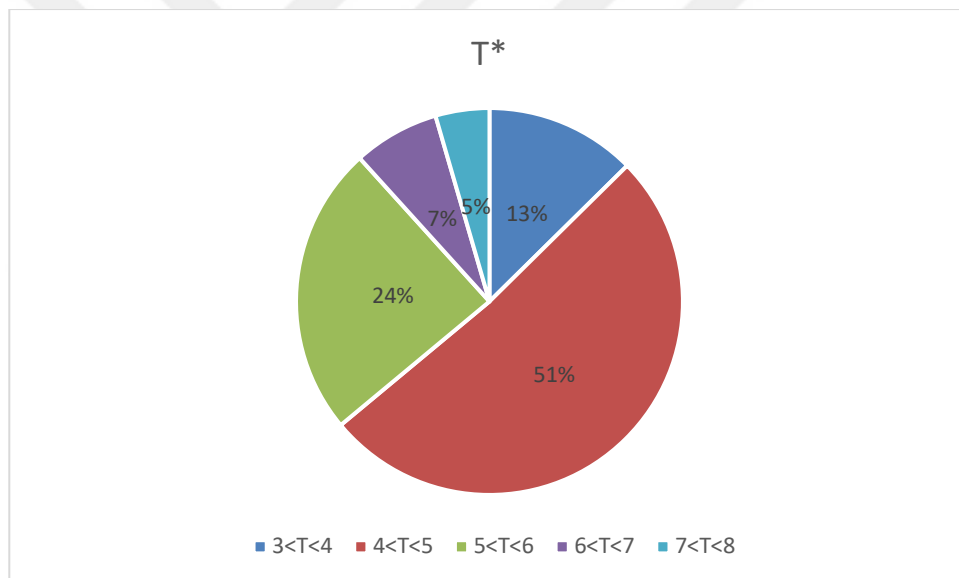


Figure 4.21 T* Distribution

As in Figures 4.20 and 4.21, the daily replenishment and every other day replenishment are not cost-oriented approaches for banks. This is one of the major findings of the study. Most of the ATMs should be replenished every four or five days according to different forecasting model outcomes. 51% of the ATMs is in the “ $4 < T^* < 5$ ” group, and 24% of the series is in the “ $5 < T^* < 6$ ” group. It should be reminded that, this thesis motivation is to identify a decision-making path for the banks, and these outcomes might change when the data or parameters like replenishment costs or overnight interest rate change. The maximum limit of replenishment period is seven days, which is

directly correlated to the weekly seasonality of the demand. The replenishment period for calculations is selected according to the best forecasting model for each ATM. In all the calculations and results ATMs are grouped according their T^* values and in total five groups are constructed; " $3 < T^* < 4$ ", " $4 < T^* < 5$ ", " $5 < T^* < 6$ ", " $6 < T^* < 7$ ", " $7 < T^* < 8$ ", respectively.

4.2.2 Creation of Replenishment Tables

Alternatively, to the replenishment decision with fixed order quantity on specific period intervals, Lot-for-lot replenishment strategy is also used in this study. The replenishment decision is followed for a range of one day to seven days, which mean banks have to visit their ATMs at least once a week. In other words, for each ATM, after finding the T^* values, 11 different calculation sheets are prepared to track the costs, service levels and average stock. In the Table 4.13, 4.14 and 4.15 the calculations for ATM#9 are given.

Table 4.13 Lot-for-lot Replenishment (1-4 days)

N109 test	DNN500	Replenishment	Stock	Cost	Replenishment	Stock	Cost	Replenishment	Stock	Cost	Replenishment	Stock	Cost
14598	18514		3917	1.93	35095	20497	10.11	68612	54015	26.64	110474	95877	47.28
20380	16580	12664	-3799	-3.75		117	0.06		33635	16.59		75497	37.23
36154	33518	33518	-2636	-2.60	75262	39226	19.34		-2519	-2.48		39343	19.40
51885	41862	41862	-10023	-9.89		-12659	-12.49	99093	47209	23.28		-12542	-12.37
39895	38466	38466	-1429	-1.41	57232	17337	8.55		7313	3.61	95625	55730	27.48
20196	18766	18766	-1429	-1.41		-2859	-2.82		-12882	-12.71		35534	17.52
23200	19958	19958	-3242	-3.20	38393	15193	7.49	58243	35043	17.28		12334	6.08
18438	18436	18436	-3	0.00		-3245	-3.20		16605	8.19		-6104	-6.02
23328	19850	19850	-3478	-3.43	55338	32011	15.79		-6723	-6.63	141550	118223	58.30
33050	35489	35489	2439	1.20		-1039	-1.03	121701	88651	43.72		85173	42.00
49065	47480	45041	-1585	-1.56	86212	37148	18.32		39586	19.52		36108	17.81
43112	38733	38733	-4380	-4.32		-5965	-5.88		-3526	-3.48		-7004	-6.91
23639	20686	20686	-2954	-2.91	43998	20358	10.04	62718	39078	19.27	84042	60402	29.79
21471	23312	23312	1841	0.91		-1113	-1.10		17607	8.68		38931	19.20
15760	18720	16879	2960	1.46	40044	24284	11.98		1848	0.91		23172	11.43
28699	21324	18364	-7375	-7.27		-4415	-4.35	109277	82426	40.65		-5527	-5.45
52452	36359	36359	-16092	-15.87	89801	37349	18.42		29974	14.78	143199	90747	44.75
26035	53442	53442	27407	13.52		11315	5.58		3940	1.94		64713	31.91
36423	35101	7694	-1322	-1.30	42083	16975	8.37	73829	41346	20.39		28290	13.95
16695	18297	18297	1602	0.79		280	0.14		24651	12.16		11595	5.72
31236	24371	22769	-6865	-6.77	40554	9598	4.73		-6585	-6.49	92432	72791	35.90
22619	16463	16463	-6156	-6.07		-13021	-12.84	79656	57037	28.13		50172	24.74
21981	25077	25077	3096	1.53	63192	41211	20.32		35055	17.29		28190	13.90
29974	38115	35019	8140	4.01		11237	5.54		5081	2.51		-1784	-1.76
45564	44648	36508	-916	-0.90	69468	35141	17.33	98932	58448	28.82	128964	83400	41.13
35629	36057	36057	427	0.21		-489	-0.48		22819	11.25		47771	23.56
19430	23308	22881	3878	1.91	48259	28829	14.22		3389	1.67		28340	13.98
24221	24952	21074	731	0.36		4609	2.27	21563	731	0.36		4120	2.03
Total Fill		752174			768352			743526			704327		
		Cash-Out Day	17		Cash-Out Day	9		Cash-Out Day	5		Cash-Out Day	5	
		Holding Cost		27.83			198.60			367.64			585.10
		Back-Out Cost		72.68			44.19			31.79			32.51
		SL		0.91			0.93			0.90			0.85
		DSL		0.39			0.68			0.82			0.82
		Total Cost		2827.83			1598.60			1300.97			1285.10

Table 4.14 Lot-for-lot Replenishment (5-7 days)

N109 test	DNN500	Replenishment	Stock	Cost	Replenishment	Stock	Cost	Replenishment	Stock	Cost
14598	18514	148940	134342	66.25	167706	153108	75.51	187664	173066	85.35
20380	16580		113962	56.20		132729	65.46		152686	75.30
36154	33518		77809	38.37		96575	47.63		116533	57.47
51885	41862		25924	12.78		44690	22.04		64648	31.88
39895	38466		-13971	-13.78		4795	2.36		24753	12.21
20196	18766	112498	92302	45.52		-15401	-15.19		4557	2.25
23200	19958		69102	34.08	179944	156744	77.30		-18643	-18.39
18438	18436		50664	24.98		138306	68.21	203984	185546	91.50
23328	19850		27336	13.48		114978	56.70		162218	80.00
33050	35489		-5714	-5.64		81928	40.40		129168	63.70
49065	47480	148930	99865	49.25		32863	16.21		80104	39.50
43112	38733		56753	27.99		-10249	-10.11		36991	18.24
23639	20686		33114	16.33	173843	150204	74.07		13352	6.58
21471	23312		11643	5.74		128732	63.48		-8119	-8.01
15760	18720		-4117	-4.06		112973	55.71	207614	191854	94.61
28699	21324	164523	135824	66.98		84274	41.56		163155	80.46
52452	36359		83372	41.12		31822	15.69		110704	54.59
26035	53442		57338	28.28		5787	2.85		84669	41.75
36423	35101		20915	10.31	151637	121002	59.67		48246	23.79
16695	18297		4220	2.08		104307	51.44		31551	15.56
31236	24371	144455	117439	57.92		73071	36.03		315	0.16
22619	16463		94820	46.76		50452	24.88	208304	186001	91.73
21981	25077		72839	35.92		28470	14.04		164019	80.89
29974	38115		42864	21.14		-1504	-1.48		134045	66.10
45564	44648		-2700	-2.66	128964	83400	41.13		88481	43.63
35629	36057	84316	48687	24.01		47771	23.56		52852	26.06
19430	23308		29256	14.43		28340	13.98		33421	16.48
24221	24952		5036	2.48		4120	2.03		9201	4.54
Total Fill		673236			652902			638417		
		Cash-Out Day	4		Cash-Out Day	3		Cash-Out Day	2	
		Holding Cost		742.40			991.94			1204.34
		Back-Out Cost		26.14			26.78			26.40
		SL		0.82			0.79			0.77
		DSL		0.86			0.89			0.93
		Total Cost		1302.40			1458.61			1604.34

Table 4.15 T* Replenishment

N109_test	DNN500	Replenishment	Stock	Cost	Replenishment	Stock	Cost	Replenishment	Stock	Cost	Replenishment	Stock	Cost
14598	18514	108173	93576	46.15	108173	93576	46.15	86559	71961	35.49	115412	100814	49.72
20380	16580		73196	36.10		73196	36.10		51581	25.44		80434	39.67
36154	33518		37042	18.27		37042	18.27		15428	7.61		44281	21.84
51885	41862	71306	56463	27.84		-14843	-14.64	71131	34674	17.10		-7604	-7.50
39895	38466		16568	8.17	108348	68453	33.76		-5221	-5.15	115412	75517	37.24
20196	18766		-3628	-3.58		48257	23.80		-20196	-19.92		55321	27.28
23200	19958	108348	85148	41.99		25057	12.36	86559	63359	31.25		32121	15.84
18438	18436		66710	32.90		6619	3.26		44920	22.15		13683	6.75
23328	19850		43382	21.39	101729	85020	41.93		21593	10.65	101729	92084	45.41
33050	35489	64966	75298	37.13		51970	25.63	64966	53509	26.39		59034	29.11
49065	47480		26234	12.94		2906	1.43		4444	2.19		9969	4.92
43112	38733		-16879	-16.65		-40206	-39.66		-38668	-38.14		-33143	-32.69
23639	20686	108348	84709	41.77	108348	84709	41.77	86559	62919	31.03	115412	91772	45.26
21471	23312		63237	31.19		63237	31.19		41448	20.44		70301	34.67
15760	18720		47478	23.41		47478	23.41		25689	12.67		54541	26.90
28699	21324	60870	79649	39.28		18779	9.26	60870	57860	28.53		25842	12.74
52452	36359		27197	13.41	89569	55896	27.57		5408	2.67	89569	62960	31.05
26035	53442		1163	0.57		29862	14.73		-20627	-20.34		36925	18.21
36423	35101	107185	71925	35.47		-6561	-6.47	86559	50136	24.72		502	0.25
16695	18297		55230	27.24		-16695	-16.47		33441	16.49		-16193	-15.97
31236	24371		23994	11.83	108348	77112	38.03		2205	1.09	115412	84176	41.51
22619	16463	84354	85729	42.28		54493	26.87	84354	63940	31.53		61557	30.36
21981	25077		63748	31.44		32512	16.03		41958	20.69		39575	19.52
29974	38115		33773	16.66		2537	1.25		11984	5.91		9601	4.73
45564	44648	74575	62784	30.96	105811	62784	30.96	74575	40995	20.22	105811	69848	34.45
35629	36057		27155	13.39		27155	13.39		5365	2.65		34218	16.87
19430	23308		7724	3.81		7724	3.81		-14065	-13.87		14788	7.29
24221	24952	33541	17045	8.41		-16496	-16.27	28853	4632	2.28		-9432	-9.30
Q*	108173	732007			640667			662939			661858		
T*	3 or 4	Cash-Out Day	2		Cash-Out Day	5		Cash-Out Day	5		Cash-Out Day	4	
Q*	86559	Holding Cost		654.00			520.95			399.18			601.58
T*	3	Back-Out Cost		20.23			93.50			97.42			65.46
		Service Level		0.89			0.78			0.80			0.80
Q*	115412	Daily Service Level		0.93			0.82			0.82			0.86
T*	4	Total Cost		1254.09			1015.13			1099.18			1161.58

In the calculation process, holding cost is the function the cash-in-stock multiplied by the holding rate (which is the overnight interest). The back-out cost is a hypothetical cost that measures the negative stocks effect. It is calculated multiplying the absolute value of the negative stocks by double of the overnight interest rate (punishment). Within the problem nature, negative stocks are omitted in next day, because the client who tried to withdraw money, does not wait in front of the ATM anymore. Two service levels are defined, the service level is the ratio of the provided cash over total demand, the daily service level measures, the stock-out days over 28 days horizon, so it calculates how many times the ATM does not respond the customer demand. Average Stock is the daily stock of the machines. The total cost is the sum of holding, back-out and replenishment costs. The replenishment cost is simply machine visit multiplied by 100 TL.

For each machine the merged tables containing the cost and service levels are constructed, Table 4.16 shows the results for the 9th and 10th ATMs.

Table 4.16 Merged Results for 9th and 10th ATMs

109, DNN500	1	2	3	4	5	6	7	T ⁻ (Q)	T ⁺ (Q)	T ⁻ (Q')	T ⁺ (Q'')
Holding Cost	17.23	212.41	384.13	607.59	815.85	1022.6 0	1210.7 9	668.38	553.76	425.06	638.39
Back-Out Cost	40.86	31.47	15.58	19.43	13.58	14.38	16.96	21.66	108.36	98.94	77.54
Service Level	0.95	0.94	0.91	0.85	0.81	0.78	0.75	0.88	0.76	0.80	0.79
Daily Service Level	0.46	0.71	0.79	0.86	0.89	0.86	0.89	0.93	0.75	0.75	0.82
Replenishment Cost	2600.0	1400.00	900.00	700.00	600.00	500.00	400.00	900.00	700.00	900.00	700.00
Total Cost	2658.0 9	1643.88	1299.7 1	1327.0 2	1429.4 3	1536.9 8	1627.7 5	1590.0 4	1362.1 2	1424.0 0	1415.93
110, DNN500	1	2	3	4	5	6	7	T ⁻ (Q)	T ⁺ (Q)	T ⁻ (Q')	T ⁺ (Q'')
Holding Cost	39.63	213.42	365.64	573.53	710.34	845.39	1089.7 4	696.51	596.94	680.88	900.00
Back-Out Cost	54.76	39.27	32.36	25.02	24.61	18.18	21.02	0.00	39.89	0.00	2.37
Service Level	0.92	0.92	0.87	0.84	0.80	0.79	0.75	0.89	0.82	0.89	0.84
Daily Service Level	0.57	0.82	0.82	0.86	0.93	0.89	0.89	1.00	0.93	1.00	0.96
Replenishment Cost	2600.0 0	1400.00	900.00	700.00	600.00	500.00	400.00	900.00	700.00	900.00	700.00
Total Cost	2694.3 8	1652.69	1298.0 0	1298.5 6	1334.9 5	1363.5 7	1510.7 6	1596.5 1	1336.8 3	1580.8 8	1602.37

For all the ATMs the best holding costs are obtained in daily or every two days replenishment case. However, these replenishment periods result with excessive replenishment costs, which increase the total cost of the system. In addition, daily

replenishment strategy results with a significantly low service-level. For instance, if the ninth ATM is replenished daily, the holding cost is 17.23 TL, but back-out cost is 40.86 TL. The service level based on satisfied demand proportion is 95%, but daily service level which corresponds the stock-out day of the ATM is only 46%. The back-out cost is 40.86 TL and total cost of the system is 2658.09 TL. However, if the ATM is replenished every four days, the holding cost increases up to 607.59 TL while the total cost drops to 1327.02 TL. Besides, the service level is 86% and the daily service level is 85%. Similar situations may be observed for all the ATMs, including the tenth ATM given in Table 4.16. Figure 4.22 shows the holding cost and total cost changement according to the alternative replenishment decisions for ATM#9 while Figure 4.23 shows the average service level vs the total cost of the system.

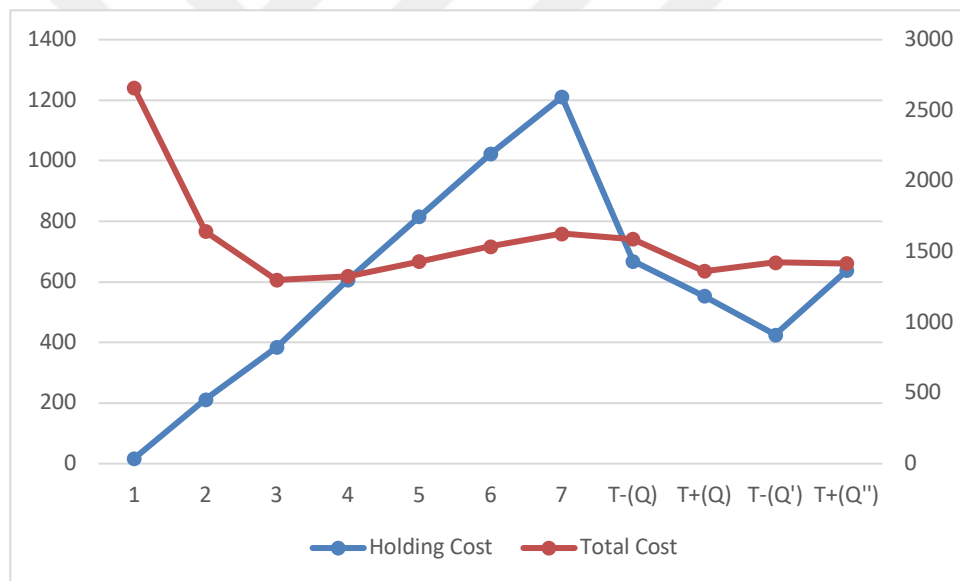


Figure 4.22 Holding vs Total Cost (ATM #9)

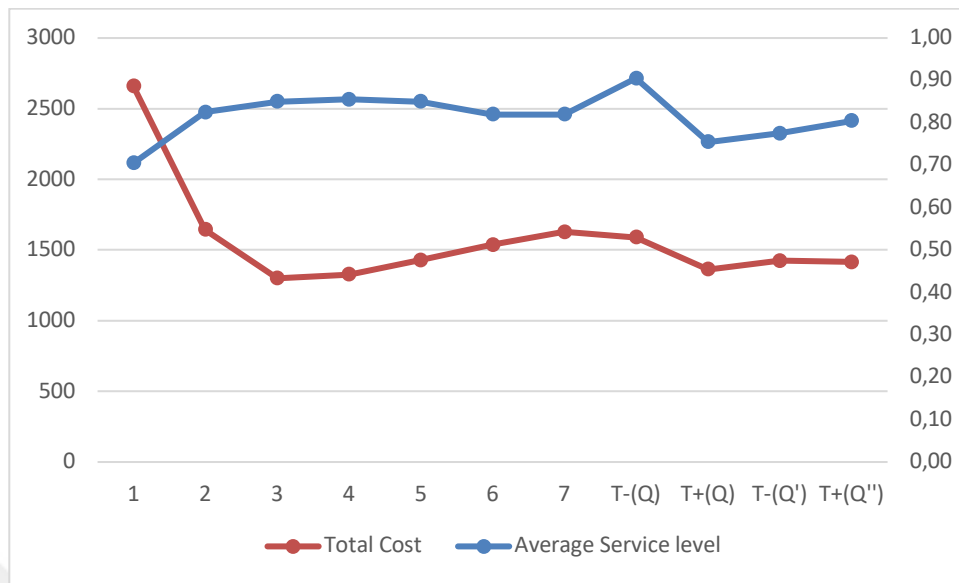


Figure 4.23 Average Service Level vs Total Cost (ATM #9)

For all 111 ATMs these steps are repeated, and for each machine the relevant cost and service levels are calculated. The next step is to choose the best replenishment policy (T^* or Lot-for-lot) and replenishment period for each ATM.

4.2.3 Building the Approaches

The two conflicting objective of the ATM management process, is to satisfy customer demand at maximum level, while reducing the inventory and replenishment costs. In this study, three approaches are designed. In the first approach, bank is completely cost-oriented, and will choose the replenishment period and refill amount according to the minimum overall cost. In the second approach bank is completely customer oriented and will choose to replenishment model that maximizes the service levels. The third approach is a trade-off between the two objectives, and find a balance among the two objectives called as the integrated approach.

4.2.3.1 Cost-Oriented Approach

The results of the cost-oriented model, in which the replenishment decision is made according to the minimum total cost is in Table 4.17 – 4.21. Where SL is the service level.

Table 4.17 Cost Oriented Results for ATMs 3<T*≤4

3<T≤4	NN5-109	NN5-110	NN5-112	NN5-130	NN5-135	NN5-145	NN5-149	NN5-158	NN5-163	NN5-176	NN5-177	NN5-178	NN5-179	NN5-194
Replenishment	3	4	T ⁺ (Q)	4	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	3	4	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)
Cost	1299.43	1266.65	1303.27	1250.01	1358.72	1294.67	1332.17	1299.66	1299.53	1270.19	1261.65	1288.93	1431.19	1263.17
Average SL	0.86	0.84	0.76	0.83	0.8	0.79	0.85	0.76	0.83	0.86	0.88	0.84	0.67	0.77

Table 4.18 Cost Oriented Results for ATMs 4<T*≤5

4<T≤5	NN5-101	NN5-102	NN5-104	NN5-106	NN5-113	NN5-114	NN5-115	NN5-116	NN5-117	NN5-118	NN5-119	NN5-121	NN5-122	NN5-124	NN5-125
Replenishment	T ⁺ (Q)	4	4	4	6	T ⁺ (Q)	4	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	4	T ⁺ (Q)	T ⁺ (Q)	4	5
Cost	1116.60	1169.71	1206.08	1128.14	1081.95	1171.43	1189.42	1140.52	1141.14	1104.18	1113.11	1178.58	1114.68	1133.05	1119.47
Average SL	0.83	0.84	0.80	0.89	0.81	0.78	0.88	0.85	0.91	0.79	0.88	0.86	0.91	0.88	0.85
4<T≤5	NN5-126	NN5-127	NN5-128	NN5-129	NN5-131	NN5-133	NN5-136	NN5-139	NN5-140	NN5-142	NN5-143	NN5-144	NN5-146	NN5-150	NN5-151
Replenishment	7	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	5	4	4	4	T ⁺ (Q)	4	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	5	4
Cost	1074.16	1202.80	1194.52	1187.96	1053.67	1109.03	1081.51	1098.50	1207.05	1077.67	1181.49	1178.76	1145.43	1102.30	1094.57
Average SL	0.77	0.76	0.80	0.79	0.83	0.84	0.85	0.86	0.84	0.85	0.90	0.79	0.89	0.77	0.87
4<T≤5	NN5-152	NN5-153	NN5-154	NN5-155	NN5-156	NN5-157	NN5-159	NN5-161	NN5-165	NN5-168	NN5-169	NN5-171	NN5-172	NN5-173	NN5-181
Replenishment	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	4	5	6	T ⁺ (Q)	T ⁺ (Q)	5	5	4	4	4	T ⁺ (Q)	4
Cost	1088.68	1145.91	1166.39	1111.85	1089.40	1088.28	1164.23	1107.10	1068.08	1076.44	1110.23	1104.31	1074.45	1136.90	1100.28
Average SL	0.88	0.81	0.76	0.86	0.88	0.82	0.72	0.84	0.79	0.87	0.82	0.87	0.91	0.81	0.90
4<T≤5	NN5-186	NN5-188	NN5-189	NN5-191	NN5-198	NN5-201	NN5-203	NN5-204	NN5-205	NN5-206	NN5-207				
Replenishment	5	5	5	4	4	5	5	T ⁺ (Q)	4	T ⁺ (Q)	4				
Cost	1076.90	1081.28	1074.14	1111.17	1068.78	1112.71	1069.42	1139.06	1116.78	1129.36	1190.48				
Average SL	0.84	0.86	0.81	0.83	0.88	0.85	0.85	0.78	0.86	0.76	0.84				

Table 4.19 Cost Oriented Results for ATMs $5 < T^* < 6$

5<T<6	NN5-105	NN5-107	NN5-108	NN5-111	NN5-123	NN5-132	NN5-137	NN5-141	NN5-160	NN5-162	NN5-170	NN5-174	NN5-180	NN5-182
Replenishment	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	7	T ⁺ (Q)	T ⁺ (Q)	7
Cost	942.08	948.19	951.88	971.53	935.15	954.50	950.48	986.13	957.94	912.45	858.63	930.80	943.44	872.22
Average SL	0.70	0.70	0.76	0.76	0.71	0.67	0.69	0.66	0.64	0.70	0.75	0.75	0.66	0.82
5<T<6	NN5-183	NN5-184	NN5-185	NN5-187	NN5-190	NN5-193	NN5-195	NN5-196	NN5-197	NN5-202	NN5-208	NN5-210	NN5-211	
Replenishment	T ⁺ (Q)	7	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	7	T ⁺ (Q)	7	7	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	7	
Cost	953.34	990.58	905.20	907.80	972.17	885.15	926.00	935.84	880.44	908.57	913.85	941.50	921.75	
Average SL	0.73	0.75	0.73	0.76	0.76	0.83	0.70	0.86	0.80	0.78	0.73	0.71	0.75	

Table 4.20 Cost Oriented Results for ATMs $6 < T^* < 7$

$6 < T < 7$	NN5-103	NN5-134	NN5-147	NN5-148	NN5-164	NN5-166	NN5-167	NN5-175
Replenishment	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$
Cost	755.56	753.80	805.60	741.40	752.31	742.60	762.03	692.61
Average Service Level	0.76	0.60	0.73	0.70	0.63	0.73	0.73	0.71

Table 4.21 Cost Oriented Results for ATMs $7 < T^* < 8$

$7 < T < 8$	NN5-120	NN5-138	NN5-192	NN5-199	NN5-200
Replenishment	7	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$
Cost	670.61	685.32	675.67	754.91	736.23
Average Service Level	0.83	0.69	0.75	0.80	0.77

In Tables 4.17 - 4.21 the problem is evaluated on five alternative T^* categories, and for each ATM, the minimum cost giving replenishment model is selected. For instance, in the first group given in Table 4.13; for ATM #30, replenishing the machine every 4 day according to the lot for lot strategy is the optimum solution for cost. It results with 1250.01 TL, with an average service level of 83%. For ATM #63 the optimal Replenishment strategy is $T^+(Q)$ indicating of replenishment every four days with a calculated fixed amount. The total cost 1299.53 TL, with an average service level of 83%. Similarly, for all the machines the results are given in Tables 4.17 – 4.21. Figure 4.24 illustrates the cost-oriented approach results for ATMs $6 < T^* < 7$.

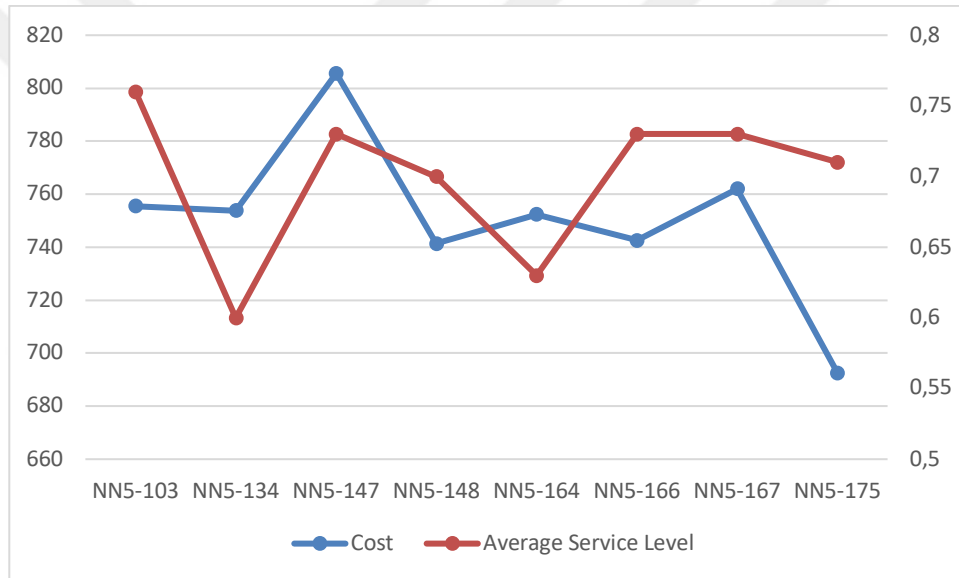


Figure 4.24 Cost-Oriented Approach Results for ATMs $6 < T^* < 7$

The total cost of the 111 ATMs in the system is 116833.98 TL, with an average cost of 1053.01 TL per ATM. The average service level of the system is 79.6%. Table 4.22 gives the total cost, average cost, and average service level per class.

Table 4.22 Cost Oriented Results per Class

	$3 < T < 4$	$4 < T < 5$	$5 < T < 6$	$6 < T < 7$	$7 < T < 8$
Total Cost	18219.23	63978.49	25157.62	6005.90	3522.74
Average Cost	1301.37	1122.43	931.76	750.74	704.55
Average Service Level	0.81	0.84	0.74	0.70	0.77

For the first group, average cost is 1301.37 TL, for the second-class average cost is 1122.43 TL. For ATMs where T^* is between five and six, the average cost 931.76, for ATMs where T^* is between six and seven, the average cost decreases to 750.74 TL and for ATMs where T^* is between seven and eight the average cost drops to 704.55 TL. As the Replenishment period, average total cost of the system decreases too. However, this situation reflects to drops in average service levels. For example, for the first two groups the average service level is greater than 80%, 81% and 84%, respectively. But when the replenishment period is greater than five, the average service level is below than 80%. For ATMs in group $5 < T < 6$ the average service level is 74%, for ATMs in group $6 < T < 7$ the average service level is 70% and for ATMs in group $7 < T < 8$ the average service level is 77%. Figure 4.25 shows the results per class.

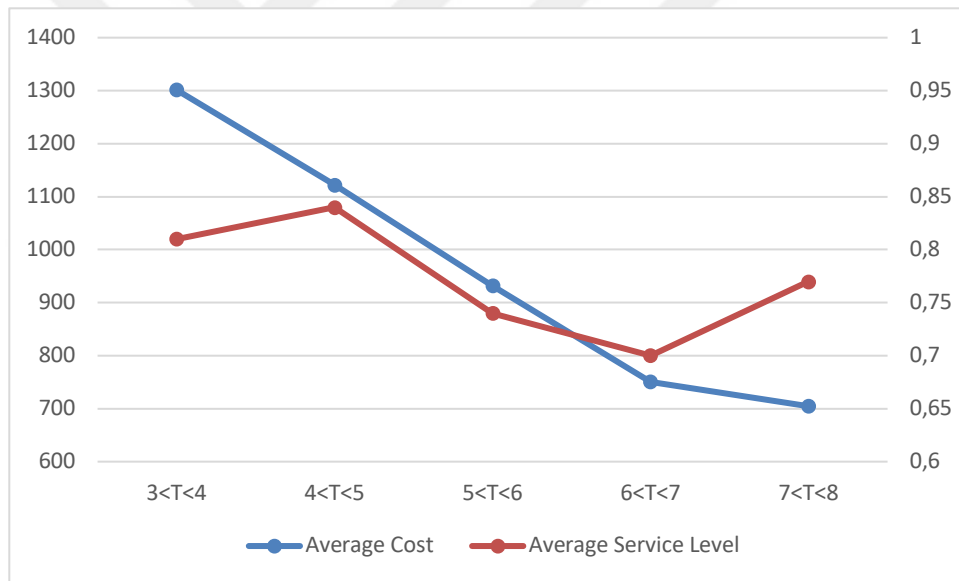


Figure 4.25 Average Service Level vs Average Cost per Class

When the replenishment period increases the average cost of the system decreases along with the service level. In addition, there is no significance dominance between replenishment models, 48 ATMs should be replenished with Lot-for-lot strategy, while 63 ATMs are suitable to be replenished by fixed amount according to their T^* values.

4.2.3.2 Customer-Oriented Approach

The second approach is to select the replenishment strategy that maximizes the average service level. In Tables 4.23 – 4.27, the selected replenishment strategy according to this approach and their corresponding costs are given.



Table 4.23 Service Level Oriented Results for ATMs 3<T*≤4

	NN5-109	NN5-110	NN5-112	NN5-130	NN5-135	NN5-145	NN5-149	NN5-158	NN5-163	NN5-176	NN5-177	NN5-178	NN5-179	NN5-194
Replenishment	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)
Cost	1574.22	1541.93	1555.01	1568.84	1610.86	1558.44	1592.94	1543.81	1619.80	1535.20	1607.94	1592.91	1569.54	1566.52
Average SL	0.91	0.93	0.96	0.91	0.95	0.97	0.96	0.96	0.90	0.93	0.96	0.95	0.92	0.91

Table 4.24 Service Level Oriented Results for ATMs 4<T*≤5

	NN5-101	NN5-102	NN5-104	NN5-106	NN5-113	NN5-114	NN5-115	NN5-116	NN5-117	NN5-118	NN5-119	NN5-121	NN5-122	NN5-124	NN5-125
Replenishment	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	5	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)
Cost	1197.41	1282.10	1345.44	1303.27	1226.45	1295.31	1262.73	1260.53	1204.95	1221.56	1289.44	1289.25	1285.43	1248.98	1258.08
Average SL	0.93	0.88	0.82	0.89	0.89	0.91	0.89	0.92	0.91	0.90	0.89	0.92	0.91	0.91	0.92
	NN5-126	NN5-127	NN5-128	NN5-129	NN5-131	NN5-133	NN5-136	NN5-139	NN5-140	NN5-142	NN5-143	NN5-144	NN5-146	NN5-150	NN5-151
Replenishment	T ⁻ (Q)	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	4	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)
Cost	1224.82	1318.19	1347.22	1316.33	1246.88	1266.82	1231.16	1268.41	1214.61	1254.23	1334.93	1271.98	1183.73	1223.06	1271.52
Average SL	0.91	0.90	0.88	0.90	0.93	0.92	0.92	0.91	0.95	0.89	0.95	0.85	0.90	0.87	0.95
	NN5-152	NN5-153	NN5-154	NN5-155	NN5-156	NN5-157	NN5-159	NN5-161	NN5-165	NN5-168	NN5-169	NN5-171	NN5-172	NN5-173	NN5-181
Replenishment	T ⁻ (Q)	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)
Cost	1248.68	1245.46	1274.88	1273.13	1284.21	1262.69	1329.36	1274.90	1225.14	1279.00	1210.20	1263.40	1262.42	1253.55	1295.23
Average SL	0.95	0.89	0.89	0.90	0.94	0.92	0.87	0.91	0.92	0.96	0.84	0.93	0.94	0.92	0.93
	NN5-186	NN5-188	NN5-189	NN5-191	NN5-198	NN5-201	NN5-203	NN5-204	NN5-205	NN5-206	NN5-207	NN5-209			
Replenishment	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)			
Cost	1273.71	1263.01	1221.08	1218.93	1234.15	1266.29	1260.35	1233.82	1254.56	1219.58	1278.07	1226.29			
Average SL	0.93	0.92	0.94	0.89	0.93	0.91	0.91	0.90	0.95	0.90	0.87	0.94			

Table 4.25 Service Level Oriented Results for ATMs $5 < T^* < 6$

	NN5-105	NN5-107	NN5-108	NN5-111	NN5-123	NN5-132	NN5-137	NN5-141	NN5-160	NN5-162	NN5-170	NN5-174	NN5-180	NN5-182
Replenishment	T(Q)	T(Q)	5	T(Q)	4	T(Q)	5	3	5	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)
Cost	1020.81	1045.11	1034.23	1039.97	1011.02	1045.08	1030.80	1141.25	1032.44	1025.45	1039.75	1034.88	1041.67	1047.28
Average SL	0.87	0.83	0.84	0.85	0.86	0.80	0.83	0.83	0.76	0.85	0.89	0.89	0.83	0.94
	NN5-183	NN5-184	NN5-185	NN5-187	NN5-190	NN5-193	NN5-195	NN5-196	NN5-197	NN5-202	NN5-208	NN5-210	NN5-211	
Replenishment	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	3	T(Q)	T(Q)	
Cost	1041.26	1104.98	1032.45	1053.92	1041.04	1061.91	1036.58	1081.70	1049.30	1021.38	1102.46	1035.44	1043.20	
Average SL	0.89	0.82	0.87	0.91	0.85	0.94	0.89	0.90	0.93	0.90	0.87	0.85	0.86	

Table 4.26 Service Level Oriented Results for ATMs $6 < T^* < 7$

	NN5-103	NN5-134	NN5-147	NN5-148	NN5-164	NN5-166	NN5-167	NN5-175
Replenishment	6	5	5	4	T(Q)	T(Q)	T(Q)	T(Q)
Cost	784.30	903.29	954.47	961.72	886.79	857.69	901.46	886.37
Average Service Level	0.85	0.82	0.86	0.85	0.81	0.84	0.85	0.82

Table 4.27 Service Level Oriented Results for ATMs $7 < T^* < 8$

	NN5-120	NN5-138	NN5-192	NN5-199	NN5-200
Replenishment	T(Q)	T(Q)	T(Q)	T(Q)	3
Cost	742.63	753.49	737.38	769.56	1028.25
Average Service Level	0.87	0.81	0.87	0.88	0.88

In the Tables 4.23 – 4.27, the problem is based on five alternative T^* categories, and for each category, the maximum service level providing replenishment model is selected. For instance, in the first group given in Table 4.23; for ATM #30, replenishing the machine with $T^-(Q)$ which corresponds to replenishing the ATM every three days with a fixed filling amount gives the optimum solution for average service level. It results with a total cost of 1568.84 TL with an average service level of 91%. If the same machine replenished with the cost-oriented approach it should be filled every four days with Lot for lot, giving a total cost of 1250.01 TL, with an average service level of 83%. Therefore, a gain of 8% in service level has a cost of 318.83 TL for this ATM.

For ATM #63, the customer-oriented approach results with $T^-(Q)$ which corresponds to replenishing the ATM every three days with a fixed filling amount gives the optimum solution for average service level. It results with a total cost of 1619.80 TL with an average service level of 90%. If the same machine replenished with the cost-oriented approach it should be filled with $T^+(Q)$ indicating of replenishment every four days with a calculated fixed amount giving a total cost 1299.53 TL, with an average service level of 83%. Therefore, a gain of 7% in service level has a cost of 320.07 TL for this ATM. Similarly, for all the machines the results are given in Tables 4.23 – 4.27.

Besides, 98 ATMs should be replenished by fixed amount according to T^* values and only 13 machines should be replenished by Lot-for-lot strategy. The total cost of the 111 ATMs in the system is 133377.61 TL, with an average cost of 1201.60 TL per ATM. The average service level of the system is 89.4%. Table 4.28 gives the total cost, average cost, and average service level per class.

Table 4.28 Service Level Oriented Results per Class

	$3 < T < 4$	$4 < T < 5$	$5 < T < 6$	$6 < T < 7$	$7 < T < 8$
Total Cost	22037.95	71876.91	28295.36	7136.09	4031.30
Average Cost	1574.14	1261.00	1047.98	892.01	806.26
Average Service Level	0.94	0.91	0.86	0.84	0.86

For the first group, average cost is 1574.14 TL, for the second-class average cost is 1261.00 TL. For ATMs where T^* is between five and six, the average cost 1047.98, for ATMs where T^* is between six and seven, the average cost decreases to 892.01 TL and

for ATMs where T^* is between seven and eight the average cost drops to 806.26 TL. As the replenishment period increase, average total cost of the system decreases too. However, this situation reflects to drops in average service levels. For example, for the first two groups the average service level is greater than 90%, 94% and 91%, respectively. But when the replenishment period is greater than five, the average service level is below than 90%. For ATMs in group $5 < T < 6$ the average service level is 86%, for ATMs in group $6 < T < 7$ the average service level is 84% and for ATMs in group $7 < T < 8$ the average service level is 86%. Figure 4.26 shows the results per class.

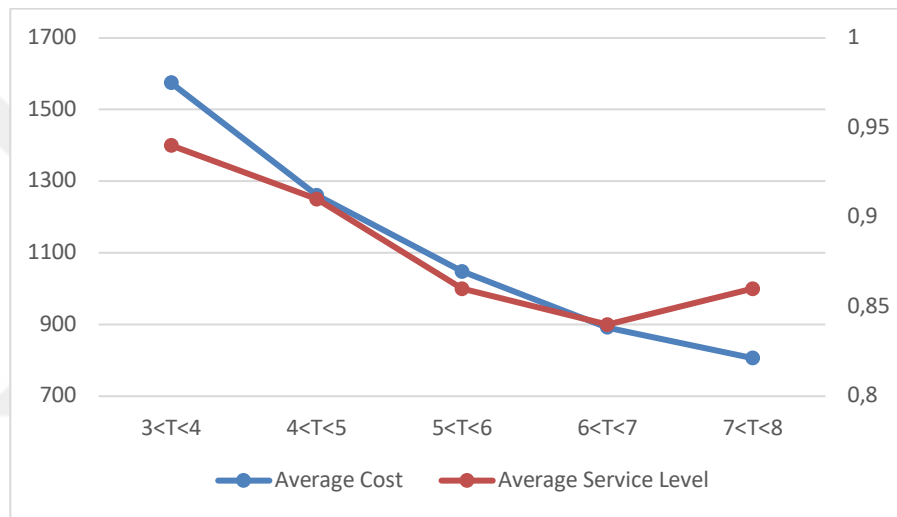


Figure 4.26 Average Service Level vs Average Cost per Class

The increment in the total cost of the system is 16493.64 TL for 111 ATMs while the average service level increased from 0.796 to 0.894. This overall trade-off should be evaluated in detail by experts in the decision-making process.

4.2.3.3 Integrated Approach

As the third decision making way, an integrated approach is built in this thesis. In this approach, every missed centesimal of the average service level is punished by multiplying 1000 TL. In other words, average service level is transformed into a cost function, and a hypothetical total cost of the system is calculated. In Tables 4.29 – 4.33, the selected replenishment strategy according to this approach and their corresponding costs are given.

Table 4.29 Integrated Approach Results for ATM 3<T*≤4

3<T≤4	NN5-109	NN5-110	NN5-112	NN5-130	NN5-135	NN5-145	NN5-149	NN5-158	NN5-163	NN5-176	NN5-177	NN5-178	NN5-179	NN5-194
Replenishment	3	4	4	4	3	T ⁺ (Q)	3	4	4	3	4	4	T ⁺ (Q)	4
H. Cost	1438.16	1431.13	1497.47	1422.38	1496.14	1503.67	1413.39	1511.16	1470.76	1413.23	1384.95	1414.93	1653.99	1442.32
Average SL	0.86	0.84	0.87	0.83	0.88	0.79	0.94	0.84	0.84	0.86	0.88	0.89	0.92	0.84

Table 4.30 Integrated Approach Results for ATM 4<T*≤5

	NN5-101	NN5-102	NN5-104	NN5-106	NN5-113	NN5-114	NN5-115	NN5-116	NN5-117	NN5-118	NN5-119	NN5-121	NN5-122	NN5-124	NN5-125
Replenishment	4	4	4	4	5	4	4	T ⁺ (Q')	4	5	4	4	T ⁺ (Q)	4	5
H. Cost	1263.16	1331.98	1410.47	1242.74	1252.73	1340.92	1310.48	1295.15	1295.38	1309.51	1237.87	1306.02	1270.64	1252.08	1266.11
Average SL	0.87	0.84	0.80	0.89	0.84	0.85	0.88	0.85	0.86	0.82	0.88	0.88	0.91	0.88	0.85
	NN5-126	NN5-127	NN5-128	NN5-129	NN5-131	NN5-133	NN5-136	NN5-139	NN5-140	NN5-142	NN5-143	NN5-144	NN5-146	NN5-150	NN5-151
Replenishment	5	T ⁺ (Q')	4	4	5	5	4	4	4	4	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q')
H. Cost	1294.33	1407.74	1384.14	1307.39	1223.95	1267.05	1234.21	1235.03	1267.67	1223.22	1277.38	1390.65	1256.68	1331.87	1219.57
Average SL	0.80	0.84	0.84	0.89	0.83	0.85	0.85	0.86	0.95	0.85	0.90	0.79	0.89	0.79	0.88
	NN5-152	NN5-153	NN5-154	NN5-155	NN5-156	NN5-157	NN5-159	NN5-161	NN5-165	NN5-168	NN5-169	NN5-171	NN5-172	NN5-173	NN5-181
Replenishment	T ⁺ (Q')	4	5	5	5	6	4	T ⁺ (Q)	T ⁺ (Q'')	5	4	4	4	T ⁺ (Q)	4
H. Cost	1205.96	1286.49	1361.31	1232.76	1205.89	1264.02	1442.07	1265.83	1266.07	1208.62	1287.66	1235.54	1167.75	1330.31	1201.15
Average SL	0.88	0.87	0.83	0.88	0.88	0.83	0.82	0.84	0.84	0.87	0.82	0.87	0.91	0.81	0.90
	NN5-186	NN5-188	NN5-189	NN5-191	NN5-198	NN5-201	NN5-203	NN5-204	NN5-205	NN5-206	NN5-207	NN5-209			
Replenishment	4	4	5	4	4	5	4	4	T ⁺ (Q')	T ⁺ (Q)	4	5			
H. Cost	1204.29	1199.13	1259.86	1280.28	1184.64	1259.59	1205.91	1332.75	1235.69	1323.04	1346.90	1255.26			
Average SL	0.87	0.89	0.81	0.83	0.88	0.85	0.87	0.85	0.88	0.90	0.84	0.82			

Table 4.31 Integrated Approach Results for ATM $5 < T^* < 6$

	NN5-105	NN5-107	NN5-108	NN5-111	NN5-123	NN5-132	NN5-137	NN5-141	NN5-160	NN5-162	NN5-170	NN5-174	NN5-180	NN5-182
Replenishment	T(Q)	T(Q)	5	5	4	5	7	5	5	5	7	T(Q')	T+(Q'')	7
H. Cost	1155.78	1212.38	1189.43	1170.00	1147.04	1208.36	1171.03	1244.69	1268.25	1161.71	1112.88	1112.20	1212.86	1050.11
Average SL	0.87	0.83	0.84	0.83	0.86	0.80	0.82	0.78	0.76	0.70	0.75	0.85	0.80	0.82
	NN5-183	NN5-184	NN5-185	NN5-187	NN5-190	NN5-193	NN5-195	NN5-196	NN5-197	NN5-202	NN5-208	NN5-210	NN5-211	
Replenishment	5	4	T+(Q'')	6	T(Q')	T+(Q)	T-(Q)	7	7	T-(Q)	6	5	7	
H. Cost	1129.64	1212.77	1137.78	1107.79	1186.88	1030.28	1147.32	1080.21	1081.02	1123.08	1125.79	1178.67	1170.72	
Average SL	0.87	0.81	0.81	0.86	0.82	0.87	0.89	0.86	0.80	0.90	0.85	0.82	0.75	

Table 4.32 Integrated Approach Results for ATM $6 < T^* < 7$

	NN5-103	NN5-134	NN5-147	NN5-148	NN5-164	NN5-166	NN5-167	NN5-175
Replenishment	6	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	7	7	T ⁺ (Q'')
H. Cost	937.43	1050.92	1043.80	1035.48	1038.39	993.55	991.02	961.21
Average Service Level	0.85	0.75	0.85	0.79	0.76	0.79	0.84	0.78

Table 4.33 Integrated Approach Results for ATM $7 < T^* < 8$

	NN5-120	NN5-138	NN5-192	NN5-199	NN5-200
Replenishment	7	7	T ⁻ (Q)	T ⁻ (Q')	7
H. Cost	844.25	940.66	868.91	875.98	948.99
Average Service Level	0.83	0.77	0.87	0.88	0.81

In the Tables 4.29 – 4.33, the problem is based on five alternative T^* categories, and for each category, the integrated approach-based replenishment model is selected. For instance, in the first group given in Table 4.29; for ATM #30, replenishing the machine every four days with lot for lot strategy gives the best result as in the cost-oriented approach. It results with a total hypothetical cost of 1422.38 TL (total cost 1250.01 TL) with an average service level of 83%. If the same machine replenished with the cost-oriented approach it should be filled every four days with Lot for lot, giving a total cost of 1250.01 TL, with an average service level of 83%. If the same machine replenished with the customer-oriented approach it should be filled with $T^-(Q)$ which corresponds to replenishing the ATM every three days with a fixed filling amount, resulting with a total cost of 1568.84 TL with an average service level of 91%.

For ATM #63, the integrated approach results with a replenishment period of for according to the lot for lot strategy, with a total hypothetical cost of 1470.76 TL (total cost 1310.76 TL), with an average service level of 84%. The customer-oriented approach results with $T^-(Q)$, results with a total cost of 1619.80 TL with an average service level of 90%. The cost-oriented approach results with $T^+(Q)$, a total cost of 1299.53 TL, with an average service level of 83%. Figure 4.27 illustrates the situation for ATM #63. Similarly, for all the machines the results are given in Tables 4.29 – 4.33.

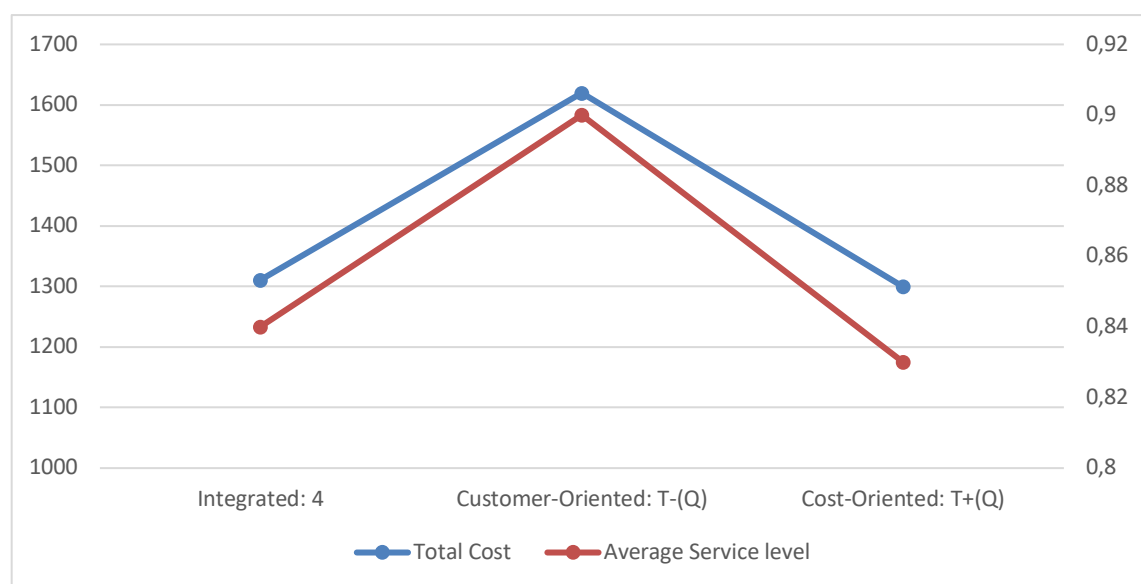


Figure 4.27 Comparison of Approaches over ATM#63

In addition, it is observed that 32 ATMs should be replenished by fixed amount according to T^* values and 79 machines should be replenished by Lot-for-lot strategy. The total hypothetical cost of the 111 ATMs in the system is 136907.81 TL, with a hypothetical average cost of 1233.40 TL per ATM. The average service level of the system is 84.4%. The actual total cost of the system is 119626.42 TL (1077.71 TL per ATM). Table 4.34 gives the total cost, average cost, and average service level per class.

Table 4.34 Integrated Approach Results per Class

	$3 < T < 4$	$4 < T < 5$	$5 < T < 6$	$6 < T < 7$	$7 < T < 8$
Total Cost	18573.68	64603.45	26348.71	6461.80	3638.78
Average Cost	1326.69	1133.39	975.88	807.73	727.76
Average Service Level	0.86	0.86	0.82	0.80	0.83

For the first group, average cost is 1326.29 TL, for the second-class average cost is 1139.39 TL. For ATMs where T^* is between five and six, the average cost 975.88 TL, for ATMs where T^* is between six and seven, the average cost decreases to 807.73 TL and for ATMs where T^* is between seven and eight the average cost drops to 727.76 TL. As the replenishment period increase, average total cost of the system decreases too. However, this situation reflects to drops in average service levels. For example, for the first two groups the average service level is greater than 85%, 86% and 86%, respectively. But when the replenishment period is greater than five, the average service level is below than 85%. For ATMs in group $5 < T < 6$ the average service level is 82%, for ATMs in group $6 < T < 7$ the average service level is 80% and for ATMs in group $7 < T < 8$ the average service level is 83%. Figure 4.28 shows the results per class.

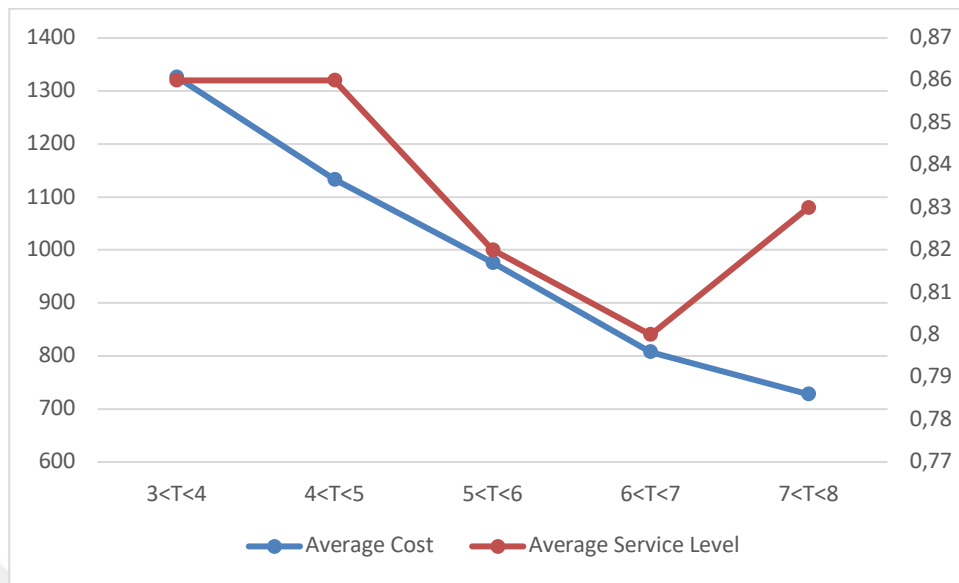


Figure 4.28 Average Service Level vs Average Cost per Class

In this thesis, three main approaches are proposed in order to help decision makers to identify the best way of replenishment of their ATMs, namely, cost-oriented approach where the only target is to minimize the total cost for each ATM, the consumer-oriented approach in which the aim is to maximize the service level, and lastly an integrated approach where the costs and service levels are both important. Table 4.35 merges the outcomes of the three approaches.

Table 4.35 Outcomes of the Three Approaches

Min Cost	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	111 ATMs
Total Cost	18219.23	63978.49	25157.62	6005.90	3522.74	116883.98
Average Cost	1301.37	1122.43	931.76	750.74	704.55	1053.01
Average Service Level	0.81	0.84	0.74	0.70	0.77	0.796
Max Service	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	111 ATMs
Total Cost	22037.95	71876.91	28295.36	7136.09	4031.30	133377.61
Average Cost	1574.14	1261.00	1047.98	892.01	806.26	1201.60
Average Service Level	0.94	0.91	0.86	0.84	0.86	0.894
Integrated Approach	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	111 ATMs
Total Cost	18573.68	64603.45	26348.71	6461.80	3638.78	119626.42
Average Cost	1326.69	1133.39	975.88	807.73	727.76	1077.72
Average Service Level	0.86	0.86	0.82	0.80	0.83	0.84

For all the three approaches the class average cost per ATM ranges between 704.55 and 1574.14 TL, while service level ranges between 0.70 and 0.94. The cost-oriented approach results with an average cost of 1053.01 TL, the consumer-oriented approach

results with an average cost of 1201.60 TL and the integrated approach results with an average cost of 1077.72 TL. Similarly, for the cost-oriented approach, average service level is 79.6%, for the customer-oriented approach, average service level is 89.4% and for the integrated approach, average service level is 84.4%. Figure 4.29 compares three approaches over all the NN5 series.

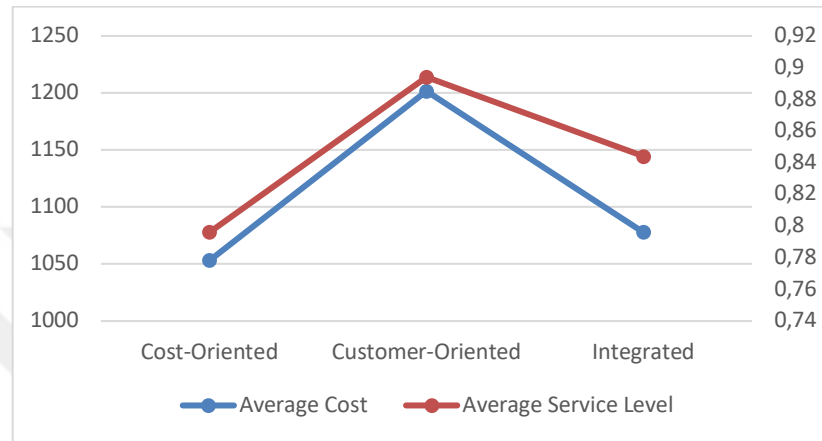


Figure 4.29 Comparison of Approaches over 111 ATMs

The trade-off between the costs and service levels are detailed in this section, where decision making procedure is validated over 28 days horizon. The next section aims to test the selected replenishment decision for all the three approaches in the following 28 days (which is unseen data in the decision-making procedure).

4.3 TESTING THE REPLENISHMENT DECISION

The calculations and tables in the testing process is the same with the previous subsection. Three approaches; cost-oriented, customer-oriented and integrated, are executed with the same logic, and the variation in the costs and service levels are tracked.

4.3.1 Cost-Oriented Approach (Test)

The results of the cost-oriented approaches are in the Tables 4.36 – 4.40.

Table 4.36 Cost-Oriented Approach Results for ATMs $3 < T^* < 4$ (Test)

$3 < T < 4$	NN5-109	NN5-110	NN5-112	NN5-130	NN5-135	NN5-145	NN5-149	NN5-158	NN5-163	NN5-176	NN5-177	NN5-178	NN5-179	NN5-194
Replenishment	3	4	$T^-(Q)$	4	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$	3	4	$T^+(Q)$	$T^+(Q)$	$T^+(Q)$
Cost	1299.71	1298.56	1546.60	1286.77	1388.66	1272.71	1315.46	1299.54	1399.29	1318.94	1254.67	1319.09	1473.52	1293.94
Average SL	0.85	0.85	0.96	0.81	0.85	0.80	0.80	0.74	0.84	0.86	0.89	0.80	0.71	0.88

Table 4.37 Cost-Oriented Approach Results for ATMs $4 < T^* < 5$ (Test)

$4 < T < 5$	NN5-101	NN5-102	NN5-104	NN5-106	NN5-113	NN5-114	NN5-115	NN5-116	NN5-117	NN5-118	NN5-119	NN5-121	NN5-122	NN5-124	NN5-125
Replenishment	$T^+(Q)$	4	4	4	6	$T^+(Q)$	4	$T^-(Q')$	$T^+(Q)$	$T^-(Q')$	4	$T^+(Q)$	$T^+(Q)$	4	5
Cost	1153.96	1162.08	1298.14	1143.07	1126.25	1176.29	1191.27	1165.93	1145.18	1187.20	1155.20	1176.10	1115.93	1208.41	1148.88
Average SL	0.77	0.86	0.90	0.86	0.83	0.81	0.84	0.82	0.83	0.82	0.88	0.87	0.81	0.89	0.83
$4 < T < 5$	NN5-126	NN5-127	NN5-128	NN5-129	NN5-131	NN5-133	NN5-136	NN5-139	NN5-140	NN5-142	NN5-143	NN5-144	NN5-146	NN5-150	NN5-151
Replenishment	5	4	$T^+(Q)$	$T^+(Q)$	4	4	4	5	$T^+(Q)$	4	5	$T^+(Q)$	7	4	$T^+(Q)$
Cost	1204.60	1225.64	1166.02	1154.43	1162.13	1113.99	1113.55	1125.69	1237.62	1115.38	1122.40	1164.71	1142.14	1187.95	1194.77
Average SL	0.89	0.75	0.79	0.74	0.89	0.88	0.93	0.89	0.90	0.86	0.85	0.89	0.86	0.90	0.84
$4 < T < 5$	NN5-152	NN5-153	NN5-154	NN5-155	NN5-156	NN5-157	NN5-159	NN5-161	NN5-165	NN5-168	NN5-169	NN5-171	NN5-172	NN5-173	NN5-181
Replenishment	$T^-(Q')$	$T^+(Q)$	$T^+(Q)$	4	5	6	$T^+(Q)$	$T^+(Q)$	5	5	4	4	4	$T^+(Q)$	4
Cost	1178.37	1163.74	1177.26	1126.13	1083.11	1140.46	1211.61	1113.58	1103.98	1069.82	1185.99	1066.54	1138.47	1164.83	1060.08
Average SL	0.80	0.76	0.78	0.85	0.83	0.84	0.83	0.79	0.83	0.80	0.80	0.85	0.92	0.81	0.86
$4 < T < 5$	NN5-186	NN5-188	NN5-189	NN5-191	NN5-198	NN5-201	NN5-203	NN5-204	NN5-205	NN5-206	NN5-207	NN5-209			
Replenishment	5	5	5	4	4	5	5	$T^+(Q)$	4	$T^+(Q)$	4	5			
Cost	1062.10	1072.84	1154.01	1141.18	1138.91	1159.69	1070.61	1178.03	1101.47	1146.77	1187.40	1128.87			
Average SL	0.84	0.85	0.87	0.83	0.82	0.86	0.83	0.75	0.89	0.78	0.85	0.80			

Table 4.38 Cost-Oriented Approach Results for ATMs $5 < T^* \leq 6$ (Test)

5<T<6	NN5-105 NN5-107 NN5-108 NN5-111 NN5-123 NN5-132 NN5-137 NN5-141 NN5-160 NN5-162 NN5-170 NN5-174 NN5-180 NN5-182													
Replenishment	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	7	T ⁺ (Q)	T ⁺ (Q)	7
Cost	919.29	958.07	961.82	946.01	939.31	919.11	927.68	1007.59	977.42	912.95	866.40	920.06	967.68	898.54
Average SL	0.74	0.75	0.73	0.70	0.73	0.76	0.73	0.81	0.73	0.75	0.76	0.82	0.72	0.78
5<T<6	NN5-183 NN5-184 NN5-185 NN5-187 NN5-190 NN5-193 NN5-195 NN5-196 NN5-197 NN5-202 NN5-208 NN5-210 NN5-211													
Replenishment	T ⁺ (Q)	7	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	7	T ⁺ (Q)	7	7	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	7	
Cost	909.96	1070.53	883.11	904.44	949.50	882.55	911.12	881.80	882.03	912.51	910.02	924.18	982.54	
Average SL	0.79	0.85	0.84	0.79	0.71	0.75	0.70	0.78	0.81	0.78	0.81	0.75	0.79	

Table 4.39 Cost-Oriented Approach Results for ATMs $6 < T^* \leq 7$ (Test)

$6 < T \leq 7$	NN5-103	NN5-134	NN5-147	NN5-148	NN5-164	NN5-166	NN5-167	NN5-175
Replenishment	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)
Cost	781.78	767.23	740.74	750.02	776.89	764.15	773.28	735.90
Average Service Level	0.82	0.73	0.82	0.67	0.71	0.78	0.72	0.75

Table 4.40 Cost-Oriented Approach Results for ATMs $7 < T^* \leq 8$ (Test)

$7 < T \leq 8$	NN5-120	NN5-138	NN5-192	NN5-199	NN5-200
Replenishment	7	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)
Cost	717.22	704.35	690.25	781.18	721.08
Average Service Level	0.80	0.74	0.77	0.80	0.67

In Table 4.36 - 4.40 the problem is evaluated on five alternative T^* categories. For instance, in the first group given in Table 4.36; for ATM #30, replenishing the machine every 4 day according to the lot for lot strategy was selected basing on validation data and same replenishment decision is applied into the test data. It results with a total cost of 1286.77 TL with an average service level of 81%. For the validation data the total cost 1250.01 TL, with an average service level of 83%. In other words, the total cost is increased slightly by 36.76 TL with a 2% increase on the average service level.

Similarly, for ATM #63 the total cost is 1399.24 TL with an average service level 84%. In the validation data the total cost for the same ATM was 1299.53 TL, with an average service level of 83%. So, the total cost fort his ATM is increased by 99.71 TL, but the average service level is dropped by 1%. For all the machines the results are given in Tables 4.36 – 4.40, and differences may be interpreted comparing to the Tables 4.17 – 4.21. Figure 4.30 illustrates the cost-oriented approach results on the test data for ATMs $6 < T^* < 7$.

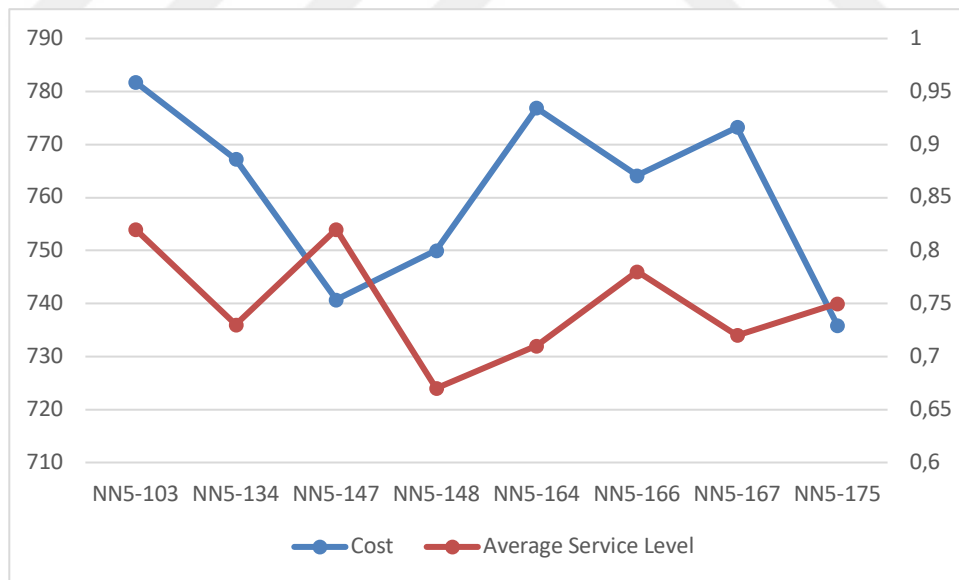


Figure 4.30 Cost-Oriented Approach Results for ATMs $6 < T^* < 7$ (test)

The total cost of the 111 ATMs in the system is 119108.78 TL, with an average cost of 1073.78 TL per ATM. The average service level of the system is 80.5%. The class based total costs and average service levels are in Table 4.41.

Table 4.41 Cost-Oriented Approach Outcomes

Validation Set	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8
Total Cost	18219.23	63978.49	25157.62	6005.90	3522.74
Average Cost	1301.37	1122.43	931.76	750.74	704.55
Average Service Level	0.81	0.84	0.74	0.70	0.77
Test Set	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8
Total Cost	18767.46	65510.77	25126.50	6089.98	3614.07
Average Cost	1340.53	1149.31	930.61	761.25	722.82
Average Service Level	0.83	0.84	0.77	0.75	0.75

In Table 4.41 the outcomes of the cost-oriented approach are compared with the replenishment decision based on the validation set. The average costs per ATM are really close to each other as the service levels. The total cost of the system increased to 119108.78 TL from 116883.98 TL which is only 1.9%. In addition, average service level of the system increased from 79.6% to 81.0%. This situation shows that the proposed cost-oriented approach is valid for the unseen test data also. In test data, average cost per ATMs that are in the first class and second class are respectively, 1340.53 TL and 1149.31 TL. For ATMs where T^* is between five and six, the average cost is 930.61 TL, for ATMs where T^* is between six and seven, the average cost decreases to 761.25 TL and for ATMs where T^* is between seven and eight the average cost drops to 722.82 TL. As the replenishment period increase, average total cost of the system decreases too. This situation reflects to drops in average service levels as in the validation data. For example, for the first two groups the average service level is greater than 80%, 83% and 84%, respectively. But when the replenishment period is greater than five, the average service level is below than 80%. For ATMs in group $5 < T < 6$ the average service level is 77%, for ATMs in group $6 < T < 7$ the average service level is 75% and for ATMs in group $7 < T < 8$ the average service level is 75%. Figure 4.31 illustrates the variation on the average total cost and average service level per class, for the validation and test data set.

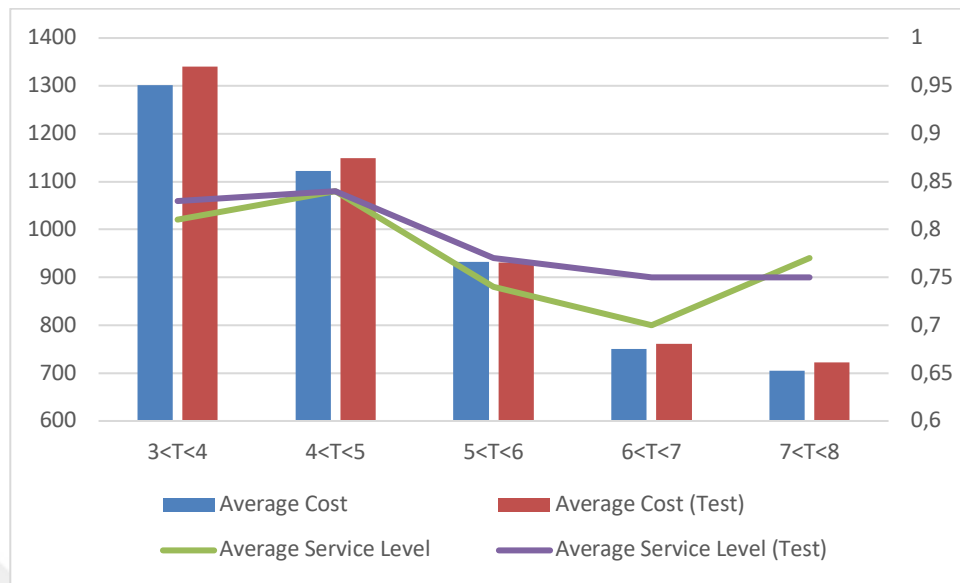


Figure 4.31 Average Cost and Service Level Comparison per Class over Validation and Test Data (Cost-Oriented Approach)

The average cost per ATM on the test data is slightly greater than the validation data cost for all the groups. However, the average service level for the test data is greater than existing average service level. Therefore, for the cost-oriented approach, the replenishment decision taken by validation data is adaptable for the test data for each class of ATMs.

4.3.2 Customer-Oriented Approach (Test)

As the next step, the customer-oriented approach is tested. Tables 4.42 - 4.46 give the outcomes of the approach on the test data set.

Table 4.42 Service Level Oriented Approach Results for ATMs $3 < T^* < 4$ (Test)

$3 < T < 4$	NN5-109	NN5-110	NN5-112	NN5-130	NN5-135	NN5-145	NN5-149	NN5-158	NN5-163	NN5-176	NN5-177	NN5-178	NN5-179	NN5-194
Replenishment	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)
Cost	1590.04	1596.51	1546.60	1565.57	1651.77	1570.00	1568.40	1543.30	1603.69	1586.86	1621.29	1532.88	1613.61	1626.32
Average SL	0.90	0.95	0.96	0.89	0.94	0.96	0.96	0.96	0.94	0.95	0.95	0.96	0.91	0.97

Table 4.43 Service Level Oriented Approach Results for ATMs $4 < T^* < 5$ (Test)

$4 < T < 5$	NN5-101	NN5-102	NN5-104	NN5-106	NN5-113	NN5-114	NN5-115	NN5-116	NN5-117	NN5-118	NN5-119	NN5-121	NN5-122	NN5-124	NN5-125
Replenishment	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	5	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)
Cost	1255.61	1264.91	1423.56	1271.70	1264.61	1342.59	1282.89	1289.09	1189.05	1292.36	1336.86	1308.01	1251.56	1325.70	1285.19
Average SL	0.90	0.91	0.93	0.88	0.94	0.92	0.87	0.90	0.86	0.90	0.90	0.95	0.89	0.89	0.89
$4 < T < 5$	NN5-126	NN5-127	NN5-128	NN5-129	NN5-131	NN5-133	NN5-136	NN5-139	NN5-140	NN5-142	NN5-143	NN5-144	NN5-146	NN5-150	NN5-151
Replenishment	T ⁻ (Q)	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	4	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)
Cost	1335.48	1372.12	1310.15	1256.55	1316.58	1284.07	1298.98	1320.51	1313.31	1301.31	1304.84	1276.77	1152.29	1315.96	1276.42
Average SL	0.91	0.87	0.89	0.86	0.92	0.92	0.96	0.92	0.88	0.90	0.85	0.92	0.86	0.94	0.94
$4 < T < 5$	NN5-152	NN5-153	NN5-154	NN5-155	NN5-156	NN5-157	NN5-159	NN5-161	NN5-165	NN5-168	NN5-169	NN5-171	NN5-172	NN5-173	NN5-181
Replenishment	T ⁻ (Q)	T ⁺ (Q'')	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)	T ⁻ (Q)	T ⁺ (Q'')	T ⁻ (Q)
Cost	1300.11	1246.50	1289.82	1292.04	1266.97	1272.86	1430.93	1247.67	1283.01	1237.46	1258.33	1273.97	1328.69	1250.21	1266.42
Average SL	0.89	0.83	0.85	0.89	0.93	0.89	0.98	0.89	0.92	0.92	0.86	0.93	0.93	0.89	0.93
$4 < T < 5$	NN5-186	NN5-188	NN5-189	NN5-191	NN5-198	NN5-201	NN5-203	NN5-204	NN5-205	NN5-206	NN5-207	NN5-209			
Replenishment	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)	T ⁻ (Q)			
Cost	1301.14	1244.74	1295.26	1254.91	1304.99	1344.16	1291.89	1264.73	1261.01	1246.64	1279.58	1262.03			
Average SL	0.90	0.94	0.91	0.85	0.87	0.87	0.86	0.87	0.94	0.87	0.86	0.91			

Table 4.44 Service Level Oriented Approach Results for ATMs $5 < T^* < 6$ (Test)

5<T<6	NN5-105	NN5-107	NN5-108	NN5-111	NN5-123	NN5-132	NN5-137	NN5-141	NN5-160	NN5-162	NN5-170	NN5-174	NN5-180	NN5-182
Replenishment	T(Q)	T(Q)	5	T(Q)	4	T(Q)	5	3	5	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)
Cost	1085.39	1082.79	1032.85	1053.77	1013.32	1074.21	1068.07	1149.59	1081.54	1061.01	1030.91	1072.29	1083.01	1014.30
Average SL	0.86	0.86	0.80	0.88	0.85	0.88	0.88	0.87	0.89	0.88	0.84	0.92	0.84	0.92
5<T<6	NN5-183	NN5-184	NN5-185	NN5-187	NN5-190	NN5-193	NN5-195	NN5-196	NN5-197	NN5-202	NN5-208	NN5-210	NN5-211	
Replenishment	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	T(Q)	3	T(Q)	T(Q)	
Cost	1078.69	1119.90	1105.61	1045.03	1061.46	1051.23	1045.52	1044.93	1012.06	1060.55	1096.42	1088.38	1064.16	
Average SL	0.90	0.90	0.92	0.88	0.88	0.91	0.88	0.88	0.86	0.87	0.84	0.90	0.87	

Table 4.45 Service Level Oriented Approach Results for ATMs $6 < T^* < 7$ (Test)

$6 < T < 7$	NN5-103	NN5-134	NN5-147	NN5-148	NN5-164	NN5-166	NN5-167	NN5-175
Replenishment	6	5	5	4	T(Q)	T(Q)	T(Q)	T(Q)
Cost	789.58	920.56	918.11	1033.98	886.31	906.16	913.55	876.48
Average Service Level	0.84	0.79	0.88	0.82	0.86	0.88	0.82	0.85

Table 4.46 Service Level Oriented Approach Results for ATMs $7 < T^* < 8$ (Test)

$7 < T < 8$	NN5-120	NN5-138	NN5-192	NN5-199	NN5-200
Replenishment	T(Q)	T(Q)	T(Q)	T(Q)	3
Cost	723.12	778.24	745.69	785.22	1041.44
Average Service Level	0.82	0.85	0.86	0.83	0.84

In the Tables 4.42 – 4.46, the problem is based on five alternative T^* categories. In the first group given in Table 4.42; for ATM #30, replenishing the machine with $T(Q)$ selected with validation data results with a total cost of 1565.57 TL with an average service level of 89%. The total cost on the validation data was 1568.84 TL with an average service level of 91%. Therefore, a drop of 2% in service level has been observed while the total cost is decreased only 3.27 TL for this ATM.

For ATM #63, $T(Q)$ is re-used, resulting a total cost of 1603.69 TL with an average service level of 94%. For the validation data the total cost was 1619.80 TL with an average service level of 90%. Therefore, an increase of 4% in service level has been observed while the total cost is decreased 16.11 TL for this ATM, supporting the utility of the selected approach on both data sets. For the test data, the total cost of the service level-oriented approach for 111 ATMs is 135727.36 TL, with an average cost of 1222.77 TL per ATM. The average service level of the system is 89.2%. The class based total costs and average service levels are in Table 4.47.

Table 4.47 Service Level-Oriented Approach Outcomes

Validation Set	$3 < T < 4$	$4 < T < 5$	$5 < T < 6$	$6 < T < 7$	$7 < T < 8$
Total Cost	22037.95	71876.91	28295.36	7136.09	4031.30
Average Cost	1574.14	1261.00	1047.98	892.01	806.26
Average Service Level	0.94	0.91	0.86	0.84	0.86
Test Set	$3 < T < 4$	$4 < T < 5$	$5 < T < 6$	$6 < T < 7$	$7 < T < 8$
Total Cost	22216.85	73415.07	28777.00	7244.72	4073.71
Average Cost	1586.92	1287.98	1065.81	905.59	814.74
Average Service Level	0.94	0.90	0.88	0.84	0.84

In Table 4.47, the outcomes of the service level-oriented approach are compared with the replenishment decision based on the validation set. The average costs per ATM are really close to each other as the service levels. The total cost of the system increased to 135727.36 TL from 133377.61 TL which is only 1.8%. In addition, average service level of the system is decreased only 0.2%, from 89.4% to 89.2%. This situation shows that the proposed service level-oriented approach is valid for the unseen test data also. In test data, average cost per ATMs that are in the first class and second class are respectively, 1586.92 TL and 1287.98 TL. For ATMs where T^* is between five and six, the average cost is 1065.81 TL, for ATMs where T^* is between six and seven, the average cost decreases to 905.59 TL and for ATMs where T^* is between seven and

eight the average cost drops to 814.74 TL. As the replenishment period increase, average total cost of the system decreases too. This situation reflects to drops in average service levels as in the validation data. For example, for the first two groups the average service level is greater than 90%, 94% and 90%, respectively. But when the replenishment period is greater than five, the average service level is below than 90%. For ATMs in group $5 < T < 6$ the average service level is 88%, for ATMs in group $6 < T < 7$ the average service level is 84% and for ATMs in group $7 < T < 8$ the average service level is 84%. Figure 4.32 illustrates the variation on the average total cost and average service level per class, for the validation and test data set.

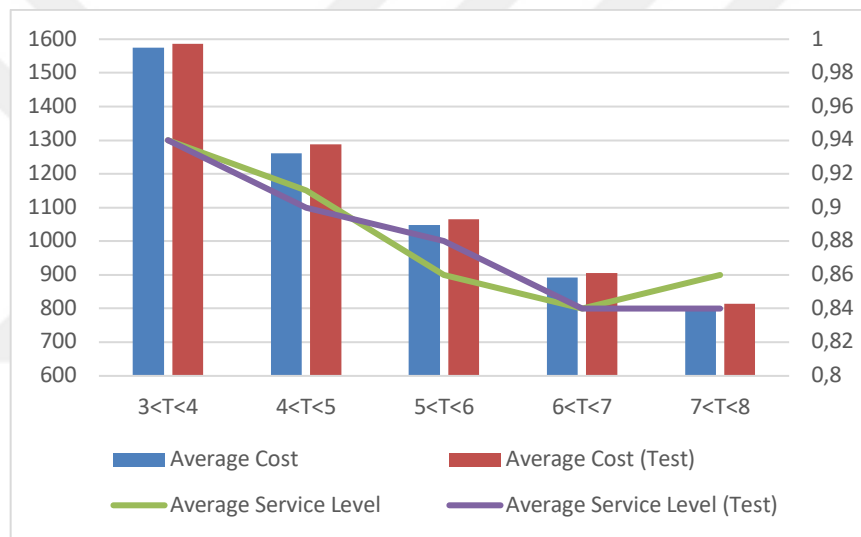


Figure 4.32 Average Cost and Service Level Comparison per Class over Validation and Test Data (Customer-Oriented Approach)

The average cost per ATM on the test data is slightly greater than the validation data cost for all the groups. However, the average service level for the test data is close to the existing average service level line. Therefore, for the customer-oriented approach, the replenishment decision taken by validation data is adaptable for the test data for each class of ATMs.

4.3.3 Integrated Approach (Test)

As the next step, the integrated approach is tested. Tables 4.48 – 4.52 give the outcomes of the integrated approach on the test data set.

Table 4.48 Integrated Approach Results for ATM 3<T*≤4 (Test)

3<T≤4	NN5-109	NN5-110	NN5-112	NN5-130	NN5-135	NN5-145	NN5-149	NN5-158	NN5-163	NN5-176	NN5-177	NN5-178	NN5-179	NN5-194
Replenishment	3	4	4	4	3	T ⁺ (Q)	3	4	4	3	4	4	T ⁺ (Q)	4
H. Cost	1449.48	1449.81	1522.43	1471.17	1443.78	1469.13	1504.37	1544.60	1474.00	1455.18	1368.40	1506.20	1706.09	1428.62
Average SL	0.85	0.85	0.83	0.80	0.92	0.80	0.88	0.83	0.90	0.86	0.89	0.83	0.91	0.88

Table 4.49 Integrated Approach Results for ATM 4<T*≤5 (Test)

	NN5-101	NN5-102	NN5-104	NN5-106	NN5-113	NN5-114	NN5-115	NN5-116	NN5-117	NN5-118	NN5-119	NN5-121	NN5-122	NN5-124	NN5-125
Replenishment	4	4	4	4	5	4	4	T ⁺ (Q')	4	5	4	4	T ⁺ (Q)	4	5
H. Cost	1294.52	1303.36	1496.04	1283.43	1249.38	1389.24	1355.66	1341.15	1316.75	1296.39	1273.35	1301.08	1303.81	1317.94	1314.68
Average SL	0.88	0.86	0.83	0.86	0.86	0.85	0.84	0.82	0.83	0.88	0.88	0.91	0.81	0.89	0.83
	NN5-126	NN5-127	NN5-128	NN5-129	NN5-131	NN5-133	NN5-136	NN5-139	NN5-140	NN5-142	NN5-143	NN5-144	NN5-146	NN5-150	NN5-151
Replenishment	5	T ⁺ (Q')	4	4	5	5	4	4	4	4	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q)	T ⁺ (Q')
H. Cost	1225.58	1477.06	1369.69	1431.86	1269.78	1254.36	1182.55	1234.36	1436.71	1255.10	1268.76	1271.70	1284.62	1275.16	1253.38
Average SL	0.91	0.80	0.88	0.80	0.89	0.86	0.93	0.89	0.88	0.86	0.85	0.89	0.86	0.90	0.86
	NN5-152	NN5-153	NN5-154	NN5-155	NN5-156	NN5-157	NN5-159	NN5-161	NN5-165	NN5-168	NN5-169	NN5-171	NN5-172	NN5-173	NN5-181
Replenishment	T ⁺ (Q')	4	5	5	5	6	4	T ⁺ (Q)	T ⁺ (Q'')	5	4	4	4	T ⁺ (Q)	4
H. Cost	1382.53	1371.66	1409.19	1325.81	1250.96	1304.70	1404.08	1319.48	1263.83	1265.55	1382.21	1220.52	1222.00	1359.69	1201.27
Average SL	0.80	0.81	0.82	0.82	0.83	0.84	0.93	0.79	0.89	0.80	0.80	0.85	0.92	0.81	0.86
	NN5-186	NN5-188	NN5-189	NN5-191	NN5-198	NN5-201	NN5-203	NN5-204	NN5-205	NN5-206	NN5-207	NN5-209			
Replenishment	4	4	5	4	4	5	4	4	T ⁺ (Q')	T ⁺ (Q)	4	5			
H. Cost	1292.45	1201.64	1288.31	1312.05	1320.67	1297.72	1271.98	1323.71	1229.60	1381.35	1335.39	1324.43			
Average SL	0.79	0.85	0.87	0.83	0.82	0.86	0.84	0.88	0.88	0.87	0.85	0.80			

Table 4.50 Integrated Approach Results for ATM $5 < T^* < 6$ (Test)

	NN5-105	NN5-107	NN5-108	NN5-111	NN5-123	NN5-132	NN5-137	NN5-141	NN5-160	NN5-162	NN5-170	NN5-174	NN5-180	NN5-182
Replenishment	T ⁻ (Q)	T ⁻ (Q)	5	5	4	5	7	5	5	5	7	T ⁻ (Q')	T ⁺ (Q'')	7
H. Cost	1227.67	1226.73	1228.05	1178.04	1164.31	1172.36	1210.04	1226.99	1195.66	1197.45	1109.12	1141.87	1245.65	1113.57
Average SL	0.86	0.86	0.80	0.85	0.85	0.85	0.85	0.84	0.89	0.83	0.76	0.86	0.73	0.78
	NN5-183	NN5-184	NN5-185	NN5-187	NN5-190	NN5-193	NN5-195	NN5-196	NN5-197	NN5-202	NN5-208	NN5-210	NN5-211	
Replenishment	5	4	T ⁺ (Q'')	6	T ⁻ (Q')	T ⁺ (Q)	T ⁻ (Q)	7	7	T ⁻ (Q)	6	5	7	
H. Cost	1160.14	1181.14	1088.08	1152.75	1183.31	1089.90	1165.69	1099.08	1074.58	1186.86	1072.96	1168.55	1195.96	
Average SL	0.86	0.88	0.88	0.81	0.86	0.80	0.88	0.88	0.81	0.87	0.86	0.87	0.79	

Table 4.51 Integrated Approach Results for ATM $6 < T^* < 7$ (Test)

	NN5-103	NN5-134	NN5-147	NN5-148	NN5-164	NN5-166	NN5-167	NN5-175
Replenishment	6	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	T ⁺ (Q'')	7	7	T ⁺ (Q'')
H. Cost	948.47	1025.04	943.63	1067.84	1048.33	977.59	1018.87	1007.22
Average Service Level	0.84	0.82	0.89	0.71	0.82	0.82	0.81	0.79

Table 4.52 Integrated Approach Results for ATM $7 < T^* < 8$ (Test)

	NN5-120	NN5-138	NN5-192	NN5-199	NN5-200
Replenishment	7	7	T ⁻ (Q)	T ⁻ (Q')	7
H. Cost	918.45	923.73	886.98	1260.04	926.96
Average Service Level	0.80	0.81	0.86	0.83	0.81

In the Tables 4.48 – 4.52, the problem is based on five alternative T^* categories. In the first group given in Table 4.48; for ATM #30, replenishing the machine every four days with lot for lot strategy selected with validation data, results with a hypothetical total cost of 1471.17 TL (total cost 1271.17 TL) with an average service level of 80%. For the validation data the total hypothetical cost was 1422.38 TL (total cost 1250.01 TL) with an average service level of 83%. Which indicates a 21.16TL increase on the system, with a drop of 3% service level.

For ATM #63, the total hypothetical cost is 1474.00 TL (total cost 1374.00 TL), with an average service level of 90%. For the validation data the total hypothetical cost was 1470.76 TL (total cost 1310.76 TL), with an average service level of 84%. Therefore, an increase of 6% in service level has been observed while the total cost is increased 63.24 TL for this ATM.

For the test data, the total cost of the integrated approach for 111 ATMs is 122687.23 TL, with an average cost of 1105.29 TL per ATM. The average service level of the system is 84.6%. The class based total costs and average service levels are in Table 4.53.

Table 4.53 Integrated Approach Outcomes (Test)

Validation Set	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8
Total Cost	18573.68	64620.73	26348.00	6462.84	3632.78
Average Cost	1326.69	1133.70	975.85	807.86	726.56
Average Service Level	0.86	0.86	0.82	0.80	0.83
Test Set	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8
Total Cost	18819.24	66212.41	27102.85	6525.97	4026.76
Average Cost	1344.23	1161.62	1003.81	815.75	805.35
Average Service Level	0.86	0.85	0.84	0.81	0.82

In Table 4.53, the outcomes of the integrated approach are compared with the replenishment decision based on the validation set. The average costs per ATM are really close to each other as the service levels. The total cost of the system increased to 122687.23 TL from 119638.02 TL which is 2.5%. In addition, average service level of the system is increased only 0.2%, from 84.4% to 84.6%. This situation shows that the proposed approach is valid for the unseen test data also.

In test data, average cost per ATMs that are in the first class and second class are respectively, 1344.24 TL and 1161.62 TL. For ATMs where T^* is between five and six, the average cost is 1003.81 TL, for ATMs where T^* is between six and seven, the average cost decreases to 815.75 TL and for ATMs where T^* is between seven and eight the average cost drops to 805.35 TL. As the replenishment period increase, average total cost of the system decreases too. This situation reflects to drops in average service levels as in the validation data. For example, for the first two groups the average service level is greater than 85%, 86% and 85%, respectively. But when the replenishment period is greater than five, the average service level is below than 85%. For ATMs in group $5 < T < 6$ the average service level is 84%, for ATMs in group $6 < T < 7$ the average service level is 82% and for ATMs in group $7 < T < 8$ the average service level is 81%. Figure 4.33 illustrates the variation on the average total cost and average service level per class, for the validation and test data set.

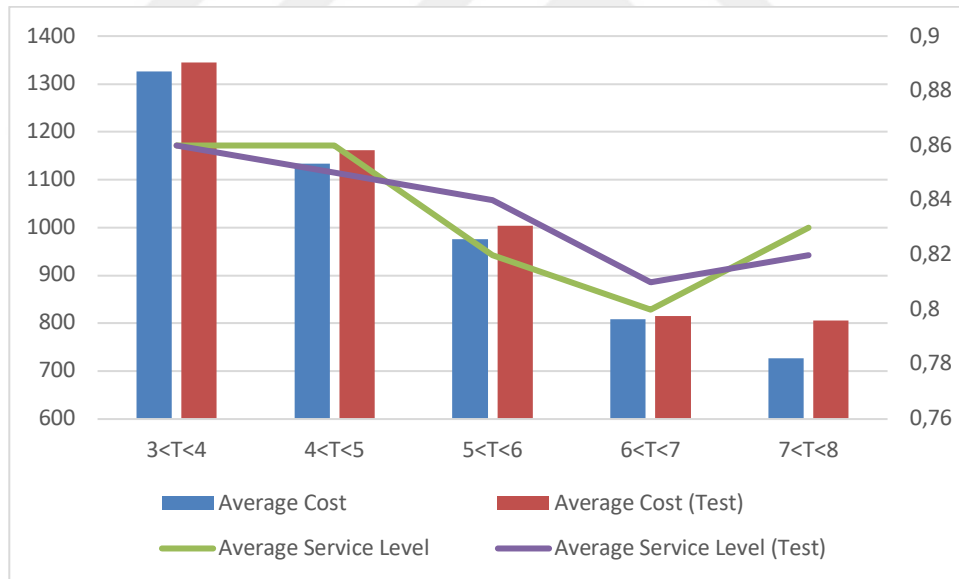


Figure 4.33 Average Cost and Service Level Comparison per Class over Validation and Test Data (Integrated Approach)

The average cost per ATM on the test data is slightly greater than the validation data cost for all the groups. However, the average service level for the test data is close to the existing average service level line. Therefore, for the integrated approach, the replenishment decision taken by validation data is adaptable for the test data for each class of ATMs.

4.4 EVALUATION OF THE RESULTS

All the three approaches are re-used for a next forecasting horizon, and the replenishment decision that is taken into account is tested on an unseen data set. The outcomes of all the approaches are in Table 4.54 for this test data.

Table 4.54 Outcomes of the Three Approaches (Test)

Min Cost	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	111 ATMs
Total Cost	18767.46	65510.77	25126.50	6089.98	3614.07	119108.78
Average Cost	1340.53	1149.31	930.61	761.25	722.81	1073.05
Average Service Level	0.83	0.84	0.77	0.75	0.75	0.81
Max Service	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	111 ATMs
Total Cost	22216.85	73415.07	28777.00	7244.72	4073.71	135957.89
Average Cost	1586.92	1287.98	1065.81	905.59	814.74	1224.85
Average Service Level	0.94	0.90	0.88	0.84	0.84	0.90
Integrated Approach	3<T<4	4<T<5	5<T<6	6<T<7	7<T<8	111 ATMs
Total Cost	18819.24	66212.41	27102.85	6525.97	4026.76	122687.23
Average Cost	1344.23	1161.62	1003.81	815.75	805.35	1105.29
Average Service Level	0.86	0.85	0.84	0.81	0.82	0.85

In test data, for all the three approaches, the class average cost per ATM ranges between 722.81 TL and 1586.92 TL, while service level ranges between 0.75 and 0.94. The cost-oriented approach results with an average cost of 1073.05 TL, the consumer-oriented approach results with an average cost of 1224.85 TL and the integrated approach results with an average cost of 1105.29 TL per ATM. Similarly, for the cost-oriented approach, average service level is 81%, for the customer-oriented approach, average service level is 90% and for the integrated approach, average service level is 85%. Figure 4.34 compares three approaches over all the NN5 series.



Figure 4.34 Comparison of Approaches over 111 ATMs (Test)

In this application, the selected replenishment strategy employing 28 days validation data, used for the unseen test data, analyzing the changement in costs and service levels. The coherency of the proposed three apporoaches are tested, and the variations are calculated. It is believed that the proposed approach is easy to implement for bank experts in order to track their costs and service levels and it is up to them to decide to follow the best approach for their company.

All the approaches are optimal strategies within self. If the bank is cost-oriented it can manage all the 111 ATMs for 119108.78 TL having an average service level of 81%. If the ATM related costs are not important to the bank, it can adapt the customer-oriented approach and may reach a service level of 90% with a total cost of 135957.89 TL. If the integrated approach is applied in the decision-making process, the system cost would be 122687.23 TL, with an average service level of 85%. All these calculations are exercised for 28 days (corresponding to four weeks), and every month as a tactical decision the replenishment period and strategy of the ATMs might be calculated, along with the repeated forecasting process.

5. CONCLUSION

The ATMs are self-service contact point of the banks with their customers. They control the cash traffic of the society, and impact every business-life. In the ATM management process, there are multiple sub-problems like security, deployment, forecasting, replenishing etc. The security of the machines is really important because they are basically cash vaults. The deployment of the ATMs is crucial, because these machines represent the bank for 7/24 and they should be accessible for customers in safe locations. In general, ATMs are located in central zones, commercial areas, shopping malls, train stations, airports, public spaces, private hospitals along with road corners, or bank branch extensions. The location of ATMs is the first factor that affects directly the total cash traffic in the machine, and a really important feature for the replenishment process.

The total cash traffic in the ATM is important and hard to interpret. Because these machines have different type of customers, regular-ones and passengers. And all these customers may act differently, plus the same customer may act differently too. Therefore, the daily cash demand of these machines is quite difficult task. Even the weather or an economic crisis, may affect the withdrawn money, and it is nearly impossible to know all the parameters. However, time series are rich data sources, in which patterns might be recognized and suitable forecasts might be realized.

Better forecasting results would help to decision-makers to better replenish their ATMs and control the unnecessary stock in the machines. ATMs have basically two problems. They have to satisfy the customer demand; therefore, they need to be replenished enough well that no stock-out situation happens. However, if they are fully replenished, banks' opportunity costs increase. Because, the stocked cash inside the machine is deprived from the overnight interest rate, which can be very costly for the countries where the interest rates are high so finding a balance for ATM stocks is crucial.

In this thesis, all the literature on the ATM related problems up to 2022, is examined and classified. Specifically, the forecasting literature on the ATM problem is deeply examined, and common approaches of the studies are gathered. It is observed that although many papers contribute to the literature, with increased forecasting accuracies using alternative methods, the outcomes of the forecasting results are not used in the replenishment process. Therefore, in this study an integrated approach is followed. Firstly, the forecasting methods namely; ARIMA, SARIMA, DNN, RNN and LSTM are employed, best performing forecasting model is selected for each ATM. The outcomes of the forecasting models are employed in the replenishment process.

Alternative performance criteria are selected in the problem, where first criterion is the cost. There are mainly three components of the total cost in the ATMs; the holding cost due to the stocked money deprived from the overnight interest rate, the back-out cost which is a hypothetical cost that used to penalize the unsatisfied customer demand and the replenishment cost. In this thesis, replenishment cost is fixed for every visit of the ATMs, considered as a service taken by a third-party company. The total cost is the sum of these three costs. The second metric is the service level which has two components. The first service level is the realized withdrawn over the total demand (amount based), and the second service level counts the cash-out occurrences (customer amount related). The average of these two service levels is employed in the decision-making process.

For each ATM, two groups of replenishment strategies are built; lot for lot strategy and optimal replenishment period strategy. For all the ATM groups calculation sheets are constructed, and all the performance metrics are calculated iterating the original test data with the selected forecasting model outcomes. The outcomes are gathered and transformed as the final input of the decision-making procedure.

Three approaches are identified in the decision-making process. The first approach objective is to minimize the total cost, the second approach objective is to maximize the average service level. The third approach penalizes the missed service level as a cost, and transform the average service level performance metric into a cost function. For all the three approaches the best replenishment strategy is chosen according to the

validation data. Then, the selected replenishing strategy is employed for test data, and the variation on the costs and service levels for all the three approaches are tracked and evaluated.

To sum up, a reproducible system is designed and easy to implement replenishment strategy is built and evaluated. The proposed decision-making procedure might be adapted from the banks and easily implemented on their data set. In addition, the outcomes of this thesis might be used from the third-party logistic companies as inputs on the routing problems. This thesis is the primary study, that takes into account the forecasting outcomes of a time series prediction problem, and evaluate it for real performance criteria of the system. It proposes a DSS that integrates the forecasting and replenishment problem, and for each ATM provides pareto-optimal solutions, that optimizes generally the whole ATM network. The adapted DSS structure in this study may be generalized for every kind of point of service (PoS) locations like vending machines or gas stations, with the relevant performance criteria to evaluate the results.

It is also the first study that approaches to the ATM replenishment problem in point of optimal inventory control structures, and compares alternative replenishment policies. It differs from the previous articles, including service level criterion on the decision making process, considering opposite sides of the problem. In addition, it proposes three generic approach in the DSS structure that may be useful for decision-makers.

The further research may consist of, transforming this decision-making procedure into an online application form, where the exhausting calculation steps of this thesis will be automatized. The forecasting process would renew it-self based on the selected frequency with the online feeded data. The group of ATMs will be constructed automatically, the performance metrics will be adjourned in daily basis and there will be parameter setups for replenishment costs and overnight interest rate.

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APPENDICES

Appendix A.

Table A.1 DNN500 Scores

DNN500	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111	
SMAPE	0.14	0.26	0.21	0.23	0.24	0.15	0.26	0.23	0.13	0.21	0.23	
MAPE	0.14	0.41	0.21	0.27	0.27	0.15	0.32	0.29	0.13	0.25	0.25	
MAE	2.86	4.15	1.82	5.59	3.61	2.63	4.13	3.35	3.69	5.52	3.46	
	N112	N113	N114	N115	N116	N117	N118	N119	N120	N121	N122	
SMAPE	0.18	0.16	0.22	0.23	0.26	0.30	0.20	0.25	0.22	0.19	0.22	
MAPE	0.19	0.17	0.24	0.29	0.33	0.44	0.20	1.56	0.24	0.22	0.24	
MAE	6.03	3.00	5.00	4.53	4.96	4.70	3.80	3.61	1.72	3.78	4.41	
	N123	N124	N125	N126	N127	N128	N129	N130	N131	N132	N133	
SMAPE	0.20	0.18	0.18	0.24	0.20	0.27	0.20	0.18	0.16	0.19	0.12	
MAPE	0.20	0.20	0.21	0.27	0.21	0.35	0.25	0.43	0.18	0.20	0.12	
MAE	2.88	3.42	3.33	4.09	4.65	5.30	4.18	4.53	2.74	3.03	2.18	
	N134	N135	N136	N137	N138	N139	N140	N141	N142	N143	N144	
SMAPE	0.27	0.24	0.18	0.20	0.23	0.24	0.26	0.29	0.17	0.22	0.30	
MAPE	0.36	0.37	0.20	0.23	0.30	0.28	0.29	0.40	0.20	0.28	0.46	
MAE	2.46	5.82	3.25	2.97	1.76	3.75	5.76	3.83	2.73	3.95	5.70	
	N145	N146	N147	N148	N149	N150	N151	N152	N153	N154	N155	
SMAPE	0.15	0.27	0.28	0.30	0.18	0.19	0.19	0.28	0.17	0.20	0.17	
MAPE	0.15	0.42	0.38	0.52	0.21	0.21	0.20	0.37	0.20	0.23	0.20	
MAE	4.48	4.18	2.53	3.06	4.83	3.46	3.28	4.63	3.68	4.21	3.05	
	N156	N157	N158	N159	N160	N161	N162	N163	N164	N165	N166	
SMAPE	0.22	0.16	0.18	0.26	0.23	0.23	0.26	0.30	0.19	0.22	0.20	
MAPE	0.26	0.16	0.18	0.32	0.26	0.25	0.30	0.36	0.20	0.24	0.20	
MAE	3.44	2.81	5.76	5.93	3.68	4.57	3.70	7.82	2.10	3.73	1.97	
	N167	N168	N169	N170	N171	N172	N173	N174	N175	N176	N177	
SMAPE	0.28	0.19	0.18	0.26	0.22	0.20	0.19	0.23	0.31	0.21	0.19	
MAPE	0.30	0.20	0.20	0.30	0.25	0.24	0.23	0.30	0.35	0.23	0.21	
MAE	2.63	3.19	3.67	3.06	3.73	3.19	3.66	3.05	3.15	5.57	4.76	
	N178	N179	N180	N181	N182	N183	N184	N185	N186	N187	N188	
SMAPE	0.13	0.15	0.25	0.16	0.15	0.21	0.26	0.21	0.24	0.18	0.19	
MAPE	0.14	0.17	0.33	0.19	0.15	0.23	0.36	0.23	0.34	0.19	0.19	
MAE	3.74	5.95	3.77	2.55	1.85	2.98	3.55	2.97	3.41	2.44	3.15	
	N189	N190	N191	N192	N193	N194	N195	N196	N197	N198	N199	
SMAPE	0.21	0.23	0.22	0.25	0.25	0.19	0.19	0.28	0.29	0.21	0.32	
MAPE	0.22	0.25	0.23	0.27	0.27	0.21	0.20	0.41	0.34	0.23	0.42	
MAE	3.80	3.53	4.80	1.97	2.83	5.18	3.01	3.13	3.24	3.96	3.10	
	N200	N201	N202	N203	N204	N205	N206	N207	N208	N209	N210	N211
SMAPE	0.28	0.22	0.22	0.21	0.14	0.16	0.17	0.16	0.30	0.18	0.17	0.23
MAPE	0.31	0.28	0.25	0.25	0.14	0.17	0.17	0.18	0.41	0.18	0.18	0.26
MAE	2.16	3.98	2.96	3.42	3.22	2.78	3.58	3.66	3.61	3.18	2.70	3.12

Table A.2 DNN1000 Scores

DNN1000	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111	
SMAPE	0.14	0.25	0.20	0.23	0.24	0.15	0.26	0.22	0.13	0.21	0.22	
MAPE	0.14	0.38	0.20	0.27	0.27	0.16	0.31	0.27	0.14	0.25	0.24	
MAE	2.82	3.92	1.75	5.61	3.62	2.75	4.09	3.17	3.76	5.56	3.42	
	N112	N113	N114	N115	N116	N117	N118	N119	N120	N121	N122	
SMAPE	0.18	0.16	0.22	0.23	0.26	0.28	0.20	0.25	0.21	0.19	0.22	
MAPE	0.19	0.17	0.24	0.30	0.33	0.43	0.21	1.48	0.24	0.21	0.24	
MAE	5.97	2.98	4.96	4.60	4.98	4.50	3.85	3.55	1.68	3.72	4.40	
	N123	N124	N125	N126	N127	N128	N129	N130	N131	N132	N133	
SMAPE	0.19	0.18	0.18	0.23	0.20	0.27	0.21	0.19	0.16	0.19	0.12	
MAPE	0.20	0.20	0.21	0.27	0.22	0.34	0.25	0.43	0.17	0.20	0.12	
MAE	2.83	3.40	3.32	3.99	4.72	5.21	4.32	4.66	2.69	3.05	2.16	
	N134	N135	N136	N137	N138	N139	N140	N141	N142	N143	N144	
SMAPE	0.25	0.23	0.20	0.19	0.22	0.23	0.27	0.28	0.17	0.22	0.30	
MAPE	0.34	0.36	0.22	0.23	0.29	0.26	0.29	0.39	0.20	0.27	0.45	
MAE	2.37	5.68	3.50	2.92	1.65	3.55	5.82	3.80	2.73	3.89	5.69	
	N145	N146	N147	N148	N149	N150	N151	N152	N153	N154	N155	
SMAPE	0.15	0.27	0.28	0.32	0.18	0.18	0.18	0.27	0.17	0.20	0.17	
MAPE	0.15	0.42	0.39	0.54	0.21	0.20	0.19	0.36	0.20	0.22	0.20	
MAE	4.51	4.12	2.58	3.28	4.84	3.32	3.20	4.57	3.63	4.06	2.99	
	N156	N157	N158	N159	N160	N161	N162	N163	N164	N165	N166	
SMAPE	0.21	0.15	0.18	0.26	0.23	0.24	0.26	0.32	0.18	0.21	0.19	
MAPE	0.26	0.16	0.18	0.31	0.26	0.25	0.30	0.37	0.20	0.23	0.20	
MAE	3.40	2.74	5.80	5.91	3.64	4.64	3.68	8.12	2.04	3.63	1.94	
	N167	N168	N169	N170	N171	N172	N173	N174	N175	N176	N177	
SMAPE	0.26	0.18	0.18	0.25	0.21	0.20	0.19	0.22	0.29	0.21	0.19	
MAPE	0.28	0.19	0.20	0.29	0.24	0.24	0.24	0.28	0.33	0.23	0.21	
MAE	2.53	3.05	3.66	2.94	3.57	3.20	3.71	2.87	2.99	5.67	4.68	
	N178	N179	N180	N181	N182	N183	N184	N185	N186	N187	N188	
SMAPE	0.13	0.16	0.25	0.15	0.14	0.21	0.25	0.21	0.24	0.17	0.18	
MAPE	0.13	0.18	0.33	0.18	0.14	0.23	0.35	0.23	0.35	0.18	0.19	
MAE	3.65	6.06	3.71	2.44	1.74	2.95	3.48	2.98	3.45	2.38	3.01	
	N189	N190	N191	N192	N193	N194	N195	N196	N197	N198	N199	
SMAPE	0.20	0.22	0.22	0.24	0.23	0.20	0.18	0.28	0.28	0.21	0.32	
MAPE	0.21	0.24	0.22	0.26	0.25	0.21	0.19	0.42	0.33	0.24	0.41	
MAE	3.72	3.44	4.69	1.93	2.66	5.28	2.94	3.13	3.16	4.05	3.04	
	N200	N201	N202	N203	N204	N205	N206	N207	N208	N209	N210	N211
SMAPE	0.26	0.22	0.21	0.20	0.14	0.15	0.17	0.18	0.27	0.18	0.17	0.22
MAPE	0.29	0.28	0.24	0.24	0.14	0.16	0.17	0.19	0.36	0.19	0.18	0.25
MAE	2.01	3.92	2.90	3.30	3.17	2.70	3.47	4.05	3.22	3.20	2.66	2.97

Table A.3 RNN Scores

RNN	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111	
SMAPE	0.15	0.26	0.20	0.21	0.26	0.17	0.29	0.25	0.13	0.21	0.25	
MAPE	0.15	0.39	0.20	0.24	0.24	0.19	0.34	0.36	0.13	0.27	0.30	
MAE	3.09	4.16	1.71	5.30	3.76	2.99	4.50	3.71	3.74	5.62	3.85	
	N112	N113	N114	N115	N116	N117	N118	N119	N120	N121	N122	
SMAPE	0.20	0.15	0.22	0.29	0.27	0.34	0.21	0.30	0.22	0.17	0.23	
MAPE	0.19	0.15	0.22	0.38	0.32	0.57	0.23	1.30	0.23	0.19	0.25	
MAE	6.56	2.65	4.69	5.75	4.93	5.45	4.07	4.08	1.73	3.41	4.54	
	N123	N124	N125	N126	N127	N128	N129	N130	N131	N132	N133	
SMAPE	0.17	0.20	0.19	0.23	0.30	0.31	0.28	0.20	0.16	0.18	0.13	
MAPE	0.17	0.20	0.20	0.26	0.27	0.33	0.34	0.46	0.20	0.19	0.14	
MAE	2.49	3.77	3.46	3.91	6.19	6.09	5.33	4.59	2.80	2.94	2.38	
	N134	N135	N136	N137	N138	N139	N140	N141	N142	N143	N144	
SMAPE	0.36	0.24	0.20	0.24	0.26	0.20	0.26	0.41	0.20	0.22	0.36	
MAPE	0.41	0.37	0.22	0.28	0.28	0.24	0.29	0.52	0.23	0.28	0.46	
MAE	3.52	5.98	3.49	3.54	1.79	3.19	5.66	5.09	3.23	3.85	6.40	
	N145	N146	N147	N148	N149	N150	N151	N152	N153	N154	N155	
SMAPE	0.17	0.29	0.33	0.43	0.18	0.17	0.22	0.29	0.15	0.20	0.22	
MAPE	0.18	0.47	0.42	1.01	0.22	0.18	0.26	0.34	0.17	0.24	0.23	
MAE	5.21	4.66	2.98	5.00	4.66	3.19	4.06	4.66	3.23	4.25	3.83	
	N156	N157	N158	N159	N160	N161	N162	N163	N164	N165	N166	
SMAPE	0.23	0.16	0.22	0.32	0.26	0.24	0.27	0.28	0.21	0.21	0.18	
MAPE	0.28	0.16	0.21	0.42	0.32	0.29	0.31	0.35	0.22	0.22	0.18	
MAE	3.67	2.80	7.10	7.49	4.08	4.89	3.80	7.50	2.29	3.56	1.80	
	N167	N168	N169	N170	N171	N172	N173	N174	N175	N176	N177	
SMAPE	0.24	0.20	0.19	0.24	0.23	0.21	0.22	0.21	0.31	0.20	0.19	
MAPE	0.27	0.23	0.20	0.29	0.27	0.26	0.29	0.29	0.45	0.23	0.22	
MAE	2.32	3.30	3.95	2.95	3.77	3.35	4.18	2.92	2.90	5.41	4.78	
	N178	N179	N180	N181	N182	N183	N184	N185	N186	N187	N188	
SMAPE	0.18	0.17	0.31	0.21	0.14	0.25	0.24	0.23	0.36	0.19	0.20	
MAPE	0.21	0.17	0.33	0.27	0.13	0.24	0.33	0.26	0.53	0.20	0.22	
MAE	5.26	6.38	4.11	3.35	1.77	3.41	3.20	3.19	5.33	2.51	3.31	
	N189	N190	N191	N192	N193	N194	N195	N196	N197	N198	N199	
SMAPE	0.21	0.32	0.22	0.25	0.23	0.25	0.16	0.34	0.25	0.22	0.46	
MAPE	0.24	0.28	0.24	0.27	0.25	0.27	0.16	0.54	0.33	0.27	0.88	
MAE	3.96	4.32	4.78	1.90	2.68	6.68	2.62	3.98	3.11	4.21	5.15	
	N200	N201	N202	N203	N204	N205	N206	N207	N208	N209	N210	N211
SMAPE	0.31	0.22	0.21	0.23	0.16	0.25	0.16	0.19	0.25	0.18	0.20	0.23
MAPE	0.38	0.27	0.25	0.26	0.17	0.23	0.15	0.23	0.32	0.19	0.18	0.27
MAE	2.52	3.79	2.80	3.44	3.72	4.33	3.32	4.47	2.82	3.23	3.00	3.04

Table A.4 LSTM Scores

LSTM	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111	
SMAPE	0.16	0.32	0.21	0.27	0.23	0.21	0.26	0.27	0.18	0.23	0.24	
MAPE	0.16	0.50	0.20	0.29	0.23	0.25	0.30	0.32	0.17	0.26	0.28	
MAE	3.24	5.25	1.84	6.15	3.39	3.91	3.87	3.72	5.38	6.10	3.73	
	N112	N113	N114	N115	N116	N117	N118	N119	N120	N121	N122	
SMAPE	0.18	0.16	0.20	0.24	0.24	0.29	0.23	0.32	0.21	0.17	0.24	
MAPE	0.18	0.16	0.22	0.29	0.34	0.41	0.21	2.49	0.21	0.20	0.27	
MAE	5.78	2.92	4.72	4.71	4.64	4.39	4.41	4.87	1.60	3.33	4.82	
	N123	N124	N125	N126	N127	N128	N129	N130	N131	N132	N133	
SMAPE	0.22	0.15	0.19	0.25	0.22	0.31	0.23	0.22	0.20	0.17	0.17	
MAPE	0.22	0.19	0.20	0.28	0.24	0.39	0.29	0.45	0.19	0.17	0.16	
MAE	3.23	3.06	3.57	4.38	4.80	6.15	4.70	5.02	3.32	2.86	3.17	
	N134	N135	N136	N137	N138	N139	N140	N141	N142	N143	N144	
SMAPE	0.32	0.25	0.17	0.20	0.21	0.22	0.24	0.32	0.21	0.23	0.33	
MAPE	0.41	0.42	0.19	0.23	0.25	0.26	0.29	0.46	0.22	0.28	0.47	
MAE	2.93	6.31	3.09	3.06	1.65	3.67	5.23	4.30	3.50	4.10	6.09	
	N145	N146	N147	N148	N149	N150	N151	N152	N153	N154	N155	
SMAPE	0.15	0.30	0.32	0.33	0.21	0.20	0.17	0.26	0.19	0.22	0.20	
MAPE	0.16	0.44	0.43	0.62	0.22	0.22	0.18	0.32	0.22	0.25	0.23	
MAE	4.72	4.54	2.99	3.21	5.45	3.79	2.99	4.30	3.93	4.50	3.55	
	N156	N157	N158	N159	N160	N161	N162	N163	N164	N165	N166	
SMAPE	0.22	0.22	0.18	0.28	0.27	0.24	0.32	0.30	0.23	0.25	0.20	
MAPE	0.25	0.20	0.17	0.39	0.29	0.27	0.31	0.35	0.22	0.25	0.18	
MAE	3.61	3.79	5.94	6.58	4.41	4.76	4.28	7.84	2.50	4.21	1.94	
	N167	N168	N169	N170	N171	N172	N173	N174	N175	N176	N177	
SMAPE	0.29	0.23	0.29	0.26	0.22	0.18	0.21	0.21	0.28	0.20	0.20	
MAPE	0.40	0.22	0.26	0.31	0.24	0.24	0.24	0.25	0.35	0.20	0.21	
MAE	2.87	3.81	5.68	3.04	3.59	2.92	4.09	2.72	2.79	5.27	4.72	
	N178	N179	N180	N181	N182	N183	N184	N185	N186	N187	N188	
SMAPE	0.14	0.16	0.30	0.17	0.13	0.22	0.35	0.22	0.31	0.17	0.18	
MAPE	0.15	0.18	0.39	0.20	0.13	0.27	0.55	0.26	0.35	0.19	0.20	
MAE	3.95	6.10	4.25	2.66	1.67	3.17	4.93	3.08	4.22	2.37	3.08	
	N189	N190	N191	N192	N193	N194	N195	N196	N197	N198	N199	
SMAPE	0.18	0.26	0.21	0.24	0.22	0.20	0.17	0.31	0.26	0.19	0.34	
MAPE	0.19	0.32	0.21	0.25	0.25	0.22	0.17	0.42	0.31	0.21	0.47	
MAE	3.44	4.01	4.57	1.89	2.60	5.37	2.69	3.48	3.06	3.60	3.18	
	N200	N201	N202	N203	N204	N205	N206	N207	N208	N209	N210	N211
SMAPE	0.28	0.23	0.20	0.24	0.14	0.16	0.17	0.19	0.29	0.19	0.16	0.22
MAPE	0.29	0.27	0.24	0.28	0.15	0.16	0.17	0.19	0.37	0.22	0.16	0.24
MAE	2.08	4.29	2.77	3.84	3.25	2.82	3.52	4.20	3.49	3.57	2.46	2.91

Appendix B.

Table B.1 Optimal T Values

	N101	N102	N103	N104	N105	N106	N107	N108	N109	N110	N111
Optimal Model	DNN 1000	DNN 1000	RNN	RNN	LSTM	DNN 500	LSTM	DNN 1000	DNN 500	DNN 500	DNN 1000
TEST	4.57	4.34	6.72	3.94	4.99	4.67	4.82	5.05	3.71	3.47	4.81
DNN1000	4.61	4.40	7.12	4.00	5.08	4.57	4.96	5.15	3.74	3.95	5.21
DNN500	4.60	4.39	7.22	3.98	5.06	4.62	4.96	5.15	3.75	3.93	5.21
RNN	4.71	4.38	6.89	4.10	5.44	4.45	5.16	4.81	3.76	3.75	4.86
LSTM	4.50	4.57	7.34	4.31	5.19	4.53	5.19	5.31	3.99	4.01	4.94
	N112	N113	N114	N115	N116	N117	N118	N119	N120	N121	N122
Optimal Model	LSTM	RNN	LSTM	DNN 500	LSTM	DNN 1000	DNN 500	DNN 500	LSTM	LSTM	DNN 1000
TEST	3.58	4.70	4.23	4.43	4.59	4.71	4.48	4.68	7.34	4.54	4.61
DNN1000	3.64	4.80	4.27	4.32	4.61	4.64	4.61	4.64	7.05	4.51	4.62
DNN500	3.64	4.83	4.28	4.33	4.62	4.70	4.62	4.69	7.03	4.54	4.62
RNN	3.75	4.83	4.50	4.21	4.74	4.65	4.43	4.90	7.50	4.67	4.58
LSTM	3.62	4.95	4.26	4.56	4.58	4.76	5.05	4.60	7.45	4.45	4.48
	N123	N124	N125	N126	N127	N128	N129	N130	N131	N132	N133
Optimal Model	RNN	LSTM	DNN 1000	RNN	DNN 500	DNN 1000	DNN 500	DNN 500	DNN 1000	LSTM	DNN 1000
TEST	5.16	4.41	4.58	4.71	4.23	4.21	4.27	3.93	4.73	4.97	4.68
DNN1000	5.38	4.41	4.64	4.86	4.26	4.21	4.22	3.95	4.84	5.17	4.70
DNN500	5.41	4.44	4.64	4.87	4.25	4.28	4.22	3.97	4.87	5.19	4.71
RNN	5.24	4.69	4.70	4.89	4.66	4.43	4.22	3.84	4.61	5.16	4.63
LSTM	5.42	4.42	4.80	5.02	4.21	4.40	4.18	4.19	5.08	5.29	4.96
	N134	N135	N136	N137	N138	N139	N140	N141	N142	N143	N144
Optimal Model	DNN 1000	DNN 1000	LSTM	DNN 1000	LSTM	RNN	LSTM	DNN 1000	DNN 1000	DNN 1000	DNN 1000
TEST	5.94	3.73	4.66	4.97	7.03	4.74	4.34	4.88	4.72	4.70	4.38
DNN1000	6.16	3.65	4.64	5.10	7.24	4.81	4.32	5.05	4.76	4.45	4.46
DNN500	6.20	3.65	4.66	5.09	7.35	4.83	4.32	5.02	4.80	4.42	4.47
RNN	6.89	3.68	4.69	5.02	7.51	4.79	4.30	5.09	4.87	4.57	4.65
LSTM	6.45	3.66	4.76	5.26	7.40	4.89	4.18	4.95	5.09	4.50	4.43
	N145	N146	N147	N148	N149	N150	N151	N152	N153	N154	N155
Optimal Model	DNN 500	DNN 1000	DNN 500	DNN 500	RNN	RNN	LSTM	LSTM	RNN	DNN 1000	DNN 1000
TEST	3.66	4.86	6.17	6.12	3.87	4.49	4.84	4.76	4.48	4.24	4.71
DNN1000	3.74	4.77	6.06	6.16	3.82	4.75	4.78	4.63	4.42	4.31	4.68
DNN500	3.77	4.77	6.08	6.15	3.83	4.77	4.78	4.63	4.43	4.32	4.67
RNN	3.65	4.69	6.42	5.37	3.71	4.73	4.48	4.88	4.45	4.21	5.00
LSTM	3.66	5.08	6.26	5.77	4.06	4.74	4.80	4.69	4.36	4.37	4.73
	N156	N157	N158	N159	N160	N161	N162	N163	N164	N165	N166
Optimal Model	DNN 1000	DNN 1000	DNN 500	DNN 1000	DNN 1000	DNN 500	DNN 1000	RNN	DNN 1000	RNN	RNN
TEST	4.94	4.77	3.58	4.02	4.78	4.61	5.21	4.09	5.92	4.64	6.40
DNN1000	4.84	4.89	3.66	4.09	5.12	4.68	5.45	4.11	6.22	4.85	6.75
DNN500	4.87	4.86	3.67	4.09	5.13	4.67	5.45	4.08	6.24	4.85	6.77
RNN	4.94	4.71	3.66	3.91	4.73	4.41	5.40	3.97	6.08	4.83	6.57
LSTM	5.24	5.19	3.69	4.02	5.23	4.45	5.78	4.03	6.61	5.11	7.05
	N167	N168	N169	N170	N171	N172	N173	N174	N175	N176	N177
Optimal Model	RNN	DNN 1000	DNN 1000	RNN	DNN 1000	LSTM	DNN 500	LSTM	LSTM	RNN	DNN 1000
TEST	6.09	4.94	4.46	5.70	4.77	4.96	4.43	5.36	6.15	3.95	4.06
DNN1000	6.25	4.91	4.60	5.85	4.77	5.02	4.37	5.42	6.36	4.05	3.98

DNN500	6.26	4.91	4.60	5.86	4.77	5.04	4.37	5.43	6.38	4.04	3.98	
RNN	6.17	4.67	4.56	5.97	4.76	5.07	4.24	5.48	5.92	3.96	3.93	
LSTM	5.97	5.36	5.02	5.93	5.00	4.92	4.46	5.47	6.34	4.25	4.06	
	N178	N179	N180	N181	N182	N183	N184	N185	N186	N187	N188	
Optimal Model	DNN 1000	DNN 500	DNN 1000	DNN 1000	LSTM	DNN 1000	RNN	DNN 500	DNN 500	DNN 1000	DNN 1000	
TEST	3.85	3.10	4.95	4.97	5.77	5.23	5.07	5.34	4.98	5.41	4.89	
DNN1000	3.85	3.09	5.16	4.85	5.70	5.23	5.02	5.51	4.97	5.45	4.87	
DNN500	3.84	3.11	5.18	4.84	5.69	5.23	5.02	5.52	4.98	5.43	4.88	
RNN	3.60	3.21	5.18	4.66	5.97	5.77	5.28	5.32	4.84	5.40	4.77	
LSTM	3.79	3.08	4.92	5.01	5.89	5.10	4.82	5.29	5.14	5.47	4.83	
	N189	N190	N191	N192	N193	N194	N195	N196	N197	N198	N199	
Optimal Model	LSTM	DNN 1000	LSTM	LSTM	LSTM	DNN 500	RNN	DNN 1000	RNN	LSTM	DNN 1000	
TEST	4.58	5.17	4.42	7.24	5.85	3.78	5.00	5.75	5.61	4.71	7.48	
DNN1000	4.62	5.21	4.46	7.26	5.80	3.85	4.97	5.67	5.64	4.67	7.14	
DNN500	4.62	5.21	4.44	7.23	5.81	3.81	4.96	5.67	5.64	4.67	7.15	
RNN	4.46	5.83	4.31	7.33	5.87	3.85	5.19	5.54	5.71	4.50	5.74	
LSTM	4.73	4.78	4.52	7.41	5.87	3.89	5.05	6.04	5.69	4.73	6.83	
	N200	N201	N202	N203	N204	N205	N206	N207	N208	N209	N210	N211
Optimal Model	DNN 1000	DNN 1000	LSTM	DNN 1000	DNN 1000	DNN 1000	RNN	DNN 500	RNN	RNN	LSTM	LSTM
TEST	7.40	4.66	5.40	4.79	4.22	4.65	4.30	4.20	5.44	4.63	5.08	5.24
DNN1000	7.04	4.68	5.62	4.88	4.24	4.64	4.44	4.25	5.80	4.75	5.20	5.36
DNN500	6.95	4.67	5.60	4.89	4.23	4.65	4.46	4.24	5.87	4.77	5.21	5.36
RNN	6.95	4.78	5.41	4.96	4.04	5.14	4.45	4.10	5.48	4.75	5.59	5.28
LSTM	7.66	4.90	5.44	5.00	4.08	4.79	4.47	4.32	5.84	4.46	5.28	5.51

BIOGRAPHICAL SKETCH

Michele CEDOLIN was born in Istanbul on April 17. 1992. He studied at Galatasaray High School and graduated in 2010. He obtained the B.S. and then master's degrees in Industrial Engineering Department of Galatasaray University in 2014 and 2016, respectively. Since December 2015, he has been working as a research assistant in Industrial Engineering Department of Galatasaray University.

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Related Publications:

Cedolin, M., & Erol Genevois, M. (2019, October). District Performance of the ATMs by Alternative DEA Techniques. In 2019 *3rd International Conference on Data Science and Business Analytics (ICDSBA)* (pp. 61-64). IEEE.

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