ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

SMART WASTE MANAGEMENT TECHNIQUES AND THEIR PERFORMANCE UNDER VARIOUS SCENARIOS

M.Sc. THESIS

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AKILLI ATIK YÖNETİM TEKNİKLERİ VE FARKLI SENARYOLARDAKİ BAŞARIMLARI

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Damla GÜLEN, a M.Sc. student of ITU Graduate School of Science Engineering and Technology 504161508 successfully defended the thesis entitled "SMART WASTE MANAGEMENT TECHNIQUES AND THEIR PERFORMANCE UNDER VARIOUS SCENARIOS", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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FOREWORD

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ABBREVIATIONS

CLV : Circular Load Variation
CULT : Collect based on Upper ad Lower Threshold
CULTwP : Collect based on Upper ad Lower Threshold with Priority
CUT : Collect based on Upper Threshold
CUTwP : Collect based on Upper Threshold with Priority
CVF : Closest Vehicle First
CVFwP : Closest Vehicle First with Priority
FLV : Fixed Load Variation
GA : Genetic Algorithm
GLCM : Gray Level Co-Occurrence Matrix
ICT : Information and Communication Technology
IMILP : Inexact Mixed Integer Linear Programming
IoCI : Internet of Cities Infrastructure
IoE : Internet of Everything
IoT : Internet of Things
IP : Internet Protocol
LoRa : Long Range
LoRaWAN : Long Range Wide Area Network
LPWAN : Low Power Wide Area Networks
M2M : Machine-to-Machine
MEMS : Micro Electrical Mechanical Systems
MCDA : Multi-Criteria Decision Analysis
MILP : Mixed Integer Linear Programming
MSW : Municipal Solid Waste
MSWC : Municipal Solid Waste Collection
NB-IoT : Narrowband IoT
RFID : Radio-frequency identification
RLV : Rectangular Load Variation
TSP : Travelling Salesman Problem
VLV : Variable Load Variation
WMU : Wireless Monitoring Units
WoT : Web of Things
WSAN : Wireless Sensor and Actuator Networks
WSN : Wireless Sensor Networks

SYMBOLS

$\mathbf{D}$	: Cost of (un)dumping per bin (from a bin to a truck)
$\mathbf{H}$	: Cost of human resource
$\mathbf{G}$	: Cost of gas mileage
$\mathbf{S}$	: Average speed in town (km/h)
$\mathbf{W}$	: Time needed to collect waste from a bin (minute)
$\mathbf{N}$	: Total number of trucks
$\mathbf{M}$	: Total number of bins
Ψ_i	: Upper threshold for waste amount of bin i
ψ_i	: Lower threshold for waste amount of bin i
ρ_i	: Penalty of bin i
$\mathbf{R_t}$	: Time needed to empty truck t at dumping area and prepare it for next trip (minute)
$\hbar$	: Distance from dumping area to central station (meter)
Δ_{ij}	: Distance between bin i and bin j (meter)
$\mathbf{t_{ij}}$	: Time needed to move from bin i to bin j (minute)
Δ_i	: Distance from bin i to dumping area (meter)
$\mathbf{r_i}$	: Distance from central station to bin i (meter)
λ_i	: Average waste arrival at bin i (kg)
$\mathbf{h_t}$	: Number of workers in truck t
Λ_i	: Capacity of bin i (kg)
δ_i	: Initial load for bin i (kg)
$\mathbf{C_t}$	: Capacity of truck-t (kg)
$\mathbf{T_i}$	: Time from central station to first bin i (minute)
$\mathbf{c_t}$	: Initial load of truck t (kg)
$\mathbf{K}$	: Threshold for count of alarmed containers
$\mathbf{k}$	: Number of alarmed containers
$\mathbf{A_i}$	: Alarm status of bin i
$\mathbf{B}$	: Alarmed container list
$\mathbf{Z_t}$	: Route of truck t
$\mathbf{L_{ij}}$	: List of containers on the shortest path between bin i and j
$\mathbf{d_t}$	: Integer variable defines the total distance covered by truck-t (meter)
$\mathbf{d}$	: Integer variable defines the total distance covered by N trucks (meter)
$\mathbf{I_t}$	: Integer variable defines the distance from central station to first bin of truck t (meter)
$\widehat{I_t}$	: Integer variable defines the distance from last bin of truck t to dumping area (meter)
τ_t	: Integer variable defines the total time of truck-t (minute)
τ	: Integer variable defines the total time of the N trucks (minute)
$\mathbf{b_t}$	: Integer variable defines the total number of bins collected by truck t
$\mathbf{F_i}$	: Integer variable defines the final load of bin i (kg)
$\mathbf{Y_t}$	: List of visited containers by truck t
$\mathbf{P_i}$	: Boolean variable defines if bin i has priority

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SMART WASTE MANAGEMENT TECHNIQUES AND THEIR PERFORMANCE UNDER VARIOUS SCENARIOS

SUMMARY

The rapid increase in the urban population and changes in consumption patterns of the individuals are leading to the necessity of systems that serve in order to increase the quality of lives. Internet of Things (IoT) being one of the major topics in Information and Communication Technology (ICT) is a strong candidate to implement these kinds of smart systems. The term smart city is introduced with the need of improving life standards of the individuals which refers to a set of smart applications in a city. The application field of smart cities includes but not limited to transportation systems, information systems, schools, hospitals, libraries and waste management system. In order to develop smart city applications, the IoT-driven sensors are required. With the use of these sensors the need for wireless sensor and actuator networks (WSAN) and wireless sensor networks (WSN) are inevitable since they provide productive and manageable service in a smart city environment.

In this thesis study, the focus is on the field of waste management in terms of smart city concept. Since the increase in the urban population will lead to a frequent increase in the produced waste levels. The problem of waste management is addressed by introducing a decision mechanism to the route optimization for the collection of waste bins in a smart city environment. Where the environment considers a WSN with bins deployed and raising alarms for certain amounts of waste levels. Related researches and implementations are investigated in detail and a new approach to address this problem is presented. Six different heuristic approaches are introduced. Different aspects are considered in each of the methods including but not limited to prioritization and threshold values for current waste levels in the waste bins. These approaches are called; *Closest Vehicle First (CVF)*, *Closest Vehicle First with Priority (CVFwP)*, *Collect based on Upper Threshold (CUT)*, *Collect based on Upper Threshold with Priority (CUTwP)*, *Collect based on Upper and Lower Threshold (CULT)*, *Collect based on Upper and Lower Threshold with Priority (CULTwP)*. In CVF and CVFwP the only condition that a bin is added to the route of a truck which collects waste from bins, is that the bin triggering an alarm. An alarm is triggered when the current waste level inside the waste bin is reached to upper threshold value which is not higher than the bin capacity. In CUT and CUTwP, the bins which triggered the alarms are added to a route in a similar manner. However, the bins which are on the truck's route but have not yet triggered alarms are also added to the related routes. Moreover, when CULT and CULTwP is considered, the bins that triggered the alarms are added to a route but the other bins on the way of a truck's route are decided to be added to the route based on its' current waste level being higher than the lower threshold value. By this way the unnecessary travel of trucks is aimed to be reduced. In addition, the three methods which are CVFwP, CUTwP and CULTwP, are the ones that considers prioritization.

The bins with priority are the ones who reach their capacity or the ones that are visited but could not be emptied because of the truck visiting the bin reached its' capacity. The bins with priority are visited earlier than the others.

The performances of the proposed methods are evaluated under several scenarios in a simulation environment. The results are observed in terms of total cost, delay per route, route count and spilled waste amount values. It is seen that all the methods are providing sufficiently good results however each method has its' own advantages and disadvantages on a distinct scenario. When smaller area is considered with less number of waste bins, CUT provides the highest cost values. CVF and CULT provides similar results. However, in general CVF tends to provide more efficient solutions in this case since it results in with less amount of waste overflow. As the area gets larger and more bins are present, CUT generates the best result in terms of cost efficiency. However, the reason behind this behaviour is the increase in the delay values which also decreases the route counts. Besides, the waste overflow amount is high. When there is an enhancement in terms of bin and truck capacities, CULT tend to perform more cost efficiently. Moreover, the combinations of different truck assignments and zoning are considered. According to the results, if a single truck is responsible from an area of bins which have same waste arrival rates, the cost is reduced. However, this cost reduction occurs based on the increase in delay which also causes higher amount of waste spillovers. In addition, when the prioritization is considered, the total costs are increasing in general. However, the aim of prioritization technique is to reduce the spilled over waste amount which is achieved by the proposed approaches.

The result of the various scenarios are presented and explained in detail in this thesis study. In order to implement these approaches in a real life scenario, the environment conditions need to be taken into consideration. The mapping of the environment conditions and effective technique for them are given in detail.

AKILLI ATIK YÖNETİM TEKNİKLERİ VE FARKLI SENARYOLARDAKİ BAŞARIMLARI

ÖZET

2050 yılına kadar şehirlerde yaşayan insan sayısının toplam nüfusa oranının üçte ikiye ulaşacağı öngörülmektedir. Şehir merkezlerinde hızla artan popülasyon ve bireylerin değişen tüketim alışkanlıkları, hayat kalitesini arttıracak platformların yaratılma ihtiyacını doğurmaktadır. Bilim ve İletişim Teknolojileri'nin ana konularından biri olan Nesnelerin İnterneti, ihtiyaç duyulan bu platformları sağlama konusunda güçlü bir aday olarak gösterilmektedir. Nesnelerin interneti, cihazların ve sensörlerin birbirleri ile veri transferi yoluyla iletişimini sağlamaktadır. Nesnelerin interneti teknolojisi sayesinde insanlar ve nesneler arasındaki etkileşim sağlandığı için nesnelerin interneti akıllı şehir uygulamalarının hayata geçirilmesinde oldukça önemli bir rol oynamaktadır.

Burada Akıllı Şehirler kavramı karşımıza çıkmaktadır. Akıllı Şehirler yaşam standartlarını yükseltmek amacıyla hayata geçirilmiş şehir yaşamında ihtiyaç duyulan bir takım servisleri konu almaktadır. Akıllı şehirlerin uygulama alanlarından bazıları sağlık, eğitim, ulaşım, kütüphaneler, bilişim sistemleri ve atık yönetimi olarak sayılabilir. Akıllı şehir uygulamaları yalnızca bu alanlarla kısıtlı kalmaz fakat en önem verilen alanlardan bazıları bu şekildedir. Akıllı şehir uygulamalarının hayata geçirilmesinde nesnelerin internetini temel alan sensörlere ihtiyaç duyulur. Bu sensörler ise bir araya getirilerek kablosuz sensör ve aktüatör ağı ve/veya kablosuz sensör ağlarında kullanılarak verimli ve gerçekleştirilebilir akıllı şehir servislerinin oluşmasını sağlarlar.

Akıllı şehir çözümlerinin sunulacağı sürdürülebilir bir alt yapı oluşturma pek çok araştırmanın konusu olmuştur. Bu tez çalışmasında akıllı şehirlerin pek çok farklı uygulama alanları arasında yer alan ve en önemlilerinden biri olan atık yönetimi bulunmaktadır. Hızla artan kentsel nüfus üretilen atık miktarının da artmasına yol açmaktadır. Atık yönetim problemine, bir karar verme mekanizması kullanılarak çöp konteynerlerinin optimize bir rota ile toplanması çözümü sunulmuştur. Problem tanımına göre kablosuz sensör ağlarından oluşturulan bir akıllı şehir ortamında, çöp konteynerlerine yerleştirilmiş sensörler algıladıkları çöp seviyelerine göre alarm tetiklemektedirler. Benzer konuda ve atık yönetimi problemine getirilen farklı yaklaşımlar üzerinde derinlemesine araştırmalar yapılmış, tez çalışması çerçevesinde sunulmuştur. Pek çok çalışma atık yönetimi konusunun farklı alanlarını ele almaktadır. Katı atık ayırma, donanımsal anlamda çözüm sunma, gelişen ülkelerde atık yönetimi ve çöp toplamada optimizasyon alanları bunlardan en çok üzerinde araştırma yapılan alanlardır. Biz yukarıda tanımı verilen probleme altı farklı sezgisel yöntem ile çözüm sunduk. Bu altı farklı yöntemin her biri tanımlanan problemi farklı açılardan çözüme ulaştırmaya çalışmaktadır. Önceliklendirme ve eşik değeleri kullanımı bu farklı yöntemlerin özelliklerindendir.

Atık yöntemi için sunulan yöntemler *İlk Önce En Yakın Araç(İÖEYA)*, *Önceliklendirmeli İlk Önce En Yakın Araç (ÖİÖEYA)*, *Üst Eşiğe Göre Toplama (ÜEGT)*, *Önceliklendirmeli Üst Eşiğe Göre Toplama (ÖÜEGT)*, *Üst ve Alt Eşiklere Göre Toplama (ÜAEGT)*, *Önceliklendirmeli Üst ve Alt Eşiklere Göre Toplama (ÖÜAEGT)* olarak adlandırılmıştır. Bu yöntemler birbirine göre bazı farklılıklarla iyileştirilmeye çalışılmış olup atık yönetimi ve çöp toplama optimizasyonuna farklı yönlerden çözüm sağlamayı amaçlamaktadır. İÖEYA ve ÖİÖEYA yöntemlerinde, ortamdan belirli sayıda alarm sinyali alındığında, alarmları oluşturan konteynerler birbirlerine olan konumlarına göre optimize bir şekilde rota oluşturularak bir araca atanırlar. Bu yöntemlerde yalnızca bir eğiş değerine ulaşıp alarm sinyali gönderen çöp konteynerlerindeki atıkların toplanması hedef alınır. Bu eşik değeri konteyner kapasitesinden yüksek olmamak kaydıyla belirlenmelidir. Bu çalışma için kullanılan eşik değeri konteyner kapasitelerinin yarısı kadardır. ÜEGT ve ÖÜEGT yöntemlerinde ise alınan alarmlar sayesinde bir rota oluşturulacağı zaman, henüz alarm durumuna ulaşmamış fakat oluşacak olan rota güzergahı üzerinde konumlanmış olan diğer konteynerler de araçlar tarafından ziyaret edilir ve buradaki çöpler de toplanır. Böylece yakıt ve zaman tasarrufu yapmak amaçlanmıştır. ÜAEGT ve ÖÜAEGT yöntemlerinde ise bir önceki yönteme bir karar mekanizması eklenir. Bu karar mekanizması araçların güzergahı üzerinde bulunan fakat alarm durumuna gelmemiş konteynerlerdeki güncel çöp seviyesini kontrol eder. Bu seviye eğer belirlenen alt eşik değerinin üstünde ise bu konteynerlerdeki çöpler de aynı araç tarafından toplanır. Böylece zaman tasarrufu iyileştirilmesi amaçlanmıştır. Bir önceki yöntemde konteynerlerdeki çöp miktarına bakılmaksızın konteynerler ziyaret edilirken oluşabilecek gereksiz masraflar bu yöntem ile azaltılmaya çalışılmıştır. Ek olarak, önceliklendirme kullanımı ise ÖİÖEYA, ÖÜEGT ve ÖÜAEGT yöntemleriyle sağlanmıştır. Önceliklendirme sistemi bir çöp konteynerlerinin kendi kapasitelerine ulaşması veya bir araç tarafından ziyaret edildiği sırada tamamen boşaltılamaması nedenleriyle bu konteynere öncelik atanmasıyla sağlanır. Bir çöp konteyneri ziyaret edildiği sırada, ziyaret eden araç kendi kapasitesine ulaşırsa derhal bu araç çöp boşaltım alanına gider. Yükünü boşaltan aracın ilk görevi ise tamamen boşaltamadığı ve en son ziyaret ettiği konteynere gitmek olur. Daha sonra ziyaret edeceği konteynerler sistem tarafından yakınlıkları göz önünde bulundurularak tekrar belirlenir. Bunun yanında, kendi kapasitesine ulaşan bir konteyner henüz bir araç tarafından ziyaret edilmediyse öncelik alır. Öncelik alan konteynerler atandıkları araçlar tarafından daha önce ziyaret edilecek şekilde ilgili rotalar ayarlanır.

Sunulan yöntemlerin performansları bir simülasyon ortamı yaratılarak pek çok farklı parametre ile farklı senaryolar kurularak izlenmiştir. Sonuçlar maliyet, gecikme süresi, rota sayısı ve taşan atık miktarları ölçütleri açısından karşılaştırılmıştır. Oluşturulan simülasyon ortamında pek çok farklı harita kullanılmıştır. Bu haritalardaki konteyner sayıları 20 ile 160 konteyner arasında değişiklik gösterir. Önerilen yöntemlerin karşılaştırılmasında kullanılan senaryolar ise kullanılan haritalar, konteyner sayıları, konteyner ve araç kapasiteleri, araç görevlendirme yöntemleri, bölgelendirme ve gelen çöp oranları anlamında değişiklikler gösterir. Önerilen yöntemlerin sunduğu sonuçlara bakıldığında tüm sonuçların yeterli ölçüde olduğu gözlemlenmiştir. Yöntemler arası farklılıklar, her yöntemin güçlü ve zayıf yönleri, daha iyi çözüm getirdiği durumlar vurgulanmıştır.

İncelenen sonuçlara göre, daha küçük alanlar göz önüne alındığında ve konteyner sayılarının az olması durumunda ÜEGT en yüksek maliyetli çözümü, İÖEYA ise

en düşük maliyetli çözümü sunmaktadır. İÖEYA ve ÜAEGT yöntemlerinin maliyet açısından çoğunlukla yakın sonuçlar sağladığı görülse de genel olarak İÖEYA yönteminin hem daha düşük maliyet sağladığı hem de daha az miktarda taşan çöp miktarına ulaştığı görülmektedir. İÖEYA yöntemi az miktarda çöp bulunduran konteynerlerin ziyaretini engellediği için ve alarm sinyali gönderen konteynerlere de yeterli sürede ulaşılabildiği için daha az karmaşık ortamlarda daha iyi sonuçlar vermektedir. Gecikme süreleri ve rota sayıları anlamında bu tür ortamlarda kayda değer bir değişim görülmemektedir. Bu durumda maliyetlerdeki farklılığı rota bazlı maliyet olarak da yorumlamak mümkündür. Alan büyüdüğü ve konteyner sayıları arttığı durumda karar mekanizmasının önemi görülmektedir. Bu durumlarda ÜEGT yöntemi maliyet anlamında en etkili sonuçları sunmaktadır. Fakat bunun sebebi gecikme sürelerindeki artış ve daha az sayıda rota izlenmesidir. Aynı zamanda en fazla taşan çöp miktarına da ÜEGT yöntemi sebep olur. Konteyner ve araç kapasiteleri arttırıldığında, daha karmaşık sistemlere servis verilebilir hale getirildiğinde ÜAEGT yönteminin en düşük maliyetleri sağladığı görülmektedir. Ek olarak, araçların görevlendirmelerindeki farklılıklar ve bölgelendirme göz önüne alındığında oluşan sonuçlar gözlemlenmiştir. Her aracın sorumlu olduğu bölgeye ait konteynerler aynı oranda gelen çöp yüzdelerine sahip ise maliyet açısından daha düşük sonuçlar sunulmaktadır. Fakat bu düşüşün sebebi artan gecikme süreleri ve azalan rota sayılarıdır. Bir yandan da taşan çöp miktarlarında artış gözlemlenmiştir. Önceliklendirme yöntemleri göz önüne alındığında ise genel olarak maliyetlerde artış gözlemlenmektedir. Fakat bu yöntemlerin amacı ortaya çıkan taşan çöp miktarını azaltmaktır ve sonuçlara bakıldığında bunun sağlandığı görülmektedir.

Pek çok farklı kriter ve değerlendirme ölçütlerine göre sonuçlar incelenmiş ve önerilen yöntemler karşılaştırılmıştır. Uygulama anlamında hangi yöntemin seçileceği uygulanacak ortam koşullarına ve uygulamanın hedeflerine göre seçilebilir. Yöntem ve durum eşleştirilmeleri ayrıntılı olarak sunulmuştur.

1. INTRODUCTION

By 2050, almost two thirds of the world's population will be living in urban areas, according to the United Nations' estimation and form immense cities [1]. The development of infrastructure and services will become the inevitable solution to satisfy the needs of these highly increased urban population [2]. Applications in the Information and Communication Technology (ICT) field, coincide with the concept of smart cities are believed to meet the needs in this area [3]. Most researchers defined the term smart cities as the application of the Internet of Things (IoT) [4]. The required solutions for these smart cities will be in the various fields not only limited but including city services infrastructure, transportation, surveillance, and technology related issues. The major impact of the implementations of these technologies and the efficient management of these services is expected to be seen on the life quality of the citizens [5].

1.1 Smart Cities And IoT Applications

The Internet of Things has many ways to be defined. Simply, it can be defined as an interconnection between devices and sensors by providing data exchange among them [6]. IoT provides communication of devices with Machine-to-Machine (M2M) connection [7] IoT has been one of the major research topics in the ICT field [8] and it aims to automate human life. The ability of IoT to connect objects with each other and provide interaction with humans with an intelligent way makes the implementation of the IoT concepts essential for smart cities [9].

In [10], a concept definition of smart city is given as, "A Smart City is a city well performing in a forward-looking way in the following fundamental components (i.e., Smart Economy, Smart Mobility, Smart Environment, Smart People, Smart Living, and Smart Governance), built on the 'smart' combination of endowments and activities of self-decisive, independent and aware citizens". Smart city's vision is

urban development [11]. In [12], regarding the close relation between the IoT and Smart City terms, these kinds of smart cities are called as Internet of Cities and a new approach to develop an infrastructure is introduced with the name Internet of Cities Infrastructure (IoCI). Integration of the IoT with ICT and other innovative technologies are required to reform the smart cities. IoT is considered to be the key enabler of developing sustainable smart cities. Other technologies that are strong candidates to achieve the idea of smart cities are cloud computing, big data remote ubiquitous remote sensing. Besides, sensor networks, three of which are wireless sensor networks (WSNs), body sensor networks, internet of everything (IoE), web of things (WoT), contribute to develop accurate smart cities by generating, collecting, processing and transferring information [13]. The relation of big data and smart cities are subjects of many other researches [14]. In addition, in some studies, the related works in the area of ICT, IoT and Smart Cities are summarized and presented within tables [15].

The assets of smart cities are not limited to but include managing schools, hospitals, libraries, the local departments, information systems, waste management systems and transportation systems [16], [17]. Thus, most wide spread implementations are smart health, smart transportation, smart lighting and disaster management [18]. These kinds of smart city applications require IoT-driven sensing [17]. ICT is also used in smart cities to improve the performance of the city assets and contribute to the interactivity of the services provided in the smart city concept [19]. Moreover, the requirement of providing productive and manageable services in a smart city are maintained by wireless sensor and actuator networks (WSAN) [20–23].Therefore, individuals' daily activities include further utilization of the IoT technologies day by day [24].

The requirement of a sustainable infrastructure to meet the demands of the citizens and introduce indispensable and advanced services are inevitable for smart cities [25]. Thus, adapting the Future Internet technologies integrating the Internet Protocol (IP) through wireless sensors to implement the IoT archetype. Various sensors are deployed in WSNs. These wireless sensors are Micro Electrical Mechanical Systems (MEMS) based devices with integrated sensing, processing, digitizing and communication skills. WSNs have their own routing and power conserving protocols which is applicable to diverse topology. WSNs and their application fields are deeply investigated in [19]. WSN constraints and emerging technologies related to it are

deeply investigated in [26] including numerous low power wireless technologies which can be utilized in WSNs. The responsibility of WSNs in the smart city concept is to collect and process information in order to meet the needs of a smart city [5]. WSNs have the ability of reforming the daily activities in every aspect for a smart city environment [27].

1.2 Smart Waste Management

IoT and WSAN compose compelling parts of smart cities. Moreover, dynamic expert systems are part of smart cities and they analyze real-time information [8]. Water, energy, transportation, waste and Information and Communication are facets of a smart city [28]. The dynamic expert systems are compelling in the waste management domain which is the focus of this study. In this specific domain of waste management, the volumetric sensors to sense waste levels of the bins in a smart city environment are used [29].

Waste production is an inevitable result of the presence of human and life. Therefore, daily life cycle will always involve waste [30]. This lead the waste management being a constantly developing concern locally and globally [11]. As the waste management has a great impact on the individuals' living standards, there are numerous researches on the problem of smart waste management. Municipal solid waste (MSW) amount is larger then the growth rate of the urbanization [31]. Besides, MSW production rate increases with the rapid urbanization growth and the living quality of the population especially in the developing countries [32]. This yields to several researchers to conduct studies on improvement ways of the developing countries and addressing the challenges for it [31–37].

IoT is not only an inseparable part of smart cities, it also has vast impact on waste management systems in the smart city concept by providing dynamicity in waste collection, construction of collection route and waste truck fleet management [38]. In addition, there are wide range of waste management activities dealing deal with waste collection, waste separation, waste recovery and recycling [25]. Furthermore, the integration of IoT-based systems to the waste management domain of smart cities are studied by many researchers [39–41]. ICT contribute to introduce dynamicity to these kinds of systems not limited to but including dynamic waste collection based

on the capabilities offered by ICT [25]. Waste collection is one of the problems that was treated statically, however nowadays newly developed sensors, actuators and IoT technologies [42] assist to maintain dynamic solutions. In this newly developed dynamic systems where bins are equipped with diverse IoT components and sensors such as temperature sensors, humidity sensors, capacity sensors, weight sensors, pressure sensors, chemical sensors and actuators [43].

As a result of the rapid growth of urban area population and changed consumption behaviours of the population, convenient management of waste generation is required in order to enhance the quality of life. A convenient waste management system needs to consider the minimization of the negative effects of the environment as the effective waste management becomes highly critical in urban areas [25]. Genuinely, to achieve the requirement of processing the waste level data of a municipal region collected from IoT and WSAN, effective and efficient decision making systems are necessary [44].

In this thesis study, the main focus is on the decision making systems introduced to the waste management problem in smart cities. A new approach to smart waste management is presented. Six heuristic models are proposed for a WSN-driven smart city environment. The proposed heuristic models address the necessity for efficient waste collection route planning where a WSN is present and a set of alarms are raised to initiate the waste collection. The proposed models are compared between each other in terms of total cost, delay per route, route counts and spilled waste amount values. Besides, their confidence intervals are also given. These approaches are called; *Closest Vehicle First (CVF)*, *Closest Vehicle First with Priority (CVFwP)*, *Collect based on Upper Threshold (CUT)*, *Collect based on Upper Threshold with Priority (CUTwP)*, *Collect based on Upper and Lower Threshold (CULT)*, *Collect based on Upper and Lower Threshold with Priority (CULTwP)*. CUT and CUTwP approaches utilize an upper threshold for the bins' waste levels whereas CULT and CULTwP takes upper and lower load thresholds into consideration. In addition, CVFwP, CUTwP and CULTwP considers prioritization of the bins. This work is organized as follows. In Chapter 2, a comprehensive study of related works in the field of waste management in smart cities is presented. Chapter 3 presents the introduced heuristic approaches to address waste management problem in detail. Chapter 4 presents numerical results under various test case scenarios by comparing the heuristic approaches with each other in terms of cost,

delay, number of routes and spilled waste amounts. Finally, Chapter 5 concludes the study and gives future directions.

2. RELATED WORK

Waste management is studied by many researchers under smart city domain. With the increase in the urban population and introduced changes in the consumption behaviours of the individuals, waste management gained importance in order to maintain a high quality life standard in urban areas. In this chapter of the study, the background information of the field waste management in terms of smart city concept is described in detail. Various studies are deeply investigated and presented with their closeness and variations to this thesis study.

As it is mentioned in the previous chapter, the urbanization speed is increasing. More than half of the world's population is living in urban centers and it is expected to be 86 per cent by 2050 for developed countries. For the developing countries the expected rate 64 per cent of the population [45]. In order to serve this rapid increase and meet the needs of the urban population, several studies are conducted in terms of waste management which includes evaluating various scheduling and routing concepts and the connection between these concepts and the basic features of a solid waste management system [46]. A comprehensive study of waste management systems and the application field in residential units is presented in [47]. Moreover, the waste management problem is considered in terms of the cloud-based platforms with the aim of fuel utilization reduction and performance enhancement in [48]. In the presented approach, the load level sensors placed on the bins in an urban area, are communication with the cloud platform. The decision making system considered in this cloud-based platform is responsible from providing efficient services for waste collection, route optimization, recycling and disposal, food industry, taxation and energy generation through waste.

Before going deep into the waste management problem, the technology behind it also requires attention. The interaction of smart cities and IoT is inevitable since IoT is believed to be the essential communication framework of smart cities [7]. The

specific requirements of IoT applications are deeply studied by many researchers such as low energy consumption, long range, low data rate and cost effectiveness. It is also pointed out that to achieve the IoT applications' demands, new wireless communication technologies are emerging such as Low Power Wide Area Networks (LPWAN) [6]. The extended technologies from LPWAN's such as Narrowband IoT (NB-IoT) and Long Range (LoRa) are discussed in [49]. Another study to address the problem of building an infrastructure to enable low-power device communication in Bristol, proposed a solution with Long Range Wide Area Network (LoRaWAN) [50].

In [7], where the LPWAN is considered as a contribution in order to make IoT idea closer to the real implementation, the main focus is on the optimization algorithms for Smart City applications, mainly municipal waste collection strategy. In the study, the previously deployed IoT infrastructure and sensor networks, based on SigFox technology, are used. The study introduces the idea of the garbage trucks have to pick up all garbage cans in a region regardless of their waste levels, even they are empty. Usage of genetic algorithm (GA) is proposed as a solution tool for garbage-collection optimization with the support of various simulated use cases. The idea of removing unnecessary bins from the trucks' routes is common between the study of [7] and this thesis.

Improving the routes generated during waste collection is the common aim of many researchers. They try to address the similar problem by introducing different kinds of technologies. One of the approaches is followed in [39], where an IoT-based system is developed to address the waste management problem by improving garbage collection routes' optimality. In the developed system, the bins which are sending waste level data to a server are deployed in a residential area. In addition, LoRa communication is implemented to send notification when the bins are full with waste [40]. A similar study is conducted in South Korea where an IoT-based system is applied to provide the waste control. According to the presented proposal, when a resident is disposing waste to the bins, Radio-frequency identification (RFID) cards inside the bins are used to identify the resident. The waste amount inside bins is weighted and a server is informed automatically. The server is responsible to process the information and provide a billing data [41].

As municipal solid waste management becomes the critical aspect with the increased urban population, many researchers have focused on the problems in this domain [7]. Source separation, collection, transfer and transportation, processing and recovery, storage and disposal are some of the challenges in this field. When the collection of waste and truck allocation problems are studied, some of the possible solutions are proposed by linear methods. However, they are insufficient in terms of efficiency in more challenging situations, mostly due to high computation delays. In more recent researches, heuristic solutions are proposed when municipal waste collection problem is addressed and represented as a Travelling Salesman Problem (TSP). Within the heuristic methods' domain, only a small number of researches propose evolutionary algorithms as a solution to the optimization of the waste collection problem. Ant Colony and Generic Algorithm (GA) are among these proposed solutions, where genetic algorithm was proven as an effective tool when TSP is considered. However it cannot be said that GA is effective for any waste collection implementation.

Another study that proposed a solution with genetic algorithm to optimize the garbage collection is provided in [11]. Again the bins are equipped with weight sensors which are sending weight data of the bins to the servers. Then the optimization algorithm is processing the data when received by the server. In addition, real-time traffic data is used to construct more efficient routes according to the traffic [51]

In one of the studies conducted [38], the high priority areas are introduced, such as schools and hospitals. In those areas the bins have higher priorities to be visited. The aim is to serve the bins with higher priority immediately. This requires a dynamic routing process. The study demonstrates four models which are dedicated truck model, detour model, minimum distance model and reassignment model. The total area is divided with a zone based approach where each zone is assigned with different priorities, bins and trucks. Hence, in some models the trucks are allowed to visit bins which are outside of their zones. To train the models, the real and synthetic data was obtained from Saint Petersburg Municipality in Russia. The performance evaluation of the models are conducted in terms of CPU time of route generation, distances, response time, routing time, collected load and fuel amounts. These metrics are evaluated under diversified scenarios where zone numbers, high priority bin numbers, trucks per zone numbers or truck capacities are changed. According the results of this study, the

reassignment model outperformed the others in most of the cases. A similar approach to the prioritization and zoning topics introduced in this study are also contributed in a different way to the heuristic approaches that will be presented in the next chapter as a part of this thesis study. Besides, the performance metrics and diversity in the scenarios are also cover in both studies.

In one of the studies where solid waste collection problem is addressed, an approach to find the optimized path and resources is presented [19]. In this study, an agent based model is proposed to provide resource optimization for solid waste collection where each bin is modeled as an agent and equipped with a sensor. The sensor is capable of detecting different levels of waste. Dynamic route optimization is obtained by developing a system which reacts upon the transferred messages containing the waste level information of the bins.

Moreover, some researchers are focused on the aspect of waste separation. In [3] the aim is to provide correct waste separation according to the characteristics of the disposed products which is not covered by many of the researches conducted in the area of waste management. In addition, another study is conducted in a municipal in Finland, in order to address the waste management problem in terms of vehicle route planning by collecting solid waste [52]. The constraints of this study are, there are trucks which collects the waste from bins and the truck capacities cannot be exceeded. 30000 bins are considered in densely and moderately populated areas. In addition, waste separation of different types of municipal solid waste in different types of bins are covered.

Among the many researchers' contributions to the waste management and monitoring subject, there are some studies which includes machine learning approaches to their proposed efficient waste management systems. Gray level co-occurrence is used in the field of solid waste management, where the level detection and classification for the bins are provided. The study [53] has contributed to the waste management problem by introducing an approach which uses gray level co-occurrence matrix (GLCM) feature extraction methods to address the solid waste bin level detection and classification problems of waste management. In addition, in another study, operation research disciplines are introduced to the proposed solution of establishing an optimal landfill site for the waste management system [54]. The aim of that study is to provide

the least negative economical, socio-environmental impacts and minimum total cost for the waste management system of Regina, a city in Canada. The introduced methods are multi-criteria decision analysis (MCDA) and inexact mixed integer linear programming (IMILP).

Furthermore, another study is conducted to develop a real time framework to monitor the bin conditions [55]. In the system, the collected solid waste data is processed by a decision algorithm in order to increase the optimization of the routing for waste collection. [56] is another route optimization study for Municipal Solid Waste Collection (MSWC) problem with the aim of cost minimization. This study is conducted with the collected data of Trabzon, a city in Turkey. In Trabzon, the trucks collecting the waste from bins are equipped with cameras. According to the results, 24% improvement in terms of total cost is achieved with the route optimization on the solid waste collection paths.

In one of the studies, the bins are equipped with wireless monitoring units (WMU). The WMUs are monitoring the remaining capacity of the bins with wireless sensors and they are reporting it to the wireless access points. These wireless access points are responsible for receiving the data for further process in a central monitoring station. According to the study, the remaining capacity of a bin is predictable by 98.3% accuracy with the provided constraint of a wireless access point serving a range of WMUs within 27m diameter [57]. Usage of a similar kind of sensor is taken into consideration in this thesis study in order to get the current level of waste in a bin. This data is valuable where it is transferred to a central unit to be processed.

Moreover, another study is conducted to address the problem of uncertainty of bins' waste levels. In that study, sensors installed in the bins are used to transfer the real time data representing the bins' waste levels. Three different approaches are introduced in order to increase the efficiency of the waste collection system. These are called limited approach, smart collection approach and smarter collection approach. First,a Cluster First-Route Second heuristic method is used in the limited approach where the bins are selected depending on their minimum fill-level thresholds per day. After a route is constructed, a Capacitated Vehicle Routing Problem (CVRP) model is used in order to optimize the route to minimize the fuel cost. Second, a Mixed Integer Linear Programming (MILP) model is applied in the second proposed approach; smart

collection approach. MILP model is introduced to construct the most efficient route with the set of bins that needs to be collected to maximize the profit per day. Finally, the last approach integrated a heuristic manner with the same MILP model from the previous approach. When the results of this study is presented, it is seen that the most efficient and generic approach is the smarter collection approach. However, the impact of two highly profit affecting metric, waste arrival and penalty cost, wasn't considered when constructing the MILP model In [58]. The methodology that this study followed, is the closest to our approach. The waste levels of the bins are processed within proposed heuristic models.

3. TECHNIQUES INTRODUCED

In this section, different methods that would address the efficient waste management problem are presented. The section consists of six subsections describing each method one by one. There are three main techniques introduced, each of them are described with their simple and improved versions in the following subsections.

The waste management problem developed in this paper use the real-time information of the bins' waste fill-level to define dynamic routes for each truck. This problem can be defined as follows: given a complete undirected graph with a set of M waste bins and a distance of $\Delta_i j$ between any two bins, a central station with a set of N trucks where all the trucks start and end their routes and a disposal area where the trucks dump the bins' waste.

Each waste bin i has a maximum capacity Λ_i. In addition, waste arrival rate being λ_i with Poisson distribution for each bin and a penalty cost p_i considered in case of an overflowed bin. Moreover, each truck t has a number of workers h_t and a maximum capacity C_t.

This section describes six different heuristic models that address the efficient waste management problem, first with the simple versions of the methods later with the improved versions considering prioritization. The first method is called Closest Vehicle First (CVF). CVF and Closest Vehicle First with Priority (CVFwP) are presented in the first two subsections respectively. The Collect based on Upper Threshold (CUT) and Collect based on Upper and Lower Threshold (CULT) methods are described afterwards including the simple and improved versions. Improved versions of these methods are called Collect based on Upper Threshold with Priority (CUTwP) and Collect based on Upper and Lower Threshold with Priority (CULTwP). The constants and inputs presented in the symbol list are being used in the notation of these heuristics.

3.1 Closest Vehicle First (CVF)

Closest Vehicle First (CVF) is a locality-based solution. The CVF model is constructed to address the problem of the waste management. It works as follows: The trucks which are ready for picking up waste bins are waiting for the bins to raise alarms. Bin i raises alarm when its waste levels increase up to Ψ_i. When k (number of alarms) is equal to K, the route including the bins which raised alarms (B) is constructed and are assigned to a truck. Route is constructed based on the distances between the bins. This is provided by Dijkstra's algorithm. The newly constructed route is assigned to a truck which is available. If there is no truck available, then the closest truck is selected and the newly constructed route is appended to the selected truck's current route. When a truck is assigned to a route, it starts to travel all the bins in its route in the given order. When the truck t reaches its capacity (C_t), it directly goes to the disposal area for dumping its load and goes back to the starting point when ready. When truck t visits the disposal area, if there are bins on its assigned route, but not served, those bins are assigned to the other trucks. If the truck t haven't reached C_t and each bin is visited on the route, Z_t is empty (there are no other bins to be emptied), a new route is constructed from the list B and assigned to the truck t. Cost of the waste collecting operation is given as below.

$$Cost = G \cdot d + \tau \cdot H \cdot h_t + \sum_{i=1}^{M} A_i \cdot \rho_i + \sum_{t=1}^{M} b_t \cdot D \tag{3.1}$$

Where G represents the cost of gas mileage, d the total distance covered by N trucks, H being cost of human resource, τ defining the total time of truck t, h_{t} being the number of workers in truck t, M representing the total number of waste bins, ρ_i penalty of bin i, A_{i} representing the alarm status of bin i, D cost of (un)dumping per bin (from a bin to a truck) and b_{t} being the total number of bins collected by truck t. Moreover, the flow chart of this model is presented in the Figure 3.1.

3.2 Closest Vehicle First With Priority (CVFwP)

Closest vehicle first with priority (CVFwP) is an improved version of the locality-based baseline solution presented in this section. In order to improve the simple version of CVF method, the prioritization criteria is introduced to the technique. The aim behind this improvement is to prevent high spillovers around bins. With the prioritization,

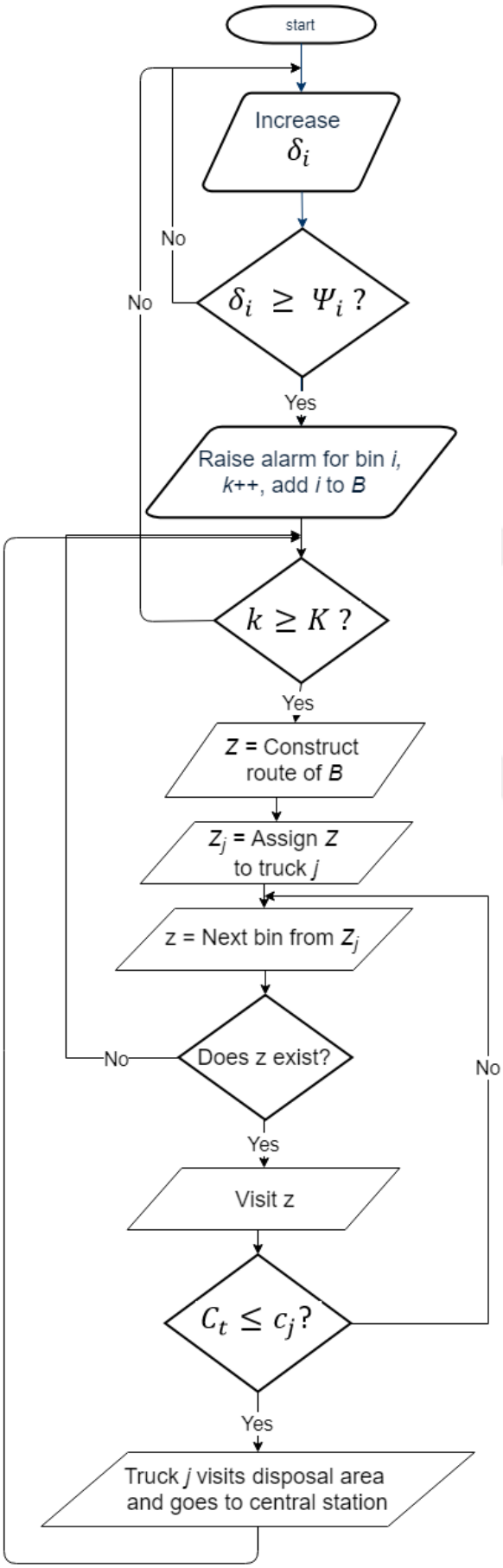

Figure 3.1 : CVF flowchart.

when bin i is visited by truck j and the truck j does not have enough capacity to collect all the waste from that bin i, it only collects the waste amount according to its capacity and bin i gets priority. When bin i has priority, it becomes the first bin to be assigned to truck j after truck j dumps the collected waste by visiting the disposal area. In addition, there is one more way that a bin can get priority. Bin i gets priority when the waste level inside that bin reaches the bin capacity. However, bin i is already assigned to a truck since it reached the threshold value before reaching the capacity. This time bin i is moved forward in the truck j's route. The flowchart of CVFwP is shown in the Figure 3.2.

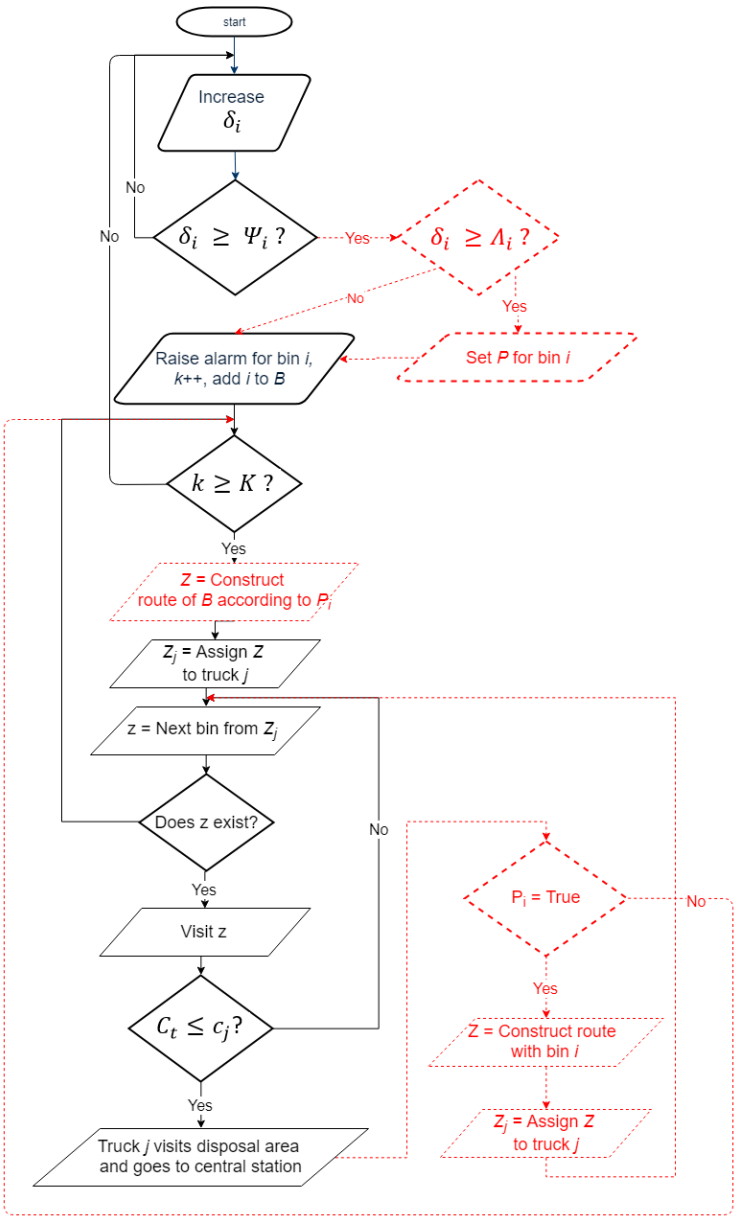

Figure 3.2 : CVFwP flowchart.

3.3 Collect Based On Upper Threshold (CUT)

In the CUT model that is developed to address the problem of waste management, first part of the model is constructed in the same manner with the CVF model presented previously. From the start until the construction of the first route the algorithm executes in the same order. When the truck i is assigned a route, it visits all the bins that are on the way from its current location to the next bin on its route. These bins which are on the shortest path between each movement of the truck is provided by the Dijkstra's algorithm. Trucks visiting the disposal area or assigning with new routes execute in the same manner as in the CVF model. Flow chart of the second model is presented in the 3.3.

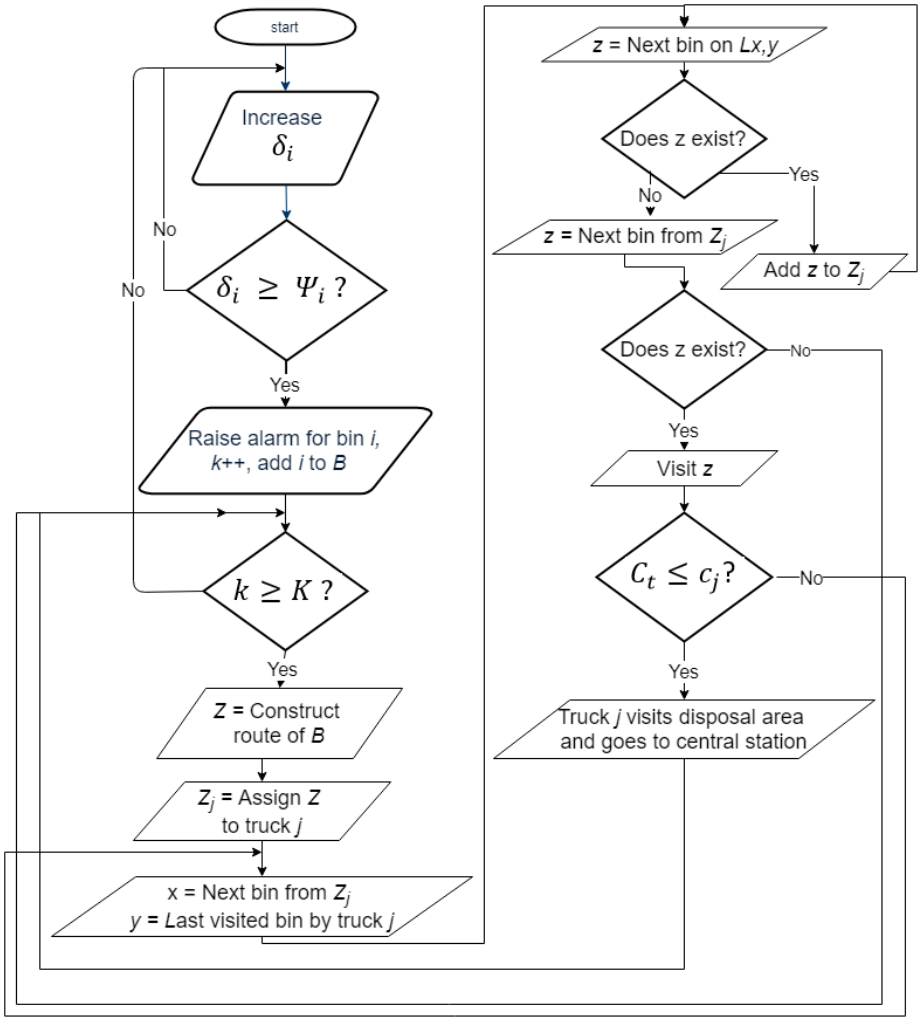

Figure 3.3 : CUT flowchart.

3.4 Collect Based On Upper Threshold With Priority (CUTwP)

In the CUTwP model, the prioritization is introduced to the CUT method. As it is explained in detail in the previous subsection, when prioritization is introduced to a model in our approaches, bin i gets priority either when it is visited by a truck but cannot be emptied or when waste level of bin i reaches its capacity. The flow chart of the model is presented in the Figure 3.4.

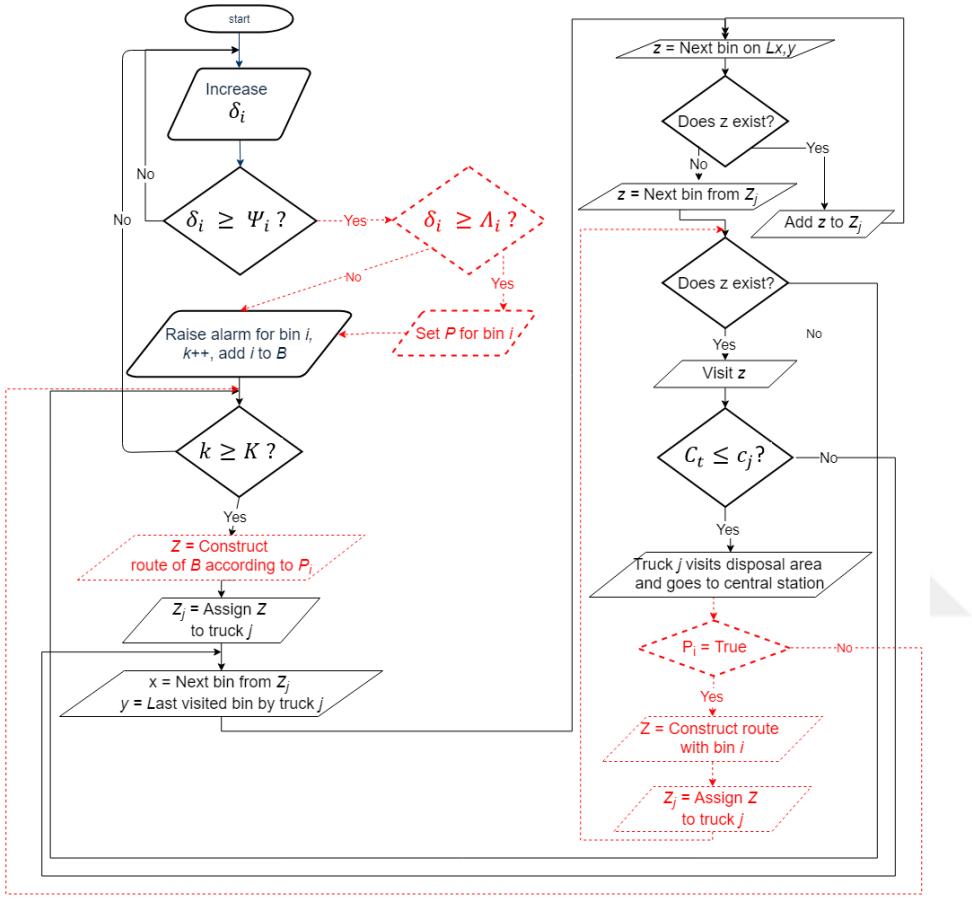

Figure 3.4 : CUTwP flowchart.

3.5 Collect Based On Upper And Lower Threshold (CULT)

In the CULT model that is developed to address the problem of waste management, general behavior of the model is constructed in the same manner with the CUT model presented previously. From the start until the construction of the first route the algorithm executes in the same order. When the truck i is assigned a route, it checks the bins that are on the way from its current location to the next bin on its route. However, it decides to add the bins on its way depending on their current waste amounts. The bins which are on the way and have waste amount higher than ψ_i (lower threshold) are

also going to be picked up by the truck i. These bins which are on the shortest path between each movement of the truck is provided by the Dijkstra's algorithm. Trucks visiting the disposal area or assigning with new routes executes in the same manner as in the CVF and CUT model. Flow chart of the last model is presented in the 3.5

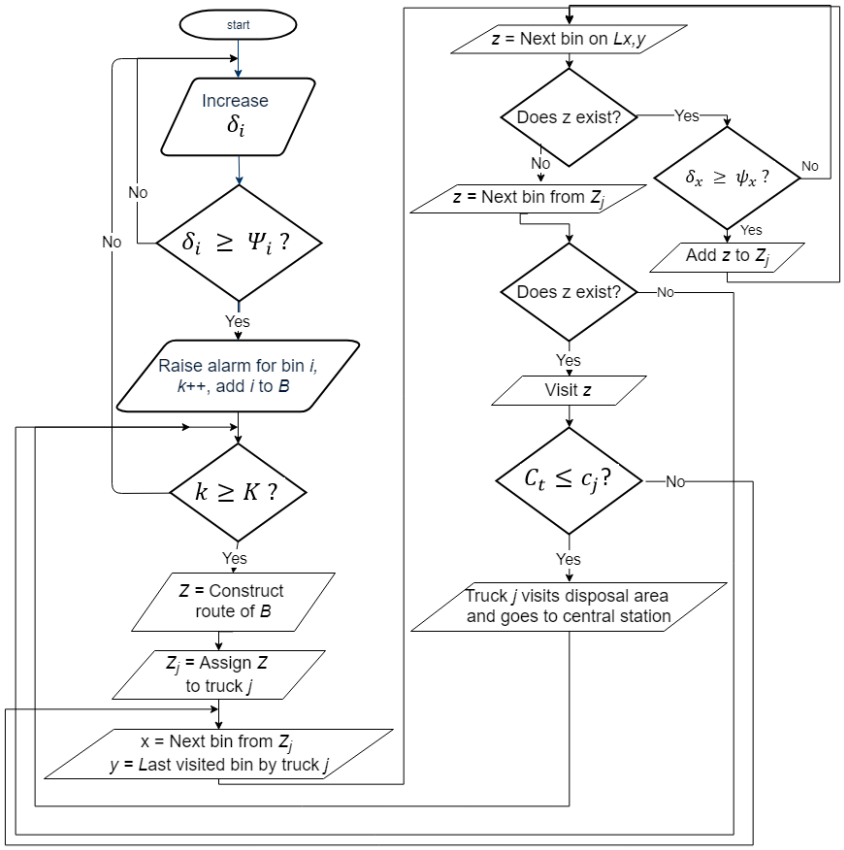

Figure 3.5 : CULT flowchart.

3.6 Collect Based On Upper And Lower Threshold With Priority (CULTwP)

In the CULTwP model, the prioritization is introduced to the CULT method in a similar manner as it is introduced to CUT and CVF methods. As it is mentioned earlier in this section, prioritization is taken into consideration, bin i gets priority either when it is visited by a truck but cannot be emptied or when waste level of bin i reaches its capacity. The flow chart of the model is presented in the Figure 3.6.

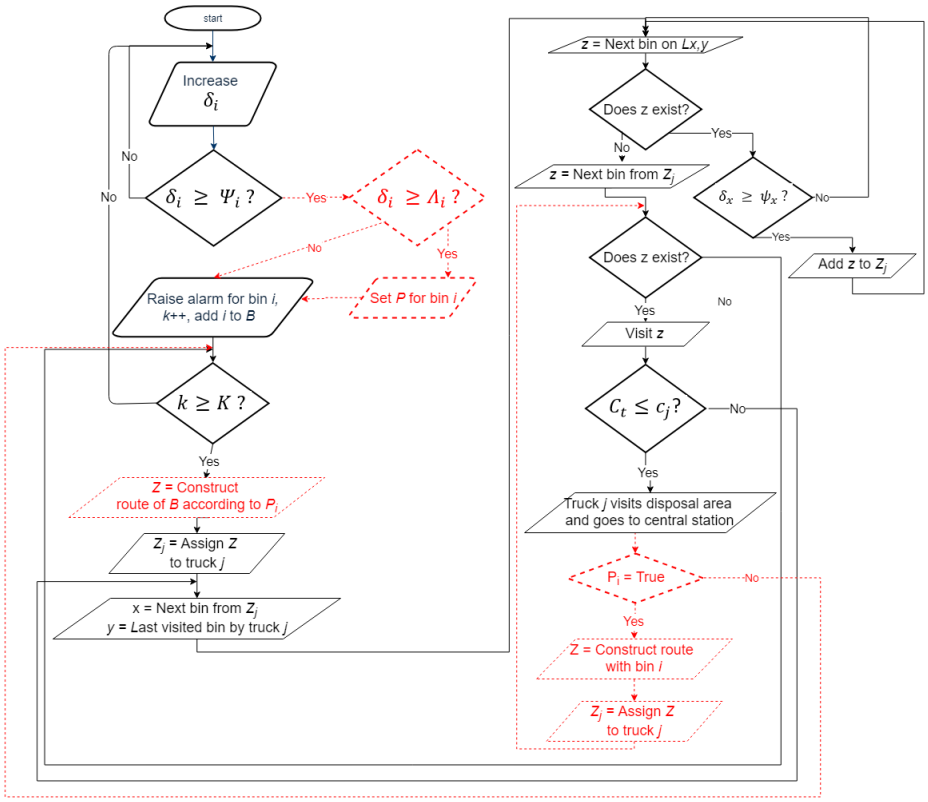

Figure 3.6 : CULTwP flowchart.

4. SIMULATION ENVIRONMENT, SCENARIOS AND RESULTS

In this section, the details of the simulation environment, scenarios and results are presented. The techniques introduced in the previous section are modeled and investigated under various scenarios on a simulation environment. The results of proposed heuristic methods are compared among each other according to different simulation scenarios and the results are interpreted. Strong and weak points of each method are emphasized.

4.1 Simulation Environment And Maps Employed

In this subsection, the simulation environment that is used for the purpose of performance evaluation of the proposed methods that are presented in this study is a Java-based home-grown simulator. The simulation environment is constructed as a model of discrete event simulation (DES). In the simulation environment, the arrival process of the waste is represented by Poisson distribution. By setting different values to the seed value, distinct instances of the bins are obtained. For each scenario, the results are presented as the average of 5 different runs with 5 different seed values.

All the scenarios which evaluate different criteria of the proposed methods are applied in the simulation environment with the maps displayed below. For the comparison, different sizes of maps which include 20, 40, 80 and 160 bins are used. The map with 40 bins is presented in 4.1. On the map, the central truck station is where the trucks start their routes and the disposal area is the place where they visit when they reach their capacity. Disposal area and the central truck station are represented in circle form. Disposal area and the central truck stations are placed distant from each other for the maps with 40. Each vertical distance of a grid on the map is 200 meters and horizontal distance is 300 meters. Bins are marked with rectangles on the map. In each scenario 2 trucks are present. These are the common settings for all the scenarios considered in this study. Rest of the maps with 20 bins, 80 bins and 160 bins are presented in Figures

4.2, 4.3 and 4.4, respectively. In 4.2, disposal area and the central truck stations are placed on the corners. However, in maps which contain 80 and 160 bins they are placed in the center of the map at the same location. All the maps are constructed by mirroring of the smaller ones.

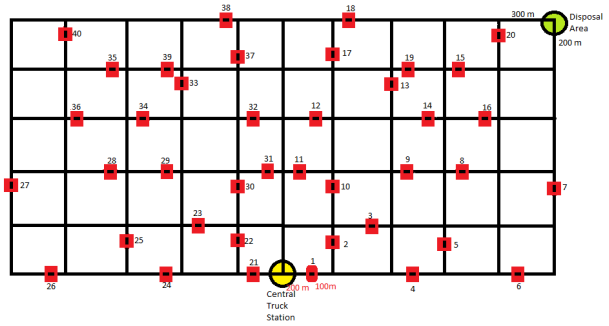

Figure 4.1 : Bin deployment map with 40 bins.

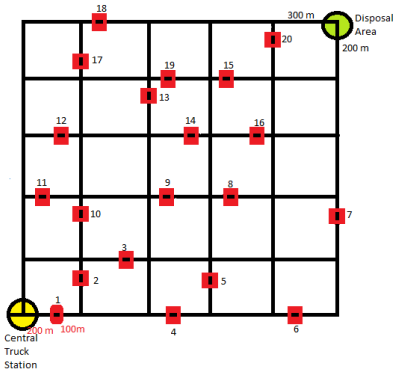

Figure 4.2 : Bin deployment map with 20 bins.

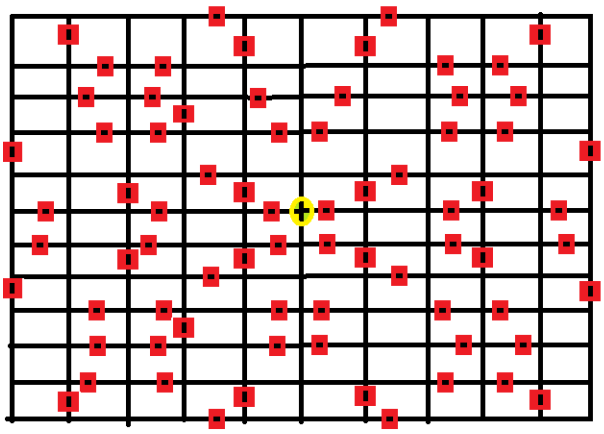

Figure 4.3 : Bin deployment map with 80 bins.

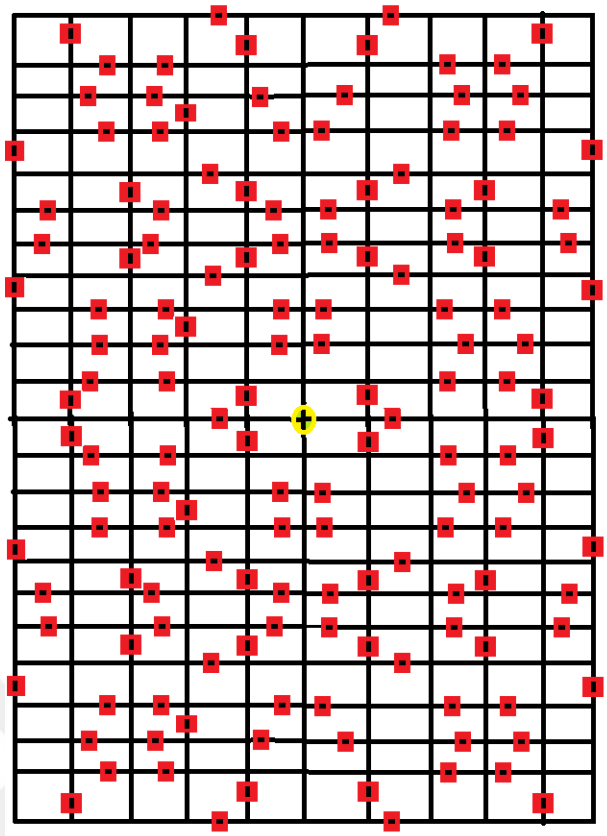

Figure 4.4 : Bin deployment map with 160 bins.

The following values are constant variables considered for all simulation scenarios in this study. There are 3 workers working for each truck (i.e. h_t) and each gets paid with $39e/$h (i.e. H). Trucks move with speed of 20km/h (i.e. S). Every time a bin is visited, time to collect the waste from a bin is 2.5 minutes (i.e. W) with a cost of 1.62 e/bin (i.e. D). In addition, the truck has the gas mileage costs of 20 e/km (i.e. G). During a simulation, each truck goes to the dumping area and empty the collected waste. It takes for each truck 12 minutes to empty the collected waste and be ready at the starting point for the next round of trip (i.e. R_t). The distance between landfill area and central station ($\hbar$) is 2500 meters for maps with 20 and 40 bins and it is 0 for the maps with higher number of bins. Penalty cost $\rho_i = 5$ e is considered additional to the initial cost, in case of an overflowed bin. Total number of trucks (N) is 2 where the total number of bins (M) change from 20 to 160 for the set of simulations used in this study. The maximum capacity of bin i (Λ_i) can take one of the values from 20, 40 and 60 kg where the lower threshold for the waste amount of bin i (ψ_i) takes the one fourth of the Λ_i which corresponds to a value in the range of [10,30] and upper threshold for the waste amount of the bin i (Ψ_i) takes half of the Λ_i which corresponds

to a value in the range of [20-60]. Initial load for bin i (δ_i) can take any value coherent with the Λ_i which means any value between 0 and 60 kg. Maximum capacity of truck t (C_t) can be one of the values from 400, 600, 1200 kg where initial load of truck t (c_t) can take values in the range of 0-1200kg depending on the simulation scenario. Δ_{ij} representing the distance between bin i and bin j changes between 200 and 2300 meters, respectively the time needed to move from bin i to bin j (t_{ij}) changes from 0.6 minutes to 6.9 minutes. The distance from bin i to the dumping area represented with Δ_i varies from 400 to 2300 meters and the distance from central station to bin i represented by r_i takes a value in the range of [200-2300] meters. The following scenarios considers the average waste arrival rate of bin i (λ_i) as one of the values from {1,3,5}kg/5min. Threshold for the count of bins that have alarmed (K) is 3 and after 3 alarms raised from different bins, a route is constructed. The number of bins that have raised alarms (k) can be any value up to the number of bins used in that simulation which is in the range of [0-160]. The alarm status of bin i (A_i) is either On or Off.

Different settings of the parameters in the simulation environment are listed in 4.1. In the following sections, these parameters are explained according to the scenarios and the result of them are presented in detail and interpreted.

After the explanation of each scenario by giving the used settings the results of them are presented. Under multiple runs, distinct instances of the given scenarios are obtained. For each scenario, the results are calculated as the average of 5 different runs. The results are observed in terms of total cost, delay per route, route counts and spilled waste. Total cost being the total cost that is calculated during the simulation run. Delay per route is calculated by total delay divided to route counts. Where the total delay is the time period that the trucks are being occupied during the 12 hour simulation runs and route counts being the total number of visits that trucks made to the disposal area during the simulation. Observing delay per route instead of total delay is decided since the total delay differs slightly among different simulations of different type of scenarios. Because the total delay is the time period equal to, 12 hours which is the duration of a simulation run minus the duration that all trucks wait for an alarm to be turned on or a route to be assigned, which are not changing much in a scenario. By comparing the delay per route parameter, it can be deduced that the routes are constructed more optimally or not. Spilled waste is the amount of waste that are spread

Table 4.1 : Performance evaluation settings.

Notations	**Value**
Cost of emptying bin (D)	1.62 €/bin
Cost of human resource (H)	39 €/h
Cost of gas mileage (G)	20 €/km
Average speed in the town (S)	20 km/h
Time needed to collect waste from a bin (W)	2.5 min
Total number of trucks (N)	2
Total number of bins (M)	{20, 40, 80, 160}
The upper threshold for the waste amount of bin i (Ψ_i)	[20–60] kg
The lower threshold for the waste amount of bin i (ψ_i)	[10–30] kg
Penalty of the overflowed bin (ρ_i)	5 €/kg
Time needed to empty truck t at the dumping area and prepare it for the next trip (R_t)	12 min
Distance from the dumping area to the central station ($\hbar$)	{0, 2500} m
Distance between bin i and bin j (Δ_{ij})	[200–2300] m
Time needed to move from bin i to bin j (t_{ij})	[0.6–6.9] min
Distance from bin i to the dumping area (Δ_i)	[400–2300] m
Distance from the central station to bin i (r_i)	[200–2300] m
Average waste arrival rate of bin i (λ_i)	{1, 3, 5} kg/5 min
Number of workers in a truck (h_t)	3
Maximum capacity of bin i (Λ_i)	{20, 30, 60} kg
Initial load for bin i (δ_i)	[0–60] kg
Maximum capacity of truck t (C_t)	{400, 600, 1200} kg
Time from the central station to the first bin i (T_i)	[0.6–6.9] min
Initial load of truck t (c_t)	[0–1200] kg
Threshold for the count of bins that have alarmed (K)	3
Number of bins that have alarmed (k)	[0–160]
Alarm status of bin i (A_i)	{On, Off}

on the floor for overflowed bins. The terms spilled waste and waste overflow will be used interchangeably in this study. Besides, 95% confidence intervals of the provided values will be shown on each of the figures.

4.2 Scenarios Evaluating The Increase In Bin And Truck Capacities

In order to evaluate the increase in the number of bins and changes in the waste arrival pattern, maps containing 20, 40, 80 and 160 bins with the waste arrival rates of 3 kg per 5 minutes. For these settings, increasing bin capacity from 20 kg to 30 kg and increasing truck capacity from 400 kg to 600 kg is observed separately. Each instance of these scenarios are solved by CVF, CUT and CULT methods presented in the previous section. Each of the methods has its own advantages and disadvantages on these scenarios. For comparison of the three methods, cost values representing the total cost of the solution, delay per route representing total time spend on each route collecting and dumping the waste, route count values representing the number of visits to the disposal area in total and spilled waste values which are the average of the spilled waste amount on each bin at the end of the simulation are used.

To evaluate the increase in bin and truck capacities, the values in the simulation are used with the following settings; N (truck count) = 2, λ_i = 3kg/5min, M = {20, 40, 80, 160}, C_t = {400, 600} kg, Λ_i = {20, 30} kg. Under a constant waste arrival rate, constant bin and truck count, increase in the bin capacity and truck capacity are observed separately and together, respectively. The values are obtained for 12 hours of simulation run. In addition, the results are presented with 95% confidence interval.

4.2.1 Total cost

In the following five figures, Figures 4.5-4.9, the change in bin and truck capacities are observed with different maps containing different amount of bins and considering distinct area sizes in terms of total cost. In the first figure, Fig. 4.5, it is observed that increase in bin or truck capacity decreases the total cost when the area for 20 bins are considered with 2 trucks. This means the trucks can provide better service with higher capacities even if the bin capacities are increased by 50% for a smaller range of area. For every scenario, CVF technique provides the lowest total cost. Since the moderate waste arrival rate of 3kg/5min is used in a smaller area for this scenario,

the bins are being visited quickly enough even if they aren't added to a truck's route immediately when an alarm is triggered in a neighbouring bin. Making unnecessary visits to the bins increases the total cost by visiting a bin more than it is needed during a simulation, only because it is closer to the alarmed bin. Visiting a bin has its own costs other than the fuel consumption. Moreover, increase in the bin capacity decreased total cost by decreasing the penalty costs coming from overflowed bins. When a bin capacity is higher, trucks have more time until it experiences overflow. When a truck capacity is bigger, it can visit more bins in a single route and saves fuel cost since it will be travelling the distance between disposal area and starting point less times. This distance has the highest value on the map when 20 bins are considered. Besides, it causes time consumption to visit the disposal area and make the truck ready which also affects the total cost directly. CVF improves its performance more when compared to other two methods at the time of a capacity increase and CUT provides the less improvement in terms of total cost.

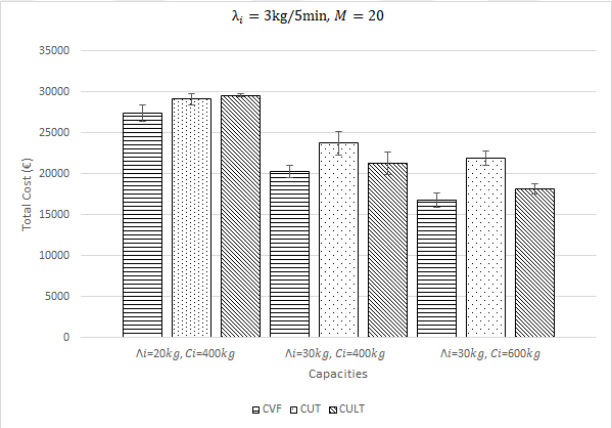

Figure 4.5 : Total cost: Increase in bin and truck capacity for 20 bins.

In Fig.4.6, the impact of bin and truck capacity increase is depicted with 40 bins. When compared with the previous scenario which considered 20 bins, increase in the bin number caused methods to perform closer to each other in terms of total cost results. For the initial case and the last case where the bin and truck capacities are increased proportionally, CVF resulted in with the highest cost and CULT produced the lowest cost. When a wider area with more bins are considered adding bins to truck routes when they contain sufficient amount of waste saves cost. Since the area is wider, trucks travel larger distances during a route. Bins added to the routes with significant amount of waste before raising alarms save time and cost in this case. When the bin

capacity is increased but the truck capacity does not change, CUT method has the highest improvement in its performance. Increasing bin capacity gives more time for a truck to visit a bin before the bin reaches its full capacity. However, when the area is wider visiting bins which are closer to the alarmed bins before they raise alarms regardless of their waste amount gains importance. Since the distance to be traveled between the bins are going to be longer, those bins that are being passed by will also generate alarms soon. Taking care of those bins in advance provides more cost efficient solutions.

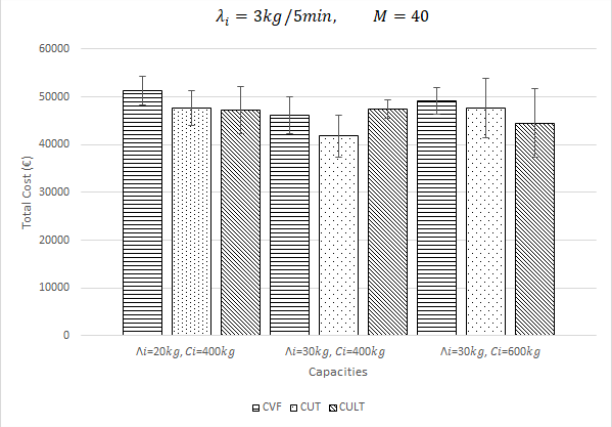

Figure 4.6 : Total cost: Increase in bin and truck capacity for 40 bins.

In order to present these methods' convenience to a real-life scenario, the maps are modified to show results with larger and more intense maps that higher number of bins. Three additional maps were used which are; (1) the map given in Figure 4.1 for the 40-bin scenario was modified, and 40 additional bins were introduced to the same region, (2) the map given in Figure 4.1 was duplicated in terms of the size and the number of bins and can be seen on Fig 4.3, (3) a map of 160 bins was deployed and can be viewed on Fig 4.4. In Fig.4.7, the area is the same as the previous case. However, now there are 80 bins placed on the map. Increase in the bin and truck capacity are observed for more intense map. From the figure, it is understood that CUT provides better solutions in terms of total cost when more intense regions are considered. Similar to the previous results, CVF approach results in with the highest total cost due to same reasons. The area did not changed when compared to the 40 bin scenarios, however the increase in the bin count emphasize the importance of adding the bins before raising alarms, since the trucks are more busy and it takes time to consider visiting a bin after it raises the alarm. It is clearly seen that increase in the bin

and truck capacity proportionally, increased the total cost for all approaches. This is the result of more bins are visited in each route which reflects on the cost directly.

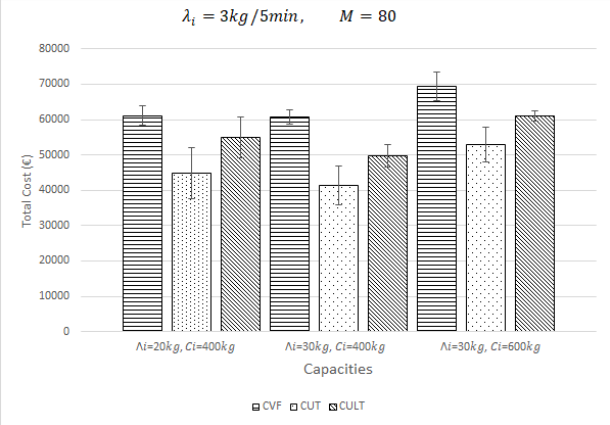

Figure 4.7 : Total cost: Increase in bin and truck capacity for 80 bins in narrow area.

In Fig4.8, 80 bins are deployed on the map twice the size of the previous case. Under these simulation settings, CUT outperformed its counterparts as it was in the previous case. Besides, CVF resulted in with the highest total cost, consistent with the previous results. Once the area that a truck needs to cover gets bigger, CUT is the better choice to be used in terms of cost saving. Increasing bin capacity decreased the total costs in general for all approaches. However, increasing bin and truck capacities in parallel caused higher cost values in the result for all three methods. Which is again due to the longer distances that trucks need to cover when their capacities are higher. In the first scenario where the starting point and disposal area are the two furthest points on the map, increasing truck capacity decreased the cost by decreasing the route counts which resulted in saving fuel and time. However for the further scenarios these points are not the furthest spots on the map. Increase in truck capacity causes more long routes for a truck and consequently increases the total cost. Moreover, improvements provided by these approaches are smaller when the bin count is increased and the area gets larger.

In Fig4.9, 160 bins are deployed on the map twice the size of the previous case. In terms of total cost, when 160 bin map is considered, CUT performs most cost efficiently and CVF is the least cost efficient solution among all three approaches coherent to the previous results. Increase in the bin and truck capacity proportionally increased the total cost in general significantly. Since the trucks can collect more they can visit more bins without visiting disposal area. This causes less optimal routes. Increase in the bin capacity decreased the total costs since the trucks have more time

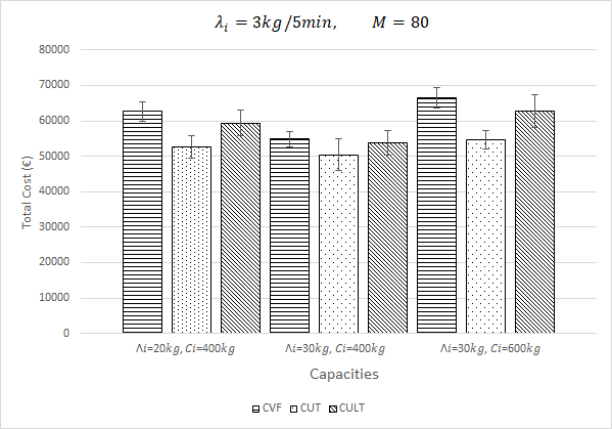

Figure 4.8 : Total cost: Increase in bin and truck capacity for 80 bins for wide area.

to collect the waste from the bins before they reach their capacities. It is observed that these three approaches are providing similar amount of improvements during these capacity increases which is around %20 between the left most three bars and the right most 3-bar columns. For the previous results where 40 bins and 80 bins are considered the CUT and CULT methods performed more cost efficiently when compared to CVF. Here, the total cost that CULT generates starts to become higher than the total cost that CVF generates. The reason behind this is the significant increase in the route counts for that method. The area is wider and the bin counts are higher that the 2 trucks can work with good performance. The results start to change in this direction.

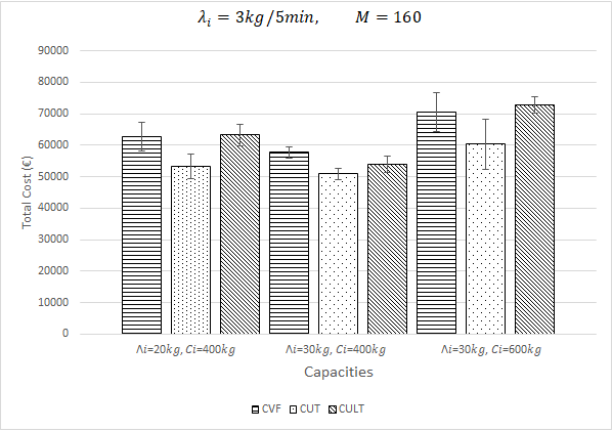

Figure 4.9 : Total cost: Increase in bin and truck capacity for 160 bins.

As anticipated, increase in map size and the bin count increased the total cost for all the three methods. Higher number of bins causing higher number of triggers at a time window it the obvious reason behind this behaviour. On the other hand, in the presence of more triggers, routes are constructed more efficiently with the decision making introduced in the methods. Therefore, as the size of the area is increased,

not a remarkable increase is observed in terms of total cost. Besides, when the bin capacity is increased, the threshold values also changed proportional to it. This increased the difference between the threshold and the capacity for bins. Therefore, trucks have longer period of time to visit a bin after it triggered an alarm. This leads to decrease in the penalty cost caused by spilled waste. CUT and CULT methods' decision mechanisms lost their importance at this scenario with the small number of bins. Their costs are higher due to the higher penalty costs. However, this situation only applies for the small areas with less number of bins. As it is seen on the previous figure, impact of the decision mechanisms introduced in CUT and CULT where are not enough time to go through same bins without picking them up is significant.

4.2.2 Delay per route

In the Figures 4.10-4.14, the previously described scenarios to observe the impact of bin and truck capacity increase on distinct maps are shown in terms of delay per route criteria. The total delay results did not show much difference between the simulations with different settings when compared to cost values. Therefore the delay per route which is effect by routes' optimality criterion and the bins' closeness is used to emphasize the methods' strengths. Decrease in the delay per route value could be said that the route was more optimized with the given configuration settings.

In Fig4.10, 20 bins are placed on the map. In the initial condition where the bin capacity is 20kg and the truck capacity is 400kg, CULT provides the fastest routes and CUT construct the longest routes. CUT visits more truck in a single route since it does not check the bin's current load and it visits the bin if it is on the way to an alarmed bin. It is expected to result in with a shorter and more optimal route, however since the map is small and the bin count is less, the time spent when a bin is visited and the waste is being picked up by the truck increases the delay of the route. When compared to the distances between bins, this delay has more impact for the small ranges. When the bin and truck capacities are increased the delay per route values decrease for each method. The most significant improvement is provided by CVF and the least impact is provided by CULT. Since CVF only considers visiting bins with triggered alarms, when the bin capacities are increased, this means trucks have more time to pick up the bins with alarms before they reach their capacity and overflow. Furthermore, increase in the

truck capacity means, more number of bins can be visited during a route. At first, it is expected to increase the route duration, however this caused the trucks to have more number of routes in a single simulation run. Due to total delay being approximately the same for each simulation, increase in the route counts decreased the delay per route. Increase in the route counts is based on the increased thresholds. Thresholds also increases proportionally with the bin capacity. This means when a bin is visited with the triggered alarm, it contains more waste. Increasing only the bin capacity increases the route counts and decreases the delay per route as expected. When the bin and truck capacity is increased together, this gives the opportunity to construct more optimal routes and routes end earlier.

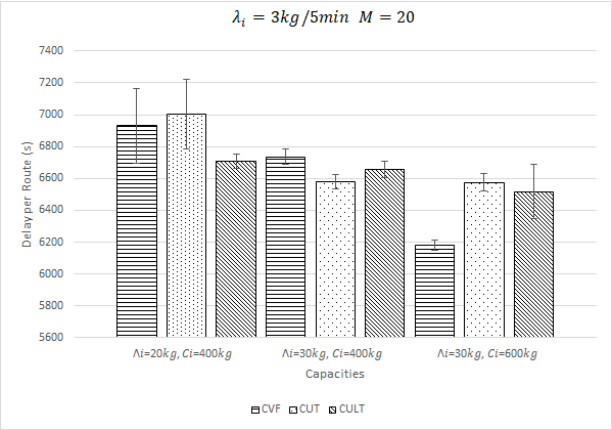

Figure 4.10 : Delay per route: Increase in bin and truck capacity for 20 bins.

In Fig4.11, 40 bins are deployed on the map twice the size of the previous case. Under all three settings, CVF provides the least delay per route values. Once the capacities are increased, the delay per route results decreased. When the bin counts are increased from 20 to 40, the improvements that the methods provide at the presence of the bin capacity increase is smaller. Increasing bin capacity has a negligible impact in terms of delay per route results. When the bin count is increased, the area that a truck needs to cover is wider. This results in more amount of waste being collected once a bin is visited and truck capacity is reached with less number of bin visits. Due to higher distances between bins the delay is increased when compared to the previous scenario with 20 bins. However, when the truck capacity is increased relatively, this decreases the delay per route results. Since there are more bins with the moderate waste arrival rate, increase in the bin and truck capacities helps the proposed methods to perform better and increase the route counts. This certainly decreases the delay per route

results. The largest improvement is provided by the CVF method. The decrease in the delay per route values is highest for the CVF's results among the three methods. This depends on the higher increase in its route count values. The logic behind the method constructs routes with only necessary bin visits. This prevents the needless delays that will be caused by picking up extra bins.

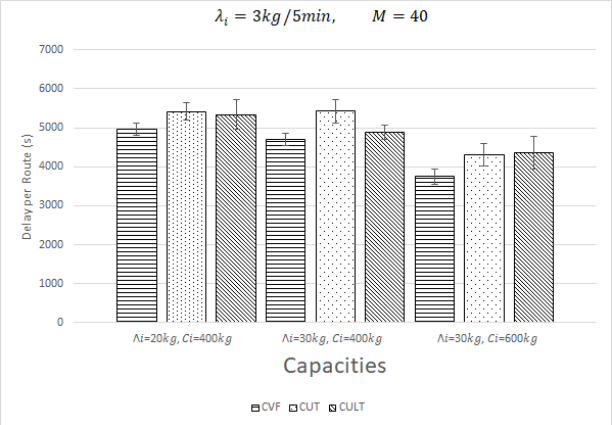

Figure 4.11 : Delay per route: Increase in bin and truck capacity for 40 bins.

In Fig4.12, 80 bins are deployed on the map of the same size of the previous case to construct a more intense scenario. In this scenario, the bins are closer to each other. CVF method performs the best in terms of delay per route values in these cases. Since the distances between bins are shorter, the trucks do not waste much time visiting a bin after it is being passed by. Contrary, preventing the unintended bin visits decreases the delay per route value by reducing the delay that would be caused by a bin pick up action. Coherent to the previous results, the highest impact is provided by CVF method when the capacities are increased. Again, bin capacity increase does not cause significant change in the delay values. However, truck and bin capacity being increased together improved the results. The reason behind this behavior is the increase in the route counts which will be discussed in the next part with the route count result figures.

In Fig4.13, 80 bins are deployed on the map twice the size of the previous case where 40 bins are used. In addition, in Fig4.14, 160 bins are deployed on the map twice the size of the previous case where 80 bins are placed to a wider area. The results show similarity between these cases. Under these conditions, CUT provides the highest and CVF provides the lowest delay per route values. When the environment is larger and the distances are higher between bins, adding bins before getting an alarm is cost effective by means of fuel and time saving. However when this is the case, the truck

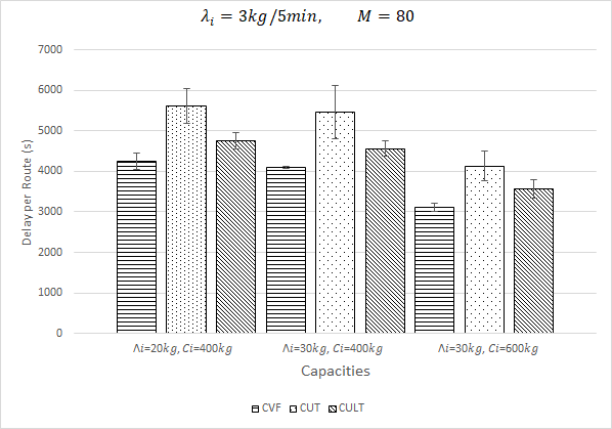

Figure 4.12 : Delay per route: Increase in bin and truck capacity for 80 bins in narrow area.

visits bins with less waste and can visit more bins in a single route. Visiting a bin has its own delay which increases the delay per route values. Visiting only the intended bins increases cost since the penalties will increase too with the spilled over wastes but it is the fastest way to solve the described waste management problem among the proposed methods.

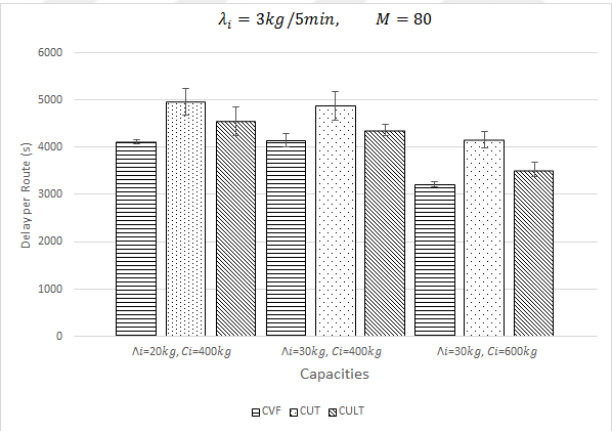

Figure 4.13 : Delay per route: Increase in bin and truck capacity for 80 bins for wide area.

4.2.3 Route count

In this subsection, the route count results are observed in the case of bin and truck capacity increments. The results are presented with the Figures 4.15-4.19. In the first figure, 20 bins are placed on the 20 bin map which was presented previously in Fig 4.2. When small range of area and small number of bins are considered the route counts do not differ considerably. Besides, the route count did not changed among proposed methods much. The highest improvement is seen on CVF's results which is increased

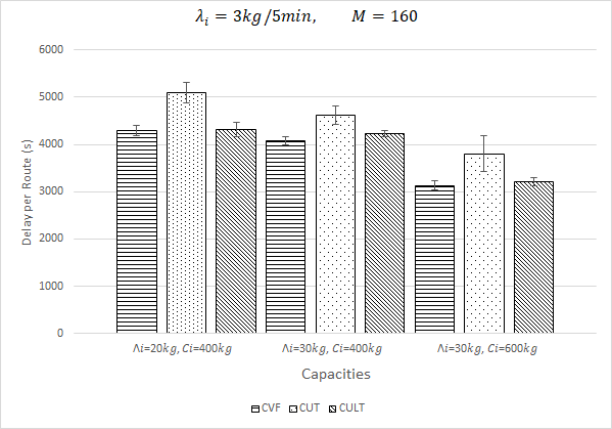

Figure 4.14 : Delay per route: Increase in bin and truck capacity for 160 bins.

by 1 more route when the bin and truck capacities are increased together. This caused the delay per route values to decrease for that method too, as it was stated early in the study. Since the area is small, the truck can visit bins that triggered alarms to make faster routes and more routes in a single simulation run. This makes the CVF the high performer method with the given settings.

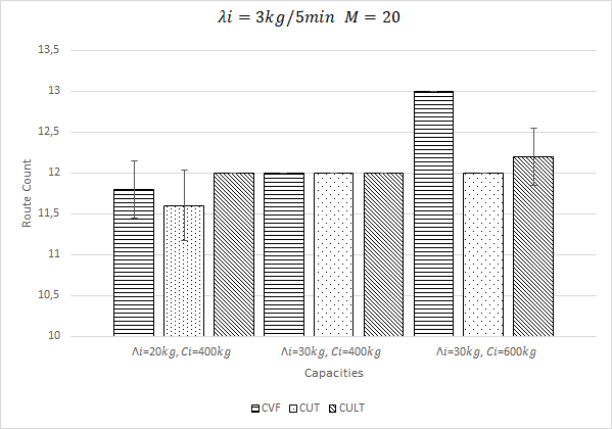

Figure 4.15 : Route count: Increase in bin and truck capacity for 20 bins.

In Fig4.16, 40 bins are deployed on the map twice the size of the previous case. Larger the map is, more visible the result differences are. Still for the initial condition of the capacities, the route counts are close among the methods. Once the capacities are increased CVF has the highest change in its' result and the highest route count. CUT and CULT have less route counts which are closer to each other. Having higher route counts reflects the truck capacity is being reached early either by picking up the bins with higher amount of wastes or by visiting more closer bins to each other. For the smaller areas and less number of bins, the route duration is shorter when the truck visits bin with higher amounts of wastes. But it will be presented in the following

figures that once the area gets larger and the bin number increases, the CVF and CULT method results in terms of route counts show converging behaviour.

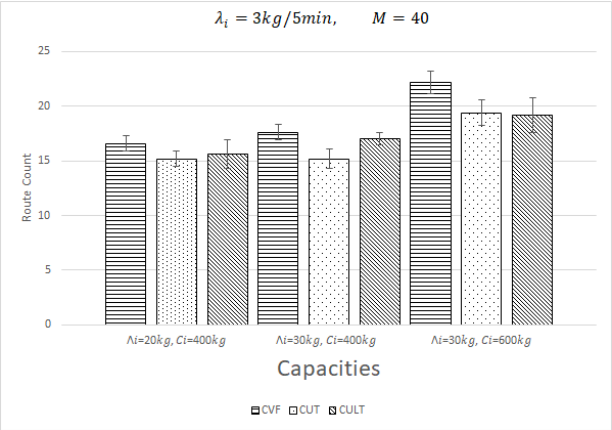

Figure 4.16 : Route count: Increase in bin and truck capacity for 40 bins.

In Fig4.17, 80 bins are deployed on the map of the same size of the previous case. More intense scenario is simulated here. It is depicted that increase in the bin capacity does not have significant impact on the route count as it was the situation for delay per route values. For the scenarios with higher bin counts, the improvements made by each method are closer to each other when there is a capacity increase. CUT method provides the less number of route counts and the CVF method provides the highest number of route counts. Higher route counts also results in with higher costs. However being able to travel more routes during the same period of time increases the service quality and the cleanness of the environment. The difference between CVF and CUT results in terms of route count is based on the decision system introduced in CUT which visits all bins on its way while heading to the actual bin with the raised alarm.

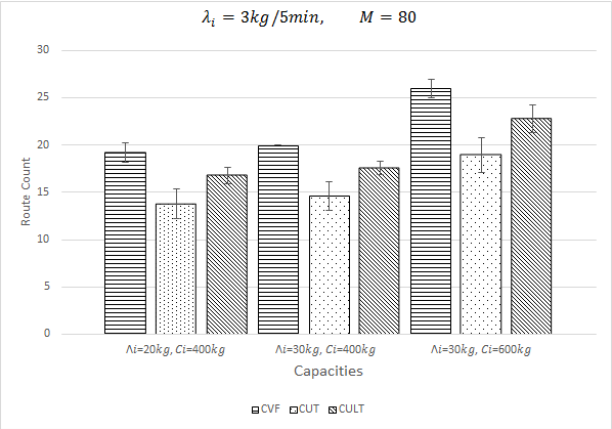

Figure 4.17 : Route count: Increase in bin and truck capacity for 80 bins in narrow area.

In Fig4.18, 80 bins are deployed on the map twice the size of the previous case with 40 bins and Fig4.19, shows the results of where 160 bins are placed on the map twice the size of the case with 80 bins on wider area. Once the bin count increases and the area gets bigger, the results show similarity. In both cases, CVF provides the highest and CUT provides the least number of routes. The most significant impact is seen on CVF's results, increase in the capacities increased highly its' route count results. The results belonging to CULT and CVF gets closer when the bin count and the area size is increased. This shows that the method CULT performs as good as the CVF approach. It could be interpreted that, CULT performs better for more intense or extreme scenarios with the provided resources.

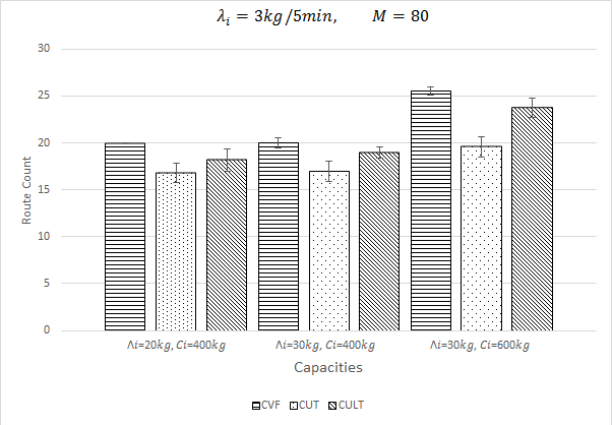

Figure 4.18 : Route count: Increase in bin and truck capacity for 80 bins for wide area.

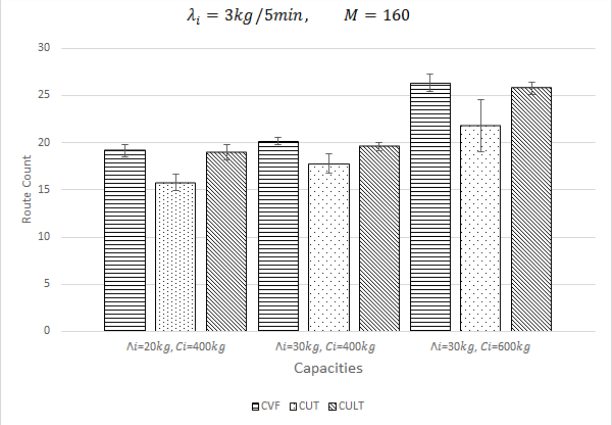

Figure 4.19 : Route count: Increase in bin and truck capacity for 160 bins.

4.2.4 Spilled waste

In this subsection, the spilled waste results are observed in the case of bin and truck capacity increments. The results are presented with the Figures 4.20-4.24. In the first

figure, 20 bins are placed on the 20 bin map which was presented previously in Fig 4.2. As the capacities increase, the spilled waste decreases. The best impact of the capacity increase is observed with CVF. The spilled waste amount becomes almost zero with the higher bin and truck capacity. Considering the bins that raised alarms are enough to reduce the spilled waste under these conditions where there are less bins and the area is small. The wide confidence intervals show that other methods can reduce the spilled waste amount highly as CVF. CUT has the highest spilled waste rate among these three approaches. Adding bins to the route before them raising an alarm caused the higher spilled waste values. As it was presented previously, CUT had the highest total cost values too. Moreover, the higher delay per route and less route count results show that CUT was not the most successful approach of them.

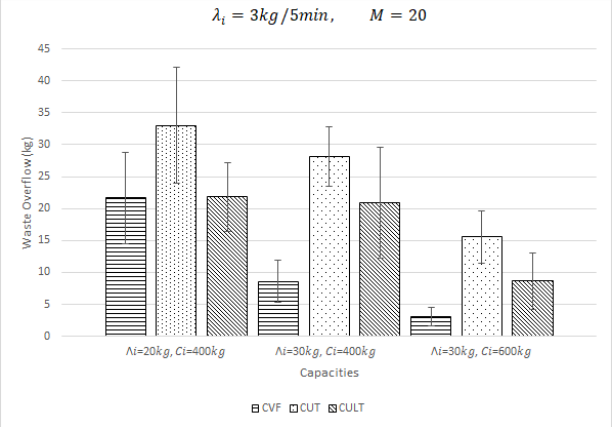

Figure 4.20 : Spilled waste: Increase in bin and truck capacity for 20 bins.

In Fig4.21, 40 bins are deployed on the map twice the size of the previous case. As the bin count increases and the area gets larger, the results of CUT and CULT becomes closer to each other. The least amount of spilled waste is produced by CVF under all capacity settings. When the bin capacity is increased, the spilled waste amount decreased in total, naturally. Although the threshold values to raise alarms are increased with the bin capacity, this did not prevent the total spilled waste amount improvement. When the truck capacity is increased with the bin capacity this improved the results better. Explicitly, results are improved with the enhancement of the capacities. The ability of the bins and trucks containing more waste, decreased the spilled waste amount in total. This shows that, for the regions that the incoming waste is higher and cannot be optimally served, the facility enhancement introduces an improvement in the results.

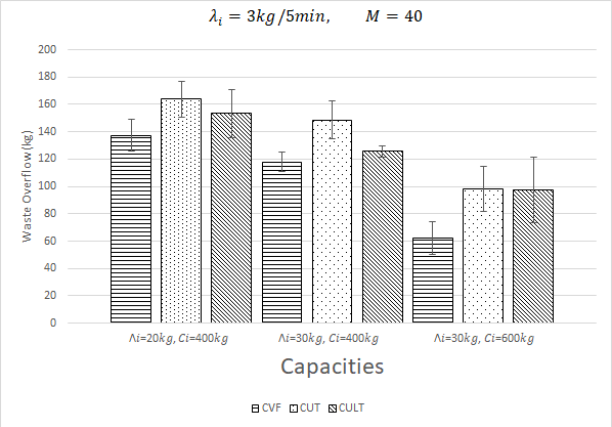

Figure 4.21 : Spilled waste: Increase in bin and truck capacity for 40 bins.

In Fig4.22, 80 bins are deployed on the map of the same size of the previous case to produce a more intense area of bins. Under these circumstances, the best performance is observed with CVF and the worst performance is observed with CUT, coherent to previous scenario results. When this more intense map scenario is compared with the next case which is presented in Fig4.23, it is seen that the more intense scenario can reach higher spilled waste amounts at the end of the simulation. This shows that the bin count is more effective on the spilled waste amount than the map size.

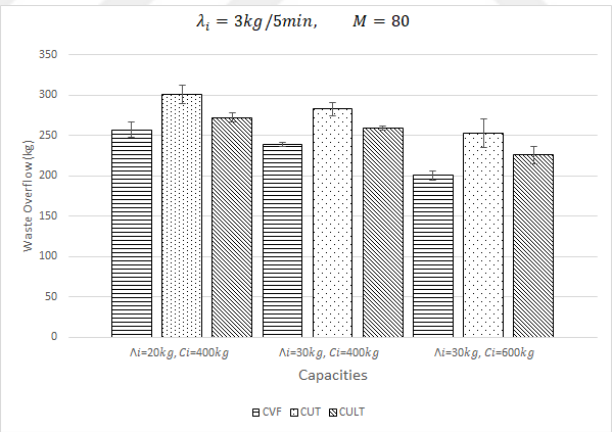

Figure 4.22 : Spilled waste: Increase in bin and truck capacity for 80 bins in narrow area.

In Fig4.23, 80 bins are deployed on the map twice the size of the previous case with 40 bins and Fig4.24, shows the results of where 160 bins are placed on the map twice the size of the case with 80 bins on wider area. As the bin count increases, the results for spilled waste amounts becomes coherent. Hence, it differs more with the increased bin and truck capacities. These increments have higher impact on CVF. The difference between CVF and CULT becomes less with the more bins on the map. This shows

that with the right amount of resources and resource capacities, for the more intense regions CULT can provide better solutions which is supported by the cases that CULT had the most cost efficient solutions previously for some cases. In addition, once the bin count is increased, the impacts of the capacity increase reduces. For the first case with 20 bins, the spilled waste amount was decreased up to %90. However when the 160 bin map is considered, that is reduced down to almost %15.

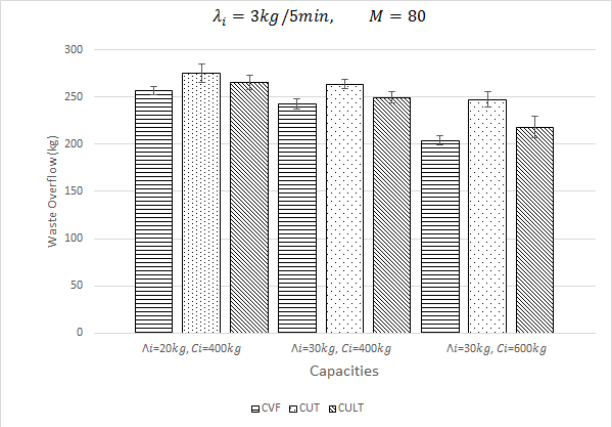

Figure 4.23 : Spilled waste: Increase in bin and truck capacity for 80 bins for wide area.

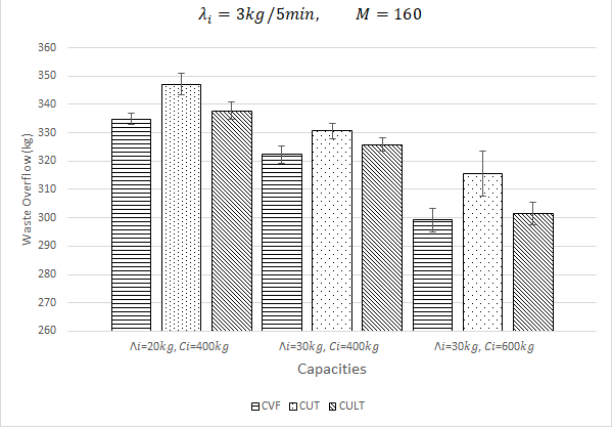

Figure 4.24 : Spilled waste: Increase in bin and truck capacity for 160 bins.

Furthermore, when the bin count is increased, the route counts start to increase too. The reason for this behaviour is that there are more triggered alarms at a specified time window during the simulation. Those alarmed bins are assigned to trucks more optimally considering the distances between them and the routes have less delay. Besides, the simulation duration is the same for all scenarios, with less delay the trucks travel more routes this results in with higher service quality in terms of waste management. However, increase in the route counts lead to increase in the total cost.

Which needs to be considered when selecting the approach to be used to address the smart waste management problem that is introduced previously. Similarly, increase in the bin and truck capacities are also increasing the total cost. Hence, this is due to providing better quality of service which is supported by the results of spilled wastes. Even though the costs are high, the spilled waste tend to decrease showing a better approach is contained in terms of environment.

4.3 Scenarios Evaluating The Different Waste Arrival Rates

Other than evaluating the increase of the bin and truck capacities, another evaluation criteria is the adaptability to changing waste arrival rates. To evaluate this criteria, simulation environment map is used with 80 bins where bin capacities are 30 kg and truck capacities are 600 kg. First, the map is not divided into zones and each bin has an arrival rate of either 1 kg per 5 min, 3 kg per 5 min or 5 kg per 5 min which is set randomly at the start of the simulation. This scenario is called Fixed Load Variation (FLV). Second, each bin on map is assigned an arrival rate of 1kg/5min, 3kg/5min or 5kg/5min at each waste level for the considered bin, randomly. This scenario is called Variable Load Variation (VLV). Third, the bins placed on the inner cycle of the map are assigned the highest arrival rate (5kg/5min), the bins at the outermost cycle of the map are assigned the lowest arrival rate (1kg/5min) and the bins placed in between these areas are assigned the average arrival rate (3kg/5min). This kind of a circular map is represented in Figure 4.25 and the scenario using the given map is called Circular Load Variation (CLV). All these scenarios are evaluated for CVF, CUT and CULT methods. The last one described, CLV, where arrival rates decreases from center to outer, is also evaluated for CVFwP, CUTwP and CULTwP.

The scenarios evaluated in this subsection shows the capabilities of the proposed heuristic methods against the frequency of the incoming waste and the change of these frequencies. For these scenarios simulation settings are given as follows; N (truck count) = 2, M (number of bins) = 80, , Λ_i = 30kg and C_t = 600kg. The 3 different waste arrival (λ_i = 1,3,5kg/5min) are assigned differently on each scenario.

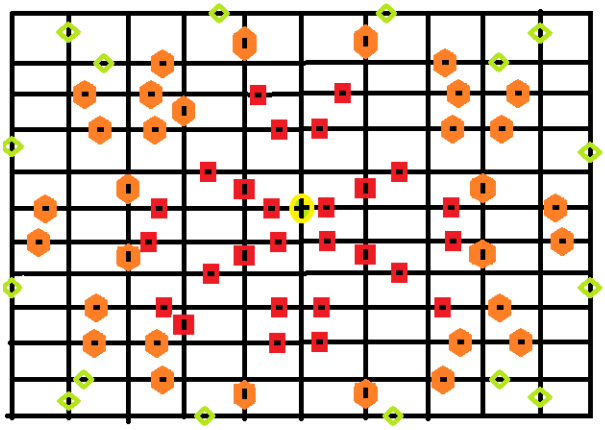

Figure 4.25 : Bin deployment map used in circular load variation scenario.

4.3.1 Total cost

The results for the three scenarios described above is presented on Fig. 4.26 in terms of total cost. It can be seen from the figure that CUT provides the lowest total cost for each method. When the waste arrival rate changes at each waste increase on the bins, the total cost decreases for each method. This is the result of having higher change to get more even waste arrival rate distribution among the bins. When the arrival rates are assigned at the beginning, the bins with higher distance to the starting and disposal areas cause higher cost. But when the arrival rates changes after each increment, there is a chance that the more distant bins can get assigned by lower arrival rates. From the same reason the circular (CLV) assignment provides a solution in between these first two scenarios for CVF, CUT and CULT. On the CLV scenario where the circular waste arrival rate assignment is considered, the solution provided by each method can be compared. It is shown that the methods that are considering the priority, provide higher total cost with wider confidence intervals. This is caused by the bins that need to be visited may be distant from the starting point of the trucks. That distance needed to be traveled two times without visiting any containers on the way. This approach is increasing the total cost however, in the following subsections it will be seen that it provides a better solution in terms of overflowed waste amount at the end of the simulations. In addition, the methods using priority (CVFwP, CUTwP and CULTwP) caused higher total cost values. Since they aim to reduce the waste overflow, they cause increase in the route counts by visiting bins with priority first and reaching the truck capacity earlier and this increases the total cost eventually. If the impact of the overflowed waste amount is reflected in the total cost more significantly, the cost values

would be enough to evaluate the best performer and the last 3 bars in the figure would be lower than the others. However, it would be hard to know the reason behind the cost consumption if that was the case. This shows the necessity of showing the two values in separate metrics. Besides, the ability of the methods to adapt change is also shown with the comparison of first two scenarios. When the arrival rates are not known and changing time to time, there is no problem serving those bins with the proposed methods. For each scenario, CVF provides the solution with highest total cost and CULT provides a solution with the total cost in between the other two solutions.

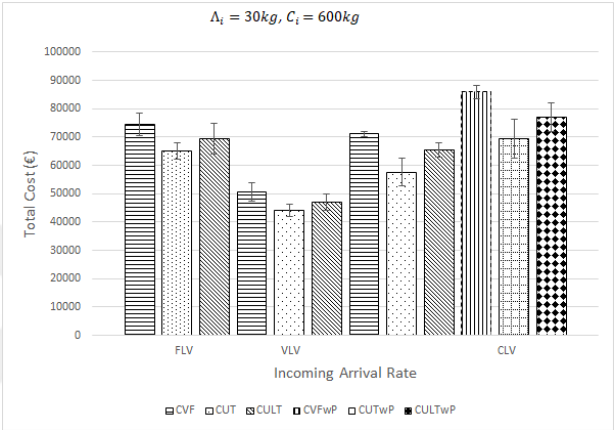

Figure 4.26 : Total cost: Different incoming waste arrival rates.

4.3.2 Delay per route

The results are compared in terms of delay per route in this subsection. It can be seen from the Fig. 4.27 that the CUT or CUTwP method provide higher delay per route results. This proves that the truck travels longer when the CUT/CUTwP method is used. It was seen from 4.26 that CUT also provides lowest total cost values. This means that the bins are visited more efficiently with more optimal routes in terms of cost and delay. And in the next subsection, this result will be supported by the results of route count values. Since CUT method visits the bins freely of the waste amount that they contain, this leads to the most optimal route among other methods in terms of cost and delay. The delay per route values increase when the incoming waste arrival rates change at each waste increment. This means the routes are constructed more optimally when there is more change in the arrival rates. For the circular assignments, the methods that consider priority provide lower delay per route solutions. Which shows the methods without priority are using more optimal routes to collect the

bins. However, the methods with priority have the strength of providing lower waste overflow. This will be supported in the following subsections of the results.

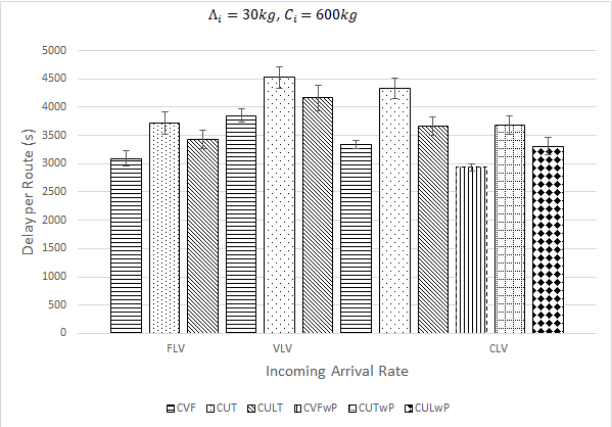

Figure 4.27 : Delay per route: Different incoming waste arrival rates.

4.3.3 Route count

The route count values for different incoming waste arrival rate scenarios are shown on 4.28. According to the results of route counts, the solutions provided by CUT/CUTwP are supported again to be the more efficient by providing less route count. Which is the result of having more optimal routes and visiting more bins which are closer to each other. However, these scenarios are only simulating medium level of bin usage. The scenarios which are considered in following subsections will present results from more extreme cases and the proposed methods will be highlighted with their weaknesses and strengths. Again for the scenario where the waste arrival rate changes randomly at each waste arrival, the route counts are fewer and when the waste arrival rate is set randomly at the start of the simulation, the route counts are the highest. This is the outcome of the chance that distant bins getting higher incoming arrival rates which cannot be changed in this considered scenario.

4.3.4 Spilled waste

In Fig. 4.29, the results of the above described scenarios are presented in terms of waste overflow. CVF provides the lowest waste overflow among the presented methods. Which shows that visiting a bin when only it is needed (the alarm is turned on) results in with the lowest waste overflow. CUT which provided the best solution in terms of total cost in the previous subsections, produce the result with the highest waste overflow. Scenario where incoming waste arrival rate changes consecutively, congruent to total

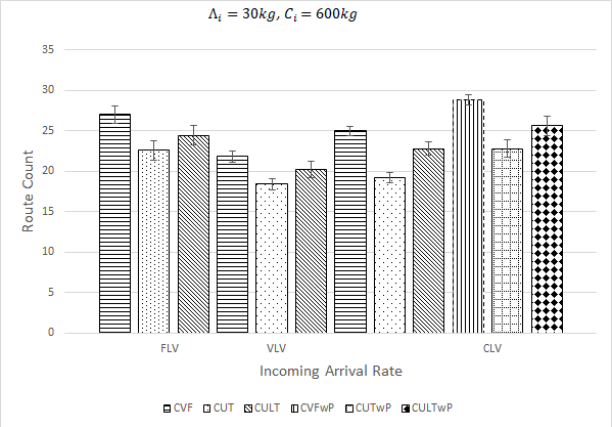

Figure 4.28 : Route count: Different incoming waste arrival rates.

cost, delay per route and route count values, the waste overflow also decreases. This supports the idea that by changing the waste arrival rate more frequently, the chance to avoid more distant bins with higher waste arrival rates decreases. Besides, the confidence interval has the widest value for the scenario considering the assignment of random waste arrival rates at the beginning. Which is the result of assigning randomly waste arrivals to the bins on the map and when the bins which are closer or more distant to the disposal area with highest or lowest arrival rate causes big differences in each iteration of the scenario. As it is mentioned in the previous subsections, the methods considering priority tag have better results in terms of waste overflow. It is presented that, on the scenario with circular waste arrival assignment, the CVFwP, CUTwP and CULTwP provides less waste overflow than CVF, CUT and CULT. The reason is that, these methods give priority to the bins which raised alarm and haven't been visited until the bin capacity is reached or cannot be emptied due the lack of truck capacity and this provides better service for those bins.

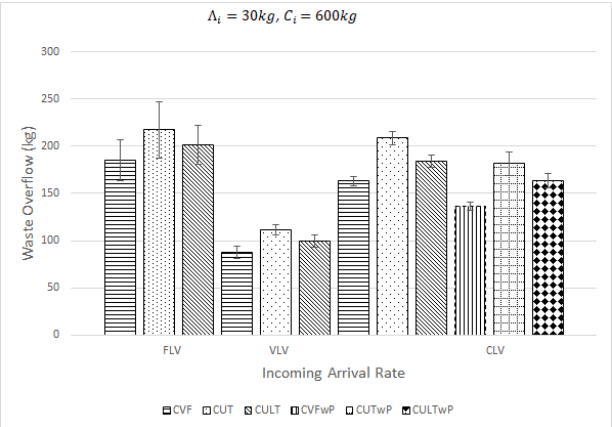

Figure 4.29 : Waste overflow: Different incoming waste arrival rates.

4.4 Scenarios Evaluating The Zoning And Truck Assignment Criteria

Other than the above mentioned criteria, other major evaluation criteria are zoning and truck assignment. The map with 80 bins is divided into 4 zones for this set of scenarios, which is shown on the Fig. 4.30. The scenarios in this section are named according to zone characteristics. The scenarios which use the map with 80 bins divided into 4 zones are called Rectangular Load Variation (RLV) scenarios and take additional letters in the name when more characteristics are added. The scenarios are named as follows: RLV_XXXX_X. First four X's can take binary values which are H (High) and L (Low), representing the corresponding zone shown on the map in the numbered order. H and L are representing waste arrival rates. H means 5kg/5min, L means 1kg/5mins. The last X can be one of the three values [V, H, D], representing the truck assignment methods as vertical, horizontal and diagonal, respectively. When a truck is assigned to a region, it can only visit bins from that specified region. Vertical assignment indicates that zones 1 and 2 are assigned to the first truck and the zones 3 and 4 are assigned to the other truck. Horizontal assignment indicates that zones 1 and 4 are assigned to one of the trucks and the other two zones are assigned to the other truck. Diagonal truck assignment indicates that zones with number 1 and 3 are assigned to the same truck and zones with number 2 and 4 are assigned to the other truck. Four different arrival rate settings (HLLL, LLHH, LHHH, HHHH), with 3 different truck assignments scenarios are studied. All these scenarios are evaluated for CVF, CUT and CULT methods. RLV_LLHH_X, is evaluated for CVFwP, CUTwP and CULTwP. The map used for the scenarios RLV_LLHH with 3 different truck assignment characteristics, is simulated with the map presented in Figure 4.31.

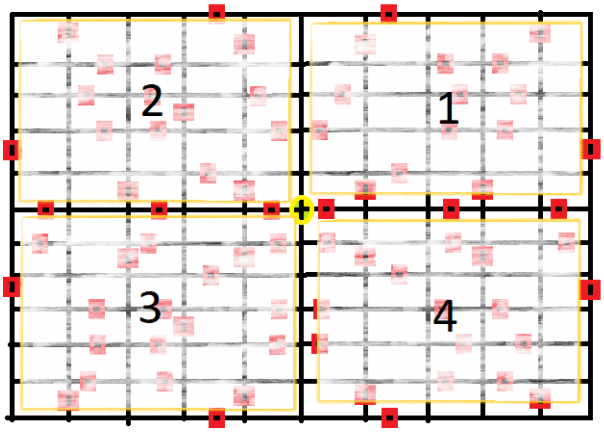

Figure 4.30 : Bin deployment map divided into 4 zones.

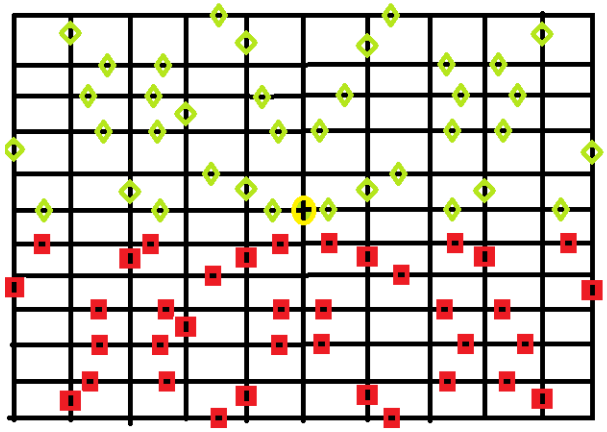

Figure 4.31 : Bin deployment map used in RLV_LLHH_X.

In addition, a scenario to consider higher modularity is considered. The results observed are coherent with the results in this scenario set. The increase in the modularity was provided by assigning different arrival rates inside the separate zones. The results are supporting the results obtained from the previous scenarios.

In this section, the results of several scenarios are presented in terms of total cost, delay per route, route counts and waste overflow in order to observe the impact of zoning and truck assignments. For the scenarios where each truck is responsible of the zones with different waste arrival rates, the total costs are presented as cost per truck values. For the all of the scenarios in this set, the route count and spilled waste amount metrics are observed but not presented since they are already evaluated in the previous scenarios and the results observed in this scenario set are also supporting the previous ones. These figures can be found in appendix. The simulation settings are as follows; N (truck count) = 2, M (number of bins) = 80, λ_i = 1,4kg/5min, Λ_i = 30kg and C_t = 600kg. For all the scenarios the smart waste management problem is addressed by three methods; CVF, CUT and CULT. In addition, the scenario RLV_HHLL_X is observed for all proposed heuristic methods in this study.

4.4.1 RLV_LLLL_X

The result of the scenario RLV_LLLL_H, RLV_LLLL_V, RLV_LLLL_D represented by RLV_LLLL_X is presented on Fig. 4.32, Fig. 4.33, Fig. 4.34 and Fig. 4.35 in terms of total cost, delay per route, route counts and spilled waste, respectively. For this scenario bins in each zone on the map are assigned with low waste arrival rate which

is 1kg/5min. The trucks are assigned to the zones horizontal, vertical and diagonal, respectively.

4.4.1.1 Total cost

On Fig. 4.32 the results are observed in terms of total cost. For all the truck assignments, CUT method provides the highest cost which differs from the results of the previous scenarios which considered different arrival rates. Here, the reason behind this behaviour is that, the incoming rate is low enough for other methods to perform well enough. In this scenario, the bins are not overflowing excessively and there is enough time to serve them after an alarm is turned on. There is no need to visit the bins on the way while visiting the bins with alarms. This causes extra cost. CVF performs better than CUT and CULT performs the best among them because of these reasons. Checking the lower threshold and visiting the bins if there is sufficient enough of waste inside is cost saving in this case. CUT works better when the arrival rates are higher and the conditions are extreme. This is a situation that can be solved by CULT the best in terms of total cost. The total costs for each truck assignment method is slightly different. However, when the wide confidence intervals are taken into consideration the total cost values tend to coincide. In the following figures where route counts and delay per route values are presented, it will be seen that they aren't changing significantly according to truck assignments. It can be said that the difference between the cost values comes from the difference between each simulation run where the seed values change and set of bins that trigger alarms change.

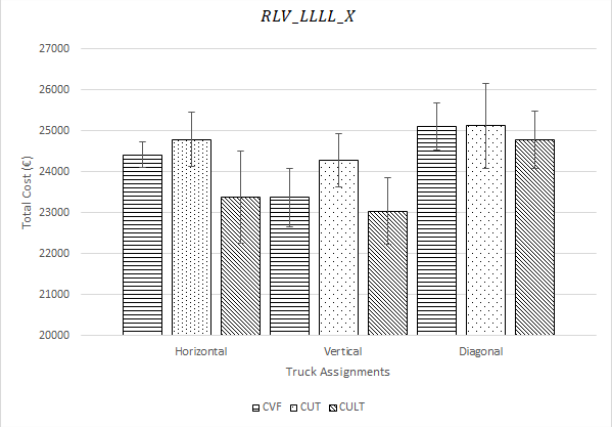

Figure 4.32 : Total cost: RLV_LLLL_X.

4.4.1.2 Delay per route

On Fig. 4.33 the results are observed in terms of delay per route. The highest delay values are observed with the method CUT which also provided the highest costs for this set of scenarios. This means the trucks on the simulation that executed CUT method, travelled longer than the other methods on the map before reaching the truck capacity. In addition, this is the result of collecting waste from bins which contain insignificant amount of waste. When the CVF and CULT are compared according to the delay per route values, the result is the opposite of result in terms of cost, which was displayed in the previous figure. However, the difference between the methods in terms of delay per route is very small when compared to the difference on cost results. Moreover, it is explainable that CVF requires less time to complete a route since it only visits the bins which raised alarms and it doesn't waste time by picking up the bins with insufficient amount of waste. Since the bins waste time when being picked up, the CVF method saves time by avoiding these unnecessary visits. The delay per route results of CULT method is between the other two methods, since there is enough time to visit the bins before they overflow but it is good to consider visiting bins with enough waste to reduce cost and time by maintaining more optimal route than CVF however the picking up the extra bins are increasing the delay per route values of the CULT method when compared to CVF.However, which are not increasing the cost as much as it is increasing for CUT. Furthermore, the delay per route values do not differ significantly when a different type of truck assignment is used which is based on the minor changes on route counts. Since the total delay does not vary much, the delay per route is mostly changes with route count values. When all the zones have the same waste arrival distribution, truck assignment methods have less impact on the delay results. These comparison is more visible for the scenario where high waste arrival rates are used for all zones.

4.4.1.3 Route count

On Fig.4.34 the results are observed in terms of route counts. These results show the opposite movement of the previous figure where delay per route is presented. This also proves that the total delay does not change much among the scenarios and when the delay per route is high, the route count is low. As it is stated, the truck assignment does

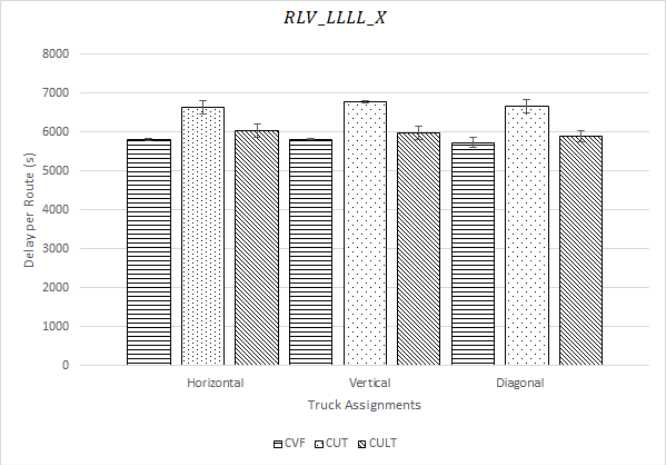

Figure 4.33 : Delay per route: RLV_LLLL_X.

not make a big difference on the results in terms of route counts. Based on the fact that all zones are assigned with same and low waste arrival rates, the route counts differ slightly. Among all three methods, CUT has the less number of routes and the CVF has the highest number of routes. However the results of CULT and CVF are highly similar. The reason behind this behavior is that the CUT method, when an alarm is triggered from a bin on the map, all the bins that the truck is going to pass by are added to its' route. Since the arrival rates are small, there is enough time to visit those bins at another time with out causing too much overflow. Considering bins with insignificant amount of waste increases the delay of the route unnecessarily and there is less number of routes can be travelled during a fixed duration of a simulation. Change in the truck assignment method does not have a great impact on route counts since the area that each truck serve is equal and the waste arrival rates are low enough to provide a high quality service.

Figure 4.34 : Route count: RLV_LLLL_X.

4.4.1.4 Spilled waste

On Fig.4.35 the results are observed in terms of spilled waste. The most critical thing that is brought to the attention is the level of spilled waste when the CUT method is used. CUT caused the highest spilled waste amounts for all the truck assignment cases under low arrival rate. Construction a route with all the bins closer to the truck was the idea started with the aim of solving the smart waste management problem more efficiently. However, this caused higher overflows for the bins. Visiting unnecessary bins caused the other bins that are raising actual alarms to wait more. For different truck assignment scenarios the improvements that the methods provide are different in terms of spilled waste. When the spilled waste amount increases for CVF slightly, it decreases for CULT from Vertical to Diagonal assignment. For each truck assignment, the areas that each truck is assigned with are similar in terms of area size on the map. For diagonal assignment there is a chance that the trucks are closer to the disposal area by the time that the truck capacity is reached. This results in with less delay and spilled waste for the bins waiting to be emptied. This also leads to smaller waste overflow for diagonal assignments. That chance of being closer to the disposal area is smaller for CVF. Visiting only the bins that triggered an alarm increases the distances travelled between two bin visits. This also causes high amount of waste to be picked up at from a single bin. Even though this caused increase the cost, it reduced the spilled waste amount and provided a better solution in terms of environment.

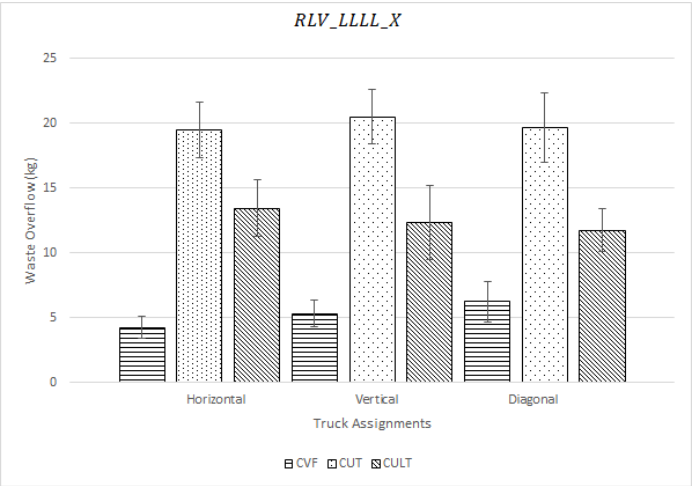

Figure 4.35 : Waste overflow: RLV_LLLL_X.

4.4.2 RLV_HLLL_X

Simulation settings used for this scenario are; bins in three zones on the map are assigned with low waste arrival rate which is 1kg/5min and the fourth zone is assigned with high waste arrival rate which is 5kg/5min. The trucks are assigned to the zones horizontal, vertical and diagonal, respectively. Results in terms of total cost per truck and delay per route are presented in Fig4.36-4.37.

4.4.2.1 Total cost

The result of the scenario RLV_HLLL_H, RLV_HLLL_V, RLV_HLLL_D represented by RLV_HLLL_X is presented on Fig. 4.36 in terms of total cost per truck. This means that each bar showing an individual truck's total cost value. It is presented per truck to make the assignment methods' differences more visible. It can be seen from the figure that once the waste arrival rate starts to increase, CUT presents more cost efficient results. The confidence intervals show that the ranges that CUT and CULT provide are very close to each other in terms of cost and CVF method provides the least cost efficient results with this arrival rate distributions. As it was seen in the previous cases, when the arrival rate starts to increase, CUT tends to provide the most cost efficient solutions. With the increasing arrival rates there won't be enough time to pass by a bin without picking it up since that bin is most likely to trigger an alarm and added to the truck's route soon. The improvements on the methods among different truck assignments show little differences. While CUT's results are decreasing from horizontal to diagonal, CVF and CULT has the highest cost when the diagonal truck assignment is applied. However, this change is negligible and based on the differences of different simulation runs. Moreover, it is also seen that the first truck which has 1 zone with high waste arrival rate is causing higher cost values, which is almost the twice the size of the second truck's cost values. This is due to increase in the route counts which is caused by the more frequent capacity reach of the truck.

4.4.2.2 Delay per route

RLV_HLLL_X is presented on Fig. 4.37 in terms of delay per route. Delay per route shows less difference when the horizontal and vertical assignments are considered which is an expected behaviour since the bins have similar distances to the waste arrival rates of a region that is assign to a truck. For all truck assignment cases, the highest

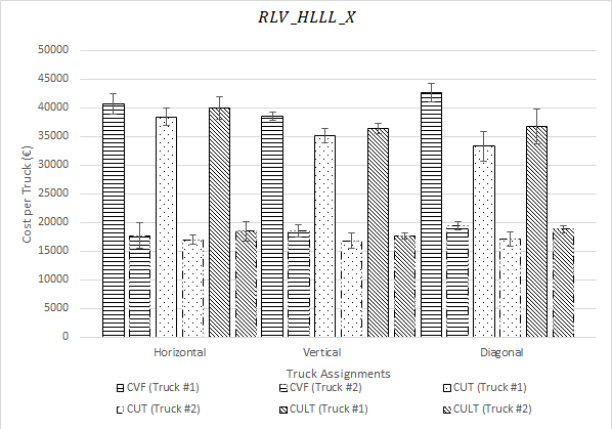

Figure 4.36 : Total cost: RLV_HLLL_X.

delay value is obtained by CUT. The delay value is caused by picking up more bins than the other approaches. With CUT more bins can be visited with less amount of wastes. The most significant rise is observed for CUT when diagonal truck assignment is used instead of vertical or horizontal assignments. When the diagonal truck assignment is applied, the area that a truck is tend to travel longer distances between two bins that triggered alarms and this has the highest impact on the CUT approach. When CUT is applied, the truck capacity is reached after more bins are visited when compared to the other approaches. With the diagonal truck assignment, there is more chance that higher number of bins are placed on the way to the alarming bin. This increases the visited bin counts and the delay related to the visits.

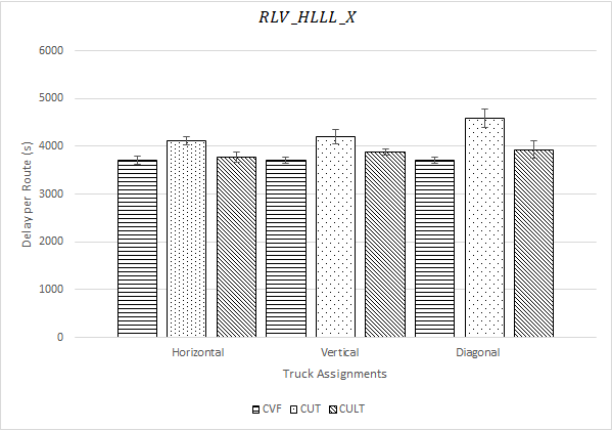

Figure 4.37 : Delay per route: RLV_HLLL_X.

4.4.3 RLV_HHLL_X

Simulation settings used for this scenario are; bins in the first two zones on the map are assigned with low waste arrival rate which is 1kg/5min and bins in the other two zones are assigned with the high waste arrival rate which is 5kg/5min. The trucks

are assigned to the zones horizontal, vertical and diagonal, respectively. Results provided by all six proposed approaches which are CVF, CVFwP, CUT, CUTwP, CULT and CULTwP in terms of total cost per truck and delay per route are presented in Figures 4.38-4.41.

4.4.3.1 Total cost

The result of the scenario RLV_HHLL_H, RLV_HHLL_V, RLV_HHLL_D represented by RLV_HHLL_X, solved by methods CVF, CUT and CULT, is presented on Fig. 4.38 in terms of total cost per truck. When the horizontal truck assignment is considered, each truck is serving to an area where all the bins are assigned with same waste arrival rates. The first truck serving the bins with high arrival rate and the second one serving the bins with low arrival rate. This results in with a lower cost in total for all methods when compared with the other assignments. Besides, the great difference between two trucks' generated cost values are also visible on the figure. When first truck is causing excessive amount of spillovers and delays, the second truck has a very low cost consumption. The aim here is to show if combining two areas with different arrival rates generates a better solution in terms of all the parameters that the results are presented in or dividing the areas with different arrival rates performs better. The figure shows when the trucks serve to an area with bins having identical arrival rates perform more cost efficiently. Cost results for diagonal and horizontal truck assignments are similar to each other, mostly when the CVF and CULT methods are considered. CUT method's results differ slightly more than these methods, however the confidence intervals show that the cost result of vertical assignment can be considered in the range of cost result of diagonal assignment for CUT method.

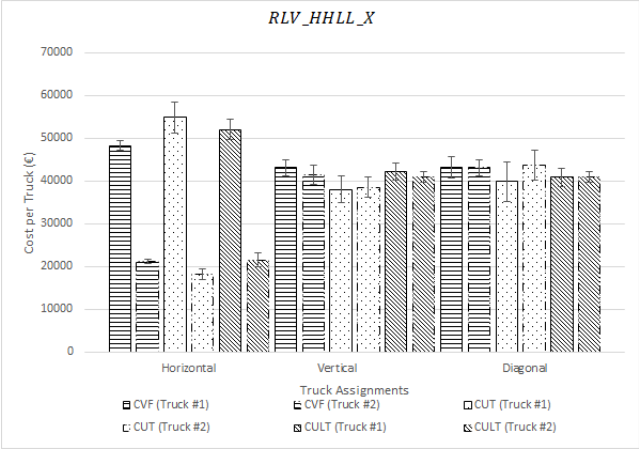

Figure 4.38 : Total cost: RLV_HHLL_X.

The result of the scenario RLV_HHLL_H, RLV_HHLL_V, RLV_HHLL_D represented by RLV_HHLL_X, solved by methods CVFwP, CUTwP and CULTwP is presented on Fig. 4.39 in terms of total cost per truck. When the priorities are considered the lowest cost is provided by CVFwP method for the horizontal truck assignment case. However, for other truck assignment cases, the cost values are higher than the previous scenario where the same settings are considered and solved with the methods without priority. Methods with priority cause higher total costs in order to decrease the waste overflows. In the following sections where the waste overflow results of the same scenarios are presented, this idea will be supported. In addition, the difference among two trucks for the horizontal assignment is wider when the priorities are considered. The cost results of the second truck do not change significantly, however the increase in the first truck's cost values cannot be negligible. This means that the second truck serve the bins that are assigned to it almost without causing spillovers. Similar to the previous figure, the best solution is presented by CVFwP for horizontal truck assignment. When the truck assignment is changed, CVFwP causes the highest costs and the CUTwP method provides the most cost efficient solution. However, the results for CULTwP and CUTwP are similar, especially when the confidence intervals are considered as in the previous figure. Moreover, the results for vertical and diagonal truck assignments are similar to each other as expected. Since they consider the same size of area for each truck, the distance the trucks have to cover are same which directly affects the total cost.

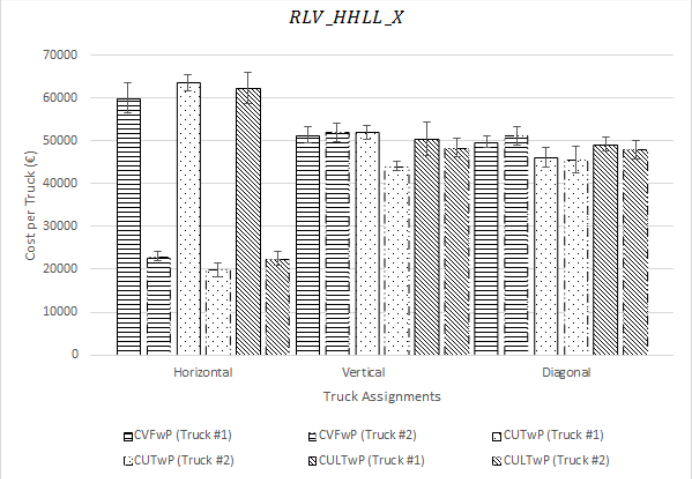

Figure 4.39 : Total cost: RLV_HHLL_X with priority.

4.4.3.2 Delay per route

Solutions provided to the scenarios RLV_HHLL_H, RLV_HHLL_V, RLV_HHLL_D by CVF, CUT CULT are represented in Fig. 4.40 in terms of delay per route. Horizontal truck assignment caused the highest delay per route values. Which is the behaviour based on the fact that a single truck is covering the area with high waste arrival rate, and the other truck is covering the area with low waste arrival rate. The delay per route is increased by this assignment since a truck can not serve fast to the bins where there are more frequent waste arrivals. The change in the truck assignment caused the highest impact on CVF. Since the other methods consider collecting extra bins on the way, changing the areas that the truck is going to cover has less effect on them. However, CVF is highly dependent on the distances between bins. It doesn't have chance to fill the truck with the waste from neighboring bins and delay values change according to the distances between bins that trigger the alarms.

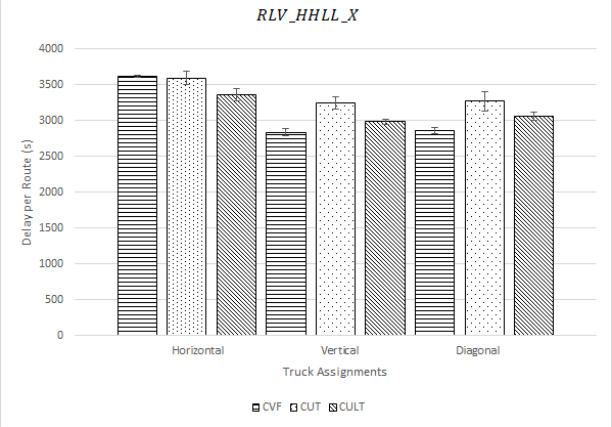

Figure 4.40 : Delay per route: RLV_HHLL_X.

Solutions provided to the scenarios RLV_HHLL_H, RLV_HHLL_V, RLV_HHLL_D by CVFwP, CUTwP CULTwP are represented in Fig. 4.41 in terms of delay per route. Delay values obtained under these settings are lower when compared to Fig 4.40. Assigning priority to the bins that could not be emptied or starting to spill waste around improves the solutions in terms of delay. The highest delay values are observed for horizontal truck assignment where the trucks are responsible of an area with distinct waste arrival rates. However, when the zones are more modular in terms of waste arrivals the provided delay per route results are smaller. Diagonal assignment increased the delays slightly when compared with vertical assignment as the area that truck covers gets bigger, coherent with the results on the previous figure.

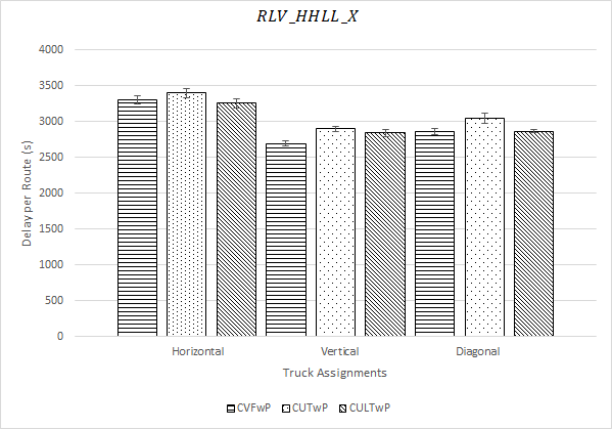

Figure 4.41 : Delay per route: RLV_HHLL_X with priority.

4.4.4 RLV_HHHL_X

Simulation settings used for this scenario are; bins in the first zone on the map are assigned with low waste arrival rate which is 1kg/5min and bins in the other three zones are assigned with the high waste arrival rate which is 5kg/5min. The trucks are assigned to the zones horizontal, vertical and diagonal, respectively. Results in terms of total cost per truck and delay per route are presented in Figures 4.42-4.43.

4.4.4.1 Total cost

The result of the scenario RLV_HHHL_H, RLV_HHHL_V, RLV_HHHL_D represented by RLV_HHHL_X is presented on Fig. 4.42 in terms of total cost per truck. With the waste arrival rate distribution considered in this setting, for each truck assignment condition, there is one truck serving an area with low and high arrival rate and the other truck serving an area with high arrival rate. For this reason, costs are expect to be similar for different truck assignments. However, for diagonal assignment, the lower costs can be explained by the disposal area placed in the center of the map. Since the trucks need to cross from that point the chance that they are closer to the disposal area when the truck capacity is reached, is higher. However, the confidence interval range is wider than the other truck assignment cases. This shows that trucks may not be close to the disposal area every time they reach their capacity. This is only a condition that happens time to time. Among the three methods, CUT method provides the lowest cost solution as it was in the previous figures where there is high waste arrival rates are considered. Consistent with the previous results, the CVF method provides the highest cost values, since it is important to add bins to the route before

them raising an alarm. When there is high waste arrival it is highly possible that the bins on the way are going to raise alarms short time after they are being passed by. Besides, the cost values generated by second truck is higher when vertical truck assignment is considered. The reason behind this behaviour is that the first truck serves the zone with higher waste arrival rates when horizontal and diagonal assignments are considered.

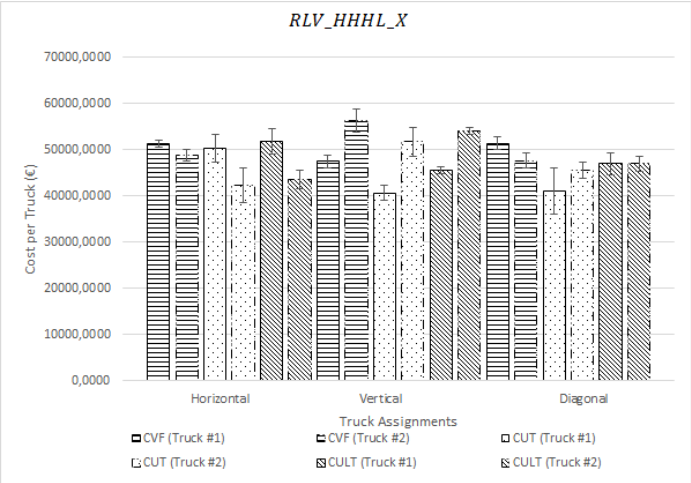

Figure 4.42 : Total cost: RLV_HHHL_X.

4.4.4.2 Delay per route

The result of the scenario RLV_HHHL_H, RLV_HHHL_V, RLV_HHHL_D represented by RLV_HHHL_X is presented on Fig. 4.43 in terms of delay per route. As compatible with the previous scenario results, CUT provides the highest delay among these three methods and CVF provides the lowest delay values for each truck assignment cases. Where vertical assignment decreases the delay per route value slightly when compared to horizontal, diagonal assignment increases it with more variation. The highest change is observed on the CUT's results. CUT is also the method which has the widest confidence interval range. This shows that the other methods perform more stable. CUT visiting more bins makes it less stable and more dependent to the status of the bins in the environment at a specific time.

4.4.5 RLV_HHHH_X

Simulation settings used for this scenario are; bins in all four zones on the map are assigned with the high waste arrival rate which is 5kg/5min. The trucks are assigned to the zones horizontal, vertical and diagonal, respectively. Results in terms of total

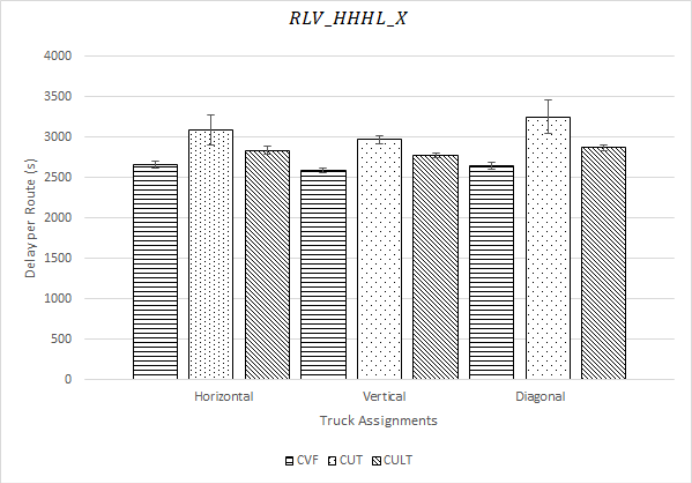

Figure 4.43 : Delay per route: RLV_HHHL_X.

cost, delay per route, route count and spilled waste are presented in Figures 4.44-4.47. This is a case similar to RLV_LLLL_X, only with the waste arrival rates being higher to simulate an extreme case of a scenario.

4.4.5.1 Total cost

The result of the scenario RLV_HHHH_H, RLV_HHHH_V, RLV_HHHH_D represented by RLV_HHHH_X is presented with the Fig. 4.44 in terms of total cost. For different truck assignments the cost results slightly differ especially when the confidence interval ranges are considered, the difference is reduced. Since all the zones are assigned with the same incoming waste arrival rate, the reason for different amounts of cost is only the truck assignment and the zone ranges. For the previous scenarios, there was also the impact of smaller or higher arrival rates. In this case that is eliminated as it was in the RLV_LLLL_X scenarios. As consistent with the cases where high waste arrival rates are considered, in this case the most cost efficient results are provided by the method CUT and the least cost efficient results are provided by the method CVF. The reason is to add bins before raising alarms to the trucks' routes is important when there is high waste arrival rates to save time and fuel by constructing more optimal routes. The range of results that CVF and CULT provide are closer to each other than the previous scenarios.

In addition, the range of results that CUT and CULT provide are closer too when the confidence intervals are taken into consideration. The reason is that it does not make much difference to check lower threshold to add the bin to the route since the lower

thresholds are reached rapidly with high waste arrival rates. Diagonal assignment assignment resulted in with lower cost values for each method compared to vertical truck assignment due to the chance that the trucks being closer to the disposal area by the time that the truck capacity is reached. However, when the confidence intervals are considered, the difference is not significant between these truck assignment cases. Because the chance of the trucks being closer to the disposal area may vary in time, it is not consistent.

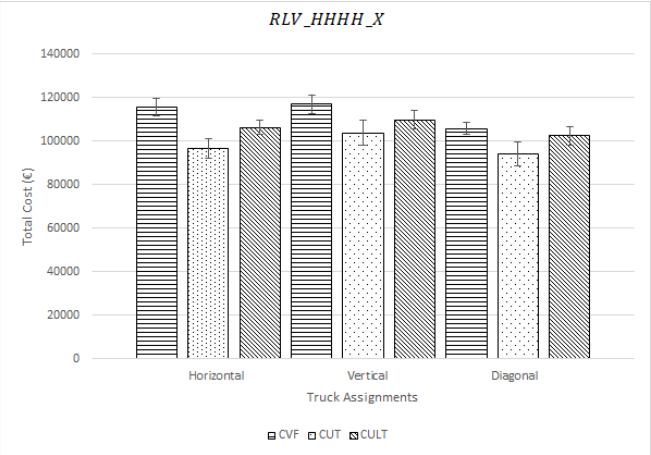

Figure 4.44 : Total cost: RLV_HHHH_X.

4.4.5.2 Delay per route

On Fig. 4.45 the results are observed in terms of delay per route. The highest delay values are provided by the solution of the method CUT which was the similar case for this set of scenarios. Trucks in the simulation where the CUT method is used, travels longer or spends more time by picking up bins. They visit more number of bins in a single route since the bins on the way are added to the route with less amount of waste. The waste from those bins occupy less amount of space in the trucks' capacity. Even though the waste levels are higher now for those bins where the arrival rate of 5kg/5min is considered, CUT could not over perform the other methods. CVF and CULT differentiate more in terms of delay per route results, when compared with the RLV_LLLL_X scenarios.

4.4.5.3 Route count

On Fig.4.46 the results are observed in terms of route counts. These results show the opposite behaviour when compared with the previous figure of delay per route results. As it was the similar case for the delay per route results, the usage of different truck

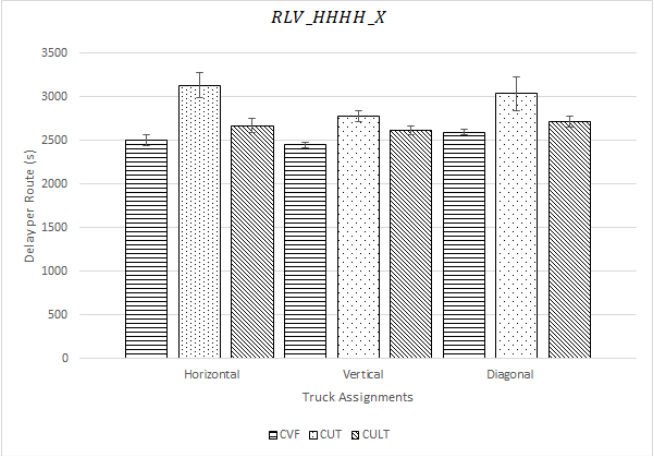

Figure 4.45 : Delay per route: RLV_HHHH_X.

assignment methods does not make a distinguishable impact on the results in terms of route counts too. Due to all zones being assigned by same and high waste arrival rates, the route counts diverge indistinctly. CUT has the lowest number of routes and the CVF has the highest number of routes. Visiting bins that have not yet triggered alarms increases the delay per route and the route values decrease with it when CUT method is applied.

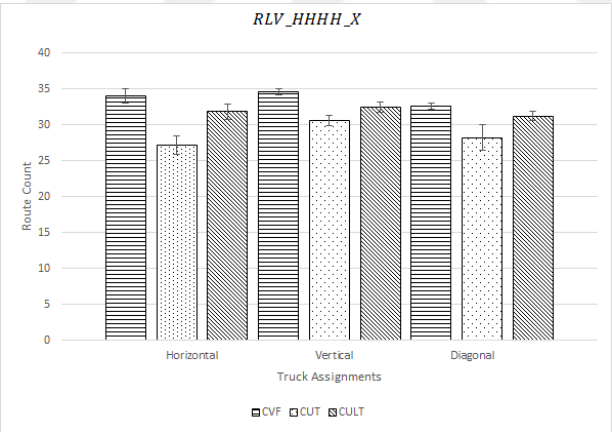

Figure 4.46 : Route count: RLV_HHHH_X.

4.4.5.4 Spilled waste

On Fig.4.47 the results are observed in terms of spilled waste. CUT caused the highest spilled waste amounts for all the truck assignment cases under high arrival rate. CUT is introduced to visit bins on the way while going to the bins with the triggered alarms. This increased the delay of the bins that actually triggered the alarms and caused more spilled waste at the end of the simulations. The impact of the different truck assignment usage is different for each method. The spilled waste amounts decreases for vertical

assignment when compared to horizontal assignment for all three methods. However, it increases for CVF and CULT and decreases for CUT when diagonal assignment is compared with horizontal assignment. The expected and the most common result is that spilled waste amount is increased by diagonal assignment since the areas that the truck visits are wider and there are more bins placed on the way. Since the CUT collects all the waste from the bins on its' way, there is higher change for the trucks being closer to the disposal area. This could decrease the spilled waste at the end of the simulation. Hence, this is not the case that happens all the time. This is depicted from the wider confidence interval ranges of the CUT method's results.

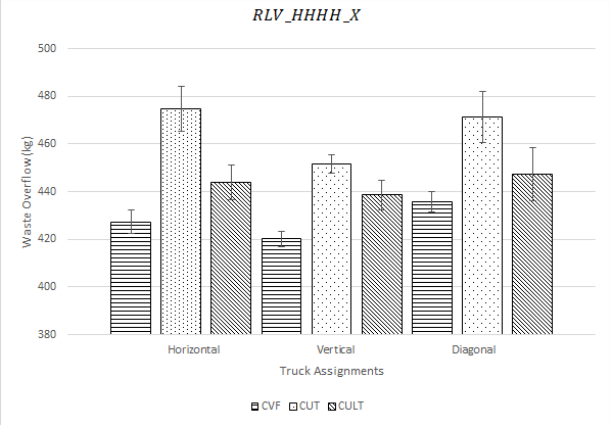

Figure 4.47 : Waste overflow: RLV_HHHH_X.

4.5 Scenarios Evaluating The Facility Enhancement

In order to get closer to a real life scenario, facility enhancement is considered. In this scenarios, the map contains 80 bins where bin capacities are 60 kg and truck capacities are 1200 kg. There are 2 trucks present on the map and the arrival rates of 1kg/5min, 3kg/5min and 5kg/5min values are used respectively.

In this scenario set, the facility enhancement is observed by increasing truck and bin capacities by 2 times in order to simulate a scenario more similar to a real life scenario. In the initial condition simulation settings are; Λ_i=30kg and C_i=600kg. For the facility enhancement scenario these capacities are Λ_i=60kg and C_i=1200kg. Three methods using priority (CVFwP, CUTwP and CULTwP) are observed on these scenarios and their ability to adapt is highlighted. Common settings used in these scenarios are waste arrival rates (λ_i=1kg/5min, 3kg/min, 5kg/5min), number of bins on the map (M = 80)

and the number of trucks ($N = 2$). The four variable being total cost, delay per route, route count and amount of overflowed waste are observed under the given parameters.

4.5.1 Total cost

Total cost changes are shown in the following figures 4.48 and 4.49. The first one showing the total cost with the initial settings and the latter one considering the increase in the capacities. In 4.48, bin capacity is 30 kg, and truck capacity is 600 kg. In 4.49, bin capacity is 60 kg and truck capacity is 1200 kg. When arrival rate is lower, it represents a more realistic scenario when the settings for initial condition is considered. The higher arrival rates are simulating more extreme cases. With the enhanced scenarios, the higher rates are more likely to be solved meaningfully.

In 4.48, for the smallest incoming waste arrival rate, all three methods performs fairly similar. Once the incoming waste arrival rate is increased CVFwP generates higher costs than other two methods and CUTwP performs better in terms of cost at the higher incoming rates. CULTwP generates the lowest cost among these two methods when the middle incoming arrival rate is considered. The reason for this change is when the bin and truck capacities are limited but the waste arrival rate is high, it is not possible to visit all the bins in the area. The bins that contain remarkable amount of waste are added to the route first to avoid time and fuel consumption by visiting bins that do not contain adequate amount of waste. However, when the waste arrival rate is increased too much, at that point adding each bin on the way to the route is the action for decreasing the total cost. By taking this action, the bins are added to the route earlier than other methods and by the time they are visited, they already contain significant amount of waste. When the sources are limited and the bins at the area in high usage, CUTwP will be the best methods in terms of total cost. When the arrival rate is manageable, not too high or not too low, CULTwP will provide the most cost efficient solution. However, if the arrival rate is not that high, all three methods perform similarly and the selection of solution can be done by looking at the implemention cost. Which corresponds to the implementation of the least complex method, CVFwP.

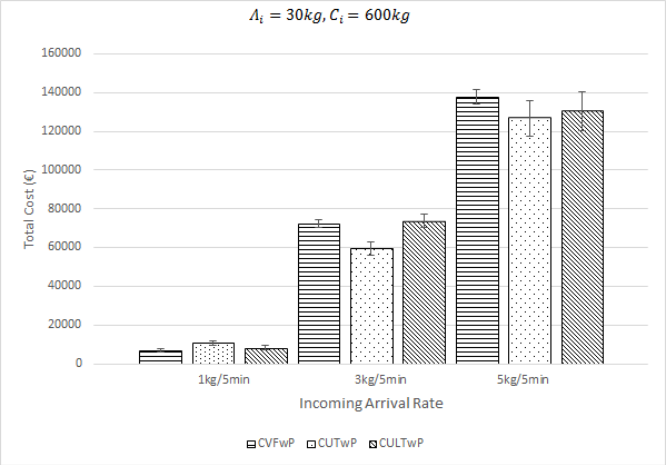

Figure 4.48 : Total cost: Facility enhancement initial case.

In 4.49, when the incoming waste arrival rate is lower, CUTwP produces highest cost and CVFwP produces the lowest cost. However, once the waste arrival rate increases, CUTwP generates the lowest cost and CVFwP generates the highest cost. Since CUTwP considers to visit bins that did not raised any alarms even if they contain very little amount of waste, bins are visited at an earlier state of time where there are less possibility of having spilled over waste around the bin. The bins are added to the route before raising alarms but when they are visited, they are mostly containing high amounts of waste. This situation leads to more efficient routes to be travelled by trucks. At the areas where the population is intense, CUTwP method can be applied and cost will be increased by means of fuel usage, payed salaries to the workers due to shorter time of service and penalties caused by spilled over wastes around bins.

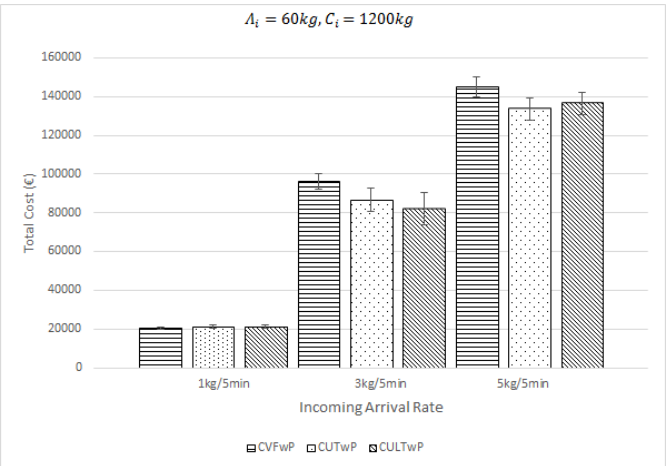

Figure 4.49 : Total cost: Facility enhancement increase in capacities.

4.5.2 Delay per route

Delay per route changes are shown in the following figures 4.50 and 4.51. The first one showing the delay per route with the initial settings and the latter one considering the increase in the capacities. In 4.50, bin capacity is 30 kg, and truck capacity is 600 kg. In 4.51, bin capacity is 60 kg and truck capacity is 1200 kg. When arrival rate is lower the delay per route results are higher in both cases when compared with the higher arrival rates. The delay per route values decrease with the increase in the waste arrival rates. When the waste arrivals are more frequent, the bins have higher level of waste contained in them when a truck visits them. This leads to the achievement of truck capacities with shorter delay time. When initial case is compared with the scenario that facility enhancement is introduced, the initial case has lower delay per route results. Even though the bin and truck capacities are increased proportionally, the trucks can travel longer by collecting more bins in at a single route duration. The threshold values are also increased with the bin capacities. However, now the bins need more amount of waste after they trigger an alarm to be fully occupied. This results in with trucks picking up bins earlier than their capacities are reached and they can visit more bins.

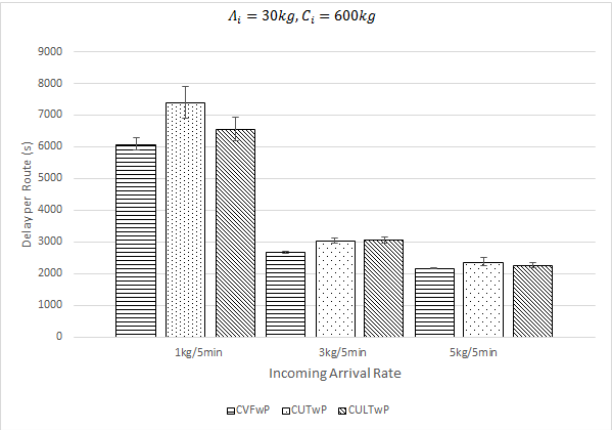

Figure 4.50 : Delay per route: Facility enhancement initial case.

4.5.3 Route count

Route count changes are shown in the following figures 4.52 and 4.53. The first one showing the delay per route with the initial settings and the latter one considering the increase in the capacities. In 4.52, bin capacity is 30 kg, and truck capacity is 600 kg. In 4.53, bin capacity is 60 kg and truck capacity is 1200 kg. When arrival rate is lower

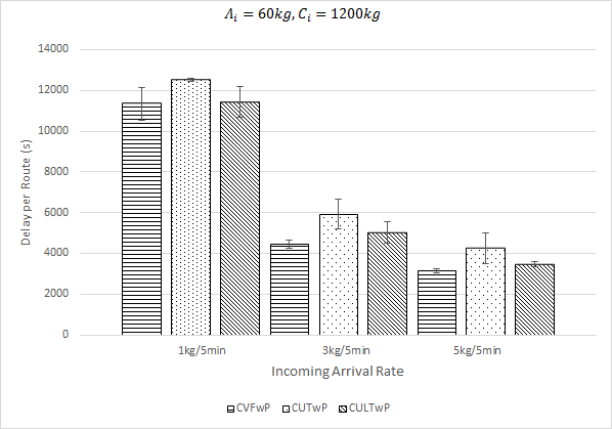

Figure 4.51 : Delay per route: Facility enhancement increase in capacities.

the route counts are less. Besides, when the capacities are increased, the route counts decrease. The reason behind this behaviour is the same in delay per route changes which stated above. The difference between the methods are more visible when the arrival rate is higher. For each condition, CUT has the lowest route counts and CVF has the highest route counts. Furthermore, the results of CVF and CULT are closer at the initial case but they differentiate more with the increase of the capacities. When the facility enhancement is applied, the bins need to receive more amount of waste before reaching their capacities. This reduces the importance of CULT method when compared with CVF.

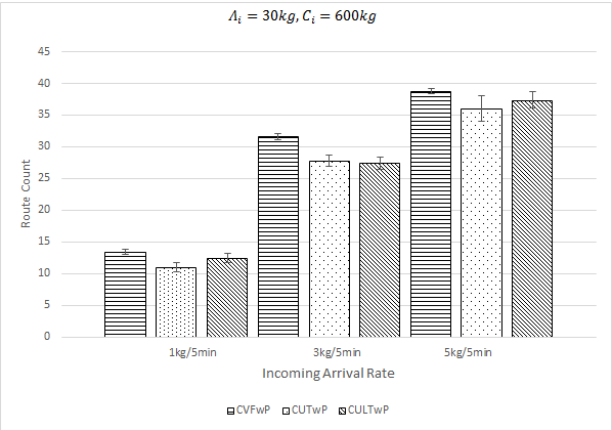

Figure 4.52 : Route count: Facility enhancement initial case.

4.5.4 Spilled waste

The amount of spilled waste changes are shown in the following figures 4.54 and 4.55. The first one showing the delay per route with the initial settings and the latter one considering the increase in the capacities. In 4.54, bin capacity is 30 kg, and truck

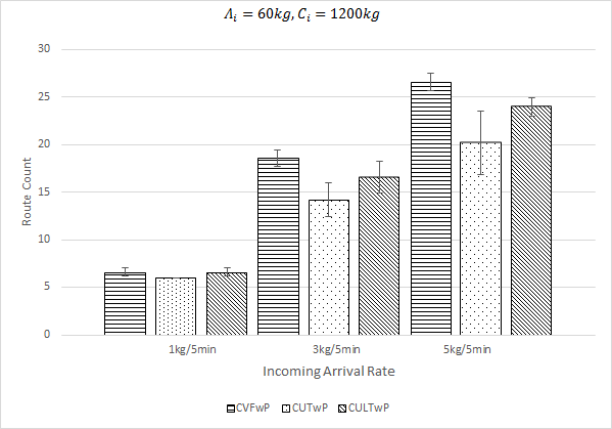

Figure 4.53 : Route count: Facility enhancement increase in capacities.

capacity is 600 kg. In 4.55, bin capacity is 60 kg and truck capacity is 1200 kg. When arrival rate is lower the spilled waste amount is almost zero. Once the arrival rate increases the spilled waste start to pile up naturally, because of the resources fail to serve with good quality. To reduce this impression, the facilities are enhanced. In 4.55 it is depicted that waste overflows are decreased. For all cases CUT has the highest amount of waste overflow as the bins which raised alarms have to wait longer times and cause high amounts of waste spillovers. Enhancement in the facilities has more improvement on the CVF and CULT methods when compared with CUT. The difference among them are more visible. CVF and CULT continues to perform similarly in terms of waste overflows even the facilities are enhanced or the waste arrival rates are increased. As the waste arrivals increase, CVF performs better with a small variance.

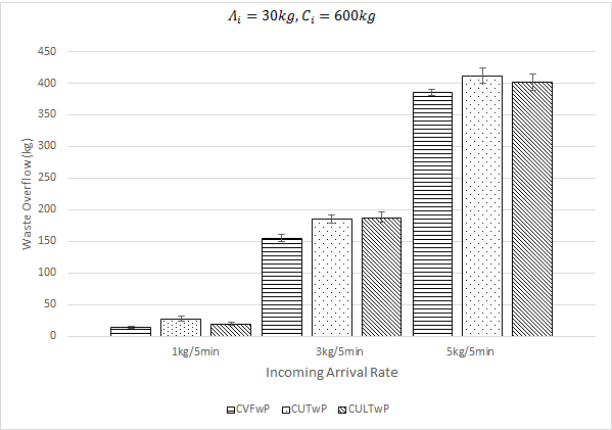

Figure 4.54 : Waste overflow: Facility enhancement initial case.

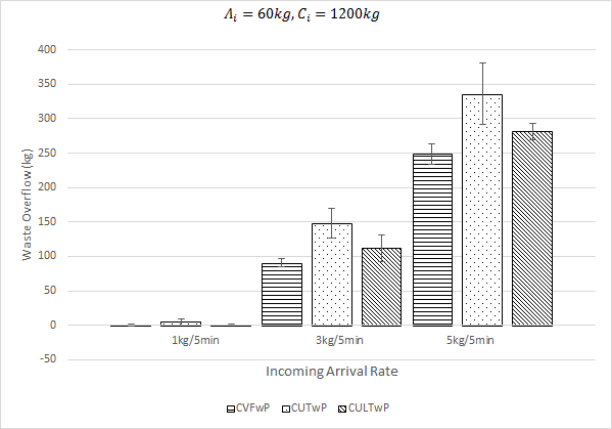

Figure 4.55 : Waste overflow: Facility enhancement increase in capacities.

4.6 Comments About The Scenarios

The proposed heuristic approaches are observed under various scenarios. Each scenario evaluating a distinct case of the environment, methods are compared in terms of the total cost, delay per route, route count and spilled waste amounts. The main evaluation criteria is considered as cost. Delay and route count values are also presented in order to justify the cost results. In addition, the spilled waste amount is shown to present the proposed approaches impact from a different angle. Observed changes are different waste arrival rates, number of bins and range of the maps used, zoning and truck assignment methods, various types of waste arrival assignment approaches and facility enhancement. It is observed that each proposed method perform reasonably under any scenario considered. However, each distinct scenario has a highest and lowest performing method. This helped to emphasize the strengths and weaknesses of the proposed methods.

CUT causes high cost values for small maps and low arrival rates. When the the area gets bigger and the waste arrival rates increase, it provided the lowest cost results in most of the simulations. However, CUT caused highest spilled wastes in most of the scenarios. The reason behind this contradiction is that, the spilled waste amounts do not have an impact on the cost values. The total cost increases with the presence of a waste overflow but the amount of spilled waste is not taken into consideration for the total cost calculation in this study. That is the reason behind sharing the spilled waste amounts of the results are important. According to the CUT's results, it also caused the highest delay per route values and lowest route counts in most of the cases. The reason

behind these results is that when CUT is applied the trucks visit more bins according to the other methods. The method adds all the bins on the way between the truck's current position and the next incoming alarm's position. This means that the bins on the way contain less amount of waste and the truck needs to visit more number of bins. The delay value from bin picking up event increased the delay per route variable for this method. In most of the cases where CUT provided the highest cost values, the reason is trucks having higher number of route counts. Only in the smaller maps with less amount of waste bins, CUT generates higher costs but with small amount of route counts. The reason for the higher cost is due to unnecessary bin visits, which contain insignificant amount of waste.

The results of CUT did not changed dramatically, however the results of CULT and CVF showed differences for distinct case of scenarios. When there are higher waste arrival rates considered with the combination of lower waste arrival rates, CULT performs more cost efficiently according to the CVF most of the times. Since adding bins with significant amount of waste to the route if they are on the way is a cost saving movement when more extreme and intense scenarios are considered. In Fig. 4.56 a summary of zoning and truck assignment scenarios are given in terms of total cost values. From left to right the methods and truck assignment combinations that are used are changing. The methods are labeled as *methodName_truckAssignment*, such as CVF_H representing the solution is provided by horizontal truck assignment and CVF method. As the waste arrival rates assigned to zones are increasing, total costs are increasing, naturally. It is seen that increasing the waste arrival rates also make the differences between the solutions provided by the proposed methods more visible. Mostly, the results vary among various proposed methods when diagonal truck assignment is used . Moreover, when HHLL waste arrival rate assignment is used on the zones, horizontal truck assignment produces the results which are the most cost efficient ones due the trucks serving areas with distinct waste arrival ratios.

CVF provides the most cost efficient results when the map is smaller and there are less number of bins. However, when the environment gets more intense CULT over performs it. For those cases visiting bins which raised alarms are not enough to propose a better solution. There comes in the CULT's decision mechanism for adding additional bins to the route. In terms of spilled waste amount, CVF always provides

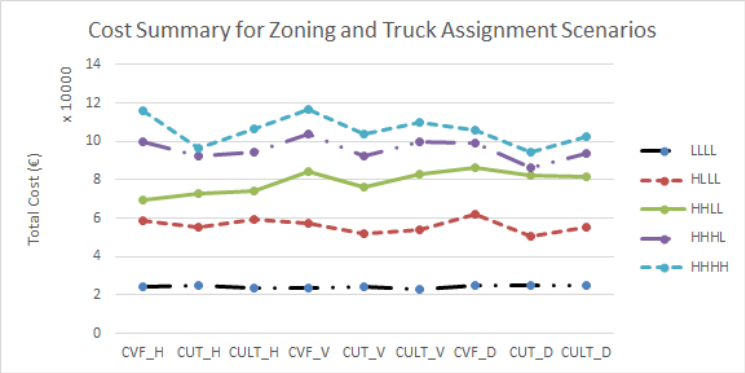

Figure 4.56 : Total cost: Summary for zoning and truck assignment scenarios.

the lowest values at the presence of the bin number or the area size changes. Changing the bins waste arrival rate assignment method or the truck assignment did not change the fact that CVF had the lowest spilled waste amount at the end of the simulations. This difference is again caused by the impact of penalties to the cost independent of the spilled waste amount.

When the methods with priority are considered, the total costs are more than the methods without priority in some cases. However, in all cases the delay values and spilled waste amounts are decreased. This is the impact of giving priority to the bins which could not be fully emptied or starting to cause waste overflows. This could increase the cost by increasing the distance that trucks travel, however it produces a better solution in terms of a cleaner environment.

5. CONCLUSIONS AND RECOMMENDATIONS

This thesis present a research in the field of ICT, focusing on IoT and smart city applications. With the rapid increase in the urban population, the requirements of the higher living standards change. Not only the urban population is growing but also the habits and consumption patterns of the population are changing. This emphasize the need for smart city applications which requires the IoT technology to be implemented. As it is stated in the first chapters, WSNs are one of the technologies that provide smart city solutions when integrated in an IoT environment. In this thesis study, the problem of waste management is addressed in terms of smart city concept. The reason behind this problem to be chosen is that, the rapid increase in the urban population is causing higher amount of waste and it has a significant impact on the living quality of residents. Many researchers have worked on the IoT and smart city applications, including waste management. Each of the works presented in the earlier chapters are focusing on another part of the problem including but not limited to hardware implementation, waste collection optimization techniques and waste separation.

The main focus in this thesis study is to propose nearly optimal heuristic methods in order to improve the waste management services in smart city environments by introducing the decision making systems. Six techniques which can be applied to a WSN-driven smart city environment are proposed. These approaches are called; *Closest Vehicle First (CVF)*, *Closest Vehicle First with Priority (CVFwP)*, *Collect based on Upper Threshold (CUT)*, *Collect based on Upper Threshold with Priority (CUTwP)*, *Collect based on Upper and Lower Threshold (CULT)*, *Collect based on Upper and Lower Threshold with Priority (CULTwP)*. These models emphasize the need for planning of an efficient waste collection route in the presence of a WSN and a set of triggered alarms to initiate the waste collection. These methods which considers current waste levels of the bins with upper and/or lower threshold levels, with or without prioritization are observed under various scenarios in the simulation environment in terms of total cost, delay per route, route counts and spilled waste

amounts. The advantages and disadvantages of each of the method on a distinct scenario are presented in detail.

According to the results of the numerous scenarios conducted during this thesis study, it is observed that each method has its advantage on a different case. When there are less number of bins and the area is narrow, the CVF approach is the best solution in terms of cost efficiency. It reduces the unnecessary visits to the waste bins and trucks can visit the bins that only triggered alarms without causing extensive overflows and penalties. However, when the bin number increases and the area gets bigger, the importance of the decision mechanism is observed, especially with CULT method.

When a smaller area is considered with less number of bins, the results provided by CUT is higher. In these kinds of environments, the delays and delay per route values do not show considerable change and the differences seen on the cost values are reflecting the cost per route values. For these kinds of situations, CVF and CULT perform relatively close to each other in terms of cost and delay. However, CVF tends to provide more cost efficient results with less amount of spilled over waste. When the area gets larger and more bins are deployed on the map, CUT generates more cost efficient results. However, this is due the increase in the delay per route values which results in with less number of routes to be conducted. Besides, the highest waste spillover amount is achieved by CUT in all the cases. When the bin and truck capacities are enhanced with the increase in the bin numbers, this constructs the environment where CULT performs most cost efficiently.

In addition, the observations are made under different combinations of truck assignments and zoning. In a situation where the bins are assigned with different arrival rates, if a truck is responsible of an area of bins where each bin has the same waste arrival rate the provided solutions are more cost efficient. However, this causes delay and spilled waste amounts to increase. When the bins are equally divided to the different trucks and each truck gets to serve a set of bins with different waste arrival rates, this increases the total cost but provides less waste overflow and delay.

Moreover, the methods which introduce the prioritization increases the total cost, however they provide a better solution in terms of spilled waste amounts. When the higher priority bins are visited earlier, there are less amount of waste that overflows.

The amount of the overflowed waste is not taken into consideration in cost calculation, that shows the necessity of presenting the results in terms of spilled waste amount.

Various scenarios are implemented under different settings and evaluation criteria. The impact of each proposed heuristic approach is presented in detail. When these approaches are considered to be applied, the environment conditions and application objectives need to be considered. The detailed results are provided with matching environments.

As for the further development of this study, it is planned to get in contact with the municipalities and share the details of our approaches and the detailed results. Besides, getting requirements, commands and suggestions from them is planned to be applied in order to improve our approaches and this thesis study.

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APPENDICES

APPENDIX A.1 : Scenario Results

APPENDIX A.1

1.1 Results From Scenarios

1.1.1 RLV_HLLL_X

1.1.1.1 Route count

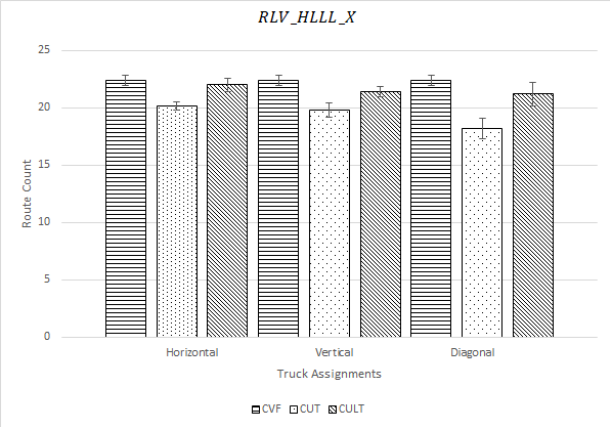

Figure A.1 : Route count: RLV_HLLL_X.

1.1.1.2 Spilled waste

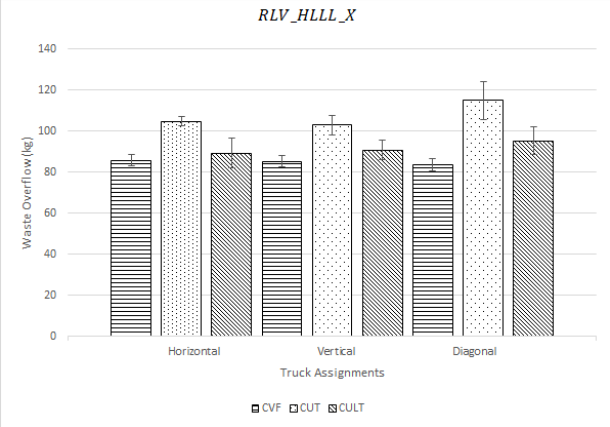

Figure A.2 : Waste overflow: RLV_HLLL_X.

1.1.2 RLV_HHLL_X

1.1.2.1 Route count

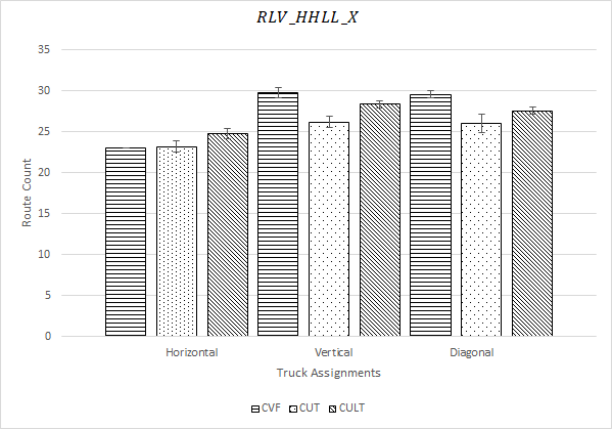

Figure A.3 : Route count: RLV_HHLL_X.

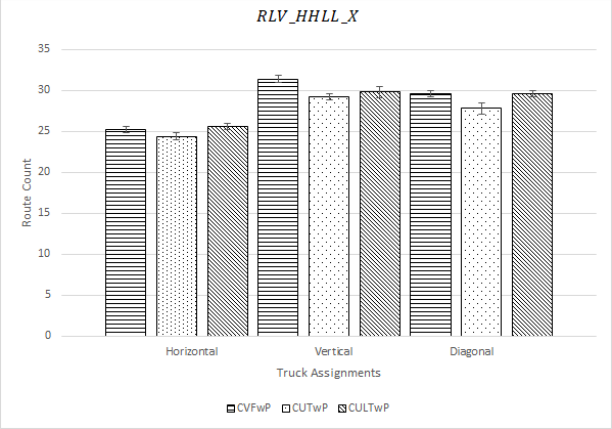

Figure A.4 : Route count: RLV_HHLL_X with priority.

1.1.2.2 Spilled waste

Figure A.5 : Waste overflow: RLV_HHLL_X.

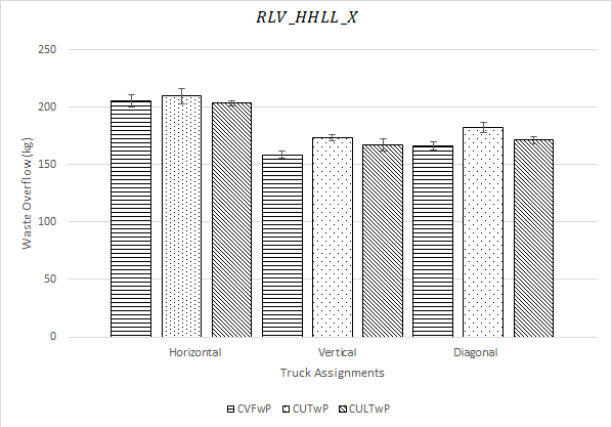

Figure A.6 : Waste overflow: RLV_HHLL_X with priority.

1.1.3 RLV_HHHL_X

1.1.3.1 Route count

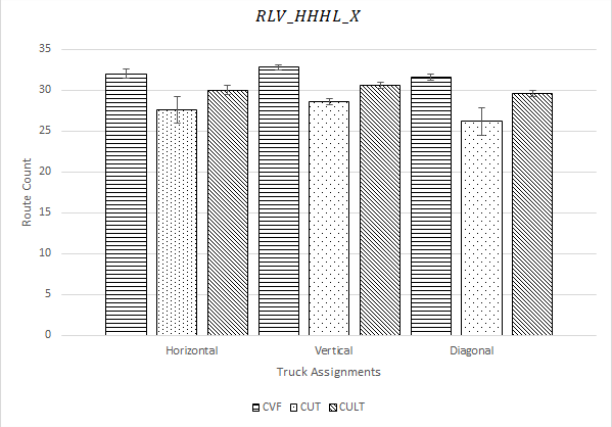

Figure A.7 : Route count: RLV_HHHL_X.

1.1.3.2 Spilled waste

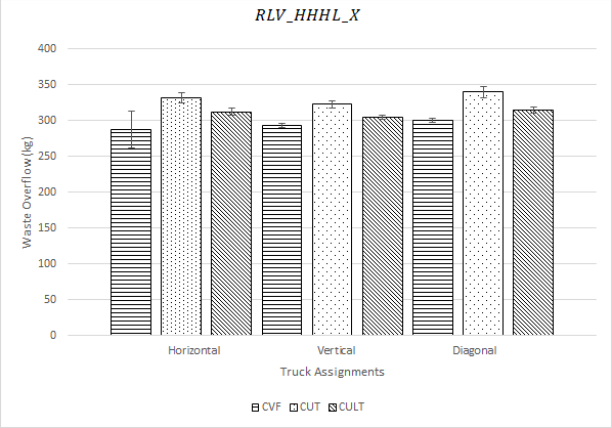

Figure A.8 : Waste overflow: RLV_HHHL_X.

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PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- Omara, A., Gülen D., Kantarci, B., Oktuğ, S., 2018. Trajectory-Assisted Municipal Agent Mobility: A Sensor-Driven Smart Waste Management System, *Journal of Sensors and Actuator Networks,* 7(3), 29.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- Özkaya Ö., Erdoğan H., Çamlı A., Gülen D., Ük N., Temizer T., Face Recognition Based Small-cycle Continuous Integration. *National Software Engineering Symposium*, September 10-12, 2018 İstanbul, Turkey.
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