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RFID for returnable container management in the automotive industry: A Discrete-Event Simulation approach

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By

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ABSTRACT

Returnable containers are a critical factor to ensure quality of manufacturing operations in the automotive industry. However, containers management is still affected by chronic issues, such as containers shortage, losses or inefficient handling. Research and industry experts agree the "Achilles's heel" of current practice is the lack of accurate and timely data about containers flow throughout the complex automotive supply chain. Moreover, containers handling operations still rely on manual operations.

Radio Frequency Identification (RFID) is a technology that allows for automatic extraction of items flow data at key points along the supply chain, without the need of manual operations, and represents a very interesting solution for returnable containers management.

RFID has already been employed in many different sectors, since giants as Wal-Mart or the United States (U.S.) Department of Defense adopted it for their supply-chain.

Several approaches have been adopted in literature to explore potential applications of this technology, but few studies focus on automotive returnable containers management.

In this work, a Discrete-Event Simulation (DES) approach is proposed to evaluate the impact of RFID on automotive returnable containers supply chain. The model has been developed in collaboration with Fiat Chrysler Automobiles (FCA).

Applying factorial design and ANOVA relevant benefits of using RFID have been identified. The same model has been used to define main influencing factors in containers supply chain performance.

DEDICATION

To my great family. Your love is my power.

ACKNOWLEDGEMENTS

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LIST OF ABBREVIATIONS/SYMBOLS

OUL – Order Up to Level

LT – Lead Time

R – Replenishment frequency

EW – Empty containers warehouse

FCA – Fiat Chrysler automobiles

NAFTA – North Atlantic Free Trade Agreement

OEM – Original Equipment Manufacturer

RFID – Radio frequency identification

UHF – Ultra High Frequency

HF – High Frequency

LF – Low Frequency

FL – Fork-Lift

DES – Discrete Event Simulation

RTI – Returnable transport item

RDR – Return discrepancy receipt

IP – Inventory position

EOP – Extension Of Plant

OH – On hand inventory

IT – In transit items

WIP – Work-In-Process

S.D. – Standard Deviation

SP - Supplier

α - Counting accuracy

α_{SP} – SP counting accuracy

α_{EW} - Empty warehouse counting accuracy

α_{Man} – Manual counting accuracy

$\overline{D_C}$ - Average containers demand at supplier location

SD_{TOT} – Total system days

SD_{SP} – Supplier empty containers system days

SD_{EW} – Empty containers warehouse system days

UE – Counting Error Uncertainty

UD – Demand Uncertainty

ULT – Lead time Uncertainty

MODEL VARIABLES

V_EW_OUT – EW Presumed containers released quantity

V_EW_EXITED – EW actual released container quantity

V_SP_IN – SP presumed inbound containers quantity

V_EW_REQ – Replenishment requirement

V_SP_REQ – Plant parts requirement converted in containers requirement

V_E_EW –EW counting error

V_E_SP - SP counting error

V_TOT_REQ_EW – EW cumulated replenishment requirement

V_TOT_SHIP_EW – EW cumulated shipped quantity

V_TOT_REQ_SP – SP cumulated requirement

V_TOT_SHIP_SP – SP cumulated shipped quantity

V_TOT_ORDERS_SP – SP total number of plant parts requirements

V_SP_SHORT – SP containers shortage counter

TRANSIT – In transit containers

PI_EW – EW physical inventory

PI_SP – SP physical inventory

SI_SP – SP system inventory

1. INTRODUCTION

1.1 Problem description

A Returnable container is a packaging solution used to avoid disposing of costly shipping material each time a product is distributed to a customer location. Most automotive parts are stored, shipped and consumed using returnable containers (Twede & Clarke, 2005).

In a typical automotive supply chain, returnable containers are shipped from an empties warehouse to the supplier, where they are filled with automotive parts and components that are shipped back to manufacturer's assembly line. Once parts in a container have been consumed, empty containers are shipped to the warehouse (often operated by a third-party logistics company) where they are sorted, treated and refurbished, ready to ship out again to the supplier (Lunani & Hanebeck, 2008).

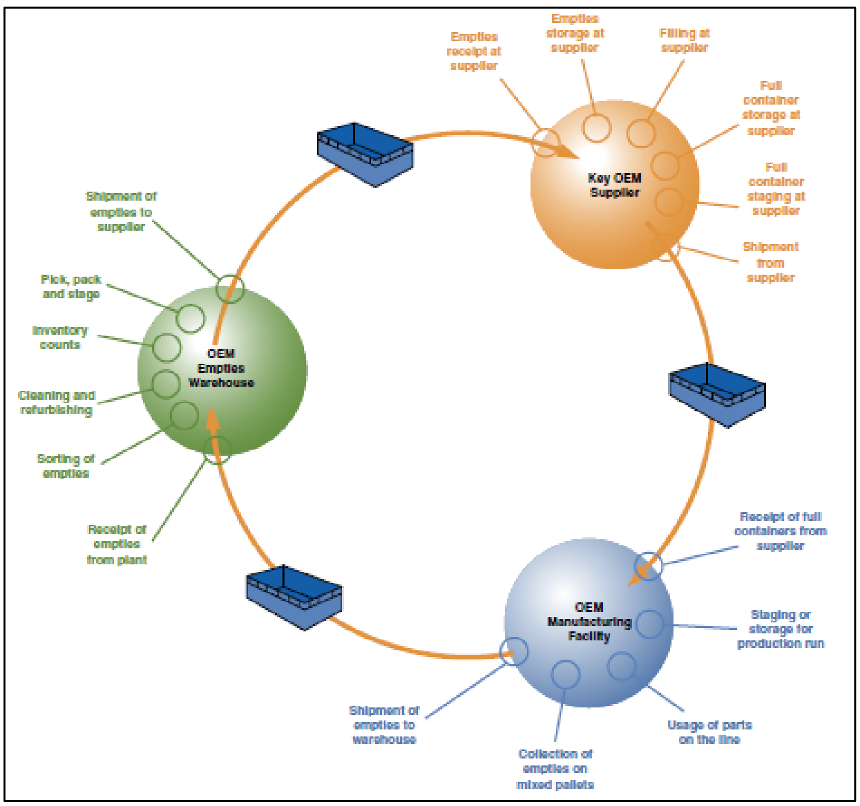

Figure 1.1 Returnable containers supply chain (Lunani & Hanebeck, 2008)

Automotive containers (See Figure 1.2) range in size from not much bigger than a shoebox to pallet-sized for larger parts. They are designed with specific vehicle programs in mind and are mostly used in conjunction with inserts that hold the parts and protect them from damage.

Figure 1.2 Automotive bulk plastic containers

Containers are a critical factor to ensure quality of manufacturing operation (Foster, Sindhu, & Blundell, 2006). In particular, OEM must ensure containers are in the right place at the right time. However, It is possible to identify some open issues with current automotive returnable container supply chain management (Lunani & Hanebeck, 2008) (Chism, 2010) (Caratti, 2013):

- Shortage: Wrong shipments and misplacement lead to 15-20% containers losses and 20-25% excess purchased containers. Containers might also be used as Work-In-Process (WIP) storage at supplier facilities.
- Substitute cost: for each lost container, it is necessary to provide suppliers with an expendable cardboard packaging as backup. The total cost is a relevant loss for the OEM, especially if express shipping is necessary.
- Inventory accuracy: container inventory is often inaccurate, and necessary containers quantity might be not properly estimated.
- Inefficient handling leads to excess inventory at location and increased operations time
- Trailers loaded with containers might sit in the yard while considered in transit, resulting in strong pickup time fluctuations, delays and missed shipments.

According to (Sheffi, 2003) , those issues are caused by lack of accurate and timely data from suppliers and service providers as to where shipments are, what the current inventory level is, and where is it located. In particular, a major source of variability is current data acquisition practice, which relies on manual operations.

One way to tackle these problems is the implementation of a tracking system (L.Thoroe, 2009). This is where Automatic Identification (AutoID) starts to play a key role.

Radio Frequency Identification (RFID) is an AutoID technology that allows for automatic extraction of the object identity at key points along the supply chain, without the need of manual operations. Unlike barcode, this technology does not require visual contact or clear line of sight, as it uses radio signals.

RFID technology can automatically generate event data that digitally describes how physical entities such as single items or pallets move through supply chain processes across different parties.

The “big bang” of RFID dates back to 2005, due to the mandates from Wal-Mart and the United States (U.S.) Department of Defense (Visich, Li, Khumawala, & Reyes, 2009). Since then, RFID has been a viable technology for implementation of supply chain improvement projects, and most of the industries using returnable containers are involved with RFID, whether directly or indirectly.

Advantages deriving from RFID can be significant in the automotive containers management. For example, IBM Global Services (Lunani & Hanebeck, 2008) developed a case study to evaluate opportunities of tracking returnable containers in the automotive industry, reporting 80% reduction in expendable cost and 5-15% reduction in fleet shrinkage. Those benefits are not limited to OEM, but extend to supplier and logistics service providers in terms of reduced labor cost and better control over transportation.

With RFID, information about containers flow can be automatically recorded, providing a new dimension of visibility. Real time data can be integrated with current OEM information system to support management process (Foster, Sindhu, & Blundell, 2006).

Additional RFID benefits include: increased material handling speed, efficiency and security in the supply chain, reduced inventory, reduced out of stock and labor cost (Visich, Li, Khumawala, & Reyes, 2009).

1.2 Research problem statement

The aim of the present work is to use Discrete Event Simulation (DES) to evaluate the impact of RFID technology on FCA returnable containers supply chain. The proposed model consists of a two-echelon closed loop automotive containers supply chain, composed of empty containers warehouse and one supplier. By means of factorial design, the main influencing variables are identified, and system performances with and without RFID are compared.

- Why returnable containers?

As previously stated, an efficient returnable containers management process is a key factor influencing automotive manufacturing operations costs.

It is possible to identify some open issues with current containers management, causing relevant financial losses for OEMs (Caratti, 2013) (Lunani & Hanebeck, 2008) (Sheffi, 2003) . Those issues can be related mainly to lack of visibility on containers fleet and human error. (Sheffi, 2003)

- Why RFID?

Radio Frequency IDentification automatically provides accurate information about items flow. Evidences from many different industries, including automotive, suggest that with visibility deriving from RFID, it would be possible to tackle chronic and wasteful containers management problems.

- Why Discrete Event Simulation (DES)?

Simulation provides a better understanding of complex systems, and the impact of changes can be examined without affecting the real system (Sharma, 2015) (A. Sarac, 2009). DES is a valuable tool that can be used to support automotive manufactures decision toward RFID.

In this thesis, RFID impact is evaluated in terms of:

- Reduced containers shortage
- Reduced Human error
- Safety stock reduction
- Increased supplier service level
- Reduced Handling time

The remainder of this work is organized as follow:

- Chapter 2: Similar studies are reviewed and compared to present work.
- Chapter 3: Research Methodology is presented
- Chapter 4: Simulation results are presented and commented
- Chapter 5: Conclusions and future work.

2. LITERATURE REVIEW

In this chapter, a general overview of RFID working principles, application and current research status will be presented.

2.1 Insight on RFID technology

The basics working principle of RFID technology will now be presented. An RFID system usually includes the following elements (Sheffi, 2003):

- An Identity tag assigned to a particular item
- A unique identification number which is stored in the tag memory
- Networked tag readers, which are able to collect the signal from tags
- Networked databases to store product information

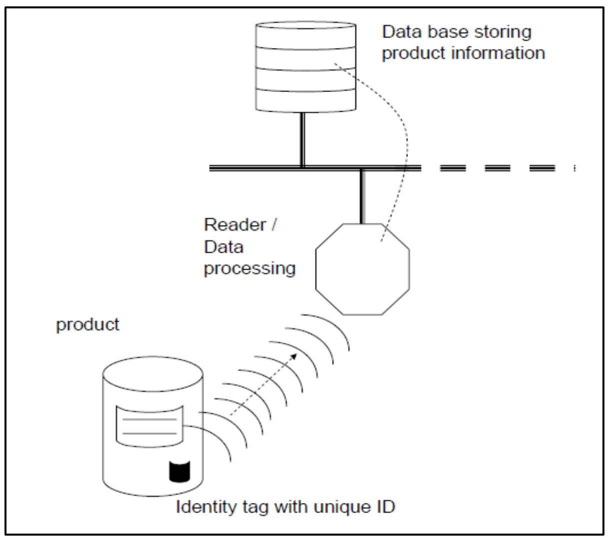

Figure 2.1 RFID system schematic (Sheffi, 2003)

The reader automatically acquires item identity by means of electromagnetic waves. Tag and reader behave like a receiver and transmitter exchanging data. This means that the item turns into a smart object, able to provide its identity. The way identification is accomplished, depends on the kind of RFID technology used. It is possible to distinguish two big families: active and passive. Both of them use radio frequency to communicate between tag and readers, but passive RFID tags are powered with the energy provided by the reading head, while active RFID rely on autonomous energy sources.

2.1.1 Active RFID

In his book, "The RF in RFID" (D.Dobkin, 2007), D. Dobkin defines active tags as "full-fledged radios, with a battery, receiver, transmitter, and control circuitry" that are applied on the item. They allow for bidirectional communication with the reader in the range of hundreds meters, and can be successfully used even in environments with significant obstructions. A system schematic is provided in Figure 2.2

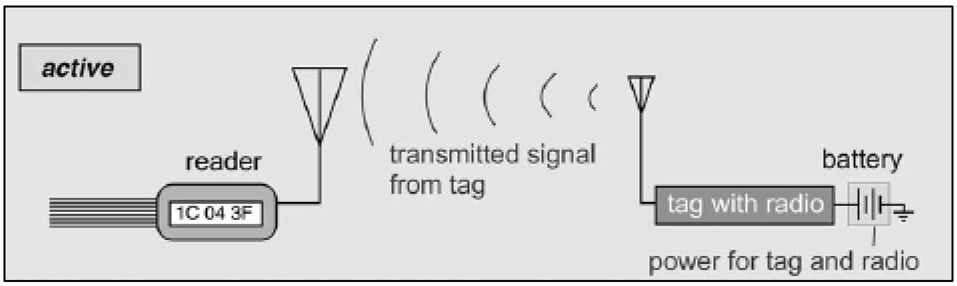

Figure 2.2 Active RFID working principle (D.Dobkin, 2007)

The tag transmit in the frequency range 303/433 MHz, either by constantly beaconing information to a reader or by transmitting only when it is interrogated by the reader (Cisco, 2014). At a typical rate of one beacon every 4 minutes, the battery is expected to last about 6 years.

Being fully functional radios, active tags are more expensive than passive tags, with a unit price range of 15-100 USD. Moreover, an active transponder must be certified as an active radio emitter and must meet several regulatory standards.

It is important to underline that having a very large reading range can be a drawback, because the reader can only detect tag presence and not its exact location. This issue can be solved with the use of multiple readers and specific algorithms, achieving a positioning accuracy in the range of few meters. An example active RFID tag is presented in Figure 2.3.

Figure 2.3 Active RFID tag (Omni-ID)

The typical application of this technology is for real-time tracking of high-value assets in closed-loop systems, such as medical equipment, computer equipment, reusable shipping containers, and assembly line WIP.

2.1.2 Passive RFID

With reference to (D.Dobkin, 2007), passive RFID technology is now described. In this case tags do not have any independent power source, and receive power from the reading device, as shown in Figure 2.4.

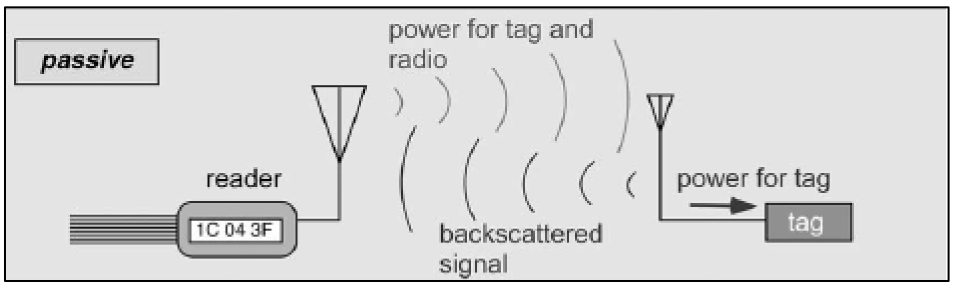

Figure 2.4 Passive RFID working principle (D.Dobkin, 2007)

The tag talks to the reader using *Backscattering*. The transmitted signal from the reader powers the tag and, at the same time, it is modified by the tag internal circuitry. The resulting backscattered signal carries the information recorded on the tag.

Passive tags are inexpensive and virtually maintenance free, since there is no battery to replace.

Reading range is much lower than active RFID, and it depends on the system operating frequencies, summarized in Figure 2.5.

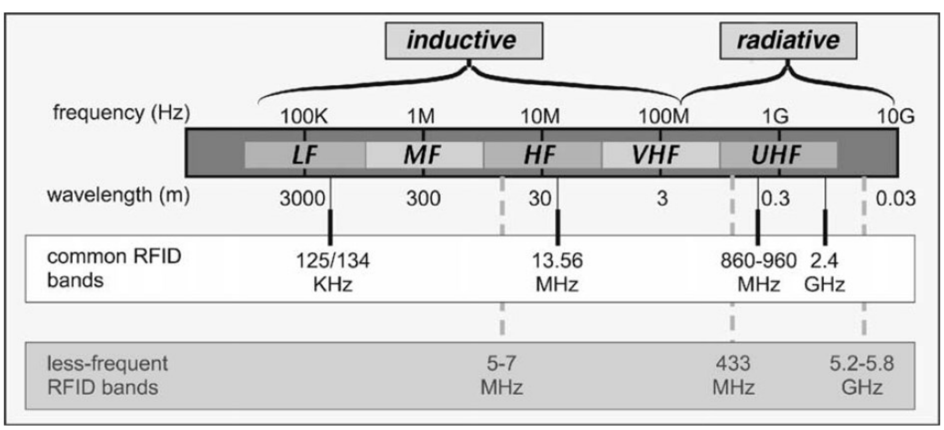

Figure 2.5 Passive RFID operating frequencies (D.Dobkin, 2007)

Ultra-High Frequency (UHF) RFID operates in the 860-960MHz range, and provides relatively long reading range, usually several meters. At the same time, it allows for high reading rate, that means it is possible to read hundreds of tags at the same time. Low frequency (LF) and High Frequency (HF) do not offer the same performance, and this is why UHF is preferred and increasingly used in supply chain management and asset tracking, where the future potential for very low-cost tags is important, and relatively long range adds flexibility in applications. Because tags are powered by the reader signal, this signal must be strong enough to activate the tag. For this reason, presence of conductive materials, such as metals, metal films, and aqueous solutions plays an important role in defining system capability of reading tag reliably. However, this reliability can be still very high. Rahmati et al (Rahmati, Zhong, Hiltunen, & Jana, 2007) shown that using multiple tags for the same item, and multiple readers for the same reading point, system accuracy can be as high as 99.9%.

Price range for one tag unit is between 0.12 and 0.22 USD, much lower than active tags. Figure 2.6 describes the anatomy of an UHF RFID tag.

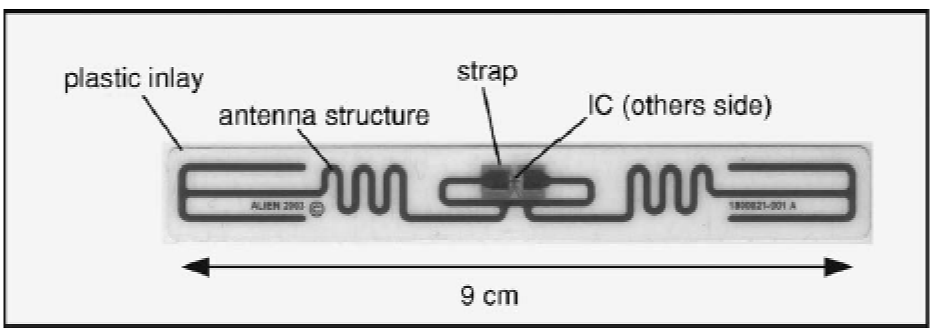

Figure 2.6 Passive RFID tag (D.Dobkin, 2007)

The cost of the reading equipment depends on the specific reading point setup. Often, RFID are used to monitor material flow through localized checkpoints, such as dock doors. An example RFID gate monitoring system, usually called RFID portal, is provided in Figure 2.7.

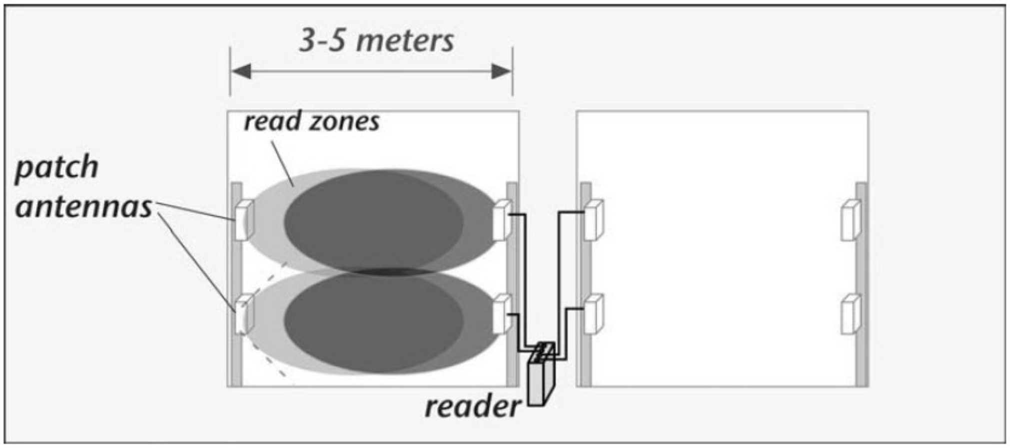

Figure 2.7 RFID portal schematic (D.Dobkin, 2007)

The reader setup should be able to read tags located anywhere within the entry region, but should not read tags located outside this region, in order to avoid false positive reads.

2.2 RIFD Technology for returnable containers tracking

Basics of RFID technology have been introduced. In this section, it will be discussed how to use passive RFID for returnable transport items tracking. In particular, best practice for containers tagging will be presented.

According to a leading RFID manufacturer (Omni-ID), when selecting the best tag model for a specific item, the following three factors should be taken into account:

- Reading range. It depends on the distance between the reader and the item to be scanned.
- Tag size. For many applications, the size is not an issue, because there is plenty of space where to place the tag. In general, the larger the tag, the better the reading range.
- Interference. The electromagnetic environment in which RFID system operates is fundamental. The right tag depends on the material of the object to be tagged.

Considering construction material, it is possible to identify two main categories of containers used by FCA NAFTA: Metal and Plastic. Some examples are provided in Figure 2.8.

Figure 2.8 FCA container models

GS1 is the main non-profit organization in charge of defining supply-chain standards. In one of his published documents, the organization defines tagging guidelines for Returnable Transport Items (RTI), such as returnable containers. Each RTI is associated with a unique identifier, called GRAI, which must be saved on tag memory. The data are captured by the RFID readers when the RTI is scanned.

The paper recommends the following:

- A minimum of two pieces of RFID tags should be placed.
- Plastic RTI should have one tag in the corner and another one in the opposite corner.

Rhamati et Al. (Rahmati, Zhong, Hiltunen, & Jana, 2007) studied the impact of two additional factors affecting RFID reliability: tag orientation and inter-tag distance. Authors demonstrated that tag orientation can reduce system performance significantly, and confirm what stated by GS1: at least 2 tags are necessary to achieve high level of reading accuracy. In particular, if two readers are used to scan an object which is enabled with at least two tags, 99.9% accuracy can be achieved. It is possible to conclude that tags and readers redundancies are fundamental in deploying RFID systems.

2.3 RFID Evaluation frameworks

Having discussed technical details, let us now focus on how RFID can generate value for the industry. In this section, the reader will be introduced to main RFID value drivers according to current literature.

Dutta et Al. (Dutta, 2007) identify three main areas where RFID can create potential value for business:

- Labor cost savings: Multiple tags can be acquired at the same time, without manipulating or scanning the object. Increased process accuracy also reduces the need for periodic inventory counts.
- Inventory shrinkage reduction: using RFID, the accurate recording of inventory by quantity and by location could result in less opportunity for mistakes and prevent or discourage theft.
- Higher visibility: RFID would enable to counteract inventory discrepancies due to shrinkage, misplacements, or transaction errors, thanks to enhanced visibility on current stock levels and location.

The authors conclude recommending the use of computational model and simulation for a more complete evaluation of specific case studies.

Curtin et Al. (Curtin, 2006) identify some potential barriers in exploiting full RFID value in a Business-to-Business (B2B) logistics structural setting: Introducing automatic items scanning might require a full process reorganization involving multiple companies. In order to get the most out of RFID it is necessary to achieve cooperation between trading partners and encourage full adoption of the technology throughout the supply chain. In addition, Authors suggest opportunities at different levels:

- Internal operations. Inside the factory of tomorrow, RFID can be used to coordinate the material flow to the point of assembly and ensure a smooth process with no waiting for materials. Vehicles being assembled in an assembly plant can be tracked as they move through a series of assembly processes at different stations in the plant. The tag will tell the reader the specific operation that needs to be done at each station, resulting in much more intelligent factories and warehouses.

- Sales and marketing. RFID help in tracking customer's needs, allowing for customized service and follow up on sales promotion. This holds mainly for the retail industry.

Baars et Al. (Baars, Gille, & Struker, 2009), identify three main categories of RFID benefits:

- Automation. Thanks to automatic data acquisition capabilities, RFID produces benefit at activity level, with reduced resource consumption. The extent of this benefit depends on the frequency of data acquisition.
- Information. RFID increases the quality of business information without modifying current structure or process.
- Transformation. An improved information base allows for re-designing the process and improving supply-chain performance.

M. Tajima (M.Tajima, 2011) distinguishes three main advantages:

- Monitoring capacity. RFID can be used in closed loop system to monitor reusable assets, as well as raw material and work-in-process inventories, and finished products. It can also monitor the use and condition of equipment and reusable assets. The author provides example of reusable assets that have been successfully tagged, determining process improvements. She also suggested RFID as the way to change supply chain strategies dynamically, for example acting on safety stocks.
- Response speed. RFID increases firm's response speed to supply chain variability by notifying personnel in real time. For example, if received contents do not match with the advance shipping notice, an alarm can be triggered immediately by the system.
- Decision-making Quality. Providing visibility data about inventory levels and location, RFID enable for risk-mitigating strategies

Moreover, the author raises an important point about security. "Data eavesdropping" is the interception of communication between tag and reader: it can be used by competitors for corporate espionage. Also Juels (Juels, 2005) discusses the potential security concern deriving from RFID.

Tags respond to reader interrogation without alerting their owners: where read range permits, clandestine scanning of tags is a plausible threat.

2.4 RFID in the automotive industry

In this section, main examples of RFID in the automotive industry will be presented, considering not only returnable containers, but also other potential applications.

Velandia et Al. (Velandia, Kaur, Whittow, Conway, & West, 2016) proposed an RFID system for managing crankshafts manufacturing and assembly. Authors first discuss current barcode technology for item level tracking, and then revise possible RFID solutions for metal parts tracking. Different bolt-integrated tags were tested for part tracking. They conclude RFID can provide several advantages to the manufacturing process, but a careful integration process of this technology is necessary, Involving both technologists and management.

Khan et Al. (Khan, et al., 2006) presented a very interesting application of RFID for vehicle components recycling: Using RFID to control closed-loop recycling would allow for automotive dump reduction.

Kirch and Poenicke (Kirch & Poenicke, 2015) studied RFID application to confirm the completion of automotive assembly processes. In particular, a wristband is proposed as viable solution to integrate automatic confirmation of tasks and operations.

Hermann et Al. (Herrmann, Rogers, Gebhard, & Hartmann, 2015) investigate the application of RFID on finished vehicle distribution. The authors identify current final processing of finished vehicle as a weak point of the supply chain. In particular, they target the lack of data transparency and the use of manual operations: considerable time can be wasted searching for specific vehicles. An RFID transponder solution is evaluated, and different application points over the vehicle are tested, to find optimal transponder position. This allows for an optimized finished vehicle steering process.

Tabanli and Ertay (Tabanli & Ertay, 2012) realized an RFID-based Kanban system to be used by an automotive safety components supplier. Traditional Kanban cards are replaced with RFID Kanban cards, to avoid losses and enable real time visibility on parts inventory. They used value-stream mapping to define the key requirements for the system. Potential cost savings are reported, but it is recommended to monitor customer satisfaction increase to fully understand the benefit of the technology.

Huang et Al. (Huang, Li, Yuan, Gao, & Rao, 2012) proposed RFID as viable solution for an effective management of Painted Body Storage (PBS) in the automotive industry. They compared different scenarios: No RFID, barcodes and two different types of RFID technology (HF and UHF). Thanks to the proposed solution it was possible to greatly reduce the workload on the employee, also increasing safety. Moreover, the RFID system provides superior visibility throughout the entire PBS process.

Holmqvist at Stefansson (Holmqvist & Stefansson, 2006) developed a case study with Volvo for aftermarket with focus on aftermarket logistics. They proposed a portable RFID system based on GSM architecture, to be used as alternative to more expensive portals setup. They report a possible 30% lead time reduction implementing the system

2.4.1 RFID for automotive containers

Some examples specifically related to automotive containers tracking are presented. Foster et Al. (Foster, Sindhu, & Blundell, 2006) developed a case study with a leading car manufacturer regarding RFID tagging of high value automotive stillages. If those transport items are not available, components may be decanted into cardboard storage to meet the demands of the OEM's schedule, which might lead to damages and additional transportation costs. Authors developed a comprehensive study of the entire stillages supply chain to assess the feasibility of an RFID tracking system.

Lunani and Hanebeck (Lunani & Hanebeck, 2008) implemented an RFID system in an automotive returnable containers supply chain, reporting positive effects on performances indicators. In particular, 80% reduction in expendable cost and 5-15% reduction in fleet shrinkage.

The reader can now appreciate the variety of RFID-related application in the automotive sector. In the present work, simulation is used to investigate potential RFID application to Chrysler supply chain. For this reason, in the next section RFID-related simulation work will be presented.

2.5 RFID and simulation

Different approaches have been used by researchers to evaluate the impact of RFID on industrial scenarios. Several researches used simulation models as a-priori evaluation tool. According to (Kleijnen, 2005), a simulation model is a computer mathematical model that is not solved analytically: time evolution of dependent variables is computed given an initial system state and values for exogenous variables. As consequence, simulation does not provide closed form results. The author further distinguishes between:

- System dynamics
- Discrete event simulation (DES)

The first approach models the company as a system with six types of flows: materials, goods, personnel, money, orders, and information. It relies on feedback principle, and a target value is compared to its realization.

The second approach considers individual events rather than flows, and takes into account uncertainties, such as variable lead time or variable demand. System dynamics models do not take into account of randomness usually.

Discrete event simulation will be considered in the following. Many researchers focused their effort on DES to evaluate RFID impact on supply chain. In the following, most relevant works for the sake of present research will be discussed. Even if not directly correlated with the automotive industry, the presented works are very important to understand the common research approach to RFID simulation.

Tellkamp and Fleisch (E.Fleisch, 2003) simulated a three stage open supply chain composed of manufacturer, distributor and retailer. The aim is to find out how the supply chain performance changes as effect or reducing or eliminating inventory inaccuracy. They distinguish four main sources of inventory inaccuracy: Incorrect deliveries, misplaced items, theft and defected products. Four performance metrics are defined: Cost of lost item, including and excluding item value, inventory inaccuracy and Out-of-stock frequency. Two sets of analysis are presented:

- Inventory is affected by inaccuracies
- Inaccuracy is eliminated, equalizing system and physical inventories.

A variance analysis is performed changing the effect of the four mentioned parameters, in order to understand the major effect on system performances. The same experiment is repeated eliminating inventory inaccuracy with RFID, to see which performance indicators benefits the most. Authors conclude that inventory inaccuracy caused by theft has the biggest impact compared to defected/damaged products and incorrect deliveries or misplacements. Automatic identification is suggested as solution to tackle those issues, increase inventory accuracy and lower supply chain cost.

Wang et Al. (Wang, 2008) proposed a multi-tier simulation approach for evaluating the impact of RFID on a pull based open supply chain with (s, S) reorder policy. Their model is a combination of different agents that simulate the behavior of real world supply chain members. The effect of RFID is simulated as reduction in response time compared to the base case. To evaluate and compare the different alternatives a total inventory cost function is defined. Authors develop a design of experiment (DOE) to track the effect of different reordering policy (with and without RFID) on total inventory cost at each location. They conclude RFID can lead to potential cost reductions.

Lee et Al. (Lee) simulated a three echelon open supply chain composed of manufacturer, distribution center and retailer, considering item-level tagging and stochastic demand. The considered inventory policy is (s, S), and performance metrics are: inventory profile, shortages and cost. Different policies are evaluated. Similarly to (E.Fleisch, 2003), the system is simulated with and without RFID to study effect on:

- Inventory accuracy. Authors assume RFID boosts inventory accuracy up to 100%. Three possible scenarios have been considered.
- Shelf replenishment policy. RFID enables for constant shelf level monitoring. Four possible scenarios have been considered
- Visibility. Thanks to RFID enhanced visibility, manufacturing quantity is calculated depending on distribution center inventory level. Four possible scenarios have been simulated

The authors conclude that, even if the considered case is too simplified to produce results that can be directly used, potential RFID advantages are clear.

Ustundag and Tanyas (A. Ustundag, 2009) developed a three-echelon pull based supply chain, made of manufacturer, distribution center and retailer using an economic order quantity inventory policy. The performance of the system is evaluated in terms of: inventory cost, theft cost and lost sales cost. Four main issues are considered: Misplacement, incomplete shipment, theft and product damage. RFID effect is simulated considering zero all those factors but damaging.

ANOVA was used to evaluate the effect of increasing product value, variable lead time and demand uncertainty. For each of those factors, three levels have been defined. They concluded that increase in product value increases savings deriving from RFID, increasing lead time and demand uncertainties decreases potential savings.

Brown et Al. (K. Brown, 2001) Investigated frequency and magnitude of errors that determine inventory inaccuracy, in an MRP based supply chain. Twelve possible scenarios have been investigated, considering different error frequencies, magnitude and position along the supply chain. Performance has been measured considering inventory carrying cost and percent of late orders. ANOVA was used to analyze the results, considering all the possible factors interactions. Authors conclude that error frequency has the biggest impact on overall system performance.

Saygin (Saygin, 2007) studied three different scenarios considering a manufacturing company inventory system:

- Base case without RFID. Simulation model mimics current inventory management operations, based on manual operations.
- RFID monitoring. RFID is simulated just for inventory monitoring purposes, and baseline inventory policy is not changed.
- RFID adaptive inventory. RFID-based automatic replenishment policy is simulated. In this case inventory inaccuracy is eliminated and baseline inventory is adapted according to demand and lead time forecasts.

The effects of different scenarios on overall system performance are compared by means of ANOVA. The proposed adaptive scenario shows overall better performances over base case.

Kang and Koh (Yang & Koh, 2002) simulated a retailer supply chain to explore the impact of shrinkage on stock-out. Their model includes random demand and inventory inaccuracy because of shrinkage. Authors proved 2.5% shrinkage leads to 50% increase in stock-out rate. Also, they conclude that indirect cost of uncounted shrinkage error is 30 times larger than direct cost of Shrinkage.

Basinger (Basinger, 2006) developed a simulation study to evaluate the impact of theft, order error, lead time, synchronization frequency, demand variability, stock-out policy and inventory policy on supply chain performance indicators degradation. The model is a three stage supply chain made of two suppliers and a buyer, and it is implemented using ARENA®. Two different inventory policies are simulated: Re-order point and periodic review. Similarly to other works, a DOE is selected as experimental procedure.

Sarac et Al. (Sarac, Absi, & Dauzere-Peres, 2008) simulated a three stage supply chain whose performance is affected by theft, misplacement and unavailable items. ARENA® was used to simulate five different scenarios:

- Base case with no RIFD
- RFID at pallet level
- RFID at item level
- Enhanced RFID system at item level
- RFID-enabled shelves, for constant products monitoring

DOE is used to analyze results. The peculiarity of this work is to consider different kind of RFID applications in the same model, so that is possible to compare costs and benefits of the alternatives.

Kim et Al. (Kim, Tang, Kumara, Yee, & Tew, 2007) proposed a simulation framework to evaluate application of RFID to automotive assembly plant shipping yards operations. RFID is investigated as viable solution to improve finished vehicle load makeup process.

Three scenarios are simulated:

- Current practice
- New practice 1: RFID system is used to reduce manual error and waiting time
- New practice 2: RFID is used together with a set of specific planning algorithm to fully utilize RFID real-time data.

Simulation results are analyzed by means of DOE and ANOVA.

2.6 RFID and Mathematical models

For sake of completeness, a brief reference to RFID-Related mathematical models is provided. According to (A. Sarac, 2009), mathematical models correspond to the simplifications of a real system through mathematical expressions in order to analyze and optimize the system according to an objective function.

Kim and Glock (T.Kim, 2014) developed a mathematical model of a closed-loop supply chain to evaluate the impact of RFID. Returnable containers are used for transporting products from a supplier to a retailer. Three different containers inventories are distinguished: used, repaired and serviceable. Authors consider two containers fleet shrinkage sources:

- Disposal: because of damaged containers that cannot be repaired.
- Loss: because of containers that are not returned to the warehouse.

Disposal rate is considered constant, return rate is random. Optimal size for repair and purchase lot is defined. Authors provide a mathematical formulation to justify RFID investment as function of increased return rate.

B. Cobb (Cobb, 2016) proposed a model of RFID enabled closed-loop supply chain with returnable containers. The approach is similar to (T.Kim, 2014). Three inventories are defined: used, repaired and serviceable. In this case both return rate and scrap rate are considered random. Also, inspection and repair rate are finite. Optimal control parameters in terms of inspection and repair cycle length are defined together with optimal safety stocks level.

Thoroe at Al. (L.Thoroe, 2009) developed a model of a closed-loop containers supply chain with constant return and scrap rate. Two containers inventories are defined: returned and serviceable.

The aim of the model is to define a new optimal inventory policy as consequence of RFID, which determines and increased return rate. In conclusion RFID allows for optimal lot size reduction and increased cost savings.

2.7 Present work and current literature

It is important to compare the present simulation work to literature, to understand innovations and similarities. Considering the presented simulation studies, it is possible to identify some common features:

- Several models make use of Design Of Experiment (DOE) and ANOVA to process results
- The vast majority of models simulate open-loop supply chains
- To our knowledge, only few DES works explore RFID impact on automotive returnable containers management
- Few models focus on simulating current manual data acquisition practice
- ARENA® simulation software is a common choice among researchers

The aim of the present work is to provide a reference for automotive returnable containers supply chain simulation, expanding current literature. In particular, proposed simulation model will present the following characteristics:

- Two-stage closed loop supply chain built around a real automotive case study
- Simulation of current data acquisition process performance based on field data
- Use of DOE and ANOVA to evaluate RFID impact on performance indicators
- Variable lead time and demand

3. METHODOLOGY

This chapter covers the explanation of the activities carried out for the development of this research. The organization of the chapter follows some of the guidelines for an effective simulation model defined by Banks et Al. (J. Banks, 2005). It is organized in three main sections:

1. Model conceptualization
2. Model realization
3. Experimental procedure

3.1 Model conceptualization

The first step is to define the model concept, understanding how the real system works. To accomplish this task, the following tools have been used

- FCA corporate material
- Interviews with management
- Visits to involved facilities

3.1.1 FCA containers supply chain overview

In this section, FCA returnable containers supply chain is introduced. As previously discussed in the introduction, a returnable container is used to carry parts to the OEM assembly line from one of the suppliers across the whole supply chain.

The containers can be located in any of the locations presented in Figure 3.1.

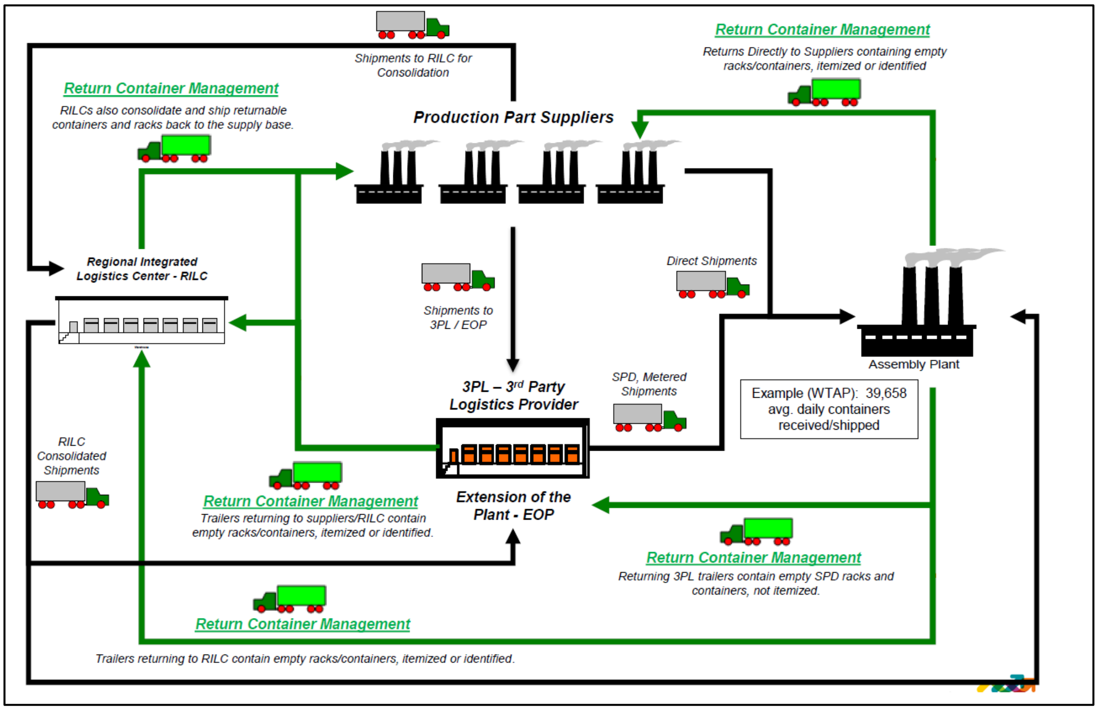

Figure 3.1 FCA returnable containers supply chain

- Assembly plant: receives full containers loaded with parts. Once parts are consumed, empty containers are shipped back to suppliers, Extension of Plant (EOP) or Regional Integrated Logistics Center (RILC)
- EOP: Extensions of Plant (EOP) are warehouses whose main functions are metering and storage. An EOP receives full containers from suppliers, and must ensure the right amount of parts arrives at the plant at the right time. Also, EOP stores empty containers from the line to avoid burdening the plant warehouse, and ensure suppliers receive the correct return of containers. Several EOPs might be assigned to the same plant.
- RILC: A Regional Integrated Logistics Center (RILC) is a facility devoted to parts crossdocking and empty containers storage and return. Full containers from many different suppliers are collected and sorted to the right assembly plant. Moreover,

empty containers from the plant are stored and returned to the right supplier in the right amount.

- Suppliers: Empty containers received from plant, EOP, RILC are loaded with needed parts at supplier location, and shipped back to the plant, EOP or RILC.

It is possible to identify two main containers categories:

- Standard containers: Containers shared by different suppliers, according to Chrysler's containers pooling system. As defined by (P. Bowman, 2009), in pooling systems containers from a variety of locations are returned to a convenient central or regional depot (RILC or EOP) where they will be sorted as required to satisfy suppliers replenishment needs. FCS containers pooling relies on SP inventory monitoring, in order to define each SP replenishment requirement.
- Unique containers: dedicated to one specific supplier. They are not pooled, but returned directly to the supplier. All containers available at plant are shipped back to SP without being pooled. In this case SP inventory is not monitored.

In the following, the case of a standard container will be considered, but focusing on one single supplier. It is possible to extend the model to a multi-supplier case, as will be discussed in chapter 5.

3.1.2 Containers fleet size and stock levels

Total time containers spend before closing supply-chain loop is defined by FCA as "Total containers system days". It is defined taking into account time containers spend in each location, either empty or full, as depicted in Figure 3.2.

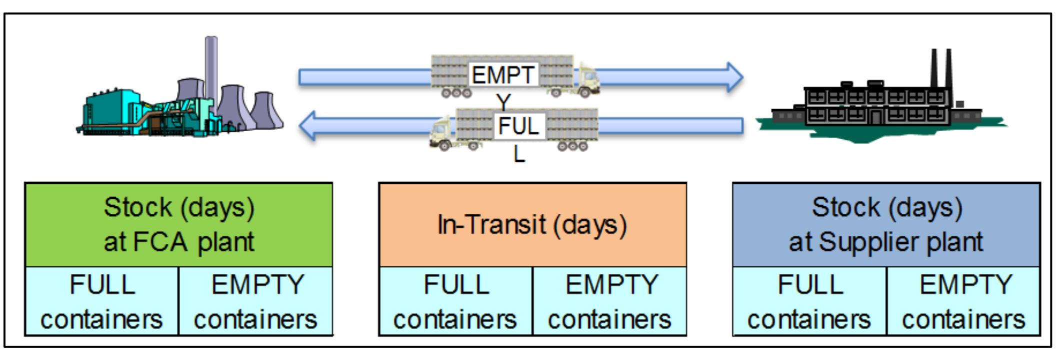

Figure 3.2 Containers system days

System days are necessary when defining total container fleet and stock levels in each location. Total fleet is defined by the following equation.

$$Fleet = \overline{D_C} \times SD_{TOT} \times Repair\ factor$$

Where:

- $\overline{D_C}$; average plant demand for parts converted in equivalent number of containers, according to container density and required part per vehicle
- SD_{TOT}; total system days
- Repair factor; Excess quantity that allow damaged containers to be removed from the system for repair

In this equation it is possible to notice that system days are directly related to containers quantity through average containers demand: system days are a measure of containers quantity. For example, stocks at supplier will be measured in terms of Supplier’s system days rather than total container units.

It is important to underline that stock levels should never go below assigned system days, in order to avoid shortage. For this reason, it is possible to consider system days as safety stocks.

In next section, it will be explained how to determine supplier replenishment requirements.

3.1.3 Supplier containers replenishment

Containers are pushed to supplier’s location based on replenishment requirement as defined by OEM containers management system. If not enough containers are available at SP, it is necessary to provide SP with cardboard expendable backups. Replenishment is defined periodically according to replenishment frequency, called “R”. After Replenishment supplier current on-hand inventory plus received quantity should reach a target level called “Float”. The float will accommodate the supplier’s container demand until next replenishment.

For sake of this work, this replenishment process will be simulated with a periodic review policy.

According to Chopra and Meindl (P.Meindl, 2013) , in periodic reviews policies inventory levels are reviewed after a fixed time period R, and an order is placed such that the level of current inventory plus the replenishment lot size equals a pre-specified level called order-up-to-level (OUL).

$$OUL = \overline{D}(R + LT) + SS$$

- $\overline{D}$ Average demand.
- R Inventory review period (Measured in time units)
- LT Lead time (Measured in time units)
- SS Safety stock (Measured number of items)

If SS is measured using supplier system days SD_{SP}, it is possible to re-arrange the previous equation

$$OUL = \overline{D_C}(R + LT + SD_{SP})$$

The replenishment quantity is defined as

$$Replenishment = OUL - IP$$

Where IP is supplier's inventory position, defined as

$$IP = OH + IT$$

- OH current on-hand inventory
- IT current in-transit quantity

This policy is implemented in the simulation model as shown in section 3.2.

3.1.4 Containers counting

When empty containers are shipped or received, inbound/outbound quantity must be verified. Current FCA practice relies on manual counting: that means there is space for human error. Containers are handled by means of forklifts, and count is performed by the forklift driver. The current counting procedure is now described, distinguishing between empty containers unloading and loading.

Empty containers unloading operations are schematized in Figure 3.3.

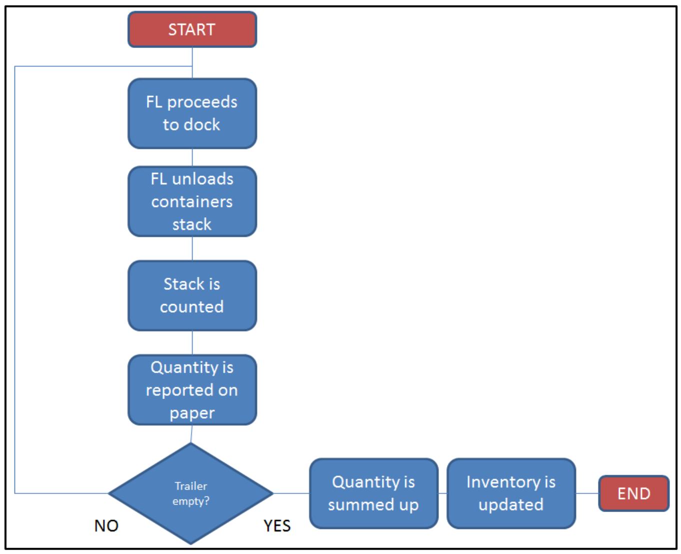

Figure 3.3 Empty containers unloading operations

When a truckload of empty containers arrives at the dock, unloading operation starts. The forklift (FL) driver moves to designated arrival dock, and set up the trailer for unloading. Containers are unloaded in stacks, depending on containers stack-ability. When a stack is removed from the trailer, FL stops and counts how many containers are in the stack, reporting the quantity on paperwork. The stack is moved to storage, and the operation is repeated until the trailer is empty. When the unloading is done, the total unloaded quantity is defined summing up all the stacks counts.

Empty containers loading operations are reported in Figure 3.4.

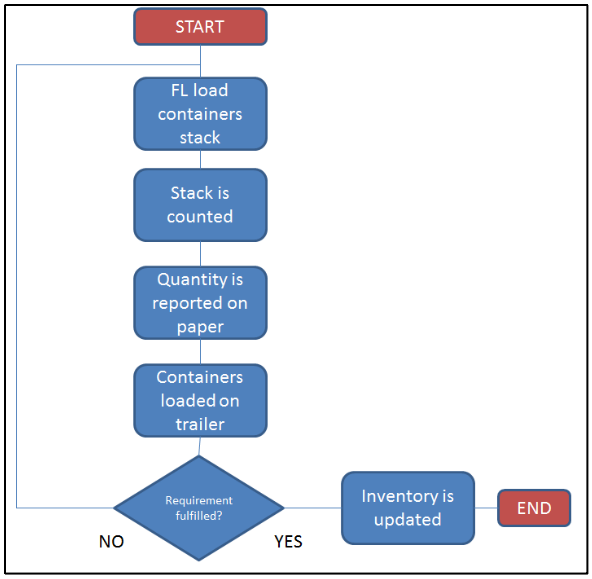

Figure 3.4 Empty containers loading operations

Paperwork with containers replenishment requirement is handled to FL driver, which retrieves the right container type in the storage. FL moves a containers stack, which is counted and loaded on trailer. The operation takes place until paperwork requirement is fulfilled.

An important remark: When supplier removes empty containers from stock, those are not counted, but just filled up with parts and shipped. Outbound containers are deducted automatically from supplier’s inventory according to total shipped parts and container density. However, an error can still occur if number of parts shipped using cardboard backups is not specified correctly. In this work, this process will be considered ideal and 100% accurate.

3.1.5 Model Concept

It is now presented the model concept used in this simulation. This model is based on real world data provided by FCA. The simulated supply chain has the following characteristics:

- Composed of two stages. Empty containers Warehouse EW (either Plant, EOP or RILC) and Supplier SP
- Single supplier using a standard container. Multi-supplier case is discussed in section 5.3.1.
- Supplier containers replenishment is done according to a periodic review policy
- RFID portals are simulated increasing EW outbound and SP inbound counting accuracy. Three different reliability levels are considered:
    - Level 1, 100% accuracy
    - Level 2, 99.9% accuracy (Rahmati, Zhong, Hiltunen, & Jana, 2007)
    - Level 3, 98 % accuracy

Single supplier model schematic is presented in Figure 3.5.

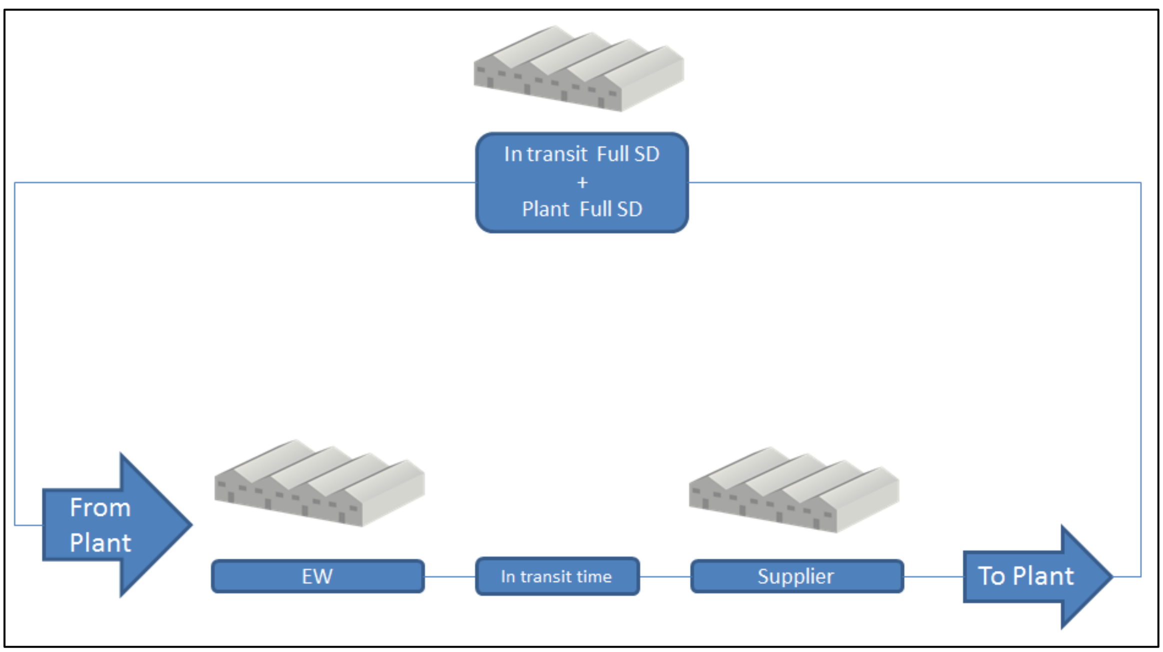

Figure 3.5 Overview of single supplier simulation model

Empty containers from the assembly line are stored at EW, and shipped periodically to SP according to replenishment requirements. Containers are counted when leaving EW and when entering SP.

Each counting processes is characterized by:

- Counting accuracy α.
- Counting Error ε. When a wrong count occurs, the difference between real and wrong quantity is the error ε.

Default values for the two parameters are defined using FCA data as explained in section 3.2.6

Once being counted at SP, containers are stored and consumed according to plant parts demand distribution. When containers leave SP storage they are deducted from inventory with no error. They are filled with parts and shipped back to plant. The total time containers spend full is simulated summing up all full containers system days. After, empty containers go back to EW to close the loop. Inbound counting at EW is not affected by error.

Total containers in the system are determined according section 3.1.2. In particular, total system days are defined as:

$$SD_{TOT} = SD_{EW} + SD_{SP} + SD_{FULL} + SD_{IT}$$

It is important to specify that:

- SD_{EW} And SD_{SP} are empty containers system days at EW and SP, respectively. Default values are defined according to OEM data, but are changed throughout the simulation procedure.
- SD_{FULL} Results from summing full system days at Plant and SP.
- SD_{IT} Results from summing Full and empty In-transit days.

System performance is evaluated with the following indicators:

- Supplier Type I service level. This indicator measure the probability supplier containers stock is enough to satisfy plant parts demand. It considers the total number of containers stock-out occurred and total number of shipments
    - $SP_{SL1} = \frac{Total\ supplier\ shipments - Total\ Stockout\ occured}{Total\ supplier\ shipments} \times 100$
- Supplier Type II service level (Fill rate). This indicator measures the total fraction of parts demand that has been shipped using containers
    - $SP_{SL2} = \frac{SP\ Total\ containers\ shipped}{SP\ Total\ containers\ requirement} \times 100$

- EW Type II service level (Fill rate). This indicator measures the total fraction of replenishment quantity that has been satisfied by EW
    - $EW_{SL2} = \frac{EW\ Total\ containers\ shipped}{EW\ Total\ containers\ requirement} \times 100$

Model inputs are distinguished between controllable and uncontrollable factors:

- Controllable factors. Influence the model in a deterministic way. In this simulation study, are considered controllable factors:
    - RFID: The decision to implement RFID is considered a controllable factor. If RFID is deployed, three different levels of accuracies are considered. If the system is not deployed, manual counting accuracy is considered.
    - EW system days SD_{EW}
    - SP system days SD_{SP}
    - Replenishment period R
- Uncontrollable factors. Cannot be controlled in a deterministic way, and depends on variations of defined statistical distributions. In this simulation study, are considered uncontrollable factors:
    - Demand distribution
    - Lead time distribution
    - Counting Error

Statistical distributions of both demand and lead time were defined for the base case with reference to real world data.

In the following section, model implementation in ARENA® will be discussed.

3.2 Model implementation

In this section, model implementation on DES software package is described. The discrete event simulation software chosen in this simulation is ARENA® V 14, by Rockwell Automation.

ARENA® simulation allows the user to represent a real world problem using a flow chart. A library of logic blocks is provided to build the flow chart. Each block is activated by an animated figure called entity, that moves throughout the chart.

Each entity represents different real world items or resources. For example, if a replenishment process is considered, the entity might represent the replenishment order going through each evaluation step until final order release.

If warehouse operation are simulated, the entity might represent items moving through the warehouse.

In this simulation model, it is possible to distiguish three entity types:

- Empty container, a single empty container entity
- Truckload, represents a truckload of empty containers
- Order, it can be considered a switch activating the containers release processes. It moves over the flowchart anf triggers operations

The role of each of those will be explained considering the five model sections:

- EW Operations Manager
- EW operations
- SP Operations Manager
- SP Operations
- Performance indicators

3.2.1 EW Operations Manager

In this model section the following tasks are accomplished

- Replenishment frequency and quantity is defined
- EW Outbound counting error is generated
- Containers shipment process is initiated

The overall block diagram is reported in Figure 3.6.

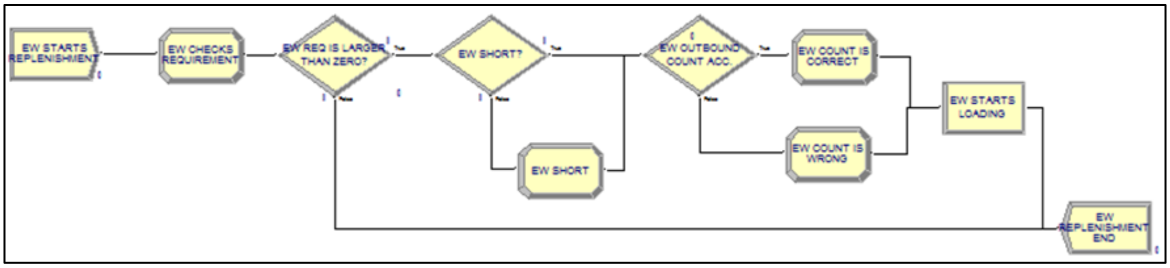

Figure 3.6 Model implementation: EW operations manager

The block "EW STARTS REPLENISHMENT" generates an order entity every R days (according to replenishment frequency). This entity moves through the block diagram simulating the process of defining and releasing replenishment.

In the block "EW CHECKS REQUIREMENT":

- SP replenishment (V_EW_REQ) is evaluated according a periodic review policy (see section 3.1.3)
- Counting error value (V_E_EW) is generated according to error distribution (See section 3.2.6)
- Total required quantity over simulation time is recorded (V_TOT_REQ_EW). See Figure 3.7.

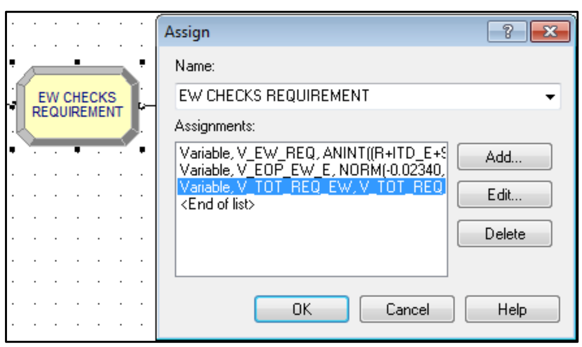

Figure 3.7 Model implementation: EW replenishment requirements

The entity moves to the next block set, as depicted in Figure 3.8.

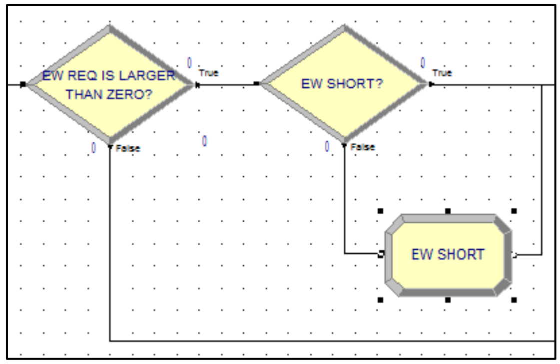

Figure 3.8 Model implementation: EW verifies availability

Here, the following tasks are accomplished:

- The replenishment sign is evaluated. If negative, the entity is discarded and no container is released. If positive, the entity proceeds.
- EW storage availability is evaluated. If not enough containers are available at EW storage, the replenishment requirement is set equal to the available quantity, in the block "EW SHORT".

The entity moves to next section (See Figure 3.9), where outbound counting accuracy is defined.

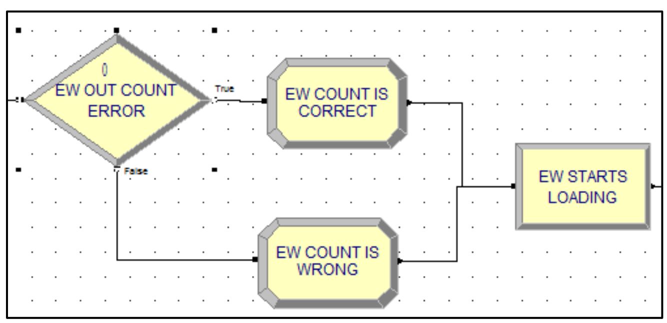

Figure 3.9 Model implementation: EW outbound counting error

The counting error accuracy can be set in the block "EW OUT COUNT. ERROR". Two alternatives are available:

- EW COUNT IS CORRECT: No error occured, the outbound counter V_EW_OUT is initialized to zero.

- EW COUNT IS WRONG: An error occured, the outbound counter is initiliazed with a percentage of the replenishment requirement (according to error V_E_EW).

When the entity crosses the block EW STARTS LOADING, the signal to release the first container is sent to the warehouse and the loading begins in model section EW OPERATIONS.

3.2.2 EW Operations

In this model section, EW warehouse operations are simulated. In particular:

- Containers are received and stored
- Containers are released from storage and loaded on trailer, according to replenishment requirement

An additional task is performed: the system is populated with the total containers quantity that will circulate during simulation.

The overall block model is presented in Figure 3.10.

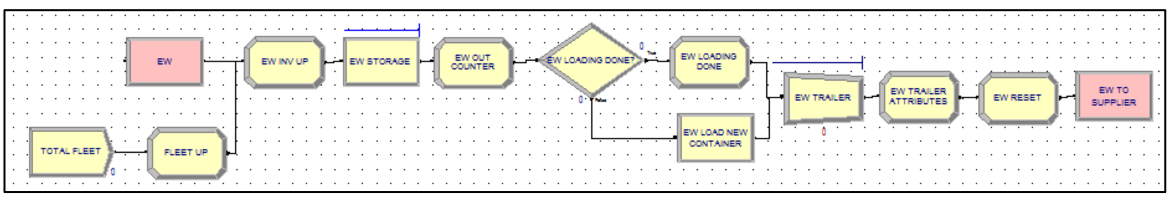

Figure 3.10 Model implementation: EW Operations

During simulation Warm-up, containers are injected from block TOTAL FLEET. Total containers injected quantity is defined according to section 3.1.2. The related blocks are reported in Figure 3.11.

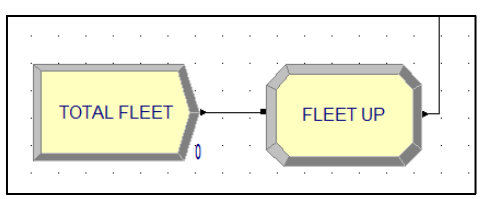

Figure 3.11 Model implementation: Total fleet

At steady state, a truckload of empty containers entities arrives at block EW. The truckload entity is split into single container entities, that are moved to storage EW STORAGE. The block

EW INV UP increases EW inventory of one unit everytime a container entity moves through (Figure 3.12).

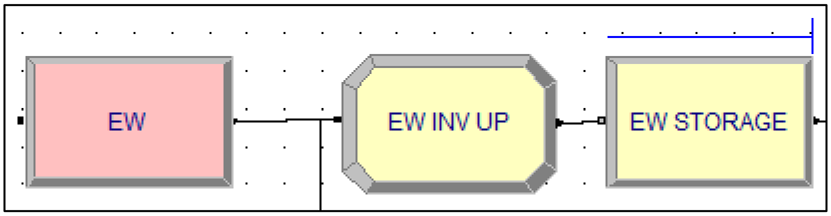

Figure 3.12 Model implementation: EW inbound containers

Containers are released from storage when the block EW STARTS LOADING (See previous section) sends a signal to EW STORAGE.

When the first container is released, loading operations start. The entity moves to EW OUT COUNTER (Figure 3.13).

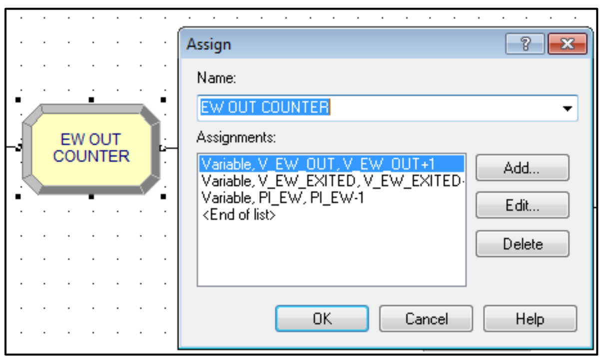

Figure 3.13 Model implementation: EW Outbound counter

Here the following variables are updated:

- V_EW_OUT. This counter has been introduced in previous section. When a container goes through, it is increased by one unit, but its initial value depends on counting error.
- V_EW_EXITED. When a container goes through, it is increased by one unit. Differently from V_EW_OUT, it is not affected by counting error, and represents the actual containers quantity moving to trailer.
- PI_EW is decreased by one unit.

The block EW LOADING DONE? Compares released containers quantity to target replenishment quantity (Figure 3.14).

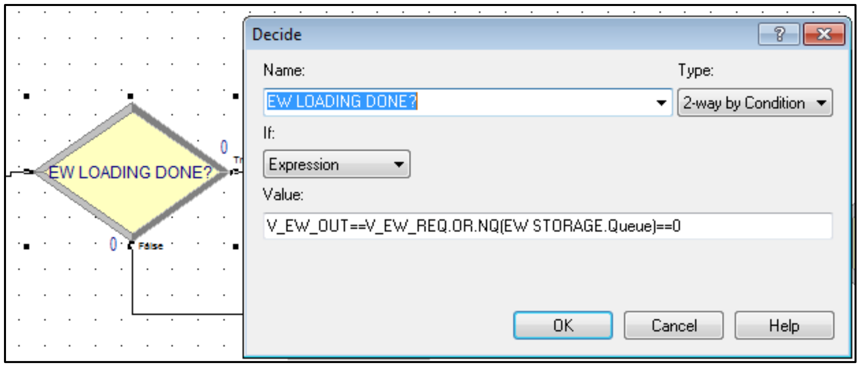

Figure 3.14 Model implementation: EW loading done?

The loading operation is considered done when the counter V_EW_OUT equals V_EW_REQ (Defined by EW Operations manager).

If loading is not completed, a new container is released by the block EW LOADS NEW CONTAINER.

If the loading is done, the entity proceeds to EW LOADING DONE, as depicted in Figure 3.15.

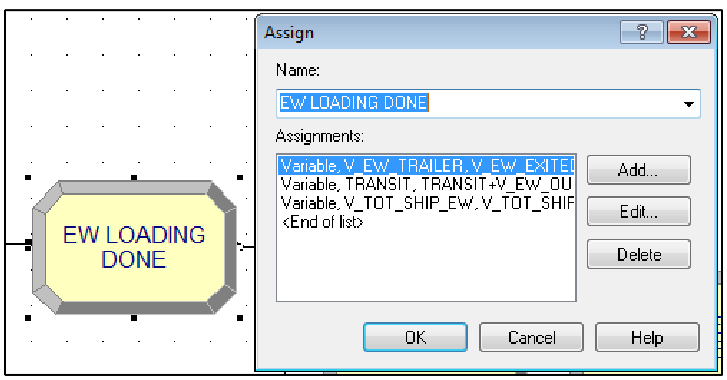

Figure 3.15 Model implementation: Loading done

The following variables are updated:

- Trailer capacity is set equal to actual released quantity (V_EW_EXITED)
- The variable TRANSIT, representing In-transit quantity, is increased of V_EW_OUT (Potentially affected by error)
- Total shipped quantity (V_TOT_SHIP_EW) is increased of Actual released amount (V_EW_EXITED)

As previously mentioned, the counter V_EW_OUT might be initialized with an error quantity. As consequence, the loading operation might end before or after the actual released quantity reaches the replenishment requirement.

All the released containers entity are batched into one single entity representing the truckload (Figure 3.16).

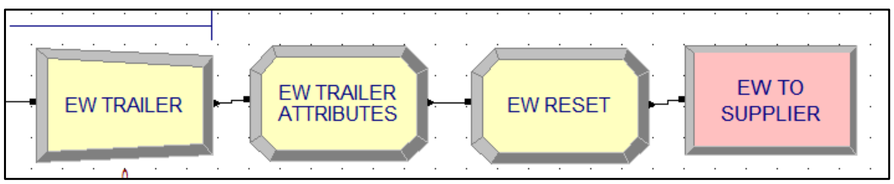

Figure 3.16 Model implementation: Truckload leaves EW

In the block EW TRAILER ATTRIBUTES, actual released amount (V_EW_EXITED) is assigned to attribute A_EW_EXITED, while presumed released quantity (V_EW_OUT) is assigned to attribute A_EW_OUT. Attributes are properties assigned to a single entity, similar to labels showing information about the entity. The importance of assigning trailer attributes will be clarified in next section.

Counters are zeroed (EW RESET) and trailer leaves EW to reach SP. In transit time to SP is defined starting from real world data (see section 3.1.5.).

3.2.3 SP Operations

In this model section, SP containers warehouse operations are simulated. In particular:

- Empty containers receiving and storaging
- Empty containers usage
- RDR generation

Overall block diagram is presented in Figure 3.17.

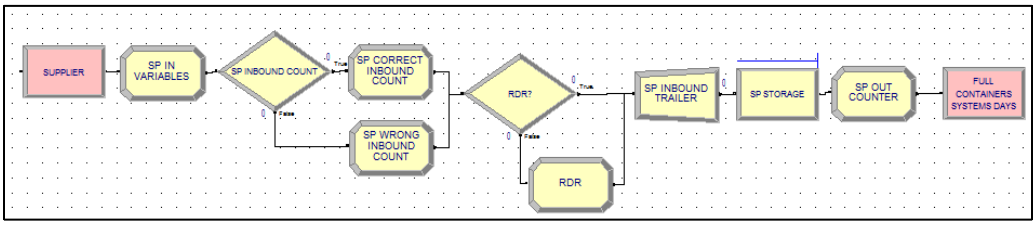

Figure 3.17 Model implementation: SP operations

A truckload of empty containers arrives at block SUPPLIER, and moves through inbound counting blocks, represented in Figure 3.18.

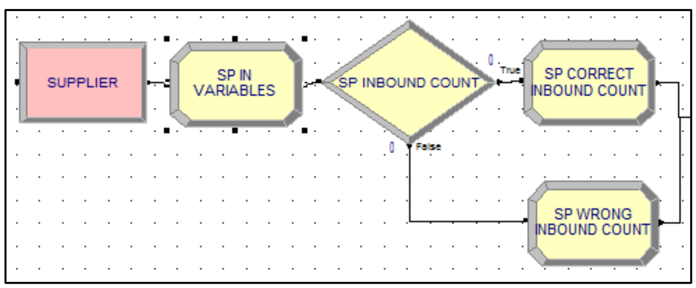

Figure 3.18 Model implementation: SP inbound counting

The block SP IN VARIABLES uses trailer attributes to define actual versus presumed inbound quantity (Figure 3.19).

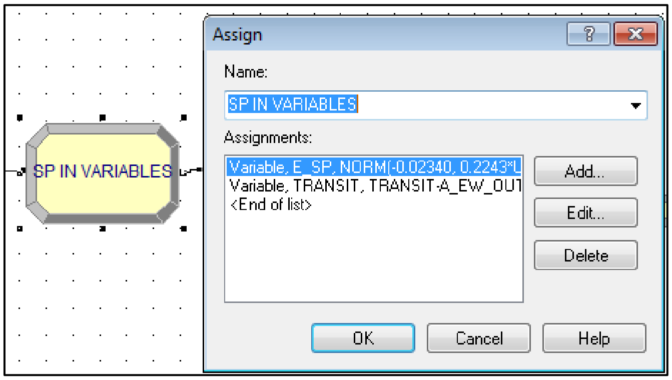

Figure 3.19 Model implementation: SP Inbound variables

This operation does not have a counterpart in real world, but it is necessary for the simulation model. In particular:

- TRANSIT is decreased by presumed shipped quantity (A_EW_OUT)
- Inbound counting error value is generated by counting error distribution and saved into variable V_E_SP

According to inbound counting accuracy, a counting error occurs. Inbound counting error block diagram is reported in Figure 3.20.

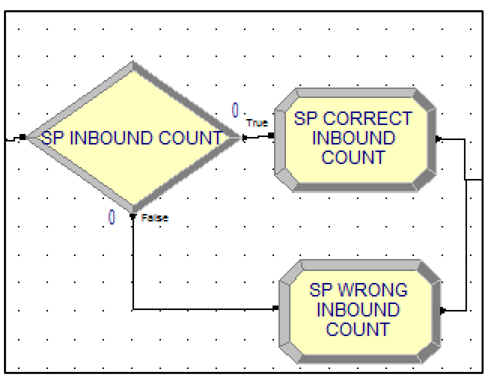

Figure 3.20 Model implementation: SP inbound count

If inbound count is wrong, truckload entity proceeds to SP WRONG INBOUND COUNT Figure 3.21.

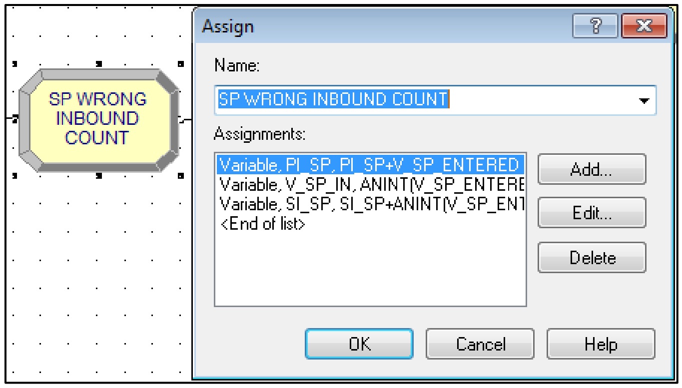

Figure 3.21 Model implementation: SP wrong inbound count

- PI_SP is updated wiht actual truckload quantity (V_SP_ENTERED)
- Wrong inbound quantity affected by error is saved into variable V_SP_IN. It is defined as percentage of actual truckload, according to generated error V_E_SP (Figure 3.22)
- SP_SP is updated with V_SP_IN

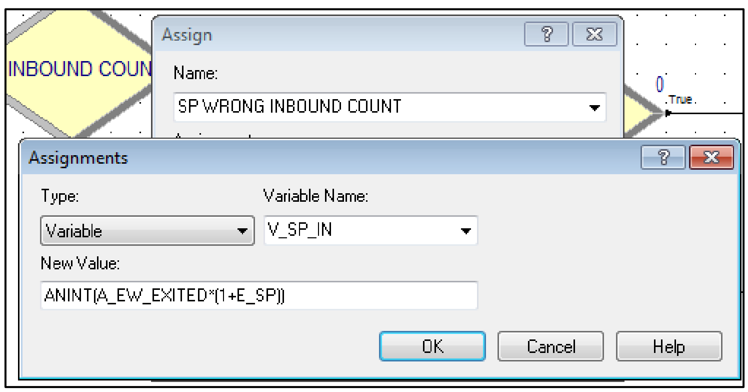

Figure 3.22 Model implementation: SP wrong inbound quantity

If count is correct, both PI_SP, SI_SP and V_SP_IN are updated with actual truckload A_EW_EXITED (Figure 3.23).

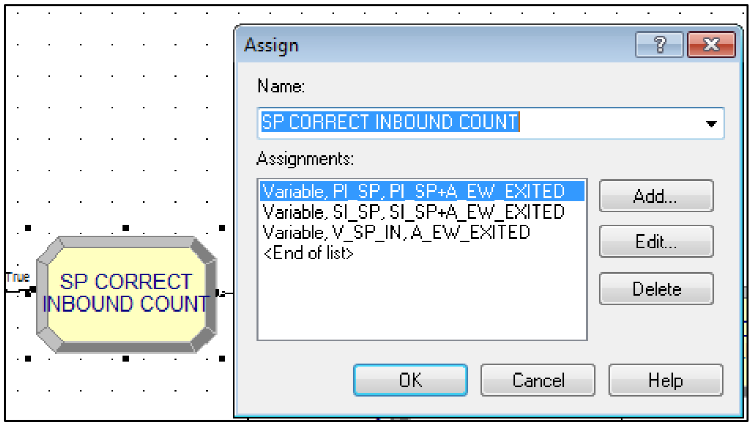

Figure 3.23 Model implementation: SP correct inbound count

If the shipment quantity notified by EW differs from what counted by SP, a RDR is generated, as shown in Figure 3.24.

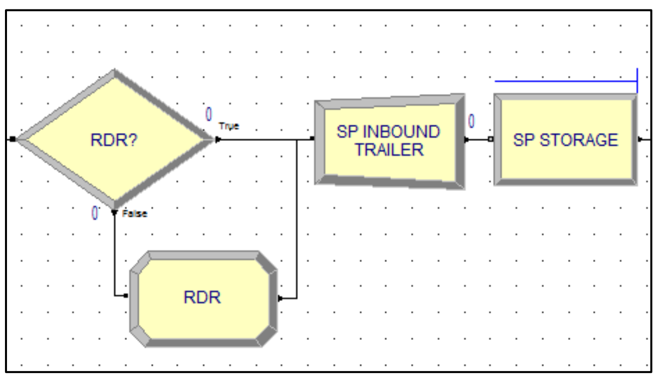

Figure 3.24 Model implementation: SP issues RDR

The truckload entity is split into single containers entity that are moved to storage. According to what defined by SP operations manager, daily containers requirement is released from storage, and enters the FULL SYSTEM DAYS (Figure 3.25).

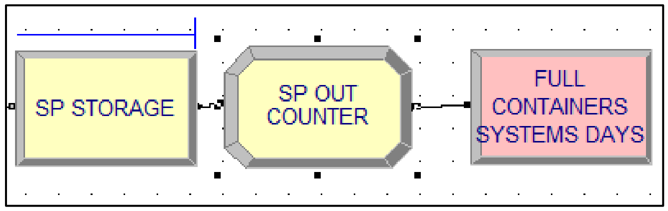

Figure 3.25 Model implementation: SP daily containers usage

Before coming back to EW and closing the loop, the truckload of empty containers will spend a constant time according to full containers system days.

No Outbound counting error is considered at SP, as mentioned in section 3.1.4.

3.2.4 SP operations manager

This model section is similar to EW operations manager. The following tasks are accomplished:

- SP Daily containers requirement is defined
- Containers stock is compared versus requirement

The overall block diagram is presented in the Figure 3.26.

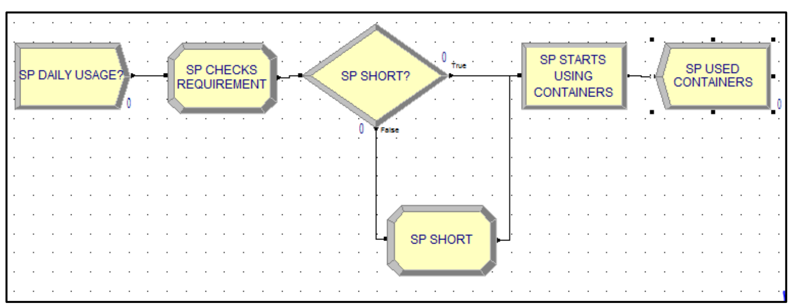

Figure 3.26 Model implementation: SP operations manager

Every day (Simulation Time) an entity representing a parts requirement is generated. The entity moves to SP CHECKS REQUIREMENTS (Figure 3.27).

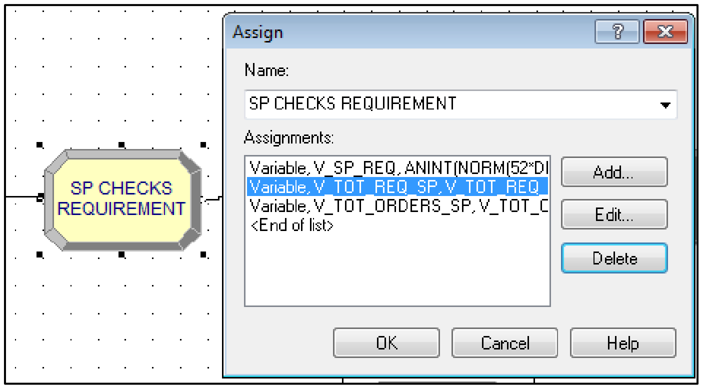

Figure 3.27 Model implementation: SP defines daily requirements

- Containers daily requirement, V_SP_REQ , is generated according to real world demand distribution (See section 3.1.5)
- Total required containers quantity over simulation time is saved into V_TOT_REQ
- Total orders number issued to supplier is saved into variable V_TOT_ORDERS

After, available containers stock is compared to requirement. If not enough containers are available, total requirement will be set equal to available stock. This is done in the following block set (Figure 3.28).

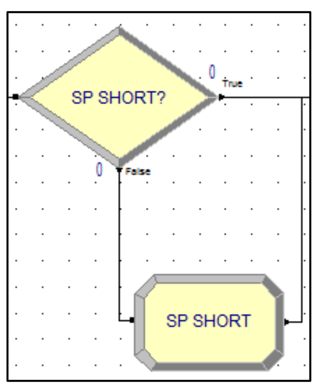

Figure 3.28 Model implementation: SP checks storage availability

If SP is short of containers, the variable V_SP_SHORT will be increased by one unit.

The block SP RELEASES REQ sends a signal to SP STORAGE, and the required amount V_SP_REQ is released from storage (Figure 3.29).

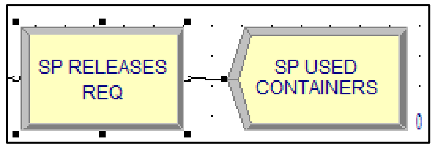

Figure 3.29 Model implementation: SP releases containers

3.2.5 Performance indicators

In previous sections, the following variables have been introduced:

- V_TOT_REQ_EW
- V_TOT_SHIP_EW
- V_TOT_REQ_SP
- V_TOT_SHIP_SP
- V_TOT_ORDERS_SP
- V_SP_SHORT

Those variables are used in the PERFORMANCE INDICATORS model section to find the three performance indicators (See section 3.1.5). The block set is represented in Figure 3.30.

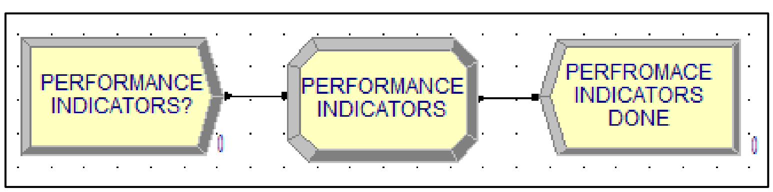

Figure 3.30 Model implementation: Performance indicators

All the three are defined over the entire simulation period and updated on weekly basis.

3.2.6 Manual counting calibration

In order to compare RFID performance to base case and calibrate the model, it is necessary to define manual counting performance. In section 3.1.5 we mentioned two parameters:

- α : Counting system accuracy
- ε : Counting error

In this chapter it will be described how to estimate the two parameters.

When containers leave FCA location, the shipped quantity is communicated to SP. Once containers get to SP location, received quantity should be verified. If the two amounts do not match, a notification is generated by SP to make OEM aware that something went wrong during shipping process. This notification is called Return Discrepancy Receipt (RDR). The OEM keeps track of:

- Total number of RDR. It is a measure of how often a counting mistake happens
- For each RDR, the difference between what shipped and what received is recorded. It is a measure of the error magnitude

It is possible to use RDRs to find how often shipped and received quantities do not match, that means a counting error occurred. An estimate of overall manual counting accuracy can be defined as follows

$$\alpha = \frac{Total\ shipments\ over\ period\ T - Total\ RDRs\ over\ period\ T}{Total\ shipments\ over\ period\ T} \times 100$$

Notice that this value is the effect of both shipping and receiving location counting accuracy

$$\alpha = \alpha(\alpha_{SP}, \alpha_{EOP})$$

It is assumed manual counting accuracy is the same for both OEM and SP:

$$\alpha = \alpha(\alpha_{SP}, \alpha_{EOP}) = \alpha(\alpha_{Man})$$

The aim is to find an estimate for α_{Man} as follows:

- Define α for a real world case
- In the simulation, change α_{Man} both at supplier and EOP until simulated α_{Sim} matches real world α
- Take corresponding α_{Man} as default for manual counting reliability

In defining real world α, EW was monitored for a period of eight months. Relevant data are collected in Table 3.1.

Table 3.1 Overall counting reliability

Total shipments in 8 months	3244
Total RDRs over in 8 months	296
α	90 %

The corresponding manual counting accuracy is defined as explained before, considering average value of α_{Sim} as obtained after 50 replications, 365 days each. Resulting value is reported in Table 3.2.

Table 3.2 Manual counting reliability

α_{Man}	83%

Using RDRs it is also possible to find the statistical distribution of error ε. For each RDR line it is possible to define occurred error ε_i as percentage of total shipped quantity, as explained in the following equation:

$$\varepsilon_i = \frac{Received_i - Shipped_i}{Shipped_i} \times 100$$

This percentage has been calculated for each RDR line in the dataset. It was possible to define counting error distribution, reported in Figure 3.31.

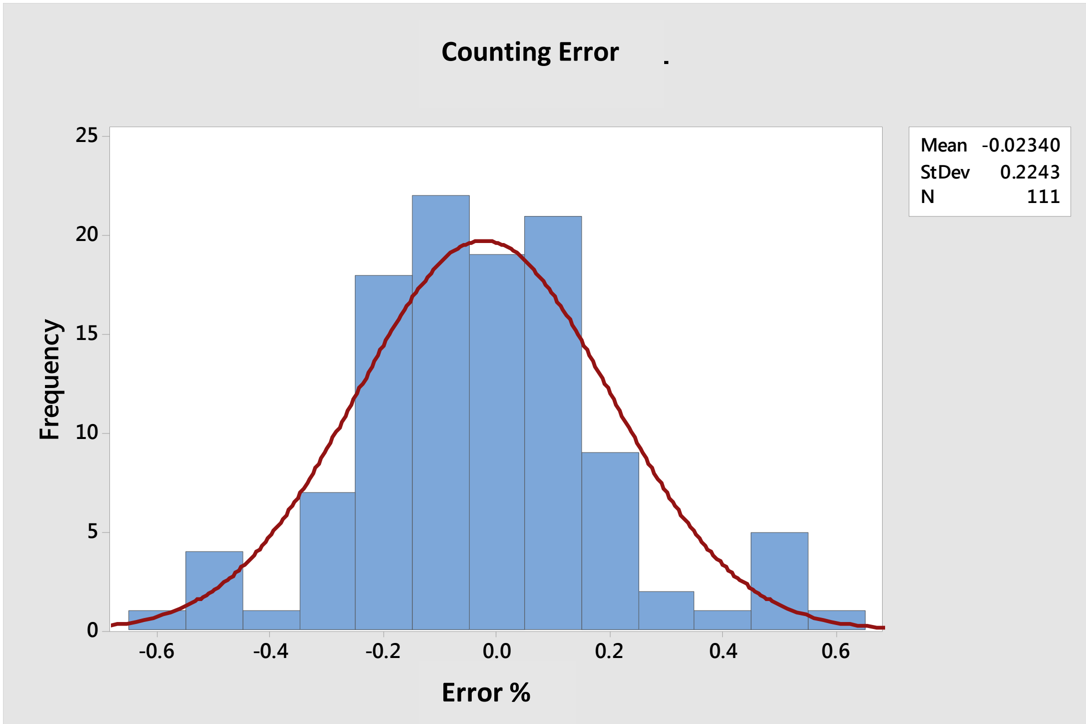

Figure 3.31 Counting error distribution

This distribution is used in the model to generate counting error ε. Together with counting accuracy α, this allows to simulate a realistic manual counting process.

3.2.7 Model Validation

In order to compare model output to real world system, the following procedure has been applied:

- One year Total containers shipped quantity has been recorded for the considered Datasets
- Total containers shipped quantity generated by the model over one year period is compared to real world data

In this way, it is possible to understand how close model operation is compared to real world. Results are shown in Table 3.3.

Table 3.3 Model Validation

Real World total shipped containers	10160
Simulation total shipped containers	9522
Matching	93.7%

3.3 Experimental procedure

In this chapter, experimental procedure is described, with reference to the work of (Montevechi, Carvalho, & Friend, 2012). Among the possible experimentation strategies, a Design Of Experiment (DOE) based on a full factorial design with two levels (Also called factorial 2^k) was chosen. This tool is used in many operational research studies due to its simplicity and effectiveness. It is possible to identify some main steps in defining a factorial design:

- Choice of factors and working levels. Factors are input parameters which compose an experiment. Levels are the possible variation for each factor. As first step is necessary to define possible levels for each considered factor. In factorial 2^k each factor is assigned with two possible levels.
- Selection of the response variables. A response variable is the performance measure to be evaluated in the experiment. It is important to determine the response variables that are really meaningful for the system under study.

- Statistical data analysis. Experimental output data must be analyzed using statistical tools. In this work, Analysis of Variance (ANOVA) is used to compare alternative scenarios.

Two sets of factors have been identified in section 3.1.5. Different experiments sets are defined:

- SET 1. Effects of controllable factors, for three different RFID accuracy levels:
    - Accuracy 1: 100%
    - Accuracy 2: 99.9 %
    - Accuracy 3: 98 %
- SET 2. Effects of uncontrollable factors
- SET 3. Testing the best case scenario, for three different RFID accuracy levels:
    - Accuracy 1: 100%
    - Accuracy 2: 99.9 %
    - Accuracy 3: 98 %
- SET 4. Sensitivity Analysis, for two different demand statistical distributions

Each experiment set is repeated for the two different Datasets:

- Dataset 1 (DATA 1). It is based on a supplier using unique containers. Nevertheless, replenishment policy will be the same of standard containers (see section 3.1.3). Statistical distributions for demand and lead time are provided in Figure 3.32 and Figure 3.33.

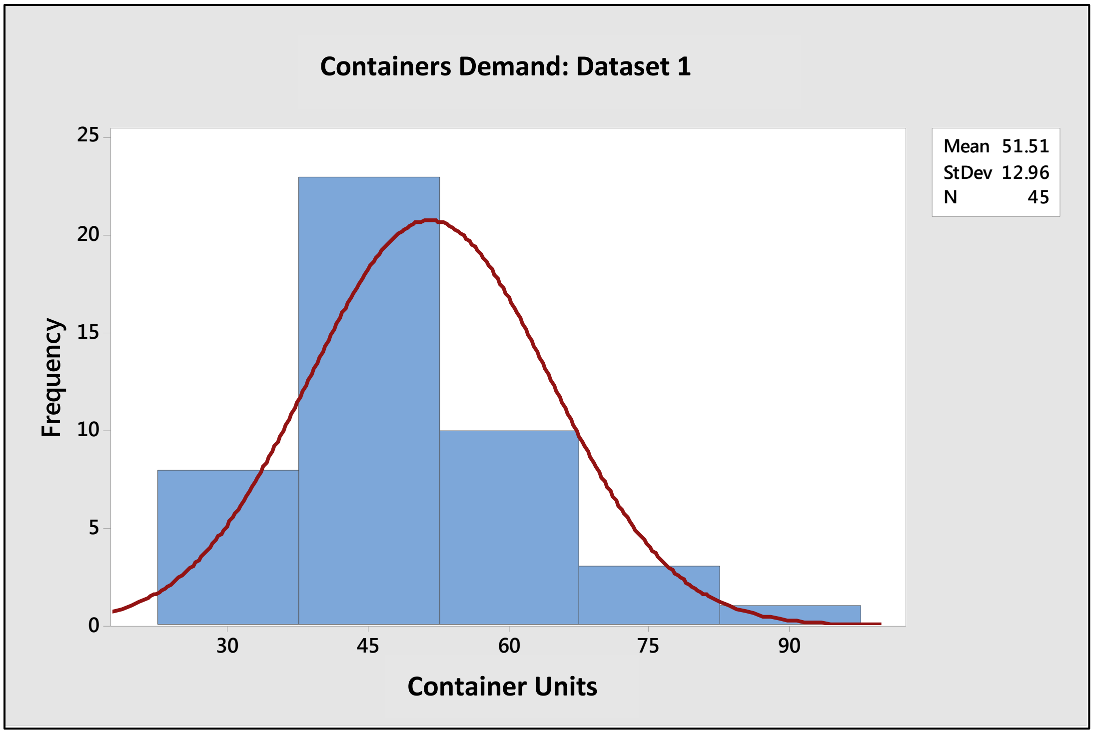

Figure 3.32 Dataset 1: Supplier Demand

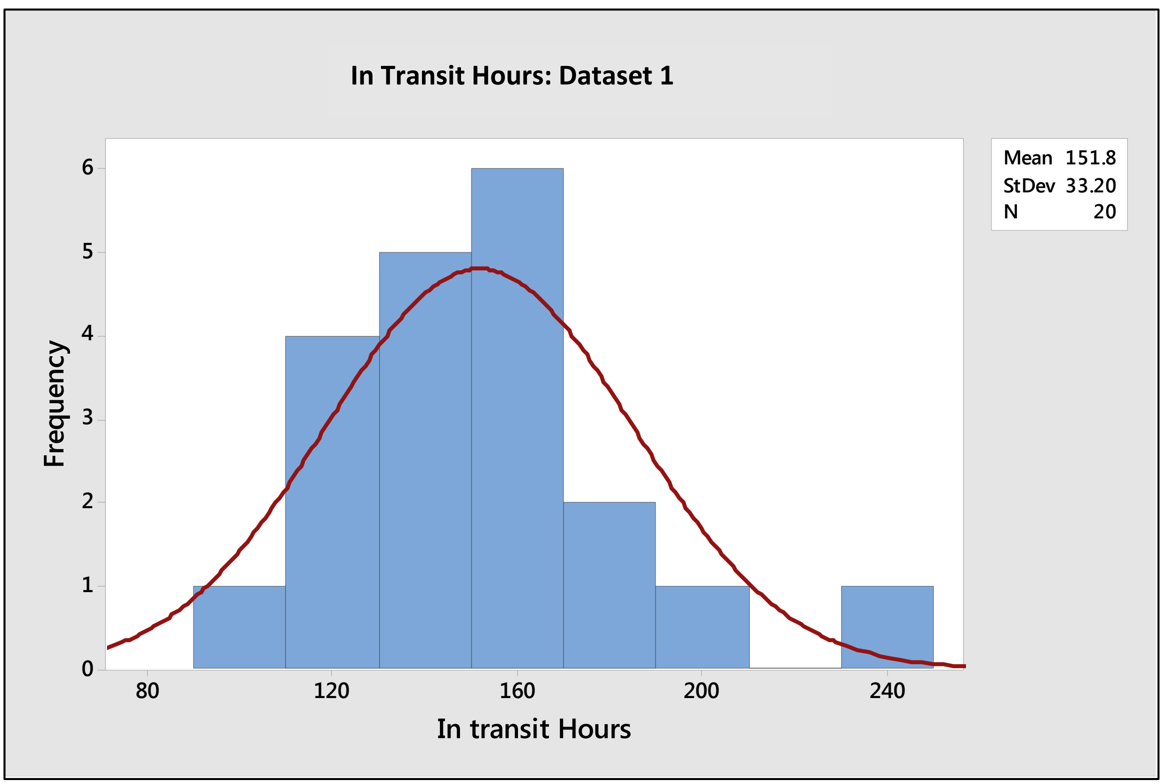

Figure 3.33 Dataset 1: Lead time

- Dataset 2 (DATA 2). It is based on a supplier using standard containers. Demand distribution is based on one year of requirements and is reported in Figure 3.34.

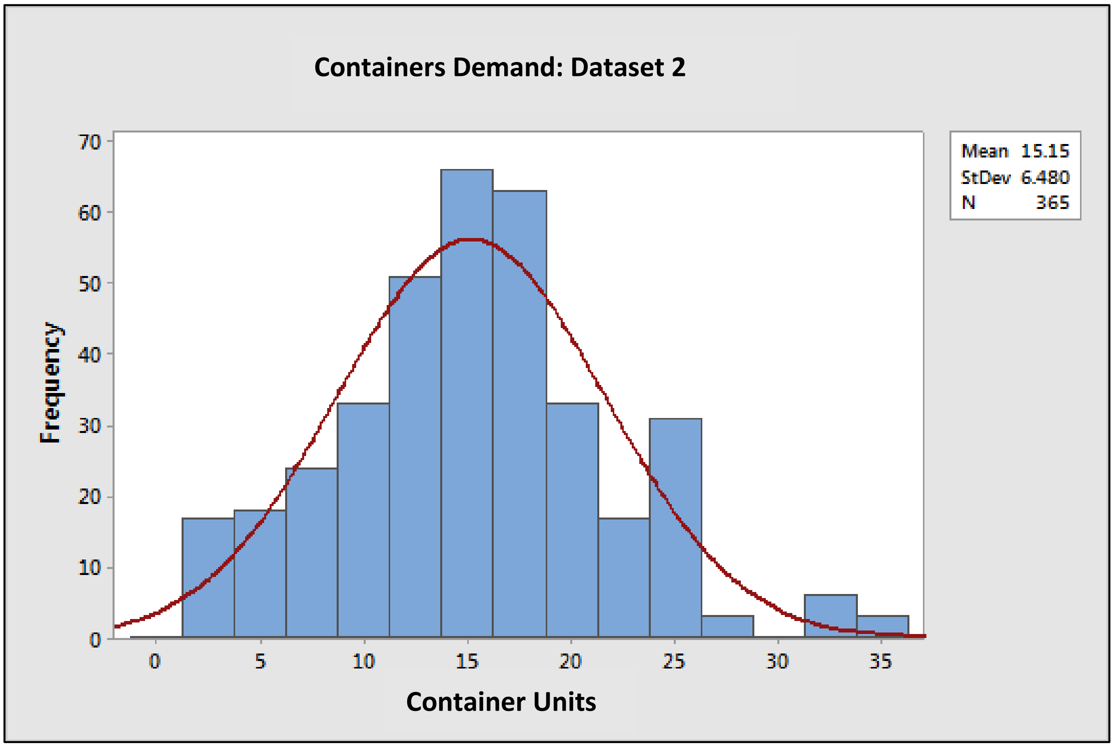

Figure 3.34 Dataset 2: Supplier Demand, Normal distribution

System performance is evaluated monitoring three performance indicators as defined in section 3.1.5. Each run of Simulation is performed as specified in Table 3.4.

Table 3.4 Replication parameters

Replication length	395 Days
Number of replications	50
Warm-up time	15 Days

Finally, additional considerations about potential handling time reduction will be included.

3.3.1 SET 1: Effect of controllable factors

In this section different combinations of controllable input factors will be tested without changing uncontrollable factor.

In particular, the following controllable factors will be changed

- Supplier's system days SD_{SP}
- EW system days SD_{EW}
- RFID switch: level 1 if RFID is used, level 0 if is not used
- Replenishment frequency R

Experiment SET 1 is repeated for both Dataset 1 and 2. Considered factors and associated levels are reported in Table 3.5 and Table 3.6.

Table 3.5 SET1: Controllable factors and levels for Dataset 1

Factor	Levels
SD_{SP}	1; 2
SD_{EW}	1; 2
RFID	0; 1
R	2; 3

Table 3.6 SET1: Controllable factors and levels for Dataset 2

Factor	Levels
SD_{SP}	1; 2
SD_{EW}	1; 2
RFID	0; 1
R	1; 1.75

If RFID = 0, counting reliability takes the default value 83%, as defined in section 3.2.6. When RFID = 1, three different RFID accuracies are considered:

- Accuracy 1: 100%
- Accuracy 2: 99.9 %
- Accuracy 3: 98 %

For both Datasets, the combination of factors resulting in the best overall performance will be tested for different levels of uncontrollable factors uncertainties (section 3.3.3).

Experiments are summarized in Figure 3.35.

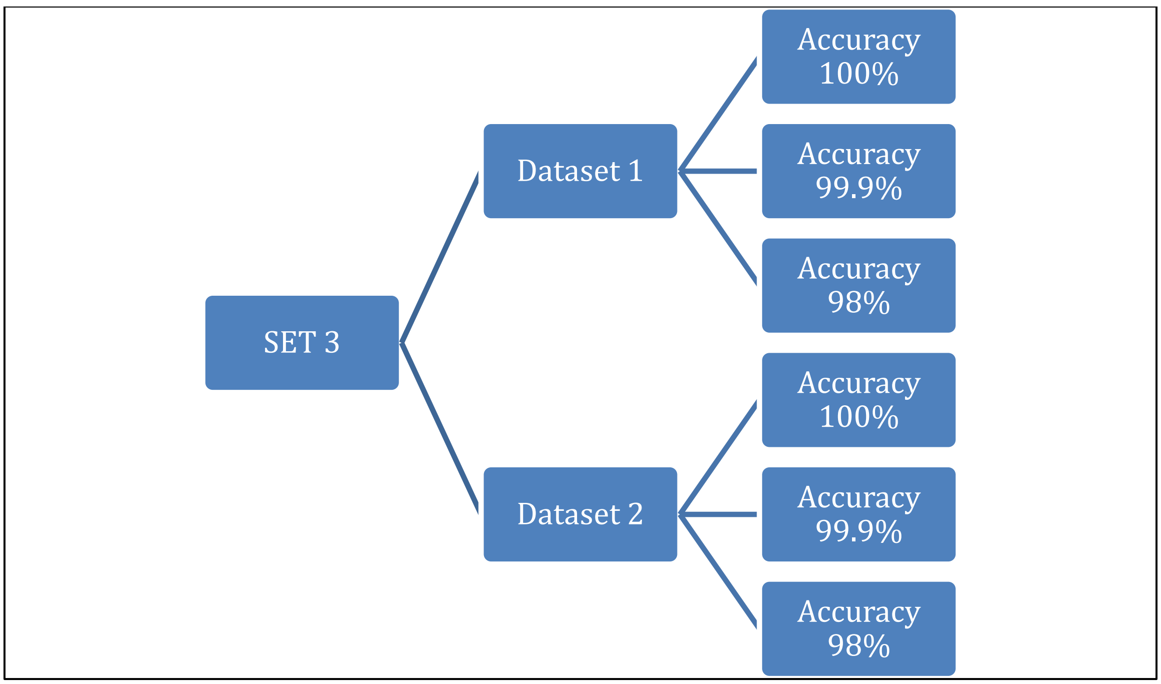

Figure 3.35 SET 1: Experiments flowchart

Additional simulations have been performed to define relevant trends. In particular, it is possible to show potential supplier safety stock reduction as consequence of RFID. The aim is to obtain a curve correlating SP safety stock with relevant performance indicator both with and without RFID.

Table 3.7 SET 1: Controllable factors for safety stock reduction, Dataset 1

Factor	Levels
SP safety stocks (Days)	1; 2; 3; 4
EW safety stocks (Days)	1; 2; 3; 3
RFID	0 ; 1

Table 3.8 SET 1: Controllable factors for safety stock reduction, Dataset 2

Factor	Levels
SP safety stocks (Days)	1; 2; 3; 4
EW safety stocks (Days)	1; 2; 3; 3
RFID	0 ; 1

Results for each scenario have been processed using MINITAB®. Once results for the full factorial plan were produced, ANOVA was used in order to define the most influential factors on performance indicators. Percentage of contribution of each factor was collected in pie charts.

3.3.2 SET 2: Effect of uncontrollable factors

In this section the base case will be tested for different combinations of uncontrollable input factors. The aim is to understand which the most relevant source of uncertainty is.

Experiments are summarized in Figure 3.35.

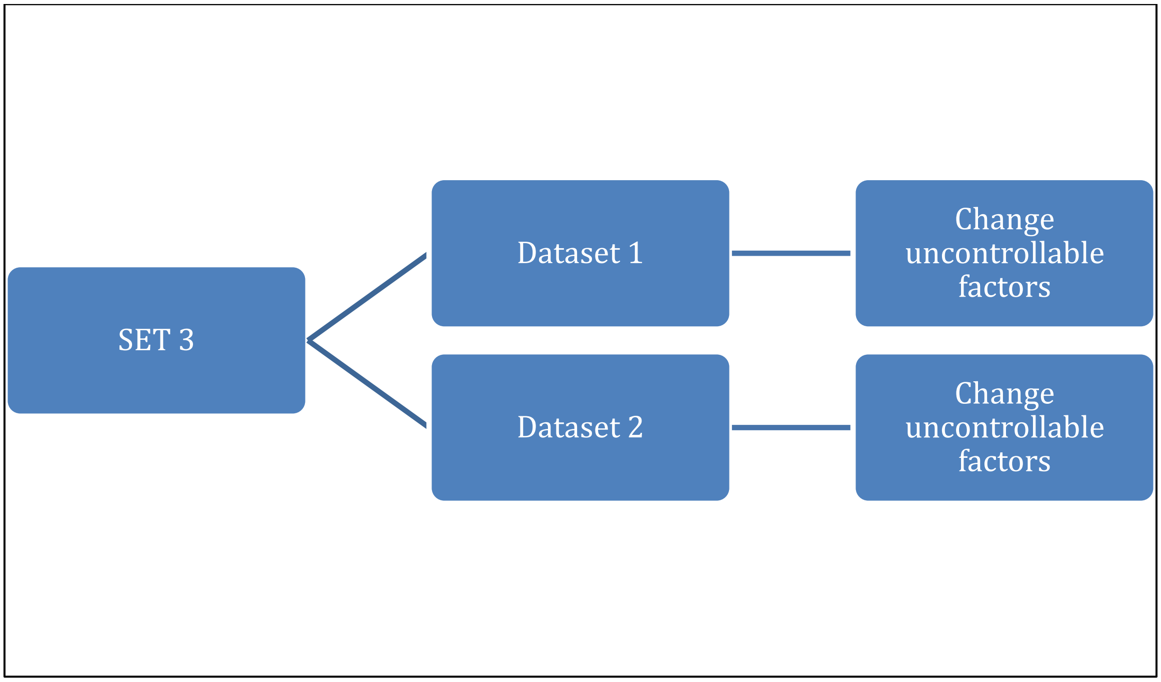

Figure 3.36 SET 2: Experiments flowchart

Controllable factors values are reported in Table 3.9 and Table 3.10.

Table 3.9 SET 2: Controllable factors and levels for Dataset 1

Factor	Levels
SD_{SP}	2
SD_{EW}	2
REP	3
Manual counting accuracy	83%

Table 3.10 SET 2: Controllable factors and levels for Dataset 2

Factor	Levels
SD_{SP}	2
SD_{EW}	1
REP	1.75
Manual counting accuracy	83%

Instead, different values will be considered for demand, lead time and counting error uncertainty, increasing or decreasing each standard deviation by 15%. This reminds the approach of (A. Ustundag, 2009). Considered levels and factors are presented in Table 3.11.

Table 3.11 SET 1: Uncontrollable factors and levels

Factor	Levels
Demand SD	-15%; +15%
Error SD	-15%; +15%
Lead time SD	-15%; +15%

3.3.3 SET3: Testing the best case scenario

In this section, each of the three best RFID scenarios from both Datasets is tested for different levels of uncontrollable factors, as defined in section 3.3.2. The test is repeated for all the three different levels of accuracy. The aim is to evaluate the impact of uncertainty on system performance in the best case.

The experiment flow chart is reported in Figure 3.37.

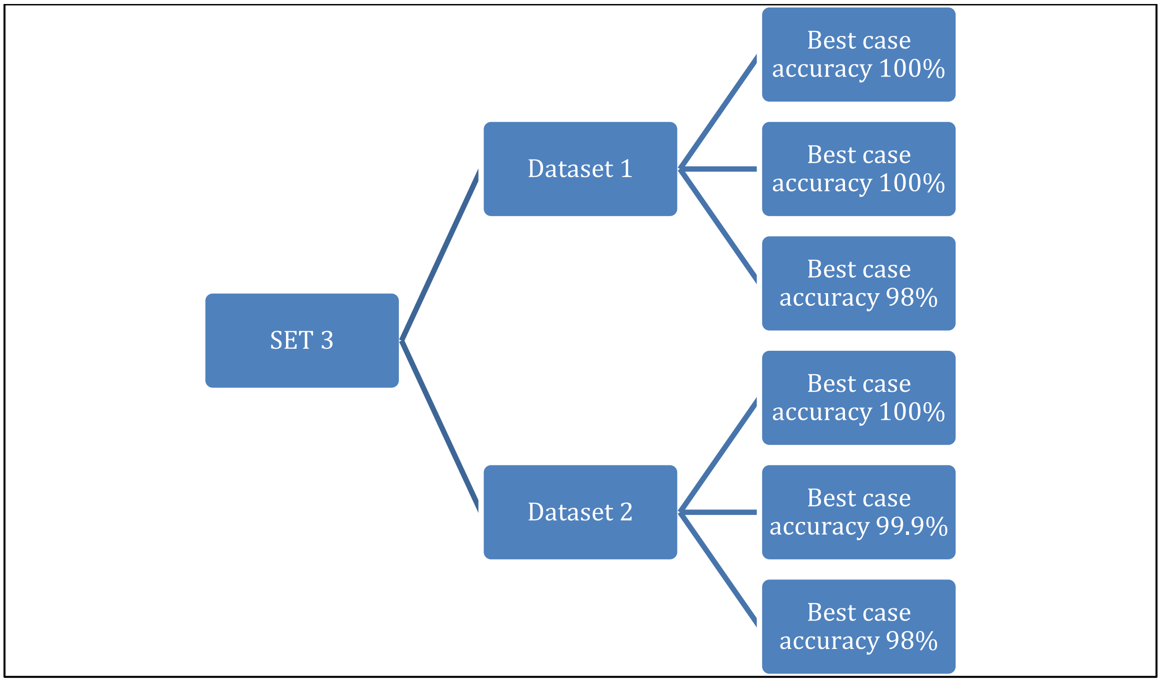

Figure 3.37 SET3: Experiments flow chart

Uncontrollable factors and levels are the same used in section 3.3.2 (Table 3.12).

Table 3.12 Sensitivity analysis: uncontrollable factors

Factor	Levels
Demand S.D.	-15%; +15%
Error S.D.	-15%; +15%
Lead time S.D.	-15%; +15%

Results from each scenario have been processed using MINITAB®. Once results for the full factorial plan were produced, ANOVA was used in order to define the most influential factors on performance indicators.

3.3.4 SET 4: Sensitivity Analysis

In this section, Dataset 2 will be tested with different statistical distributions, to analyze the effect on system performance. This analysis is performed just on the second dataset because more data are available for this supplier.

The base case demand distribution is:

- Normal

In addition to base case, two more distributions are considered:

- 3-Parameters Weibull
- Gamma

They are reported in Figure 3.38 and Figure 3.39, respectively.

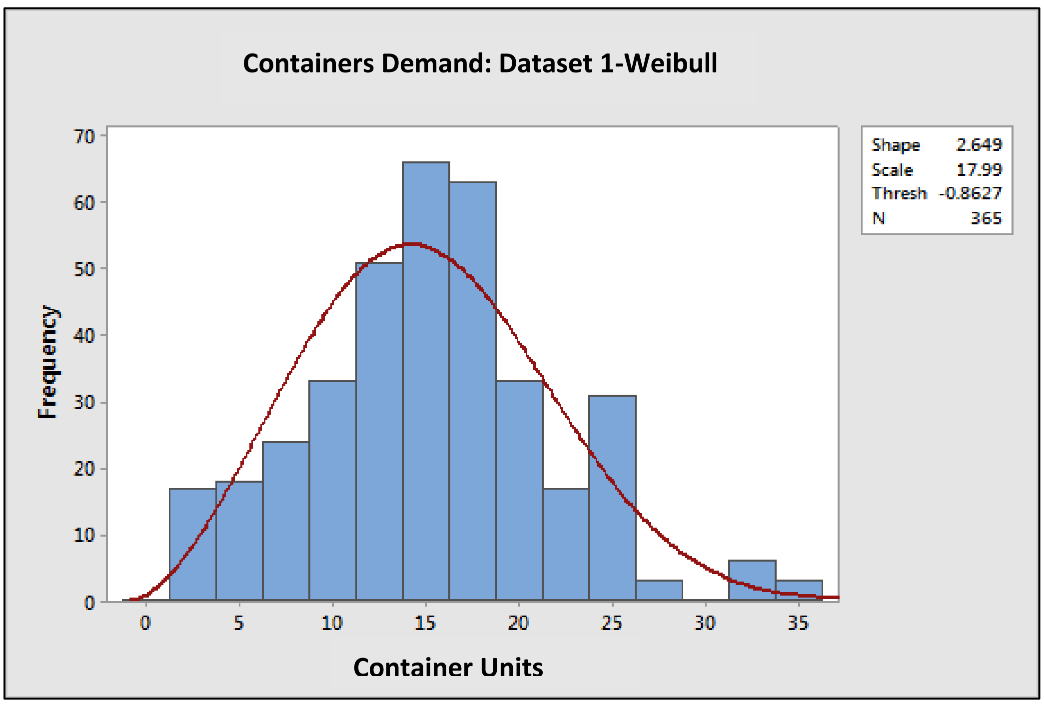

Figure 3.38 Dataset 2: Supplier Demand, Weibull distribution

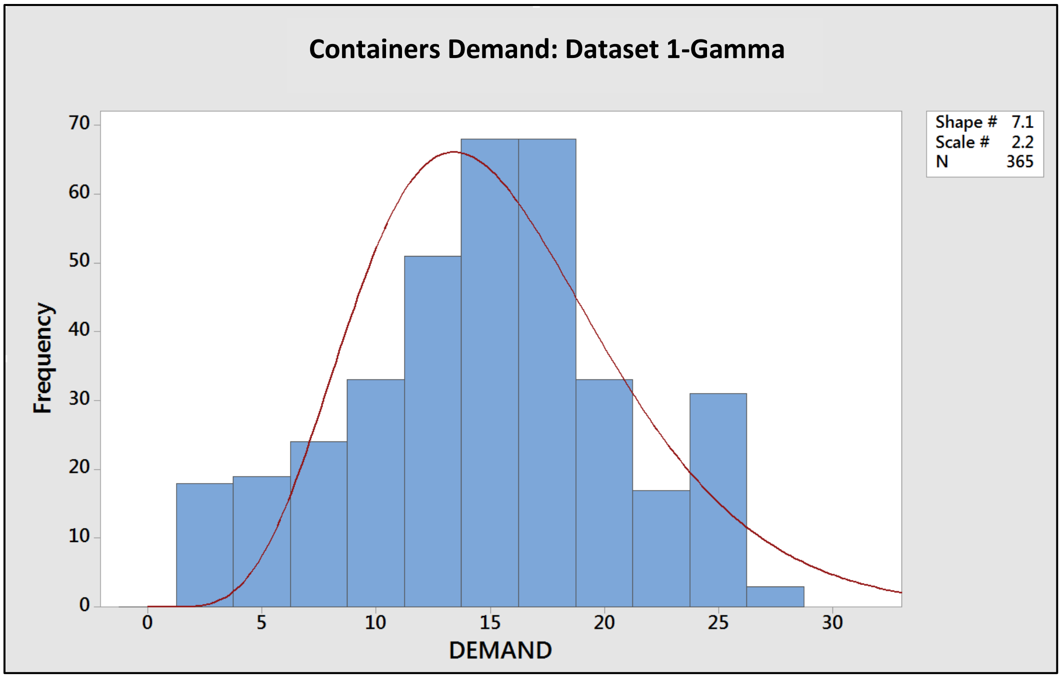

Figure 3.39 Dataset 2: Supplier Demand, Gamma distribution

The same experiments of SET1 will be performed, but for just one value of RFID accuracy: 100%. Table 3.13 reports controllable factors for this experiment set.

Table 3.13 SET4: Controllable factors

Factor	Levels
SD_{SP}	1; 2
SD_{EW}	1; 2
RFID	0; 1
R	1; 1.75

Results from each scenario have been processed using MINITAB®. Once results for the full factorial plan were produced, ANOVA was used in order to define the most influential factors on performance indicators.

3.3.5 Handling time reduction

With RFID, manual counting is no longer needed, and it is possible to achieve containers handling time reduction. A simple algorithm to estimate this time reduction is presented in Figure 3.40.

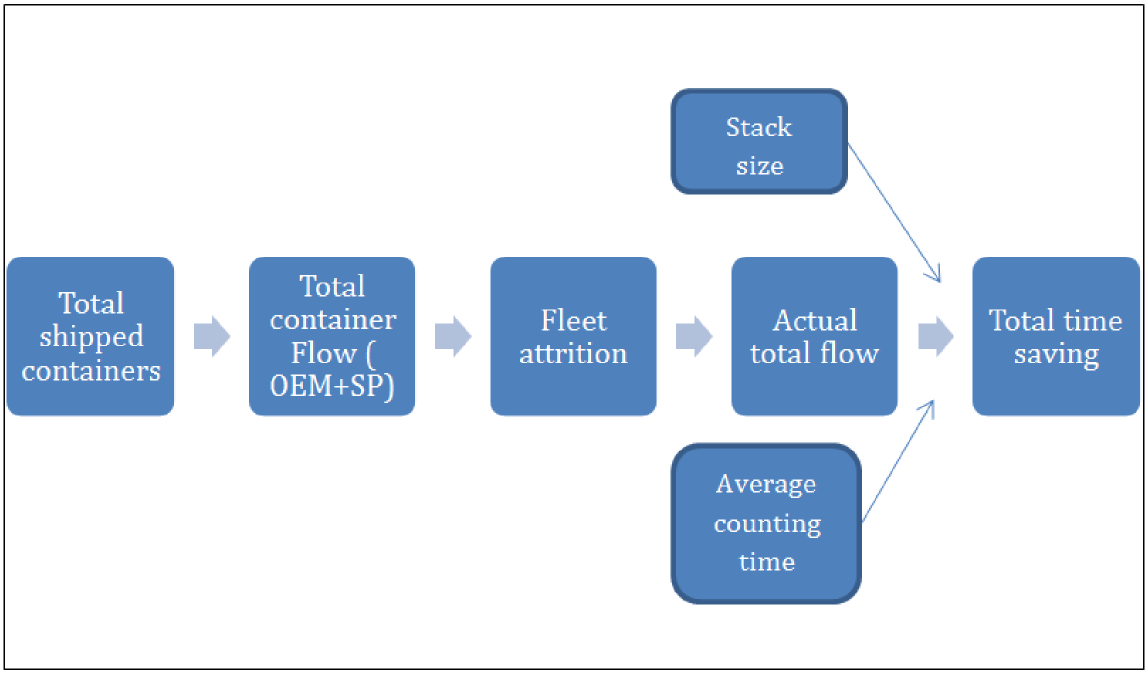

Figure 3.40 Handling time reduction algorithm

The algorithm works as follows:

- Total shipped containers quantity is defined, according to FCA records.
- Total containers flow is defined. Containers will be counted twice: before leaving EW and when arriving at SP. To estimate total time reduction, is then necessary to consider total flow through both sides:

$$Total\ flow = 2 \times Total\ shipped$$

- A fraction of total shipped container might not reach SP for multiple reasons. This percentage is called "Attrition", and it is fundamental to find the actual flow of containers

$$Actual\ flow = Attrition\ \times Total\ flow$$

- Once the total flow is available, it is possible to convert containers number in equivalent containers stacks. This is done because containers are not counted one at the time (see section 3.1.4), but are counted in stacks. Thus the total counting time is related to total stacks number. In general, even for the same container type, stack size can be different: FL driver does not always move the same quantity of containers at the same time. In this algorithm, it is assumed stack size is always the maximum possible for that container model.

- A measure of average stack counting type is necessary. In order to accomplish this task, manual counting time data have been recorded on the field, using stop-watch analysis.
- Finally, time saving estimate is defined as follows:

$$Total\ time\ saving = Avg.Stack\ counting\ time\ \times Total\ stacks$$

The method followed to measure stack counting time is reported.

Loading and unloading operations is provided in section 3.1.4. Among all the sub-operations, only those that can actually be eliminated using RFID are considered. In particular:

- Unloading
  - Count containers in the stack
  - Update paperwork
- Loading
  - Check paperwork
  - Count stack

The stopwatch is activated when the operator starts counting, and stopped when the paperwork is put away.

With collected data it was possible to define average stack counting time. The presented method wants to give a simple estimate of one small part of total possible time savings deriving from RFID. There is one main limit coming from the data collection procedure: Measured times are referred to different containers type and stack sizes. This is because most of the time different container models are mixed in the same trailer.

4. RESULTS ANALYSIS

4.1 SET 1-Data 1

The following table reports the full factorial plan developed for the study of controllable factors for Dataset 1. The effect of four different factors with two levels each has been evaluated using three performance indicators (see section 3.3.1). Table 4.1 reports results for 100% accuracy.

Table 4.1 Full factorial plan for SET 1-Data 1: 100% RFID accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	0	2	95.86	97.74	60.88
2	2	0	2	97.57	98.77	71.5
2	2	1	2	92.33	95.67	74.31
1	1	0	2	91.59	95.19	64.21
1	2	1	3	94.95	97.29	87.2
2	1	0	3	91.75	94.6	70.49
2	2	0	3	95.46	97.18	68.3
1	2	1	2	96.38	98.06	70.05
2	1	1	2	98.3	99.18	84.28
2	2	1	3	89.95	93.31	67.88
1	1	1	2	93.17	95.77	78.49
2	1	1	3	93.8	96.06	64.81
1	1	1	3	96.54	97.91	75.64
1	1	0	3	88.68	92.4	63.65
1	2	0	3	93.01	95.55	61
2	1	0	2	94.09	96.67	74.24

Table 4.2 shows results for 99.9 % RFID accuracy.

Table 4.2 Full factorial plan for SET 1-Data 1: 99.9 % RFID Accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	0	2	95.86	97.74	60.88
2	2	0	2	97.57	98.77	71.5
2	2	1	2	92.31	95.66	74.29
1	1	0	2	91.59	95.19	64.21
1	2	1	3	94.92	97.27	87.12
2	1	0	3	91.75	94.6	70.49
2	2	0	3	95.46	97.18	68.3
1	2	1	2	96.37	98.06	70.03
2	1	1	2	98.28	99.17	84.24
2	2	1	3	89.94	93.3	68
1	1	1	2	93.13	95.75	78.63
2	1	1	3	93.79	96.06	64.93
1	1	1	3	96.52	97.91	75.79
1	1	0	3	88.68	92.4	63.65
1	2	0	3	93.01	95.55	61
2	1	0	2	94.09	96.67	74.24

Table 4.3 shows results for 98 % RFID accuracy.

Table 4.3 Full factorial plan for SET 1-Data 1: 98% RFID Accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	0	2	95.86	97.74	60.88
2	2	0	2	97.57	98.77	71.5
2	2	1	2	92.21	95.58	73.5
1	1	0	2	91.59	95.19	64.21
1	2	1	3	94.83	97.18	85.67
2	1	0	3	91.75	94.6	70.49
2	2	0	3	95.46	97.18	68.3
1	2	1	2	96.35	98.03	69.4
2	1	1	2	98.2	99.13	82.97
2	2	1	3	89.93	93.2	66.99
1	1	1	2	92.89	95.56	77.14
2	1	1	3	93.71	96	64.06
1	1	1	3	96.39	97.8	74.53
1	1	0	3	88.68	92.4	63.65
1	2	0	3	93.01	95.55	61
2	1	0	2	94.09	96.67	74.24

To isolate the impact of RFID, the following tables (Table 4.4, Table 4.5, Table 4.6, Table 4.7) present performance indicators for the four following cases:

- No RFID
- RFID 100% accuracy
- RFID 99.9% accuracy
- RFID 98% accuracy

Table 4.4 SET 1-Data 1: NO RFID

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	0	2	91.59	95.19	64.21
2	2	0	2	94.09	96.67	74.24
1	1	0	2	95.86	97.74	60.88
2	1	0	3	97.57	98.77	71.5
2	2	0	3	88.68	92.4	63.65
1	1	0	3	91.75	94.6	70.49
1	2	0	3	93.01	95.55	61
2	1	0	2	95.46	97.18	68.3

Table 4.5 SET 1-Data 1: RFID with 100% accuracy

SD $_{EW}$	SD $_{SP}$	RFID	REP	SP $_{SL1}$ %	SP $_{SL2}$ %	EOP $_{SL2}$ %
2	2	1	2	92.33	95.67	74.31
1	2	1	3	94.95	97.29	87.2
1	2	1	2	96.38	98.06	70.05
2	1	1	2	98.3	99.18	84.28
2	2	1	3	89.95	93.31	67.88
1	1	1	2	93.17	95.77	78.49
2	1	1	3	93.8	96.06	64.81
1	1	1	3	96.54	97.91	75.64

Table 4.6 SET 1-Data 1: RFID with 99.9% accuracy

SD $_{EW}$	SD $_{SP}$	RFID	REP	SP $_{SL1}$ %	SP $_{SL2}$ %	EOP $_{SL2}$ %
2	2	1	2	92.31	95.66	74.29
1	2	1	3	94.92	97.27	87.12
1	2	1	2	96.37	98.06	70.03
2	1	1	2	98.28	99.17	84.24
2	2	1	3	89.94	93.3	68
1	1	1	2	93.13	95.75	78.63
2	1	1	3	93.79	96.06	64.93
1	1	1	3	96.52	97.91	75.79

Table 4.7 SET 1-Data 1: RFID with 98% accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
2	2	1	2	92.21	95.58	73.5
1	2	1	3	94.83	97.18	85.67
1	2	1	2	96.35	98.03	69.4
2	1	1	2	98.2	99.13	82.97
2	2	1	3	89.93	93.2	66.99
1	1	1	2	92.89	95.56	77.14
2	1	1	3	93.71	96	64.06
1	1	1	3	96.39	97.8	74.53

Figure 4.1 compares maximum SP_{SL1} improvements for each level of RFID accuracy.

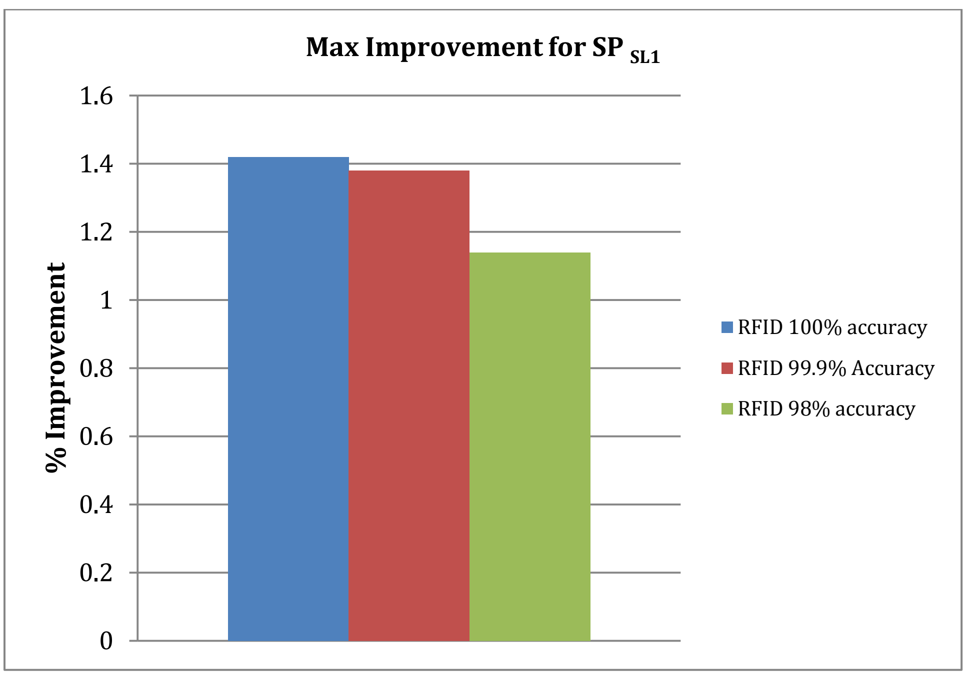

Figure 4.1 SET 1-Data 1: Maximum Improvement for SP_{SL1}

Figure 4.2 compares maximum SP_{SL2} improvements for each level of RFID accuracy.

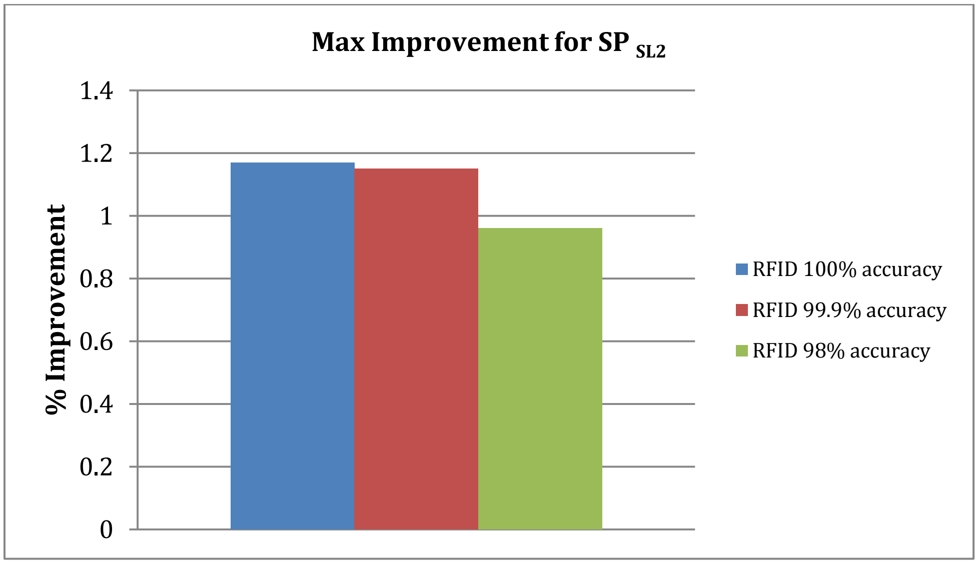

Figure 4.2 SET 1-Data 1, Maximum Improvement for SP_{SL2}

Figure 4.3 compares maximum EW_{SL2} improvements for each level of RFID accuracy.

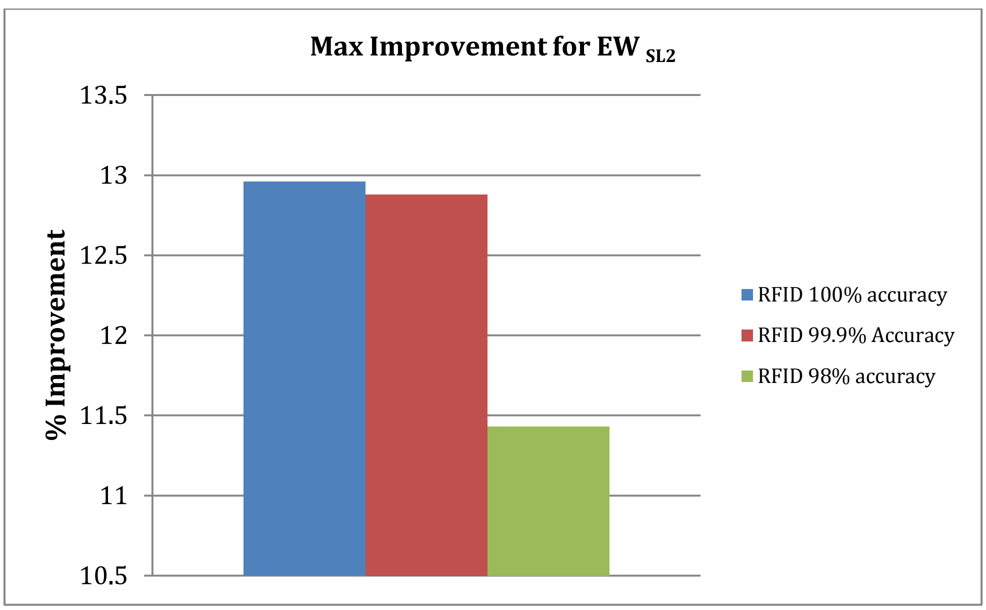

Figure 4.3 SET 1-Data 1, Maximum Improvement for EW_{SL2}

It is possible to notice that RFID leads to better overall performances in all of the considered combinations. In particular, considering Ideal RFID:

- EW FR improvement up to 12.96%
- SP SL improvement up to 1.42%
- SF FR improvement up to 1.17%

The best combination of factors for different accuracy levels is reported in Table 4.8.

Table 4.8 Best case scenarios for SET 1-Data 1

RFID Accuracy	SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EW_{SL2} %
100%	2	2	1	2	98.3	99.18	84.28
99.9 %	2	2	1	2	98.28	99.17	84.24
98%	2	2	1	2	98.2	99.13	82.97

To quantify the contribution of each factor on overall performance, three sets of ANOVA tables are now presented.

4.1.1 SET 1-Data 1: SP_{SL1}

In this section, the effect of the different factors on SP_{SL1} is evaluated by means of ANOVA tables. The results are presented for three different RFID system accuracies.

Table 4.9 reports ANOVA results with 100% RFID accuracy.

Table 4.9 SET 1-Data 1: ANOVA for SP_{SL1} with 100% RFID accuracy

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	25.578	23.27%	25.578	25.5783	230.87	0.000
SD SP	1	57.798	52.59%	57.798	57.7980	521.68	0.000
RFID	1	3.432	3.12%	3.432	3.4318	30.97	0.000
REP	1	21.879	19.91%	21.879	21.8790	197.48	0.000
Error	11	1.219	1.11%	1.219	0.1108		
Total	15	109.906	100.00%				

Table 4.10 reports ANOVA results with 99.9% RFID accuracy.

Table 4.10 SET 1-Data 1: ANOVA for SP_{SL1} with 99.9% RFID accuracy

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	25.427	23.17%	25.427	25.4268	233.92	0.000
SD SP	1	57.950	52.81%	57.950	57.9502	533.13	0.000
RFID	1	3.285	2.99%	3.285	3.2852	30.22	0.000
REP	1	21.879	19.94%	21.879	21.8790	201.28	0.000
Error	11	1.196	1.09%	1.196	0.1087		
Total	15	109.737	100.00%				

Table 4.11 reports ANOVA results with 98% RFID accuracy.

Table 4.11 SET 1-Data 1: ANOVA for SP_{SL1} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	24.602	22.57%	24.602	24.6016	259.60	0.000
SD SP	1	58.446	53.62%	58.446	58.4460	616.73	0.000
RFID	1	2.641	2.42%	2.641	2.6406	27.86	0.000
REP	1	22.278	20.44%	22.278	22.2784	235.08	0.000
Error	11	1.042	0.96%	1.042	0.0948		
Total	15	109.009	100.00%				

It is possible to conclude:

- Supplier system days is the most influencing parameter in all the considered cases (up to 52.81%)
- RFID influences SP_{SL1} up to 3.432%
- Replenishment frequency can influence up to 20.44%.

Results are summarized in three pie charts (Figure 4.4, Figure 4.5 and Figure 4.6).

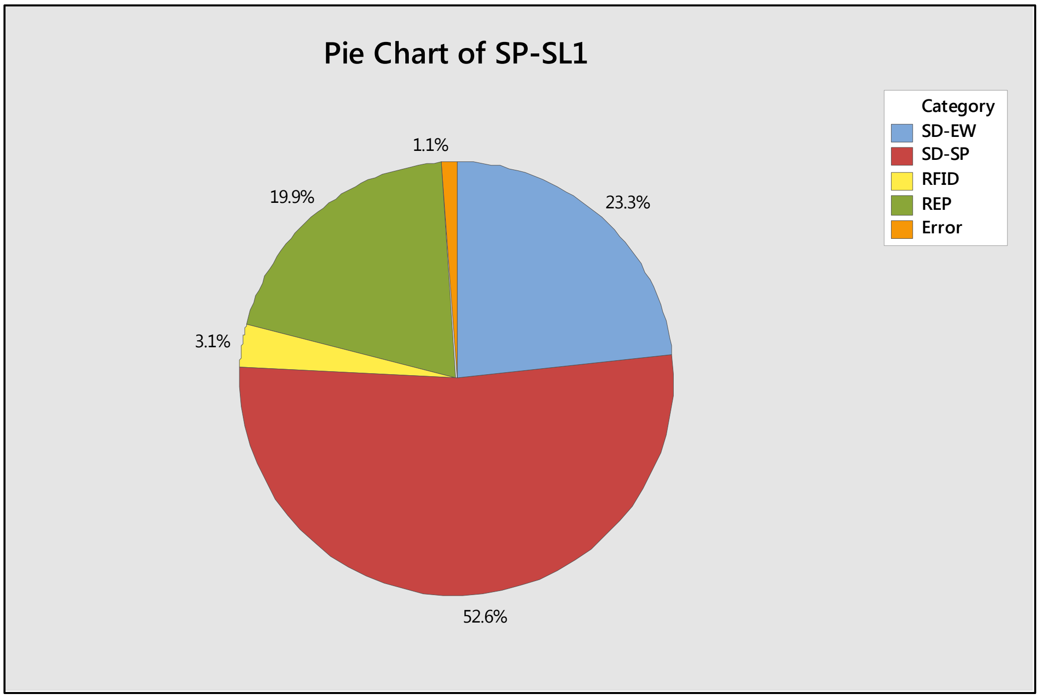

Figure 4.4 SET 1-Data 1: Pie chart for SP_{SL1} and 100% RFID accuracy

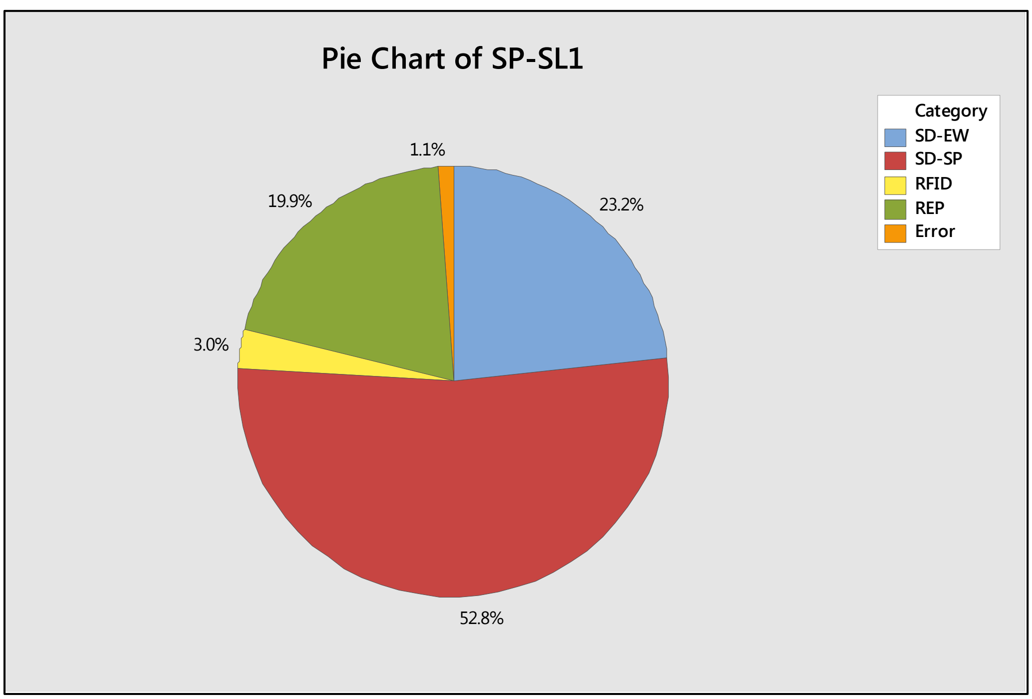

Figure 4.5 SET 1-Data 1: Pie chart for SP_{SL1} and 99.9% RFID accuracy

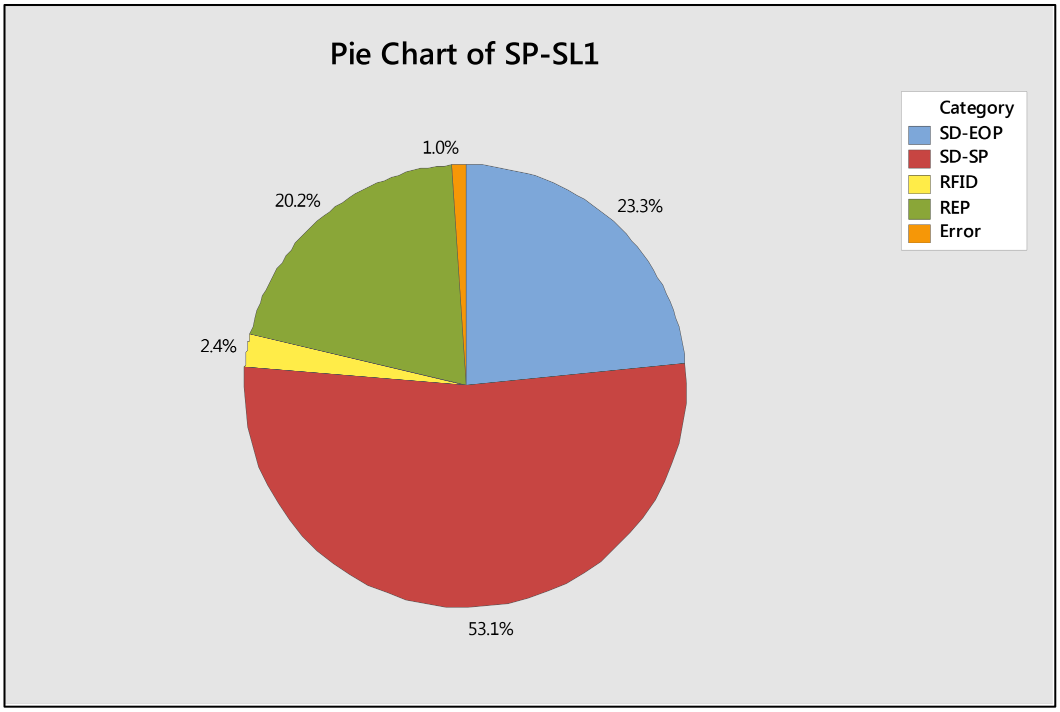

Figure 4.6 SET 1-Data 1: Pie chart for SP_{SL1} and 98% RFID accuracy

4.1.2 SET 1-Data 1: SP_{SL2}

In this section, the effect of the different factors on SP_{SL2} is evaluated by means of ANOVA tables. The results are presented for three different RFID system accuracies.

Table 4.12 presents results for RFID accuracy 100%.

Table 4.12 SET 1-Data 1: ANOVA for SP_{SL2} and 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	11.206	20.91%	11.206	11.2058	97.26	0.000
SD SP	1	23.888	44.57%	23.888	23.8877	207.33	0.000
RFID	1	1.658	3.09%	1.658	1.6577	14.39	0.003
REP	1	15.583	29.07%	15.583	15.5828	135.25	0.000
Error	11	1.267	2.36%	1.267	0.1152		
Total	15	53.601	100.00%				

Table 4.13 presents results for RFID accuracy 99.9%.

Table 4.13 SET 1-Data 1: ANOVA for SP_{SL2} and 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	10.890	20.25%	10.890	10.8900	106.15	0.000
SD SP	1	24.552	45.66%	24.552	24.5520	239.31	0.000
RFID	1	1.199	2.23%	1.199	1.1990	11.69	0.006
REP	1	16.000	29.76%	16.000	16.0000	155.96	0.000
Error	11	1.129	2.10%	1.129	0.1026		
Total	15	53.770	100.00%				

Table 4.14 presents results for RFID accuracy 98%.

Table 4.14 SET 1-Data 1: ANOVA for SP_{SL2} and 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	10.890	20.25%	10.890	10.8900	106.15	0.000
SD SP	1	24.552	45.66%	24.552	24.5520	239.31	0.000
RFID	1	1.199	2.23%	1.199	1.1990	11.69	0.006
REP	1	16.000	29.76%	16.000	16.0000	155.96	0.000
Error	11	1.129	2.10%	1.129	0.1026		
Total	15	53.770	100.00%				

It is possible to conclude:

- All considered factors are significant
- Supplier system days SD SP is the most influencing parameter (Up to 45.66%)
- RFID contributes up to 3.09% of the phenomena

Those results are summarized in the following pie charts (Figure 4.7, Figure 4.8 and Figure 4.9).

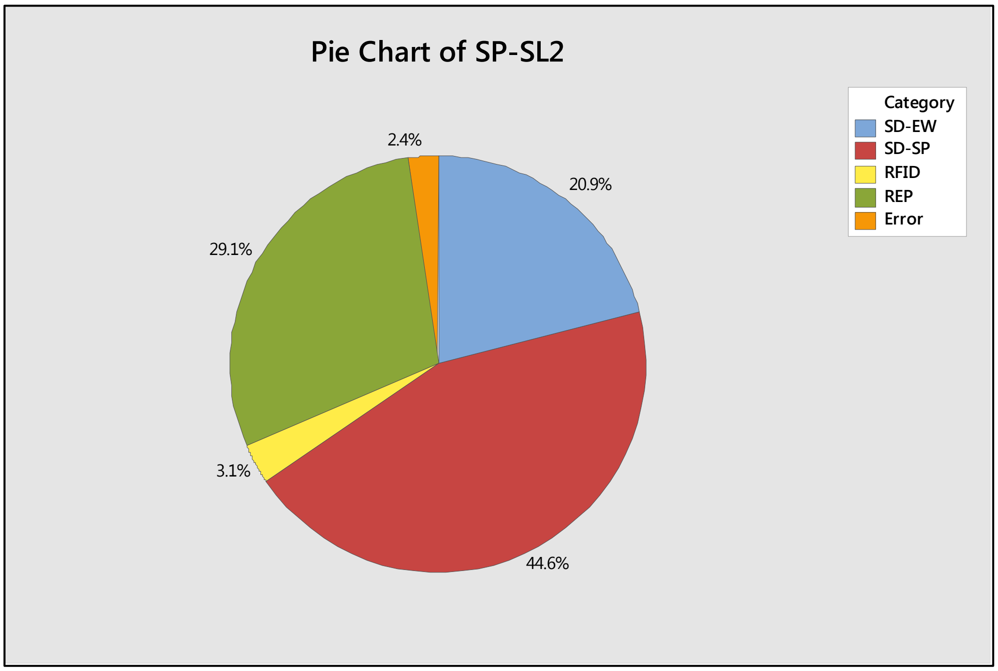

Figure 4.7 SET 1-Data 1: Pie chart for SP_{SL2} and 100% RFID accuracy

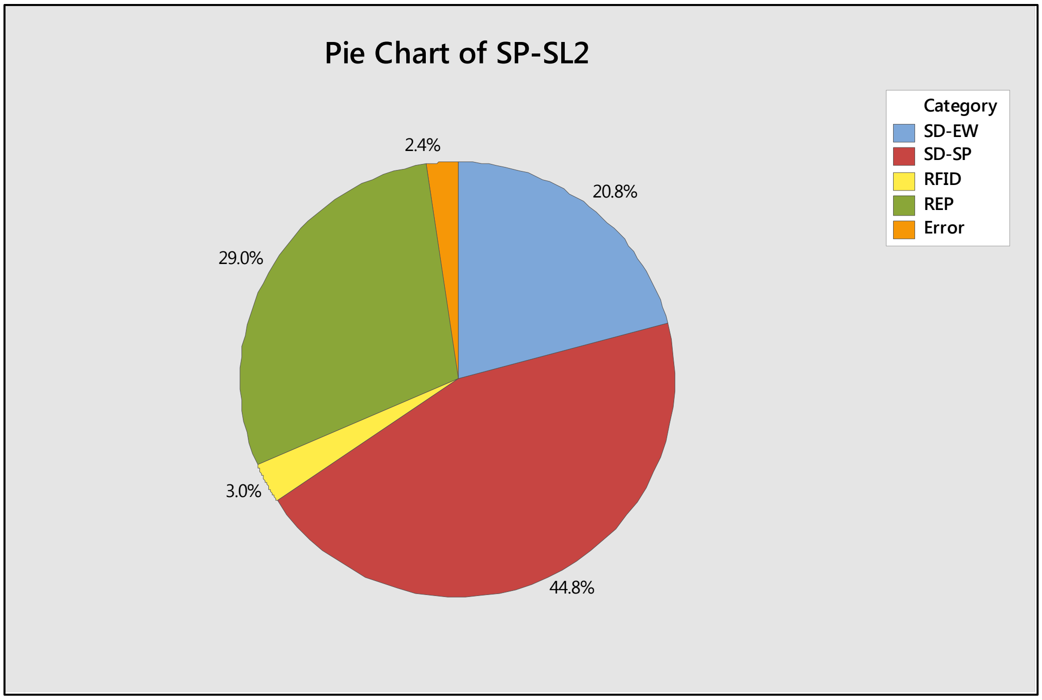

Figure 4.8 SET 1-Data 1: Pie chart for SP_{SL2} and 99.9% RFID accuracy

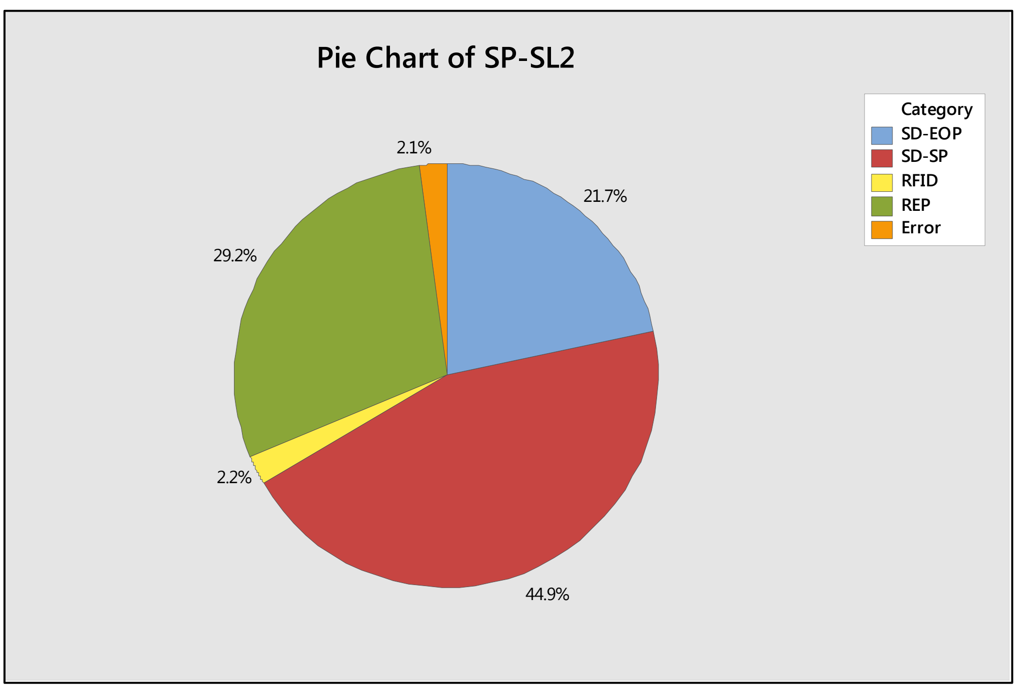

Figure 4.9 SET 1-Data 1: Pie chart for SP_{SL2} and 98% RFID accuracy

4.1.3 SET 1-Data1: EW_{SL2}

In this section, the effect of the different factors on EW_{SL2} is evaluated by means of ANOVA tables. The results are presented for three different RFID system accuracies.

Table 4.15 presents results for RFID accuracy 100%.

Table 4.15 SET 1-Data 1: ANOVA for EW_{SL2} and 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	433.89	48.50%	433.89	433.889	96.14	0.000
SD SP	1	35.88	4.01%	35.88	35.880	7.95	0.017
RFID	1	295.50	33.03%	295.50	295.496	65.47	0.000
REP	1	79.74	8.91%	79.74	79.745	17.67	0.001
Error	11	49.65	5.55%	49.65	4.513		
Total	15	894.66	100.00%				

Table 4.16 presents results for RFID accuracy 100%.

Table 4.16 SET 1-Data 1: ANOVA for EW_{SL2} and 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	434.20	48.40%	434.20	434.201	92.36	0.000
SD SP	1	36.03	4.02%	36.03	36.030	7.66	0.018
RFID	1	292.32	32.58%	292.32	292.325	62.18	0.000
REP	1	82.86	9.24%	82.86	82.856	17.63	0.001
Error	11	51.71	5.76%	51.71	4.701		
Total	15	897.12	100.00%				

Table 4.17 presents results for RFID accuracy 100%.

Table 4.17 SET 1-Data 1: ANOVA for EW_{SL2} and 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD Ew	1	411.58	51.51%	411.58	411.583	96.71	0.000
SD SP	1	33.79	4.23%	33.79	33.785	7.94	0.017
RFID	1	224.93	28.15%	224.93	224.925	52.85	0.000
REP	1	81.95	10.26%	81.95	81.948	19.26	0.001
Error	11	46.81	5.86%	46.81	4.256		
Total	15	799.06	100.00%				

It is possible to conclude:

- All the factors are significant
- EW system days is the most relevant factor in the three cases (Max 51.51%)
- RFID can influence EOP_{SL2} up to 33.03%

Results are summarized in Figure 4.10, Figure 4.11 and Figure 4.12.

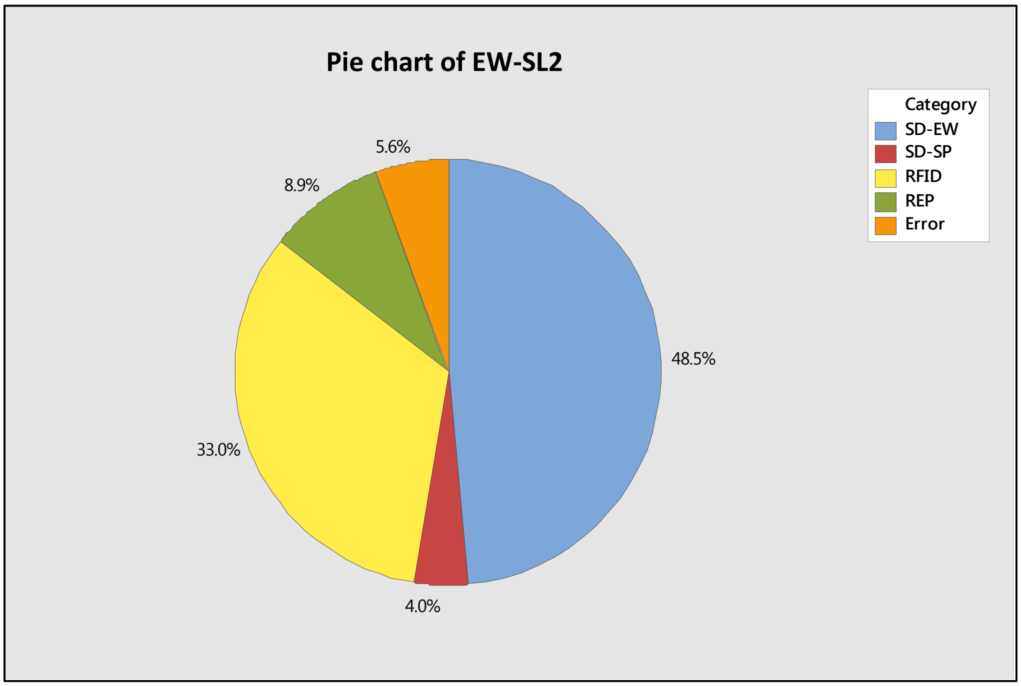

Figure 4.10 SET 1-Data 1: Pie chart for EW_{SL2} and 100% RFID accuracy

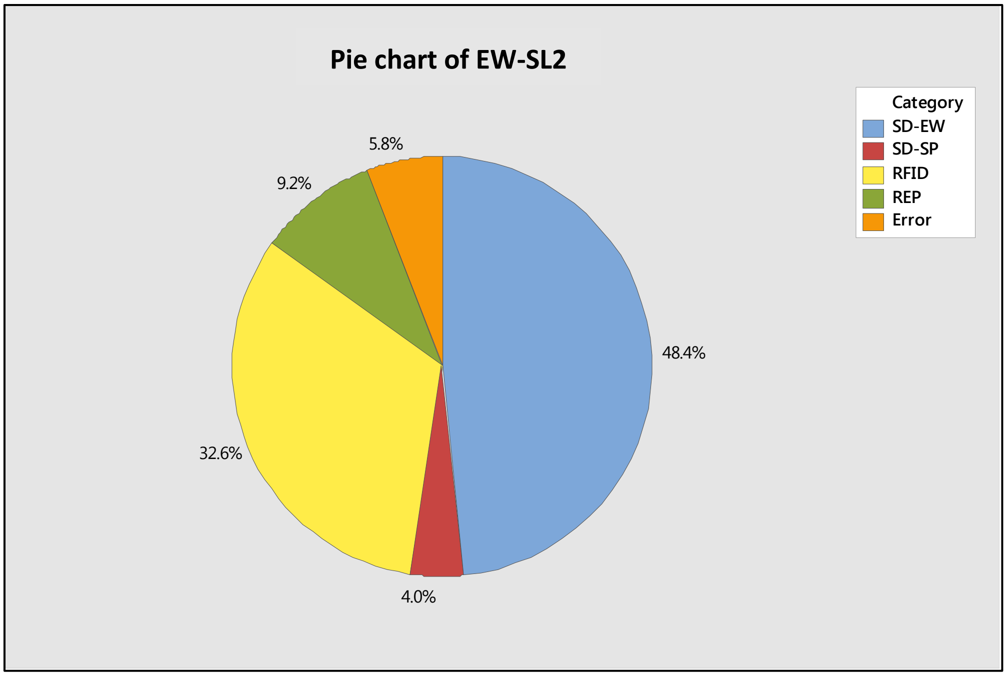

Figure 4.11 SET 1-Data 1: Pie chart for EW_{SL2} and 99.9% RFID accuracy

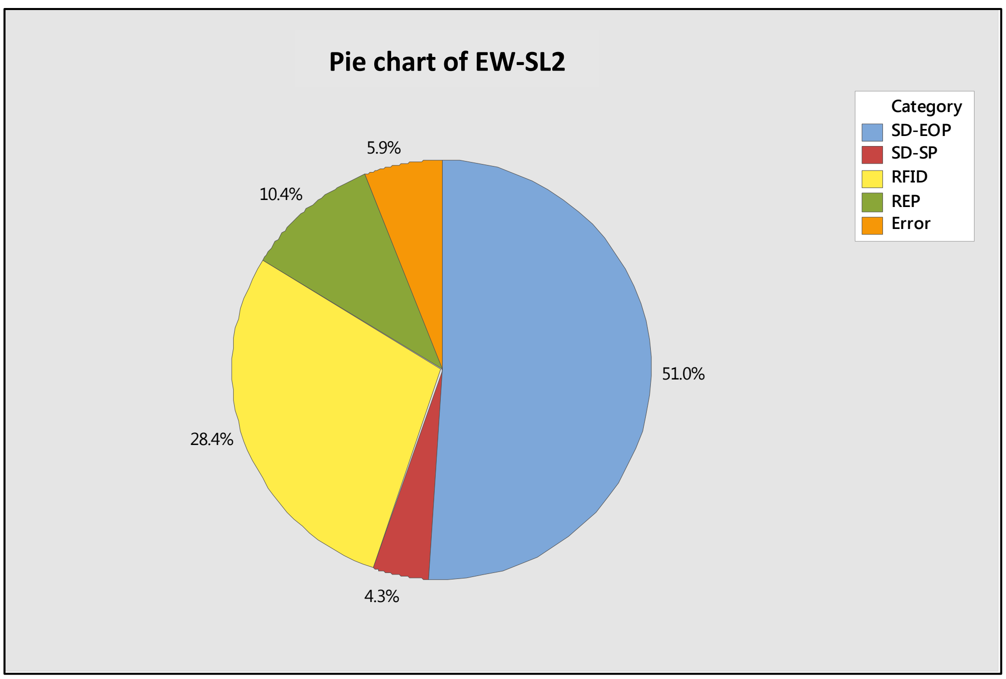

Figure 4.12 SET 1-Data 1: Pie chart for EW_{SL2} and 98% RFID accuracy

In the following, supplier performance indicators SP_{SL1} and SP_{SL2} are evaluated for different values of SD_{SP}, with and without RFID. In this case, considered RFID accuracy is 100%. The other factors are kept constant. This is done to evaluate possible SD_{SP} reduction without affecting supplier performance.

Figure 4.13 reports SP_{SL1} as function of SD_{SP}.

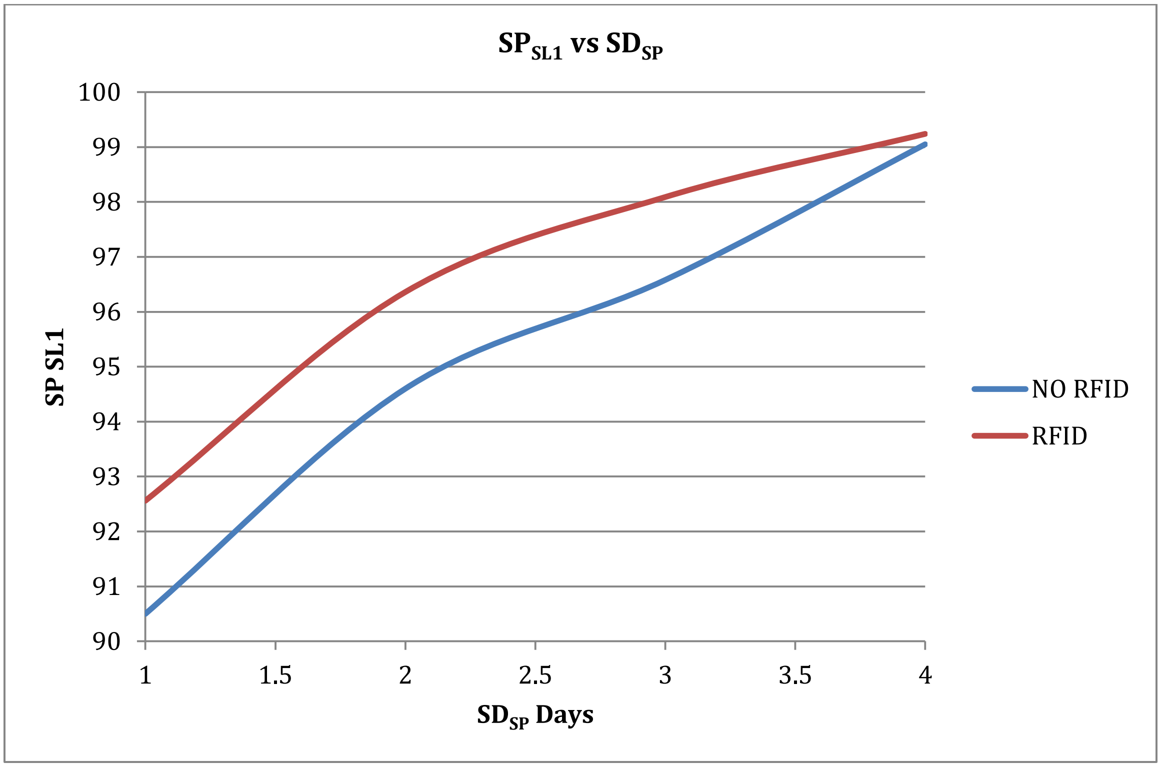

Figure 4.13 SET 1-Data 1: SP_{SL1} as function of SD_{SP}

Figure 4.14 reports SP_{SL2} as function of $SD_{SP.}$

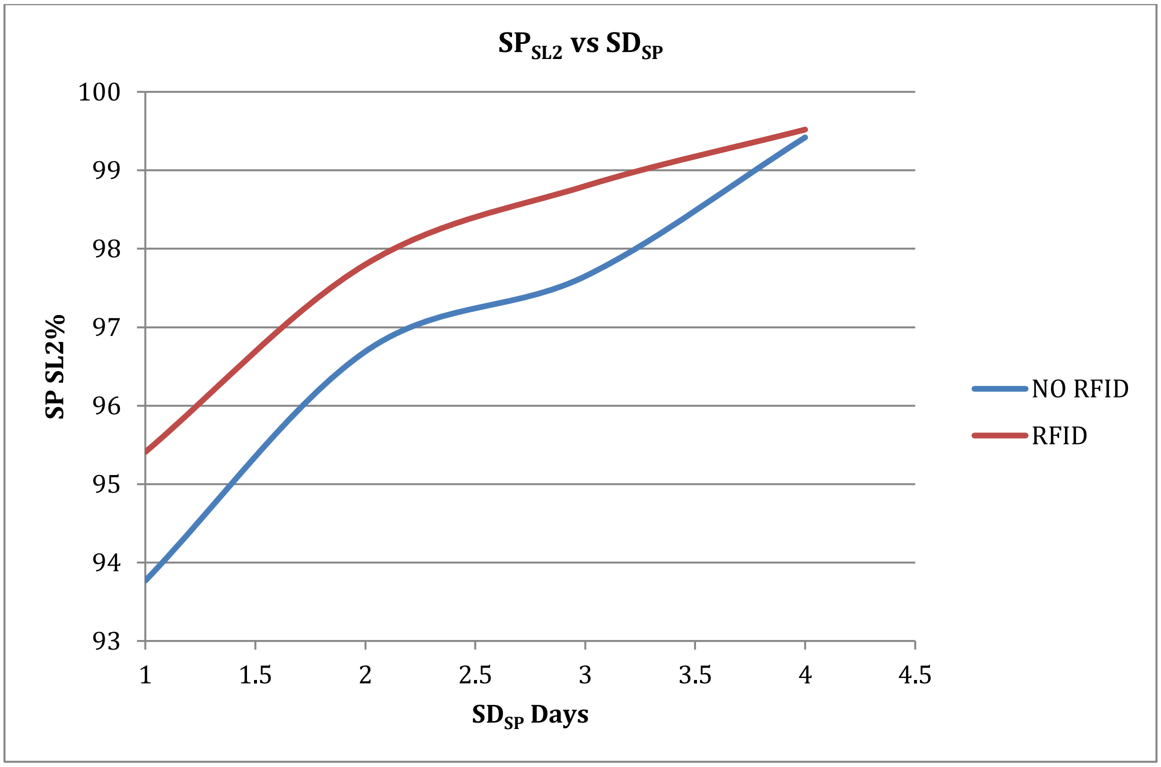

Figure 4.14 SET 1-Data 1: SP_{SL2} as function of SD_{SP}

From those charts it is possible to conclude that using RFID would allow for supplier system days reduction for the same level of system performance. To better understand how to use those charts, let us consider Figure 4.15.

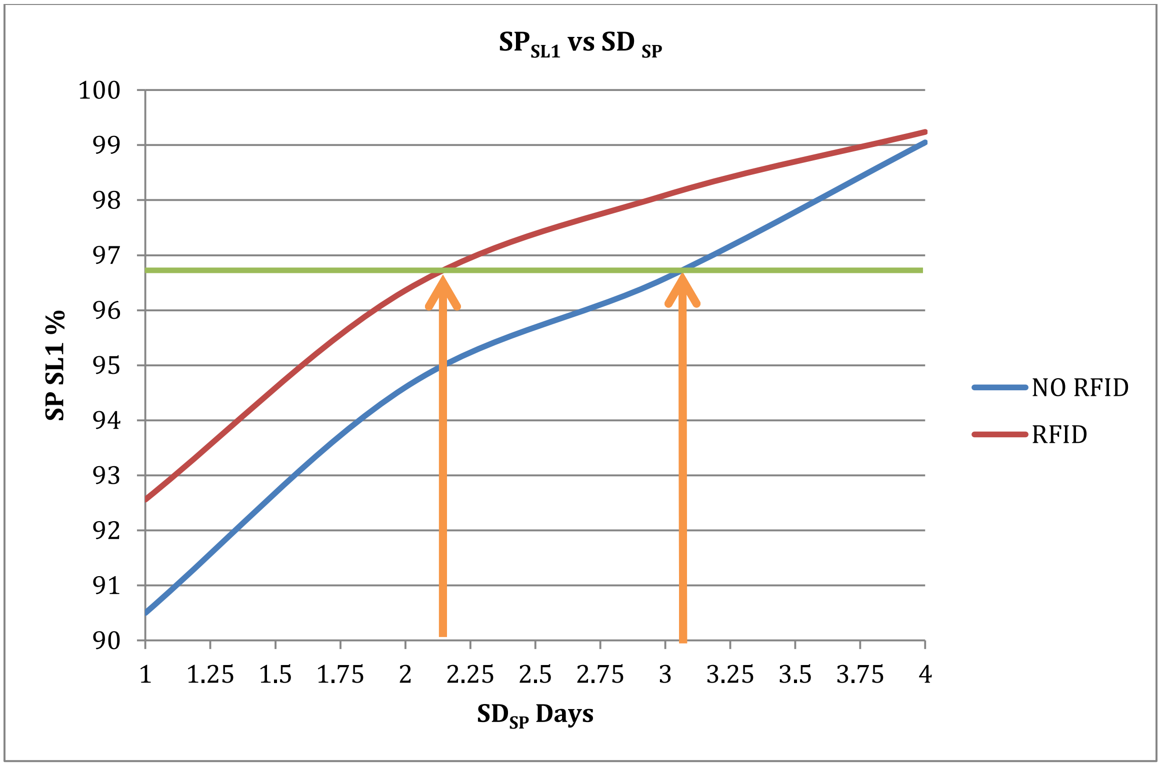

Figure 4.15 SET 1-Data 1: Potential safety stock reduction

For example, it is desired to achieve SP_{SL1} = 97%:

- With RFID, SP_{SD} = 2.25 Days
- Without RFID, $SP_{SD} \approx 3.25$ Days

That means the same performance can be achieve with almost one system day less. This results in:

- Reduced Fleet
- Reduced safety stocks

4.2 SET 1-Data 2

The following table reports the full factorial plan developed for the study of controllable factors for dataset 2. The effect of four different factors with two levels each has been evaluated using three performance indicators (see section 3.3.1). Table 4.18 reports results for 100% accuracy.

Table 4.18 Full factorial plan for SET 1-Data 2: 100% RFID accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
2	1	1	1	98.25	98.32	91.13
1	2	1	0	93.03	95.55	94.02
1	2	1	1	95.87	97.49	97.57
1	1	1.75	1	95.01	96.12	83.66
2	2	1	1	98.25	98.32	96.37
2	2	1.75	0	95.92	96.45	85.63
2	2	1	0	97.13	97.79	91.73
1	1	1.75	0	91.08	94.15	73.88
2	1	1.75	1	96.62	96.75	82.63
1	1	1	1	95.66	97.45	93.18
1	2	1.75	1	96.06	96.63	94.06
1	1	1	0	92.04	94.86	83.21
2	2	1.75	1	96.79	96.82	92.91
2	1	1	0	96.94	97.68	83.4
2	1	1.75	0	96.05	96.55	72.84

Table 4.19 shows results for 99.9 % RFID accuracy.

Table 4.19 Full factorial plan for SET 1-Data 2: 99.9 % RFID accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
2	1	1	1	98.24	98.32	91.27
1	2	1	0	93.03	95.55	94.02
1	2	1	1	95.88	97.5	97.57
1	1	1.75	1	95	96.12	83.78
2	2	1	1	98.24	98.32	96.38
2	2	1.75	0	95.92	96.45	85.63
2	2	1	0	97.13	97.79	91.73
1	1	1.75	0	91.08	94.15	73.88
2	1	1.75	1	96.62	96.75	82.74
1	1	1	1	95.57	97.41	93.23
1	2	1.75	1	96.05	96.62	94.09
1	1	1	0	92.04	94.86	83.21
2	2	1.75	1	96.79	96.82	92.93
2	1	1	0	96.94	97.68	83.4
2	1	1.75	0	96.05	96.55	72.84

Table 4.20 shows results for 98 % RFID accuracy.

Table 4.20 Full factorial plan for SET 1-Data 2: 98% RFID accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
2	1	1	1	98.21	98.32	90.51
1	2	1	0	93.03	95.55	94.02
1	2	1	1	95.43	97.39	97.63
1	1	1.75	1	94.5	95.88	83.59
2	2	1	1	98.24	98.32	96.44
2	2	1.75	0	95.92	96.45	85.63
2	2	1	0	97.13	97.79	91.73
1	1	1.75	0	91.08	94.15	73.88
2	1	1.75	1	96.51	96.72	82.48
1	1	1	1	95.19	97.28	92.7
1	2	1.75	1	95.41	96.33	93.49
1	1	1	0	92.04	94.86	83.21
2	2	1.75	1	96.69	96.79	92.36
2	1	1	0	96.94	97.68	83.4
2	1	1.75	0	96.05	96.55	72.84

The following tables (Table 4.21, Table 4.22, Table 4.23 and Table 4.24) report performance indicators for the four different cases:

- No RFID
- RFID 100% accuracy
- RFID 99.9% accuracy
- RFID 98% accuracy

Table 4.21 SET 1-Data 2: NO RFID

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
1	2	1	0	93.03	95.55	94.02
2	2	1.75	0	95.92	96.45	85.63
2	2	1	0	97.13	97.79	91.73
1	1	1.75	0	91.08	94.15	73.88
1	1	1	0	92.04	94.86	83.21
2	1	1	0	96.94	97.68	83.4
2	1	1.75	0	96.05	96.55	72.84

Table 4.22 SET 1-Data 2: RFID with 100% accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
2	1	1	1	98.25	98.32	91.13
1	2	1	1	95.87	97.49	97.57
1	1	1.75	1	95.01	96.12	83.66
2	2	1	1	98.25	98.32	96.37
2	1	1.75	1	96.62	96.75	82.63
1	1	1	1	95.66	97.45	93.18
1	2	1.75	1	96.06	96.63	94.06
2	2	1.75	1	96.79	96.82	92.91

Table 4.23 SET 1-Data 2: RFID with 99.9% accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
2	1	1	1	98.24	98.32	91.27
1	2	1	1	95.88	97.5	97.57
1	1	1.75	1	95	96.12	83.78
2	2	1	1	98.24	98.32	96.38
2	1	1.75	1	96.62	96.75	82.74
1	1	1	1	95.57	97.41	93.23
1	2	1.75	1	96.05	96.62	94.09
2	2	1.75	1	96.79	96.82	92.93

Table 4.24 SET 1-Data 2: RFID with 98% accuracy

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
2	1	1	1	98.21	98.32	90.51
1	2	1	1	95.43	97.39	97.63
1	1	1.75	1	94.5	95.88	83.59
2	2	1	1	98.24	98.32	96.44
2	1	1.75	1	96.51	96.72	82.48
1	1	1	1	95.19	97.28	92.7
1	2	1.75	1	95.41	96.33	93.49
2	2	1.75	1	96.69	96.79	92.36

Figure 4.16 compares maximum SP_{SL1} improvements for each level of RFID accuracy.

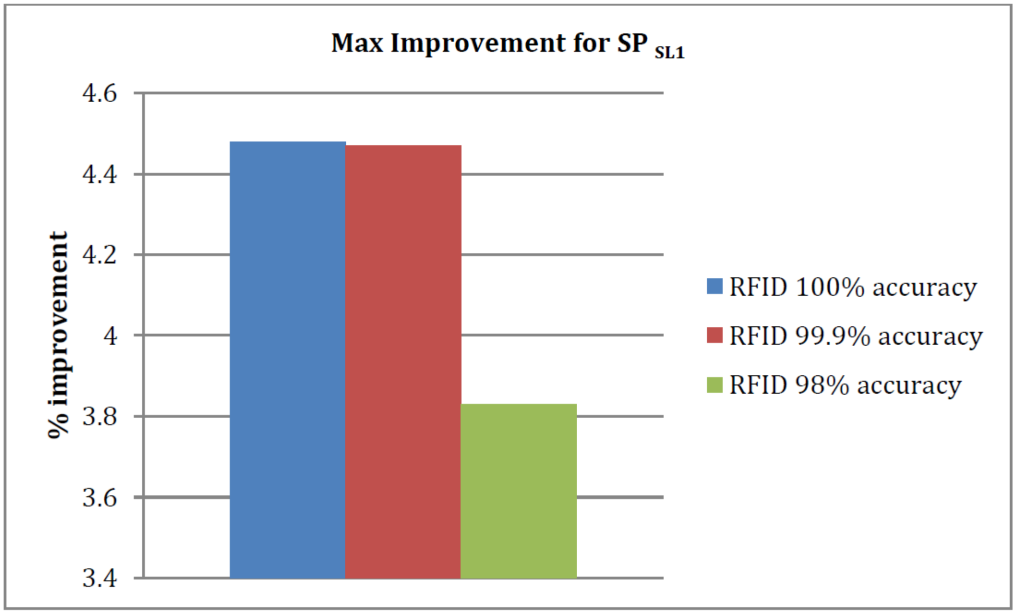

Figure 4.16 SET 1-Data 2: Maximum Improvement for SP_{SL1}

Figure 4.17 compares maximum SP_{SL2} improvements for each level of RFID accuracy.

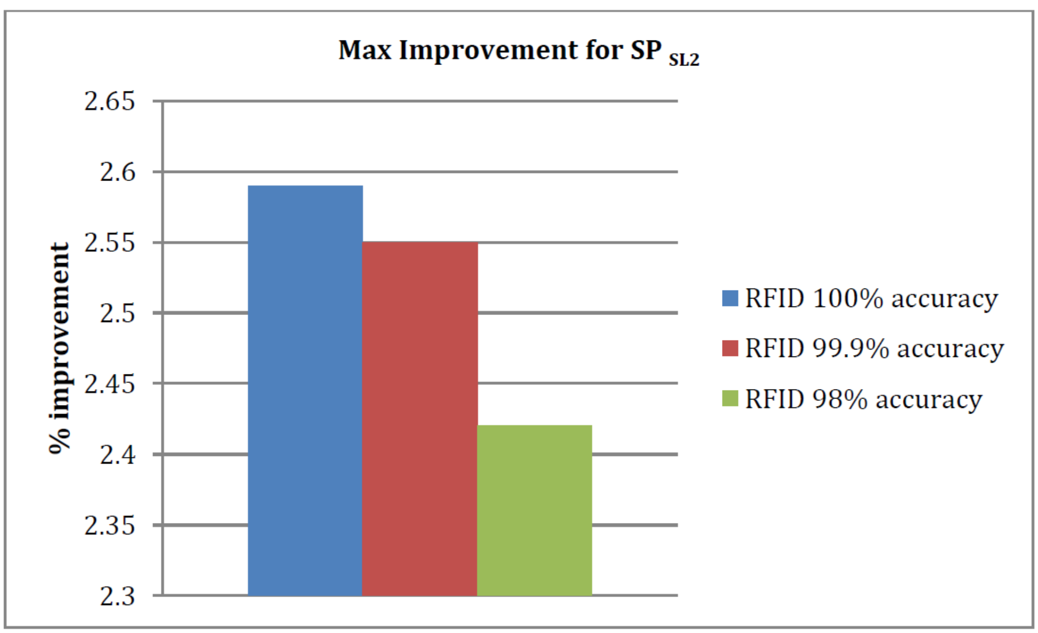

Figure 4.17 SET 1-Data 2: Maximum Improvement for SP_{SL2}

Figure 4.18 compares maximum EW_{SL2} improvements for each level of RFID accuracy.

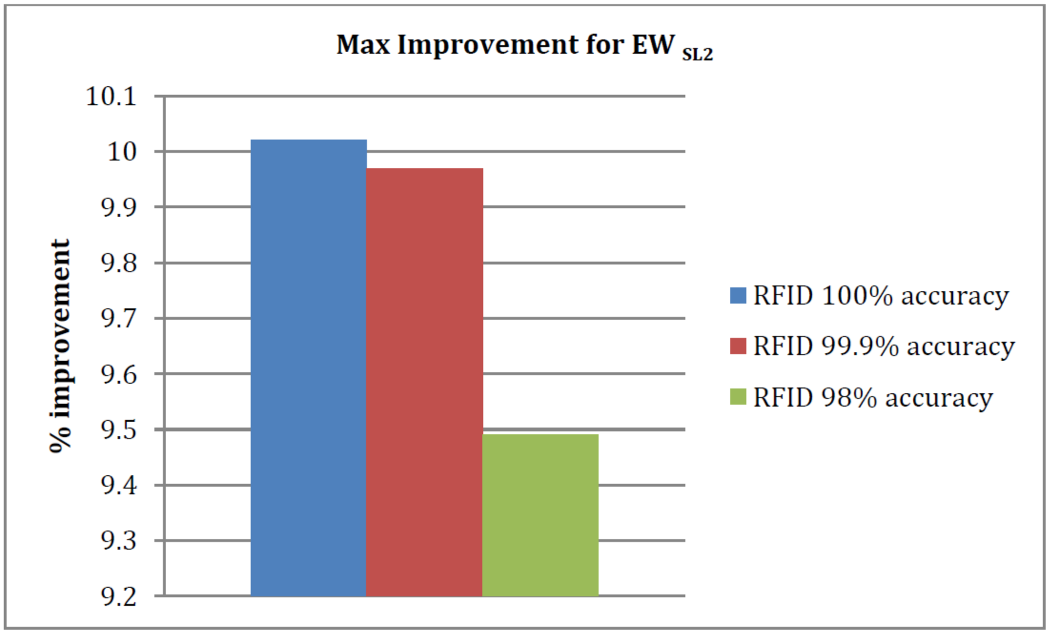

Figure 4.18 SET 1-Data 2: Maximum Improvement for EW_{SL2}

It is possible to notice that RFID leads to better overall performances in all of the considered combinations. In particular:

- EW_{SL2}improvement up to 10.02 %
- SP_{SL1} improvement up to 4.48 %
- SP_{SL2} improvement up to 2.59 %

The best combination of factors for different accuracy levels is reported in Table 4.25.

Table 4.25 SET 1-Data 2: Best case scenario

RFID Accuracy	SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EW_{SL2} %
100%	2	2	1	1	98.25	98.32	96.37
99.9 %	2	2	1	1	98.24	98.32	96.37
98%	2	2	1	1	98.24	98.32	96.44

To quantify the contribution of each factor on overall performance, three sets of ANOVA tables are now presented.

4.2.1 SET 1-Data 2: SP_{SL1}

In this section, the effect of the different factors on SP_{SL1} is evaluated by means of ANOVA tables. The results are presented for three different RFID system accuracies.

Table 4.26 reports ANOVA results with 100% RFID accuracy.

Table 4.26 SET 1-Data 2: ANOVA for SP_{SL1} with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	41.0240	53.44%	41.0240	41.0240	49.21	0.000
SD EW	1	0.5550	0.72%	0.5550	0.5550	0.67	0.432
R	1	4.0602	5.29%	4.0602	4.0602	4.87	0.049
RFID	1	21.9492	28.59%	21.9492	21.9492	26.33	0.000
Error	11	9.1710	11.95%	9.1710	0.8337		
Total	15	76.7595	100.00%				

Table 4.27 reports ANOVA results with 99.9% RFID accuracy.

Table 4.27 SET 1-Data 2: ANOVA for SP_{SL1} with 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	41.2806	53.89%	41.2806	41.2806	49.98	0.000
SD EW	1	0.5929	0.77%	0.5929	0.5929	0.72	0.415
R	1	3.9800	5.20%	3.9800	3.9800	4.82	0.051
RFID	1	21.6690	28.29%	21.6690	21.6690	26.23	0.000
Error	11	9.0860	11.86%	9.0860	0.8260		
Total	15	76.6086	100.00%				

Table 4.28 reports ANOVA results with 98% RFID accuracy.

Table 4.28 SET 1-Data 2: ANOVA for SP_{SL1} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	47.0253	62.24%	47.0253	47.0253	77.35	0.000
SD EW	1	0.5293	0.70%	0.5293	0.5293	0.87	0.371
R	1	4.4838	5.93%	4.4838	4.4838	7.38	0.020
RFID	1	16.8305	22.28%	16.8305	16.8305	27.68	0.000
Error	11	6.6877	8.85%	6.6877	0.6080		
Total	15	75.5565	100.00%				

It is possible to conclude:

- Supplier system days is the most influencing parameter in all the considered cases (Up to 62.24%)
- SD_{EW} is not a significant Factor (P-Value>>0.05)
- RFID influences SP_{SL1} up to 28.59 %
- Replenishment frequency can influence up to 5.93%.

It is possible to notice that RFID contribution for Dataset 1 is much larger than Dataset 2. As it will be clear in next experiment set, this can be related to the short lead time and reduced lead time impact.

Results are summarized in three pie charts (Figure 4.19, Figure 4.20, Figure 4.21).

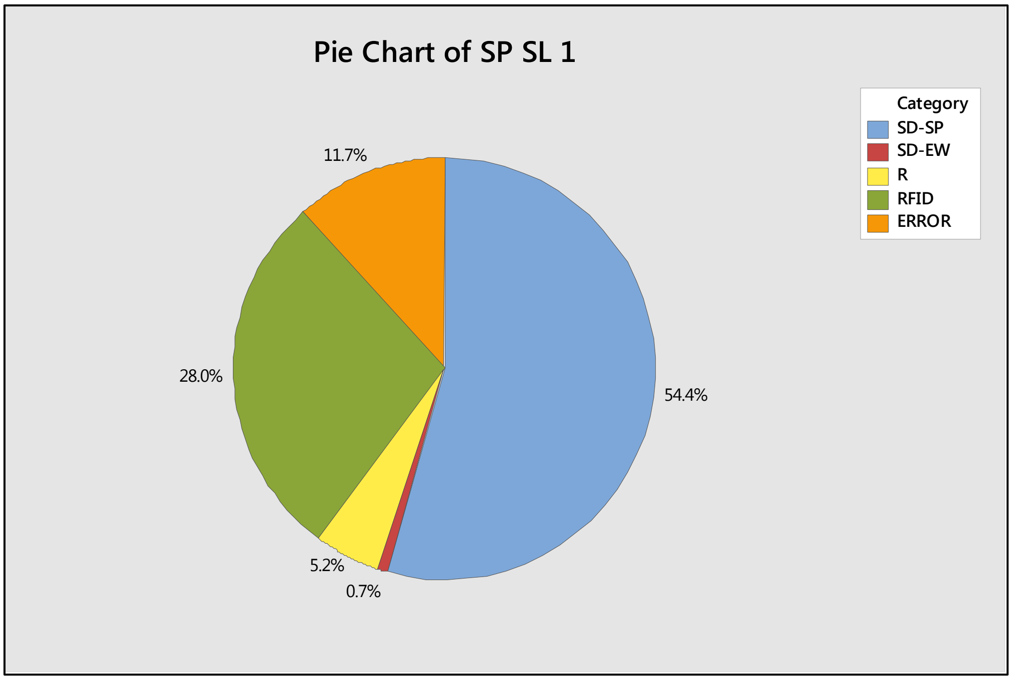

Figure 4.19 SET 1-Data 2: Pie chart for SP_{SL1} and 100% RFID accuracy

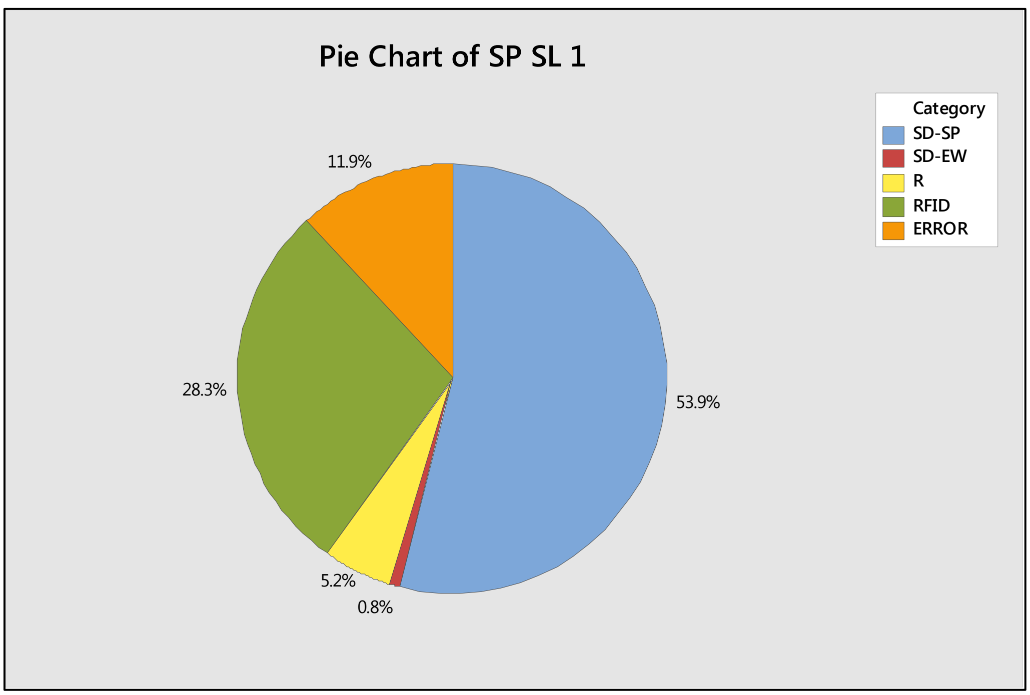

Figure 4.20 SET 1-Data 2: Pie chart for SP_{SL1} and 99.9% RFID accuracy

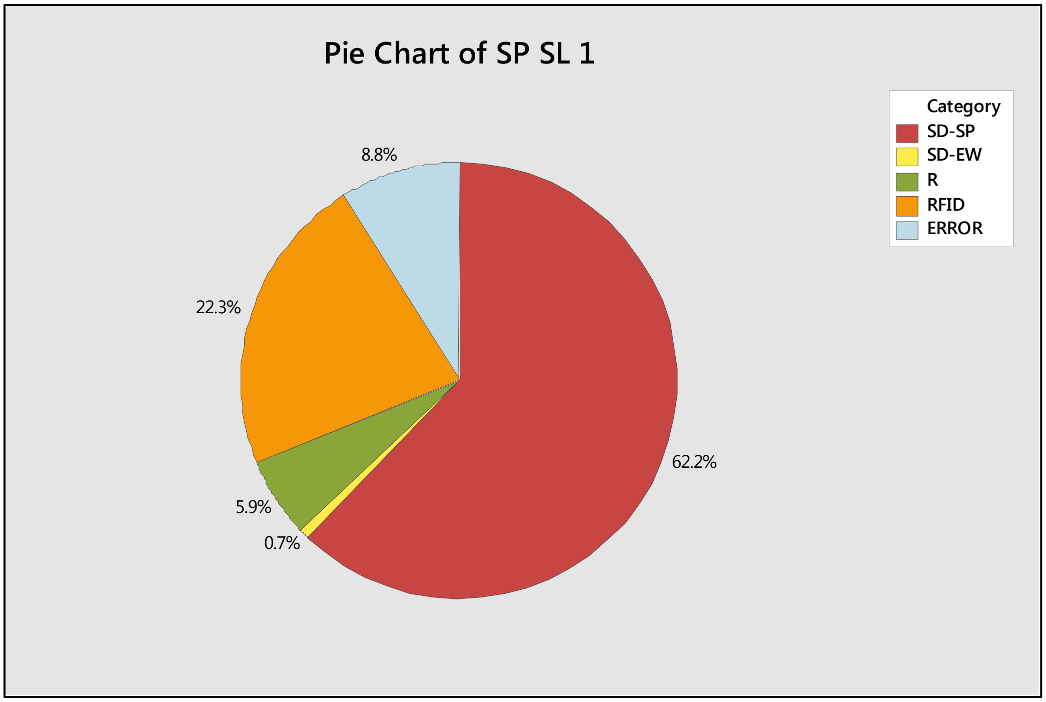

Figure 4.21 SET 1-Data 2: Pie chart for SP_{SL1} and 98% RFID accuracy

4.2.2 SET 1-Data 2: SP_{SL2}

In this section, the effect of the different factors on SP_{SL2} is evaluated by means of ANOVA tables. The results are presented for three different RFID system accuracies.

Table 4.29 presents results for RFID accuracy 100%.

Table 4.29 SET 1-Data 2: ANOVA for SO_{SL2} and 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	9.4403	35.61%	9.4403	9.4403	28.06	0.000
SD EW	1	0.1073	0.40%	0.1073	0.1073	0.32	0.584
R	1	6.0639	22.88%	6.0639	6.0639	18.03	0.001
RFID	1	7.1958	27.15%	7.1958	7.1958	21.39	0.001
Error	11	3.7005	13.96%	3.7005	0.3364		
Total	15	26.5077	100.00%				

Table 4.30 presents results for RFID accuracy 99.9%.

Table 4.30 SET 1-Data 2: ANOVA for SO_{SL2} and 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	9.5018	35.92%	9.5018	9.5018	28.57	0.000
SD EW	1	0.1139	0.43%	0.1139	0.1139	0.34	0.570
R	1	6.0393	22.83%	6.0393	6.0393	18.16	0.001
RFID	1	7.1423	27.00%	7.1423	7.1423	21.47	0.001
Error	11	3.6587	13.83%	3.6587	0.3326		
Total	15	26.4560	100.00%				

Table 4.31 presents results for RFID accuracy 98%.

Table 4.31 SET 1-Data 2: ANOVA for SO_{SL2} and 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	10.6276	40.39%	10.6276	10.6276	38.65	0.000
SD EW	1	0.1089	0.41%	0.1089	0.1089	0.40	0.542
R	1	6.4770	24.61%	6.4770	6.4770	23.56	0.001
RFID	1	6.0762	23.09%	6.0762	6.0762	22.10	0.001
Error	11	3.0246	11.49%	3.0246	0.2750		
Total	15	26.3143	100.00%				

It is possible to conclude:

- Supplier system days SD SP is the most influencing parameter (Up to 40.39%)
- RFID contributes up to 27.15 %
- Again, SD_{EW} is not a significant Factor (P-Value>>0.05)

Those results are summarized in the following pie charts (Figure 4.22, Figure 4.23 and Figure 4.24).

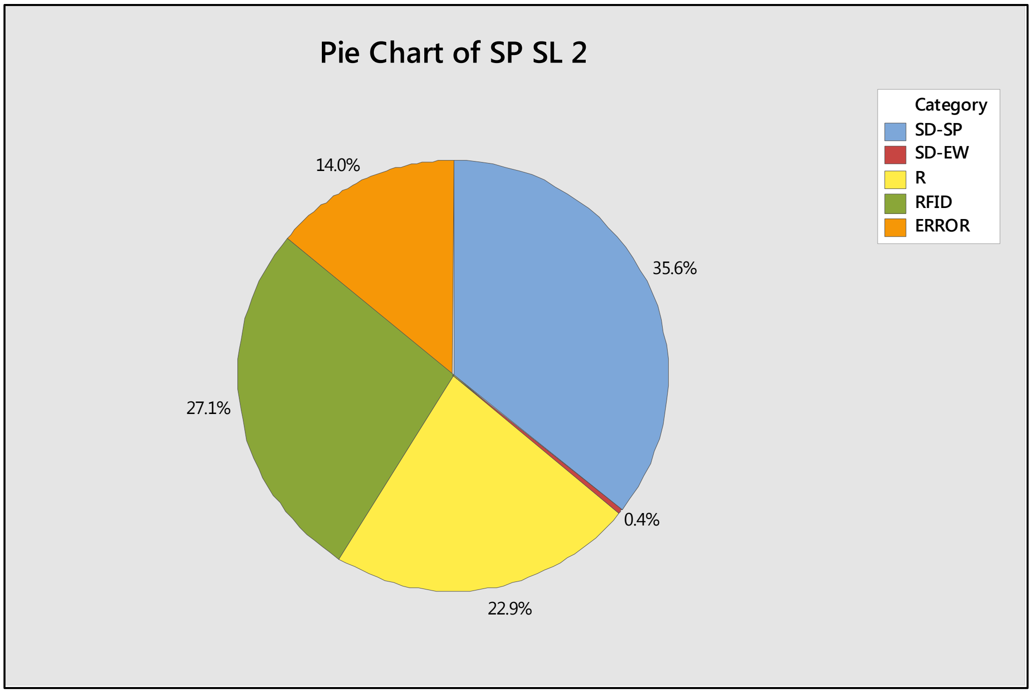

Figure 4.22 SET 1-Data 2: Pie chart for EOPSL2 and 100% RFID accuracy

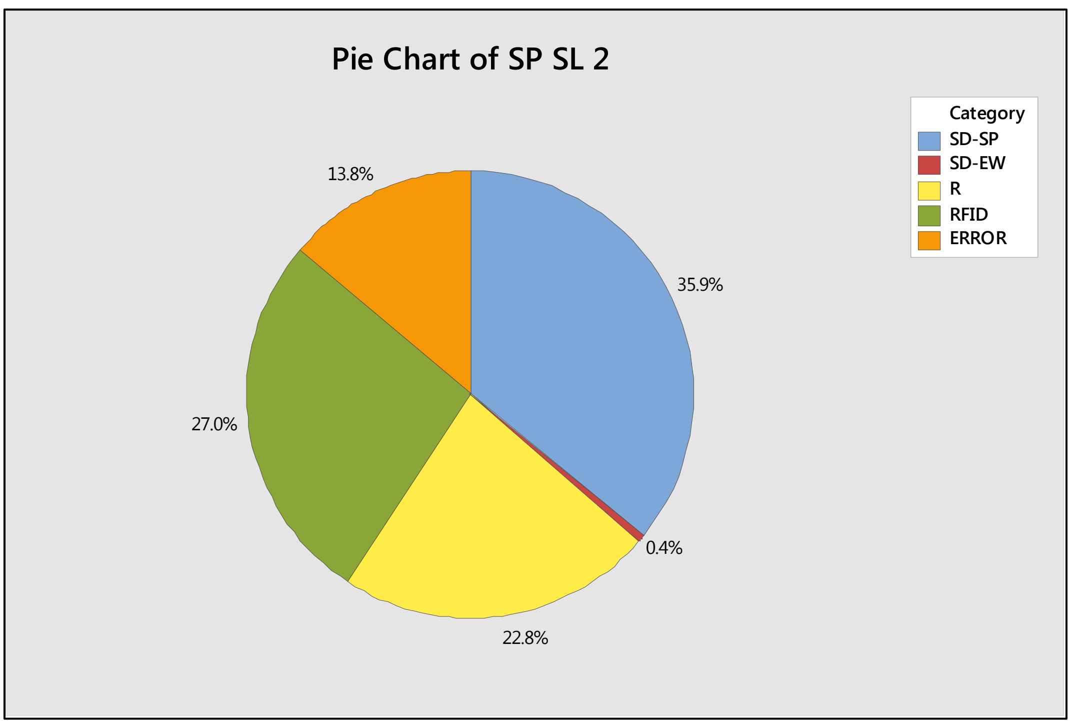

Figure 4.23 SET 1-Data 2: Pie chart for SPSL2 and 99.9% RFID accuracy

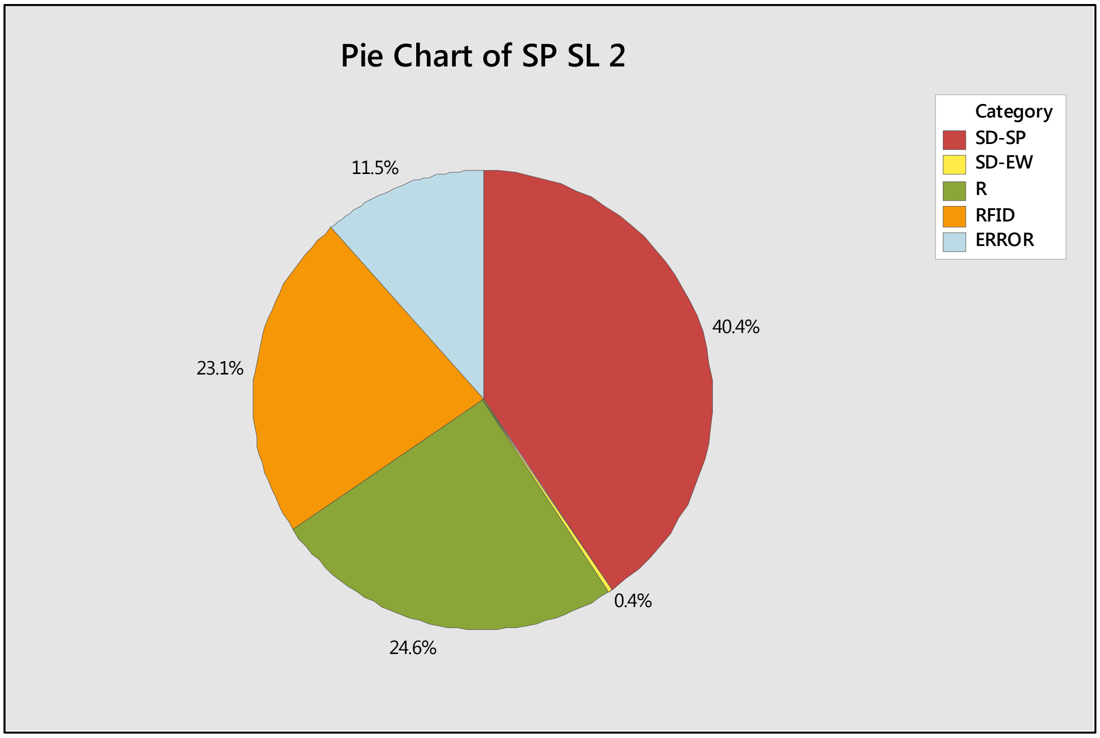

Figure 4.24 SET 1-Data 2: Pie chart for SPSL2 and 98% RFID accuracy

4.2.3 SET 1-Data 2: EW_{SL2}

In this section, the effect of the different factors on SP_{SL2} is evaluated by means of ANOVA tables. The results are presented for three different RFID system accuracies.

Table 4.32 presents results for RFID accuracy 100%.

Table 4.32 SET 1-Data 2: ANOVA for EW_{SL2} and 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	4.622	0.55%	4.622	4.622	1.33	0.273
SD EW	1	342.435	40.82%	342.435	342.435	98.56	0.000
R	1	220.077	26.23%	220.077	220.077	63.34	0.000
RFID	1	233.631	27.85%	233.631	233.631	67.24	0.000
Error	11	38.218	4.56%	38.218	3.474		
Total	15	838.984	100.00%				

Table 4.33 presents results for RFID accuracy 99.9%.

Table 4.33 SET 1-Data 2: ANOVA for EW_{SL2} and 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	4.537	0.54%	4.537	4.537	1.28	0.281
SD EW	1	339.112	40.40%	339.112	339.112	96.04	0.000
R	1	219.484	26.15%	219.484	219.484	62.16	0.000
RFID	1	237.314	28.28%	237.314	237.314	67.21	0.000
Error	11	38.839	4.63%	38.839	3.531		
Total	15	839.286	100.00%				

Table 4.34 presents results for RFID accuracy 98%.

Table 4.34 SET 1-Data 2: ANOVA for EW_{SL2} and 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	4.829	0.59%	4.829	4.829	1.66	0.225
SD EW	1	345.495	42.05%	345.495	345.495	118.50	0.000
R	1	222.830	27.12%	222.830	222.830	76.43	0.000
RFID	1	216.311	26.33%	216.311	216.311	74.19	0.000
Error	11	32.072	3.90%	32.072	2.916		
Total	15	821.537	100.00%				

It is possible to conclude:

- SD_{SP} is not a significant Factor (P-Value>>0.05)
- EW system days is the most relevant factor in the three cases (Up to 42.05%)
- RFID can influence EW_{SL2} up to 27.85 %

Results are summarized in Figure 4.25, Figure 4.26 and Figure 4.27.

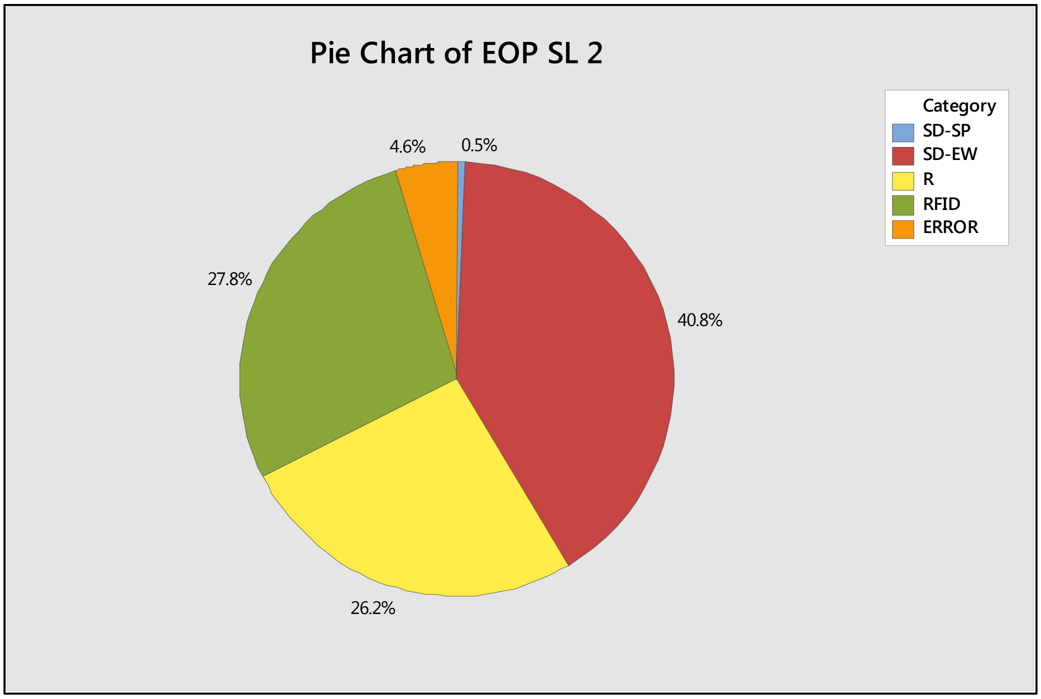

Figure 4.25 SET 1-Data 2: Pie chart for EW_{SL2} and 100% RFID accuracy

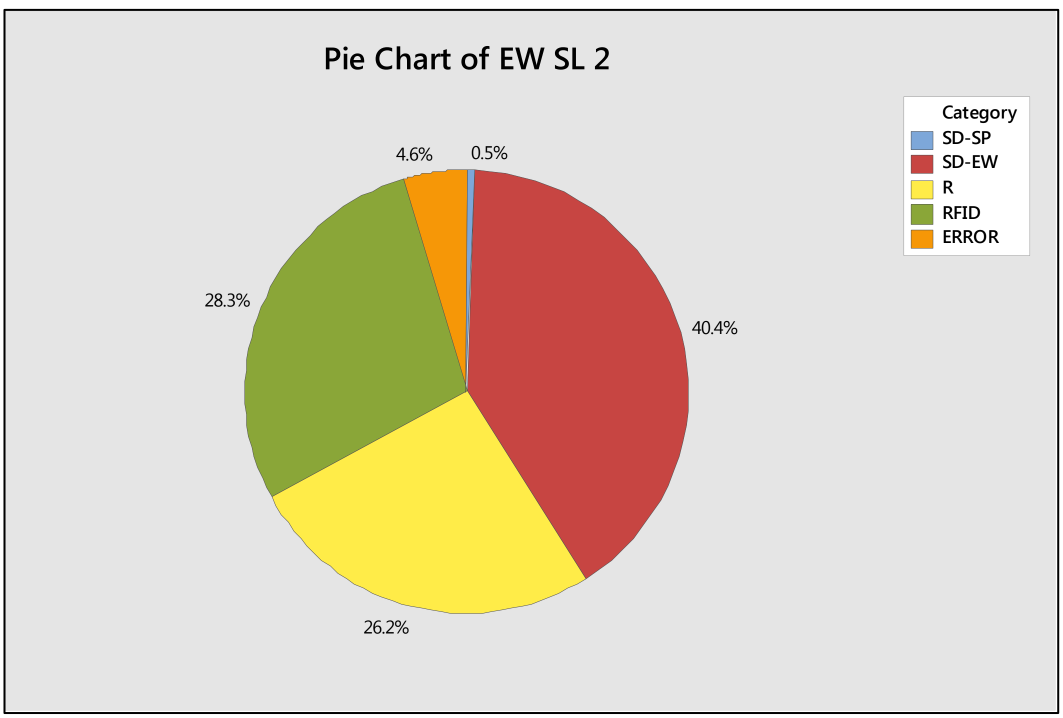

Figure 4.26 SET 1-Data 2: Pie chart for EW_{SL2} and 99.9% RFID accuracy

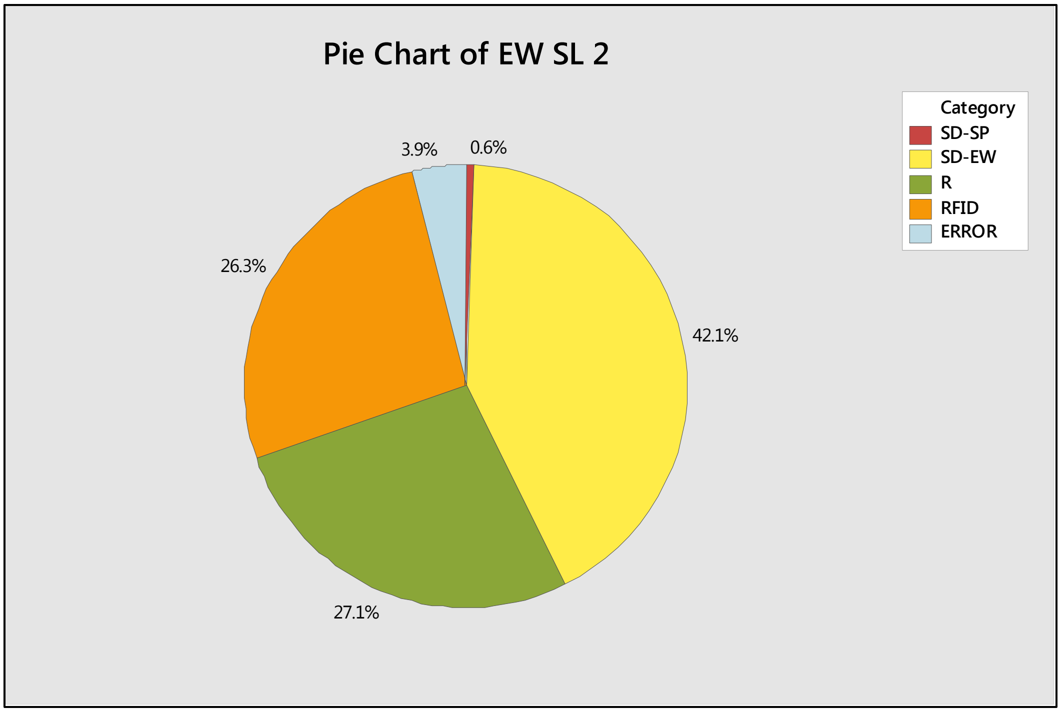

Figure 4.27 SET 1-Data 2: Pie chart for EW_{SL2} and 98% RFID accuracy

Same as section 4.1, the performance indicators SP_{SL1} and SP_{SL2} are evaluated for different values of SD_{SP}, with and without RFID. Considered RFID accuracy is 100%. The other factors are kept constant.

Figure 4.28 reports results for SP_{SL1} Figure 4.13.

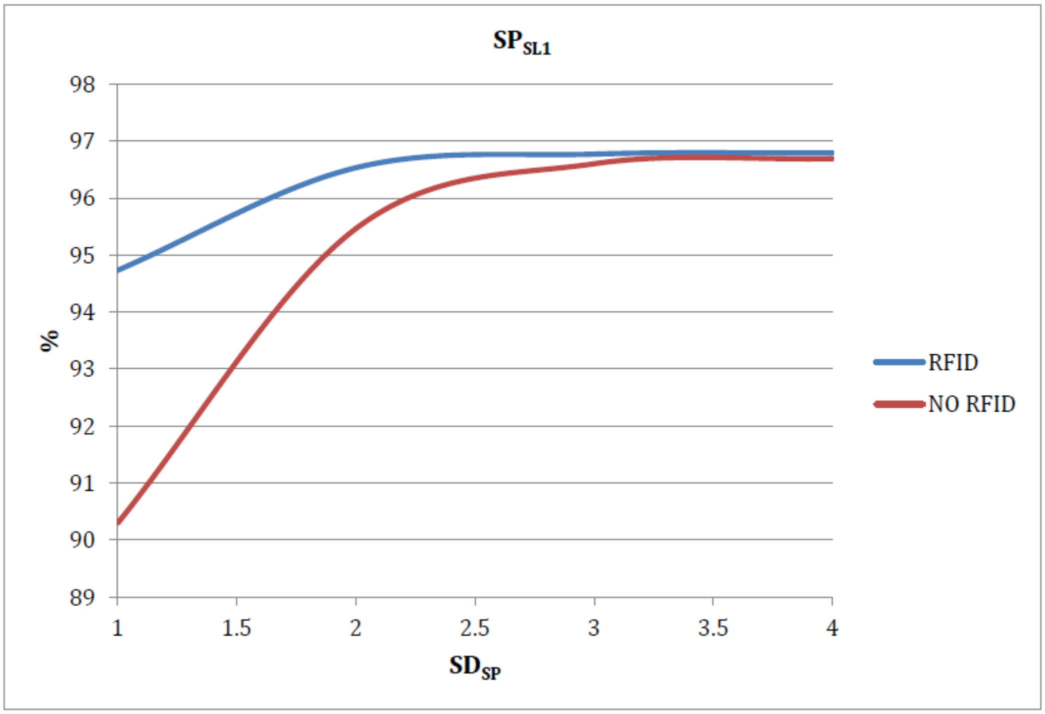

Figure 4.28 SET 1-Data 2:SP_{SL1} as function of SD_{SP}

Figure 4.29 reports SP_{SL2} as function of SD_{SP}.

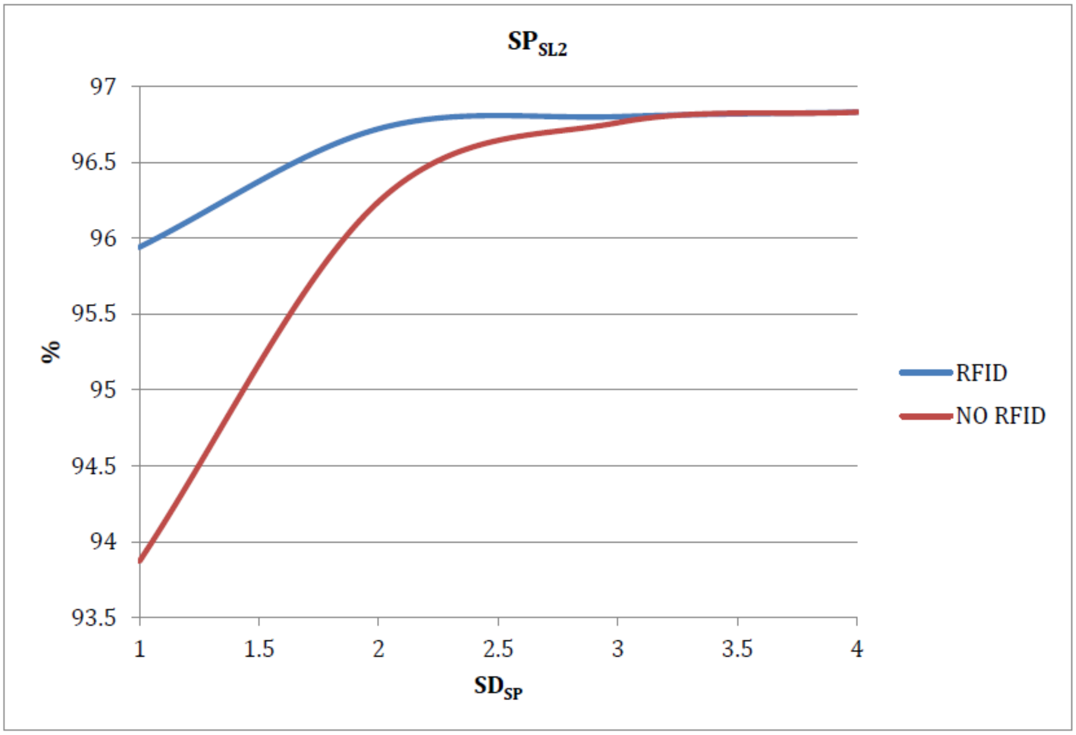

Figure 4.29 SET 1-Data 2: SP_{SL2} as function of SD_{SP}

Same as section 4.1 , from those charts it is possible to conclude that using RFID would allow for supplier system days reduction and same level of system performance.

4.3 SET 2-Data1: Effect of uncontrollable factors 1

In this section, the effect of uncertainty on Dataset 1 is investigated. Table 4.35 reports the full factorial plan developed for the study of uncontrollable factors.

Table 4.35 SET2-Data1: Full factorial plan for uncontrollable factors

UE	UD	ULT	SP_{SL1}	SP_{SL2}	EW_{SL2}
0.85	1.15	0.85	95.15	97.08	68.01
1.15	0.85	0.85	95.62	97.42	64.76
0.85	0.85	1.15	94.71	96.74	65.14
1.15	1.15	1.15	92.83	95.04	67.12
0.85	0.85	0.85	95.88	97.58	67.29
0.85	1.15	1.15	93.71	95.87	69.54
1.15	0.85	1.15	93.94	96.09	62.08
1.15	1.15	0.85	94.57	96.58	65.51

To quantify each factor contribution, Three ANOVA tables are now presented.

4.3.1 SET 2-Data1: SP_{SL1}

Table 4.36 reports results for SP_{SL1}.

Table 4.36 SET 2-Data1: ANOVA for SP_{SL1}

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.7750	10.56%	0.7750	0.77501	24.95	0.008
UD	1	1.8915	25.78%	1.8915	1.89151	60.89	0.001
ULT	1	4.5451	61.96%	4.5451	4.54511	146.32	0.000
Error	4	0.1243	1.69%	0.1243	0.03106		
Total	7	7.3359	100.00%				

It is possible to conclude that:

- All factors are significant
- Uncertainty on lead time is the most significant factor (61.96%)
- Counting error uncertainty is the least significant factor (10.56%)

Results are summarized in Figure 4.30.

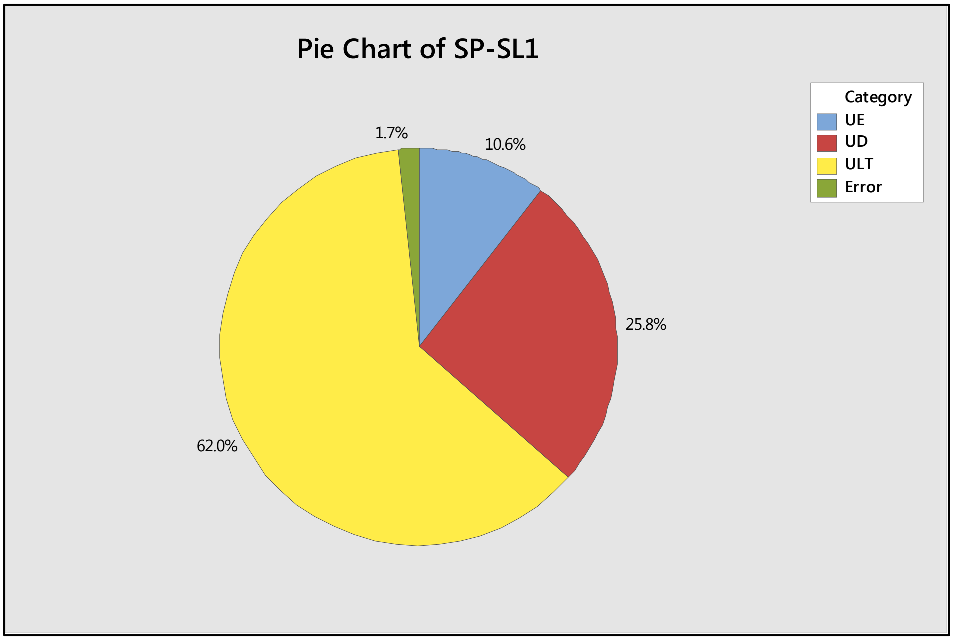

Figure 4.30 SET 2-Data1: Pie chart for SP_{SL1}

4.3.2 SET 2-Data1: SP_{SL2}

Table 4.37 reports results for SP_{SL2} .

Table 4.37 SET 2-Data1: ANOVA for SP_{SL2}

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.5724	11.25%	0.5724	0.57245	14.04	0.020
UD	1	1.3284	26.10%	1.3284	1.32845	32.58	0.005
ULT	1	3.0258	59.45%	3.0258	3.02580	74.21	0.001
Error	4	0.1631	3.20%	0.1631	0.04077		
Total	7	5.0898	100.00%				

It is possible to conclude that:

- All the factors are significant
- Lead time uncertainty is the most significant factor (59.45%)
- Counting error uncertainty is the least significant factor (11.25%)

Results are summarized in Figure 4.31.

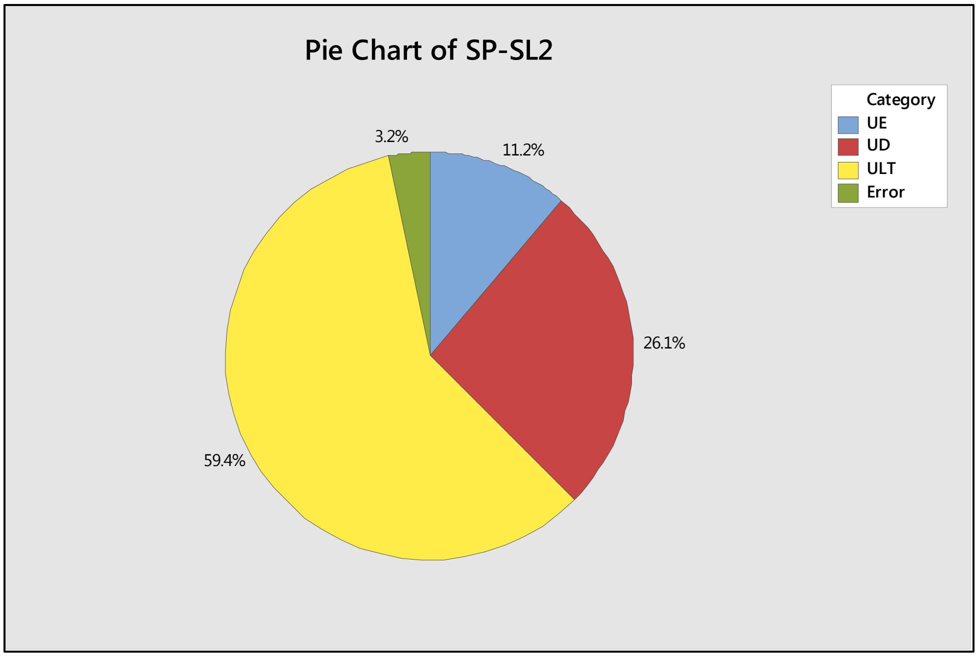

Figure 4.31 SET 2-Data1: Pie chart for SP_{SL2}

4.3.3 SET 2-Data1: EW_{SL2}

Results for EOP_{SL2} are reported in Table 4.38.

Table 4.38 SET 2-Data1: ANOVA for EW_{SL2}

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	13.8075	37.21%	13.8075	13.8075	6.85	0.059
UD	1	14.8785	40.09%	14.8785	14.8785	7.38	0.053
ULT	1	0.3570	0.96%	0.3570	0.3570	0.18	0.696
Error	4	8.0681	21.74%	8.0681	2.0170		
Total	7	37.1111	100.00%				

It is possible to conclude that:

- Lead time uncertainty is not a significant factor (P-value >>0.05)
- Both UE and UD have a P-value slightly larger than 0.05. Thus, their significance is uncertain, but it is not possible to state the two factors are not statistically significant
- Uncertainty on demand has the largest contribution (40.09%)

Results are summarized in Figure 4.32.

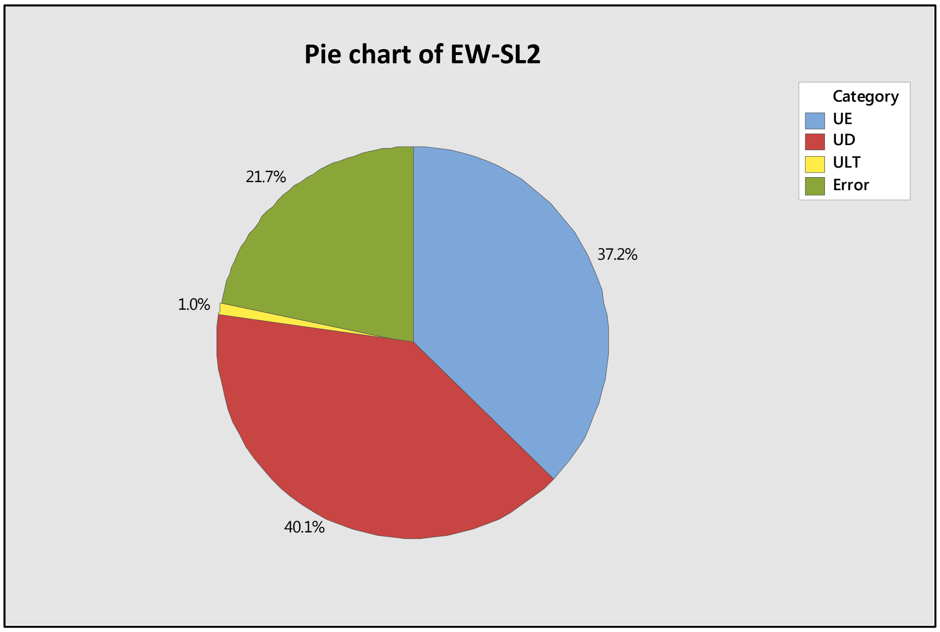

Figure 4.32 SET 2-Data1: Pie chart for EW_{SL2}

4.4 SET 2-Data 2: Effect of uncontrollable factors

In this section, the effect of uncertainty on Dataset 2 is investigated. Table 4.39 reports the full factorial plan developed for the study of uncontrollable factors.

Table 4.39 Full factorial plan for SET 2-Data 2

UE	UD	ULT	SP $_{SL1}$	SP $_{SL2}$	EOP $_{SL2}$
0.85	1.15	0.85	96.27	96.60	75.41
1.15	0.85	0.85	95.31	96.15	74.31
0.85	0.85	1.15	96.04	96.52	72.50
1.15	1.15	1.15	95.17	96.04	74.63
0.85	0.85	0.85	95.95	96.44	72.17
0.85	1.15	1.15	95.18	95.89	71.57
1.15	0.85	1.15	96.31	96.68	75.14
1.15	1.15	0.85	95.39	96.07	72.16

To quantify each factor contribution, Three ANOVA tables are now presented.

4.4.1 SET 2-Data 2: SP_{SL1}

Table 4.40 reports results for SP_{SL1}.

Table 4.40 SET 2-Data 2: ANOVA for SP_{SL1}

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	1.54880	92.49%	1.54880	1.54880	94.30	0.001
ULT	1	0.02880	1.72%	0.02880	0.02880	1.75	0.256
UD	1	0.03125	1.87%	0.03125	0.03125	1.90	0.240
Error	4	0.06570	3.92%	0.06570	0.01642		
Total	7	1.67455	100.00%				

It is possible to conclude that:

- ULT and UD are not significant (P-Value>>0.05)
- UE contributes for 92.49 %

Results are summarized in Figure 4.33.

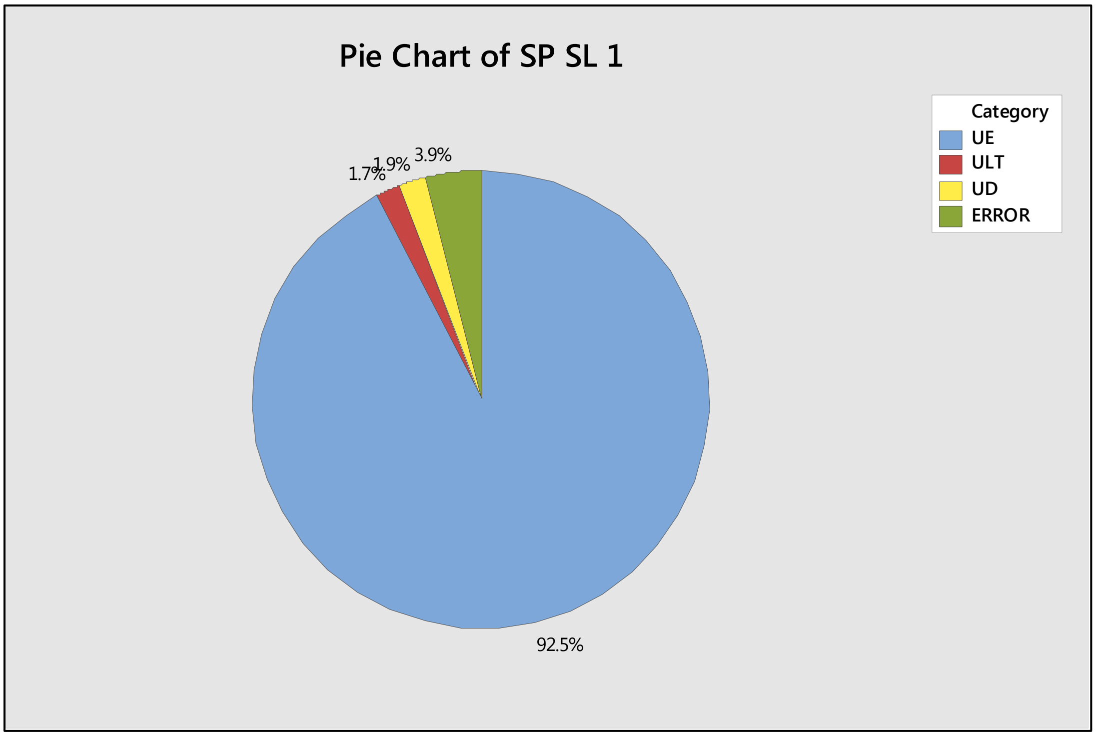

Figure 4.33 SET 2-Data 2: Pie chart for SP_{SL1}

4.4.2 SET 2-Data 2: SP_{SL2}

Table 4.41 reports results for SP_{SL2} .

Table 4.41 SET 2-Data 2: ANOVA for SP_{SL2}

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.546012	89.00%	0.546012	0.546012	502.08	0.000
ULT	1	0.025313	4.13%	0.025313	0.025313	23.28	0.008
UD	1	0.037813	6.16%	0.037813	0.037813	34.77	0.004
Error	4	0.004350	0.71%	0.004350	0.001087		
Total	7	0.613487	100.00%				

It is possible to conclude that:

- All the factors are significant
- UE is the most significant factor (89 %)

Results are summarized in Figure 4.34.

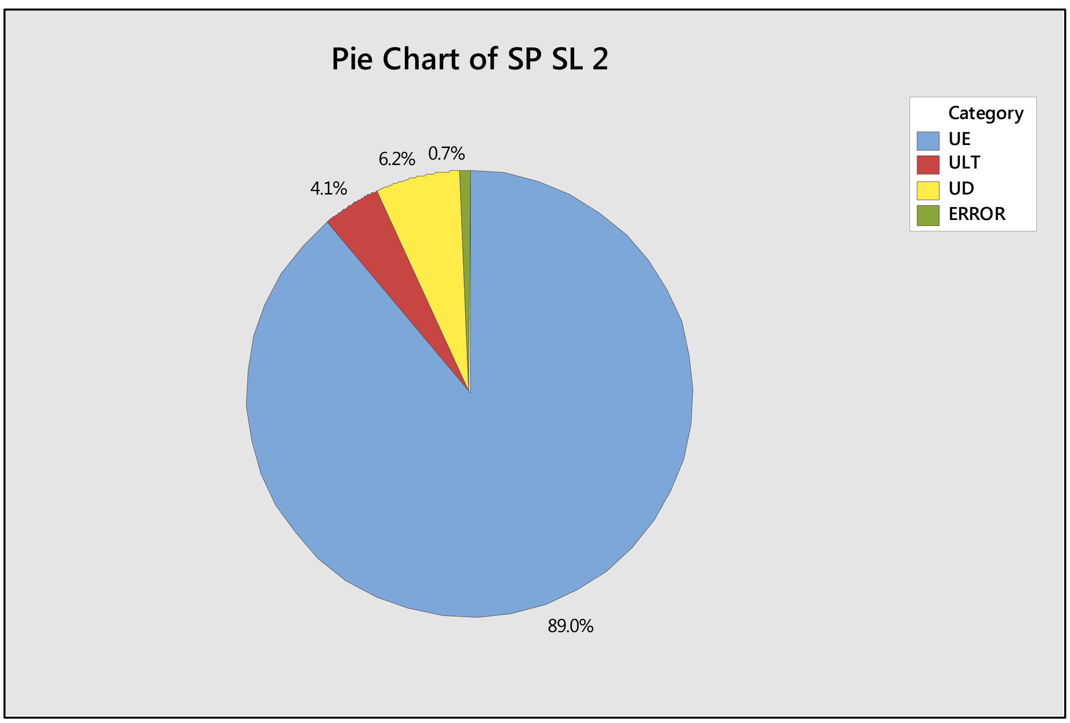

Figure 4.34 SET 2-Data 2: Pie chart for SP_{SL2}.

4.4.3 SET 2-Data 2: EW_{SL2}

Results for EOP_{SL2} are reported in Table 4.42.

Table 4.42 SET 2-Data 2: ANOVA for EW_{SL2}

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.8128	4.91%	0.8128	0.8128	9.07	0.040
ULT	1	0.0136	0.08%	0.0136	0.0136	0.15	0.717
UD	1	15.3735	92.84%	15.3735	15.3735	171.46	0.000
Error	4	0.3586	2.17%	0.3586	0.0897		
Total	7	16.5586	100.00%				

It is possible to conclude that:

- ULT is not a significant factor (P-value >>0.05)
- Differently than before, UD is the most significant factor, contributing 92.84%

Results are summarized in Figure 4.35.

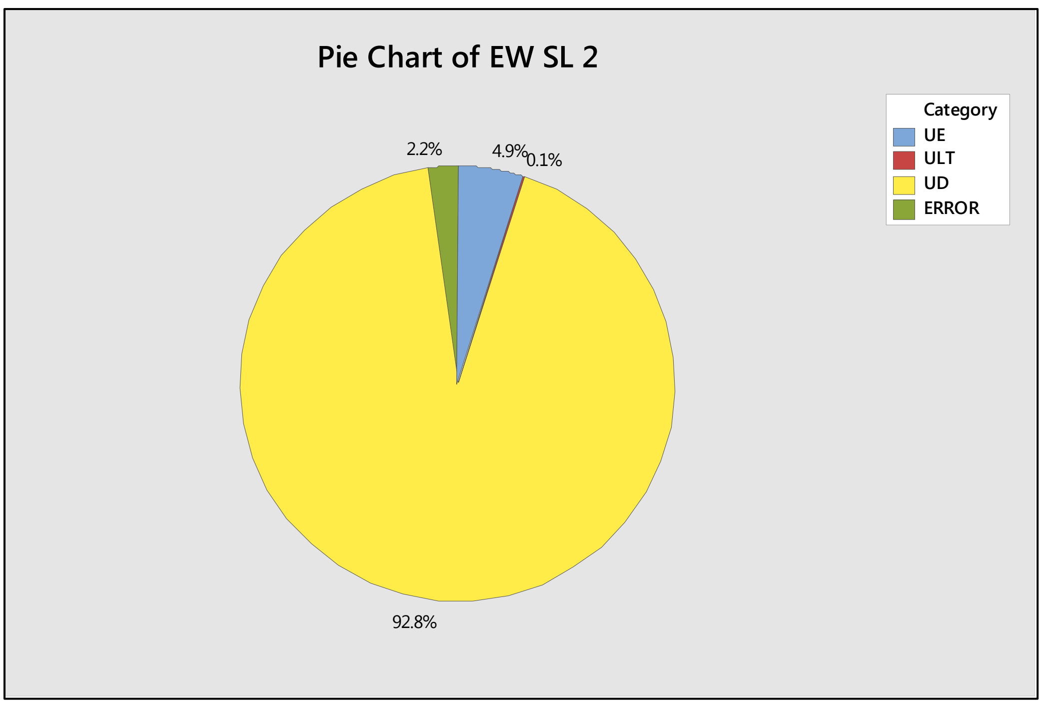

Figure 4.35 SET 2-Data 2: Pie chart for EW_{SL2}

4.5 SET 3-Data 1: Testing the best case scenario

The best combination of controllable factors for Dataset 1 (see Table 4.8) is tested for each level of RFID accuracy and different levels of uncontrollable factors. The three following tables (Table 4.43, Table 4.44 and Table 4.45) summarize full factorial plans for the three different accuracies.

Table 4.43 SET3-Data1: Full factorial plan for RFID accuracy 100%

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %
0.85	1.15	0.85	98.25	99.2	83.13
1.15	0.85	0.85	99.03	99.62	85.26
0.85	0.85	1.15	98.33	99.22	85.91
1.15	1.15	1.15	97.62	98.74	83.92
0.85	0.85	0.85	99.03	99.62	85.26
0.85	1.15	1.15	97.62	98.74	83.92
1.15	0.85	1.15	98.33	99.22	85.91
1.15	1.15	0.85	98.25	99.2	83.13

Table 4.44 SET3-Data1: Full factorial plan for RFID accuracy 99.9%

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %
0.85	1.15	0.85	98.26	99.19	83.05
1.15	0.85	0.85	99.02	99.62	85.14
0.85	0.85	1.15	98.3	99.21	85.94
1.15	1.15	1.15	97.59	98.73	83.96
0.85	0.85	0.85	99.02	99.62	85.17
0.85	1.15	1.15	97.59	98.73	83.96
1.15	0.85	1.15	98.28	99.2	85.94
1.15	1.15	0.85	98.25	99.19	83.02

Table 4.45 SET3-Data1: Full factorial plan for RFID accuracy 98%

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %
0.85	1.15	0.85	98.27	99.18	81.74
1.15	0.85	0.85	98.97	99.57	98.3
0.85	0.85	1.15	98.28	99.15	84.83
1.15	1.15	1.15	97.4	98.59	82.75
0.85	0.85	0.85	99.03	99.6	98.3
0.85	1.15	1.15	97.48	98.67	83.05
1.15	0.85	1.15	98.09	99.08	84.4
1.15	1.15	0.85	98.2	99.14	81.32

4.5.1 SET3-Data1: SP_{SL1}

Results for SP_{SL1} at different level of accuracy are reported in Table 4.46, Table 4.47 and Table 4.48.

Table 4.46 SET3-Data1: ANOVA for SPSL1 with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.00000	0.00%	0.00000	0.00000	0.00	1.000
UD	1	1.11005	55.59%	1.11005	1.11005	1812.33	0.000
ULT	1	0.88445	44.29%	0.88445	0.88445	1444.00	0.000
Error	4	0.00245	0.12%	0.00245	0.00061		
Total	7	1.99695	100.00%				

Table 4.47 SET3-Data1: ANOVA for SPSL1 with 99.9% RFID accuracy

Analysis of Variance							
Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.00011	0.01%	0.00011	0.00011	0.20	0.678
UD	1	1.07311	52.39%	1.07311	1.07311	1907.76	0.000
ULT	1	0.97301	47.50%	0.97301	0.97301	1729.80	0.000
Error	4	0.00225	0.11%	0.00225	0.00056		
Total	7	2.04849	100.00%				

Table 4.48 SET3-Data1: ANOVA for SPSL1 with 98% RFID accuracy

Analysis of Variance							
Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.00045	0.00%	0.00045	0.00045	0.18	0.697
UD	1	8.40500	85.09%	8.40500	8.40500	3280.00	0.000
ULT	1	1.46205	14.80%	1.46205	1.46205	570.56	0.000
Error	4	0.01025	0.10%	0.01025	0.00256		
Total	7	9.87775	100.00%				

It is possible to conclude:

- In all of the three scenarios counting error uncertainty does not influence the result (P-value >>0.05)
- UD does contribute significantly to overall performance, up to 85.09%

Results are summarized in Figure 4.36, Figure 4.37 and Figure 4.38.

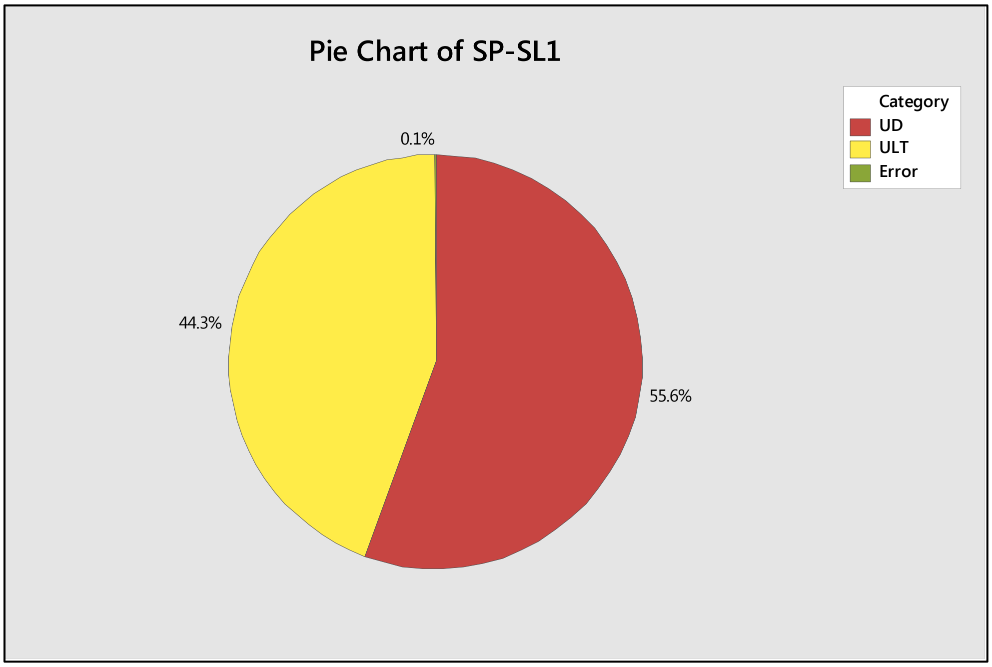

Figure 4.36 SET3-Data1: PIE chart for SP_{SL1} and 100% RFID accuracy

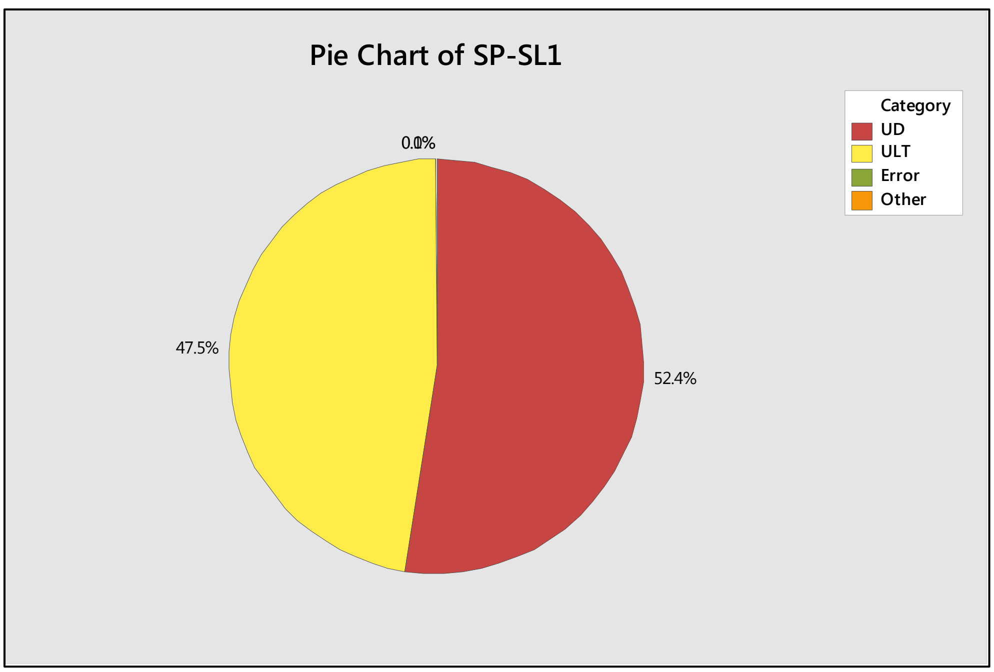

Figure 4.37 SET3-Data1: PIE chart for SP_{SL1} and 99.9% RFID accuracy

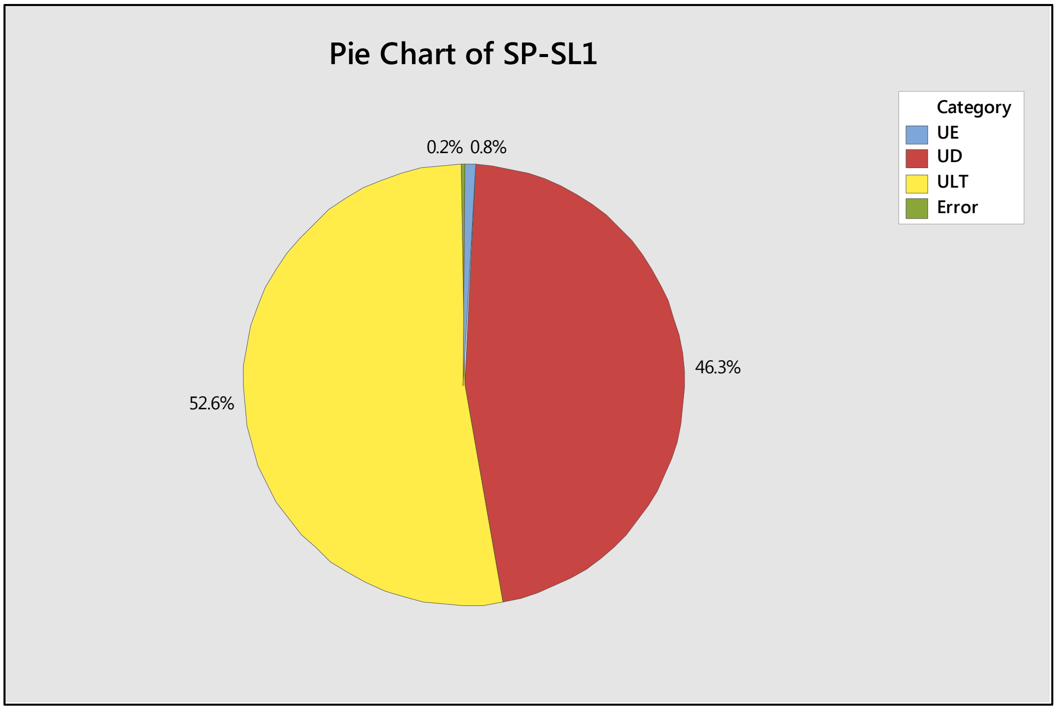

Figure 4.38 SET3-Data1: PIE chart for SP_{SL1} and 98% RFID accuracy

4.5.2 SET3-Data1: SP_{SL2}

Results for SP_{SL2} at different level of accuracy are reported in Table 4.49, Table 4.50 and Table 4.51.

Table 4.49 SET3-Data1: ANOVA for SP_{SL2} with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
UD	1	0.405000	52.15%	0.405000	0.405000	900.00	0.000
ULT	1	0.369800	47.62%	0.369800	0.369800	821.78	0.000
Error	4	0.001800	0.23%	0.001800	0.000450		
Total	7	0.776600	100.00%				

Table 4.50 SET3-Data1: ANOVA for SP_{SL2} with 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000012	0.00%	0.000012	0.000012	0.05	0.838
UD	1	0.409513	51.62%	0.409513	0.409513	1560.05	0.000
ULT	1	0.382813	48.25%	0.382813	0.382813	1458.33	0.000
Error	4	0.001050	0.13%	0.001050	0.000262		
Total	7	0.793388	100.00%				

Table 4.51 SET3-Data1: ANOVA for SP_{SL2} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.006050	0.66%	0.006050	0.006050	9.13	0.039
UD	1	0.414050	44.87%	0.414050	0.414050	624.98	0.000
ULT	1	0.500000	54.19%	0.500000	0.500000	754.72	0.000
Error	4	0.002650	0.29%	0.002650	0.000663		
Total	7	0.922750	100.00%				

It is possible to conclude that:

- UE is significant only when RFID accuracy is 98%
- Uncertainty on lead time is the most significant factor, up to 54.19%

Results are summarized in Figure 4.39, Figure 4.40 and Figure 4.41.

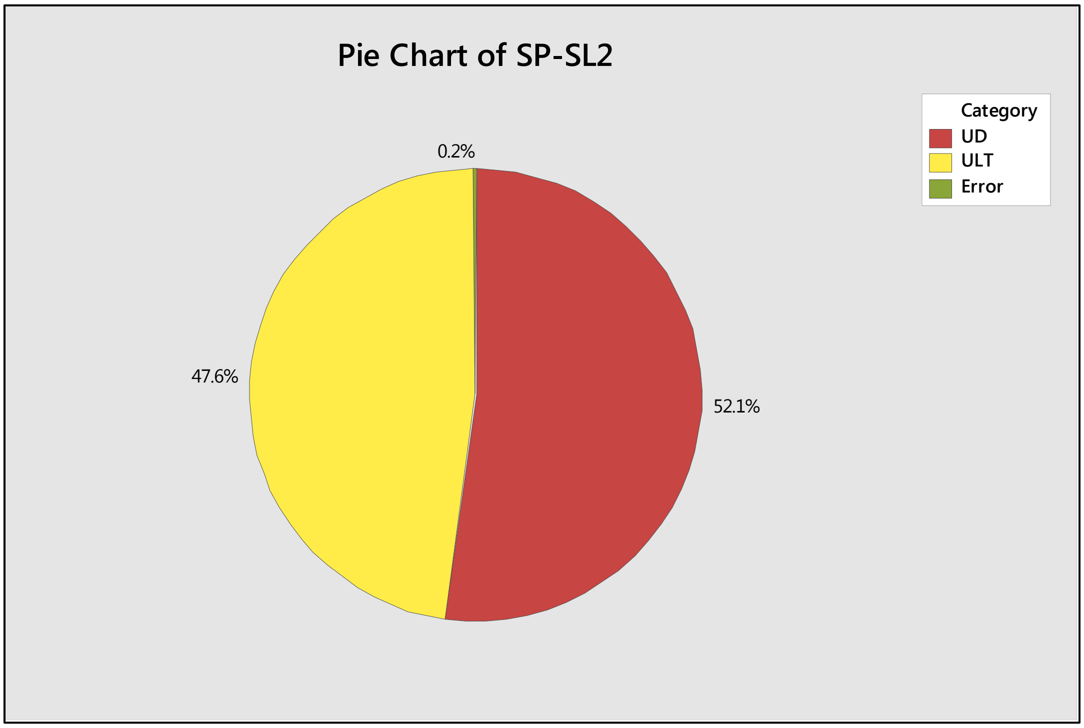

Figure 4.39 SET3-Data1: PIE chart for SP_{SL2} and 100% RFID accuracy

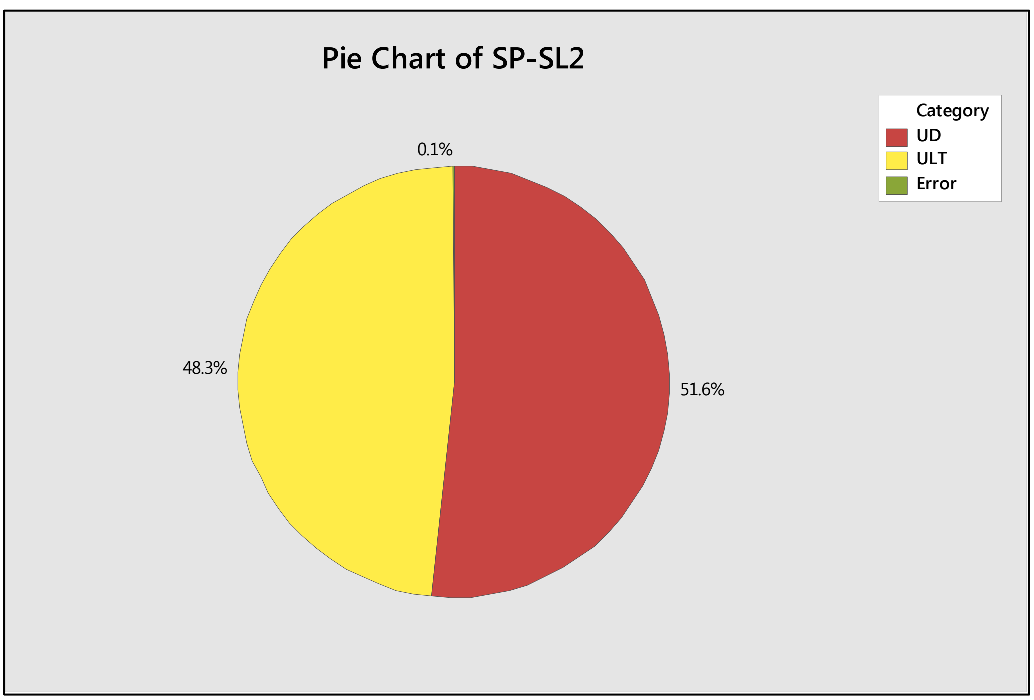

Figure 4.40 SET3-Data1: PIE chart for SP_{SL2} and 99.9% RFID accuracy

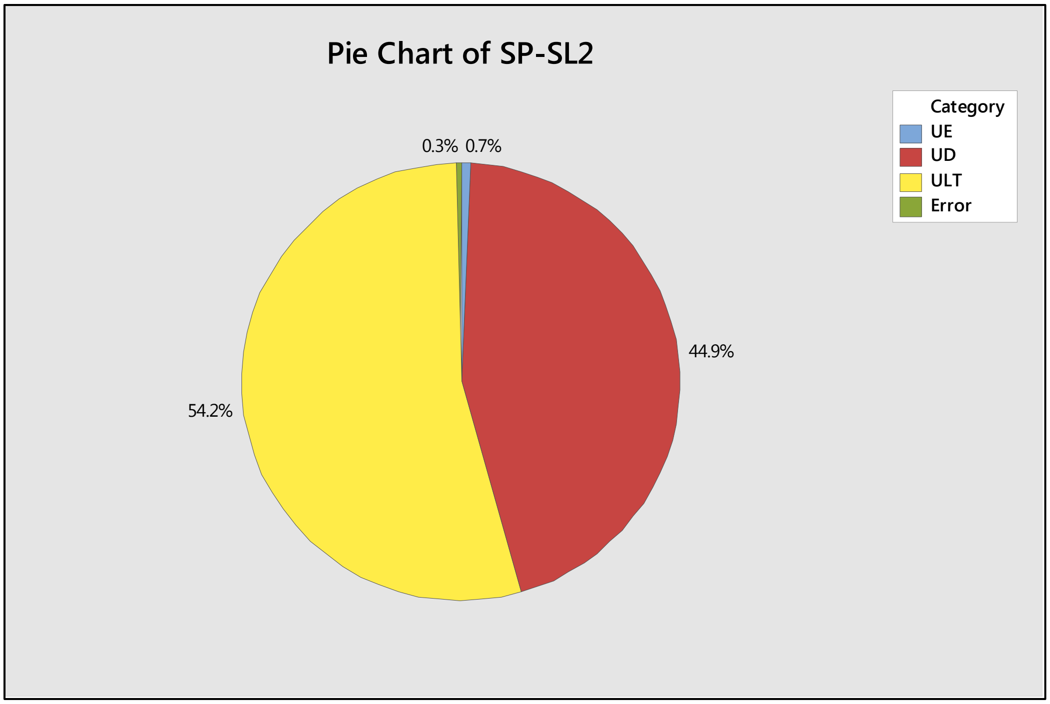

Figure 4.41 SET3-Data1: PIE chart for SP_{SL2} and 98% RFID accuracy

4.5.3 SET3-Data1: EW_{SL2}

Results for EOP_{SL2} at different level of accuracy are reported in Table 4.52, Table 4.53 and Table 4.54.

Table 4.52 SET3-Data1: ANOVA for EW_{SL2} with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.00000	0.00%	0.00000	0.00000	0.00	1.000
UD	1	8.48720	89.02%	8.48720	8.48720	3464.16	0.000
ULT	1	1.03680	10.87%	1.03680	1.03680	423.18	0.000
Error	4	0.00980	0.10%	0.00980	0.00245		
Total	7	9.53380	100.00%				

Table 4.53 SET3-Data1: ANOVA for EW_{SL2} with 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.00045	0.00%	0.00045	0.00045	0.18	0.697
UD	1	8.40500	85.09%	8.40500	8.40500	3280.00	0.000
ULT	1	1.46205	14.80%	1.46205	1.46205	570.56	0.000
Error	4	0.01025	0.10%	0.01025	0.00256		
Total	7	9.87775	100.00%				

Table 4.54 SET3-Data1: ANOVA for EW_{SL2} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.165	0.05%	0.165	0.165	0.01	0.943
UD	1	170.848	47.43%	170.848	170.848	6.03	0.070
ULT	1	75.830	21.05%	75.830	75.830	2.68	0.177
Error	4	113.387	31.48%	113.387	28.347		
Total	7	360.229	100.00%				

It is possible to conclude that:

- Demand uncertainty is the most significant factor, up to 89.02%
- UE is not a significant Factor (P-Value>>0.05)

Results are summarized in Figure 4.42, Figure 4.43 and Figure 4.44.

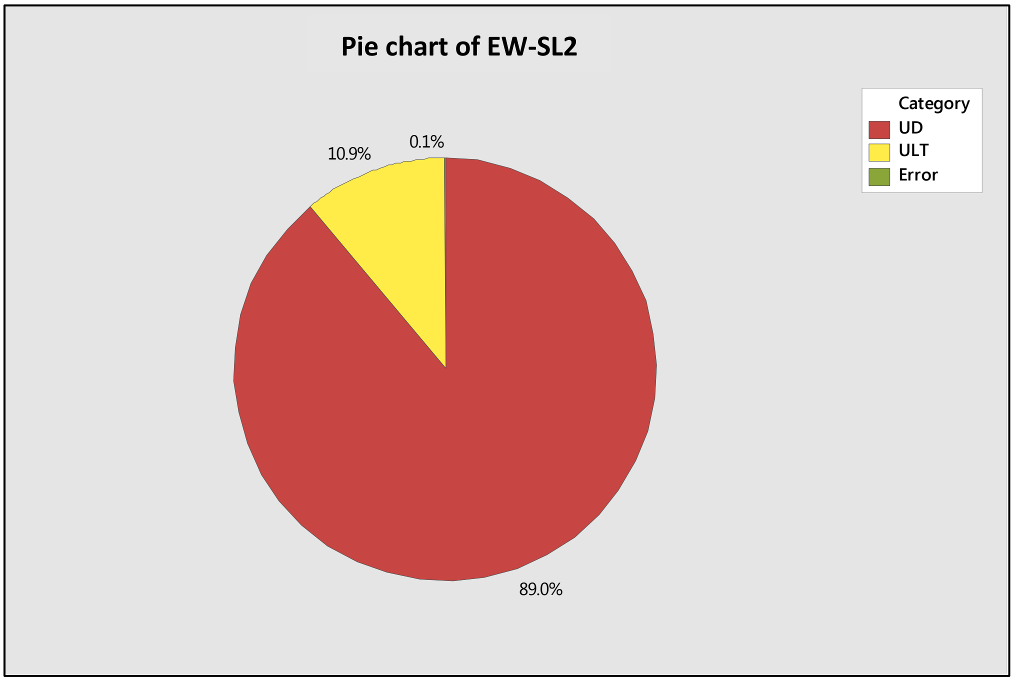

Figure 4.42 SET3-Data1: PIE chart for EW_{SL2} and 100% RFID accuracy

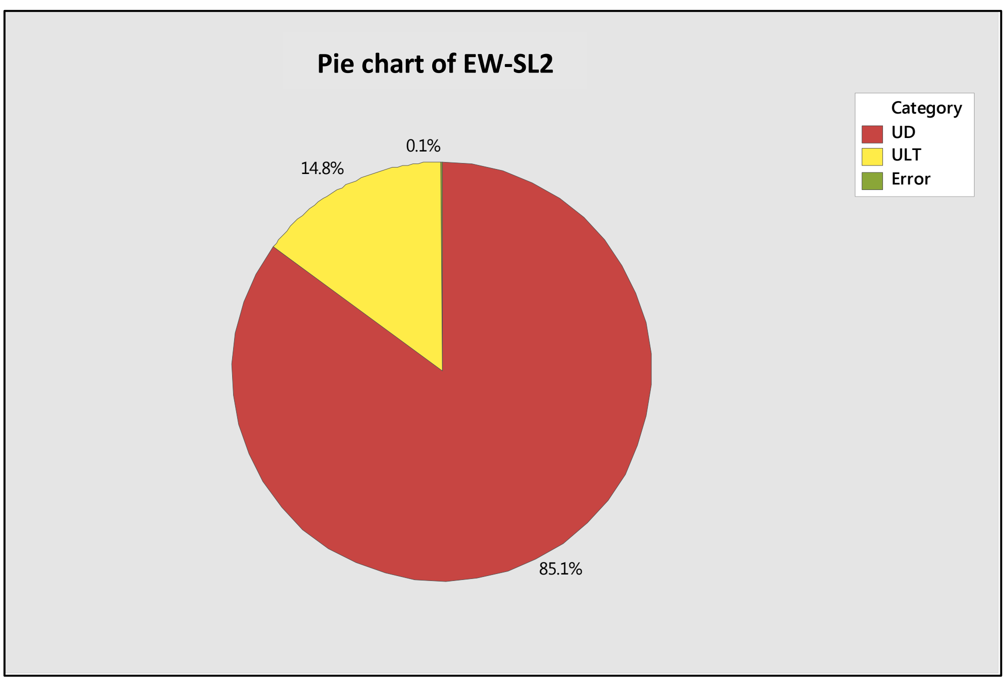

Figure 4.43 SET3-Data1: PIE chart for EW_{SL2} and 99.9% RFID accuracy

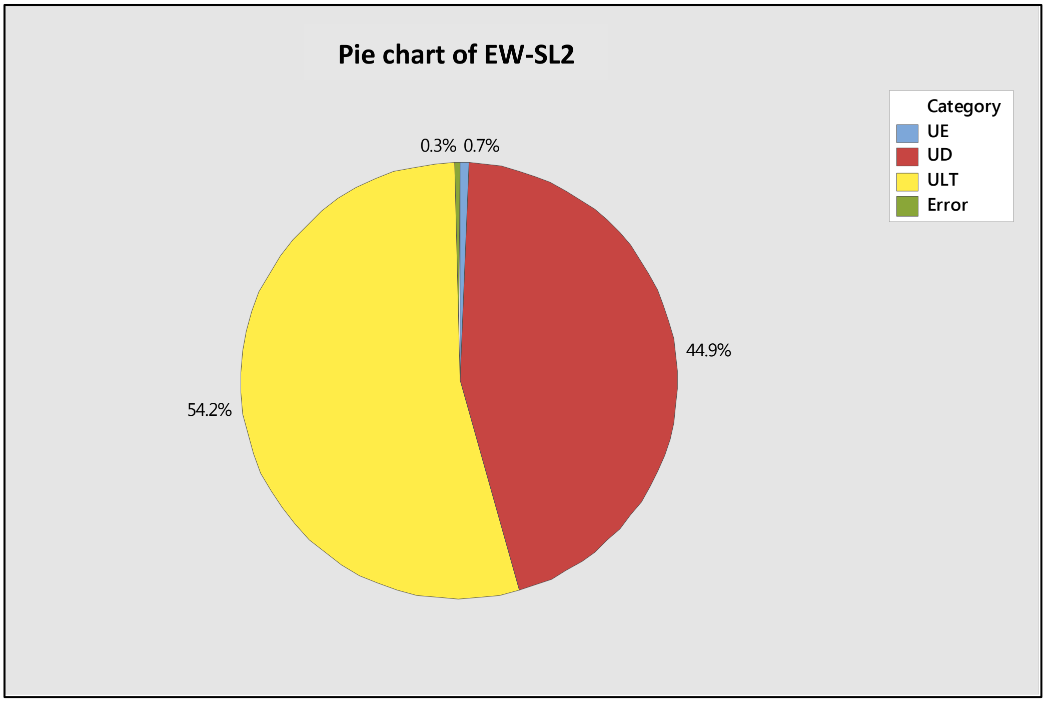

Figure 4.44 SET3-Data1: PIE chart for EW_{SL2} and 99.9% RFID accuracy

4.6 SET3-Data 2: Testing the best case scenario

The best combination of controllable factors for Dataset 2 (see Table 4.25) is tested for each level of RFID accuracy and different levels of uncontrollable factors. The three following tables (Table 4.55, Table 4.56, Table 4.57) summarize full factorial plans for the three different accuracy level.

Table 4.55 SET3-Data2: Full factorial plan for RFID accuracy 100%

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %
0.85	0.85	0.85	98.32	98.35	96.54
1.15	1.15	0.85	98.25	98.28	96.53
0.85	1.15	1.15	98.08	98.25	96.11
1.15	0.85	0.85	98.32	98.35	96.54
0.85	0.85	1.15	98.18	98.34	96.10
1.15	0.85	1.15	98.18	98.34	96.10
0.85	1.15	0.85	98.25	98.28	96.53
1.15	1.15	1.15	98.08	98.25	96.11

Table 4.56 SET3-Data2: Full factorial plan for RFID accuracy 99.9%

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %
0.85	0.85	0.85	98.31	98.35	96.53
1.15	1.15	0.85	98.25	98.28	95.62
0.85	1.15	1.15	98.08	98.25	96.12
1.15	0.85	0.85	98.31	98.35	96.53
0.85	0.85	1.15	98.19	98.34	96.10
1.15	0.85	1.15	98.19	98.34	96.10
0.85	1.15	0.85	98.25	98.28	96.53
1.15	1.15	1.15	98.08	98.25	96.13

Table 4.57 SET3-Data2: Full factorial plan for RFID accuracy 98%

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %
0.85	0.85	0.85	98.30	98.35	96.55
1.15	1.15	0.85	98.21	98.27	96.49
0.85	1.15	1.15	98.07	98.24	96.04
1.15	0.85	0.85	98.28	98.35	96.51
0.85	0.85	1.15	98.16	98.34	96.04
1.15	0.85	1.15	98.13	98.32	95.91
0.85	1.15	0.85	98.21	98.27	96.58
1.15	1.15	1.15	98.02	98.22	95.79

4.6.1 SET3-Data2: SP_{SL1}

Results for SP_{SL1} at different level of accuracy are reported in Table 4.46, Table 4.47 and Table 4.48.

Table 4.58 SET3-Data2: ANOVA for SP_{SL1} with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
ULT	1	0.014450	22.95%	0.014450	0.014450	128.44	0.000
UD	1	0.048050	76.33%	0.048050	0.048050	427.11	0.000
Error	4	0.000450	0.71%	0.000450	0.000113		
Total	7	0.062950	100.00%				

Table 4.59 SET3-Data2: ANOVA for SP_{SL1} with 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
ULT	1	0.014450	25.02%	0.014450	0.014450	46.24	0.002
UD	1	0.042050	72.81%	0.042050	0.042050	134.56	0.000
Error	4	0.001250	2.16%	0.001250	0.000312		
Total	7	0.057750	100.00%				

Table 4.60 SET3-Data2: ANOVA for SP_{SL1} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.001250	1.88%	0.001250	0.001250	5.88	0.072
ULT	1	0.016200	24.42%	0.016200	0.016200	76.24	0.001
UD	1	0.048050	72.42%	0.048050	0.048050	226.12	0.000
Error	4	0.000850	1.28%	0.000850	0.000212		
Total	7	0.066350	100.00%				

It is possible to conclude:

- In all of the three scenarios counting error uncertainty does not influence the result (P-value >>0.05)
- uncertainty on lead time does contribute significantly to overall performance, up to 76.33 %

Results are summarized in Figure 4.45, Figure 4.46 and Figure 4.47.

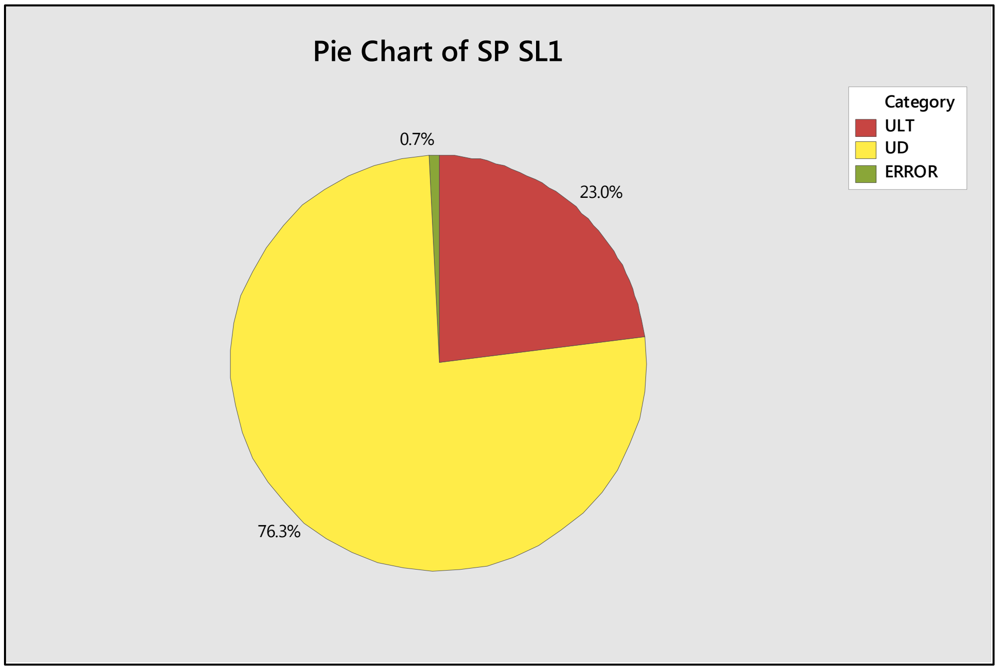

Figure 4.45 SET3-Data2: PIE chart for SP_{SL1} and 100% RFID accuracy

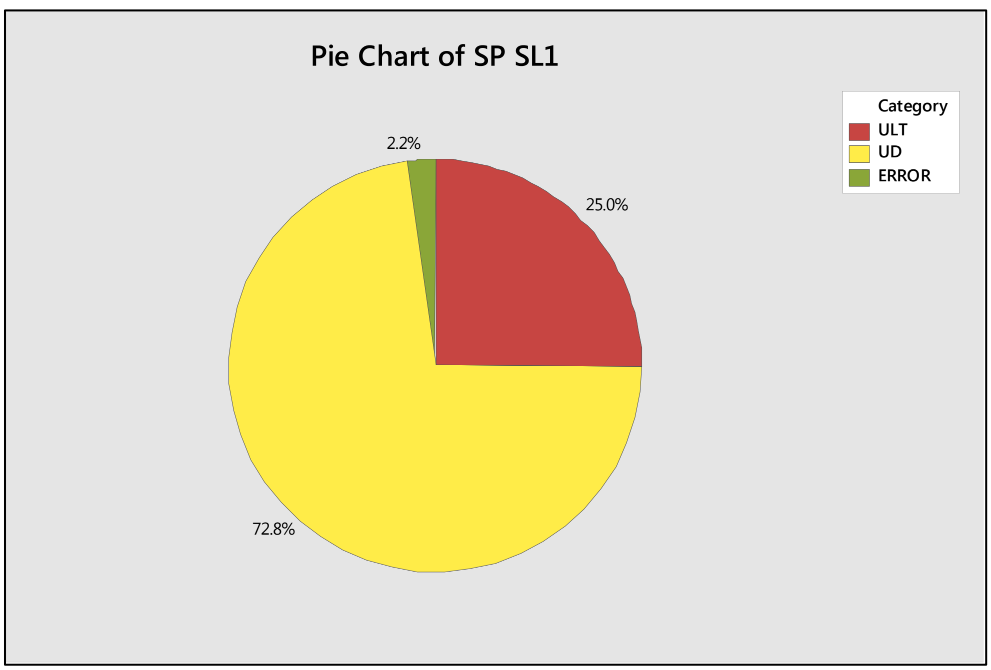

Figure 4.46 SET3-Data2: PIE chart for SP_{SL1} and 99.9% RFID accuracy

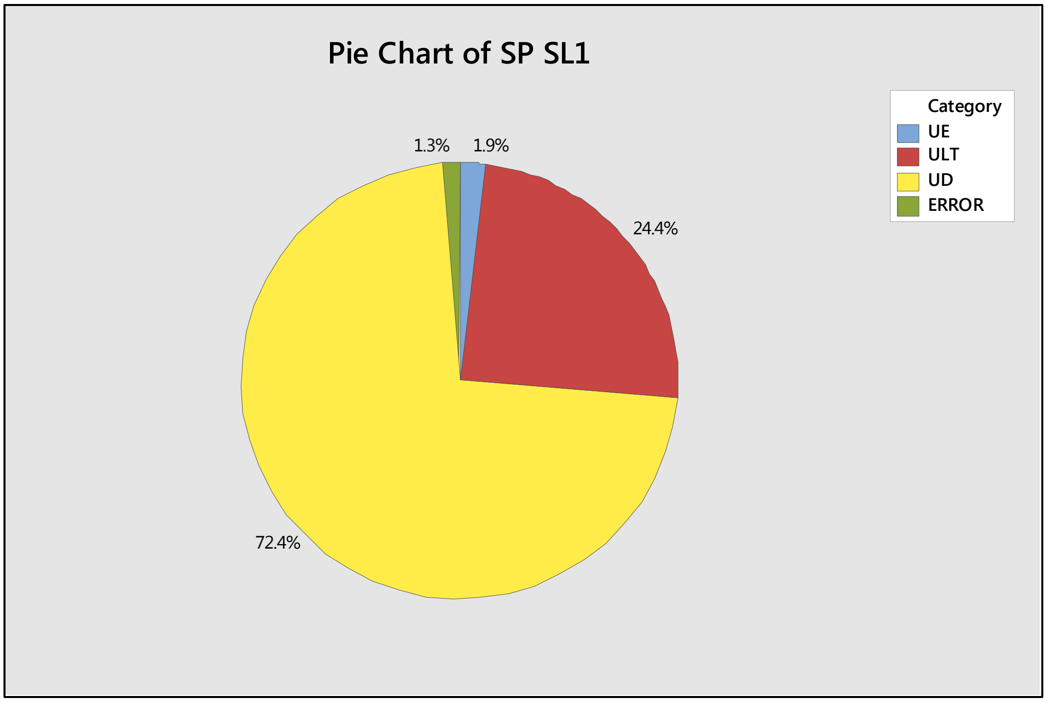

Figure 4.47 SET3-Data2: PIE chart for SP_{SL1} and 98% RFID accuracy

4.6.2 SET3-Data2: SP_{SL2}

Results for SP_{SL2} at different level of accuracy are reported in Table 4.61, Table 4.62 and Table 4.63.

Table 4.61 SET3-Data2: ANOVA for SP_{SL2} with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
ULT	1	0.012800	92.75%	0.012800	0.012800	256.00	0.000
UD	1	0.000800	5.80%	0.000800	0.000800	16.00	0.016
Error	4	0.000200	1.45%	0.000200	0.000050		
Total	7	0.013800	100.00%				

Table 4.62 SET3-Data2: ANOVA for SP_{SL2} with 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
ULT	1	0.012800	92.75%	0.012800	0.012800	256.00	0.000
UD	1	0.000800	5.80%	0.000800	0.000800	16.00	0.016
Error	4	0.000200	1.45%	0.000200	0.000050		
Total	7	0.013800	100.00%				

Table 4.63 SET3-Data2: ANOVA for SP_{SL2} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000200	1.08%	0.000200	0.000200	2.00	0.230
ULT	1	0.016200	87.10%	0.016200	0.016200	162.00	0.000
UD	1	0.001800	9.68%	0.001800	0.001800	18.00	0.013
Error	4	0.000400	2.15%	0.000400	0.000100		
Total	7	0.018600	100.00%				

It is possible to conclude that:

- UE is not a significant Factor (P-Value>>0.05)
- ULT contributes up to 92.75%

Results are summarized in Figure 4.48, Figure 4.49 and Figure 4.50.

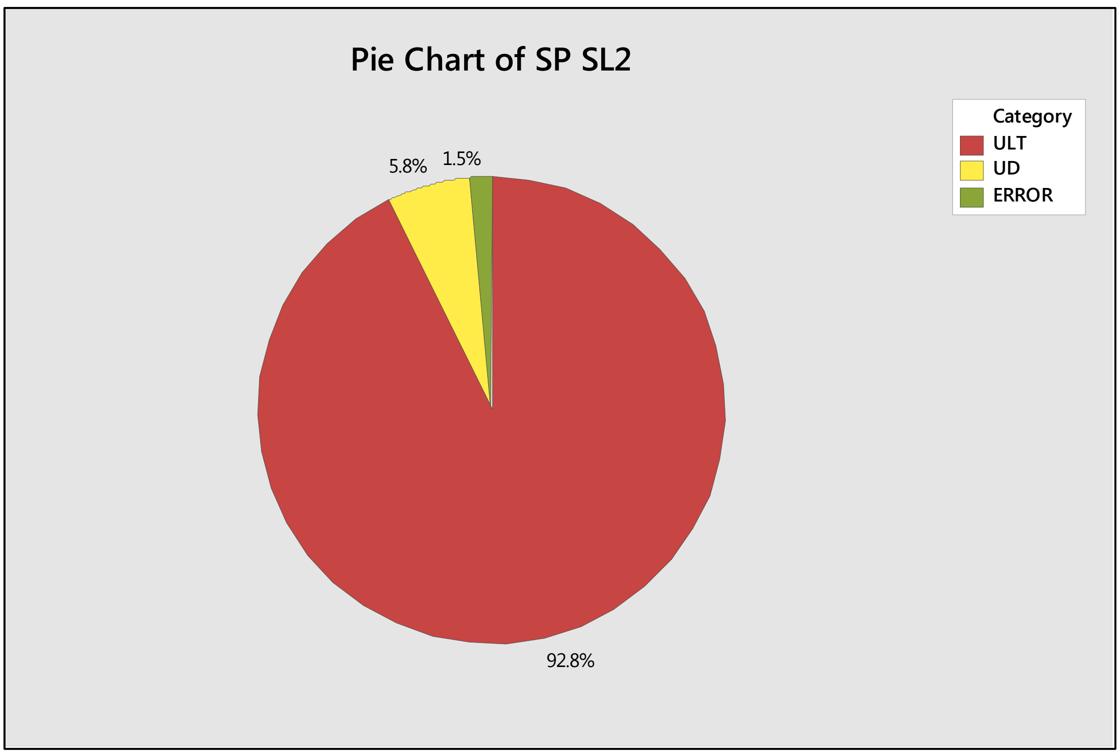

Figure 4.48 SET3-Data2: PIE chart for SP_{SL2} and 100% RFID accuracy

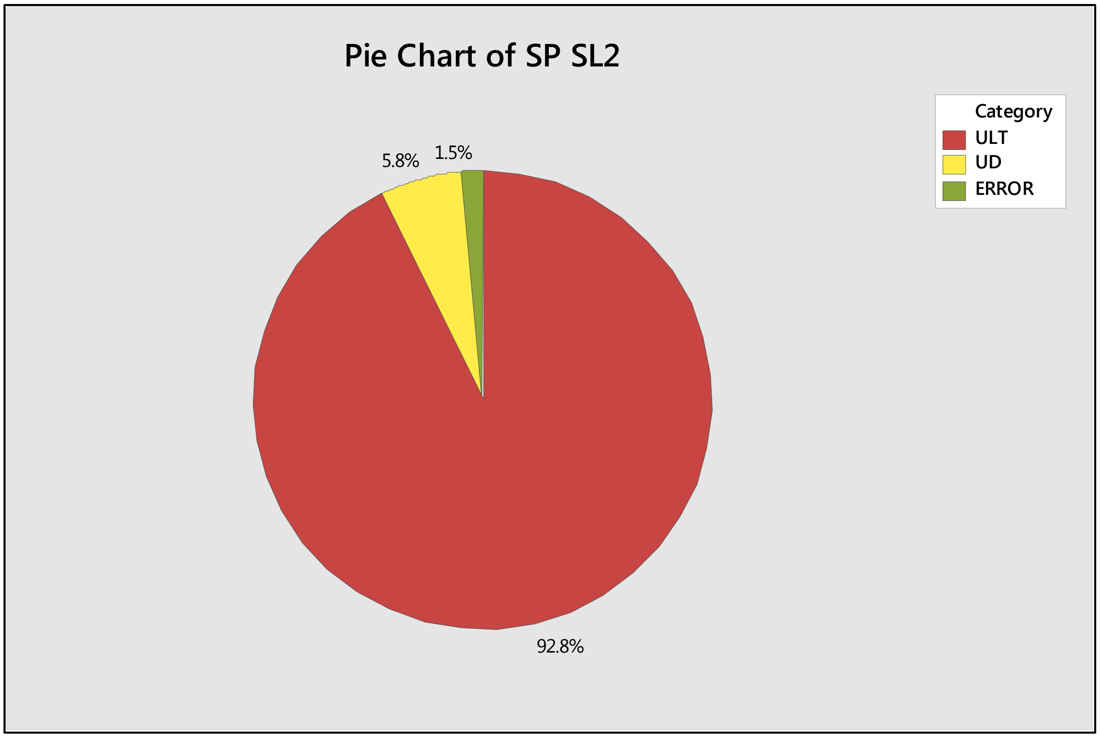

Figure 4.49 SET3-Data2: PIE chart for SP_{SL2} and 99.9% RFID accuracy

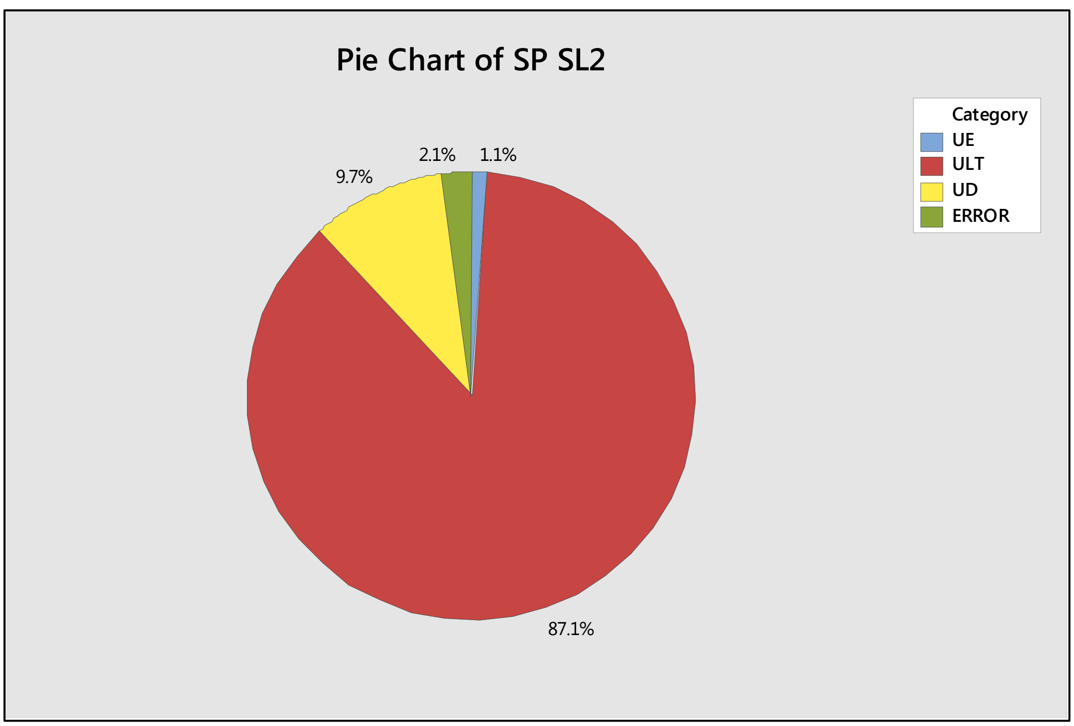

Figure 4.50 SET3-Data2: PIE chart for SP_{SL2} and 98% RFID accuracy

4.6.3 SET3-Data2: EW_{SL2}

Results for EOP_{SL2} at different level of accuracy are reported in Table 4.64, Table 4.65 and Table 4.66.

Table 4.64 SET3-Data2: ANOVA for EW_{SL2} with 100% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
ULT	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
UD	1	0.369800	99.95%	0.369800	0.369800	7396.00	0.000
Error	4	0.000200	0.05%	0.000200	0.000050		
Total	7	0.370000	100.00%				

Table 4.65 SET3-Data2: ANOVA for EW_{SL2} with 99.9% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
ULT	1	0.000200	0.06%	0.000200	0.000200	1.45	0.294
UD	1	0.344450	99.78%	0.344450	0.344450	2505.09	0.000
Error	4	0.000550	0.16%	0.000550	0.000138		
Total	7	0.345200	100.00%				

Table 4.66 SET3-Data2: ANOVA for EW_{SL2} with 98% RFID accuracy

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
UE	1	0.032513	4.40%	0.032513	0.032513	9.19	0.039
ULT	1	0.001512	0.20%	0.001512	0.001512	0.43	0.549
UD	1	0.690312	93.48%	0.690312	0.690312	195.14	0.000
Error	4	0.014150	1.92%	0.014150	0.003538		
Total	7	0.738487	100.00%				

It is possible to conclude that:

- When RFID accuracy is 100% or 99.9 %, UD is the only significant factor, contributing up to 99.95%
- UE is significant only when RFID accuracy is 98%.

Results are summarized in Figure 4.51, Figure 4.52 and Figure 4.53.

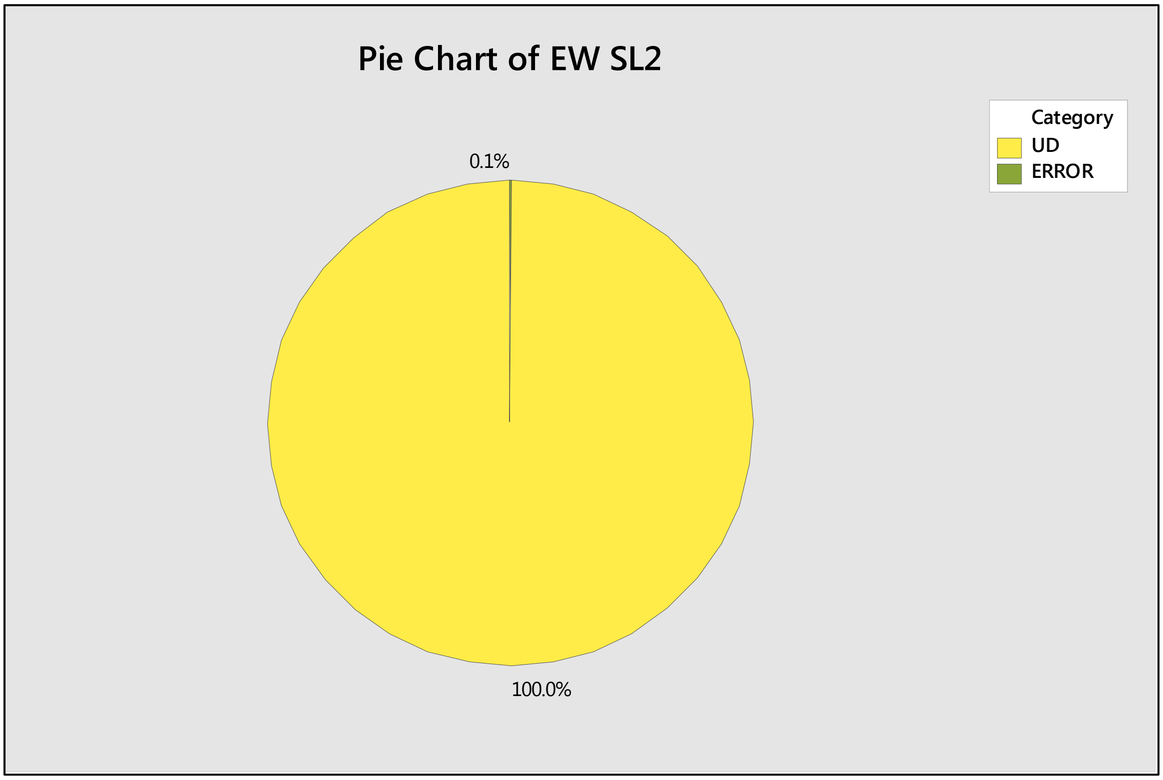

Figure 4.51 SET3-Data2: PIE chart for EW_{SL2} and 100% RFID accuracy

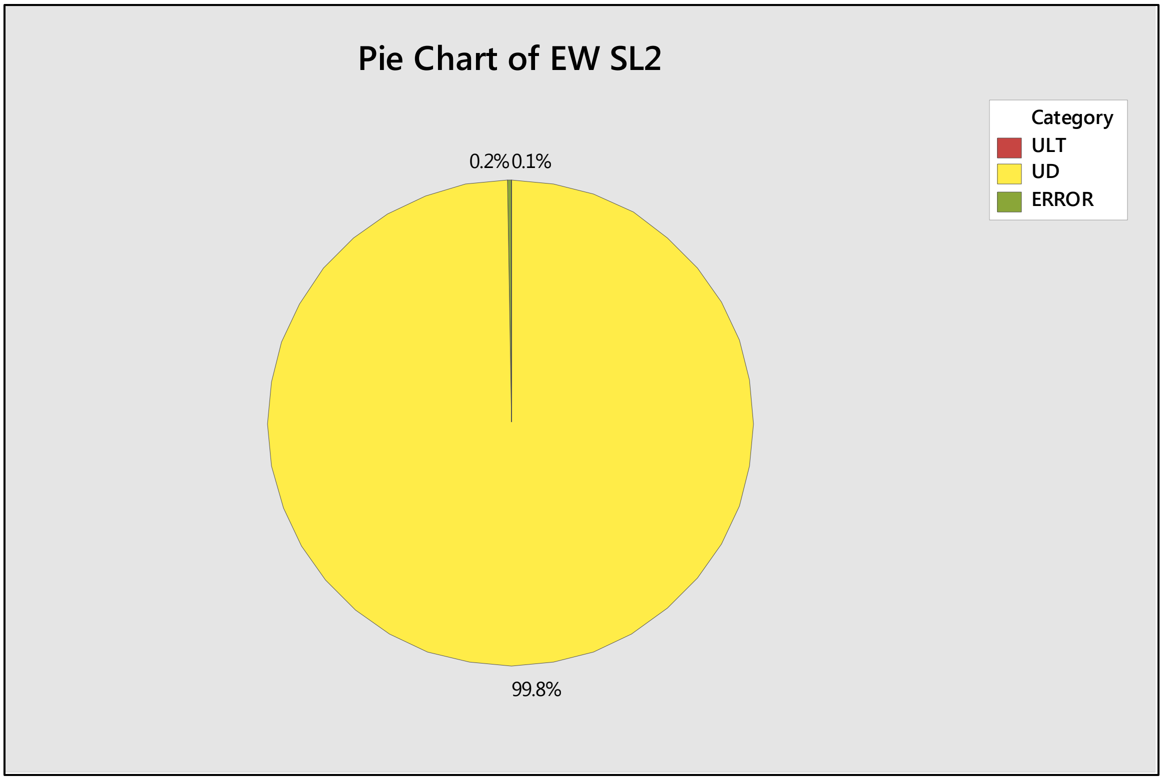

Figure 4.52 SET3-Data2: PIE chart for EW_{SL2} and 99.9% RFID accuracy

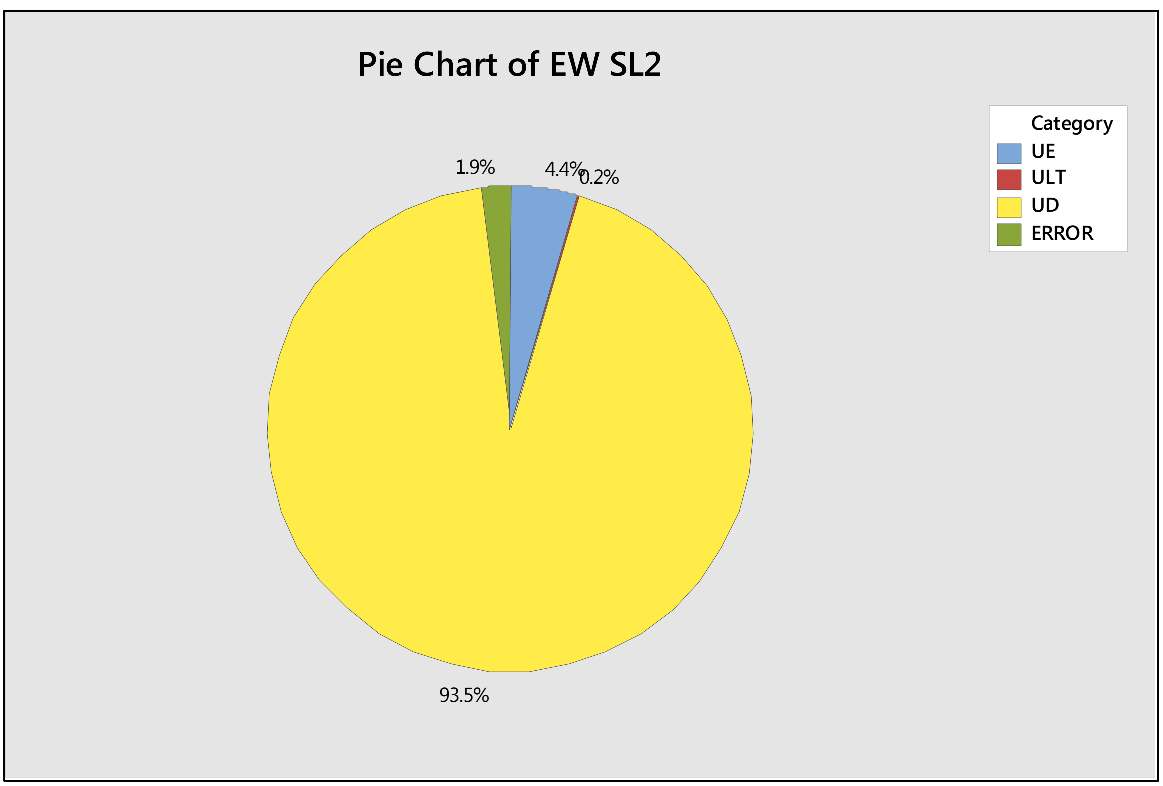

Figure 4.53 SET3-Data2: PIE chart for EW_{SL2} and 98% RFID accuracy

4.7 SET 4: Sensitivity Analysis

Table 4.67 and Table 4.68 report full-factorial plan results for Weibull and Logistics demand distribution, respectively.

Table 4.67 SET 4: Full factorial plan for Weibull distribution

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
2	1	1	1	98.25	98.32	91.13
1	2	1	0	91.25	94.72	93.76
1	2	1	1	95.04	97.19	97.44
1	1	1.75	1	93.69	95.59	81.68
2	2	1	1	98.15	98.32	96.25
2	2	1.75	0	95.52	96.24	83.97
2	2	1	0	96.54	97.6	92.97
1	1	1.75	0	88.72	93.09	73.54
2	1	1.75	1	96.41	96.69	80.44
1	1	1	1	94.13	96.93	91.33
1	2	1.75	1	95.58	96.49	93.57
1	1	1	0	89.28	93.49	82.52
2	2	1.75	1	96.75	96.83	92.34
2	1	1	0	96.33	97.44	79.59
2	1	1.75	0	95.32	96.16	72.79

Table 4.68 SET 4: Full factorial plan for Gamma distribution

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
2	1	1	1	98.25	98.32	91.13
1	2	1	0	91.97	95.18	94.8
1	2	1	1	95.67	97.46	97.51
1	1	1.75	1	94.73	95.94	83.39
2	2	1	1	98.18	98.33	96.34
2	2	1.75	0	95.41	96.16	85.14
2	2	1	0	97.08	97.86	93.34
1	1	1.75	0	90.29	93.87	73.71
2	1	1.75	1	96.53	96.72	82.25
1	1	1	1	95.15	97.24	92.78
1	2	1.75	1	95.94	96.54	94.13
1	1	1	0	90.59	94.47	86.13
2	2	1.75	1	96.77	96.8	92.9
2	1	1	0	97.04	97.81	81.28
2	1	1.75	0	95.46	96.24	72.91

Similarly to SET 1, the following tables (Table 4.69, Table 4.70, Table 4.71 and Table 4.72) report performance indicators for the four different cases:

- No RFID with Weibull Demand
- RFID, Weibull Demand
- No RFID, Gamma Demand
- RFID, Gamma Demand

Table 4.69 SET 4: NO RFID with Weibull demand

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
1	2	1.75	0	91.58	94.14	85.66
1	2	1	0	91.25	94.72	93.76
2	2	1.75	0	95.52	96.24	83.97
2	2	1	0	96.54	97.6	92.97
1	1	1.75	0	88.72	93.09	73.54
1	1	1	0	89.28	93.49	82.52
2	1	1	0	96.33	97.44	79.59
2	1	1.75	0	95.32	96.16	72.79

Table 4.70 SET 4: RFID with Weibull Demand

SD_{EW}	SD_{SP}	RFID	REP	SP_{SL1} %	SP_{SL2} %	EOP_{SL2} %
2	1	1	1	98.25	98.32	91.13
1	2	1	1	95.04	97.19	97.44
1	1	1.75	1	93.69	95.59	81.68
2	2	1	1	98.15	98.32	96.25
2	1	1.75	1	96.41	96.69	80.44
1	1	1	1	94.13	96.93	91.33
1	2	1.75	1	95.58	96.49	93.57
2	2	1.75	1	96.75	96.83	92.34

Table 4.71 SET 4: NO RFID with Gamma Demand

SD $_{EW}$	SD $_{SP}$	RFID	REP	SP $_{SL1}$ %	SP $_{SL2}$ %	EOP $_{SL2}$ %
1	2	1.75	0	91.58	94.14	85.66
1	2	1	0	91.97	95.18	94.8
2	2	1.75	0	95.41	96.16	85.14
2	2	1	0	97.08	97.86	93.34
1	1	1.75	0	90.29	93.87	73.71
1	1	1	0	90.59	94.47	86.13
2	1	1	0	97.04	97.81	81.28
2	1	1.75	0	95.46	96.24	72.91

Table 4.72 SET 4: RFID with Gamma Demand

SD $_{EW}$	SD $_{SP}$	RFID	REP	SP $_{SL1}$ %	SP $_{SL2}$ %	EOP $_{SL2}$ %
2	1	1	1	98.25	98.32	91.13
1	2	1	1	95.67	97.46	97.51
1	1	1.75	1	94.73	95.94	83.39
2	2	1	1	98.18	98.33	96.34
2	1	1.75	1	96.53	96.72	82.25
1	1	1	1	95.15	97.24	92.78
1	2	1.75	1	95.94	96.54	94.13
2	2	1.75	1	96.77	96.8	92.9

Figure 4.54 compares maximum SP_{SL1} improvements for the two different distributions.

Figure 4.54 SET 4: Maximum Improvement for SP_{SL1}

Figure 4.55 compares maximum SP_{SL2} improvements for each level of RFID accuracy.

Figure 4.55 SET 4: Maximum Improvement for SP_{SL2}

Figure 4.56 compares maximum EOP_{SL2} improvements for each level of RFID accuracy.

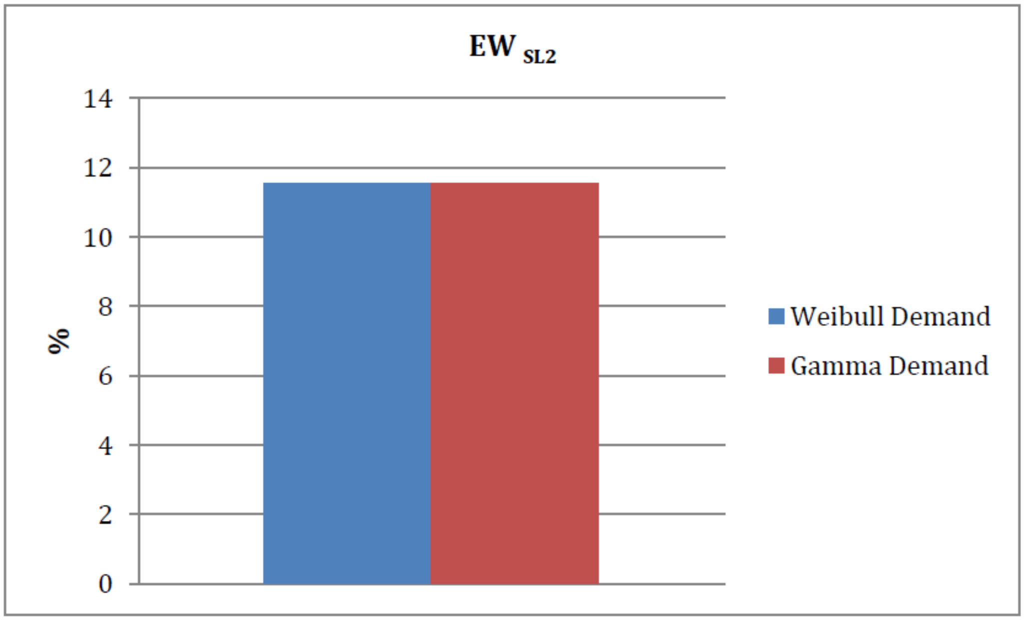

Figure 4.56 SET 4: Maximum Improvement for EW_{SL2}

4.7.1 SET 4: SP_{SL1}

In this section, the effect of the different factors on SP_{SL1} is evaluated by means of ANOVA tables. The results are presented for two different demand distributions.

Table 4.73 SET 4: ANOVA for SP_{SL1} and Weibull Demand

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	72.250	56.76%	72.250	72.250	54.65	0.000
SD EW	1	4.285	3.37%	4.285	4.285	3.24	0.099
R	1	1.823	1.43%	1.823	1.823	1.38	0.265
RFID	1	34.398	27.02%	34.398	34.398	26.02	0.000
Error	11	14.542	11.42%	14.542	1.322		
Total	15	127.297	100.00%				

Table 4.74 SET 4: ANOVA for SP_{SL1} and Gamma Demand

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	51.840	52.40%	51.840	51.840	44.45	0.000
SD EW	1	1.300	1.31%	1.300	1.300	1.11	0.314
R	1	3.258	3.29%	3.258	3.258	2.79	0.123
RFID	1	29.703	30.02%	29.703	29.703	25.47	0.000
Error	11	12.828	12.97%	12.828	1.166		
Total	15	98.928	100.00%				

It is possible to conclude:

- SD EW and R are not significant in both cases
- RFID contribution is larger in the case of Gamma Demand (30.02%)

Results are summarized in Figure 4.57, Figure 4.58 and Figure 4.59.

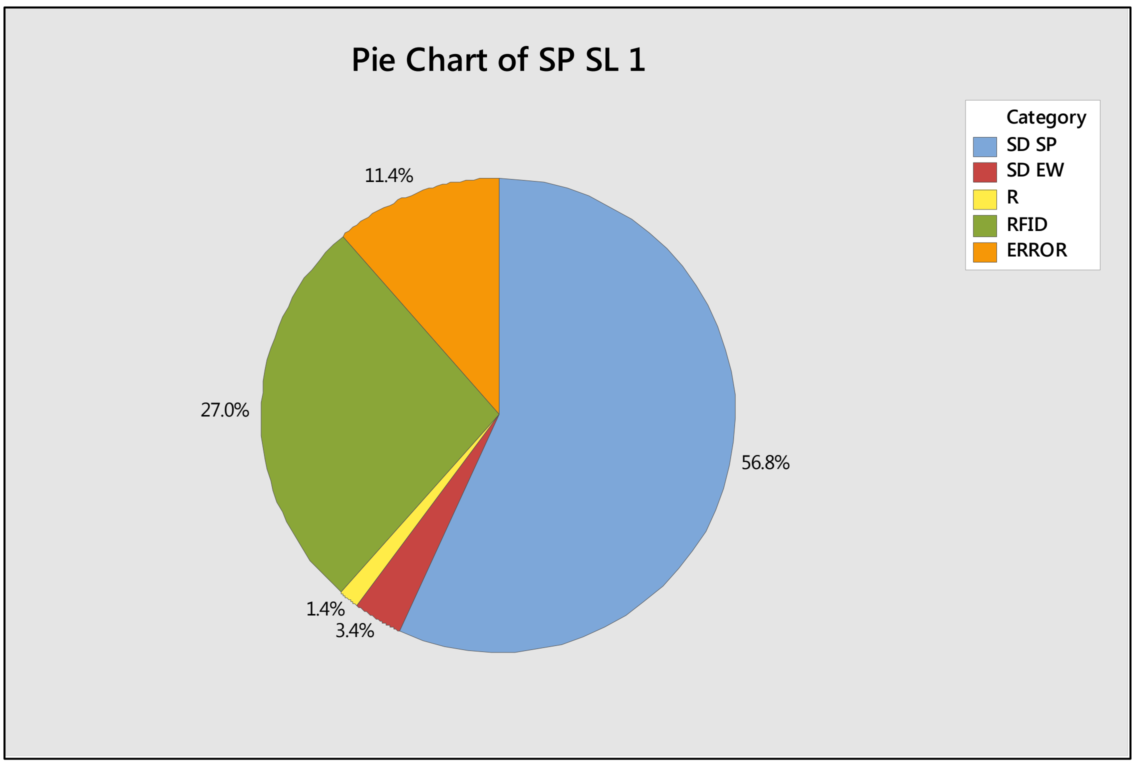

Figure 4.57 SET 4: Pie chart for SPSL1 with Weibull Demand

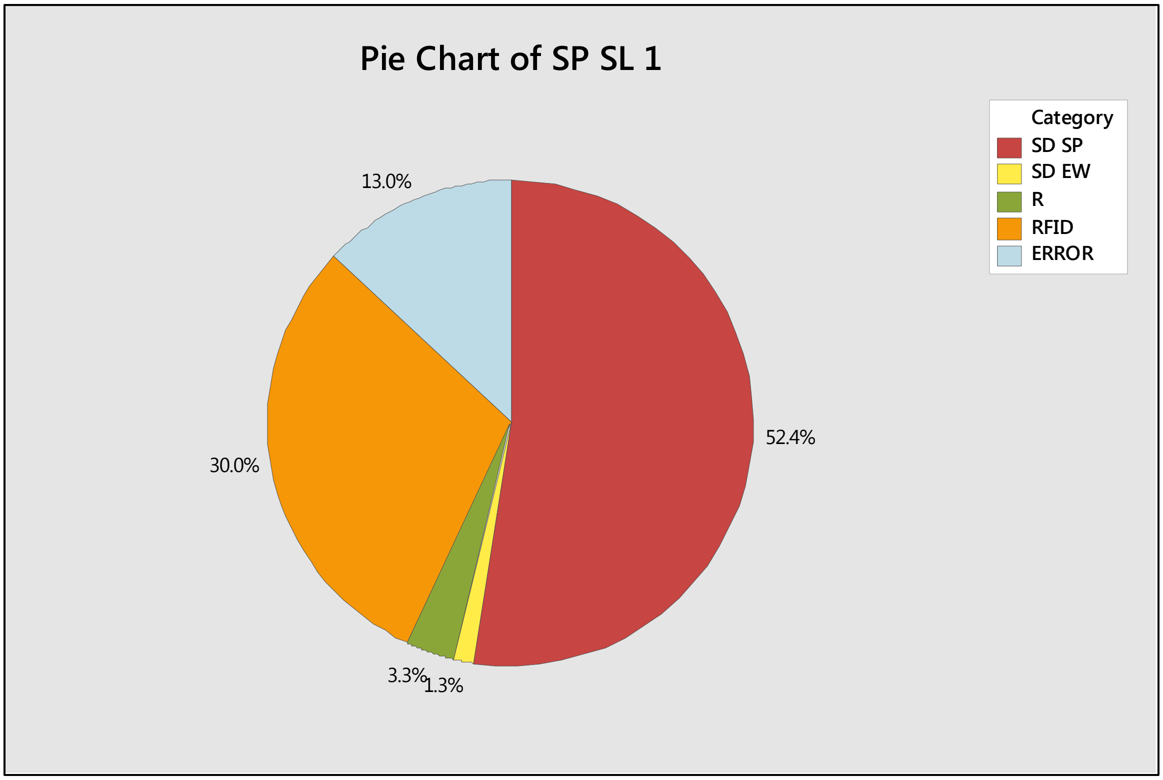

Figure 4.58 SET 4: Pie chart for SPSL1 with Gamma Demand

4.7.2 SET 4: SP_{SL2}

In this section, the effect of the different factors on SP_{SL1} is evaluated by means of ANOVA tables. The results are presented for two different demand distributions in Table 4.75 and Table 4.76

Table 4.75 SET 4: ANOVA for SP_{SL2} and Weibull Demand

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	15.9201	41.30%	15.9201	15.9201	31.62	0.000
SD EW	1	0.9120	2.37%	0.9120	0.9120	1.81	0.205
R	1	4.8180	12.50%	4.8180	4.8180	9.57	0.010
RFID	1	11.3569	29.46%	11.3569	11.3569	22.55	0.001
Error	11	5.5389	14.37%	5.5389	0.5035		
Total	15	38.5459	100.00%				

Table 4.76 SET 4: ANOVA for SP_{SL2} and Gamma Demand

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	11.2225	36.64%	11.2225	11.2225	29.58	0.000
SD EW	1	0.2162	0.71%	0.2162	0.2162	0.57	0.466
R	1	6.5792	21.48%	6.5792	6.5792	17.34	0.002
RFID	1	8.4390	27.55%	8.4390	8.4390	22.25	0.001
Error	11	4.1729	13.62%	4.1729	0.3794		
Total	15	30.6299	100.00%				

It is possible to conclude:

- SD EW is not significant
- RFID contribution is larger in the case of Weibull Demand (29.46%)
- R contribution is larger in the case of Gamma Demand (21.48%)

Results are summarized in Figure 4.59 and Figure 4.60.

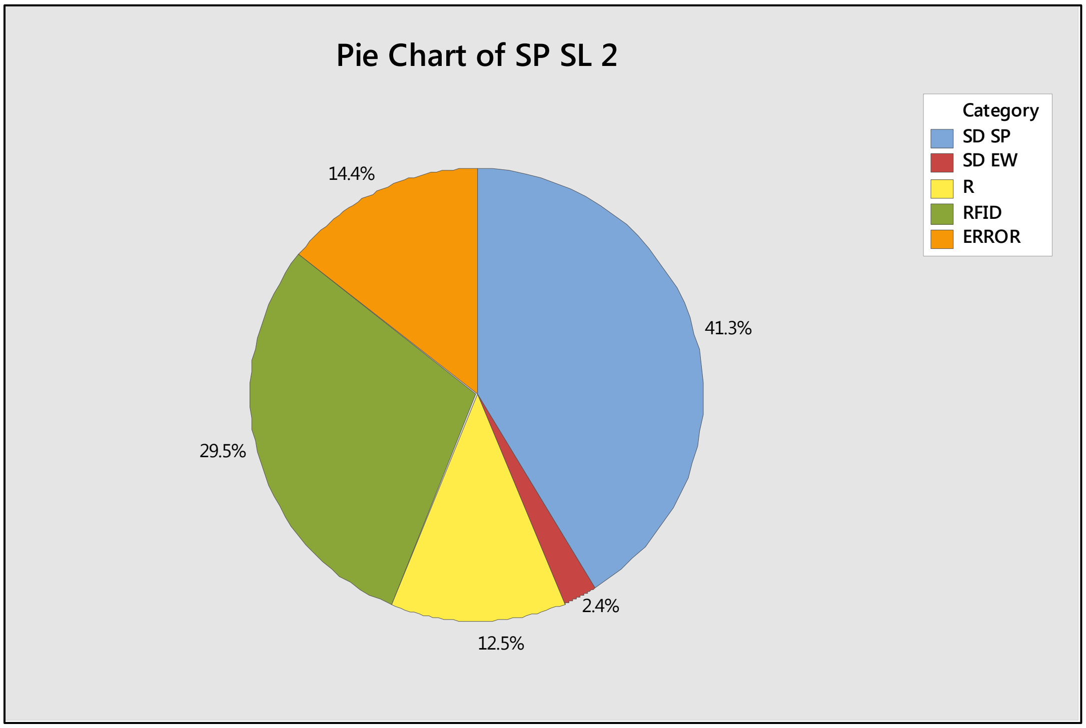

Figure 4.59 SET 4: Pie chart for SP_{SL2} and Weibull Demand

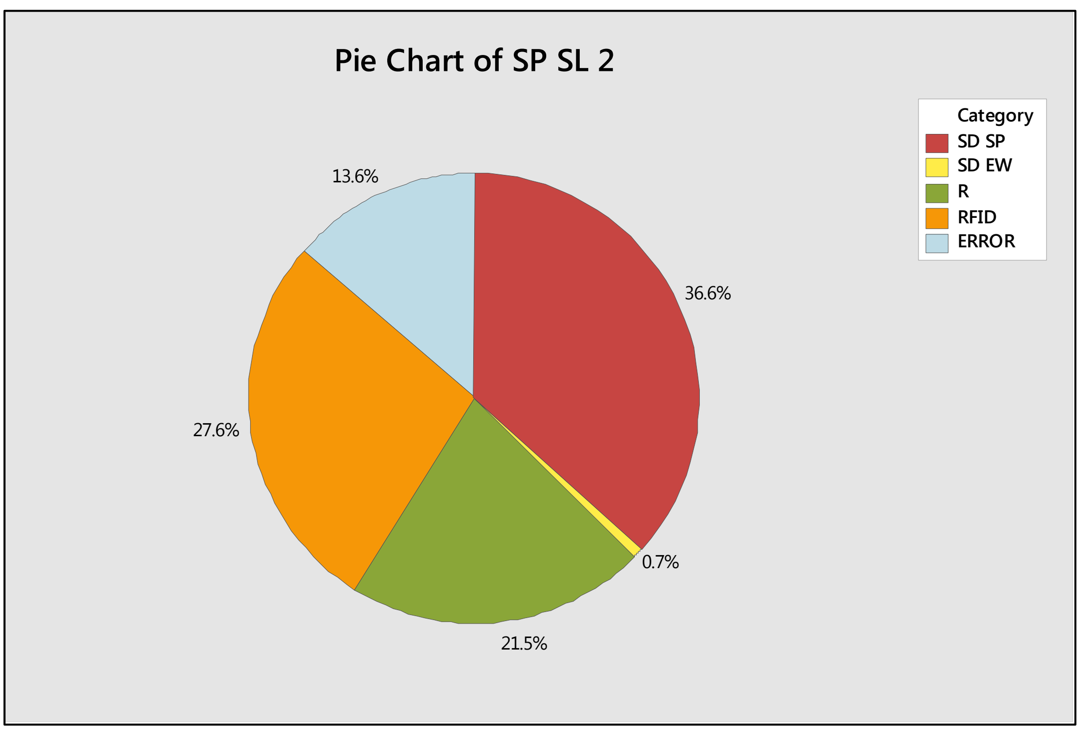

Figure 4.60 SET 4: Pie chart for SP_{SL2} and Gamma Demand

4.7.3 SET 4: EW_{SL2}

In this section, the effect of the different factors on SP_{SL1} is evaluated by means of ANOVA tables. The results are presented for two different demand distributions in Table 4.77 and Table 4.78.

Table 4.77 SET 4: ANOVA for EW_{SL2} and Weibull Demand

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	6.275	0.68%	6.275	6.275	2.03	0.182
SD EW	1	429.940	46.57%	429.940	429.940	138.91	0.000
R	1	232.562	25.19%	232.562	232.562	75.14	0.000
RFID	1	220.374	23.87%	220.374	220.374	71.20	0.000
Error	11	34.046	3.69%	34.046	3.095		
Total	15	923.198	100.00%				

Table 4.78 SET 4: ANOVA for Ew_{SL2} and Gamma Demand

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
SD SP	1	10.27	1.17%	10.27	10.272	2.43	0.147
SD EW	1	363.28	41.46%	363.28	363.284	85.95	0.000
R	1	249.80	28.51%	249.80	249.798	59.10	0.000
RFID	1	206.35	23.55%	206.35	206.353	48.82	0.000
Error	11	46.49	5.31%	46.49	4.226		
Total	15	876.20	100.00%				

It is possible to conclude:

- SD_{SP} is not significant
- RFID contribution is larger in the case of Weibull Demand (23.87%) but very similar to the result for Gamma Demand (28.51%)
- R contribution is larger in the case of Gamma Demand (28.51%)

Results are summarized in Figure 4.61 and Figure 4.62.

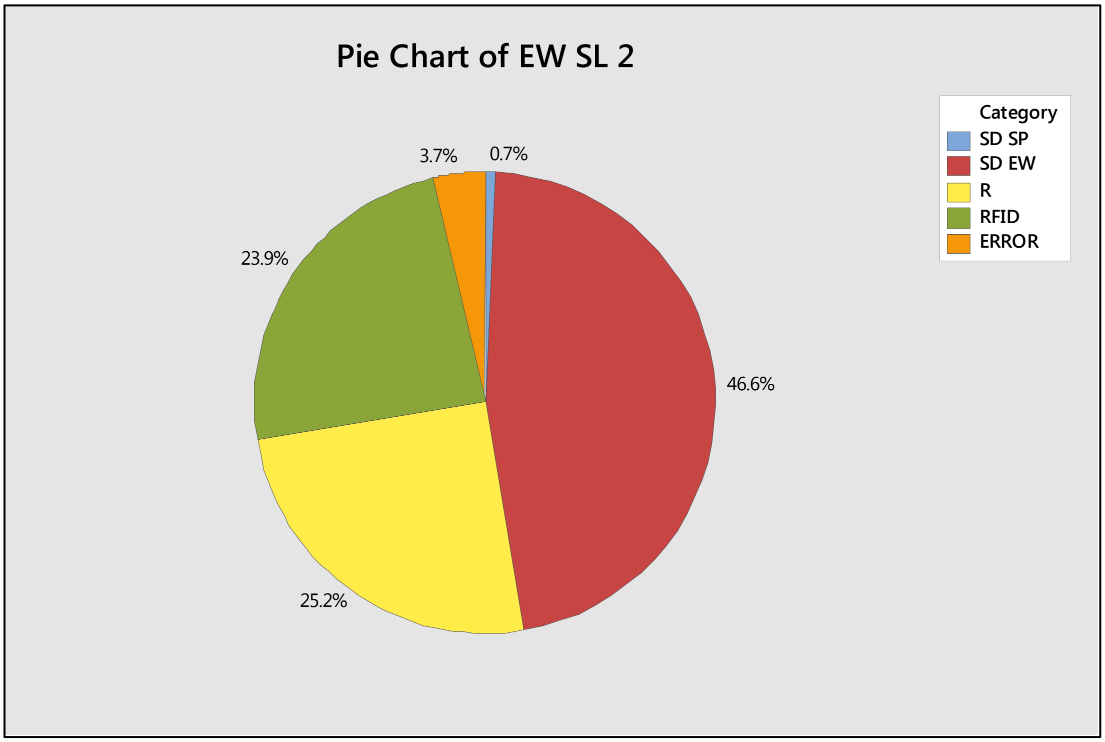

Figure 4.61 SET 4: Pie chart for EW_{SL2} and Weibull Demand

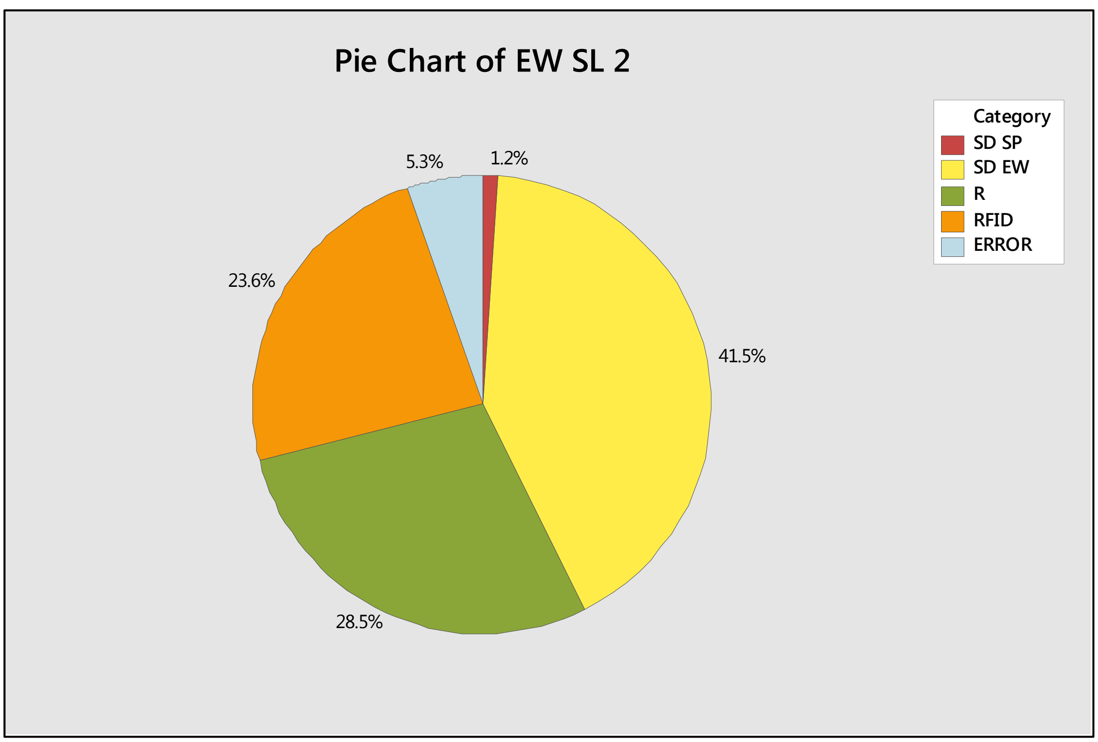

Figure 4.62 SET 4: Pie chart for EW_{SL2} and Gamma Demand

4.8 Handling time reduction

Stack counting time distribution has been defined over a sample of 32 measures (Table 4.79).

Table 4.79 Average stack counting time

Average Stack counting time	8.54 Sec

Potential time reduction is defined for a standard pooled container in Table 4.80.

Table 4.80 Time reduction for standard pooled container

Total shipped 0CC00091 (Y 2016)	884057
Total Flow	1768114
Attrition	6.3%
Actual total flow	1656723
Stack size	9
Stacks (rounded)	98229
Average stack counting time	8.42 Sec
Yearly handling time reduction	430 Hours

This result holds for just one of the forty standard pooled containers, so potential savings are much higher than the presented result.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

A Discrete-Event simulation model of an automotive returnable containers supply chain was presented. This model, developed in collaboration with FCA, has been used to evaluate the impact of RFID technology on a real world closed loop supply chain, consisting of:

- Warehouse of empty containers (EW)
- Supplier (SP) using empty containers to ship parts to assembly plant
- Assembly Plant (AP)

Empty containers are sent to the supplier and filled with parts. Supplier sends full containers to the assembly plant, where parts are consumed and empty containers are returned to the warehouse.

The focus is just on empty Containers: full containers operations and usage is simulated as a delay from the moment full containers leave supplier until when they come back to warehouse, closing the loop.

Two different Suppliers, corresponding to two different Datasets were analyzed. The two Datasets are named Data 1 and Data 2.

Current manual container counting procedure has been considered. The impact of RFID has been simulated increasing current counting system reliability. In particular, three levels have been considered:

- 100% Accuracy
- 99.9 % Accuracy
- 98% Accuracy

Relevant data about the real world system to model were collected either visiting involved facilities or using OEM material. The model was developed using ARENA® simulation package.

Model input factors were distinguished in:

- Controllable. Control factors affecting the model in a deterministic way. In Particular
    - Supplier containers safety stock, SD_{SP}
    - Warehouse (EW) containers safety stock, SD_{EW}
    - Supplier empty containers replenishment frequency, R
    - RFID. If not used, counting process reliability goes to default manual counting accuracy.
- Uncontrollable. Cannot be controlled in a deterministic way, and depends on variations of defined statistical distributions. In particular:
    - Demand distribution
    - Lead time lead time distribution
    - Counting error

System performance was evaluated with three indicators:

- Supplier Type I service level, SP_{SL1}
- Supplier Type II service level (Fill rate), SP_{SL2}
- EW Type II service level (Fill rate), EW_{SL2}

Using factorial design and ANOVA, three main experiment sets were developed for both Datasets:

- SET 1: Effect of controllable factors. In this set, different combinations of controllable input factors are be tested without changing uncontrollable factors.
- SET 2: Effect of uncontrollable factors. In this set, different combinations of uncontrollable input factors are tested without changing controllable factors.
- SET 3: Best case scenario from SET 1 is tested under SET 2 conditions.
- SET 4: Experiments from SET 1 are repeated changing Data 2 demand distribution.

Stop watch analysis of current manual counting process has been performed to highlight possible handling time reduction deriving from RFID.

5.2 Conclusions

Conclusion will be distinguished according the two Datasets.

5.2.1 Conclusion: Dataset 1

It is possible to conclude that RFID improves overall system performance for all the considered accuracy levels. In particular the following potential improvements were found to be possible:

1.1 Up to 12.96 % increase in EW_{SL2}

1.2 Up to 1.42 % Increase in SP_{SL1}

1.3 Up to 1.17 % increase in SP_{SL2}

1.4 Safety stock and fleet size reduction with same performance level

1.5 Reduction in handling time

Some general consideration have been done regarding the influence of controllable and uncontrollable factors on performance indicators

- Supplier Type I service level, SP_{SL1}.
    - Supplier system days is the most influencing controllable parameter on containers shortage
      (Up to 52.81%)
    - Replenishment frequency is a determinant factor in limiting shortage
      (Up to 20.44%)
    - Uncertainty on lead time is the most significant uncontrollable factor causing shortages
      (Up to 61.96%)
    - Counting error uncertainty is significant only when RFID accuracy is 98%

- Supplier Fill rate, SP_{SL2}.
    - Supplier system days SD_{SP} is the most influencing controllable factor (45.66%)
    - Lead time uncertainty is the most significant uncontrollable factor (59.4%)
    - Counting error uncertainty is significant only when RFID accuracy is 98%

- EW Fill rate, EW_{SL2}.
    - EW system days is the most relevant control factor (Up to 51.51%)
    - RFID strongly influences EW fill rate (Up to 33.03%)
    - Demand uncertainty is the most significant uncontrollable factor influencing EW_{SL2} both in base and best scenario.
    - Counting error uncertainty is significant only when RFID accuracy is 98%

5.2.2 Conclusion: Dataset 2

It is possible to conclude that RFID improves overall system performance for all the considered accuracy levels. In particular the following potential improvements were found to be possible:

- EW_{SL2}improvement up to 10.02 %
- SP_{SL1} improvement up to 4.48 %
- SP_{SL2} improvement up to 2.59 %
- Safety stock and fleet size reduction with same performance level

Some general consideration have been done regarding the influence of controllable and uncontrollable factors on performance indicators

- Supplier Type I service level, SP_{SL1}.
    - Supplier system days is the most influencing parameter for all the considered accuracy levels (Up to 62.24%)
    - SD_{EW} is not a significant Factor
    - ULT and UD are not significant
    - RFID influences SP_{SL1} up to 28.59 %

- Supplier Fill rate, SP_{SL2}.
    - Supplier system days SD_{SP} is the most influencing parameter (Up to 40.39%)
    - RFID contributes up to 27.15 %
    - Again, SD_{EW} is not a significant Factor
    - UE is the most significant factor

- EW Fill rate, EW_{SL2}.
    - SD_{SP} is not a significant Factor (P-Value>>0.05)
    - EW system days is the most relevant factor in the three cases (Up to 42.05%)
    - RFID can influence EW_{SL2} up to 27.85 %
    - UD is the most significant factor

5.2.3 Further Considerations

Based on the result obtained from section 4.7 and section 4.8, it is possible to conclude:

- RFID impact changes for different demand distribution types.
- Dataset 2 shows better improvement deriving from RFID. The shorter lead time results in reduced variability because of Lead time uncertainty. This means that counting error uncertainty is a more relevant source of variability that RFID can fix.
- Considering the entire container fleet, handling time could be reduced by 430 Hours per year using RFID.

5.3 Recommendations and future improvements

It is possible to define the following areas of improvement for the present model:

- Multi-supplier case. In this work a single supplier has been considered. In real world, the same container model can be shared by many different suppliers. It would be interesting to extend the current model to a multi-supplier case.
- Material requirement Planning (MRP). Supplier Containers usage has been defined based on Demand Data record, without simulating the actual Material Requirement Planning (MRP) used by FCA.
- Different kind of RFID system can be simulated. For example, the application of RFID to material handling equipment (such as Forklifts).
- Containers losses. The presented model does not consider containers losses. Further work about the effect of fleet shrinkage on overall system performance should be included.
- Full containers operations should be included in the model, to improve effectiveness.

5.3.1 Multi-supplier case

As mentioned before (see section 3.1.1) in a container pooling system, the same standard container model can be shared among several supplier. In the present work, a standard container was considered, but focusing on just one supplier (see section 3.1.5). Thanks to the modularity of the present Simulation model, it is possible to extend it to a multi-supplier case, according to Figure 5.1.

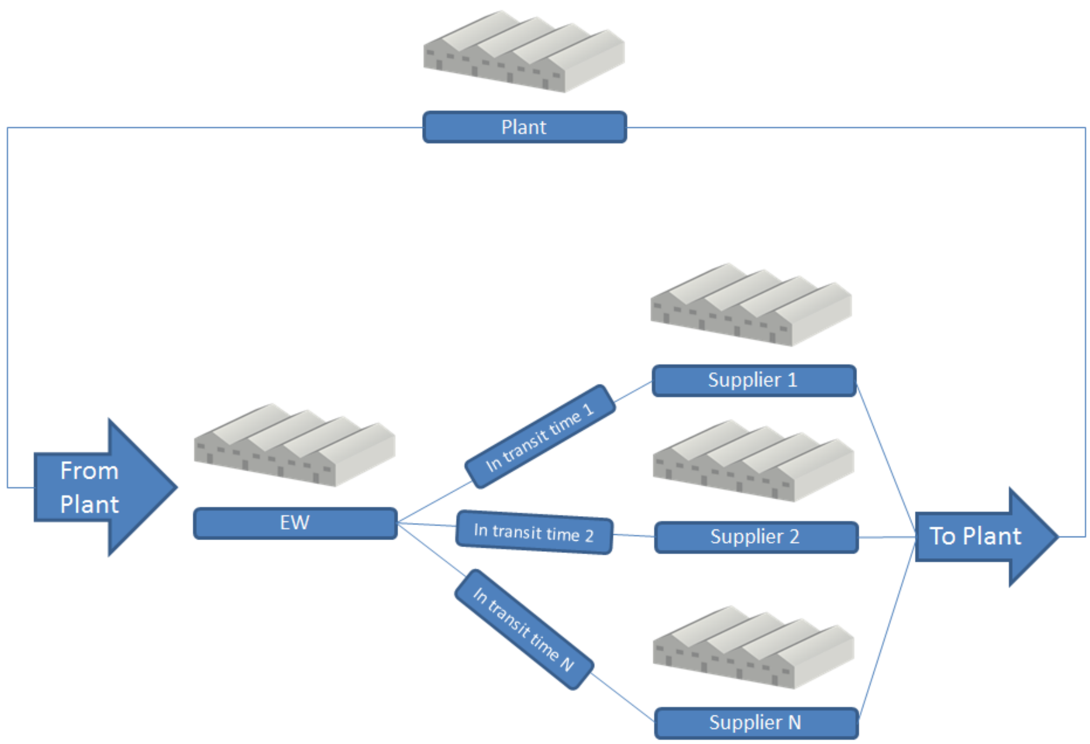

Figure 5.1 Scheme for Multi supplier case

In particular, it would be interesting to consider all the suppliers serving the same plant with one specific standard container model. In the following, necessary steps to extend the present model to a multi-supplier case are presented:

- Define Parts demand for each supplier and convert to equivalent container demand
- Define Lead time for each supplier
- Define Replenishment frequency for each supplier
- Define total containers return rate

Once those data are available, it is necessary to:

- Add necessary supplier model blocks
- Modify EW Operations manager (See section 3.2.1)

In particular, EW operations manager for the multi-supplier case, should be able to define replenishment requirement for each supplier, considering Warehouse availability.

5.3.2 Material Requirement Planning

In the presented model, supplier containers replenishment has been simulated using an OUL policy. On the other Hand, the actual system used by the OEM to define Supplier Parts Requirement has not been simulated. Those requirements are based on a Material Requirement Planning system, as depicted in Figure 5.2.

11-12-2000	Overdue	Week 1	Week 2	Week 3	Week 4
Item: Seat		LT = 2	SS = 0	LS = LFL	UM = Each
Gross Requirement	0	0	0	135	0
Scheduled Receipt	0	50	0	0	0
Projected On Hand	60	110	110	0	0
Projected Net Requirement	0	0	0	25	0
Planned Order Receipt	0	0	0	25	0
Planned Order Release	0	25	0	90	60

Figure 5.2 Example of MRP

According to (Gobetto, 2014), in a Material Requirements Planning (MRP) each product is broken down in terms of subcomponent and relative base materials, according to what established by the Bill of material (BOM). The MRP systems allow to plan the material demand, both for semi-finished products that are purchased from the outside, and for semi-finished products produced inside the company. Simulating the actual MRP system used by FCA NAFTA would greatly increase the effectiveness of the model, since it would allow for a realistic simulation of supplier containers needs.

5.4 Concluding Remark

Even with its current limitations, this work wanted to provide some guidelines in understanding impact of RFID in industrial scenarios. Thanks to the collaboration of FCA, it was possible to study a real industrial problem, collecting data from the field and interacting with the complexity of automotive supply chain. Even if this model is based on real world data, some assumptions would need further investigations. For this reason, numerical results should not be used directly, but to understand relevant trends and opportunities of using RFID.

We hope our work can be the starting point of an effective improvement of current containers management combining simulation with field studies, in a broader effort of phasing automotive industry supply chain to industry 4.0.

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