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Optimization of Automated Guided Vehicles (AGV) Fleet Size With Incorporation of Battery Management

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WITH INCORPORATION OF BATTERY MANAGEMENT

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ABSTRACT

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An important aspect in manufacturing automation is material handling. To facilitate material handling, automated transport systems are implemented and employed. The AGV (automated guided vehicle) has become widely used for internal and external transport of materials. A critical aspect in the use of AGVs is determining the number of vehicles required for the system to meet the material handling requirements.

Several models and simulations have been applied to determine the fleet size. Most of these models and simulations do not incorporate the battery usage of the vehicles and the effect it can have on the throughput and the number of AGVs required for the system. The goal of this research is to develop a simulation model to determine the optimized number of AGVs that is capable of increasing throughput while meeting the material handling requirements of the system. This model incorporates the battery management aspect and issues, which are usually omitted in AGV research. This includes the charging options and strategies, the number and location of charging stations, maintenance, and extended charging. The analysis entails studying various scenarios by applying different charging options and strategies and changing different parameters to achieve improved throughput and an optimized AGV fleet size.

The results clearly show that battery management can have a significant effect on the average throughput and the AGV usage. It is important that the battery management of the AGVs is addressed adequately to run an AGV system efficiently.

This dissertation was only made possible by the guidance and strength that Allah Almighty blessed me with, El Hamdo le Allah.

This effort is dedicated to:

My Parents, for the continued sacrifices you make for us. Thank you for being the best role models you can be and always encouraging us to be better and always putting us first. I am grateful for everything you have done and continue to do for us. Thank you for everything. I love you very much, El Hamdo le Allah.

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NOMENCLATURE

AGV Automated Guided Vehicle

AGVS Automated Guided Vehicle System

FMS Flexible Manufacturing System

SoC State-of-charge

SoH State-of-health

JIT Just-in-time

LGV Laser Guided Vehicle

MAB Minimum Acceptable Charge Level for Automatic Charging

DOE Design of Experiments

DASE Design and Analysis of Simulation Experiments

VRLA Valve-regulated lead acid

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CHAPTER 1

INTRODUCTION

Manufacturing automation has become increasingly vital as the need to be competitive and remain productive increases. Material handling plays a significant role in manufacturing automation and to facilitate material handling, automated transport systems are implemented and employed. In the recent years, the automated material handling system has quickly developed as the complexity of manufacturing system has increased immensely. With the flexibility and accuracy of the AGV (automated guided vehicle) system and the ability to respond to changes in production, its use in modern manufacturing environments has increased significantly and they started to play an especially significant role (Fazlollahtabar and Mehrabad, 2015).

The AGV is a driverless material handling system that is battery powered and computer controlled and is used for the transporting of finished and unfinished goods in an industrial environment (Fazlollahtabar and Mehrabad, 2015). The AGVs can travel forwards and backwards and usually navigate by using sensors and stationary beacons on a network of guide paths which are pre-determined. A laser guided vehicle (LGV), on the other hand, is a type of AGV but does not require guide paths and is equipped with a laser beacon that rotates and scans around the vehicle for laser targets which are mounted on columns and walls. The reflections from these targets are measured relative to angles from the vehicle and triangulated to allow the vehicle to determine its position. Transporting of loads which consists of picking up a load at a certain location and transporting it to a certain destination is based on the assignment to the AGVs and is generated by an external system (Fazlollahtabar and Mehrabad, 2015). An automated guided vehicle system (AGVS) is composed of a fleet of automated guided vehicles which are battery powered and equipped with manual or automated pick-up and drop-off mechanisms as well as automated obstacle-detection capability, an external system that uses a software to generate dispatching and routing rules, and a navigation network (Choobineh, Asef-Vaziri, and Huang, 2012).

The use of AGVs and the number of areas of application has grown significantly since their introduction. They are implemented and employed to provide efficient solutions for many applications including: manufacturing facilities, container terminals, part transportation in heavy industries, warehousing and distribution facilities, and flexible manufacturing systems. With the use of AGVs, there are many challenges that are faced and many opportunities for improvement. Determining the optimum number of AGVs to use in a system is critical. Several models and simulations have been developed to determine the optimum number of AGVs to use in the system. Most of the models developed are geared towards Flexible Manufacturing Systems (FMS) or flow shops. In addition, it is very rare that any of the models or simulations developed have incorporated battery management issues, which include the charging, charging stations, and battery life of the AGVs (McHaney, 1995; Ebben, 2001; Vis, 2006; Le-Anh and De Koster, 2006; Kabir and Suzuki, 2018).

1.1 Motivation

This research is motivated by a real manufacturing facility that uses LGVs (a specific type of AGVs) as a primary material handling system. Although the specifics of this facility will not be used in this research, the methodology is generalizable to other facilities with AGV material handling system. The model will capture the AGVs' movements to pick up and drop off material between the different pick up and drop off points such as the warehouse and the different areas in the facility such as assembly lines. The model will also capture the AGVs' regular visits to the charging stations. Planned AGV maintenance and extended charging will also be incorporated in the model.

The developed simulation model is used to study and analyze aspects related to the AGV batteries and their effect on throughput and AGV fleet size. This includes the charging strategies, the number and location of charging stations, maintenance, and extended charging. Various scenarios will be studied by applying different charging strategies and changing different parameters to achieve improved throughput and an optimized AGV fleet size.

1.2 Research Purpose and Objectives

The purpose of this research is to develop a discrete event simulation model of a manufacturing facility to determine the optimized number of AGVs that is capable of increasing throughput while meeting the material handling requirements of the system. The material handling requirements of the system are the required transportation tasks of the system which includes the number of loaded and empty trips the AGVs have to make based on the number of required pickups and drop offs of loads which is based on the demand. The proposed model will incorporate battery management aspects and issues that are typically omitted in AGV research. This means that the travel time of the AGV to and from the battery charging stations and the time the AGV charges is incorporated. This is a significant addition because most models do not incorporate it although it can have a significant effect on throughput and the number of AGVs needed. It also provides a more realistic model that shows the effect of battery management. The analysis will entail studying various scenarios by applying different charging options and strategies and changing different parameters to achieve improved throughput and an optimized AGV fleet size.

The contribution of this work revolves around the following two objectives:

1) Developing a valid discrete-event simulation model for a generic but complex manufacturing facility that includes operations, processes, logistics, resources, and battery management.

2) Using the developed simulation model to study and analyze aspects related to the AGV batteries and their effect on throughput and AGV fleet size. This includes the charging options and strategies, the number and location of charging stations, maintenance, and extended charging.

CHAPTER 2

LITERATURE REVIEW

This chapter is dedicated to discuss the background of the study. The first section of this chapter presents the extensive literature review for the models and simulations developed to determine AGV optimal fleet size. In the second section, the literature of the models and simulations developed that incorporated AGV battery management is also reviewed. The last section summarizes the findings and discusses the knowledge gaps in the existing literature.

2.1 Overview of Models and Simulations Developed to Determine AGV Optimal Fleet Size

Research areas that are concerned with this work include studies that use discrete-event and other simulation and optimization models with a focus on optimizing AGV fleet size and optimizing battery management. Many of the researchers employ operation research decision making methodologies for dealing with such complex and challenging problems to achieve near-optimal solutions. Some of the methods include, among others, simulation methods, optimization methods (mathematical programming, dynamic programming, etc.), heuristics, optimization search approaches like tabu search, genetic algorithms and others. Many researchers used both analytical and simulation models.

Determining the number of vehicles required in an AGVS is very important and some of the major vehicle estimating models that have been used include regression, travel time, queuing, and network models (Le-Anh and De Koster, 2006). To determine the optimal AGV fleet size required that is capable of meeting all requirements, many factors have to be considered. Some of the factors include: the number of units that need to be transported, the speed of the vehicle and the times at which loads need to be transported, the costs of the system, the capacity of the vehicle, traffic congestion, vehicle dispatching strategies and the number and location of pickup and delivery points, and the layout of the system and guide path (Vis, 2006).

Fleet size estimation can be determined with deterministic and stochastic data. With deterministic data, the parts that need to be moved are known and are ready for delivery at the start of the planned time, or their availability time is known. On the other hand, for a stochastic system, delivery requests are random or stochastic and are served by vehicles selected in real-time (Koo, Jang, and Suh, 2005). Although most analytical models tend to underestimate the number of vehicles required compared to simulation results, deterministic approaches such as linear programming models and network flow models can be used before the start of real operation to approximate the number of vehicles required, while Stochastic models such as queuing networks try to incorporate external influences (Vis, 2006).

Rajotia, Shanker, and Batra (1998) determine the required AGV fleet size using analytical and simulation modeling. They state that the procedure of determining optimal fleet size is initiated by identifying how an AGV spends its time in the system. They also identify a complete vehicle journey for the purpose of a load transportation task with three points of interest: (1) an origin of journey where the vehicle is located at the time of load transport assignment, (2) a load pickup (P) point where the vehicle is required to be loaded, and (3) a load delivery (D) point where the vehicle is unloaded, the last point becomes the origin for the next journey (Rajotia et al., 1998). They define three mutually exclusive states the vehicle can be in as follows: load handling, empty travel, and waiting and blocking. Calculating the total handling time in which it is assumed that jobs enter in and depart from the same receiving/shipping center, the total empty travel time, and the waiting and blocking time and taking the ratio of these three calculations and the effective time a vehicle is available gives the number of vehicles required in the system (Rajotia et al., 1998).

In their proposed model the objective was to minimize the empty vehicle travel time, and the number of empty trips that originated from a station is equal to the number of loaded trips that end there, and the number of empty trips terminated at the station is equal to the number of loaded trips that start from there. The initial estimate of the fleet size is validated using simulation. They determined that their proposed model could be used as an analytical tool before the simulation phase, as the results were close to the simulation results although the different models either under or overestimated the actual number of AGVs required (Rajotia et al., 1998).

Approximating the empty travel time of a vehicle can be difficult. There have been several proposed assumptions and methods to calculate this time. Maxwell and Muckstadt (1982) proposed a time independent analytical model to estimate the minimum number of vehicles necessary to meet the material handling requirements. They use an integer programming formulation for seeking the optimum solution. Beisteiner and Moldaschi (1983) approximated the total empty vehicle travel time in the first case to be equal to the product of the total number of empty trips. In the second case, they approximated the total empty vehicle travel time to be equal to the total loaded vehicle travel time.

Heijden et al. (2002) developed several planning methods for empty vehicle management in automated transportation networks and used simulation to evaluate the planning options on their performance in terms of AGV requirements and empty travel distances. They determined that both the information about upcoming orders and planning coordination between terminals gives a considerable benefit in terms of fill rates. Further research is needed to better estimate the vehicle empty travel and time lost that is caused by vehicle interference (Le-Anh and De Koster, 2006).

Determining the vehicle waiting and blocking time will depend on the AGV system. There are many factors that affect the waiting and blocking time including the guide path layout, the vehicle dispatching and routing strategies, and the vehicle rules and clearance procedures at intersections (Rajotia et al., 1998). It is very common that the layout of the system and the guide path have already been defined before the minimum number of vehicles required is determined (Vis, 2006). To approximate the empty travel and waiting time, Kulwiec (1982) and Kulwiec (1984) used a factor of 0.2 to 0.4, and used a factor of 0.15 to approximate the blocking time. In determining the fleet size, Koff (1987) proposed a facility-dependent empirical factor that ranged from 0.1 to 0.15 of the total loaded travel time to approximate both idle waiting and blocking time.

Sinriech and Tanchoco (1992) developed a multi-criteria optimization model using two goals, cost and throughput performance. They assume that the costs related to the guide path configuration are fixed. They use a trade-off ratio between the goals to determine the number of AGVs needed in the system.

Arifin and Egbelu (2000) used analytical and simulation modeling to determine the number of AGVs in an FMS environment. The analytical method considered the empty travel time, load handling time, and waiting and blocking time. They formulated a mixed integer program with the objective of minimizing empty trips and used simulation to validate the initial estimates of fleet size.

Koo et al. (2005) presented an analytical procedure to determine the number of vehicles required which considered a stochastic system where the specific times and locations of delivery requests were not known in advance but the total delivery requirements during a planning period were known. They used a queuing model to estimate part waiting times for different vehicle dispatching rules for which the part waiting times consisted of both assignment waiting time and empty vehicle travel time. They defined the assignment waiting time as the time delay that a part has to wait until a vehicle becomes available before its delivery request can be assigned to this vehicle. They also used simulation to verify their model, which showed that their proposed model provided a good estimation for the required number of AGVs.

Choobineh et al. (2012) used multi-class closed queuing networks to model the movement of AGVs in a manufacturing environment. They used a linear program to model the steady-state behavior of the closed queuing network for which the optimal value is the estimation of the minimum fleet size required. The results of the comparison between the analytical model and the simulation showed that the analytical model provided a good estimate for the required number of vehicles in almost 90% of the scenarios.

Chang, Huang, and Yang (2014) proposed a formulation and solution method called Simulation Sequential Metamodeling (SSM) to determine the optimal fleet size in a semiconductor manufacturing system. They constructed a series of metamodels for an empirical study on real data to validate the feasibility of the simulation sequential modeling approach. SSM builds metamodels, which are response curves that can well represent the functional relationship between the inputs and outputs of a simulation model thus covering all the essential manufacturing details and reducing the assumptions that tend to be made in analytical models.

Egbelu (1987) proposed four analytical models to determine the required number of vehicles based on data which included the number of workstations in the facility and the expected number of loaded trips between stations. He concluded that the acceptability of an estimating technique is a function of the dispatching rules in force. Kumar and Jayant (2015) developed a simulation model of a theoretical system with a job shop environment which was based on JIT philosophy. The transportation time was balanced for a layout of an automotive assembly line environment with several vehicles and heuristic dispatching rules were proposed based on that transportation time. Their results clearly showed the significance of the appropriate choice of both the number of AGVs and the AGVs dispatching rule to enhanced transportation efficiency. By knowing and understanding the relationship between vehicle requirements and dispatching policies, raw analytical estimates can be properly adjusted to obtain a more accurate measure of requirements without resorting to detailed simulation analysis, which is usually, too expensive to undertake during the search phase of the material handling equipment to be selected (Le-Anh and De Koster, 2006).

Koo, Lee, and Jang (2004) proposed a new fleet management procedure and incorporated the adjustment of the number of vehicles that results from unexpected events that occur during real operation. In the initial step of their model, they determine the lower bound on the fleet size at a container terminal while in the second phase they implement a tabu search algorithm to route the vehicles with the minimum number of vehicles so that all transportation jobs are completed in time. They increase the number of vehicles stepwise by one until this time constraint is satisfied.

Kasilingam and Gobal (1996) presented a simulation based cost model to approximate the number of AGVs needed to meet the material handling requirements. Their approximation is based on the total of the idle times of vehicles and machines and the waiting times of the transported parts. Their results show that an increase in the number of vehicles decreases the waiting times of parts and the idle times of machines, but it also results in an increase in the idle times of the vehicles.

Yifei et al. (2010) used a two-step approach to determine the AGV fleet size in an FMS. In the first step, they estimate the number of vehicles required for which they adopt one of the non-simulation approaches proposed by Egbelu (1987) in estimating the vehicle requirement. In the second step, a simulation model of the AGVS is operated to determine the optimal number of vehicles. The estimate value found in the first step is used as the initial value in the simulation process and that showed that starting with the estimate in the simulation model reduced the simulation times.

2.2 Overview of Models and Simulations Developed with AGV Battery Management

In many manufacturing facilities and distribution areas, AGVs travel short distances and have enough idle time during which their batteries can be replaced or charged. However in manufacturing systems with unpredictable AGV routes and transportation systems AGVs need to travel long distances and as a result have short idle times (Vis, 2006). With the short idle times the AGVs will have to get their batteries replaced or charged during production times which will in turn reduce their availability and affect the throughput. Although battery management can have a significant effect on the throughput of the system, it is hardly addressed in AGV research (Vis, 2006).

A battery management system can be very beneficial in ensuring the proper performance of the battery and in reducing premature battery failure (Williams, 2010). Some of the imperative factors related to the battery management of AGVs include the capacity of the battery charging stations, its location, how long a particular AGV will operate before it needs to be recharged, and the AGVs' available idle times (Le-Anh and De Koster, 2006).

AGV battery replacement or recharge is disregarded in most studies on AGV systems and although the battery life and its charging can become limiting factors in an AGV system, AGV battery usage is frequently omitted in simulation (McHaney, 1995). Some of the reasons they are omitted is that there is not a full understanding of the complex interactions of the AGVs and the effect on the batteries, they are assumed to have minimal impact on the AGV system, the throughput, and the number of vehicles required (McHaney, 1995).

McHaney (1995) reviewed several general schemes for battery replenishment including:

automatic battery swap, manual battery swap, opportunity charge, automatic charge, a combination system which consisted of both opportunity charging and automatic charging, and the use of charge rails. The difference between a manual battery swap and an automatic battery swap is that in an automatic battery swap a machine is utilized to exchange the depleted battery with a fully charged battery, which usually requires less time to complete than a manual battery swap in which an operator would be required to swap the battery manually.

In systems like assembly systems where there are short expected stops and there is idle time that is available in an AGV's normal cycle, opportunity charging is used to keep the batteries charged (McHaney, 1995). In systems where there is a lot of available natural idle time, opportunity charging has less effect on the number of vehicles in an AGV system as it does not affect the availability of an AGV to fulfill transportation tasks.

Automatic charging which is used in many charging schemes today is setup so that an AGV will run until its battery charge has decreased to a certain predefined level. Once this level is reached, the AGV is routed to a charging station where the battery is recharged to an adequate level. McHaney (1995) states that this type of charging is used when there is hardly any time for opportunity charging as the AGVs have very little idle time and it also reduces the cost that is associated with the battery change stations and the personnel associated with battery swapping. Since automatic charging does not use the natural idle time available, it affects the availability of an AGV to fulfill transportation tasks and thus may have the effect of increasing the required number of vehicles in a system.

Combination systems incorporate both opportunity charging and automatic charging. In general terms these systems can function as opportunity charge systems in which the battery levels will continue to decrease but when they reach a predefined level, they are routed to charging stations where AGVs are recharged for longer periods of time (McHaney, 1995). They can also function in a similar way to an opportunity charge system but when the AGV is routed to the charging station, the battery is recharged to an adequate level.

McHaney (1995) concludes and shows in his example model that battery constraints should not be overlooked and need to be considered as they can become limiting factors which in turn affects the throughput, system congestion, fleet size, and cost.

Ebben (2001) considered several options with regards to battery recharging: recharging the battery inside the AGV, battery swap, and charge rails. As with a battery swap the batteries are recharged outside the AGV, the AGV is still available and can fulfill transportation tasks and thus there is little to no effect on the operational time of the AGVs. He states that one of the major disadvantages with the battery swap option is that special battery stations are required. In the case that is studied, the option of recharging the battery inside the AGV is not considered as it would require a significant increase in the number of AGVs since with this option the AGVs are not available to fulfill transportation tasks when they are recharging (Ebben, 2001). The last option considered was the charge rails and since the AGVs are moving while being recharged in certain areas of the track network by being attached to a charge rail, the system performance is not affected. One of the advantages this option has over the other two is that investment in additional batteries is not needed (Ebben, 2001).

In regards to battery replacement, three options were considered and they were as follows: replace the battery when it does not have enough charge to perform the next task, replace the batteries of all AGVs before a peak period, and the last option is to change the battery when an opportunity arises. With the first option, when an AGV receives a task from vehicle scheduling the battery charge is checked and if it is not sufficient to complete the job, the availability of another AGV to complete the job is checked. If no other AGVs are available, the selected AGV has to go to a battery station while completing the job (Ebben, 2001). Although the second option of changing the batteries of all AGVs before a peak period would be attractive as all AGVs would have a fully charged battery during peak periods, this option was not considered in the case studied as the peak periods were very lengthy and would require that the batteries to be changed at least once during the peak period (Ebben, 2001).

Changing batteries at a suitable time without interrupting production rather than during peak periods can significantly increase production and can add 30 minutes or more of productive work per lift truck each day (Williams, 2010). The last option considered of changing the battery when an opportunity arises would not affect the productivity of the AGV but the number of battery swaps would increase. Opportunities that arise is when an AGV is idle or waiting for several reasons including waiting for a new task assignment or waiting at the entrance of a bidirectional track (Ebben, 2001). As the AGVs have to travel to replace their batteries, the locations and number of the battery stations becomes very critical to determine optimally or near optimally.

Ebben (2001) adopted the following battery management strategy in the case presented: when an AGV receives a new task assignment, the battery charge level is checked, and if the remaining charge is adequate for the AGV to drive to its new destination and from this destination to the closest battery station it does not have to swap its battery. In the case where the remaining charge is not adequate, the AGV is sent to the closest battery station to replace its battery. One of the assumptions made was that both loaded and empty AGVs can replace their batteries. In the case presented in Ebben (2001), the swap opportunity was utilized when the battery charge was not sufficient to drive from the current location to the furthermost possible destination in the network and from there to the closest battery station. AGVs will replace batteries more than needed, but the battery swaps can take place without real loss of time. The author concluded that unlike most internal transportation systems, an automated transportation network cannot neglect battery constraints.

Yifei et al. (2010) developed a parameterized simulation model of an AGVS in a FMS and incorporated battery management. They also stated that battery management is usually omitted in research although it can have significant effects on the performance of an AGVS. In their model they considered unidirectional AGVS and use automatic recharging as their type of charging. The results showed the relationship that exists between the number of AGVs when battery management is included and when excluded to measure the effect it can have on throughput or processing times. Also, the results showed that when the number of AGVs is increased it reaches a point at which there is enough idle AGV time that battery management has little or no effect. There are many aspects of battery management that they did not consider including the location, number, and the battery charging scheme of the battery charging stations.

Oliveira et al. (2011) also notes that battery management is not included in many AGVS studies. They developed a battery management system that can estimate the battery utilization for a certain route using a method based on Extended Kalman Filter (EKF) that estimates the state of charge (SoC) of the batteries. They noted that the battery life can be increased by preventing battery discharging.

Bian et al. (2015) developed an event-driven assignment model which considered battery capacity in which empty AGVs are always available for assignment. Their model also incorporated battery capacity in the dispatching decision for the AGV in which an AGV with insufficient charge is not available for any assignment until that AGV has been charged.

Fatnassi and Chaouachi (2015) note that in AGV research battery usage is usually not included and specifically distance constraints relative to the AGV's batteries are usually omitted from the literature. They investigated a charging strategy for an AGV through dealing with a specific scheduling problem with the assumption that there is only one charging location. They developed a linear programming heuristic and defined when each AGV has to return to the charging location while satisfying a set of transportation requests.

Davina, Duinkerken, and Lodewijks (n.d.) researched the effects of different design aspects of battery management using discrete event simulation and a specific hospital case. They studied the influence of battery capacity on the number of AGVs required to handle a certain demand and the impact of two dispatching rules based on the remaining battery capacity. Their results showed that changing the battery capacity has a significant influence on the average pick up times of jobs. They emphasized the importance of incorporating battery management in simulations.

Kawakami and Takata (2011) developed a battery management simulation to evaluate battery related costs which included the cost for battery chargers, the cost for replenished batteries, and labor costs associated with battery charging. These costs were evaluated under a variety of AGV operation modes like timing of charge. In their model they adopted battery swapping for the charging of the batteries and they used valve-regulated lead acid (VRLA) as most AGVs usually utilize them because of their high reliability and low cost. VRLA batteries are designed to be maintenance free and the hydrogen that is emitted is recombined internally so that the electrolyte does not need replacing over the life of the battery (PowerThru, n.d.). In addition, the valve is installed to release any excess pressure that may build up if the battery was failing (PowerThru, n.d.). Timing of charge and timing of battery disposal are two very important factors in battery management. For timing of charge, if AGVs are charged frequently, battery life is extended but the productivity is reduced due the unavailability of the AGVs. As for timing of battery disposal, if AGVs continue to be used with deteriorated batteries, the number of charging occurrences increases thus again reducing the productivity, making the AGVs unavailable (Kawakami and Takata, 2011).

For the AGVs to operate efficiently and for a cost effective battery management strategy, it is vital to estimate the state-of-charge (SoC) and state-of-health (SoH). Kawakami and Takata (2011) defined the SoC as the ratio of residual capacity to nominal capacity of the battery and the SoH as the ratio of available capacity to nominal capacity. So as the battery discharges the SoC decreases and as the battery deteriorates the SoH decreases. In their simulation, they varied the SoC and SoH and showed the effects on the labor cost for battery charging, the cost associated with losses due to AGV stoppage, the acquisition cost for chargers, and the acquisition cost for replenished batteries. The results showed that it is very important to select an appropriate SoH value of when to dispose of a battery and an appropriate SoC value of when the battery is charged.

Kabir (2016) noted that the literature on AGV systems generally ignores battery management as it is assumed that the effect of battery management is negligible. He also stated that the location of battery stations and the issue of how battery management can affect the AGV fleet size have gotten very scant attention in the literature. The results of the study also showed that a firm can have better productivity consistently if it considers the travel distance and waiting time while routing an AGV for battery replacement.

Kabir and Suzuki (2018) developed a discrete event simulation model to explore the possibility of increasing manufacturing capacities in the short run through battery management of automated guided vehicles. They noted that there has not been sufficient research in this area in spite of the imperative role of battery management in determining the throughput and performance of an AGV system. They stated that although many complex models of AGV systems have already been built, there has been hardly any papers that explored how adjusting the battery charging durations can enhance the manufacturing efficiency. Their research focused on studying how varying the length of charging time can increase the output of a manufacturing system without increasing the number of AGVs. In their research, lead acid batteries were used and the type of charging used was automatic charging. The results of their simulation showed that a company can increase its manufacturability flexibility considerably if it reduces the targeted state of charge (SOC) for its AGV batteries. Firms can you use this method to increase productivity to meet sudden increases in the market demand without having to invest in additional AGVs (Kabir and Suzuki, 2018). Another important issue of an AGVS that can be significantly affected by battery management is dispatching, for which there has been a number of scholarly works but very few of them incorporated battery management in the dispatching decision for the AGVs (Kabir and Suzuki, 2018).

Kabir and Suzuki (2019) developed discrete event simulation models to explore how different routing techniques for the battery management of AGVs can affect the performance of a system. They noted that the literature on the battery management of AGVs is sparse and that it is important that battery management of the AGVs is addressed adequately to run an AGV system efficiently. Their study used different heuristics to route the AGVs to battery stations at a manufacturing facility when the depleted batteries of the AGVs need to be replaced (battery swapped) with fully charged batteries (Kabir and Suzuki, 2019). The effects of these different heuristics on the productivity of the facility were then compared. The four heuristics used in this study were: selecting the nearest battery station (NBS), selecting minimum delay battery station

(MDBS), selecting the nearest battery station from initial point (NBSIP), and selecting the nearest battery station to drop-off point (NBSDP). Their study did not consider opportunity swap as the research was based on a busy facility where there is not much AGV idle time. The results of their simulation showed that MDBS performed the best in terms of productivity of the system. MDBS heuristic selects the battery station that will minimize total time for traveling and waiting at the battery station. It was also found that the more frequently a system allows the AGVs to make decisions about battery swapping or not, the better the productivity of that system (Kabir and Suzuki, 2019).

2.3 Research Gap and Research Questions

Determining the optimized number of AGVs that is capable of meeting the material handling requirements of the system thus maximizing the throughput rate is important. Several models and methods have been applied to determine the fleet size. Most of these models and methods do not incorporate the battery usage of the vehicles and the effect it can have on the throughput and the number of AGVs required for the system. The goal of this research is to develop a discrete event simulation model to determine the optimized number of AGVs that is capable of meeting the material handling requirements of the system thus maximizing the throughput rate. This model will incorporate the battery management aspect and issues, which are usually omitted in AGV research. With this research gap, the following research questions will be addressed:

1) What is the most favorable opportunity charging strategy to optimize the AGV fleet size and meet the material handling requirements of the system? This will include the most favorable minimum charge level to send the AGV for opportunity charging, the most favorable minimum critical ratio to release the AGV from opportunity charging, how long

to wait before sending an idle AGV for opportunity charging, how long the AGV should charge for, and the dispatching rule when charging.

2) What is a more favorable number and location of charging stations to optimize the AGV fleet size and meet the material handling requirements of the system? This will also take into consideration centralized VS decentralized charging, and the capacity of each of the charging stations.

3) What is the most favorable automatic charging strategy to optimize the AGV fleet size and meet the material handling requirements of the system? This will include the most favorable minimum critical ratio to release the LGV from charging, how long the AGV should charge for, and the dispatching rule when charging.

The developed discrete even simulation model will be used to address the research questions and will incorporate the maintenance and extended charging of the AGVs which is usually not included in the models developed in AGV research.

CHAPTER 3

METHODOLOGY

This chapter is dedicated to discuss the research methodology utilized. The simulation model structure is discussed along with the different parts and functions of the simulation which provides a clear understanding of the logic implemented. The simulation results are then compared to the actual output data obtained for verification and model validation.

3.1 Simulation Model

A discrete event simulation model is developed based on an existing base model to test the research questions in this study. Arena software (version 15.0) is used to extend, run, and test the simulation model. There are many reasons for selecting simulation to be used in this research. In modeling complex systems like AGV systems, since there are many variables and parameters, using the simulation technique is very useful in modeling these systems (Kesen and Baykoc, 2007). Simulation also allows to accurately depict the real system as there are less assumptions made compared to any analytical model and it takes into account the randomness and interdependencies which are prevalent in the real environment. As many scenarios need to be evaluated, simulation makes it easy to make changes and run the simulation many simulated months and view the results very quickly. With the animated visualizations it makes it possible to track each event and verify the model. The animated visualization also makes it easy to communicate a complex model like an AGV system and ensure the audience understand the model.

This research is motivated by a real manufacturing facility that uses LGVs (a specific type of AGVs) as a primary material handling system. Although the specifics of this facility will not be disclosed in this research, the methodology will be generalizable to other similar facilities with an AGV material handling system. The model will capture the AGVs' movements to pick up and drop off material between the different pick up and drop off points such as the warehouse and the different areas in the facility such as assembly lines. The model will also capture the AGVs' regular visits to the charging stations. Planned AGV maintenance and extended charging will also be incorporated in the model. AGVs can do automatic charging, opportunity charging, and extended charging. In the model, automatic charging is setup so that an AGV will run until its battery charge has decreased to a certain predefined level. Once this level is reached, the AGV is routed to a charging station where the battery is recharged to an adequate level. Opportunity charging is setup so that if an AGV is idle it can go charge until there is a transportation task. Extended charging is overnight charging and is defined as charging two AGVs per night for 8 hours.

The developed simulation model is used to study and analyze aspects related to the AGV batteries and their effect on throughput and AGV fleet size. This includes the charging strategies, the number and location of charging stations, maintenance, and extended charging. Various scenarios will be studied by applying different charging strategies and changing different parameters to achieve improved throughput and an optimized AGV fleet size.

3.2 Simulation Model Structure

The manufacturing facility under study consists of 15 AGVs and 3 charging locations with specified capacities. Within the facility there are 22 drop off areas and 16 pickup areas and each of them has a specified capacity. A basic layout of the manufacturing facility with the charging locations is displayed in Figure 1. The manufacturing facility is made up of 3 plants and a warehouse as shown in the figure. It is important to note that the AGV pathways are unidirectional in the whole facility except one area in the facility which is bidirectional.

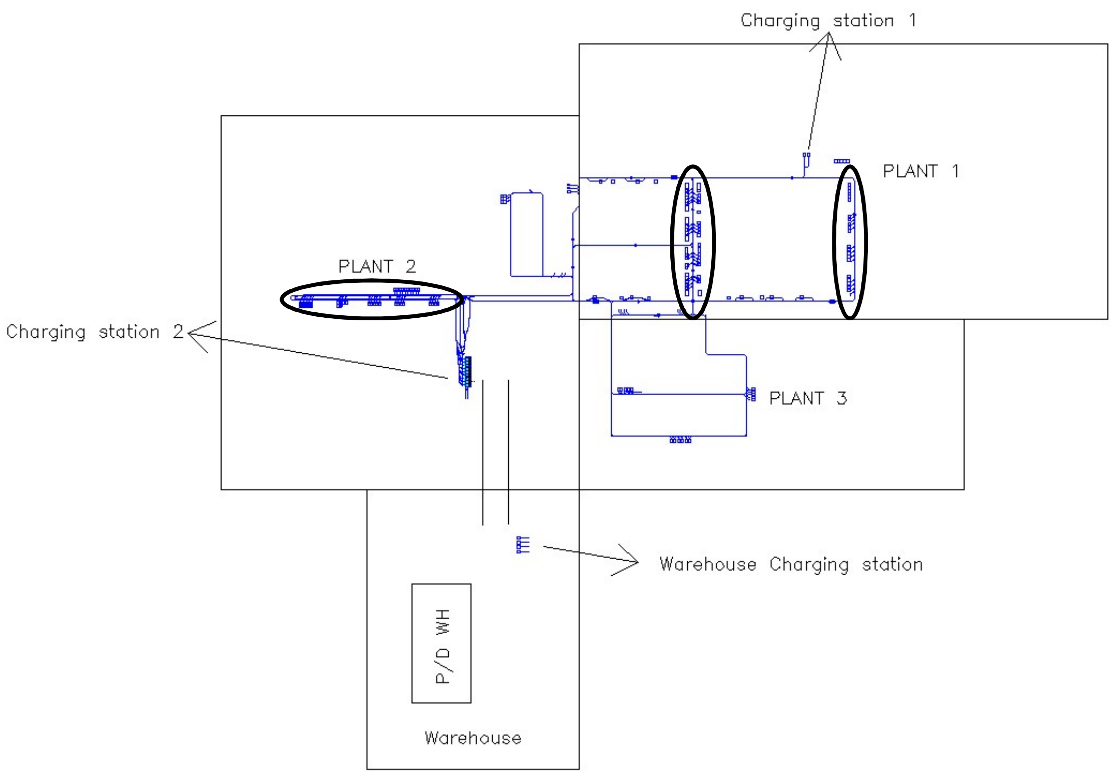

Figure 1: Basic Layout of Manufacturing Facility

To ensure that only one AGV at a time can access a specific drop off or pickup area, blocking zones (BZ) are modeled in the drop off / pickup areas so that other AGVs have to wait for their turn. Some of the pickup and drop off areas are circled in Figure 1. P/D WH is the pickup and drop off area for the warehouse.

3.2.1 Load Pickup

The logic in Figure 2 represents how loads are created and driven to be picked up by AGVs and transported to a certain location. This particular case is demonstrated for a pickup area in Plant 1, and other areas follow a similar logic. Entities (loads) are created at a certain rate according to a statistical distribution that is based on historical data. The number of loads created was recorded and verified to ensure this number is realistic. The entities are directed to a station that physically represents the pickup area. The loads are then assigned an attribute that represents the drop off location. In this case, the load will be dropped off at the warehouse. The load then occupies a space that is modeled as a resource. The amount of space is dictated by the number of pick up squares at the actual area. In case of this pickup area, there are 10 pickup spaces (or squares) and a load would occupy one of them. If all spaces are occupied, the load will have to wait in line until one becomes available. In the model, the pickup spaces are defined as a resource and for this particular pickup area it has a capacity of 10.

Once a space is occupied, an AGV transporter is requested if available; otherwise, a variable is assigned to 1 to request AGV to be released if any are opportunity charging. If none are opportunity charging, the load will have to wait until an AGV becomes available to come for pickup.

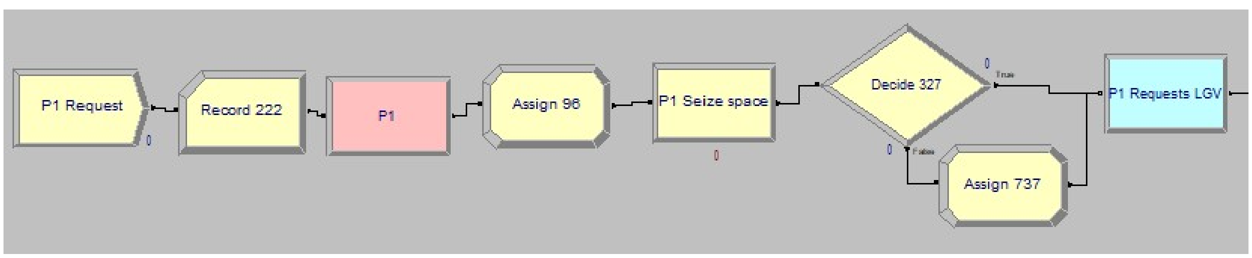

Figure 2: Load (entity) Creation for Pickup

The remainder of the logic is then continued in Figure 3 in which the AGV picks up a load, the variable requesting an AGV is turned back to zero indicating that an AGV is no longer needed. When the AGV arrives to pick up the load, a resource defined as Blocking Zone (BZ) with capacity of 1 is seized to model the fact that no other AGV can get into the area to pick up or drop off before this resource is released. Note that there is only one BZ resource per area (for all pick up and drop off spaces). The pickup location is then saved in order to later calculate the distance traveled between pick up locations and drop off locations. Before the load is transported, the entity goes into the submodel displayed in Figure 4 which models the potential for the AGV to stop due to various reasons or errors.

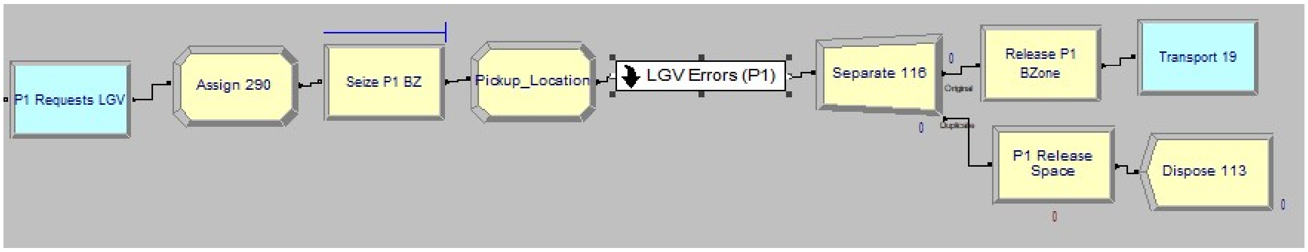

Figure 3: Load (entity) Pickup

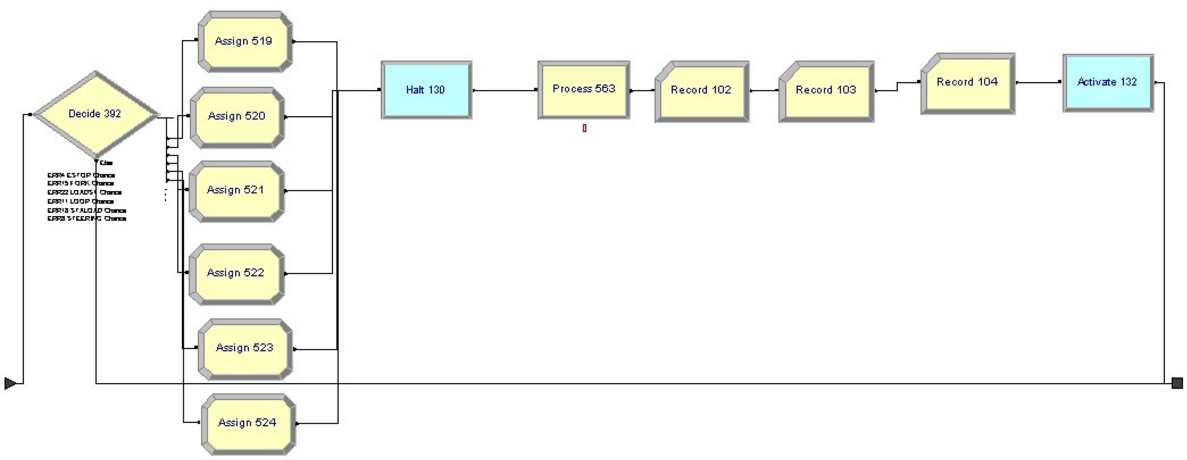

Figure 4: Submodel for LGV Errors

For the submodel shown in Figure 4, the most common reasons that make the AGVs stop are considered and are associated with Event Codes which are referred to in the simulation as errors. Based on historical data of errors, the simulation will make the AGV stop with a certain probability. If the AGV happened to stop, the simulation will halt it for a duration that is also based on a distribution derived from the historical data. Once the AGV resumes working, the entity then releases both the space and the blocking zone. The entity is then transported by the AGV to the warehouse. The previous logic is repeated for the various areas including the warehouse and the different drop off areas.

3.2.2 Load Drop Off

The logic in Figure 5 represents the process of dropping off loads (entities) at a certain drop off location. This particular case is demonstrated for a drop off area in Plant 1. Loads get assigned a drop off location somewhere else in the model according to the historical data depending on how often areas receive loads. Upon the arrival of the AGV with a load to an area, the AGV seizes the Blocking Zone (BZ) for the area to prevent other AGVs from getting access to the area in the meantime. If the BZ is already occupied by another AGV, the current AGV will have to wait until the BZ becomes available. Once the AGV seizes the BZ, it then seizes a drop off space at which the load is placed. Drop off spaces have been modeled as resources that must be acquired before loads can occupy them. The number (or capacity) of such resources represents the number of spaces available in the plant for the specific area. In this example, the drop off area has 5 drop off spaces that are modeled as a resource with a capacity of 5.

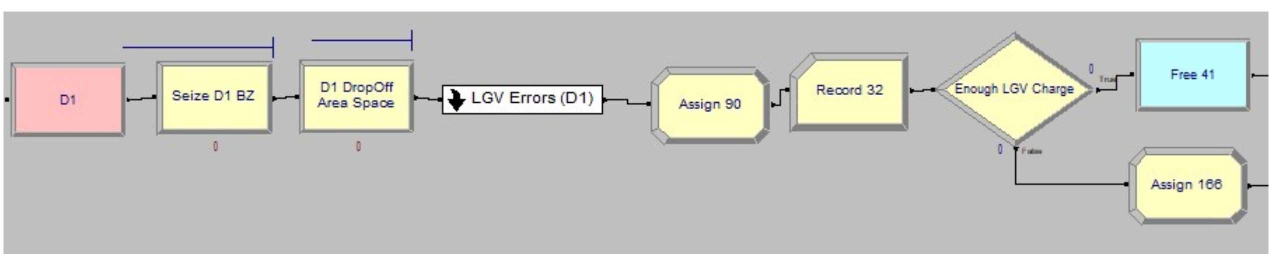

Figure 5: Load (entity) Drop Off

After the space is seized, there is a possibility that the AGV gets stuck for one of the different reasons discussed previously. The submodel AGV Errors (D1) has the exact same logic like the pickup area discussed earlier with the difference being that the statistics are collected for this specific drop off area. Upon the completion of the drop off activity, an assign module is used to give the entity controlling the AGV three important attributes shown in Figure 6. It first assigns the network location for this particular AGV within the network. Second, it calculates the amount of battery used (ElecUsed) to perform this drop off by multiplying the battery consumption rate factor by the distance traveled between the pickup location and the drop off location. This is achieved using the IDSNET variable in Arena. Finally, the battery level is updated by subtracting the ElecUsed from last recorded battery charge level. The description of the battery consumption is provided in the AGV charging section.

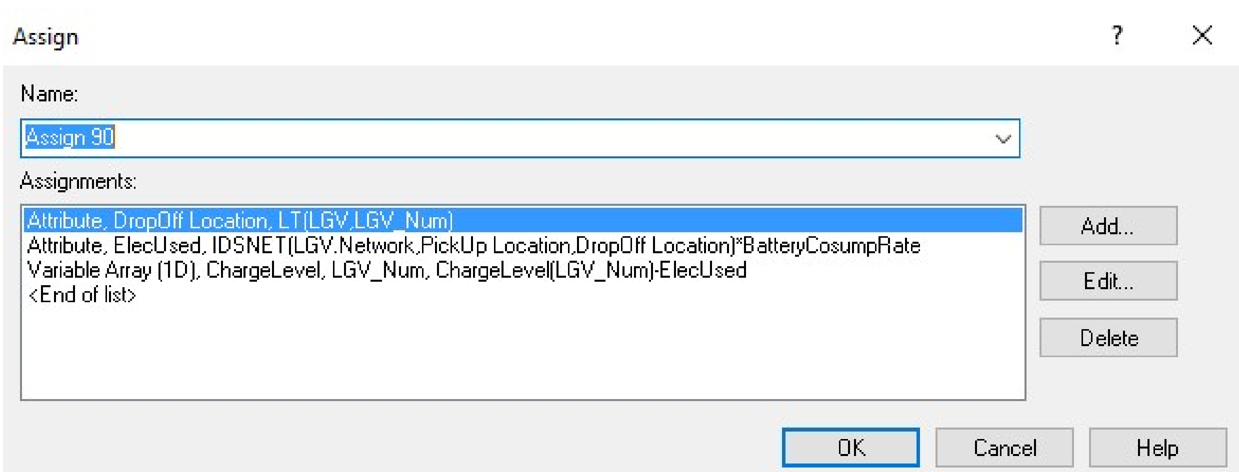

Figure 6: Attribute and Variable Assignment

After this assignment, the number of drop off statistic is updated. Figure 7 describes the logic afterwards where the model checks whether the AGV battery is still above the minimum acceptable battery level of 30%. This minimum acceptable battery level is for automatic charging and is based on the recommendation of the battery manufacturer. The minimum acceptable battery level for automatic charging will be referred to as MAB. If this condition is met, the AGV is then freed to serve the next request waiting, and it releases both the drop off space and the Blocking

Zone (BZ) to be used by other loads. If the condition is met and the AGVs have no work to do, they go to a charging area for what is known as "opportunity charging" to charge the battery instead of leaving the AGV idle. To accomplish this, and after the AGV, the space and BZ are freed, the AGV is delayed for a short time to give a chance for a new order to put a hold on this AGV. If after this short delay, there are still no orders for it, it is allocated and routed to a charging area for opportunity charging. The logic for selecting a charging area is discussed in the AGV Charging section.

If the AGV's charge level falls below the MAB of 30%, the AGV is immediately routed to a charging area after the drop off space and BZ are released for use by other AGVs. The logic for other drop off areas is very similar to the logic described here except for the information and data that are area-specific.

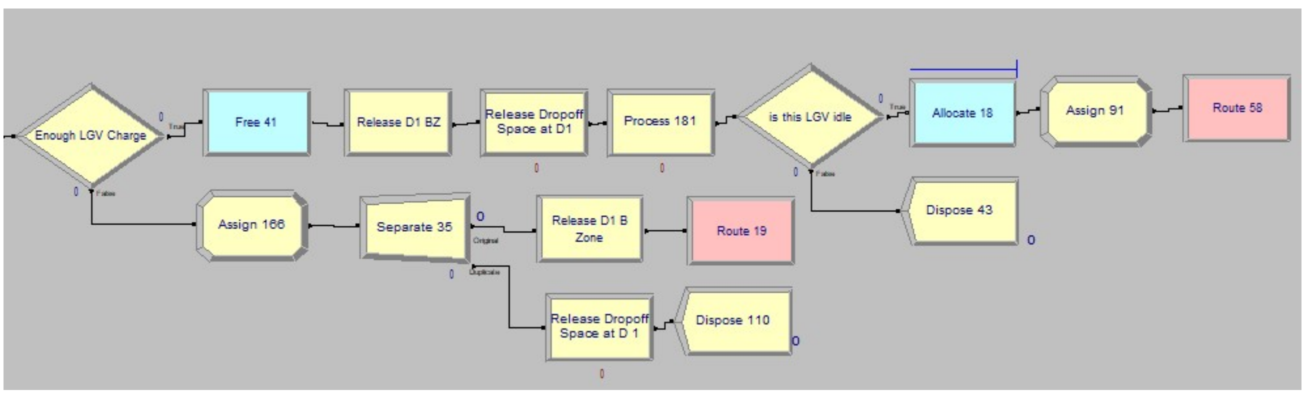

Figure 7: Load (entity) Drop Off

3.2.3 AGV Charging

The section titled "Choose a Charging Station" in the model is displayed in Figure 8 and is used as a decision making function to determine to which charging area to send AGVs depending on whether they need opportunity charging, extended (overnight) charging, or to bring the battery level above the MAB. Note that this part of the model does not correspond to a physical area, but rather is used purely as a decision support function to aid the AGVs to make a decision on where to charge depending on their charge level, location, and the availability of chargers. As mentioned previously, there are three charging stations: charging station 1 with 2 chargers, charging station 2 with 7 chargers, and the warehouse charging station with 4 chargers. Whenever a decision needs to be made regarding charging, the “choose charging station” logic is used. Upon the arrival of the entity that controls the AGV to this section, it follows the following rules:

1. If the AGV needs extended (overnight) charging, it is sent to charging station 2. Extended charging is defined as charging two AGVs per night for 8 hours. The Extended charging logic cycles through the AGVs at the rate of two per night.
2. If the AGV requires automatic charging (i.e., when charge level falls below MAB of 30%), it is sent to charging station 2 if a charger is available; otherwise it is sent to the closest of the other two charging stations depending on the AGV’s current location.
3. If the AGV is going for opportunity charging, it is sent to the closest charging area if a charger is available. If not, it is sent to the next closest.

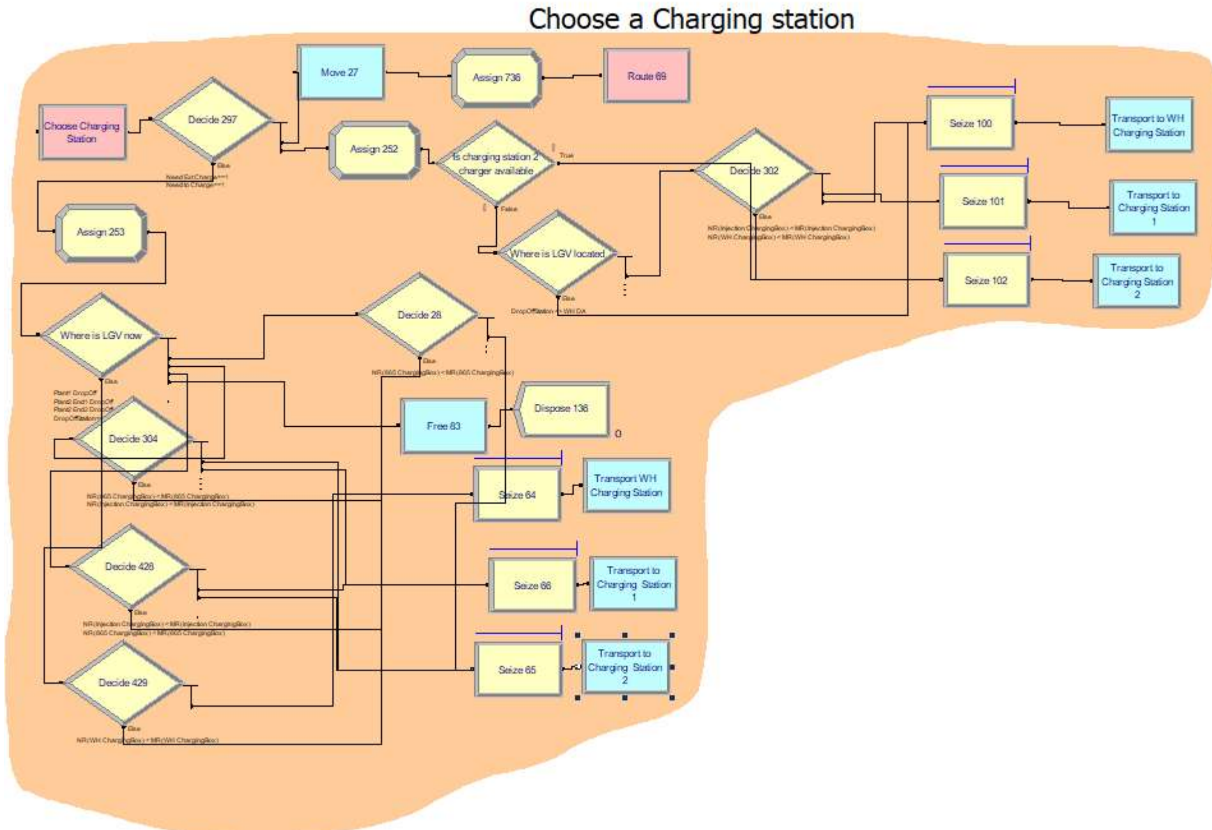

Figure 8: Logic for Choosing a Charging Station

Upon the arrival of the AGV (and the controlling entity) to one of the three charging areas (see Figure 9 for charging station 2), the model makes some important assignments as shown in Figure 10:

1. It marks the start of charging time to track how much charging to do

2. Records the AGV location

3. Records the amount of battery used (ElecUsed) from the last operation

4. Updates the charge level by subtracting the ElecUsed

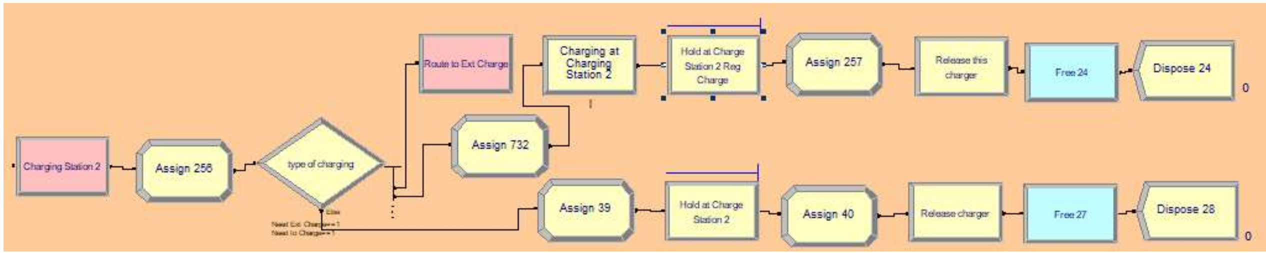

Figure 9: Charging Station 2

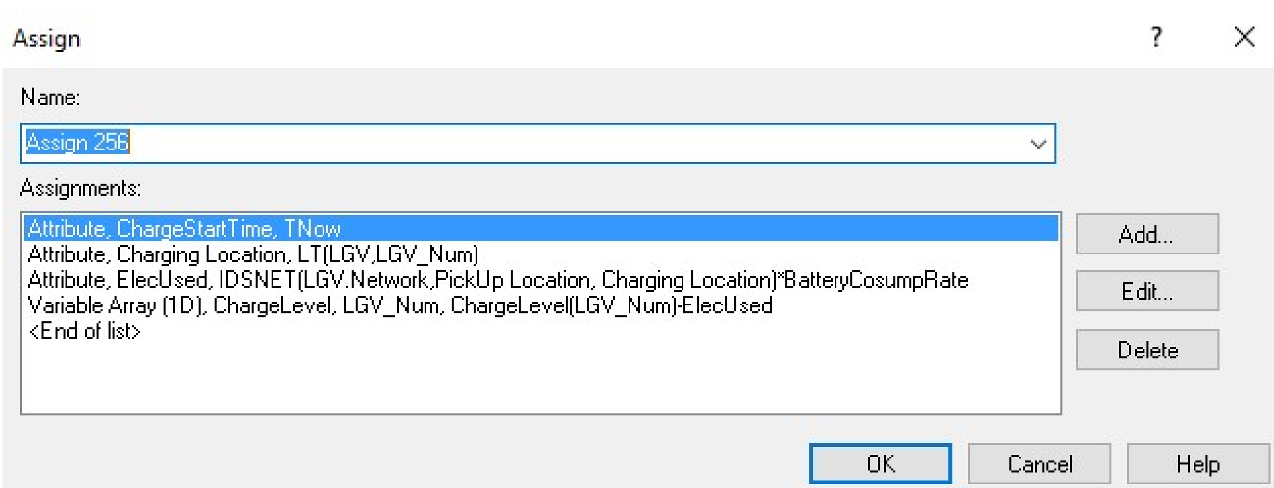

Figure 10: Attribute and Variable Assignments of Charging Station 2

If the charging needed is Extended charging (overnight charging), the AGV is routed to the Extended Charging logic. If the charging required is due to reaching the MAB, the AGV is then placed on the charger for a period of time enough to bring the charger level to at least 35%. It is then kept on the charger as long as there is no requests for it. The charge level is then recorded by using the following equation:

$$Min(100, ChargeLevel(LGV\_Num) + (ChargeEndTime - ChargeStartTime) * ChargeRate) \quad (1)$$

The charge rate is assumed to be 8.75 which was based on the assumption that the AGV battery needs 8 hours to charge from 30% to 100%. Therefore, the AGV charge rate is 8.75% per an hour of charging. So if the AGV is at 50% charge level, and charges for 2 hours, the charge level of the AGV after 2 hours of charging would 50% + (8.75%*2) = 67.5%.

The minimum critical ratio is the ratio of the battery charge level to the distance to the pickup destination. The minimum critical ratio would apply to both opportunity charging and automatic charging. So before the AGV is released to be considered for a transportation task from either automatic charging or opportunity charging it needs to meet the minimal critical ratio.

The last condition is when the AGV arrives to the charging area for opportunity charging, in which case it will be held on the charger until it is requested by a pickup order. The logic for the Warehouse Charging Station and Charging Station 1 are similar to Charging Station 2 discussed above.

3.2.4 AGV Battery Consumption Rate

For the simulation to capture the points in time at which the minimum battery level is reached, it is necessary to know the rate at which AGV battery is consumed per distance unit. Such consumption rate is dependent on several factors including whether the AGV is loaded, empty or double-stacked, the terrain of the AGV pathways, the number of turns, among some other factors. It is necessary to get an average factor under different conditions to use in the simulation.

A small scale *time-and-motion* study was conducted by observing different AGVs (empty and loaded) going between different areas and the battery levels were recorded. Since the distances between the different points are known, it was possible to calculate the consumption rate per foot which turned out to be 0.0011/ft. This factor is multiplied by the distance when a load is dropped off and before the AGV is freed to pick up another load according to the following equation:

$$ElecUsed = IDSNET(LGV.Network, PickUpLocation, DropOffLocation) * BatteryConsumptionRate \quad (2)$$

The function IDSNET is a built-in Arena function that returns the distance traveled between two locations on a certain network.

To verify the consumption rate, the ampere draws for the different activities of an AGV presented in McHaney (1995) were used. Kabir and Suzuki (2018) also used the ampere draws presented by McHaney (1995). Table 1 shows the data presented in Kabir and Suzuki (2018).

Ampere draws for different activities of an AGV.
Source: McHaney (1995).

AGV activity	Ampere draw from battery
Blocking	5 A
Traveling empty	40 A
Traveling loaded	60 A
Accelerating empty	55 A
Accelerating loaded	75 A
Decelerating empty	55 A
Decelerating loaded	50 A
Picking	60 A
Dropping	40 A

Table1: Ampere draws for activities of an AGV (Source: Kabir and Suzuki, 2018)

The AGV considered in the model has a battery capacity of 310 ampere-hours. Each time an AGV performs an activity, the corresponding ampere draw is calculated. The ampere-hours lost by the battery is calculated by multiplying the ampere draws for that activity by the number of hours the AGV performs that activity. For our example: the AGV traveled 923 ft in 4.8 minutes. The AGV traveled loaded for 1.0 minutes, traveled empty for 2.8 minutes, and dropped off for 1 minute. The ampere draws for an AGV traveling loaded is 60 A. So the AGV lost 1 ampere-hours (i.e., 60 A×0.0167 h). The ampere draws for an AGV traveling empty is 40 A. Therefore, the AGV lost 1.87 ampere-hours (i.e., 40 A×0.0467 h). The ampere draws for an AGV dropping off is 40 A. Therefore, the AGV lost 0.67 ampere-hours (i.e., 40 A×0.017 h). So the AGV lost a total of 3.54 ampere-hours which is 1.14 % of the charge level. Based on the *time-and-motion* study the consumption rate was 0.0011 / ft. If the AGV traveled 923 ft, then the charge level used is 1.015, which is 1.02 % since the total charge level is 100. Using this data, we verified that the result of the *time-and-motion* study is a good estimation of the consumption rate. It was decided to use the consumption rate developed through the *time-and-motion* study instead of implementing the actual ampere draws for each of the activities which would take into consideration: the AGV being loaded or empty, the terrain, the acceleration and deceleration, and the different speeds in the different areas of the facility. The reason for this is the level of complexity required to implement in the simulation model. In addition, any changes to the facility or loads in the different areas would require these values to be changed in the specific areas. The minimal gain in the accuracy of the calculation of the consumption rate is not worth the complexity of implementation especially because the consumption rate developed through the *time-and-motion* study provided approximately 90% accuracy.

3.2.5 Input Analysis

For a simulation to be valid, it needs to be driven by valid data input. To obtain valid data, historical data is queried and fitted into statistical distributions that represent the different rates, frequencies, and processing times.

The demand level or the rate at which entities (loads) are created at each pickup area is based on historical data. The historical data was queried and fitted into a statistical distribution that represented the rate at which entities are created. This was applied to each of the pickup areas. As an example of a pickup area in Plant 1, the fitting results are displayed in Figure 11 and Table 2.

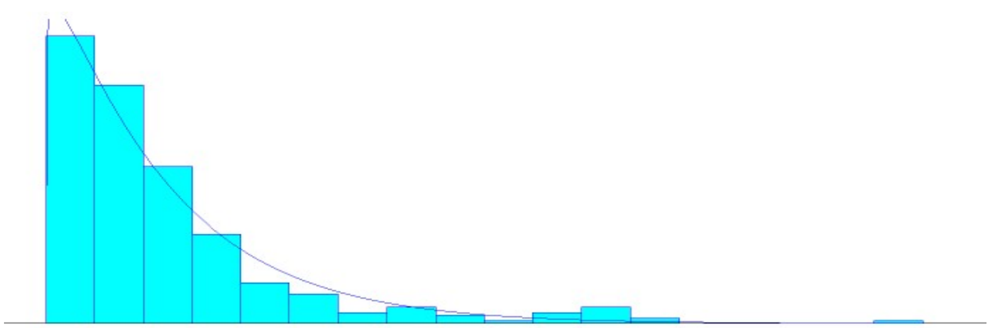

Figure 11: Histogram and Distribution for Pickup Area in Plant 1

Distribution:	Gamma
Expression:	6 + GAMM(531, 1.08)
Square Error:	0.002633
Chi Square Test	
Number of intervals	8
Degrees of freedom	5
Test Statistic	14.2
Corresponding p-value	0.0162
Kolmogorov-Smirnov Test	
Test Statistic	0.0715
Corresponding p-value	0.063
Data Summary	
Number of Data Points	338
Min Data Value	6
Max Data Value	4220
Sample Mean	579
Sample Std Dev	603

Table 2: Distribution and Input Data Summary for Pickup Area in Plant 1

Based on the results for this specific pickup area, a Gamma distribution was the best fit although it did not pass the chi-square but did pass the K-S test. This distribution was accepted to model the demand generation for loads at this area with the interarrival time following this Gamma distribution.

As another example of a pickup area, this is in Plant 2, the fitting results are displayed in Figure 12 and Table 3.

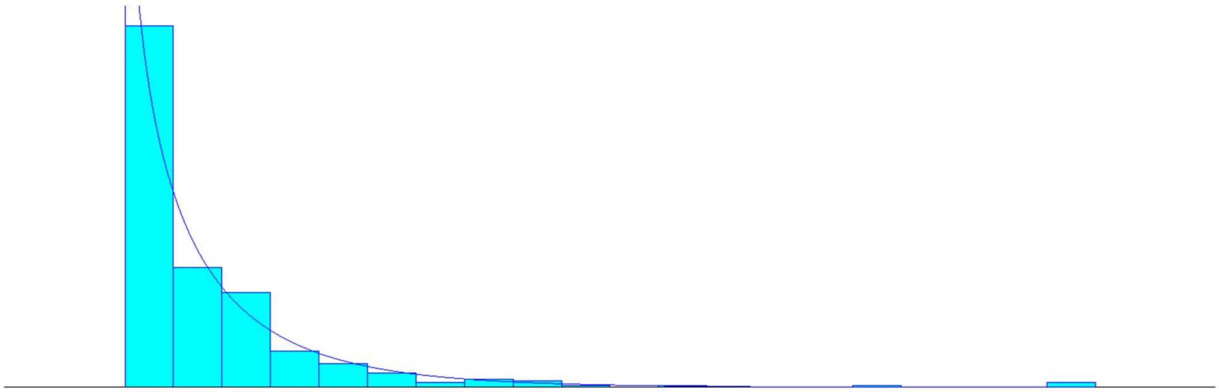

Figure 12: Histogram and Distribution for Pickup Area in Plant 2

Distribution:	Weibull
Expression:	WEIB(201, 0.822)
Square Error:	0.002704
Chi Square Test	
Number of intervals	7
Degrees of freedom	4
Test Statistic	7.82
Corresponding p-value	0.0987
Kolmogorov-Smirnov Test	
Test Statistic	0.0313
Corresponding p-value	> 0.15
Data Summary	
Number of Data Points	430
Min Data Value	0.15
Max Data Value	2630
Sample Mean	226
Sample Std Dev	316

Table 3: Distribution and Input Data Summary for Pickup Area in Plant 2

Based on the results for this specific pickup area, a Weibull distribution was the best fit as it did pass both the chi-square test and the K-S test. This distribution was accepted to model the demand generation for loads at this area with the interarrival time following this Weibull distribution. This input analysis process is followed with all areas at which pickup events occur.

When loads are picked up from the warehouse by the AVGs, they are dropped off at the different plants based on their predefined destination as specified by a bar code on each load. The AGVs pass by a scanner to read the bar code and deliver the load accordingly. The demand for dropping off loads differs by area where some areas receive more loads than others. Historical data is used in the simulation to probabilistically determine where to drop off the load. This distribution is included in the model as an empirical distribution.

3.2.6 Number of Replications

The replication length used for this model was 6 months. It was noted that the model goes into steady state after about 30 days; therefore, a simulation warm-up period of 30 days (720 hours) was used. The number of loads dropped off at the different areas reflects the amount of throughput in the system. At first, the number of replications tested was 10. With 10 replications the half width of the 95% confidence interval of throughput was between 9% and 13% of the average throughput for each of the drop off areas, this is displayed in Table 4.

Drop off Area	Average Throughput	Half Width	Half Width Percentage of Avarage Throughput
1	22.30	2.78	12.47%
2	37.80	4.66	12.33%
3	3017.10	288.78	9.57%
4	1046.30	109.32	10.45%
5	1193.30	122.76	10.29%
6	2001.00	207.38	10.36%
7	741.20	73.37	9.90%
8	792.80	94.38	11.90%
9	3341.20	336.06	10.06%
10	351.10	34.28	9.76%
11	1175.30	139.30	11.85%
12	7096.40	708.68	9.99%
13	147.50	15.34	10.40%
14	5738.40	609.70	10.62%
15	752.10	81.55	10.84%
16	3669.90	377.05	10.27%
17	421.30	50.59	12.01%
18	4553.60	495.53	10.88%
19	170.30	20.26	11.90%
20	4096.10	413.87	10.10%
21	2132.00	219.57	10.30%
22	60429.90	6958.24	11.51%

Table 4: Average Throughput and Half Width with 10 replications

To determine the number of replications to be used the confidence interval method is used. The advantage of the confidence interval method is, that it uses output data from the model and it also provides a statistical measure of precision (Hoad et al., 2010). To have confidence in the results and conclusions, the desired confidence interval reliability is between 0.90 and 0.95, which means a half width between 5% and 10%. In order to try to achieve this, the number of replications was changed to 30 replications. With 30 replications the half width of the 95% confidence interval of throughput was no more than 10% of the average throughput for each of the drop off areas except for the second drop off area that has one of the smallest number of drop offs, this is displayed in Table 5.

Drop off Area	Average Throughput	Half Width	Half Width Percentage of Avarage Throughput
1	20.80	1.94	9.33%
2	36.57	3.74	10.23%
3	2881.70	234.57	8.14%
4	998.87	82.41	8.25%
5	1133.63	93.38	8.24%
6	1908.17	155.87	8.17%
7	708.83	57.43	8.10%
8	753.03	63.57	8.44%
9	3186.70	259.88	8.16%
10	333.53	27.97	8.39%
11	1111.50	93.97	8.45%
12	6748.03	547.71	8.12%
13	144.17	11.54	8.00%
14	5489.17	442.82	8.07%
15	726.20	60.04	8.27%
16	3521.47	286.52	8.14%
17	394.93	33.89	8.58%
18	4371.17	365.02	8.35%
19	162.97	14.63	8.98%
20	3908.00	316.28	8.09%
21	2039.70	167.21	8.20%
22	57941.80	4986.26	8.61%

Table 5: Average Throughput and Half Width with 30 replications

To determine the number of replications required to achieve a half width (Hoad et al., 2010) between 5% and 10% the below formula is used to estimate the number of replications needed for a specific half width.

$$n = t^2_{n-1,1-\alpha/2} \frac{s^2}{h^2} \tag{3}$$

n is the number of replications

$t_{n-1,1-\alpha/2}$ is the t distribution critical value which is also dependant on the number of replications

h is the specific half width to be achieved

s is the sample standard deviation

Since the right side of the equation still depends on the number of replications n, an approximation of the sample size required can be done by replacing the t distribution critical value in the formula with the standard normal critical value. The equation would be as follows:

$$n \cong z_{1-\alpha/2}^{2} \frac{s^{2}}{h^{2}} \tag{4}$$

$z_{1-\alpha/2}^{2}$ is the standard normal critical value which is 1.96 for a 95% confidence interval

h is the specific half width to be achieved which is about 7.5%

s is the sample standard deviation for each of the drop off areas. The standard deviation for each of the drop off areas from the 30 replication run is displayed in Table 6.

Drop off Area	Average Throughput	Sample Standard Deviation
1	20.80	5.21
2	36.57	10.02
3	2881.70	628.27
4	998.87	220.73
5	1133.63	250.09
6	1908.17	417.49
7	708.83	153.82
8	753.03	170.25
9	3186.70	696.04
10	333.53	74.91
11	1111.50	251.69
12	6748.03	1466.95
13	144.17	30.92
14	5489.17	1186.03
15	726.20	160.80
16	3521.47	767.39
17	394.93	90.77
18	4371.17	977.66
19	162.97	39.19
20	3908.00	847.11
21	2039.70	447.83
22	57941.80	13354.94

Table 6: Average Throughput and Sample Standard Deviation with 30 replications

The number of replications required to achieve a half width of the 95% confidence interval of throughput of 7.5% of the average throughput for each of the drop off areas is displayed in Table 7.

Drop off Area	Average Throughput	Sample Standard Deviation	7.5% Half Width	Number of Replications
1	20.80	5.21	1.56	43
2	36.57	10.02	2.74	51
3	2881.70	628.27	216.13	32
4	998.87	220.73	74.92	33
5	1133.63	250.09	85.02	33
6	1908.17	417.49	143.11	33
7	708.83	153.82	53.16	32
8	753.03	170.25	56.48	35
9	3186.70	696.04	239.00	33
10	333.53	74.91	25.01	34
11	1111.50	251.69	83.36	35
12	6748.03	1466.95	506.10	32
13	144.17	30.92	10.81	31
14	5489.17	1186.03	411.69	32
15	726.20	160.80	54.47	33
16	3521.47	767.39	264.11	32
17	394.93	90.77	29.62	36
18	4371.17	977.66	327.84	34
19	162.97	39.19	12.22	39
20	3908.00	847.11	293.10	32
21	2039.70	447.83	152.98	33
22	57941.80	13354.94	4345.64	36

Table 7: Required Number of Replications to Achieve a Half width of the 95% Confidence Interval of Throughput of 7.5% of the Average Throughput

Based on the results in table 7 the approximate number of replications needed to achieve a half width of the 95% confidence interval of throughput of 7.5% of the average throughput for each of the drop off areas is 35 replications. To confirm this approximation the model was run with 35 replications and the results are displayed in Table 8.

Drop off Area	Average Throughput	Half Width	Half Width Percentage of Avarage Throughput
1	20.71	1.86	8.98%
2	36.14	3.48	9.63%
3	2874.89	220.34	7.66%
4	991.97	76.30	7.69%
5	1126.46	87.17	7.74%
6	1902.77	145.80	7.66%
7	700.94	53.49	7.63%
8	750.23	59.91	7.99%
9	3176.23	244.24	7.69%
10	330.91	25.46	7.69%
11	1107.97	86.57	7.81%
12	6717.63	507.90	7.56%
13	144.49	10.63	7.36%
14	5455.71	413.10	7.57%
15	723.14	55.23	7.64%
16	3501.09	267.58	7.64%
17	391.80	30.72	7.84%
18	4347.60	339.81	7.82%
19	161.37	13.41	8.31%
20	3895.57	296.19	7.60%
21	2030.26	154.92	7.63%
22	58007.37	4604.55	7.94%

Table 8: Average Throughput and Half Width with 35 replications

With 35 replications the half width of the 95% confidence interval of throughput was between 7% and 8% of the mean for most measures. Hence, it was concluded that this is a good number of replicates and will be used for evaluating the scenarios and addressing the research questions.

3.2.7 Model Validation

To validate the model, its output is compared with the real historical data. If the model is valid to a good degree of confidence, it should produce results that are close to the real data; however, it is not expected to produce the exact same output like the historical real data because the model is probabilistic and will always deviate from the real data due to natural variability; otherwise it will be a deterministic model that will always produce the same results, which is not what is expected from a simulation model.

The metric used to validate the model is the number of loads dropped off at the different areas, which reflects the amount of throughput in the system. Table 9 shows a comparison of the real data and the simulation results in terms of the number of drop offs over 6 months.

	Real Data	Simulation			
				95 % Confidence Interval	
Drop off Area	Real Number of Drop Offs	Average Throughput	Half Width	Lower Limit	Upper Limit
1	21	20.71	1.86	18.85	22.57
2	37	36.14	3.48	32.66	39.62
3	2886	2874.89	220.34	2654.55	3095.23
4	993	991.97	76.30	915.67	1068.27
5	1134	1126.46	87.17	1039.29	1213.63
6	1925	1902.77	145.80	1756.97	2048.57
7	704	700.94	53.49	647.45	754.43
8	761	750.23	59.91	690.32	810.14
9	3197	3176.23	244.24	2931.99	3420.47
10	324	330.91	25.46	305.45	356.37
11	1118	1107.97	86.57	1021.40	1194.54
12	6780	6717.63	507.90	6209.73	7225.53
13	147	144.49	10.63	133.86	155.12
14	5497	5455.71	413.10	5042.61	5868.81
15	731	723.14	55.23	667.91	778.37
16	3523	3501.09	267.58	3233.51	3768.67
17	391	391.80	30.72	361.08	422.52
18	4362	4347.60	339.81	4007.79	4687.41
19	161	161.37	13.41	147.96	174.78
20	3923	3895.57	296.19	3599.38	4191.76
21	2030	2030.26	154.92	1875.34	2185.18
22	61587	58007.37	4604.55	53402.82	62611.92

Table 9: Comparison between the Number of Real Drop Offs and Simulated Drop Offs

The simulation results are based on running the model for 35 replicates with each replicate being 6 months. Although there are differences between the simulated and real data, it is expected to have some differences due to the stochastic nature of the model but in all cases the real data falls within the 95% confidence interval, which is a good indication of validity.

Table 10 shows the difference between the number of real drop offs and the number of simulated drop offs. The last column shows the difference as a percentage between both which is less than 1% for most of the drop off areas. This is a very strong indication of the model's validity.

Drop off Area	Real Number of Drop Offs	Average Throughput	Difference Between Real and Simulated Drop Offs	Absolute Difference in Drop Offs	% Difference
1	21	20.71	0.29	0.29	1.38%
2	37	36.14	0.86	0.86	2.32%
3	2886	2874.89	11.11	11.11	0.38%
4	993	991.97	1.03	1.03	0.10%
5	1134	1126.46	7.54	7.54	0.66%
6	1925	1902.77	22.23	22.23	1.15%
7	704	700.94	3.06	3.06	0.43%
8	761	750.23	10.77	10.77	1.42%
9	3197	3176.23	20.77	20.77	0.65%
10	324	330.91	-6.91	6.91	2.13%
11	1118	1107.97	10.03	10.03	0.90%
12	6780	6717.63	62.37	62.37	0.92%
13	147	144.49	2.51	2.51	1.71%
14	5497	5455.71	41.29	41.29	0.75%
15	731	723.14	7.86	7.86	1.08%
16	3523	3501.09	21.91	21.91	0.62%
17	391	391.80	-0.80	0.80	0.20%
18	4362	4347.60	14.40	14.40	0.33%
19	161	161.37	-0.37	0.37	0.23%
20	3923	3895.57	27.43	27.43	0.70%
21	2030	2030.26	-0.26	0.26	0.01%
22	61587	58007.37	3579.63	3579.63	5.81%

Table 10: Difference between the Number of Real Drop Offs and Simulated Drop Offs

3.3 Review of Design of Simulation Experiments

In Design of Experiments (DOE) terms, experimental designs designate how to vary the settings of factors (variables) which can be qualitative or quantitative to see if and how they affect the response (Sanchez, 2007). Due to the fact that analyzing one factor at a time does not consider the interactions between the parameters, which can significantly affect solution quality and performance, Design and Analysis of Simulation Experiments (DASE) techniques are utilized to structure and organize the simulation experiments. A design is a matrix where every column corresponds to a factor, and the entries within the column are settings for this factor. Each row represents a particular combination of factor levels, and is called a design point (Sanchez, 2007). It is important that scenarios are not chosen randomly, or a trial-and-error approach is utilized, as it can use up a great deal of time without addressing the fundamental questions and can lead to confounded factor effects. There are several possible designs for simulation experiments. A summary from the literature of the possible designs is detailed below.

Factorial Designs: In factorial designs, also called gridded designs, each factor is tested in combination with every level of every other factor and they are based on a grid. They allow the examination of more than one factor at a time and can be used to identify important interaction effects. 2^k designs examine each of k factors at two levels and are the most commonly used designs as they are easy to construct, readily explainable, and require no expert judgment other than the parameter ranges.

Finer grids are used for more complex metamodels, for instance 3^kdesigns deal with three levels per factor, so the general form for finer grids is m^kdesigns. The larger the value of m for an m^k factorial design, the better its space-filling properties (Sanchez, 2007). For each factor the number of levels are one greater than the highest-order power of that variable in the model, and the factorial design permits the estimation of coefficients for all cross-product terms. These designs are not efficient when more than a few factors are included, because when k increases, the number of scenarios n grows exponentially.

Resolution 3, 4, and 5 Fractional Factorial Designs: A design's resolution determines the complexity of metamodels that can be fit, with higher-resolution designs allowing more complex models (Kleijnen et al., 2005). The number of runs is reduced as high-order interactions are assumed to be not valuable or important and can be eliminated. For metamodels with main effects only, it can be proved that the most efficient designs are R3 and R4 designs (Kleijnen et al., 2005). If two factor interactions are of interest then R5 design should be used. Saturated or nearly-saturated fractional factorials are very efficient (relative to full factorial designs) when there are many factors (Sanchez, 2007). These designs will not reveal the underlying structure of the response surface if strong interactions exist but are ignored during the setup of the experiment.

Latin Hypercube Sampling (LHS): LHS sampling provides a flexible way of constructing efficient designs for quantitative factors. They have some of the space-filling properties of factorial designs with fine grids, but require orders of magnitude less sampling (Sanchez, 2007). Space-filling designs are suitable for simulations which are very complex and involve many variables with complicated interrelationships. LHS maximizes the minimum distance between design points but requires even spacing of the levels of each factor. LHS designs provide an orthogonal array that randomly samples the entire design space broken into regions of equal probability. LHS is useful especially for exploring the interior of the parameter space and for limiting the experiment to a fixed or a user-defined number of combinations. This technique ensures that the entire range of each parameter is sampled. LHS designs are well suited for situations involving a relatively large number of factors. Random LHS designs have good orthogonality properties if the number of levels are much larger than the number of factors, but for smaller designs some factors might have high pairwise correlations (Sanchez, 2007). There are two approaches, one approach is to generate many random LHS designs and then choose a good one. Alternatively, nearly orthogonal Latin hypercube (NOLH) designs have been developed that have good space-filling and orthogonality properties for a small or moderate number of factors. LHS designs work best when most factors have many levels.

Sequential Bifurcation (SB): Sequential bifurcation is a sequential screening approach in which it is tried to identify a subset of the original factors that have significant main effects. Sequential bifurcation is also an appropriate choice when the number of factors is very large. Although it quickly eliminates unimportant factors so that future experiments can focus on those that seem important, it usually requires stronger assumptions about the nature of the response surface. Another drawback of this method is that factors may be excluded from further consideration that have significant impact in the form of interactions. To avoid this error, designs that permit evaluation of interactions as well as main effects need to be used.

Central Composite Designs (CCD): CCD augments a resolution 5 design such that the purely quadratic effects can also be estimated (Kleijnen, 2008). Central Composite Designs (CCD) are first-order designs with additional center and axial points to facilitate estimating the parameters of a second-order model. CCD is capable of addressing non-linearity and continuous factors. CCDs are rather inefficient because they use inefficient resolution 5 designs and add 2k axial points and a center point to provide five values per factor result (Kleijnen, 2008).

3.4 Design of Experiments to Address Research Questions

The simulation model will first be run with the current locations and capacities of the charging stations, the current opportunity charging strategy, and the current automatic charging strategy. The results of the throughput and the AGV utilization will be recorded and tabulated. Below are the research questions mentioned previously:

1) What is the most favorable opportunity charging strategy to optimize the AGV fleet size and meet the material handling requirements of the system? This will include the most favorable minimum charge level to send the AGV for opportunity charging, the most favorable minimum critical ratio to release the AGV from opportunity charging, how long to wait before sending an idle AGV for opportunity charging, how long the AGV should charge for, and the dispatching rule when charging.
2) What is a more favorable number and location of charging stations to optimize the AGV fleet size and meet the material handling requirements of the system? This will also take

into consideration centralized VS decentralized charging, and the capacity of each of the charging stations.

3) What is the most favorable automatic charging strategy to optimize the AGV fleet size and meet the material handling requirements of the system? This will include the most favorable minimum critical ratio to release the AGV from charging, how long the AGV should charge for, and the dispatching rule when charging.

To address the second research question the simulation model will be run with several different scenarios. The scenarios that will be run are displayed in Table 11. When running the scenarios with 2 charging stations or 3 charging stations, the effect of having a charging station capacity of 7 or 6 and 5 or 4 respectively will not provide additional value to the results and the additional different combinations are not run as the changes to the results will be very minimal and will not change the outcome of the evaluation. Also the different combinations of different capacities that can exist when running with 2 or 3 charging stations are not included as the focus is on the evaluation of centralized VS decentralized charging strategy and the number of charging stations. The results from all scenarios will be analyzed and compared. The combined total capacities of the charging stations is 13.

			Charging Station Capacity		
Scenario	**Number of Charging Stations**	**Centralized VS Decentralized**	**Charging Station 1 Capacity**	**Charging Station 2 Capacity**	**Warehouse Charging Station Capacity**
1	1	Centralized	0	13	0
2	1	Centralized	13	0	0
3	1	Centralized	0	0	13
4	2	Decentralized	0	7	6
5	2	Decentralized	6	7	0
6	2	Decentralized	6	0	7
7	3	Decentralized	4	5	4
8 (Current Model)	3	Decentralized	2	7	4

Table 11: Scenarios Evaluated for Number and Location of Charging stations

As the system uses both opportunity charging and automatic charging strategies, it is important to note that the changes in an opportunity charging strategy can have an effect on automatic charging and vice versa. For this reason, to address the first and the third research questions, the simulation model will be run with several different scenarios that would include both the opportunity charging and the automatic charging. It is important to also note that different charging strategies are better suited for different types of batteries and chargers. For example, flooded lead acid batteries and lead acid batteries that require equalization should not be opportunity charged as it can significantly affect the life of the battery. The simulation can be updated with the different charge rates and consumption rates based on the different battery types and chargers used.

A full factorial design of experiments will be conducted to address the first and third research questions. The reason for doing a full factorial design is to be able to study the joint effects of several factors (or interactions) on a response by simultaneously changing the levels of factors. Also the full factorial design is able to examine all the combinations of all levels of all factors. The advantages of full-factorial design are orthogonality, no aliasing concerns, and all main factors and all interactions can be evaluated (Khuri and Mukhopadhyay, 2010). Sequential bifurcation is not used because although it quickly eliminates unimportant factors so that future experiments can focus on those that seem important, some of the factors may be excluded from further consideration that have significant impact in the form of interactions. Central composite designs are not used because they use inefficient resolution 5 designs and add 2k axial points and a center point to provide five values per factor result (Kleijnen, 2008). The rule of thumb is to use a full factorial design when the number of factors or process parameters is less than or equal to 4 (Antony, 2014). The number of factors in the DOE is 4 and doing the full factorial design we are able to look at the main effects and all the two way interactions and their effects. Table 12 shows the factors and levels that will be evaluated.

Factors	Levels		
	Current Model	Level 1	Level 2
Minimum Charge level (Opportunity Charging)	None	80	90
Minimum Critical Ratio (Battery Charge Level / Distance to pickup destination)	None	0.035	0.045
Wait time (Opportunity Charging)	1.5 minutes	3 minutes	6 minutes
Charge time and dispatching rule (Automatic Charging)	Mandatory charge to 35% then begin charging for a maximum of 120 minutes and realease at any time an AGV is required	Mandatory charge to 40% then begin charging for a maximum of 120 minutes and realease at any time an AGV is required and ratio is greater than minimum critical ratio	Mandatory charge to 50% then begin charging for a maximum of 120 minutes and realease at any time an AGV is required and ratio is greater than minimum critical ratio

Table 12: Factors and Levels for Design of Simulation Experiments

Since there are 3 levels and 4 factors, there will be a total of 81 runs (3^4). The minimum charge level for opportunity charging is the maximum charge level at which the AGV battery needs to be to be able to do opportunity charging. If the AGV battery charge level is higher than the minimum charge level the AGV is not able to do opportunity charging. For example if the minimum opportunity charge level is set to 80, and if the AGV battery level is checked and is 81, the AGV does not go to do opportunity charging and remains idle until a request is received. The minimum critical ratio is the ratio of the battery charge level to the distance to the pickup destination. For example, if the minimum critical ratio is set to 0.04, and if the AGV battery level is 40 and the distance to the pickup destination is 750 ft, then the ratio is 40/750 = 0.05 and the AGV can be released to be selected from the available AGVs to fulfill the request. If the ratio was less than 0.04 the AGV would continue to charge and would not be released. The minimum critical ratio would apply to both opportunity charging and automatic charging.

The wait time for opportunity charging refers to the time an AGV waits when it is idle to respond to any AGV requests before it can be considered for opportunity charging. The charge time and dispatching rule for opportunity charging is the amount of time the AGV charges for and the dispatching rule is the condition for when the AGV stops charging and responds to requests. The charging is conditional which means that the AGV charges until a condition is met. One of the conditions is that an AGV request is received and the other condition is a specified amount of time reached while charging. The last factor is the charge time and dispatching rule for automatic charging. The difference between automatic charging and opportunity charging is that for automatic charging the AGV has to go charge once it reaches the MAB, which is recommended by the battery manufacturer. The MAB used in the model for automatic charging is 30%.

The experiments will be run and analyzed and compared based on the throughput and AGV utilization. Based on the results from the experiments the optimized AGV fleet size can be determined. The model can be used as a platform and can also then be updated to evaluate different batteries and charger systems and their effects on the throughput and AGV fleet size.

CHAPTER 4

SIMULATION RESULTS

This chapter will discuss the results of the simulation runs and an analysis of the results.

4.1 Number and Location of Charging Stations

The model was run with the 8 scenarios shown in Table 11. The model was updated to reflect each of the different scenarios. The results for the 8 scenarios run are shown in Table 13. The average throughput, which is the number of loads dropped off is recorded for each of the drop off areas and the AGV usage is recorded. For the AGV usage the number recorded is the average number of busy AGVs.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
Drop Off Area	Average Throughput	Average Throughput	Average Throughput	Average Throughput	Average Throughput	Average Throughput	Average Throughput	Average Throughput
1	12.91	7.80	19.77	19.00	15.66	17.66	15.00	20.71
2	23.80	14.14	33.48	36.68	31.48	32.63	26.26	36.14
3	1917.69	1137.46	2716.63	2797.37	2389.14	2452.51	2086.74	2874.89
4	659.26	392.26	945.17	971.49	834.11	850.49	723.51	991.97
5	748.57	441.94	1070.80	1099.17	940.34	962.89	816.34	1126.46
6	1271.97	751.37	1827.71	1874.60	1598.83	1642.57	1400.51	1902.77
7	470.57	278.03	659.31	688.11	580.77	599.86	503.77	700.94
8	499.40	301.06	725.29	733.20	633.91	647.80	545.69	750.23
9	2112.80	1255.91	3006.03	3116.34	2637.34	2716.40	2299.11	3176.23
10	214.71	127.86	308.31	315.91	269.26	275.51	234.40	330.91
11	742.34	435.74	1055.14	1084.80	922.69	954.60	805.97	1107.97
12	4485.80	2665.26	6413.69	6589.03	5630.63	5775.60	4896.23	6717.63
13	97.91	59.43	137.54	139.14	121.97	127.60	107.80	144.49
14	3642.14	2169.71	5211.74	5348.20	4525.71	4686.63	3973.51	5455.71
15	484.80	287.20	699.94	711.83	600.17	621.77	526.40	723.14
16	2319.09	1387.66	3325.34	3430.94	2898.40	2991.11	2547.23	3501.09
17	259.23	153.77	370.37	385.57	326.46	334.60	281.46	391.80
18	2904.49	1730.14	4089.40	4245.63	3623.51	3742.83	3128.51	4347.60
19	104.77	63.43	147.57	153.71	133.29	137.17	114.40	161.37
20	2602.69	1542.14	3695.49	3808.09	3236.46	3355.20	2810.57	3895.57
21	1338.43	799.17	1925.29	1966.77	1685.60	1726.31	1458.26	2030.26
22	39475.00	17137.69	54307.09	57190.91	49503.20	47727.09	41569.91	58007.37
	AGV Usage	AGV Usage	AGV Usage	AGV Usage	AGV Usage	AGV Usage	AGV Usage	AGV Usage
	10.45	14.57	9.52	8.36	8.53	9.90	10.31	8.35

Table 13: Throughput Results of Scenarios for Number and Location of Charging Stations

Looking at the results, it is clear that the location and number of charging stations can have a significant effect on the throughput and the AGV usage. For the first three scenarios there was only one charging location. Although for each of the three scenarios the charging station capacity was 13 there were significant differences in the average throughput and AGV usage.

For example for the second scenario due to the location of charging station 1 the AGV usage was maximized as the total number of AGVs is 15.

For scenarios 4 through 6, there were two charging station locations. It is important to note that although having a decentralized charging may provide advantages of the AGVs being able to reach a charging station quicker and not require additional travel to reach the charging station, it may not improve the throughput and AGV usage compared to a centralized charging strategy. Looking at scenario 3, the average throughput is higher than two of the scenarios with two charging station locations but the AGV usage did increase by approximately one AGV.

Looking at the results for scenario 8 which is the current model it is clear that the number, locations, and capacities of the charging stations were not randomly selected and were well thought out. As the results indicate, scenario 8 had the highest average throughput and the lowest AGV usage.

In conclusion, choosing the number, location, and capacity of charging stations is very important and can have a significant impact on the throughput and the usage of the AGVs, which in turn will optimize the AGV fleet size. This model can be used as a tool to evaluate the number and location of charging stations that should be used and the capacities of each of the charging stations. In many cases the options for the locations of the charging stations can be predetermined due to the layout and available facilities but this tool can evaluate these predetermined locations and determine the best options to optimize both the throughput and the AGV fleet size.

4.2 Results for Design of Simulation Experiments with Full Factorial Design

The 81 runs and their order is shown below in Table 14.

Run Order	Minimum Charge Level for Opportunity Charging	Minimum Critical Ratio	Wait Time Before Opportunity Charging (Minutes)	Mandatory Charge To Percentage and Dispatching Rule for Automatic Charging
1	None	None	1.5	35
2	None	None	1.5	40
3	None	None	1.5	50
4	None	None	3	35
5	None	None	3	40
6	None	None	3	50
7	None	None	6	35
8	None	None	6	40
9	None	None	6	50
10	None	0.035	1.5	35
11	None	0.035	1.5	40
12	None	0.035	1.5	50
13	None	0.035	3	35
14	None	0.035	3	40
15	None	0.035	3	50
16	None	0.035	6	35
17	None	0.035	6	40
18	None	0.035	6	50
19	None	0.045	1.5	35
20	None	0.045	1.5	40
21	None	0.045	1.5	50
22	None	0.045	3	35
23	None	0.045	3	40
24	None	0.045	3	50
25	None	0.045	6	35
26	None	0.045	6	40
27	None	0.045	6	50
28	80	None	1.5	35
29	80	None	1.5	40
30	80	None	1.5	50
31	80	None	3	35
32	80	None	3	40
33	80	None	3	50
34	80	None	6	35
35	80	None	6	40
36	80	None	6	50
37	80	0.035	1.5	35
38	80	0.035	1.5	40
39	80	0.035	1.5	50
40	80	0.035	3	35
41	80	0.035	3	40
42	80	0.035	3	50
43	80	0.035	6	35
44	80	0.035	6	40
45	80	0.035	6	50
46	80	0.045	1.5	35
47	80	0.045	1.5	40
48	80	0.045	1.5	50
49	80	0.045	3	35
50	80	0.045	3	40
51	80	0.045	3	50
52	80	0.045	6	35
53	80	0.045	6	40
54	80	0.045	6	50
55	90	None	1.5	35
56	90	None	1.5	40
57	90	None	1.5	50
58	90	None	3	35
59	90	None	3	40
60	90	None	3	50
61	90	None	6	35
62	90	None	6	40
63	90	None	6	50
64	90	0.035	1.5	35
65	90	0.035	1.5	40
66	90	0.035	1.5	50
67	90	0.035	3	35
68	90	0.035	3	40
69	90	0.035	3	50
70	90	0.035	6	35
71	90	0.035	6	40
72	90	0.035	6	50
73	90	0.045	1.5	35
74	90	0.045	1.5	40
75	90	0.045	1.5	50
76	90	0.045	3	35
77	90	0.045	3	40
78	90	0.045	3	50
79	90	0.045	6	35
80	90	0.045	6	40
81	90	0.045	6	50

Table 14: 81 runs for Full Factorial Design

This was generated using Minitab software. The model was updated to reflect each of the different runs. The results for the 81 runs are displayed in Table 15. The average throughput for each of the drop off areas is recorded and the AGV usage is recorded. For the AGV usage the number recorded is the average number of busy AGVs.

Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
20.71	19.28	19.06	19.06	20.83	21.37	22.83
36.14	34.94	33.48	35.54	36.94	39.03	42.23
2874.89	2727.40	2583.97	2838.43	2883.80	2952.09	3194.00
991.97	948.17	895.03	993.29	1011.86	1039.89	1110.03
1126.46	1075.54	1006.31	1119.83	1146.69	1170.77	1257.43
1902.77	1820.63	1720.43	1907.03	1945.31	1986.51	2116.11
700.94	662.46	630.71	697.40	709.83	730.03	773.17
750.23	719.46	668.34	749.69	765.40	787.00	839.57
3176.23	3013.71	2851.09	3153.34	3209.06	3302.94	3510.74
330.91	311.60	294.80	321.63	327.69	335.00	360.51
1107.97	1058.34	999.17	1097.46	1124.60	1147.89	1236.34
6717.63	6385.46	6043.89	6674.29	6810.97	7006.11	7458.23
144.49	136.74	130.57	147.11	150.17	150.60	162.09
5455.71	5196.34	4902.34	5420.46	5532.74	5676.60	6032.20
723.14	687.14	652.97	723.77	737.86	752.74	808.66
3501.09	3330.57	3136.89	3478.40	3538.09	3641.69	3878.60
391.80	376.00	353.66	391.86	396.91	407.14	431.43
4347.60	4137.60	3899.97	4312.66	4373.03	4510.51	4792.49
161.37	153.46	142.97	155.49	159.83	166.14	175.54
3895.57	3718.91	3502.31	3888.31	3944.57	4058.29	4310.97
2030.26	1933.11	1813.09	2001.83	2031.60	2103.31	2214.51
58007.37	53664.66	51671.00	56933.91	58146.71	59891.03	64636.06
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
8.35	8.79	8.90	8.31	7.95	7.69	6.96

Run 8	Run 9	Run 10	Run 11	Run 12	Run 13	Run 14
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
21.20	20.48	19.68	18.86	17.63	20.28	20.83
37.57	38.34	35.11	34.08	33.51	36.83	36.66
3076.37	3024.54	2771.09	2689.94	2601.09	2919.40	2814.14
1061.34	1048.57	955.51	939.89	896.89	1014.46	989.03
1214.03	1190.57	1090.23	1062.49	1023.71	1155.29	1112.37
2047.31	2023.74	1833.71	1786.51	1736.66	1965.74	1885.40
747.34	727.23	674.80	659.09	631.97	712.97	694.63
817.49	793.77	720.77	712.60	678.89	768.26	745.29
3404.74	3338.66	3050.74	2987.74	2880.23	3252.66	3133.49
345.23	338.86	317.60	307.49	296.77	331.14	318.97
1184.86	1167.63	1058.97	1041.91	1006.69	1120.14	1096.31
7219.29	7116.37	6465.69	6315.66	6096.23	6880.23	6646.46
157.77	152.17	138.83	135.34	134.69	149.34	146.80
5827.57	5765.71	5251.14	5127.77	4950.43	5585.09	5379.03
777.80	770.37	695.51	678.94	655.34	745.23	720.77
3736.94	3690.86	3364.60	3282.00	3162.57	3565.09	3437.03
417.80	412.03	376.54	368.86	358.23	394.94	383.54
4650.66	4568.03	4188.89	4080.09	3921.71	4433.14	4268.66
171.40	165.89	153.23	151.06	144.03	157.26	155.06
4183.86	4110.66	3755.74	3674.49	3536.06	4006.40	3849.31
2164.63	2115.91	1948.91	1903.00	1829.00	2079.60	1989.80
62176.37	60894.11	54644.71	52006.06	51620.63	57194.69	56021.34
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
7.37	7.48	8.95	9.28	9.07	8.47	8.52

Run 15	Run 16	Run 17	Run 18	Run 19	Run 20	Run 21
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
19.37	22.54	19.97	22.49	15.17	15.17	15.17
34.51	41.31	37.66	40.54	23.49	23.49	23.94
2724.43	3239.74	3002.06	3211.83	1869.46	1869.46	1869.46
956.51	1109.86	1051.34	1113.80	641.06	641.06	641.09
1076.09	1275.29	1186.43	1262.17	733.03	733.03	733.00
1834.29	2150.54	2018.60	2140.34	1250.26	1250.26	1250.29
672.97	781.20	727.97	781.54	459.54	459.54	459.54
720.89	846.94	792.91	847.69	490.83	490.83	490.83
3056.40	3569.49	3323.46	3552.11	2067.77	2067.77	2067.80
310.06	366.91	339.43	361.94	212.26	212.26	212.26
1059.74	1253.17	1163.20	1242.23	715.43	715.43	715.46
6445.40	7567.86	7067.11	7528.83	4374.86	4374.86	4374.80
138.89	163.97	152.74	164.34	94.86	94.86	94.86
5220.91	6133.29	5726.91	6106.26	3542.89	3542.89	3542.89
697.49	814.54	762.26	815.17	469.23	469.23	469.23
3341.17	3909.94	3678.86	3912.91	2279.31	2279.31	2279.26
375.80	435.23	411.43	437.14	253.91	253.91	253.94
4136.03	4861.46	4571.60	4844.11	2815.66	2815.66	2815.63
151.11	177.66	163.06	177.89	102.03	102.03	102.03
3724.97	4381.71	4112.03	4371.00	2550.23	2550.23	2550.20
1930.91	2261.29	2109.97	2264.57	1324.54	1324.54	1324.54
54467.69	64330.46	59491.31	64240.86	38511.17	38511.17	38511.26
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
8.70	7.38	8.05	7.32	10.28	10.28	10.28

Run 22	Run 23	Run 24	Run 25	Run 26	Run 27	Run 28
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
14.94	14.94	14.94	12.00	10.57	12.20	24.11
27.83	27.83	27.83	21.80	20.48	21.54	42.46
2144.23	2144.23	2144.23	1784.23	1665.97	1785.74	3387.60
746.74	746.74	746.74	617.11	577.20	616.31	1172.43
846.94	846.94	846.94	694.37	650.03	698.26	1323.49
1439.43	1439.43	1439.43	1180.66	1111.40	1187.80	2259.06
519.00	519.00	519.00	426.40	401.97	431.20	820.11
569.20	569.20	569.20	469.40	437.46	469.54	894.06
2368.94	2368.94	2368.94	1959.40	1834.66	1979.37	3751.51
243.43	243.43	243.43	199.49	188.17	201.06	384.74
825.46	825.46	825.46	689.80	645.71	689.86	1290.63
5059.37	5059.37	5059.37	4156.51	3910.89	4196.00	7960.37
109.17	109.17	109.17	89.97	86.00	92.28	172.74
4098.23	4098.23	4098.23	3374.46	3171.71	3398.23	6424.91
543.14	543.14	543.14	450.03	423.60	450.20	858.94
2620.46	2620.46	2620.46	2167.11	2036.46	2184.80	4114.00
291.71	291.71	291.71	239.60	226.26	242.43	460.14
3237.83	3237.83	3237.83	2655.97	2502.31	2692.69	5120.03
119.51	119.51	119.51	99.17	93.20	98.88	186.94
2915.69	2915.69	2915.69	2407.23	2264.43	2427.20	4615.26
1502.74	1502.74	1502.74	1247.23	1169.57	1256.03	2374.94
44645.11	44645.11	44645.11	36881.89	34841.29	37252.31	70347.26
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
9.37	9.37	9.37	10.32	10.58	10.28	5.09

Run 29	Run 30	Run 31	Run 32	Run 33	Run 34	Run 35
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
24.11	24.11	23.34	24.31	23.68	21.97	23.60
42.46	42.46	44.37	43.06	44.48	42.80	44.17
3387.60	3387.60	3382.00	3366.60	3389.66	3389.09	3375.51
1172.43	1172.43	1165.80	1162.83	1170.71	1178.06	1167.40
1323.49	1323.49	1329.86	1332.66	1334.06	1335.17	1337.60
2259.06	2259.06	2263.26	2254.29	2262.31	2272.91	2283.94
820.11	820.11	824.46	815.49	819.86	819.94	822.26
894.06	894.06	895.80	889.03	884.37	886.29	891.29
3751.51	3751.51	3736.06	3728.57	3732.11	3754.49	3736.80
384.74	384.74	376.46	379.60	387.86	383.89	379.91
1290.63	1290.63	1302.09	1294.63	1306.97	1306.86	1306.51
7960.37	7960.37	7904.14	7923.40	7950.71	7986.11	7948.71
172.74	172.74	167.80	169.63	172.51	174.20	172.51
6424.91	6424.91	6427.63	6415.57	6444.57	6451.94	6448.17
858.94	858.94	845.83	861.51	860.20	858.60	848.77
4114.00	4114.00	4112.97	4095.71	4110.06	4139.46	4111.03
460.14	460.14	465.34	458.63	465.14	458.80	459.57
5120.03	5120.03	5083.46	5078.03	5099.11	5119.23	5127.86
186.94	186.94	182.37	181.34	182.66	184.74	190.20
4615.26	4615.26	4566.31	4585.09	4603.71	4622.57	4596.23
2374.94	2374.94	2369.60	2367.06	2368.40	2375.89	2383.54
70347.26	70347.26	70228.89	70289.26	70222.71	70340.97	70241.20
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
5.09	5.09	5.07	5.07	5.07	5.07	5.07

Run 36	Run 37	Run 38	Run 39	Run 40	Run 41	Run 42
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
23.23	24.31	24.31	24.31	25.23	25.23	25.23
42.91	42.17	42.17	42.17	43.40	43.40	43.40
3356.54	3386.23	3386.23	3386.23	3358.80	3358.80	3358.80
1156.06	1171.31	1171.31	1171.31	1172.69	1172.69	1172.69
1319.29	1322.00	1322.00	1322.00	1339.06	1339.06	1339.06
2248.31	2256.43	2256.43	2256.43	2262.94	2262.94	2262.94
821.09	820.14	820.14	820.14	834.37	834.37	834.37
885.49	892.63	892.63	892.63	896.31	896.31	896.31
3722.29	3749.51	3749.51	3749.51	3729.60	3729.60	3729.60
379.34	384.71	384.71	384.71	381.43	381.43	381.43
1296.31	1291.14	1291.14	1291.14	1310.11	1310.11	1310.11
7881.00	7952.17	7952.17	7952.17	7943.43	7943.43	7943.43
170.97	172.06	172.06	172.06	174.00	174.00	174.00
6392.54	6416.80	6416.80	6416.80	6431.77	6431.77	6431.77
846.34	857.49	857.49	857.49	856.29	856.29	856.29
4096.91	4112.89	4112.89	4112.89	4130.34	4130.34	4130.34
458.60	459.63	459.63	459.63	465.40	465.40	465.40
5074.09	5118.46	5118.46	5118.46	5114.14	5114.14	5114.14
184.43	186.17	186.17	186.17	185.91	185.91	185.91
4563.37	4616.46	4616.46	4616.46	4622.77	4622.77	4622.77
2364.26	2374.97	2374.97	2374.97	2381.06	2381.06	2381.06
70340.26	70359.77	70359.77	70359.77	70189.00	70189.00	70189.00
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
5.06	5.13	5.13	5.13	5.20	5.20	5.20

Run 43	Run 44	Run 45	Run 46	Run 47	Run 48	Run 49
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
23.91	24.11	23.26	17.08	17.08	17.08	9.97
44.94	45.08	42.00	32.57	32.57	32.57	17.20
3403.23	3398.46	3332.51	2574.60	2574.60	2574.14	1337.20
1169.66	1169.29	1159.03	901.17	901.17	901.00	462.06
1345.60	1330.60	1328.54	1015.51	1015.51	1015.03	523.11
2276.17	2255.43	2244.43	1725.86	1725.86	1725.31	889.17
824.09	821.09	825.11	632.49	632.49	632.34	329.49
893.09	884.37	884.51	684.23	684.23	684.97	351.60
3761.66	3731.20	3704.11	2867.83	2867.83	2867.14	1483.54
381.77	383.11	374.57	289.49	289.49	289.46	151.40
1317.29	1306.49	1297.40	1000.31	1000.31	1000.20	513.49
7997.63	7942.49	7910.17	6086.20	6086.20	6084.91	3148.46
174.20	170.26	170.11	132.97	132.97	132.89	67.14
6495.40	6422.51	6383.94	4908.49	4908.49	4907.43	2557.49
856.29	849.17	852.94	661.29	661.29	661.17	346.91
4150.54	4099.29	4100.14	3149.26	3149.26	3148.34	1630.71
467.60	462.03	455.83	354.31	354.31	354.26	186.11
5149.69	5097.74	5074.20	3913.14	3913.14	3911.86	2022.83
192.03	187.40	183.66	144.20	144.20	144.14	72.31
4637.23	4586.51	4575.09	3528.69	3528.69	3527.71	1826.69
2393.74	2360.74	2358.40	1811.06	1811.06	1810.49	940.31
70195.54	69988.31	70237.37	53570.17	53570.17	53557.23	27895.49
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
5.90	6.00	6.31	8.72	8.72	8.72	11.75

Run 50	Run 51	Run 52	Run 53	Run 54	Run 55	Run 56
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
11.83	10.14	0.46	0.46	0.46	22.74	22.74
21.48	18.20	1.26	1.26	1.26	41.68	41.68
1605.40	1448.49	83.97	83.97	83.97	3384.94	3384.94
556.43	504.40	28.06	28.06	28.06	1157.51	1157.51
631.63	567.31	33.80	33.80	33.80	1339.09	1339.09
1070.57	976.71	54.71	54.71	54.71	2263.03	2263.03
396.63	349.46	21.26	21.26	21.26	829.23	829.23
420.03	378.43	21.60	21.60	21.60	895.77	895.77
1764.26	1598.06	93.03	93.03	93.03	3741.60	3741.60
183.54	162.06	9.03	9.03	9.03	385.34	385.34
612.46	555.97	31.46	31.46	31.46	1301.49	1301.49
3786.20	3382.69	192.17	192.17	192.17	7934.51	7934.51
80.14	72.51	4.00	4.00	4.00	175.77	175.77
3046.46	2759.03	155.03	155.03	155.03	6448.74	6448.74
411.20	366.86	21.11	21.22	21.11	859.20	859.20
1962.74	1771.60	97.08	97.08	97.08	4117.74	4117.74
223.37	200.34	10.63	10.62	10.63	461.60	461.60
2418.80	2189.69	126.03	126.03	126.03	5109.51	5109.51
85.83	79.80	4.74	4.74	4.74	187.46	187.46
2179.86	1967.46	110.00	110.00	110.00	4613.00	4613.00
1127.03	1014.69	58.43	58.43	58.43	2377.23	2377.23
33328.46	30113.80	1673.71	1673.71	1673.71	70198.77	70198.77
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
11.18	11.53	14.81	14.81	14.81	5.27	5.27

Run 57	Run 58	Run 59	Run 60	Run 61	Run 62	Run 63
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
22.74	24.63	24.63	24.63	23.94	24.68	24.20
41.68	42.23	42.23	42.23	45.03	42.83	43.57
3384.94	3383.63	3383.63	3383.63	3365.77	3350.57	3383.46
1157.51	1170.66	1170.66	1170.66	1172.83	1166.46	1169.11
1339.09	1349.46	1349.46	1349.46	1327.74	1315.69	1330.63
2263.03	2251.89	2251.89	2251.89	2267.71	2248.51	2265.49
829.23	824.91	824.91	824.91	821.40	813.09	819.97
895.77	895.40	895.40	895.40	895.31	880.54	893.94
3741.60	3743.40	3743.40	3743.40	3740.03	3730.49	3748.20
385.34	383.89	383.89	383.89	379.89	375.77	382.86
1301.49	1300.97	1300.97	1300.97	1309.11	1301.46	1318.31
7934.51	7948.06	7948.06	7948.06	7946.17	7918.40	7954.03
175.77	173.66	173.66	173.66	173.00	170.03	171.14
6448.74	6444.26	6444.26	6444.26	6444.40	6405.80	6452.31
859.20	846.23	846.23	846.23	854.43	847.14	851.26
4117.74	4152.09	4152.09	4152.09	4118.57	4090.37	4135.63
461.60	462.89	462.89	462.89	454.03	459.57	458.37
5109.51	5099.09	5099.09	5099.09	5095.06	5079.11	5116.86
187.46	183.40	183.40	183.40	186.57	180.66	186.20
4613.00	4616.37	4616.37	4616.37	4615.20	4569.71	4602.11
2377.23	2392.51	2392.51	2392.51	2392.63	2374.20	2391.40
70198.77	70211.20	70211.20	70211.20	70319.83	70342.83	70241.14
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
5.27	5.25	5.25	5.25	5.23	5.23	5.24

Run 64	Run 65	Run 66	Run 67	Run 68	Run 69	Run 70
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
23.17	23.17	23.17	22.60	22.97	22.57	24.06
42.91	42.91	42.91	42.91	43.03	43.74	42.17
3394.80	3394.80	3394.80	3343.60	3344.74	3341.71	3412.17
1159.74	1159.74	1159.74	1162.74	1163.37	1156.54	1182.09
1336.37	1336.37	1336.37	1325.94	1331.03	1324.54	1337.17
2270.29	2270.29	2270.29	2256.94	2251.34	2248.03	2277.29
828.66	828.66	828.66	811.60	817.29	811.54	821.29
889.77	889.77	889.77	886.51	889.60	888.49	885.14
3749.97	3749.97	3749.97	3719.74	3708.06	3710.43	3738.23
382.40	382.40	382.40	379.14	377.77	378.63	381.46
1303.97	1303.97	1303.97	1309.31	1308.91	1308.83	1309.09
7940.66	7940.66	7940.66	7905.60	7911.54	7908.23	7954.09
174.60	174.60	174.60	171.80	171.86	171.60	170.91
6456.71	6456.71	6456.71	6413.60	6406.46	6403.40	6469.97
864.69	864.69	864.69	847.77	850.26	846.91	858.34
4126.14	4126.14	4126.14	4091.11	4099.74	4090.80	4149.29
463.89	463.89	463.89	456.00	455.77	454.51	465.26
5119.09	5119.09	5119.09	5083.63	5086.94	5073.49	5109.29
188.14	188.14	188.14	185.60	185.20	184.26	189.46
4618.71	4618.71	4618.71	4578.09	4577.17	4563.69	4624.46
2383.63	2383.63	2383.63	2365.80	2373.20	2359.83	2365.06
70197.11	70197.11	70197.11	70173.51	70174.11	70181.69	70215.86
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
5.28	5.28	5.28	5.28	5.28	5.28	5.32

Run 71	Run 72	Run 73	Run 74	Run 75	Run 76	Run 77
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**	**Average Throughput**
23.54	22.91	23.94	23.94	23.94	23.74	23.74
43.94	42.68	42.94	42.94	42.94	40.57	40.57
3415.69	3345.17	3313.80	3313.80	3313.80	3223.89	3223.89
1178.00	1160.77	1153.94	1153.94	1153.94	1107.60	1107.60
1343.06	1321.03	1317.89	1317.89	1317.89	1277.69	1277.69
2267.26	2250.40	2225.60	2225.60	2225.60	2151.46	2151.46
828.69	818.31	815.71	815.71	815.71	786.03	786.03
895.54	877.74	883.54	883.54	883.54	842.89	842.89
3766.91	3693.00	3667.74	3667.74	3667.74	3573.86	3573.86
382.66	381.20	376.14	376.14	376.14	366.89	366.89
1309.60	1299.69	1280.34	1280.34	1280.34	1252.09	1252.09
7968.49	7875.60	7773.74	7773.74	7773.74	7586.40	7586.40
170.54	170.63	168.89	168.89	168.89	163.00	163.00
6465.43	6390.71	6310.60	6310.60	6310.60	6150.17	6150.17
855.86	848.49	842.77	842.77	842.77	813.46	813.46
4157.57	4096.57	4041.29	4041.29	4041.29	3949.26	3949.26
461.97	460.46	455.51	455.51	455.51	438.26	438.26
5140.54	5071.97	5002.94	5002.94	5002.94	4865.29	4865.29
189.86	190.46	183.17	183.17	183.17	175.63	175.63
4630.80	4552.37	4531.69	4531.69	4531.69	4383.69	4383.69
2373.94	2360.57	2332.23	2332.23	2332.23	2265.31	2265.31
70157.34	69792.14	69150.11	69150.11	69150.11	66825.20	66825.20
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**	**AGV Usage**
5.34	5.42	5.48	5.48	5.48	6.22	6.22

Run 78	Run 79	Run 80	Run 81
Average Throughput	**Average Throughput**	**Average Throughput**	**Average Throughput**
23.74	14.28	14.28	14.28
40.57	26.88	26.88	26.88
3223.89	2160.06	2160.06	2160.06
1107.60	760.03	760.03	760.03
1277.69	857.37	857.37	857.37
2151.46	1459.66	1459.66	1459.66
786.03	530.43	530.43	530.43
842.89	577.23	577.23	577.23
3573.86	2397.97	2397.97	2397.97
366.89	243.37	243.37	243.37
1252.09	850.29	850.29	850.29
7586.40	5095.46	5095.46	5095.46
163.00	107.17	107.17	107.17
6150.17	4146.71	4146.71	4146.71
813.46	541.66	541.66	541.66
3949.26	2658.77	2658.77	2658.77
438.26	292.66	292.66	292.66
4865.29	3272.23	3272.23	3272.23
175.63	121.89	121.89	121.89
4383.69	2958.46	2958.46	2958.46
2265.31	1526.89	1526.89	1526.89
66825.20	45421.17	45421.17	45421.17
AGV Usage	**AGV Usage**	**AGV Usage**	**AGV Usage**
6.22	9.44	9.44	9.44

Table 15: Results of Full Factorial Design

To be able to analyze the factorial design without having to look at each individual drop off area, the sum of the average throughput for all drop off areas was calculated for each of the runs as shown below in Table 16.

Run	Sum of average throughput	Run	Sum of average throughput	Run	Sum of average throughput
1	98395.25	28	117985.73	55	117845.95
2	92111.52	29	117985.73	56	117845.95
3	87952.05	30	117985.73	57	117845.95
4	97060.79	31	117697.84	58	117900.83
5	99004.49	32	117716.30	59	117900.83
6	101876.68	33	117835.85	60	117900.83
7	109363.74	34	118103.98	61	117948.65
8	105441.57	35	117896.78	62	117687.91
9	103474.50	36	117623.63	63	117940.19
10	93512.00	37	117967.45	64	117915.42
11	89963.87	38	117967.45	65	117915.42
12	88212.96	39	117967.45	66	117915.42
13	98488.18	40	117848.05	67	117533.54
14	95844.92	41	117848.05	68	117550.36
15	93095.63	42	117848.05	69	117473.46
16	109694.40	43	118151.30	70	117982.15
17	101910.31	44	117515.68	71	118027.23
18	109439.76	45	117517.32	72	117022.87
19	64796.99	46	90000.92	73	115894.52
20	64796.99	47	90000.92	74	115894.52
21	64797.48	48	89979.67	75	115894.52
22	74889.10	49	46762.68	76	112262.38
23	74889.10	50	55924.35	77	112262.38
24	74889.10	51	50487.70	78	112262.38
25	61823.83	52	2831.57	79	76020.64
26	58269.34	53	2831.67	80	76020.64
27	62383.93	54	2831.57	81	76020.64

Table 16: Sum of Average Throughput

Using Minitab software the factorial design was analyzed. Based on the pareto chart shown in Figure 13 and the results in Table 17 in appendix A, all main effects except for factor D (Automatic charging charge time and dispatching rule) have significant effects on the average throughput and are statistically significant. In addition to that, the interaction effects AB, BC, and AC also have significant effects on the average throughput and are also statistically significant.

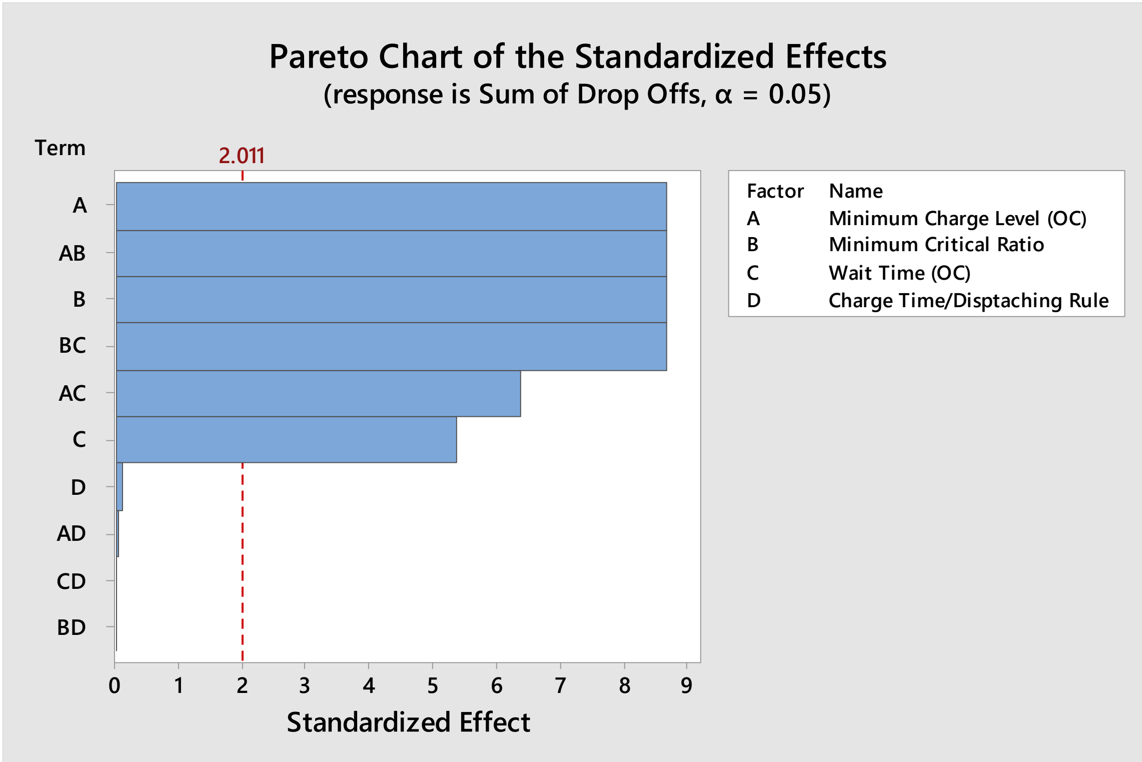

Figure 13: Pareto Chart of Standardized Effects for Sum of Average Throughput

Based on the pareto chart shown below in Figure 14 and the results in Table 18 in appendix A, all main effects except for factor D (Automatic charging charge time and dispatching rule) have significant effects on the AGV usage and are statistically significant. In addition to that, the interaction effects AB, BC, and AC also have significant effects on the AGV usage and are also statistically significant.

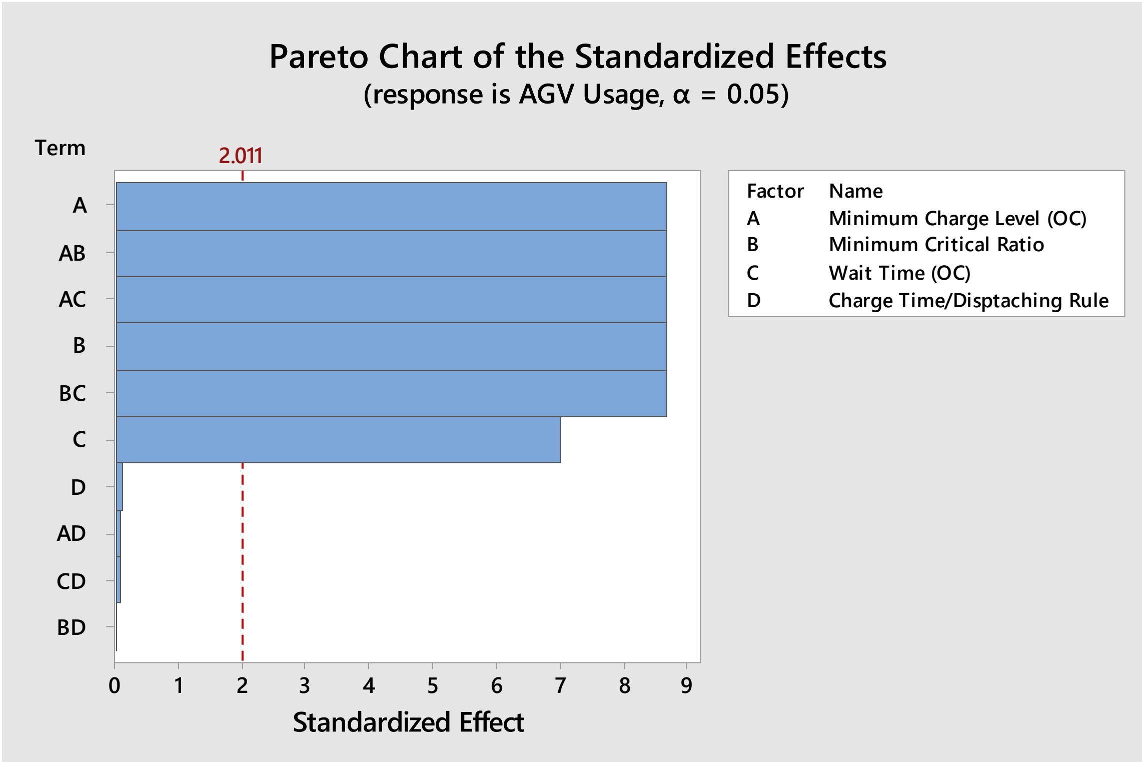

Figure 14: Pareto Chart of Standardized Effects for AGV Usage

Based on the model summary shown below for both the Sum of average throughput and AGV usage it shows that the model provides a good fit to the data.

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7455.97	95.63%	92.72%	87.56%

Sum of Average Throughput

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.474327	97.82%	96.37%	93.80%

AGV Usage

Based on the residual plots for both the Sum of average throughput (Figure 15) and AGV usage (Figure 16) it shows that the model meets the assumptions of the analysis.

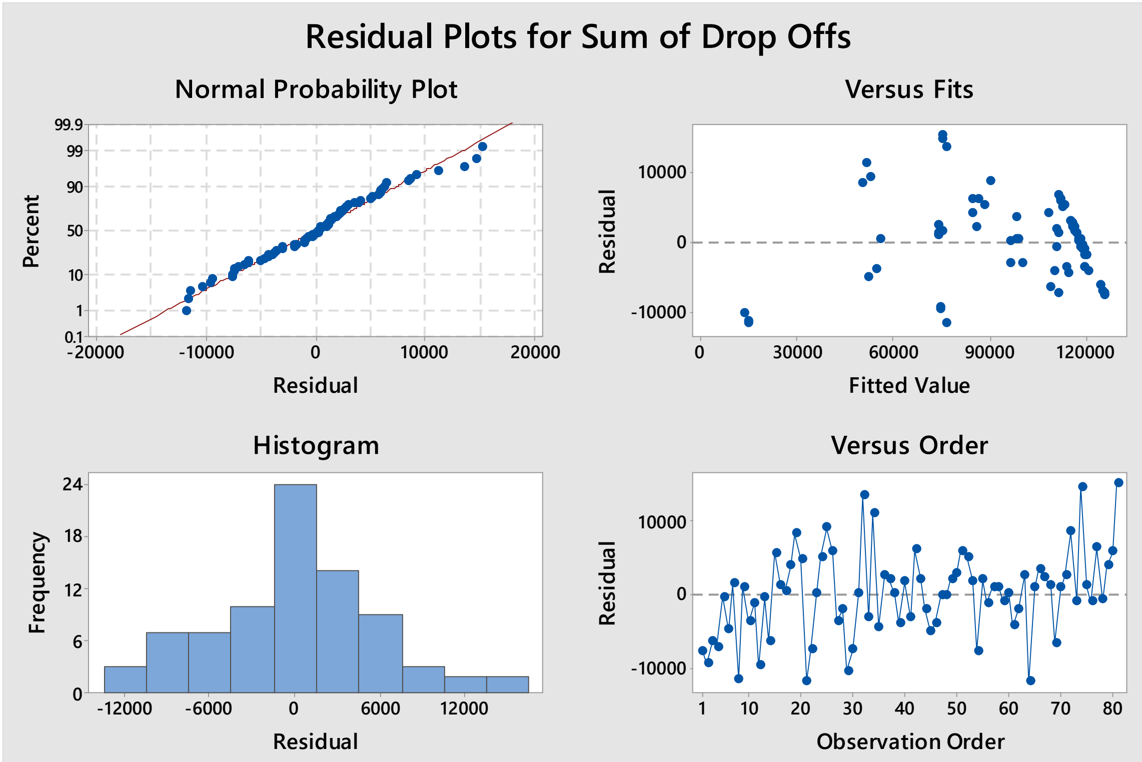

Figure 15: Residual Plots for Sum of Average Throughput

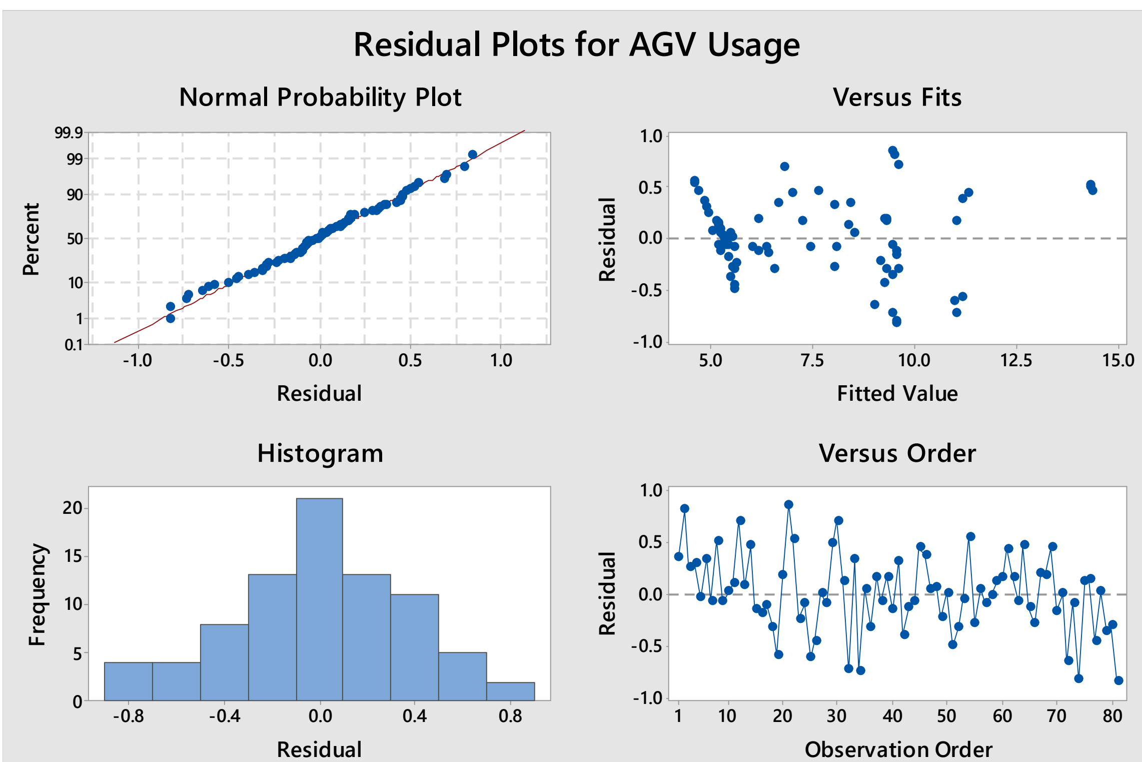

Figure 16: Residual Plots for AGV usage

As displayed in the results, increasing the minimum critical ratio reduced the average throughput and increased the AGV usage. As the minimum critical ratio increases, less AGVs are made available to respond as they do not meet the criteria, therefore the response time increases and the available AGVs may have to travel longer distances to complete the transportation tasks which leads to less transportation tasks getting completed. Increasing the wait time increased the average throughput and reduced the AGV usage in most cases.

In most cases, adding the minimum charge level for opportunity charging increased the average throughput and reduced the AGV usage. As less AGVs are sent to opportunity charging they are available to respond to transportation tasks. In the cases with 80 as the minimum opportunity charge level, high minimum critical ratio, and high wait time the average throughput decreases significantly and the AGV usage increases. The reason for this is that the AGVs have a long wait time which means they will respond to more consecutive requests which reduces their battery level. So when they are sent to opportunity charging and with the high minimum critical ratio, they are not released for a longer period of time.

From the results, it is very clear that battery management can have a significant effect on the average throughput and the AGV usage. In one of the runs (34) the average throughput increased by 20% which is significant. In some cases the AGV usage was reduced by 3 AGVs. On the other hand, there were some cases where, based on the factors settings the AGV, usage increased by 6 AGVs. This tool can be used to determine the optimal fleet size to be used to meet the material handling requirements. For example, run 34 had one of the highest average throughputs and one of the lowest AGV usages. Run 34 is repeated and the AGV number is reduced from 15 to 12 and the results are displayed below in Table 19.

15 AGVs	12 AGVs
Average Throughput	**Average Throughput**
21.97	23.37
42.80	43.43
3389.09	3372.17
1178.06	1177.00
1335.17	1345.20
2272.91	2265.71
819.94	819.43
886.29	887.34
3754.49	3744.51
383.89	377.60
1306.86	1303.09
7986.11	7919.00
174.20	172.46
6451.94	6432.23
858.60	857.74
4139.46	4113.40
458.80	454.91
5119.23	5108.74
184.74	186.43
4622.57	4618.03
2375.89	2382.91
70340.97	70192.03
AGV Usage	**AGV Usage**
5.07	5.14

Table 19: Comparison of run 34 with different number of AGVs

The results show that the sum of average throughput only decreased by 307.25 when using 12 AGVs. This is a clear indication that with 12 AGVs you can meet the material handling requirements and reduce the number of AGVs needed by 3. Also since the AGV usage is still at 5.14, there is still an opportunity to reduce the number of AGVs even further while still meeting the material handling requirements. Heijden, Harten, and Ebben (2002) stated that the cost of an AGV is approximately $75,000. With this cost of an AGV, this would be a significant savings and would additionally improve the AGV congestion thus improving the overall AGV efficiency. When the number of AGVs increases the system experiences more congestion due to blockage, and after a certain point the marginal benefit of adding an AGV in the system becomes disadvantageous because of the additional congestion created as a result of adding the AGV (Kabir, 2016).

4.3 Battery Life Incorporation

Managing the timing of battery charge helps avoid deterioration which eventually helps reduce battery related costs and improve the efficiency of AGVs (Kawakami and Takata, 2011). It is important to manage the batteries well so that they last longer and the overall cost for batteries is reduced (Kabir, 2016). In many applications for the AGVs, their batteries are not charged to a full charge (SoC of 100%). When a battery is given less than a full charge, this undercharging deteriorates the health of the battery thus decreasing the State-of-health (SoH) (C&D Technologies, 2012c). Other factors that can lead to the deterioration of the battery are overcharging, temperature, and cycle service. A reduction to 80% of the rated capacity is usually defined as the end of life for a lead-acid battery (PowerThru, n.d.). When it is below 80% the rate of deterioration accelerates and the battery is more prone to sudden failure from a mechanical shock or high discharge rate.

The design life of a battery is the life expectancy the manufacturer says the battery is capable of, provided that all of the specification parameters are maintained (Lambert, 2016). The specifications parameters may include, the operating temperature, the number of discharges, the frequency of discharges, and the depth of discharges. The service life of a battery designates approximately how long a battery of a given design life will remain reliable, given the real world environment in which it is used (Lambert, 2016).

Being able to determine the effect of the deterioration of batteries overtime and determining when the batteries need to be replaced is very important as it can have significant effects on the AGV efficiency thus affecting the throughout and AGV usage. If the battery is at a SoH of 80%

that means it would need to charge more frequently thus not being available to fulfill transportation tasks which affects the throughput.

The model developed can be used to simulate the deterioration of the battery overtime and the effect it will have on the average throughput and AGV usage. This can help firms in determining when the batteries would need to be replaced and the expected effects on average throughput and AGV usage. The service life of a valve-regulated lead acid (VRLA) battery with a design life of 4 to 5 years is approximately 3 to 4 years (PowerThru, n.d.). As mentioned previously, a reduction to 80% of the rated capacity is usually defined as the end of life for a lead-acid battery. It is assumed for the purpose of the simulation that the deterioration of the battery for each year is the same. So in 3 years for the battery to be reduced to 80% it deteriorates by 6.7% each year. To simulate that with the 6 month replication length, every 2 months the battery SoH will be decreased by 6.7%. Displayed in Table 20 is a run with 6 months with no deterioration of the batteries (SoH is 100% for the 6 months), a run with 6 months with a deterioration of 6.7% every 2 months (first 2 months SoH is 93.3%, second 2 months SoH is 86.6%, and last 2 months SoH is 80.0%), and a run with 6 months with a deterioration of 20% (SoH 80%) for all 6 months.

	Without AGV Battery Deterioration (100% all 6 months)	With AGV Battery Deterioration (93.3%, 86.6%, 80.0%)	With AGV Battery Deterioration (80.0% all 6 months)
Drop Off Area	**Average Throughput**	**Average Throughput**	**Average Throughput**
1	20.71	20.63	19.03
2	36.14	37.00	33.29
3	2874.89	2869.94	2720.31
4	991.97	1002.86	941.37
5	1126.46	1121.40	1080.26
6	1902.77	1926.29	1817.77
7	700.94	698.91	669.66
8	750.23	743.94	707.06
9	3176.23	3184.57	3001.29
10	330.91	325.37	304.51
11	1107.97	1105.63	1052.09
12	6717.63	6762.43	6387.06
13	144.49	145.14	136.11
14	5455.71	5495.37	5203.69
15	723.14	724.94	686.26
16	3501.09	3517.34	3315.09
17	391.80	387.09	372.69
18	4347.60	4351.29	4104.34
19	161.37	155.97	149.49
20	3895.57	3916.86	3713.86
21	2030.26	2025.60	1925.49
22	58007.37	55450.57	51599.97
	AGV Usage	**AGV Usage**	**AGV Usage**
	8.35	8.93	9.42
	Sum of Average Throughput	**Sum of Average Throughput**	**Sum of Average Throughput**
	98395.25	95969.14	89940.69

Table 20: Comparison of run with and without AGV battery deterioration

Based on the above results, it is clear that battery deterioration can have a significant effect on the throughput and AGV usage. This was simulated for only 6 months, so the effect of the battery deterioration would be much larger if it was simulated for 3 years. Being able to determine the effect of the deterioration of batteries overtime and determining when the batteries need to be replaced is very important as it can have significant effects on the AGV efficiency thus affecting the throughout and AGV usage.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

Manufacturing automation has become increasingly vital as the need to be competitive and remain productive has become a necessity to stay in business. Material handling plays a significant role in manufacturing automation and to facilitate material handling, automated transport systems are implemented and employed. Determining the number of AGVs to use in a system is critical. Several models and simulations have been developed and applied to determine the AGV fleet size. Most of these models and simulations do not incorporate the vehicles' battery usage, management, battery life, and the effect it can have on the throughput and the number of AGVs required for the system.

We developed in this research a framework for evaluating AGV dispatching and charging strategies where a discrete event simulation model for common manufacturing facilities incorporating battery management aspects and issues, which are usually omitted in AGV research. The framework entails system modeling, validation, experimentation, and finally arriving to the best operational strategies for the AGV system as a material handling system. In the case under investigation, the analysis entailed studying various scenarios by applying different charging options and strategies and changing different parameters to achieve improved throughput and an optimized AGV fleet size.

Below are the first and third research questions:

1) What is the most favorable opportunity charging strategy to optimize the AGV fleet size and meet the material handling requirements of the system? This will include the most favorable minimum charge level to send the AGV for opportunity charging, the most favorable minimum critical ratio to release the AGV from opportunity charging, how long

to wait before sending an idle AGV for opportunity charging, how long the AGV should charge for, and the dispatching rule when charging.

3) What is the most favorable automatic charging strategy to optimize the AGV fleet size and meet the material handling requirements of the system? This will include the most favorable minimum critical ratio to release the AGV from charging, how long the AGV should charge for, and the dispatching rule when charging.

Both the first and third research questions were addressed. All main effects (A: Minimum Charge level for opportunity charging, B: Minimum critical ratio, C: Wait time for opportunity charging) except for factor D (Automatic charging charge time and dispatching rule) had significant effects on both the average throughput and the AGV usage and are statistically significant. In addition to that, the interaction effects AB, BC, and AC also had significant effects on both the average throughput and the AGV usage and are also statistically significant. In most of the cases, adding the minimum charge level for opportunity charging increased the average throughput and reduced the AGV usage. As less AGVs are sent to opportunity charging they are available to respond to transportation tasks. Increasing the minimum critical ratio reduced the average throughput and increased the AGV usage. As the minimum critical ratio increases, less AGVs are made available to respond, therefore the response time increases and the available AGVs may have to travel longer distances to complete the transportation tasks, which leads to less transportation tasks being completed. Increasing the wait time increased the average throughput and reduced the AGV usage in most cases.

Below is the second research question:

2) What is a more favorable number and location of charging stations to optimize the AGV fleet size and meet the material handling requirements of the system? This will also take

into consideration centralized VS decentralized charging, and the capacity of each of the charging stations.

The second research question was addressed. Based on the results it is clear that the location and number of charging stations can have a significant effect on the throughput and the AGV usage. For the first three scenarios there was only one charging location. Although for each of the three scenarios the charging station capacity was 13 and there were significant differences in the average throughput and AGV usage. In the second scenario, due to the location of charging station 1 the AGV usage was maximized (14.57) as the total number of AGVs is 15.

The results clearly show that battery management can have a significant effect on the average throughput and the AGV usage. In one of the runs, the average throughput increased by 20% which is significant and in another run the AGV usage was reduced by 3 AGVs. On the other hand there were some cases, where based on the factors settings, the AGV usage increased by 6 AGVs. Based on the approximate cost of an AGV of $75,000, reducing the required number of AGVs would provide significant savings and would additionally improve the AGV congestion thus improving the overall AGV efficiency. It is important that the battery management of the AGVs is addressed adequately to run an AGV system efficiently. This framework and simulation tool can be used to determine the optimized fleet size to be used to meet the material handling requirements.

The effect of battery deterioration was also researched and although the results were based on a 6 month simulation, the results showed that battery deterioration can have a significant effect on the throughput and AGV usage. In the simulation run with a deterioration of 20% (SoH 80%) for all 6 months, the average throughput decreased by about 9% and the AGV usage increased by about 13% in comparison to the simulation with no deterioration of the batteries (SoH is 100%) for all 6 months. Being able to determine the effect of the deterioration of batteries overtime and determining when the batteries need to be replaced is very important as it can have significant effects on the AGV efficiency thus affecting the throughout and AGV usage.

Future research includes investigating the effects on throughput and AGV usage for: (I) Different battery chargers that have different charge rates and different batteries that have different capacities and different consumption rates. Based on the evolving technology for both batteries and battery chargers, the decision on which battery and battery charger to use will become more difficult. (II) Different battery charging strategies like battery swapping. Battery swapping would be divided into automatic battery swapping and manual battery swapping. For automatic battery swapping, an automatic battery swap machine is utilized to exchange the depleted battery with a fully charged battery, which usually requires less time to complete than a manual battery swap in which an operator would be required to swap the battery manually. (III) Zone assignments to subsets of AGVs. This would mean that AGVs would be divided into several groups and each group of AGVs would be assigned to a specific area instead of having all AGVs being able to respond to all transportation tasks. (IV) Mathematical programming for AGV optimal assignment. This would mean that the decision of which AGV should respond to which transportation task would be based on an algorithm. (V) Additional scenarios can be studied that consider more or less than two AGVs going through extended charging each night.

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Appendix A:

Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	98298	828	118.65	0.000
Minimum Charge Level (OC)				
0	-10284	1172	-8.78	0.000
80	-3739	1172	-3.19	0.002
Minimum Critical Ratio				
0.000	13417	1172	11.45	0.000
0.035	12817	1172	10.94	0.000
Wait Time (OC)				
1.5	4566	1172	3.90	0.000
3.0	2185	1172	1.86	0.068
Charge Time/Disptaching Rule				
35	467	1172	0.40	0.692
40	-186	1172	-0.16	0.874
Minimum Charge Level (OC)*Minimum Critical Ratio				
0 0.000	-2022	1657	-1.22	0.228
0 0.035	-3036	1657	-1.83	0.073
80 0.000	9893	1657	5.97	0.000
80 0.035	10471	1657	6.32	0.000
Minimum Charge Level (OC)*Wait Time (OC)				
0 1.5	-9854	1657	-5.95	0.000
0 3.0	-195	1657	-0.12	0.907
80 1.5	9523	1657	5.75	0.000
80 3.0	-1193	1657	-0.72	0.475
Minimum Charge Level (OC)*Charge Time/Disptaching Rule				
0 35	1299	1657	0.78	0.437
0 40	-913	1657	-0.55	0.584
80 35	-877	1657	-0.53	0.599
80 40	703	1657	0.42	0.673
Minimum Critical Ratio*Wait Time (OC)				
0.000 1.5	-6732	1657	-4.06	0.000
0.000 3.0	-2246	1657	-1.36	0.182
0.035 1.5	-6867	1657	-4.14	0.000
0.035 3.0	-2909	1657	-1.76	0.086
Minimum Critical Ratio*Charge Time/Disptaching Rule				
0.000 35	295	1657	0.18	0.860
0.000 40	-19	1657	-0.01	0.991
0.035 35	538	1657	0.32	0.747
0.035 40	-425	1657	-0.26	0.799
Wait Time (OC)*Charge Time/Disptaching Rule				
1.5 35	481	1657	0.29	0.773
1.5 40	42	1657	0.03	0.980
3.0 35	-902	1657	-0.54	0.589
3.0 40	696	1657	0.42	0.676

Table 17: Coefficients for Sum of Average Throughput

Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	7.3585	0.0527	139.62	0.000
Minimum Charge Level (OC)				
0	1.4441	0.0745	19.37	0.000
80	0.0463	0.0745	0.62	0.537
Minimum Critical Ratio				
0.000	-1.2570	0.0745	-16.87	0.000
0.035	-0.9622	0.0745	-12.91	0.000
Wait Time (OC)				
1.5	-0.3552	0.0745	-4.77	0.000
3.0	-0.2004	0.0745	-2.69	0.010
Charge Time/Disptaching Rule				
35	-0.0289	0.0745	-0.39	0.700
40	0.0211	0.0745	0.28	0.778
Minimum Charge Level (OC)*Minimum Critical Ratio				
0 0.000	0.432	0.105	4.10	0.000
0 0.035	0.575	0.105	5.46	0.000
80 0.000	-1.072	0.105	-10.17	0.000
80 0.035	-0.976	0.105	-9.26	0.000
Minimum Charge Level (OC)*Wait Time (OC)				
0 1.5	0.906	0.105	8.59	0.000
0 3.0	0.037	0.105	0.35	0.729
80 1.5	-0.736	0.105	-6.99	0.000
80 3.0	0.048	0.105	0.45	0.652
Minimum Charge Level (OC)*Charge Time/Disptaching Rule				
0 35	-0.064	0.105	-0.60	0.548
0 40	0.086	0.105	0.82	0.417
80 35	0.040	0.105	0.38	0.709
80 40	-0.063	0.105	-0.59	0.555
Minimum Critical Ratio*Wait Time (OC)				
0.000 1.5	0.600	0.105	5.70	0.000
0.000 3.0	0.200	0.105	1.90	0.064
0.035 1.5	0.462	0.105	4.39	0.000
0.035 3.0	0.152	0.105	1.44	0.156
Minimum Critical Ratio*Charge Time/Disptaching Rule				
0.000 35	-0.006	0.105	-0.06	0.955
0.000 40	-0.001	0.105	-0.01	0.989
0.035 35	-0.044	0.105	-0.42	0.678
0.035 40	0.036	0.105	0.34	0.735
Wait Time (OC)*Charge Time/Disptaching Rule				
1.5 35	-0.024	0.105	-0.23	0.818
1.5 40	0.011	0.105	0.11	0.916
3.0 35	0.084	0.105	0.80	0.429
3.0 40	-0.064	0.105	-0.60	0.548

Table 18: Coefficients for AGV Usage

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