A methodology for the determination of an optimised fleet size in a closed loop supply chain

By

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DECLARATION

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Master of Engineering is entirely my own work, and that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

Signed: Alan O'Donovan ID No.: 13210423 Date: 18th August 2017.

Alan O'Donovan

DEDICATION

I would like to dedicate this work to my wife, Shelley and two children Millie-Mai and Cormac.

ACKNOWLEDGEMENTS

I remember where all this began…. I was sitting around a table in a cafeteria in UL, Limerick with Ken Daly and Paul Young in 2012 discussing projects … it was an Irish Centre for Manufacturing Research event ….. and in that moment I realized that I wanted to understand the world of advanced analytics a little better.

You see for the previous year I had had the pleasure of working with my colleagues in DCU, Dr. Paul Young, Dr. John Geraghty, Dr. PJ Byrne, Dr. Paul Liston, Dr. Anna Rotondo, Dr. Neill Byrne and from UL Dr.Cathal Heavy and Dr. Birkan Can as part of the Irish Centre for Manufacturing research. We spent many days visiting companies, talking to engineers and managers about analytics and how we could help their company become more competitive…. I loved being part of it… even if I was 'just' the industry expert on the team…. however I wanted more….

All of these people were a source of inspiration for me to complete this research masters; you made advanced analytics look fun, exciting and necessary. I want to thank you for providing me with the motivation for starting and completing this body of work.

I would like to say a special thanks to Dr. John Geraghty and Dr. Anna Rotondo who became my eventual co-supervisors. You provided me with great insight and more importantly your time when I needed it.

Lastly where would I be without my family; Shelley my beloved and driven wife, Millie-Mai my beautiful and artistic daughter and Cormac my handsome and sports mad son; you've been great and an absolute solid foundation for me in the last 3 years … thank you so much for all the support.

ABSTRACT

Within an organisation calibration kits are used every day to ensure that the machines are ready for production whether that's after a preventative maintenance or a qualification activity post a machine down event. The Calibration kit process allows engineers to check critical process attributes that effect production. In many organisations calibration kits can outnumber the quantity of production units in process by up to 3 times. This is largely due to factory management only being concerned with calibration kit management when a production line is stopped due to waiting for a calibration kit. In recent years there has been significant work completed on the Calibration kit process from a demand and supply side however the key components of the Calibration kit process and its inherent variability make the management of the Calibration kit process extremely difficult. Breaking down the Calibration kit process to its most basic of functions show that it can be defined as a reusable article within a closed loop supply chain.

The management issues that affect RA's (Reusable articles) within a closed loop supply chain such as Calibration kits include fleet size definition, control and improvement of return rate and control and improvement of cycle time. To date 'pool managers' have struggled with this aspect of RA management given the variability that exists in the system when it comes to cycle time, quality and fleet shrinkage. To date the methodologies for determining fleet size within an RA process have ranged from 'rules of thumb' to the development of optimised simulation models. However the issues with these methodologies to date range from inappropriate assumptions in the analytical space to a time consuming overly complex process in the area of optimised simulation modelling.

The research presented in this thesis, investigates and tests if it possible to find a balance between the basic rules of thumbs which are easy to interpret/ apply and the area of optimised simulation modelling which is at the upper echelons of advanced analytics but is sometimes out of reach of a fleet size manager due to lack of time, data and expertise. The results of this work established that it is possible to determine a generalizable analytical model for fleet sizing that would adequately replicate the results of a simulation based optimisation approach. The model, although showing positive results from an accuracy and robustness perspective, is limited by the maximum and minimum of fleet size requirements borne from the data on which it has being trained and therefore is not generalizable to problems where fleet sizes larger than 45 may be required. But it should be possible to extend the analytical model for such problem domains.

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CHAPTER 1: INTRODUCTION

1.1 Research Motivation

The research conducted for the purposes of this thesis stems from an industrial case study. The company from which the initial case study was drawn is a multi-national organisation in the Electronic Devices and Information Technology sector. The Calibration kit process is one of the key building blocks when it comes to ensuring a quality product out the back door. Calibration kits are used every day to ensure that the machines are ready for production whether that's after a preventative maintenance or a qualification activity post a machine down event. The Calibration kit process allows engineers to check critical process attributes that effect production.

Calibration kits outnumber the quantity of production units in process by up to 5 times. The Calibration kit provision process can be considered as almost a factory within a factory. The Calibration kit process as highlighted throughout this thesis is sometimes seen as the 'Black Sheep'[1] of the family and hence has less focus placed on it, that is until a lack of the appropriate Calibration kits cause a line down or a machine to go into 'Wait CALIBRATION KIT' mode where questions regarding Calibration kit management and Clean cycle time etc. come into play.

The objective of anyone working on Calibration kits is to 'Provide the right Calibration kit, of the right quality, at the tool, on time in a cost effective manner'. In order to ensure this high service level is maintained there is a significant level of over investment in calibration kits hence the reason why we have a 5:1 ratio when it comes to kits: production. It is in this area that this research will be focused. In recent years there has been significant work completed on the Calibration kit process from a demand and supply side, however, the key components of the Calibration kit process and its inherent variability make defining fleet size a very difficult task. Breaking down the Calibration kit process to its most basic of functions shows that it can be defined as a reusable article within a closed loop supply chain; the definition of which is:

"The term reusable articles (RA) refers to products that are used multiple times by different users. This definition implies that the use by each user is of relatively short duration (compared with

article lifetime) and does not deteriorate the product. It also implicitly states that RA require a reconditioning process which should remain short and simple, in order to enable quick utilization by the next user" [2]

The management issues that affect RA's (Reusable articles) within a closed loop supply chain such as Calibration kits include fleet size definition, control and improvement of return rate and control and improvement of cycle time (other issues exist within the literature review such as balance between multiple depots, however, these are not being addressed in this research).

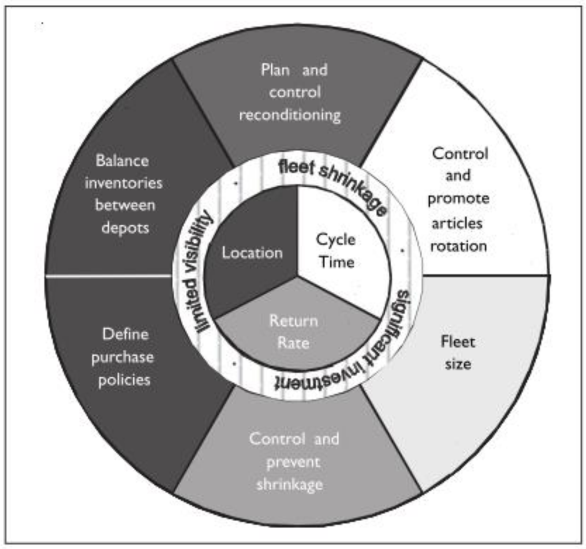


Figure 1 A management model for reuse CLSC [3]

To date 'pool managers' have struggled with this aspect of RA management given the variability that exists in the system when it comes to cycle time, quality and fleet shrinkage. The reported methodologies for determining fleet size within an RA process have ranged from 'rules of thumb' to the development of optimised simulation models. However, the difficulties for real world application of these methodologies range from inappropriate assumptions in the analytical space to a time consuming overly complex process in the area of optimised simulation modelling.

In order to ensure an holistic view of the problem it will be necessary to consider the problem quantitatively and qualitatively; hence a mixed method approach known as triangulation will be adopted in this research. Qualitative data will be gathered through a range of interviews with subject matter experts whilst quantitative data will be retrieved from the ERP system.

The primary objective for this research is to investigate and test whether it is possible to strike a balance between the basic rules of thumbs which are easy to interpret/ apply and the area of optimised simulation modelling which is at the upper echelons of advanced analytics but is sometimes out of reach of a fleet size manager due to lack of time, data and expertise. To further this objective, this thesis provides an analysis and review of what is currently being done in the world of this industry sector regarding fleet size definition and the methodologies being administered for reusable articles in closed loop supply chains outside of this industry.

The analytical sections of this thesis are aimed to test the hypothesis that fleet size quantities developed as part of an optimised simulation model can be replicated adequately with a cross industry generalizable analytical model thus enabling fleet size managers to benefit from the application of optimized simulation modelling through an easily applicable analytical model.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction and Section Layout

The focus of this chapter is to provide the reader with a background on why the area of fleet size modelling of a reusable article is worthy of interest and research. Section 2.2 addresses how global and European legislation paved the way for creating an environment that made consumers and producers aware of how products and services have impacts on the environment and availability of natural resources; a key driver for incorporating green reusable initiatives. Section 2.3 describes what a Reusable article is and provides definitions of the different types that are available. In section 2.4 the current problems with Reusable Articles according to research are discussed and it is clearly demonstrated why the area of Fleet sizing is of interest and value. In order to provide the reader with some understanding of how such fleet sizing problems for reusable articles have been addressed in the past in section 2.5 an outline of the methodologies used by other researchers, the motivations for such choices and critique their application is provided. Lastly the development of a methodology will always be constrained by the era in which it was incorporated and this has been taken into account when analyzing the opinions of those who have gone before.

2.2 Green Legislation

In today's economic environment an organisation's '*green credentials*' can be the difference between winning and losing business. Companies, today, invest significant amounts of money in the area of reducing their carbon footprint as a means to gain favour with an ever more aware consumer who cares about how the raw materials were grown/sourced/created, how the end product was produced and logistically how it was delivered to the shop from which they purchased it.

This care/awareness, however, was not borne out of thin air; in the 1990's global governing bodies realised that given the level of reliance by the global economy on natural resources such as fuel, metals, water, minerals to name a few that a problem was on the horizon. The European commission "*proclaimed that all products caused environmental degradation in some way, whether from their manufacturing, use or disposal*" [3]. In 1997 Ernst and Young were requested to complete a report for the European Commission to determine the need for an Integrated Product Policy (IPP) that would address the entire life cycle of a product from '*cradle to grave*' regarding their environmental impact [4]. Prior to 1997, product policies were being introduced in multiple countries across the EU, however, these efforts were inconsistent and caused some concerns such as possible development of trade barriers across the EU if different countries had different product policies and a perceived '*Lack of a level playing field*'[4]

It was evident that there was a need for a consistent European policy to negate gaps across member states. In addition, to these concerns the idea of Europe having a competitive edge due to the promotion of an '*environmentally superior*' [4] product was very attractive. After Ernst and Young consulted with producers and consumers a definition and framework for the IPP was suggested; the IPP definition was to be described as a ***"Public Policy which explicitly aims to modify and improve the environmental performance of product systems"*** The framework around which this IPP would be built was based on the following 5 measures [4]:

1. Measures aimed at **<u>reducing</u>** and **<u>managing waste</u>** generated by the consumption of products.
2. Measures targeted at the **<u>innovation of more environmentally</u>** sound products.
3. Measures to **<u>create markets</u>** for more environmentally-sound products.
4. Measures for **<u>transmitting information</u>** up and down the product chain.
5. Measures which allocate **<u>responsibility for managing the environmental burdens</u>** of product systems.

Following on from this report the Commission adopted a communication on IPP in June 2003 promoting 'life-cycle' thinking when it came to environmental impact and since then it has been followed up by numerous initiatives at both national and international levels to compliment the endeavour such as the Environmental Impact of Products (EIPRO) which was used to determine those products that had the greatest environmental impact throughout their life cycle and the

PEF (Product Environmental Footprint) methodology that carries out studies to measure the environmental performance of a product throughout its life cycle. The later of these initiatives was developed to support the Europe 2020 strategy which was kicked off in 2010 and with it a flagship initiative to create a Resource Efficient Europe.

2.2.1 Impact of this legislation

This continued focus by Europe over almost two decades has ensured that there is now a society where responsible manufacturing and development of products is an expectation and is seen as a key differentiator when choosing products. This evidence can be seen in research conducted by the Boston Consulting Group in 2008 (report published Jan. 2009) [22]where consumers were asked 'How does the quality of green products compare with that of conventional alternatives?' As can be seen in Figure 2 the results of this question clearly shows that, across five major economies, more than 35% of customers found there to be better quality whereas only between 4 and 7% deemed a negative response regarding the quality of green products.

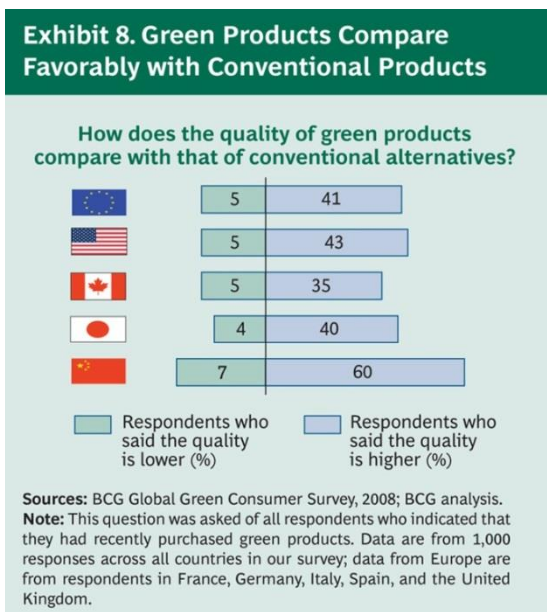


Figure 2 BCG Global Green Consumer Survey 2008 [22]

Although this is encouraging news for those companies that have engaged on the roadmap to a greener footprint and a measure of the work that government agencies have achieved in the last few decades, the drive to purchase green across the entire spectrum of products is not evident for all product types. For example when a consumer purchases an item of clothing versus a food item or purchases a holiday versus a piece of electronic equipment does that consumer apply the same level of interrogation when identifying a green provider versus a non-green provider? Probably not and there is evidence to show that this is the case in Figure 3 and 4 below.

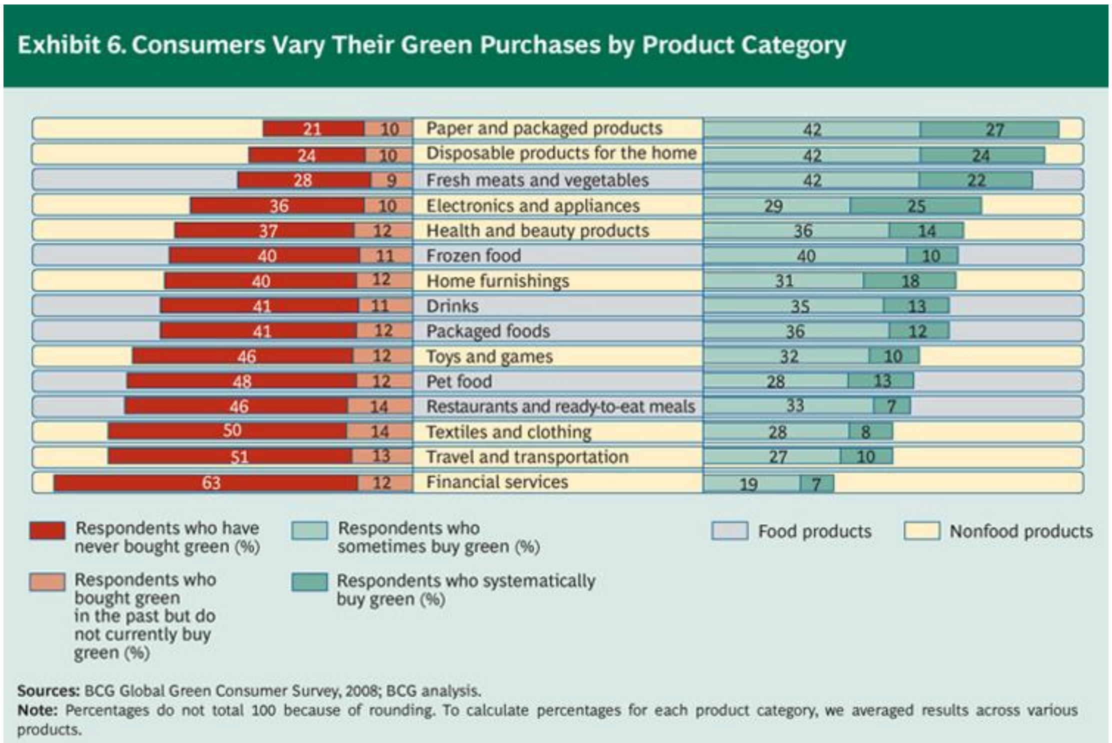


Figure 3 Consumers Green Purchases by Category [22]

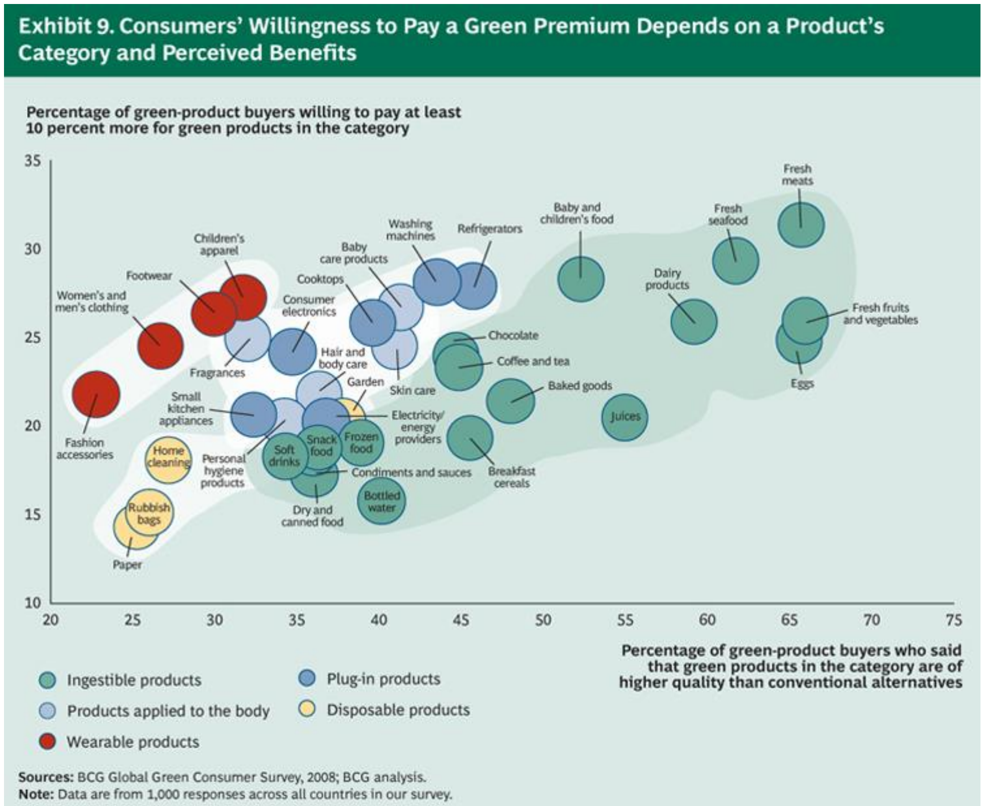


Figure 4 Willingness to pay a green premium [22]

The BCG analysis looked at the percentage of people who bought green items and assigned them to one of four categories based on their response:

1. Respondents who have never bought green.
2. Respondents who bought green in the past but do not currently buy green.
3. Respondents who sometimes buy green.
4. Respondents who systematically buy green.

In product categories such as paper and packaged products, disposable products for the home and fresh meat and vegetables we see a high level of '*sometimes buy green*' and '*systematically buy green*'. However, when it comes to product categories like clothes, travel and financial services consumers tend to ignore this aspect as there are high levels of '*never bought green*' and '*bought green in the past but do not currently buy green*'. Is this because there is very little communication about the green credentials of a bank or airline? Is it because consumers don't care? Or is it because the efforts in reform by government bodies have been predominantly in the area of Manufacturing? All of these hypotheses perhaps warrant testing, however, the perception of what makes something green varies quite differently when compared and contrasted across the world as illustrated by Figure 5 below:

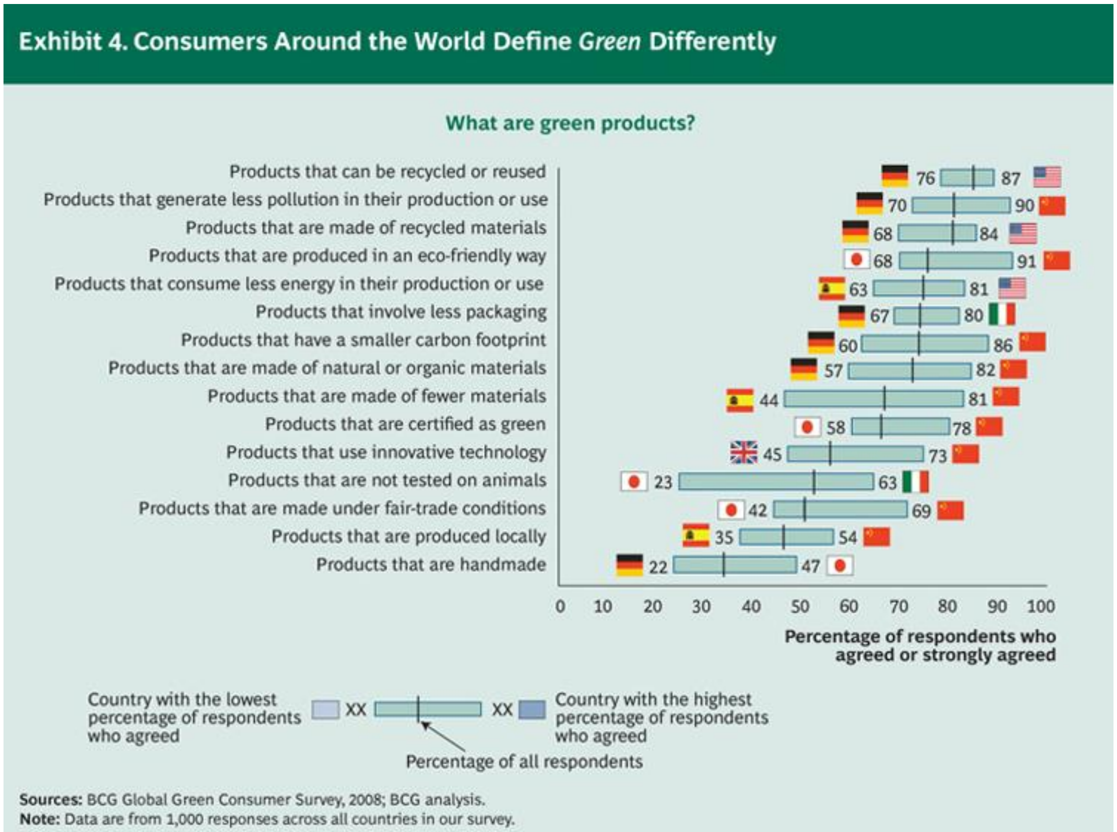


Figure 5 Consumers around the world define 'Green' differently [22]

As can be seen from the graphical interpretation of the analysis in Figure 5, taking the five major economies once again, the most widely recognised attribute of ‘green’ is:

1. Products that can be recycled or reused.

Followed closely by:

2. Products that generate less pollution in their production or use.
3. Products that are made of recycled materials.
4. Products that are produced in an eco-friendly way.

Consideration of this analysis provides every manufacturer or service provider with a 'blueprint' of what is required if they want to develop a green offering. However, such a development needs to be managed within a defined structure to ensure a holistic approach is taken. The Four P's (see Figure 6 below) is one of those structures and identifies the key areas to focus on such as Planning, Promotion, Products and lastly Processes which is specifically concerned with '*Reducing waste in operations*' and encouraging others (suppliers) to operate in a green way. It is in this area that the area of reusable article minimization can be primarily viewed as a key contributor. A manufacturer that has a methodology whereby they can optimise the quantity of reusable articles required (such as pallets, cylinders, trolleys, calibration kits) can in turn reduce the waste in their operations. This is the area where this research is focused; the. optimisation of the safety stocks of reusable articles and can be used to drive these key deliverables.

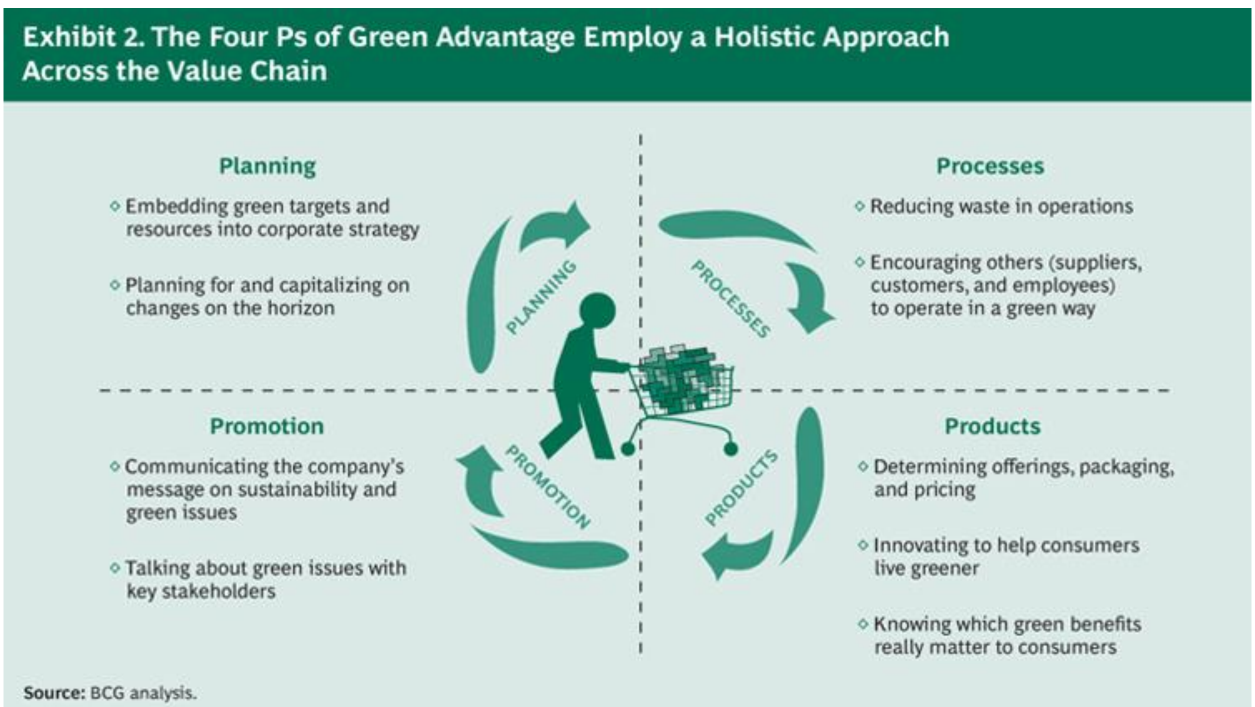


Figure 6 The 4 P's of Green Advantage [22]

2.3 What are Reusable Articles

The term Reusable Article was first proposed by Carrasco-Gallego et al. [2]; the aim of such a proposition was "*To define the reusable articles term and to build a typology for them, identifying similarities and differences between the different categories*" [2]. The combination of these classes allowed for the proliferation and transference of results obtained for one type of RA to the other types. This is of extreme benefit when one looks at the uneven spread of academic research completed across the different categories to date.

According to [1] an RA "*refers to products that are used multiple times by different users*"; by its definition alone an RA can be thought of as a product whose use is short when compared to the entire lifecycle of the product itself. Given that this product will be used by multiple *different users* the expectation is that the use of such an article does not deteriorate the product beyond a state where a simple short reconditioning activity cannot bring it back to a reusable state and make it unrecognizable from a brand new equivalent product.

2.3.1 The Reusable Article Types

The typology developed by [1] identifies 3 categories of RA.

1. Returnable Transportation Items (RTI)
2. Returnable Packaging Materials (RPM)
3. Reusable Products (RP)

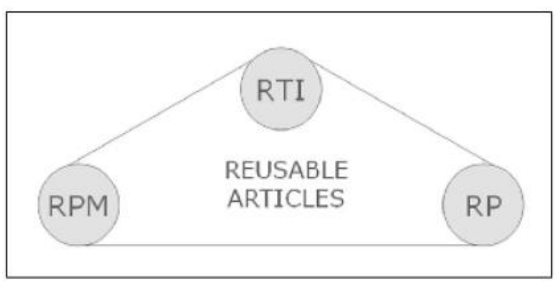


Figure 7: Reusable Articles (RA): RTI, RPM and RP [2]

In order to fully understand what an RA is, it is useful to demonstrate some simple examples of items that fall into these relevant categories. Returnable Transportation Items (RTI) which can be described as "*secondary and tertiary packaging materials which are used for assembling goods in material handling and transportation in the supply chain and then returned for further usage*" [2] can include pallets, railcars, crates, and totes. Looking at these examples it is clear why the terms tertiary and secondary are used as these items don't come into direct contact with the product that is consumed by the customer at the end of the line.

Reusable Packaging Materials (RPM) refers to packaging that is in direct contact with the product such as glass bottles, gas cylinders, and beer kegs, for example. this packaging can be referred to as primary packaging.

Lastly we have reusable products (RP) which as the term states are products that are reused multiple times and, to be clear, by multiple different users; examples of such products include wheelchairs, surgical equipment, library books, rental videos, and service tools. It is in this category that the specific articles investigated in this research fall. However, given the similar logistical characteristics across the entire RA topology it is possible to derive learnings from the other groups also which was the intention of Carrasco-Gallego et al. [2] in the first instance.

2.4 Problems with the management of RA's

The main function for inventory management of any item in a supply chain is to ensure that the organisation has enough on-hand to meet demand allowing for the inherent variability in their system but not too much as it ties up capital in stock and warehouse costs that could be used for investment in other parts of the business. RA's are no different from this perspective, however, there are additional complexities in a closed loop process. For example, the fact that the efficient and effective management of reusable articles is heavily reliant on return rates; how quickly reusable stock returns to stockpoint and secondly the quality/state in which they are returned both of which are very difficult to manage due to the variation in behavioural standards of the customers of the RA.

Through the in-depth research that Carrasco-Gallego et al. [2] has carried out they have identified five main issues when it comes to managing a closed loop supply chain.

1. Defining the Fleet size dimension.
    - This is a problem for reusable articles from a customer satisfaction perspective and tied up capital. If the fleet size is not sufficiently large fleet size the RA process will not able to meet demand, resulting in unhappy customers and lost business. If the fleet size is too big it means that the RA process is unnecessarily tying up capital in stock which could be used elsewhere.

2. Control and prevent Fleet shrinkage.
    - Fleet shrinkage is a phenomenon that occurs when the fleet reduces in size over a period of time. This can occur due to three main reasons:
        i. Quality – Irreparably damaged.
        ii. Structural – Stolen or resold.
        iii. Incidental – Lost by a 3^{rd} party.
3. Define purchase policies for new articles.
    - This is an issue when trying to understand at what point in time does a reusable article go from '*In Use*' to '*Lost*' and so trigger a new purchase.
4. Plan and control reconditioning activities.
    - When planning for the correct/appropriate fleet size there is a need to understand how the reconditioning portion of the process is being planned and managed.
    - This aspect feeds directly into the fleet sizing model and so an understanding of the cycle times involved in reconditioning need to be well understood.
5. Balance Inventory between depots.
    - This is an issue when RA's don't need to return to the original depot that released them. In such a scenario there will be a need to ensure that the balance of load across the supply chain is appropriate.

The research presented in this thesis will focus on '*Defining the Fleet size dimension*' as it is the most relevant problem to the sponsoring organisation who currently lack the ability to analytically define appropriate fleet sizes for RAs and rely heavily on tacit knowledge of the personnel assigned to this role.

2.4.1 Defining the Fleet size dimension

Defining the fleet size dimension is vitally important when trying to ensure a functioning, well-oiled operation; it is very easy to 'sandbag' and invest a significant amount of capital in order to prevent a lines down situation. However, as stated before this can result in tying up capital in stock and incurring holding costs. The difficulty when addressing the fleet sizing problem is the variability within a system;[2] suggests that the fleet sizing question is a 'function of two variables, demand and cycle time'. Given that these variables are stochastic in nature it has been suggested by [2] that a way to combat this is through the addition of safety stock factors. This is a blunt tool to use when in fact the use of some elegant advanced analytic tools could allow an RA manager to determine appropriate levels based on the characteristics of the variation inherent in demand and cycle time. At the time of writing [2] did note the difficulty in tracking the RA's and in turn gathering and analysing data about cycle time and so this may be the reason why the 'Safety factor' angle was taken as a preferred option. In the period since publication of their article tracking technologies such as RFID has become more affordable, reliable and robust which opens the way for advanced analytics.

2.5 Methodologies used to calculate Fleet Size

The methodologies to calculate fleet size have largely been dictated over the years by certain motivations and technology limitations. When studying the literature around fleet size calculation it can be surprising, at first, the number of researchers that are motivated to apply those methodologies that sacrifice ability to apply real world criteria in exchange for analytical models such as queuing theory, linear programming and optimisation techniques which drive gross assumptions and limits the application to real world settings. For example, Ingals et al. [5] identified problems that had to be reduced to problems that were '*simple, usually single product, single stage, just to make the problem tractable*'. Other examples of analytical work include Roy et al [7] who modelled fleet size using a server queuing construct. There is also a body of work in the Automated Guided Vehicle (AGV) research literature that aims to determine fleet size through analytical models such, Min et al [8], Hung et al [9] and Rajotia et al [10]. Turnquist et al [11] also aimed to develop an analytical model for fleet size determination that can be used across various reusable shipping containers and material handling equipment. In addition to these analytical models there are environments where rules of thumb or very simplistic deterministic formulae are used to identify fleet size estimation such as Bryson [12] who describes that the quantity of kegs required for every tap in a retail establishment is 7 or Carrasco-Gallego et al. [13] who develops formula that accounts for average demand (D) during time t, average number of times (T) the fleet item is used during time t and adds on a safety factor to account for variability in demand (Sd) and cycle time (Sct) (see Equation 1)

$$N = \frac{\boldsymbol{D}}{\boldsymbol{T}}(\mathbf{1} + \boldsymbol{Sd})(\mathbf{1} + \boldsymbol{Sct})$$

Equation 1

The use of such methodical approaches is 'surprising' as the problems that are being dealt with are not small by any means from a capital investment perspective. The reusable articles that have been reviewed as part of this research have shown to cost millions in investment, such as the keg example above who use a rule of thumb as their guide could with an average distribution network require an investment of $500,000. Other examples include the analysis completed by Koenigsberg [6] who used queuing models to determine the performance of a fleet of liquid natural gas vessels that in 1974 cost $90 to $120 million each. Carrasco-Gallego et al. [2] have through their research identified further examples of large investment, such as a multinational chemical company who invested €2 million in one line of gas cylinders, a petrochemical company who invested €600 million in LPG cylinders, an OEM (Original Equipment Manufacturer) whose stocks levels of spare parts/service tools whose number could not be exactly quoted but runs into the millions and lastly Flora Holland who have invested in a fleet of carts worth an estimated €30 million. In industries such as food and drink or oil refining the unit cost of an individual reusable article (for example Beer Keg =$100, LPG cylinder =€20, Flora cart =€500) is not large, resulting in an impression across the organisation that management of RAs is not an important issue. However, when these costs are considered collectively as illustrated by the above cases the true importance of RA fleet management is exposed.

This poses the question then as to why it is an issue for researchers and industrial practitioners to invest RA fleet management strategies and policies in particular the fleet sizing problem, in a more expensive model such as discrete event simulation. Especially when the return on investment is greater and the risk of not getting the fleet size correct even greater again regarding losing customers through stock outs or an inability to invest in marketing or human resources because of capital being tied up. Through the research I have completed speed of turnaround can be an issue; advanced techniques such as simulation can be relatively data heavy leading to long model development, execution and analysis times. For example in the AGV field researchers have quoted the complex nature of applying simulation studies to the AGV sector and stated them as being a "*time-consuming process*" [9]. In addition to the time taken to develop such a model let's look at the problems being analysed, is there a reason for wanting to develop a simpler analytical model for future use? Firstly looking at these problems from a frequency perspective they are not likely to change on a daily basis. Fleet size calculations for liquid natural gas vessels, gas cylinders, carts etc. are not decisions made on a weekly basis they are in fact predominantly strategic decisions possibly requiring a yearly review at most, hence, the ability to be able to analyse these problems quickly using simplistic solutions does not appear to have a huge advantage. However, given the perception of how complex and time consuming discrete event simulation modelling projects are to undertake, even a yearly review may force people down the analytical route; for example Byrne et al. [14] states that simulation models are often created with the intention of being "*one off projects that are not maintained beyond the initial analysis*". This is an opinion held by many and dates back to the early 1970's when Koenigsberg [6] commented on how the simulation structure was '*complex*' and '*costly*'. As can be seen from more recent publications such as Min et al [8] and Hung et al [9] simulation modelling is still seen as being reported as time consuming and so analytical models have been preferred in these situations. There is no doubt that simulation is indeed a time consuming process given the data heavy environment in which it works, however, it must be argued that given the nature of the level of investment involved in the majority of these projects that the risk to take a less comprehensive approach from the start may not be wise if steps to validate the analytical output with a simulation model afterwards are not taken.

This reflection, therefore, possess the central hypotheses for this research in this thesis that the ideal approach methodological approach to investigating and resolving industrial scale RA fleet sizing problems is to:

1. Spend the time to develop a discrete event simulation which will act as your reference point.
2. Develop an equivalent analytical model that can adequately and robustly replicate the answers from the simulation output.

Why is it worth defending the position of an advanced analytical technique such as discrete event simulation? Is it really worth the time, cost and effort to invest in such a method? The literature read as part of this research would suggest so; even those researchers that are promoting analytical methods through their research are trying to compare and imitate the output of an equivalent simulation model; as the saying goes '*Imitation is the sincerest form of flattery*'. In 1974, Koenigsberg et al [6] used analytic cyclic queuing models to determine performance measures for a fleet of liquid natural gas vessels and, importantly, the motivation for this work was to "*reduce the need for costly simulation in the evaluation of fleet performance*" such as those which had been used and documented four years earlier by Kaplan et al. [23]. Kaplan's work involved taking into account variables such as weather, maintenance schedules, load and unload storage availability etc. items that would now appear as the norm but at the time probably seemed like an expensive exercise. Throughout the Koenigsberg paper, the performance measure for evaluation of efficiency and effectiveness of the proposed analytical methodology is by comparison with the results from Kaplan's simulation study. Therefore, despite the motivations of Koenigsberg et al. to provide an alternative analytical modelling approach, it is clear that they placed value, merit and trust in a simulation model. Further examples from Min et al. [8] Hung et al. [9] and Rajotia et al. [10] show the practice of using simulation model output as the basis for measuring the performance of their analytical models. Indeed, as highlighted above, a route for many researchers in the initial stages is to build/reference a simulation model of the actual problem and then replicate the output utilising an analytical technique.

So are there any drawbacks to the analytical methodologies being developed versus a purely discrete event simulation modelling approach? The literature on Linear Programming offers a starting point to answer this question. Linear programming is the most commonly compared analytical methodology optimisation. Ingalls [5] provides an interesting view stating that "*the plan that an optimization gives you may be a good one, but it is wrong*". The reason for making such a statement is based on the fact that optimisation is inherently poor when operating within a stochastic environment. The optimization of a problem is based off of assumptions that are true at one point in time, however, once the system moves away from that point in time the assumptions have already changed, e.g. demand has changed, cost of material has changed, how the material is being delivered will have changed, in essence changing the results of the optimal solution. As outlined by Kochenberger et al. [15] "*optimization by itself provides an excellent method to select the best element in terms of some system performance criteria, from some set of available alternatives, in the absence of uncertainty*". However, such an environment does not exist in the '*real world*' as outlined by Dan Gilmore [16] of Supply Chain Digest who points out the fact that for optimization there is a requirement to fix demand over a specific time frame; in the real world this is not how demand performs and although an additional analysis with a new demand can be run "*optimization in general is not good at handling highly variable demand or input systems*".

On the other hand Simulation excels in complex, highly variable environments where the required output from the model is a robust evaluation. Ingalls et al. [5] outlines a number of situations where simulation is the better tool when compared against optimization; such as occasions where there is a need to evaluate rule based systems, he states that these types of problems are "*too complicated to optimize*", where as "*Simulation is an excellent tool to evaluate the effectiveness of a given rule*". They also states that variance is "*the primary reason for using simulation over optimization"*. Within the simulation environment any process can be characterised with an appropriate fitted distribution to describe the variance in the system where as "*optimization will not capture supply chain dynamics*" where variance is evident. Lastly Ingalls et al. [5] highlights that management when assessing problems don't want the most optimal solution they want the most robust solution; the solution that can deal with all the variances in a given system. They state that for management an "*optimal supply chain is robust*" and "*only through simulation would you be able to identify the most robust solution*". Other researchers have also outlined the value of utilising simulation in a supply chain environment such as Wang et al. [17] who comments on how the use of simulation enables "*significant improvements in lowering inventory costs*" and Chang et al. [18] who highlight how the ability to be able to plan and test scenarios in the supply chain before implementing a project is now becoming a necessity for supply chain management. However, as outlined by [15] simulation is excellent at building a "*representation of a complex system in order to better understand the uncertainty in the systems* *performance*" but when it comes to solution analysis, even in a relatively simple model, the ability to be able to test all permutations is almost impossible.

What if we were to take the best of both methodologies? This is known as Optimised Simulation and as demonstrated by Chang et al [19] and Kochenberger et al [15] is superior when compared against Optimisation and Simulation individually. An optimised simulation model is made up of two distinct pieces; a Simulation Model and an Optimization model. The analyst models the logic of the system as s/he would normally do through a simulation exercise taking account of input parameters that will be available to act as levers when it comes to building the optimisation model itself. As stated before, when a system is complex in nature a trial and error approach in order to determine the best solution rarely yields a successful result and so this is why the implementation of an optimisation algorithm is required for guidance. Kochenberger et al. [15] treats the simulation block as a '*black box*' which in theory it is as all the analyst is interested in is the "*evaluation of performance from the simulation*" (see Figure 8).

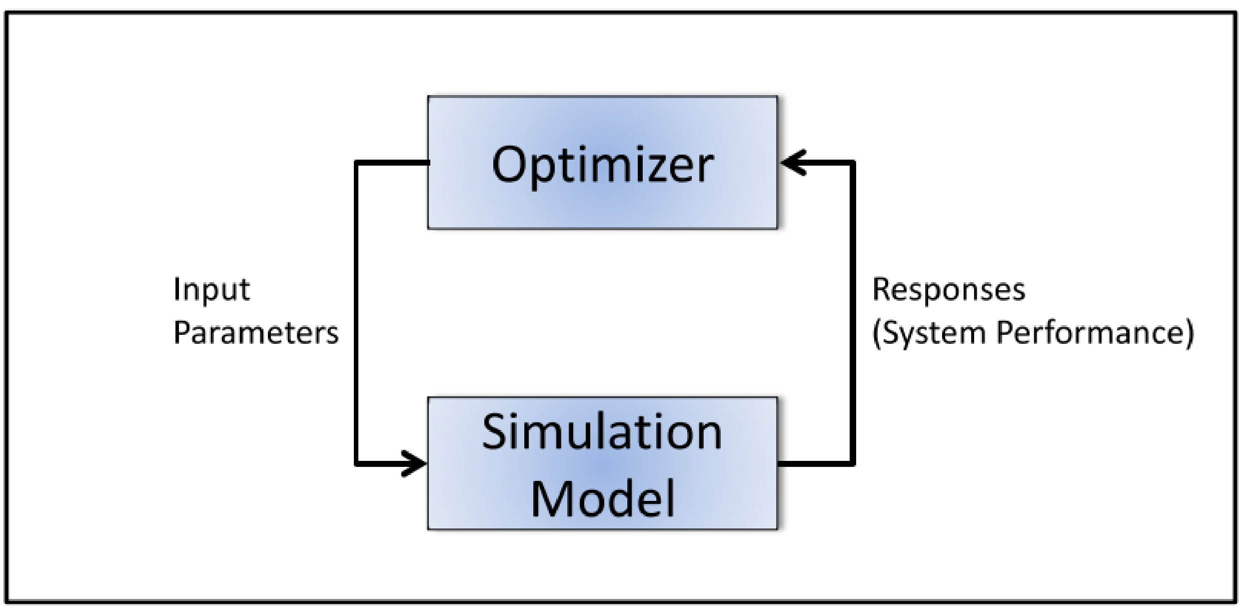


Figure 8: Black box approach to Simulation as devised by Kochenberger

The approach taken by this setup is that the optimiser takes a set of input variables that are bounded by minimum and maximum possibilities to insert into the simulation model. The simulation model is then run with these input parameters after which the results of the simulation model are evaluated. The results of such an evaluation are recorded after which the next scenario of input parameters is inserted and evaluated. The model continues to loop through this cycle until a set of criteria are met regarding maximum run time or convergence of results at a certain percentage level.

The application of Simulation and Optimization methodologies allows for the development of a powerful framework that utilises the strength in both; from optimisation the analyst has a technique that can select the best answer available whilst building the logic of the problem in simulation allows the analyst to take account of any variability that may exist in the system. In a world where variability exists everywhere and there's a necessity to identify the best solution as quickly as possible optimised simulation is quickly becoming the tool of choice.

One of the main motivations for developing analytical models is to provide a solution that can replicate that of the simulation model and reduce the complexity and data requirements generated by such a development. Following in the footsteps of Koenigsberg it is now necessary to identify an efficient method to replicate the output from an Optimised Simulation approach. If successful it would greatly reduce complexity, data and run time in order to address the hypothesis postulated earlier that industrial scale RA fleet sizing problems can be addressed with a level of accuracy approaching that of simulation modelling and the effort and timeliness of analytical modelling through a hybrid simulation, analytical modelling approach.

CHAPTER 3: PROBLEM DEFINITION AND METHODOLOGY DEVELOPMENT

3.1 Introduction and Section Layout

Chapter 3 is about setting the scene for the reader, highlighting the issues, looking at the data gathered and describing the development of the methodology that will attempt to add to the knowledge around fleet sizing in a reusable article environment. Section 3.2 will provide an overall view of the Calibration Kit, its uses and current management structures. Section 3.3 will detail the systems that are in place to monitor calibration kit usage and the algorithms which trigger actions in the current process flow. Section 3.4 will describe the research methodology that was implemented and the reasons for incorporating this method. Section 3.5 will detail how the data was gathered and the processes involved in ensuring a rounded non-biased investigation. Lastly section 3.6 will provide a detailed description of the methodology outlining its inputs, processes and outputs, how it was developed and how it should be used.

3.2 What are Calibration kits?

To understand the problem the reader must first have a good understanding of the Calibration kit process which includes a description of what Calibration kits are, the management structures within which they live, a detailed description of the cradle to grave process. So what are Calibration kits? At their most basic level they are used to monitor specific parameters within the production facility that enable the production team to have better confidence in the quality of the process. Calibration kits are sourced from multiple vendors globally and for this reason can sometimes vary in quality; hence all kits are inspected prior to use.

Calibration kits, as can be seen from Figure 9, enter the process via a route structure; this means that calibration kits get locked into routes that are module and test specific; this is primarily driven by a cost focus, i.e. it places the emphasis of purchasing the calibration kit on the module itself as a means to drive responsibility for costs incurred for calibration kit usage. As will be demonstrated later, this system creates an environment that is counter-productive to ensuring an efficient calibration kit process.

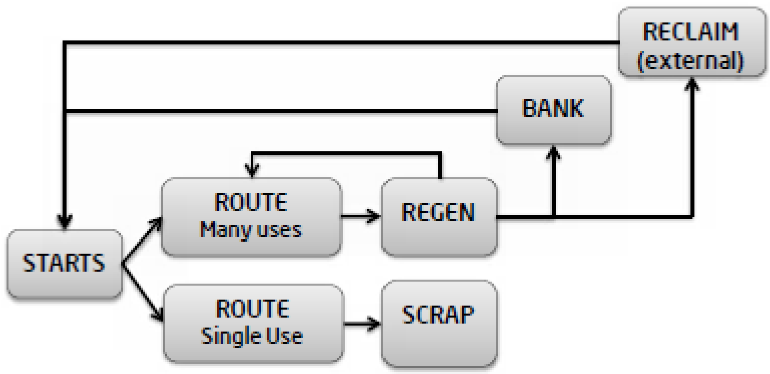


Figure 9 Typical Calibration kit Route Structure

A route can be described as a particular set of operations that the calibration kit must pass through in order to ensure its readiness. Each route has been designed in such a way to account for where the calibration kit has been and where it's going. For example some routes have pre-processing steps (5%) such as an extra cleaning step that prepares it for use. Once the calibration kit has come through the pre-processing step or straight out of starts, if no pre-processing step exists, it will enter a CKR state (Calibration Kit Ready). The calibration kit will stay in this state until a module requires it; once the module calls the kit it will move into a CKI state (Calibration Kit In-use).

The Calibration kit will stay in the CKI state until the kit is processed out of the module area. Ideally this should happen once the kit has been used. However as will be shown later on, this does not happen in many cases and the knock on effects for calibration kit management can be quite serious. The purpose of the kits and '*health*' of the area will determine the consumption rate of kits; this is susceptible to large variation and, hence, adds to the management complexity of such an RA.

Once processed out of the CKI operation the kit will be either scrapped as it may be a one-time use or it may be sent to Clean where it will be cleaned and brought back to a reusable state before entering the CKR state again; 80% of routes fall into the latter option.

Table 1 Example of route with operations

Order	Operation	Description
1	9050	Start
2	6770	Clean Step 1
3	6790	Clean Step 2
4	8880	CKR
5	8890	CKI

As can be seen from Figure 9 those Calibration kits that can be re-used follow a cyclical pattern where after being used they can go to:

1. 'Clean' for cleaning and returning back into the route they came from for module re-use.
2. 'Bank' where they are relieved of their route constraint but must hold within their contamination group. This relief of route constraint means that any other module that is allowed to pull from the calibration kit's designated contamination level can do so.
3. 'Reclaim' where kits are sent off site for cleaning; these kits are not tied to any contamination level and can be assigned to any route once brought back in house.

There are trigger points regarding usage that will determine which of the three routes the calibration kit will take.

3.2.1 The Clean Process

The cleaning aspect of this process is a key characteristic when it comes to the Calibration kit fitting within the typology of a 'Reusable Article' grouping. The expectation is that once through clean, which is typically short and relatively inexpensive; the article is fit for use for the next customer. Given the high volume of calibration kit's in the organisation sponsoring this research, management have identified the economic benefits of having the clean process running in house versus sending to outside vendors. For the purposes of this study this also negates an issue commonly seen in a Closed Loop Supply Chain (CLSC) studies where parts of the process are unobservable which can increase management complexity.

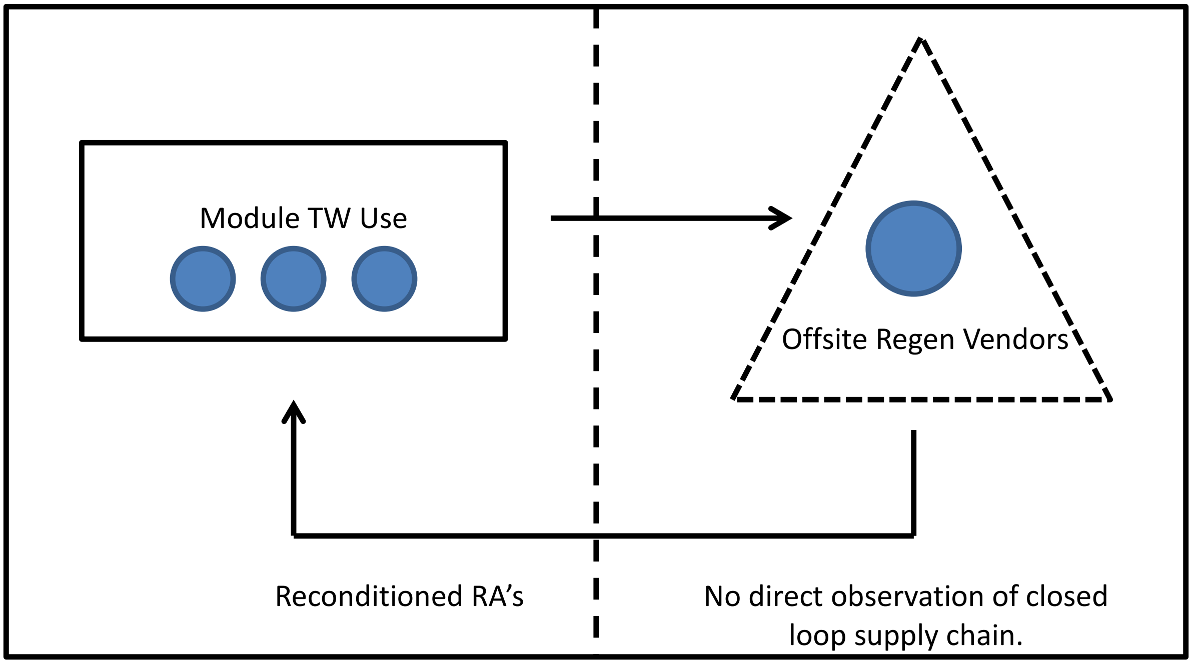


Figure 10 CLSC with unobservable clean

The clean process is specific to each route; the options available to a calibration kit when it comes to clean are numerous and are derived by the engineering team. These options are made available through the dedication of machines to the clean process within the facility; there are some exceptions where calibration kits will compete for machine time with production items, however, these are in the minority. The clean process can be made up of any combination of these offerings; these combinations have been carefully designed to ensure the calibration kit once through the operations is fit for use.

Calibration kits circulate this clean process for a prescribed period of time after which the calibration kit will be moved onto another route, into the bank or offsite for reclaim. The number of times a calibration kit can traverse a particular route is very much route and test dependent and varies throughout.

3.2.2 The Bank Process

Calibration kits that enter the bank may need to be cleaned in Clean; the Calibration kits that don't require this step go straight to the bank at the end of the route flow assuming all other criteria regarding usage etc. is met. The bank works on a FIFO rule in order to avoid a scenario where the bank contains stagnant inventory. Once the Calibration kits enter the bank they become the property of the Calibration Kit Group; this is the group responsible for starting kits into the facility; all other Calibration kits belong to the module teams. A typical Bank process is illustrated in Figure 11.

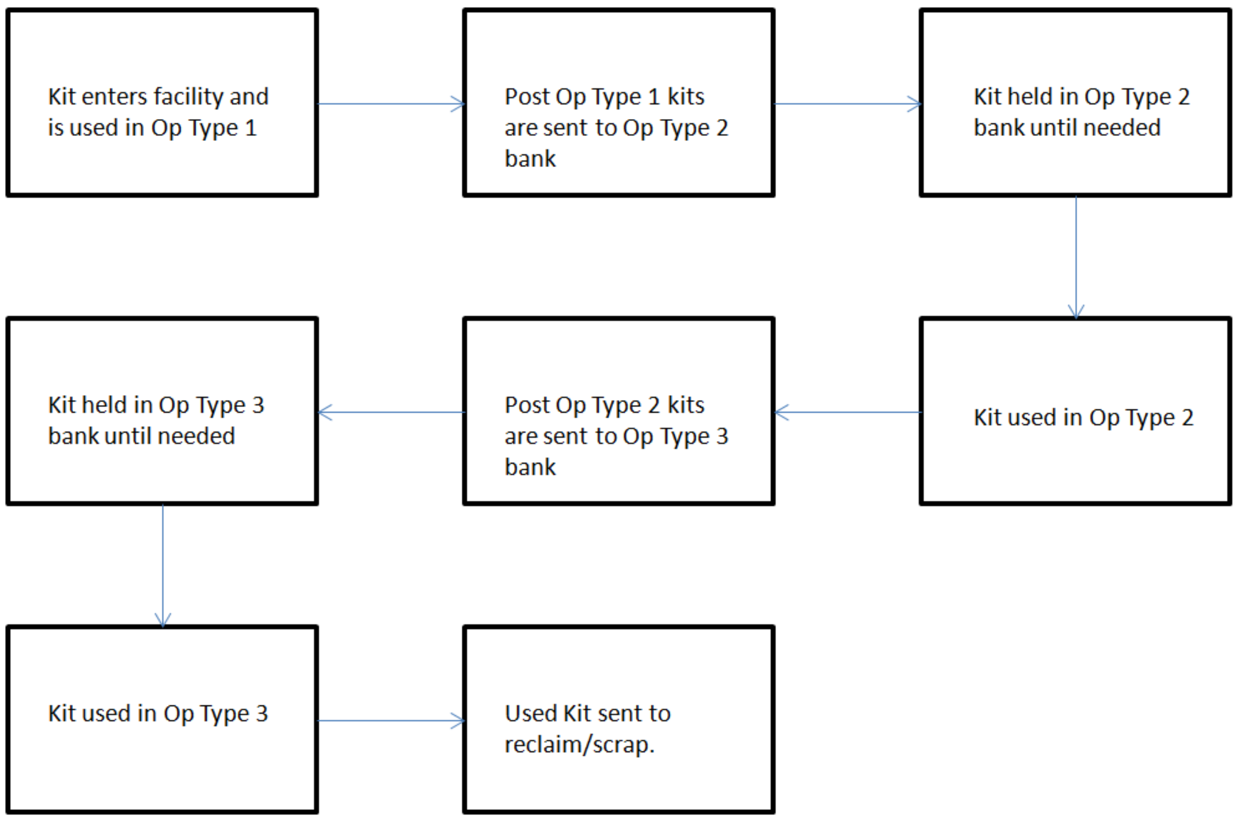


Figure 11 Typical Bank Process

The bank is broken up into five different contamination levels and depending on where the Calibration kit has arrived from will determine what level it enters; this is to ensure that once the Calibration kits are released from these banks by the Calibration kit Group that no cross contamination occurs. Bank kits are regarded as a great opportunity for saving the company money; although they are not regarded as a high standard kit there is more value seen in keeping the Calibration kits and reusing them for a limited purpose than selling them to an outside company. No cost is generally associated with having kits in a bank, however, as will be shown later, this is a misconception given the storage and cleaning costs required when using a Calibration kit of any grade.

3.2.3 The Reclaim Process

As seen in the previous section, kits cycle through a bank process until they reach a point where they are sent to a third party vendor for reclaim. This process results in the removal of any contaminants. Before sending the kits back to the customer they are cleaned and checked for particle counts on the surface to ensure they match customer specifications. The kit that returns post this process has the same functionality as that of a new Calibration kit.

3.2.4 Roles and Responsibilities

This process has to be managed by various personnel such as the MT Calibration kit coordinator, MT Calibration kit coordinator's supervisor and shift manager. To aid the running of the Calibration kit process a web based system has been put in place called the '*Calibration Kit Decision Engine'* (CKDE). This system will be explained in more detail later on when the current methodology for determining appropriate calibration kit numbers is described; however in this section it's important to understand the level of human activity and cooperation currently required in ensuring the calibration kit process works as it should. Appendix 9 is an extract detailing roles and responsibilities from the calibration kit training manual.

As can be seen from the appendix there is a lot of focus placed on ensuring the Calibration kit process is given full attention all the way from MT to Shift Manager; as part of this research how such a process works in reality and how it can be improved will be investigated.

3.3 Calibration Kit Management Systems

There are many systems regarding the controlled movement of Calibration kits, however, the two that are being addressed as part of this research is the system that is used to prioritise and drive the Calibration kit process through Clean; The Calibration Kit Decision Engine (CKDE) and the KIT report (Kit Inventory Tracking) which is used for tracking usable inventory.

3.3.1 Calibration Kit Decision Engine

The CKDE was introduced as a means to provide a forward looking system that incorporated consumption rates and replenish times. A key differentiator for the CKDE versus historical systems is its incorporation and monitoring of a dynamic consumption pattern for each route; this is achieved via measuring 4 day and 30 day rolling averages of Calibration kit consumption through the CKR operation; the highest of which is used in the following formula to calculate a Days of Inventory number (DOI)

$$\boldsymbol{DOI} = \frac{\boldsymbol{Good\ inventory}}{\boldsymbol{usage\ rate}} - \boldsymbol{time\ to\ replenish}$$

Equation 2

The $Good\ inventory$ in the formula can be described as kits that are located at CKR plus CKI.

- Usage Rate is the highest average consumption rate between the 4 and 30 day rolling period.
- Time to replenish represents the time it takes to get Calibration kits through the clean process.

In the example below there are 100 Calibration kits between CKR and CKI; the worst case usage rate is 10 kits per day; and the time it currently takes to get these kits through the clean process is 3 days. The result from this particular calculation is that this route has 7 days of inventory.

Example:

CKR		CKI		Use			Replen			
(75	+	25	/	10	)	-	3	=	7	Days of Inventory

It is this DOI number that is used to prioritise what work should be expedited through the clean process first, e.g. those with the lower days of inventory being run first. This methodology has proven hugely successful and resulted in the standardisation of what was a complex system; reduced the amount of Wait CK downtime; identified areas that were significantly over inventory which could be eliminated thus freeing up storage resources and reduced the level of micro management and human input that was required to keep the system operating.

However, the system can be improved further by addressing certain aspects of the DOI formula. Its success in achieving what has been outlined above is largely down to its simplicity; easy to understand, easy to compute and easily transferrable to any route/technology. What it does sacrifice for this simplicity is the exclusion of variability and visibility of kit status.

Good Inventory is characterised by the addition of CKR and CKI; it's absolutely acceptable to assume that those kits in the CKR state are Good Inventory as they are sitting in an operation post clean/starts and are ready to be used by the module. CKI kits on the other hand are kits that are being used by the Module and the assumption being made by the DOI formula is that these are Good Inventory. In fact these Calibration kits could already be used and simply have not been processed through to clean; a common example of poor Calibration kit management as has been shown through previous investigations within the facility. In the example above there is a relatively low quantity of kits sitting in CKI. However imagine if the Good Inventory categories were reversed with CKR=25 and CKI=75 with 50 of the CKI already used; the formula is not sensitive to such idiosyncrasies.

The next aspect of the DOI formula is the Usage figure; this number is defined as the highest number of a 30 day or 4 day rolling average figure. In the case of the usage figure the company are at least including a short and long term view, however, they are still not capturing the variability around the 4 day and 30 day usage which leaves the calculation susceptible and blind to the actual characteristics surrounding the consumption of the calibration kits. For example, what if a spike in usage occurs due to a 'kit heavy' scheduled preventative maintenance; this will automatically cause the 4 day average to increase dramatically and continue to drive increased focus on this route over an extended period of time resulting in wasted efforts and mismanaged resources.

Lastly the replenish variable which represents the time taken to clean the calibration kit and get it back into the resource pool ready for reuse again uses a static number. As per before this method of determining time to replenish is not sensitive to the variability around a process that contains high levels of variability due to the requirement to sometimes share resources with production and deal with large dumps of kits due to mismanagement of kits in the modules. For example should a process have a highly variable replenishment rate with a 95% confidence interval of between 2 and 6 days on the occasions where the process runs at the higher the facility could realistically go '*lines down*' for a Wait Calibration Kit event or worse again drive the purchase of new kits.

3.3.2 Calibration Kit Monitoring System

The second method currently being used for the management of the calibration kits is a monitoring system that details what operation the kits are in, (e.g. In use, ready, specific clean stage) and their DAO (Days At Operation – see Figure 12). This allows the CK management team to determine and characterise how the modules are managing their CK resources. For example, in one of the reports made available by the CK management team to this study a route was highlighted that had been designated as a priority 1. This route was demanding a lot of resources in order to ensure there was no Wait CK event incurred. However, on closer inspection of the report it was pointed out that the DAO (Days at Operation) figures for a substantial quantity of the kits where very similar (see Figure 12) which highlighted the fact that the kits were used, not moved through the process after their use and when it was evident they were running out they were simply moved through all the kits in one go thus causing a dump into the clean process and a potential for forced purchase of new kits or a Wait CK status.

DAO	Held	TW Hold	Stores	Use Limit
0.3	N		N	1
6.2	N		N	1
0.1	N		N	1
1.3	N		N	1
1.3	N		N	1
1.1	N		N	1
1	N		N	1

Figure 12 Days at Operation screen shot

This report provides the organisation with not only tracking of the kits and their status, but also a measure of how the modules are managing their TW's. At the time of performing this research the report was driving a '*calibration kit bootcamp*' whose main purpose was to educate the modules on how to manage the kits, however, uptake was less than satisfactory and points to possibly the level of priority which is given to a process that obviously needs major attention.

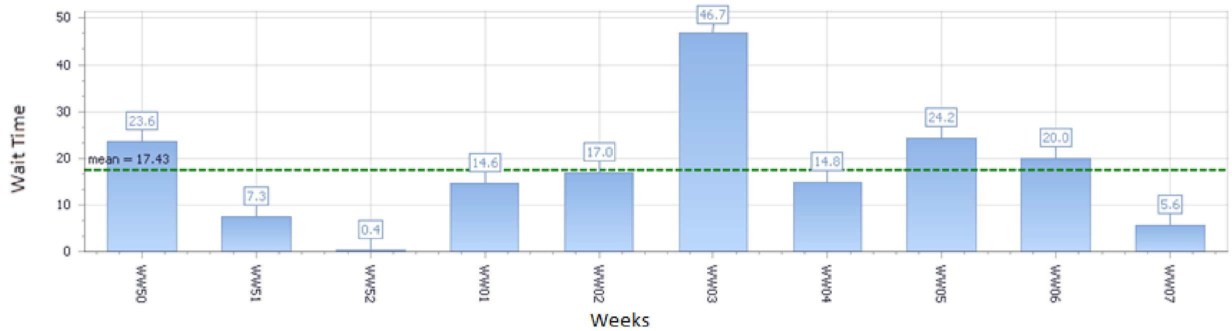


Figure 13 Calibration Kit wait hours monitoring by week

3.4 Research Methodology

The goal for the output of this research was to develop a methodology that would address all aspects of the fleet sizing problems for reusable articles and be generalizable across different industry sectors. To view the problem holistically it was necessary to consider it quantitatively and qualitatively; hence a mixed method approach was adopted in this research.

The mixed method selected was '*triangulation*' with a specific flavour known as '*between methods*'; a term that was coined by Denzen as highlighted by Jick [20]. The idea is that through this methodology the researcher will use two or more distinct methods that the researcher hopes are congruent and yield comparable results when examining the same dimension of a research problem.

The dimension of this research problem was the current procedures and processes being used when defining a fleet size dimension for a reusable article and clearly understanding the problems being experienced. From a qualitative perspective it was decided to carry out surveys/interviews with a cohort of people who had daily interactions, use and intimate knowledge of the journey with which the process had evolved and matured.

Quantitatively, access to the management systems for the calibration kits plus data from the ERP system was provided by the company allowing process mapping to be conducted on how the calibration kits flowed, analysing time stamps and obtaining a general objective understanding of the efficiency of the process. This allowed for cross-validation of what was being learned as part of the survey process and gave confidence that a similar picture was being seen through both lenses.

Lastly in order to test for cross industry generalization the model derived with the sponsor company would be applied to a problem from a medical device company whose raw data was available from a previous project.

3.5 Data Gathering

3.5.1 Qualitative Data Gathering

A key part of this research involved sitting with people who knew the process best. These were people who had been working within the constraints of the current system; people who had strong opinions on what worked and what didn't; people who had actively tried to make the system better by implementing projects that had received worldwide commendation. The objectives for each meeting were simply to:

1. Attain a better understanding of the Calibration kit process.
2. Document issues perceived by those who knew the area best.
3. Use these findings plus the literature review to define a focused problem statement.

As part of this research the problem statement was investigated with seven employees whose combined experience amounted to 114 years. The group was made up of two Calibration kit owners who worked in the Calibration Kit Group and are responsible for ensuring the Calibration kit process runs as smoothly as possible; this ranged from organising the starting of the relevant Calibration kits to monitoring/enforcing module management of Calibration kits. The group also included two clean engineers who are machine owners for the equipment responsible for carrying out the reconditioning of the kits post module usage. The clean engineers are responsible for ensuring the machines are running optimally and are available for processing Calibration kits when they arrive from the module areas. Further, the group consisted of two area managers who were responsible for managing the people working in the clean process and ensuring the area metrics were being met, ensuring that tools were logged into 'Wait Calibration kit' as little as possible and that the availability and cycle time of kits did not in any way effect the running of production. The last member of the group was the organisation's 'Calibration kit expert'; this is not the official title of this employee, however, they represent the greatest body of knowledge regarding the Calibration kit process. This person worked on improvement projects to the Calibration kit process for the last 4-5 years which has culminated in the stripping back and rebuilding of the process itself. These efforts have made significant improvements from a visibility and inventory reduction perspective.

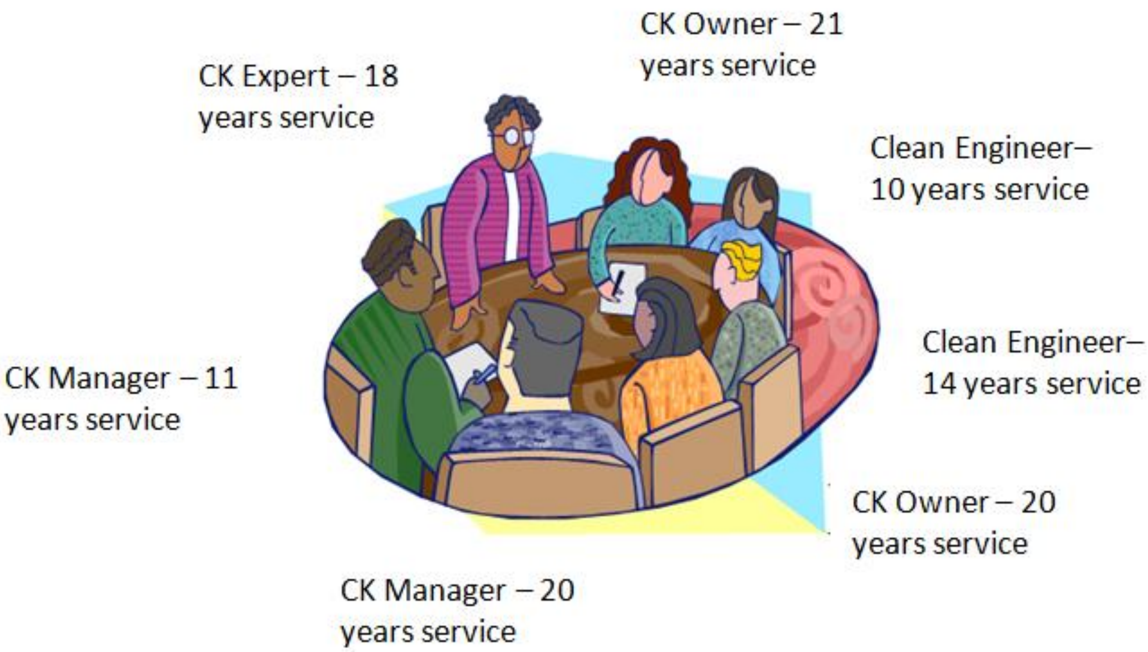


Figure 14. Interviewees, their roles and years of service

For anonymity reasons the interviewees are referred to as I1, I2…..I7 and there was no particular order to the interviewee's schedule. Appendix E is a summary of the feedback from each of the seven interviewees.

Post the interview process it was possible to break the feedback into 2 categories:

1. Problems with current process.
2. Wish list characteristics for new methodology.

In Category 1 the following items were the most evident:

- Calibration kit Mismanagement.
- No feed strategies for different areas.

- Hard coded rules causing increase in inventory.
- Cycle Time not being monitored for entire flow.

Whilst, in Category 2 the following items were the most evident:

- Minimize Calibration kit inventory.
- Incorporation of variability to reflect reality.
- Easily transferrable to other technologies.
- Provide an experimental platform.

3.5.2 Quantitative Data Gathering

The Quantitative data gathered came from multiple sources ranging from the web based front end interfaces where data had to be visually interpreted and extracted for analysis to running SQL query code to pull raw data from the relevant ERP systems. The following subsections will detail the data extracted, the systems they came from and the insight that was gained.

3.5.2.1 Calibration Kit Decision Engine (CKDE) Data

The Calibration kit Decision Engine was introduced as a means to provide a forward looking system that incorporated consumption rates and replenishment times. This web based front end interface provided data about those routes that were being classified as high priority according to their consumption and regeneration characteristics. The CKDE provided the user with a list of routes, their respective on hand quantity and a derived days of inventory number which characterised the routes from an efficiency perspective.

At the time of the research there were approximately 550 routes in the system and so the CKDE was used in this research to ensure the model developed did not include routes that had very little or no activity on them. In addition to route efficiency the CKDE system provided a list of operations that the kits would travel through on their recurrent cycle; this provided a template to develop a matrix that would demonstrate common operations/machines/flows across the multiple different routes. This was important to understand as the CK expert had advised that any methodology being developed should be around the operations versus the routes as this is how machine groups and areas planned their workload.

Lastly, as outlined above the CKDE system provided an up-to-date picture of the current on hand inventory that was contained in each of the routes; this information was key to backing up what was learned in the interviews/surveys. The data showed major over investment in a large quantity of routes where an inflated ‘Days of inventory’ figure was a proxy for such inefficiencies. Using this data it was possible to establish a baseline what the starting point was for inventory levels validated against current understanding and measure the impact a new and improved methodology could bring.

3.5.2.2 Calibration Kit Monitoring System (CKMS)

Within the CKMS an opportunity was provided to see how kits were managed within the different routes by getting a look at the ‘*Days at operation*’ metric which recorded a time stamp on when kits were moved from one operation to another. The quantitative data here provided verification around the dumping of Kits into the clean area as well as cross validation surrounding the verbal accounts from the interviewees about calibration kit mismanagement.

3.5.2.3 ERP System Data

Probably the most important quantitative data that was gathered was that which was extracted from the company’s ERP system. The description of data gathered is detailed in Table 2 and Table 3. The data gathered using the ‘Module usage’ extract allowed for the characterisation and cross validation of how calibration kits were being demanded, used and managed within the different module areas. Given that the data was being recorded at the kit ID level meant that it was possible to track exactly what time each kit was spending in each of the operations. The data gathered using the ‘Clean’ extract allowed for the characterisation of how kits were being cleaned and sent back to the ‘CK Ready’ staging area; again due to the fact the kits were being tracked at an individual ID level it was possible to measure the length of time each individual kit spent going through the clean process.

Table 2 Module Usage Data Gathering

Variable	Description
KIT Number	Unique ID for Calibration Kit
Operation	The operation number that the kit is being moved into
Previous Out Date	This is the time stamp received by the Calibration Kit after being moved out of previous operation.
In Date	This is the time stamp received by the Calibration Kit after being moved into the current operation
Out Date	This is the time stamp received by the Calibration Kit after being moved out of the current operation
Route	This is the route to which the calibration kit has been assigned.
Previous Operation	The previous operation number with which the kit was moved out of.
Operation Description	Details the name of the current operation
Previous Operation Description	Details the name of the previous operation
Old Quantity	The Qty of Test parts within the calibration kit after being moved out of previous operation
New Quantity	The Qty of Test parts within the calibration kit after being moved out of current operation
Operator of Previous Operation	Name of operator who processed kit through previous operation.
Operator of Current Operation	Name of operator who processed kit through current operation

Table 3 Clean Data Gathering

Variable	Description
Kit Number	Unique ID for Calibration Kit
Operation	The clean operation number that the kit is being moved into
Clean	Description of the clean operation grouping
Contamination	This is the contamination level that the Calibration kit is assigned to use based on usage.
Recipe Description	Description of the clean recipe.
Last Entity	The name of the Entity which the calibration kit went through
Route	This is the route to which the calibration kit has been assigned.
Previous Out Date	This is the time stamp received by the Calibration Kit after being moved out of previous operation.
In Date	This is the time stamp received by the Calibration Kit after being moved into the current operation
Out Date	This is the time stamp received by the Calibration Kit after being moved out of the current operation

3.5.2.3.1 Demand Characterization

In Figure 15, on the next page, the demand for the calibration kit is characterised by how often a kit is moved out of the CK Ready staging area (Step 1). For this, characterization kit ID is not important as it only necessary to understand how often the kits within this route are being demanded and to determine the intervals between these demand periods.

3.5.2.3.2 Module Usage Characterization

To characterise how Modules use the kits the time stamps between moving out of step 1 and out of step 3 are analysed. The correct way that kits should be processed is once moved out of step 1 they are automatically moved into 'CK In Use' (step 2) this provides two functions; 1. The calibration kit management group have a visibility of what kits are being used and 2. Tracking how long the kits are being used in the module. However, in reality what is happening is kits are being moved out of step 1, being used by the modules and once finished then processed through steps 2 and 3 instantaneously; this provides a headache for the CK management group as they have little visibility of what kits are being used. As a response, over time, due to this behaviour they have assumed that once kits move out of CK Ready they are 'In Use' even if they haven't been 'moved in'; hence the assumption above. In the analysis conducted for this research the CK ID's are tracked and how long they spend between step 1 and step 3 is monitored; this provides raw data that allows for characterisation of time spent in the module areas.

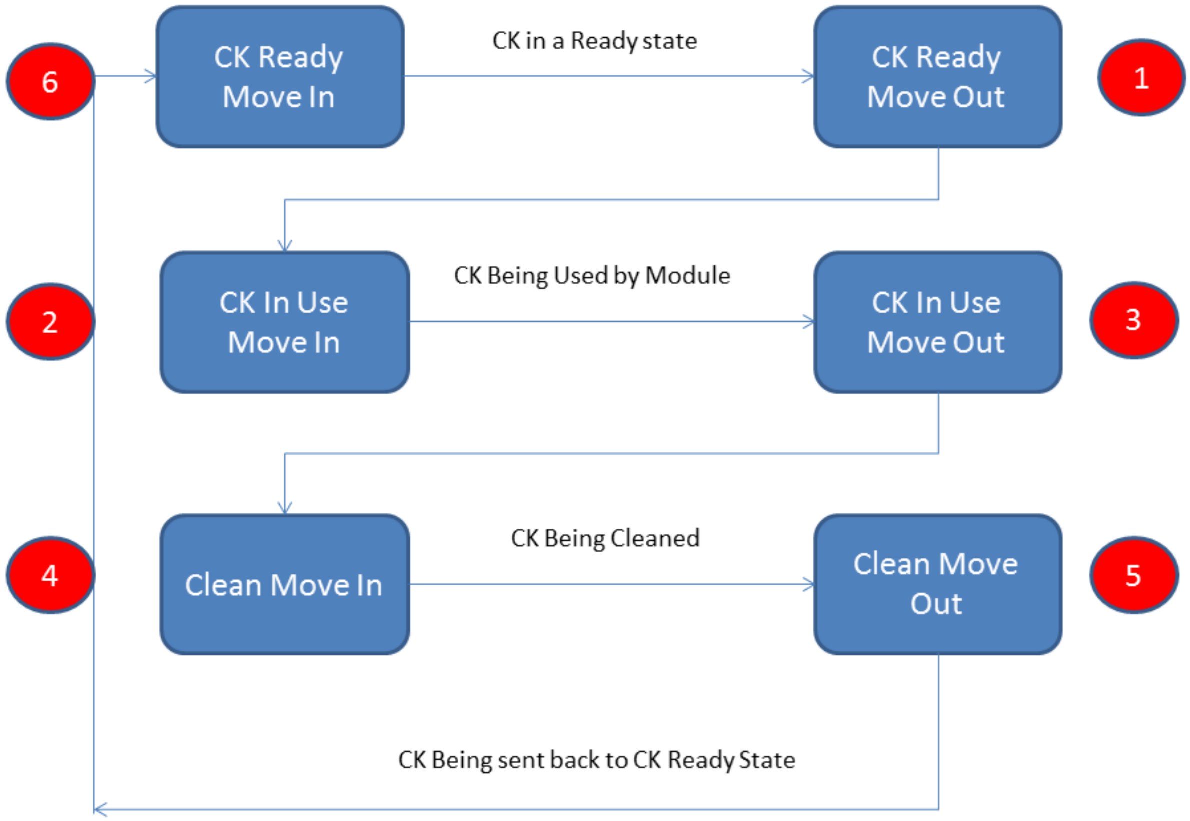


Figure 15 Calibration Kit process flow

3.5.2.3.3 Clean Process Characterization

Once the modules are finished with the kit they move it out of the 'CK in Use' step and into the first operation of the clean process. The clean process can contain from 1-6 operations depending on what route the kit is on. The purpose of the clean process is to bring the kit back to a state that allows the kit to be reused. In Figure 16 above the clean process is characterised by taking the period between the time stamps at "Clean Move In" (4) and "Clean Move Out" (5). Again due to the data being recorded at the kit ID level there is full traceability of the kits and hence accurate determination of the clean process duration.

3.6 Methodology Development

3.6.1 Initial Findings

After reviewing the current process in place through the quantitative analysis and liaising with those people with system knowledge from a qualitative perspective it is evident that the methodology to be developed needs to address a couple of key points.

1. **Minimise calibration kit inventory**; at the time of research the calibration kit quantity had reached levels that were five times greater than the quantity of production items running through the line. It was evident, therefore, that the model needed to be able to incorporate optimisation.
2. **Incorporation of variability to reflect reality;** Up until now the only level of dynamism within the current offering was a short and long term measure of consumption; the platform and methods being used were not suitable for a stochastic environment and so the offering also needed to be able to incorporate the stochastic characteristics of demand and cycle time at a granular level.
3. **Easily transferrable to other technologies and calibration kit tracking systems;** The idea of having a method that was 'generic' or technology agnostic came through very strong when talking to personnel who had been involved in the day to day running of the current systems. The effort up till now was to ensure the current system was simplified so as that it could be used and managed; there was an understanding that a certain percentage of accuracy was lost due to the over simplification. The requirement, therefore, for a new offering is that it needed to be both simple to operate and understand whilst engineering the complexity into the background away from the user.
4. **Provide an experimental platform;** With the current systems there was no capability to test strategic 'what-if' analyses. For example at the time of the research being completed a new plant was being built which was expected to be calibration kit heavy from a usage perspective however there was no platform on which to test the usage against actual number, just deterministic models with high levels of safety stock built in to prevent any downtime which was likely to result in over investment in Calibration kits.

Based on the literature review and the findings regarding the benefits of optimised simulation it was clear that this was the platform of choice on which the methodology should be built.

3.6.2 Model Design

In order to ensure the design met the needs of the 'customer' it was necessary to establish a strong collaborative working relationship with the calibration kit expert. Meetings were held at regular intervals to ensure that the model was on the right track from a development perspective and to secure end user credibility in the final offering delivery.

3.6.2.1 Proof of Concept Design

Learnings from the data gathering exercise were used to develop an initial proof of concept for one of the modules which would form the basis for the first working session with the calibration kit expert on what the model/methodology should look like.

The initial model was a proof of concept to determine positioning from a customer demand perspective rather than a fully developed model capable of addressing all requirements from the data gathering session. The model consisted of the following four parts.

1. Starts and Attribute Setting – The purpose of this section of the model was to set the usage rate of the calibration kits and provide every Route with a specific attribute that would enable manipulation of any kit that went through that route in the rest of the model.
2. Routing and Module Usage – This section of the model assigns the time spent by the kit in a module and guides it to the appropriate clean operation post usage using the attribute set in section 1.
3. Clean – This part of the model assigns a time to the kit and filters it through the appropriate tools based on its route attribute.
4. Exit – This allows the kit to leave the model and analysis.

Immediate feedback from the calibration kit expert was unhappy for the research to proceed in this direction. This person had global experience working on calibration kit issues and so had a unique view and opinion on how things work. They could also see how such a model could be used on following technologies and so wanted to ensure that whatever was created on this technology could be transferred to other technologies down the road. They highlighted the desire for it to be simple, stating "*if it becomes overly complicated and complex it won't be used and would become difficult to maintain*". The initial feeling was that the level of complexity was really high regarding the calibration kit process they had had spent the last 2 years trying to simplify the process and take an abstract view of it in order to make it manageable sacrificing some accuracy e.g. 80% accurate versus overly complex for 90-95% accuracy.

They suggested that it would be more reasonable to look at this model development process from an operation perspective rather than a route perspective. Their reasoning for this was that the ‘Clean’ area when processing kits didn’t batch by route but rather by operation and many different routes contain the same operation. However, the concern with this approach was, that the goal was to look at the entire flow/cycle and so how would the model allow a user to experiment with the way modules managed their routes if the logic of the routes weren’t built in?

The calibration kit expert suggested that that this shouldn’t be the purpose of the model and suggested that it would be much more worthy to prove the ROI of changing the way wafers arrive at clean and then reverse engineer how this would translate into module calibration kit management i.e. show the effect of a different way of sending calibration kits into clean e.g. batching, etc. and then allow the areas to take an action of how to implement such a change. The outcome of this meeting was an action to test this proposal by building a second prototype.

Three months of Calibration kit data were reviewed to see whether it was possible to simulate it by operation. This review revealed that there was no standard process flow; many operations existed across many routes, with the entry into that operation and exit out of that operation very rarely the same. Without knowledge of the routing logic of each kit e.g. the route it was on, how could an arrival distribution be determined and then how could it be decided where to send it?

For example say operation 1234 is being sourced from multiple different areas/routes all running on one type of entity within clean:

Source 1 - 1234 -------------->

Source 2 - 1234 -------------->   Entity XYZ

Source 3 - 1234 -------------->

Below is an example of how the operation sits in the process flow of three different route/sources. Source 1 shows once a kit is used it enters the clean operation '1234' and once completed is ready for reuse in the module again. In source 2 operation '1234' is part of a four operation clean route which has 7123 as its point of entry and 7345 as it exit point. Lastly, source 3 shows operation '1234' as part of a three operation clean route which has 6345 as its entry point and 6325 as its exit.

Source 1 Module ----> 1234 ----> Module

Source 2 Module ---> 7123 ----> 6543 -----> 1234 -----> 7345-----> Module

Source 3 Module ---> 6345 ---> 1234 ---> 6325 ----> Module

There are two main issues with this when trying to determine a routing logic for model development:

1. The fact that 1234 is being fed from three different areas could mean that the arrival rate distribution could be multimodal and possibly prove difficult to fit a distribution to.
2. Once the TW's have finished processing how can I determine where they go next in the example above 1 goes back to the module, one goes to 7345 and the other goes to 6325.

The only way to avoid these issues is to revert back to the route method and design each arrival rate and process flow individually.

3.6.2.2 Initial Model Design

Based on findings from the proof of concept and feedback from the CK expert it became clear that a route centric model would allow for the development of a methodology capable of addressing the key customer requirements.

3.6.2.2.1 Data Input

The Data input for the model could be broken into three distinct steps/ groups as depicted in Figure 16. During the data gathering exercise a picture was built up of the process flow from a quantitative and qualitative perspective. Quantitatively the kit level detail provided route mapping information for specific routes that kits were on and qualitatively details were gathered around the rules that governed the running of the entities in the clean area.

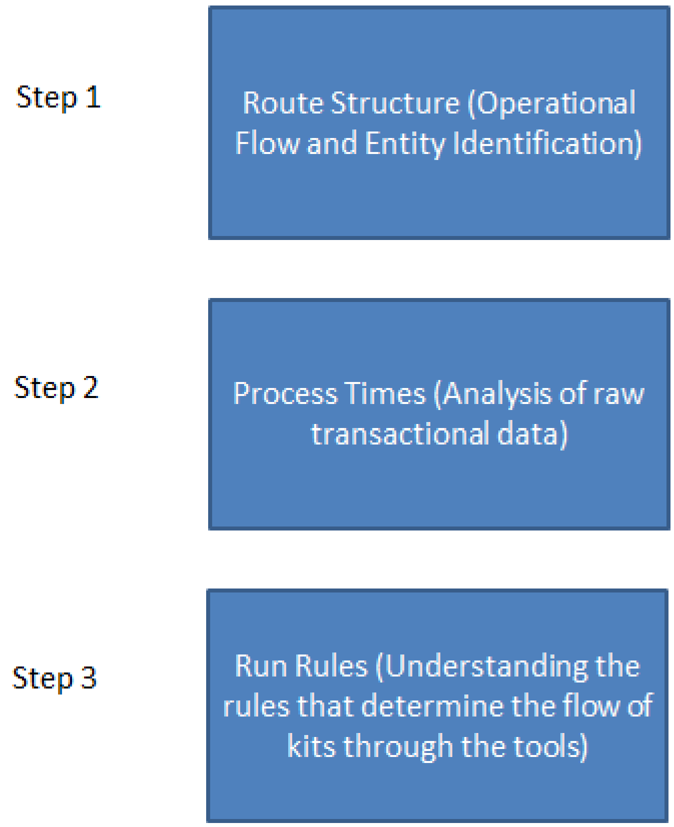


Figure 16 Input Data Groups

<u>Step 1 Route Determination</u>

The first step in route determination involved breaking down the multitude of routes to those that would provide the most value for the sponsor company and demonstrate the value of the implementation of such a methodology. Working with the Calibration Kit expert the routes were reviewed and the ones that were consistently high on the priority list and deemed costly to run/manage were chosen; this reduced the quantity of routes 37. Once identified a matrix was developed similar to that in Figure 17 to show the operation flow and machine groups involved in each of the routes.

Route	Operation	Entity	Operation	Entity	Operation	Entity
Route1	6330	Tool1	6337	Tool5	6627	Tool4
Route2	6365	Tool2	9225	Tool3		
Route3	6365	Tool3				
Route4	6514	Tool9	6543	Tool2	6633	Tool1
Route5	6521	Tool10				
Route6	6528	Tool6	7237	Tool4		
Route7	6533	Tool7				
Route8	6533	Tool8				
Route9	6539	Tool2	7237	Tool9	6609	Tool10
Route10	6540	Tool9	6360	Tool7	7250	Tool8
Route11	6544	Tool3	7242	Tool5	6605	Tool1
Route12	6544	Tool12				
Route13	6581	Tool8	6537	Tool3	6557	Tool7
Route14	6581	Tool14	6537	Tool1	6557	Tool3
Route15	6581	Tool2	6537	Tool5	7255	Tool6
Route16	6581	Tool5	6537	Tool3		
Route17	6581	Tool3	6544	Tool1	6612	Tool7
Route18	6581	Tool10	6544	Tool1	9168	Tool3
Route19	6581	Tool11	6599	Tool12	6557	Tool1

Figure 17 Example of Route detail from an operation flow and tool perspective

Step 2 Raw Data Analysis

The second step involved analysing the raw data from the company ERP system to determine the transactional time stamps. Before engaging in this exercise it was necessary to determine what was needed to be represented in the model and then identify how these aspects could be derived from the raw data. Three pieces of information were identified as being key to the generation of the model; Demand intervals for each route, time spent by the kits in each module and lastly time spent cleaning the kits for reuse in each of their individual process steps.

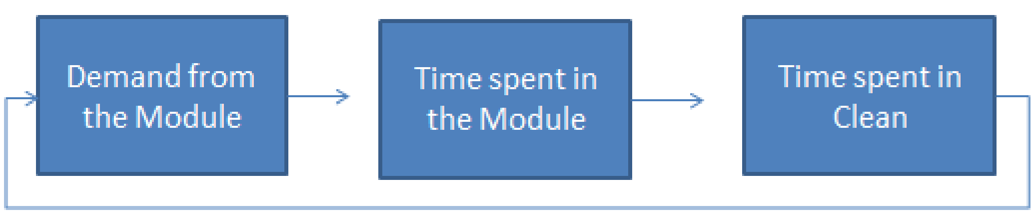


Figure 18 Data Inputs for the Model

Module Demand Interval

Demand from the Module was derived by subtracting the time stamps between each of the Calibration Kit Ready move out events. Calibration Kits sit in the 'Calibration Kit Ready' state until the module requires it. The time stamp is recorded when the calibration kit is moved out of this operation we then look to the next event when the next kit is required; it is the time in between these events that provide us with a newly derived metric known as the 'Module Demand Interval'.

$$\boldsymbol{Module\ Demand\ Interval} \\ = \boldsymbol{CK\ Ready\ Move\ Out\ Time\ Stamp}\ (\boldsymbol{Kit\ number}) \\ - \boldsymbol{CK\ Ready\ Move\ Out\ Time\ Stamp}\ (\boldsymbol{Kit\ number} + \mathbf{1})$$

Equation 3

Module Usage Duration

The time spent in the Module is characterised by the time between the Module moving the kit **out** of a 'Calibration Kit Ready' state and the moving it **into** the first operation of the clean process. A module will request a kit when required and bring it into its area for use; the kit will remain in this area until all usable components within the kit have been consumed after which the kit is moved out of the module and into the first clean operation. This newly derived metric is known as 'Module Usage duration'.

$$Module\ Usage\ Duration \\ = CK\ Ready\ Move\ Out\ Time\ Stamp - Clean\ Move\ In\ Time\ Stamp$$

Equation 4

Clean Duration

The metric measuring the time it takes to clean the kit is known as 'Clean Duration'; the time begins from the when the kit is processed out of 'calibration kit in use' and into the first clean operation. The time ends when moved out of the last clean operation and into 'Calibration Kit Ready' state. In this initial model the interest was in mapping the complete clean process as it will allow for the experimentation of run rules within the module areas, hence, the actual cycle time for each process step were recorded.

$$Process\ Time\ of\ Clean\ Operation(n) \\ = Clean\ Step\ Queue\ Time\ (n) + \Sigma Clean\ Step\ Process\ Time\ (n_1 \ldots n_i)$$

Equation 5

Step 3 Run Rules

In order to determine how kits are moved through the different clean areas as part of the qualitative data gathering any batching rules or customized run rules that are in place on the different machine groups were recorded. This allowed for the development of very detailed models mirroring the logic of how kits are processed through the different areas. Details of these run rules can be seen in Appendix F.

3.6.2.2.2 Model Design

The initial model design is broken into a Two-phase process. Phase 1 (see Figure 19) includes the building of the 'Demand block' (Block 1) and 'Clean block' (Block 2). This is then reviewed by the Calibration kit customers to ensure the model is on the right track. Phase 2 includes developing the 'Usage block' to describe how kits are used and managed within the different modules.

Block 1 is where the demand distribution characteristics are assigned to the 37 different routes. Block 2 contains all the entity types within the clean process and allows for the flow of kits through the different entities based on the quantitative process flow feedback. Within the entity block there is the ability to build in the logic of the run rules associated with each entity based on the route and kit in question.

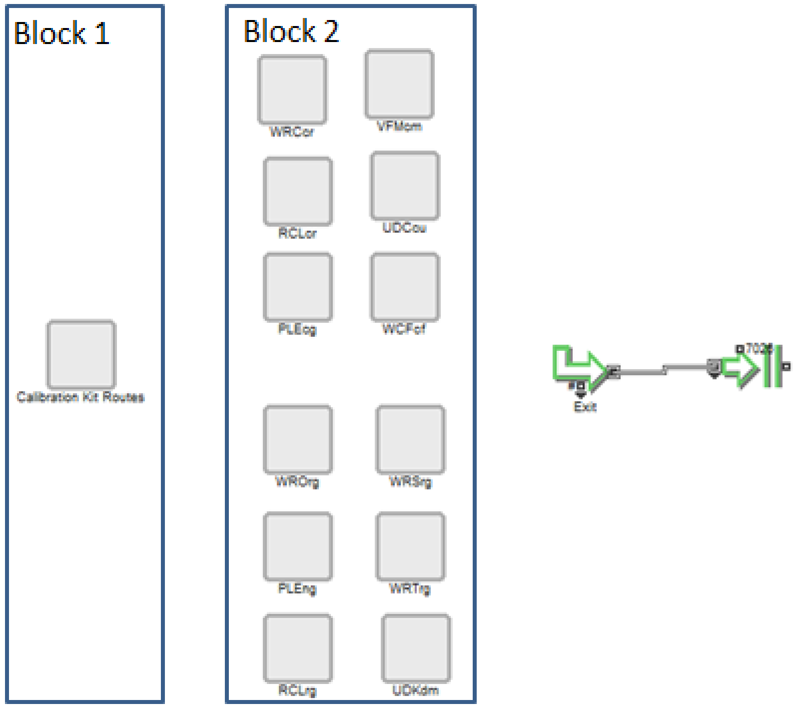


Figure 19 Initial Model Design - Phase 1

3.6.2.2.3 Block Detail

The details of the components are provided in Table 7 in Appendix A

3.6.2.2.4 Model Design Review

This initial incomplete model design was brought in front of the content expert and academic supervisor for review. The initial response was that the model was too complicated and complex. The calibration kit expert feared that there was no easy way that this model could be replicated on another technology given that very specific run rules had been built into the model that would not necessarily be required on another site. Hence Phase 2 of the model building activity was postponed (Usage Block) and we revisited the entire model design.

3.6.2.3 Model Design Revision 2

In order to improve the usability of the model it was agreed that some of the functionality of the model would be compromised such as the ability to experiment at a machine level from a run rule perspective. The main objective for developing such a model was to identify what the appropriate level of safety stock should be for the calibration kits for this technology and future technologies. When reviewing the customer requests it was seen as an acceptable compromise as long as the ability to predict appropriate calibration kit size quantity was still available.

In approaching the second revision of the model it was necessary to determine what were the most basic of functions that were required from the model. It was necessary to return, therefore, to the most basic question; how is an RA defined?

*"The term reusable articles (RA) refers to products that are **used multiple times** by **different users.** This definition implies that the use by each user is of relatively short duration (compared with article lifetime) and does not deteriorate the product. It also implicitly states that RA require a **reconditioning process** which should remain short and simple, in order to enable quick utilization by the next user"* [2]

From this definition it can be seen that for an RA there are two distinct activity steps in the form of "Use" and "Reconditioning"; the demand for the items would be determined by how often the users used the calibration kits and obviously these calibration kits will need to reside in a resource pool. Another distinctive feature of this re-design would be that entity level blocks were no longer required. In the previous design a block was included for each different reconditioning machine. However, given that the client was no longer interested in the experimentation of the run rules within a machine it allowed for simplification of the conceptual model as depicted by Figure 20 below.

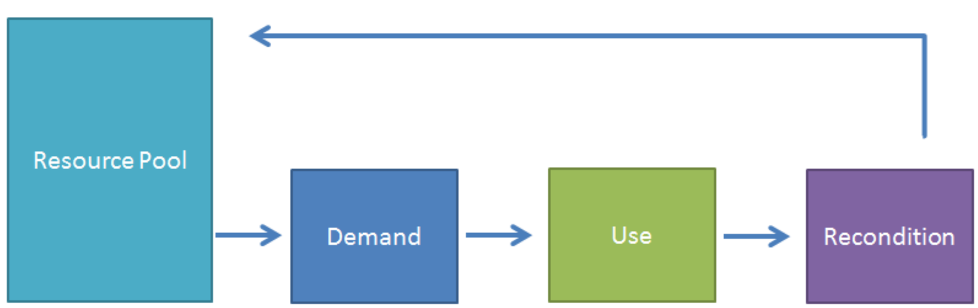


Figure 20 Model Design Revision 2

With the restructuring of the model it became necessary to review the quantitative data that had been collected and determine the level of detail required for the new revision. Previously each step and the equivalent run rules associated with the process flow were being analysed. However, given that the new model would not be concerned with the inner workings of each machine and their process flow all that was necessary to understand from the quantitative data was the time stamps at each gate.

3.6.2.3.1 Input Data

Module Demand Interval

As per before Demand from the Module was derived by subtracting the time stamps between each of the Calibration Kit Ready move out events. Calibration Kits sit in the 'Calibration Kit Ready' state until the module requires it. The time stamp is recorded when the calibration kit is moved out of this state. The time between these events provides the derived metric in Equation 6 below and is known as the 'Module Demand Interval'.

$$Module\ Demand\ Interval = \ CK\ Ready\ Move\ Out\ Time\ Stamp\ (n) - \ CK\ Ready\ Move\ Out\ Time\ Stamp\ (n+1)$$

Equation 6

Module Usage Duration

The time spent in the Module is characterised by the time between moving the kit **out** of a 'Calibration Kit Ready' state and the moving it **into** the first operation of the clean process. A module will demand a kit when required and bring it into its area for use; the kit will remain in this area until all usable components within the kit have been consumed after which the kit is moved out of the module and into the first clean operation. This newly derived metric is shown in Equation 7 and is known as 'Module Usage duration'.

$$Module\ Usage\ Duration = \ CK\ Ready\ Move\ Out\ Time\ Stamp - \ Clean\ Move\ In\ Time\ Stamp$$

Equation 7

Clean Duration

In the previous model the reconditioning aspect of the design proved the greatest modelling challenge. In this revision the client is not interested in the inner workings or process flow of the machine and indeed is not even interested in the machine as a block, e.g. time within the machine. This allowed for aggregation of all the reconditioning steps for each route into a single input and output process.

This simplified approach was taken for a number of reasons. But primarily the simplification was implemented because one of the objectives of the design was to create a model that was generalizable across all other technologies and ideally across industries. The reconditioning activities in the process being modelled have developed over time and are customised for the routes that are running (as evidenced by Table 4 below); However, each route has different combinations and quantities of process steps which if designed into the model would make the model non-generalizable for any other technology.

Table 4 Reconditioning Routes

Route	Operation	Entity	Operation	Entity	Operation	Entity
Route1	6330	Tool1	6337	Tool5	6627	Tool4
Route2	6365	Tool2	9225	Tool3		
Route3	6365	Tool3				
Route4	6514	Tool9	6543	Tool2	6633	Tool1
Route5	6521	Tool10				
Route6	6528	Tool6	7237	Tool4		
Route7	6533	Tool7				
Route8	6533	Tool8				
Route9	6539	Tool2	7237	Tool9	6609	Tool10
Route10	6540	Tool9	6360	Tool7	7250	Tool8
Route11	6544	Tool3	7242	Tool5	6605	Tool1
Route12	6544	Tool12				
Route13	6581	Tool8	6537	Tool3	6557	Tool7
Route14	6581	Tool14	6537	Tool1	6557	Tool3
Route15	6581	Tool2	6537	Tool5	7255	Tool6
Route16	6581	Tool5	6537	Tool3		
Route17	6581	Tool3	6544	Tool1	6612	Tool7
Route18	6581	Tool10	6544	Tool1	9168	Tool3
Route19	6581	Tool11	6599	Tool12	6557	Tool1

In this model, the metric measuring the time it takes to clean the kit is known as 'Clean Duration'; the time begins from the when the kit is processed out of 'calibration kit in use' and into the first clean operation. The time ends when moved out of the last clean operation and into 'Calibration Kit Ready' state.

$$Clean\ Duration = \ CK\ In\ Use\ Move\ Out\ Time\ Stamp - \ Clean\ Move\ Out\ Time\ Stamp$$

Equation 8

This level of analysis now simplifies the model into needing only three time based inputs and has removed the necessity to model individual process steps enabling a generalizable solution across technology and industry.

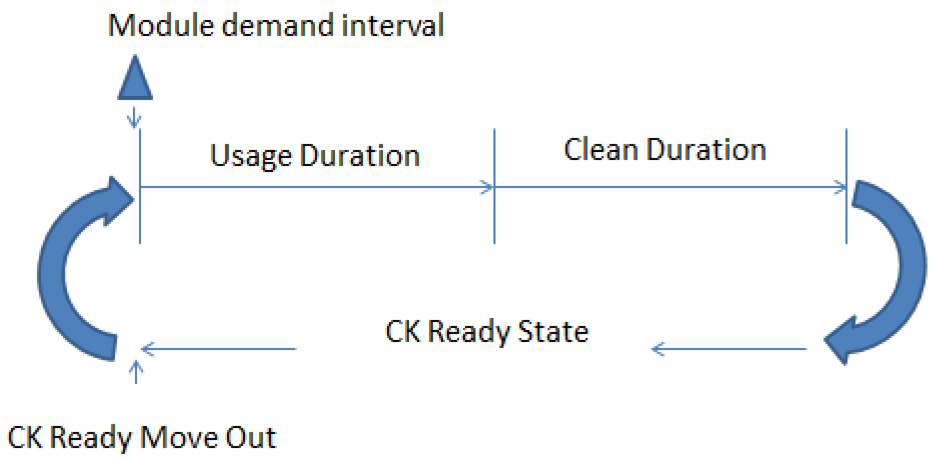


Figure 21 Model Design

3.6.2.3.2 Model Design

This Simulation model is broken into three distinct blocks; "Calibration Kit Demand", "Calibration Kit Use and Clean" and "Calibration Kit Pool" as depicted in Figure 22.

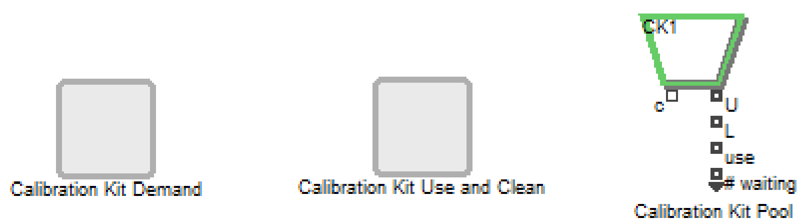


Figure 22: Principle Simulation Model blocks.

The Calibration Kit Demand block is where the demand distribution characteristics are assigned to the 37 different routes. The characteristics of the 37 demand routes are defined by creating empirical distributions utilising the newly defined metrics. In the previous models attempts were made to fit the data to distributions using the software package "StatFit". However, it was found for some routes that this did not provide adequate results. It was, therefore, necessary to create empirical distributions which reflected the actual performance of kits through the different stages of the process. It should be noted that using the empirical distribution does have its limitations such as only being able to operate within the bounds of the data historically seen.

The “Calibration Kit Use and Clean” block contains 37 different routes which contains details on the length of time kits spend in their respective modules from a usage perspective. It also takes the length of time it takes for a kit to move through the clean process as an individual measure. Both of these stages lead time characteristics are defined by creating separate empirical distributions utilising the defined metrics.

3.6.2.3.3 Block Detail

The details of the components of each block and their respective function is provided in Table 7 in Appendix B.

3.6.2.3.4 Model Revision 2 Design Validation

After the completion of this model design a validation took place with the Calibration kit expert and academic supervisor. This design met the requirements that were set out post the Initial model development,

- Generalizable across technologies and industries.
- Easy to maintain given only three specific inputs.
- Provide the ability to be able to quantify safety stock levels for the routes of choice.

As discussed in the literature review chapter, the use of simulation models provides a means to experiment with parameters, for example in this instance, a safety stock level that will enable the user to never have a ‘Wait Calibration Kit’ status.

As discussed earlier, to arrive at the optimum answer through trial and error is not possible given the complexity and stochasticity of the system. As stated in the literature review an Optimised Simulation proposal provides the ability to be able to account for variability through the discrete event simulation model portion whilst the addition of an optimizer on top of the simulation logic will enable accelerated experimentation within certain confines to arrive at an optimised answer that meets certain criteria.

3.6.2.3.3 Optimiser Design

As part of this model design ExtendSim has an evolutionary optimizer functionality which will be used to build an optimised simulation model. The mechanics for the optimizer in ExtendSim is contained within one block as detailed in Appendix C, Table 9. The addition of the optimiser on top of the Simulation model marks the final addition to the model development and in the next Chapter the capabilities of the model are tested to ensure that the final offering is fit for purpose.

CHAPTER 4: RESULTS AND ANALYSIS

4.1 Introduction and Section Layout

The purpose of this chapter is to highlight how the methodology is being utilized in an industrial environment, the potential gains from such an implementation and the possibilities for adding to the knowledge base for fleet size calculations of reusable articles. Section 4.2 will provide the user with information regarding the validation of the simulation model and its raw data. Section 4.3 will compare the output of the model and how the implementation of an optimised simulation model affects the current fleet size estimation versus what is actually being kept as safety stock. Section 4.4 will detail how the optimised simulation model compares against a proposed fleet size calculation formula developed by Carrasco-Gallego; a leading researcher in the area of reusable articles management. Lastly 4.5 provides details on a proposed fleet size calculation model that attempts to build upon the current Carrasco-Gallego model to improve those results when compared against the optimised simulation model.

4.2 Model Validation

The purpose of model validation is to establish that the outputs of the model don't show any statistically significant difference from what would be expected from the real world system that has been modelled. If a model can be shown to be valid, then it can be accepted that any inferences about the operation of the system derived from the model will be valid in the real world system. The model validation process, if conducted in cooperation with the client, can assist in establishing client credibility in the model and it's outputs, thereby, giving them confidence to recommend changes to the real world system based on the analysis conducted with the model. Prior to validating the model output, it is recommended that the analyst also validates the assumptions of the model, especially those concerning the use of the input data in the model.

4.2.1 Data Cleansing

The input data for the model as stated before can be broken into the following categories: Demand, Use and Recondition.

Before applying the data to a simulation model it is necessary to focus on the data to make sure the logic holds and that the data at a high level makes sense, i.e. there are no anomalies or missing data. In addition to this, it is necessary to apply statistical methodologies to identify potential outliers. According to Maletic et al. [24] the data cleansing process can be broken down into 3 main steps:

1. Define and determine error types.
2. Search and identify error instances
3. Correct the uncovered instances.

The error types that are defined here as part of step 1 can be broken into 3 categories;

1. Non logical anomalies
2. Missing/Incomplete Data
3. Outliers

Non Logical

From a logic perspective it is required to consider whether the data makes sense, for example when a calibration kit is moved from a ready state to an in use state and then to the regeneration phase do the times look reasonable. In certain cases the data showed that the model would move the calibration kit into the use state and then into the replenishment state within a couple of seconds. To resolve this, advice was sought from content experts who have a tacit knowledge of the calibration kit process. This discussion revealed that on certain occasions employees will use the calibration kits physically but refrain from moving them on the system until the calibration kit has been fully used and is then 'logged' through the system in a matter of seconds. From a data perspective this resulted in several incorrect demand signals and unrealistic usage times which when trying to fit standard distributions such as those seen in Fig.23 or derive an empirical distribution caused issues.

Beta Distribution (*min, max, p, q*) ....
Binomial Distribution (*n, p*) ....
Cauchy Distribution (*theta, lambda*)
Chi Squared Distribution (*min, nu*)
Discrete Uniform Distribution (*min, max*) ....
Erlang Distribution (*min, m, beta*) ....
Exponential Distribution (*min, beta*)...........................
Extreme Value Type 1A Distribution (*tau, beta*) ....
Extreme Value Type 1B Distribution (*tau, beta*).........
Gamma Distribution (*min, alpha, beta*) ....
Geometric Distribution (*p*)...
Hypergeometric Distribution (*s, m, M*).......................
Inverse Gaussian Distribution (*min, alpha, beta*) ....
Inverse Weibull Distribution (*min, alpha, beta*)..........
Johnson SB Distribution (*min, lambda, gamma, delta*).
Johnson SU Distribution (*xi, lambda, gamma, delta*) ..
Laplace Distribution (*theta, phi*) ....
Logarithmic Distribution (*theta*)..................................
Logistic Distribution (*alpha, beta*) ....
Log-Logistic Distribution (*min, p, beta*) ....
Lognormal Distribution (*min, mu, sigma*) ....
Negative Binomial Distribution (*p, k*) ....
Normal Distribution (*mu, sigma*) ....
Pareto Distribution (*min, alpha*)..................................
Pearson 5 Distribution (*min, alpha, beta*) ....
Pearson 6 Distribution (*min, beta, p, q*) ....
Poisson Distribution (*lambda*).....................................
Power Function Distribution (*min, max, alpha*) ....
Rayleigh Distribution (*min, sigma*) ....
Triangular Distribution (*min, max, mode*) ....
Uniform Distribution (*min, max*).................................
Weibull Distribution (*min, alpha, beta*)........................

Figure 23 StatFit Distributions

The process undertaken to carry out such a validation involved initial qualitative clarification with the engineers and process owners on the validity of such a transaction; in this engagement we queried what an appropriate time for a transaction should be and identified a limit where the time was unrealistic and down to inappropriate human logging behaviour. Once verified that such an anomaly was indeed an issue a quantitative analysis was conducted of the newly derived variables identified in the input data above and highlighted those occasions where the kit was processed; these data points were then removed.

Missing/Incomplete Data

Missing/Incomplete data can be defined as those line items where the analyst doesn't have a full complement of data in order to derive the new variables as highlighted in previous sections. For example, it was observed within the dataset that it was possible on occasion to have a time stamp for a calibration kit move out of the 'Ready State' and into the 'Use State' but no time stamp for when it reached the 'Regeneration' step. This was due to the fact that a Kit was still in use when the data extract was taken or simply removed from the process for other reasons. It was deemed appropriate to remove all such instances of incomplete data from the dataset before deriving the empirical distributions for the input variables.

Outliers

Observed data can often contain outliers that have unusually large or small values when compared to the other data points observed in the dataset. These outliers can be caused by inaccurate data logging, manual override or an unusual event such as a kit going missing that means the time associated with a particular calibration kit was skewed in some way. According to Osborne et al. [23] outliers can have a "*deleterious effect on statistical analysis:*

1. *Outliers generally serve to increase error variance and reduce the power of statistical tests.*
2. *If non-randomly distributed, they can decrease normality (and in multivariate analyses, violate assumptions of sphericity and multivariate normality), altering the odds of making both Type I and Type II errors.*
3. *They can seriously bias or influence estimates that may be of substantive interest."*

The classical approach to determining outliers is the standard deviation method. This is a labelling methodology that attempts to identify those points that fall outside the boundaries of $\bar{x} \pm 3\sigma$; where $\bar{x}$ and σ are the mean and standard deviation of the dataset, respectively.

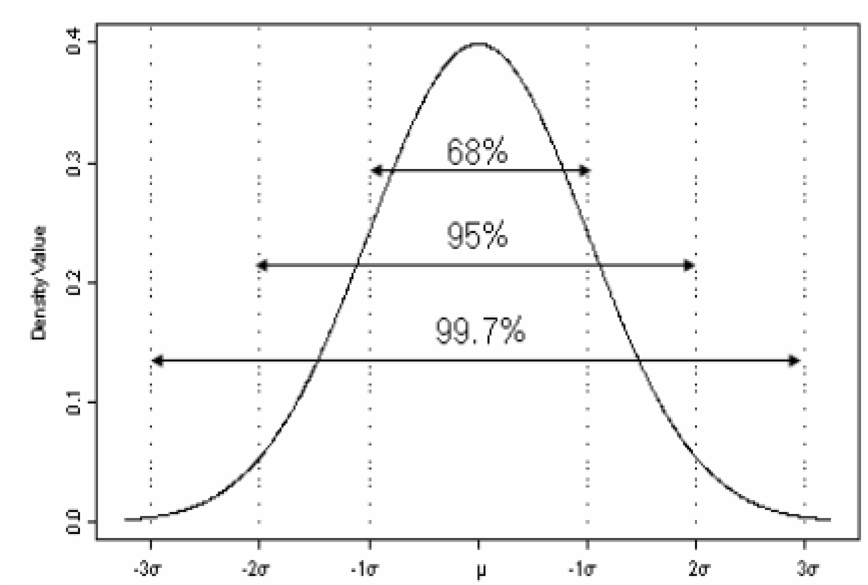


Figure 24 Probability density function for a normal distribution according to the standard deviation.

As can be seen from Figure 24 above under a normal distribution 68% of the data seen is expected to lie within 1σ of the mean, 95% of the data seen is expected to lie within 2σ of the mean and lastly 99.7% of the data that seen is expected to lie within 3σ of the mean. When using the 3σ cut-off as the point for labelling data as outliers an analyst is stating that if a point is greater than 3σ away from the mean the probability that that particular data point is part of this normal distribution is very small and so should be removed.

However not all data can be described using a normal distribution and with it the ability to apply the purest sense of the SD method is questionable. With such a departure from the normal distribution it is possible to transform the data utilising common transformations such as logarithm and square root transformation. The intention of such an action is to see can a non-normal dataset be transformed into a normal distribution which will allow for the application of the SD methodology. Figure 25 provides an example, from the dataset collected for this research, of one of the calibration kit routes whose data was originally skewed and therefore, non-normal. Figure 26 depicts post transformation showing Normal distribution characteristics which enabled application of the SD methodology.

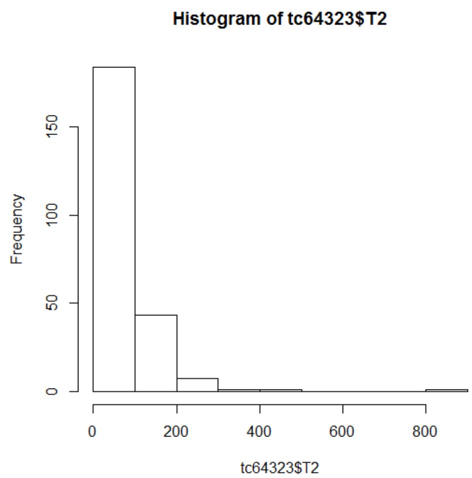


Figure 25 Histogram of route showing skewed distribution

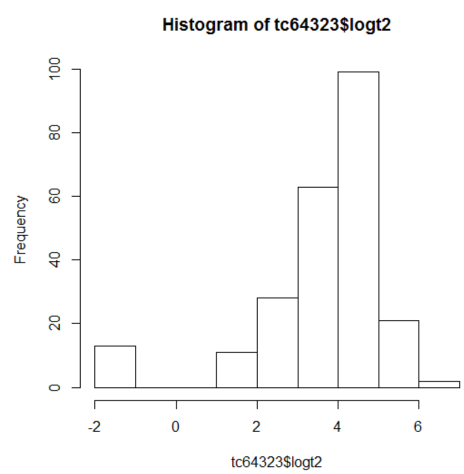


Figure 26 Histogram of route showing normal distribution characteristics post log transformation

When data is skewed and a transformation technique does not provide a curve with Normal distribution characteristics it is possible to apply Chebyshev's theorem (see Figure 27) which states that for any numerical data set:

1. at least $3/4$ of the data lie within two standard deviations of the mean, that is, in the interval with endpoints $x- \pm 2s$ for samples and with endpoints $\mu \pm 2\sigma$ for populations;
2. at least $8/9$ of the data lie within three standard deviations of the mean, that is, in the interval with endpoints x$- \pm 3s$ for samples and with endpoints $\mu \pm 3\sigma$ for populations;

3. at least $1 - \frac{1}{k^2}$ of the data lie within k standard deviations of the mean, that is, in the interval with endpoints $x - \pm ks$ for samples and with endpoints $\mu \pm k\sigma$ for populations, where k is any positive whole number that is greater than 1.

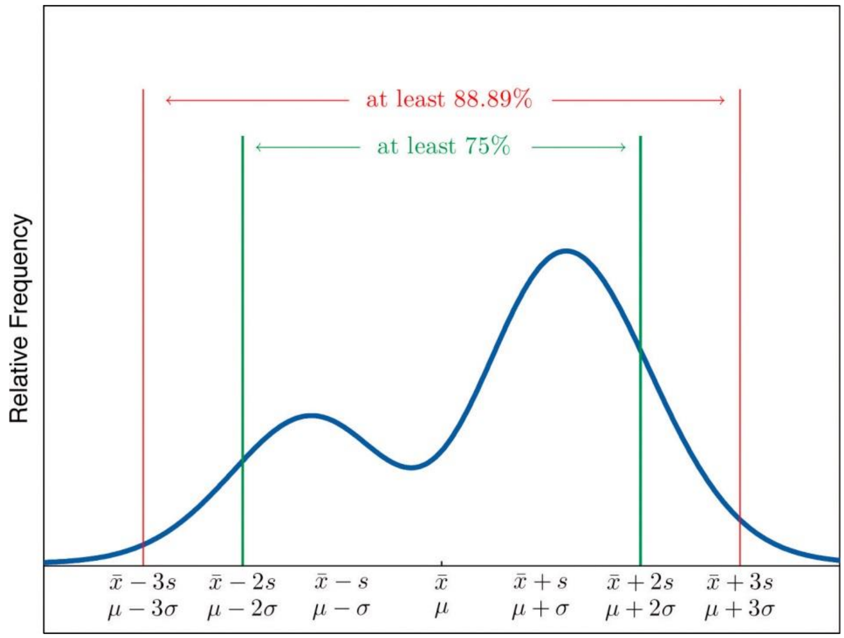


Figure 27 Chebyshev's theorem

It is important when understanding Chebyshev's theorem that close attention is paid to the fact that it guarantees the **minimum** proportion of data that resides within the standard deviations of a numerical dataset; there is a possibility that a bigger proportion may exist. For the analysis conducted within this research an outlier limit of 4σ was applied, which according to Chebyshev's theorem states that a minimum of 94% of data resides within these boundaries. Any point that falls outside this limit was removed from the dataset.

4.2.2 Verification and Validation of Simulation Model

The verification of a simulation model is concerned with ensuring the **model is built right**; validation of a simulation model is concerned with **building the right model.**

Verification

The verification of a model can be thought of as a process that ensures the model's logic is correct; for example when an analyst changes something to increase the process time at a certain step it should be verified that there is an overall reduction in output if the run time is the same in both conditions of the model. In order to ensure due diligence is applied to this step the following steps were followed in this study:

Examine Code:

Have any code that is contained in the model reviewed by a third party; the model concerned in this research contains linear programming code (see Figure 28) in order to minimize the quantity of kits required. This code was verified by academic supervisors as well as work colleagues to ensure appropriateness.

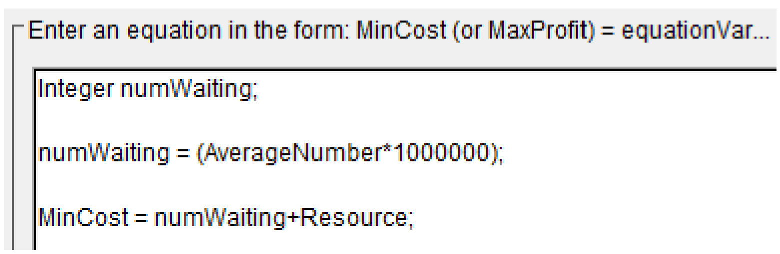


Figure 28 Minimization code for Fleet size determination

Flow Diagram:

The purpose of this step is to outline the model's logic and trace every possible way in which the item can travel within the model based on the different decision points contained within the model. The easiest way to do this is physically create a visual representation of the model logic as shown in Figure 29. This flow diagram was used to verify the flow logic within the model with system experts.

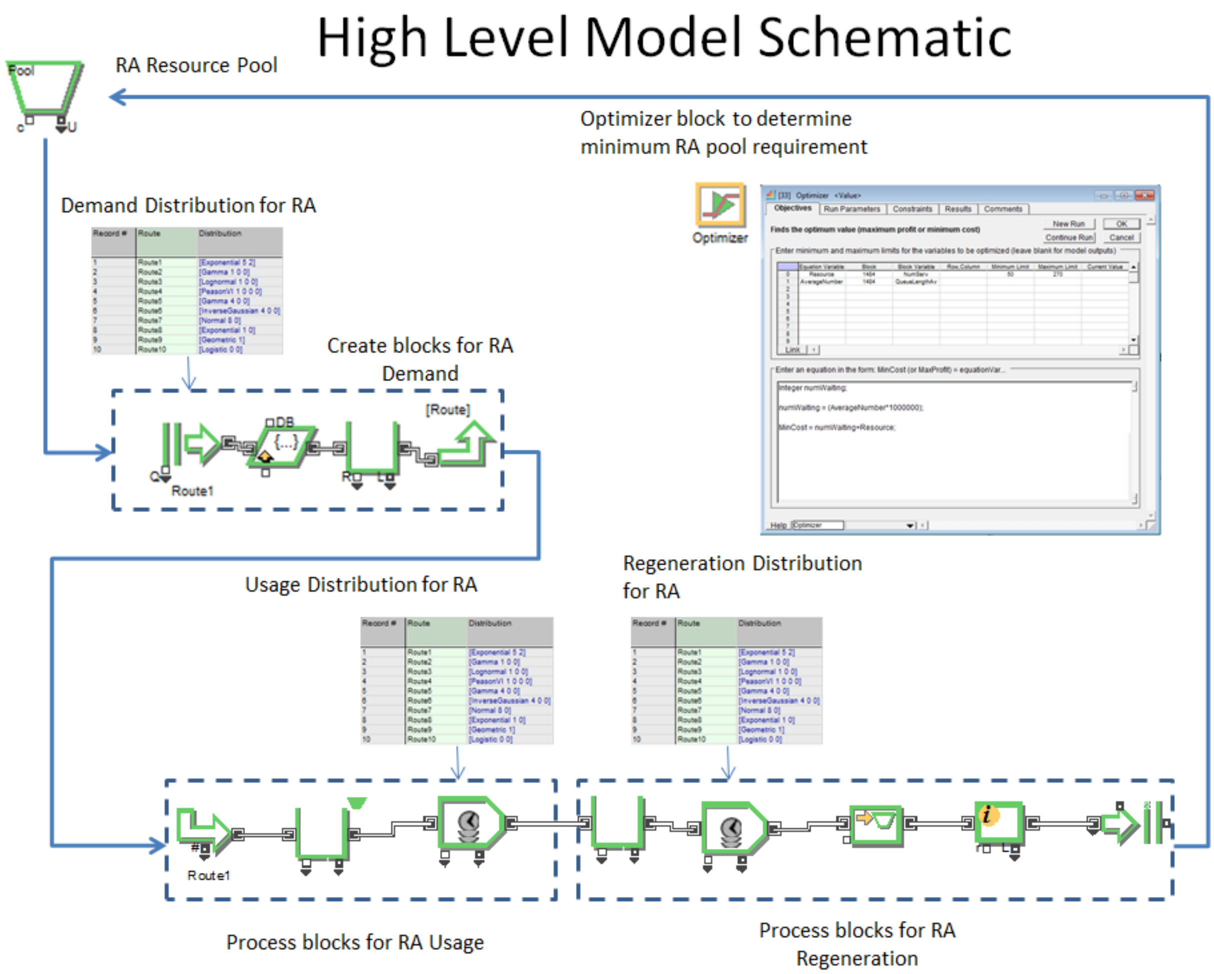


Figure 29 High Level model schematic of model

<u>Model Output</u>

This step can be thought of through the following analogy: "*when building a car if I turn the steering wheel right, the car goes right*". Therefore, this is a step for checking that when changes are made to the input parameters in a number of ways that an **<u>equivalent expected</u>** change in output is recorded. In this model a number of inputs were changed such as the regeneration time of the calibration kit to verify that the quantity of required stock increased when input parameters got perceivably worse.

<u>Validation</u>

Validation can be seen as an iterative process whereby the model is constantly being revised, modified and compared to the real world as illustrated in Figure 30. Naylor et al. [21] formulated a three step approach which is widely used and provides a structure for the validation of this model.

1. Build a model that has high face validity.
2. Validate model assumptions.
3. Compare the model input-output transformations to corresponding input-output transformation for the real system.

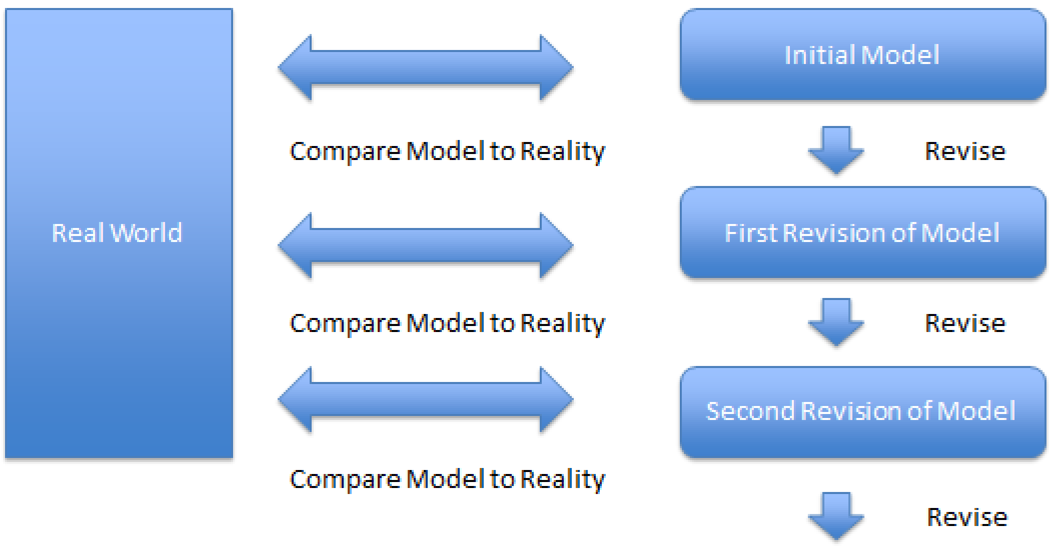


Figure 30 Iterative Simulation Model Validation process

<u>Valid Model Assumptions</u>

Assuming condition number 1 is satisfactorily met by the current build, e.g. the model has the ability to be validated the next key question to ask is whether the model data assumptions are correct. When data is collected for this model it is necessary to ensure that the data is reliable and that due diligence has been conducted in the statistical validation of that data before being input into the model. The key data inputs into this model can be described as:

1. Inter-arrival times demand signals for the calibration kits and a route specific level.
2. Usage times of calibration kits by a module at a route specific level.
3. Replenishment times to return the calibration kits back to 'ready to use' state.

The analysis of the data prior to application to a model involves ensuring that the probability distribution chosen to represent the random sample of input data is representative of the input parameters. This can be achieved through using off the shelf packages such as © StatFit which automatically tries to fit a range of different distribution types to the data and provides a ranking list of those which fit the input data best. However, there are occasions where even the best fitting distribution is inadequate as a means of representing the input parameter. In these scenarios an empirical distribution of the data can be created which mirrors the input parameter from a proportion perspective and always provides an appropriate representation of the input data. An empirical distribution can be created very simply in the following way.

1. Identify the parameter of interest for example time between arrivals.
2. Determine the count of each measure for example zero time between arrival = 5, 24 hours between arrival = 8 etc.
3. Divide these counts by total calibration kit arrival quantity to derive proportion of arrivals with zero hours, 24 hours etc.

The result of this calculation is a table with a list of times and their respective proportions which provides the appropriate distributions for the simulation model. These calculations were completed at a calibration kit route level for each of the three input parameters (see Figure 31).

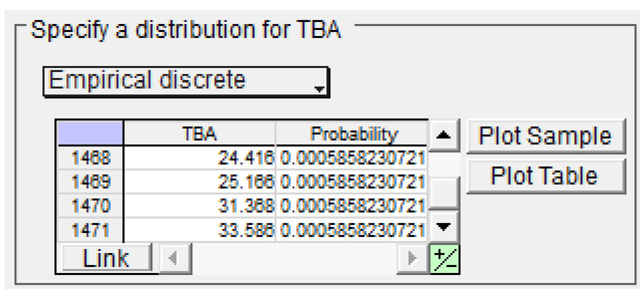


Figure 31 Example of empirical distribution

<u>Input / Output transformation validation</u>

The model in question has three main inputs that have been derived from the raw data for each individual route being analysed; namely:

1. Inter-arrival times of demand signals from the modules. Individual empirical distribution defined for each route which will be randomly sampled from by the simulation model.
2. Usage times of calibration kits. Individual empirical distribution defined for each route which will be randomly sampled from by the simulation model.
3. Replenishment times of calibration kits. Individual empirical distribution defined for each route which will be randomly sampled from by the simulation model.

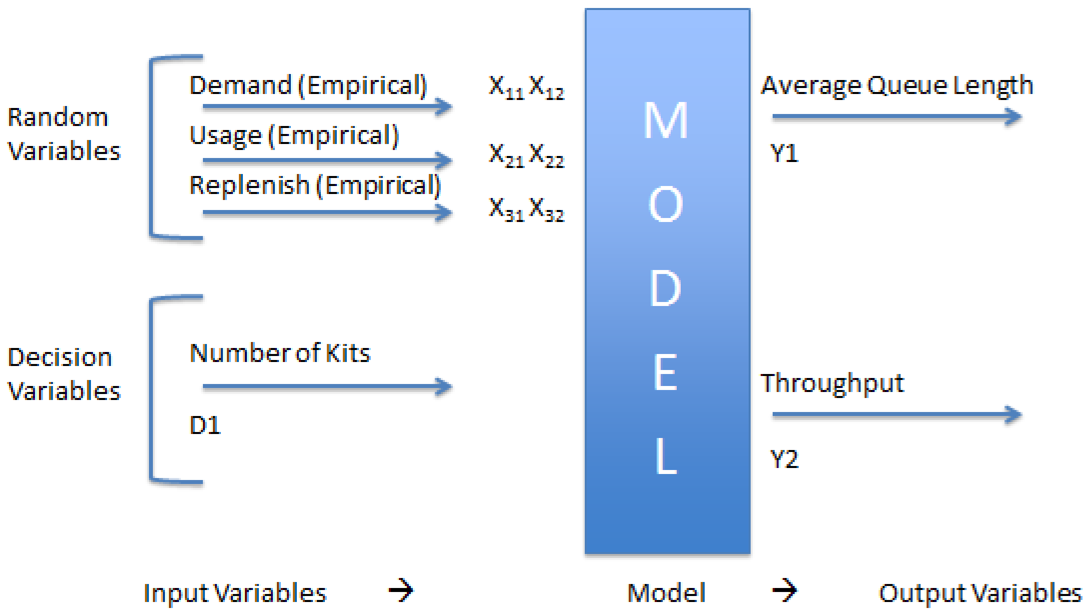


Figure 32 Input / Output Transformation diagram

Figure 32 provides a depiction of the Input/Output transformation processes in the simulation model. The X variables represent those variables that characterize the system, of which there are three variables that fall into this category; namely Demand, Usage and Replenishment. The decision variables are denoted by the letter 'D' of which there is one in this model; that being the number of kits to enter into the system. Lastly the output variables are denoted by the letter Y, of which there are two; Average Queue length and Throughput of the system. In this system the model will take Inputs X and D and produce output Y, as represented by Equation 9.

$$\boldsymbol{f}(\boldsymbol{X}, \boldsymbol{D}) = \boldsymbol{Y}$$

Equation 9

With this understanding of the Input/Output transformation processes, it is now required to analyse the model outputs for Type I and Type II errors. Type I errors are instances where the null hypothesis (H_0) is rejected when it is true. In the case of validation of a simulation model this would represent the probability of falsely rejecting the hypothesis that the model is a valid representation of the real world system. Type II errors are the corollary of Type I errors and in the instance of simulation model output validation would represent the probability of accepting a model as a valid representation of the real world system when in fact it is not. In order to test the validity of the model, ten replications of the simulation model were conducted and the output variable throughput ($Y2$) was used in the validation tests. A sample of the results from each replication is shown in Table 5 for one particular route.

Table 5 Results of 10 replications of one route from the Calibration Kit process.

Replication	Y2 = Throughput
1	264
2	277
3	225
4	278
5	264
6	224
7	237
8	240
9	255
10	289
Sample mean	255
Standard deviation	22.94

In this route it is known that the real world throughput is 263 units. Knowing that $Z2 = 263$ and the sample mean response from the model $Y2 = 255$ with standard deviation of 22.94 across 10 replications allows us to perform a formal statistical test of the null hypothesis. The null hypothesis can be described in the following way:

$$H_0\ (Null) Model = Real\ World :\ E(Y2) = 263\ units$$

$$versus$$

$$H_a\ (Alternative) Model \neq \text{Real World: } E\ 263\ units$$

If H_0 is not rejected after carrying out the t test then there is no reason to consider the model as being invalid. However if H_0 is rejected after the t test, the model has to be rejected and, hence, there is a need to review the model and its inputs to see if anything can be done to improve the outcome.

The test that is being carried is called the t test which is appropriate for such an analysis as we're comparing the differences between two means and is carried out in the following way:

1. Choose a level of significance α and sample size n. For our model we have set these parameters as $\alpha = 0.05$ and $n = 10$.
2. Carry out calculation of the average of Y2 and the sample standard deviation S over n replications. $\overline{Y2} = \frac{1}{n}\sum_{i=1}^{n} Y2_i = 255$ units and $S = \sqrt{\frac{(Y2_i - \overline{Y2})^2}{n-1}} = 22.94$ units, where $n = 1, \dots, 10$
3. Obtain the critical value of t from the t Tables. For a two-sided test such as this, use $t_{\frac{\alpha}{2}, n-1}$; ($n - 1$ is the degrees of freedom). From the t Tables, $t_{0.025,9} = 2.262$ for a two-sided test.
4. Compute the test statistic: $t_0 = \frac{\overline{Y2} - \mu_0}{\frac{S}{\sqrt{n}}}$ where μ_0 is the specified value in the null hypothesis, H_0. Here μ_0= 263 units, so that $t_0 = \frac{255 - 263}{\frac{22.94}{\sqrt{10}}} = -1.061$
5. For the two-sided test, if $|t_0| > t_{\frac{\alpha}{2}, n-1}$, reject H_0. Otherwise, do not reject H_0.

Since $|t_0| = 1.061 < t_{0.025,9} = 2.262$, it is appropriate to accept H_0 and conclude that the model is valid in its prediction of average unit throughput in this first test.

The second part of the test is to ensure that there is enough power, β, to reject the model if H_0 is indeed false. This is achieved by trying to ensure that β is as large as possible. β depends on the sample size n and on the true difference between $E(Y2)$ and μ_0. In order to calculate the power of analysis one must first decide what practical significant difference is required to reject H_0 if the true means of the throughput number from the model, $E(Y2)$, differed from the actual throughput in the system, $\mu_0 = 263$. In this analysis a practical significant difference is being set at 10% or (263 - 26.3 = 236.7). In conducting the 'Power' test the main objective is to determine the appropriate number of samples/replications needed in order achieve a power of 0.90. There are many online tools that enable the quick calculation of these results one of which was used during this research and is illustrated in Figure 33.

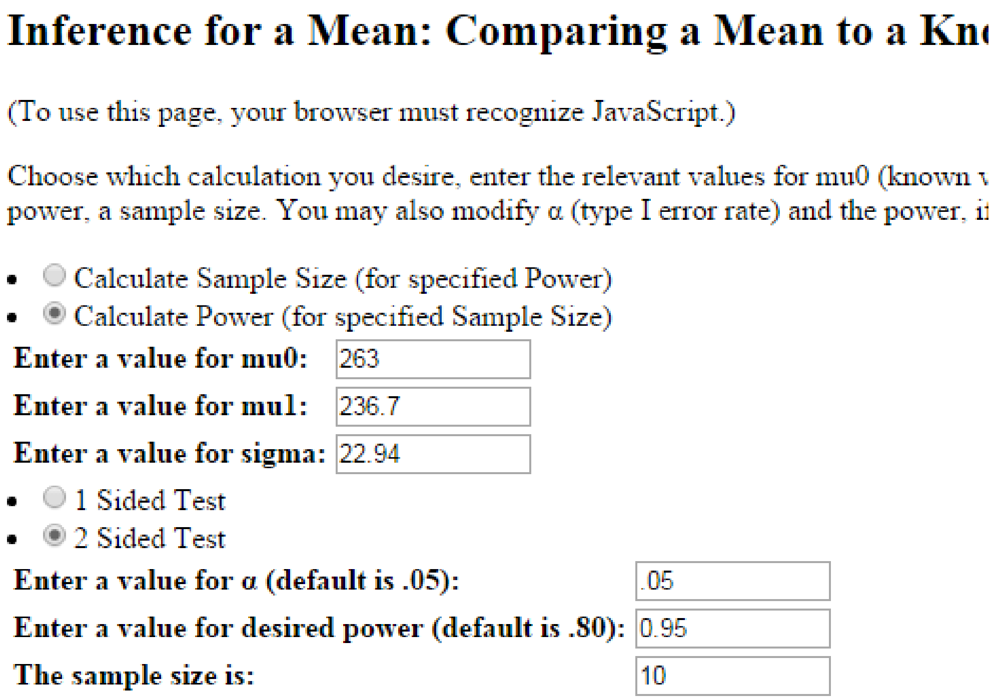


Figure 33 Online power calculation

As can be seen from Figure 33 above, when we enter 10 as the sample quantity the result of this Power test calculated $\beta = .0.95$ this is above the goal of $\beta =$ 0.90 and so the sample size of 10 replications is adequate for this particular model analysis. This analysis was calculated for each of the routes in our cohort of data; with no model moving onto the 'Power' test stage until the throughput of the model had been validated and passed the t-test. The models that fail the t test are reviewed thoroughly working from the ground up looking at the raw data to determine any anomalies missed; moving onto the model inputs and logic of the model that was built. If a model passes the t test the power calculation is conducted to determine whether the sample size is appropriate. The results in all cases determined that a sample size of 10 replications was an adequate quantity.

4.3 Actual Kit Vs Minimized Proposal

Following on from the verification and validation stage, a group of 21 simulation models that statistically represent their equivalent 21 routes were retained. The optimizer functionality built on top provides the capability to determine what the minimum quantity of calibration kits should be in order to never have a stock out versus current actual kit quantity.

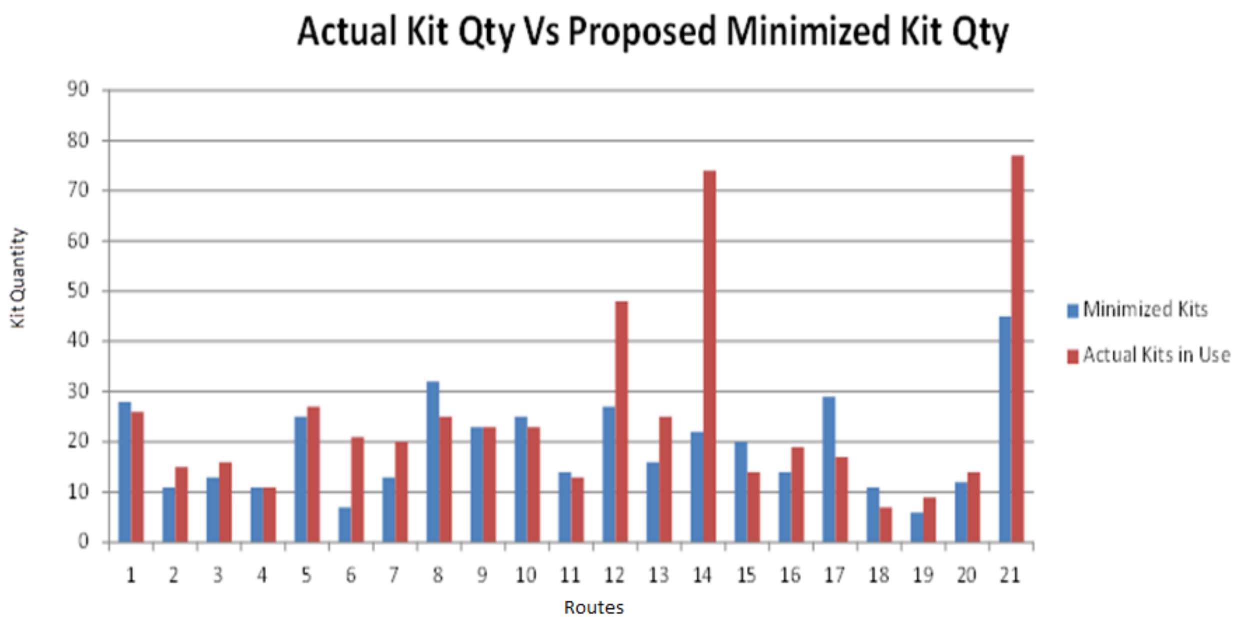


Figure 34 Actual Kit Quantity Vs Proposed Minimized Kit Quantity

In Figure 34, above, it can be seen that there are a number of routes that are definitely over stocked when it comes to calibration Kit quantities. Route 12, 14 and 21 are the obvious choices for immediate intervention. However, an interesting fact about this picture is that not all routes are over consigned; over 50% of the routes have a relatively appropriate level of stock for their usage pattern and indeed some haven't got enough according to the model. This may in fact point to the qualitative feedback received from the experts who identified the highly variable nature of the mismanagement of the calibration kit process across the modules. When identifying evidence of mismanagement it is important to not only concentrate on those routes that have too much inventory of Kits but also those, such as routes 8, 15 and 17, that don't have enough inventory. A follow up exercise would be interesting in order to investigate whether this lack of kit has affected their performance from a 'Wait Kit' perspective.

In summary if the company were to implement the kit quantities as per the optimised simulation model they would see a reduction in kit quantity of 120 kits across the 21 routes or a 21% total calibration kit reduction.

4.4 Model Comparison with Carrasco-Gallego analytical model

In the previous section it has been demonstrated how the use of optimised simulation can provide insights into areas where improvements can be made in the inventory level of Kits, however, this is not the only method. Through the research carried out thus far it can be seen that there are four major types of models that have been used by different researchers in this area of study:

1. Analytical Models (Queuing Theory, Linear Programming, etc.)
2. Rules of Thumb/Deterministic Formula
3. Simulation
4. Optimised Simulation

There's no doubting that the simulation and optimised simulation techniques are superior from an accuracy perspective given the fact that we are sampling from the range of historical data seen versus using averages. Variability can be fully accounted for beyond the basic descriptive methods. This is backed up by the fact that those researchers that are promoting analytical methods through their research demonstrate the strength of those approaches by comparing and imitating the output of an **equivalent** simulation model.

So why are Simulation and optimised simulation not used all the time? Well as it turns out advanced techniques such as simulation can be quite data heavy and in turn slow. The key message here is that Simulation is seen as the source of truth when comparing equivalent analytical models. This demonstrates the power and trust placed in Simulation from a results perspective however given the amount of researchers looking to replicate such results with analytical models it points to an inherent difficulty with the Simulation process as it stands today.

One of the most comprehensive bodies of work in the area of 'reusable articles' was carried out by researcher Ruth Carrasco-Gallego, hence it makes sense to take the fleet size formula developed by Carrasco-Gallego and apply to the cohort of data that gathered over the course of this research effort to see how this analytical model performs when estimating fleet size. The Carrasco-Gallego formula was given previously in Equation 1 but for convenience of the reader is presented here again in Equation 10. The formula, as noted earlier, accounts for average demand (D) during time t, average times (T) fleet item is used during time t and adds on a safety factor to account for variability in demand (Sd) and cycle time (Sct). In order to utilise the formula it is necessary to derive the appropriate variables as inputs into the model.

$$\boldsymbol{N = \frac{D}{T}(1 + Sd)(1 + Sct)}$$

Equation 10

The 'T' variables for each route were derived in the following way:

1. Calculate the average usage time per kit (47.18 hours in one case).
2. Calculate the average regeneration time per kit in the route in question (27.05 hours).
3. Calculate the total time, t ,by subtracting first date from last date and transform to hours (6422 hours).
4. Apply data to the following model $T = Total\ Time\ /\ (Avg\ Usage\ +\ Avg\ Regen)$ (resulted in 86.51 times for the example route). This represents the amount of times an RA is used in time period, t.

The 'D' variables (Demand) for each route is simply calculated by summing the number of times the unit was demanded in time ,t. (1094 times in this case). Applying this to the Carrasco-Gallego formula without consideration of the safety factors will yield a lower limit for the fleet size ($N = 1094/86.51 = 12.64$). The missing piece is the safety factors and for this piece of the analysis the optimised simulation model results can be used to determine whether this safety factor is relatively constant. This can be achieved by plotting the optimised simulation results against the

Carrasco-Gallego raw fleet size number (N=D/T) and analysing the percentage difference between the two datasets.

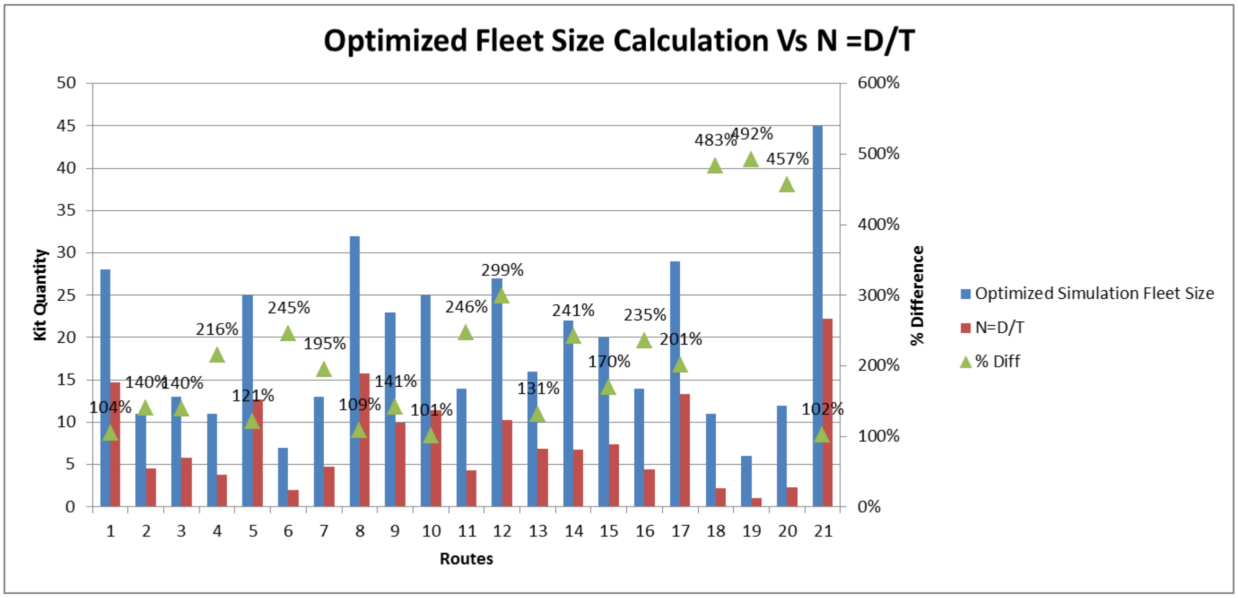


Figure 35 Comparison between Fleet Size Calculation Vs N=D/T

As can be observed from the graph in Figure 35, above, the gap between the optimised simulation results and the raw fleet size calculations derived from $N = D/T$ is not consistent. This makes it difficult to generalise such a model in industry given the impact that the safety factor has on the end results when compared to the optimised simulation model output. Carrasco-Gallego has stated that these safety factors represent the variability in demand and cycle time. The next step is to calculate the coefficient of variation (C_v) for Usage (UC_v), Replenishment (RC_v) and Arrival (AC_v) rates to see whether there is any relationship between these and the % difference.

$$C_v = \frac{\sigma}{\mu}$$

Equation 11

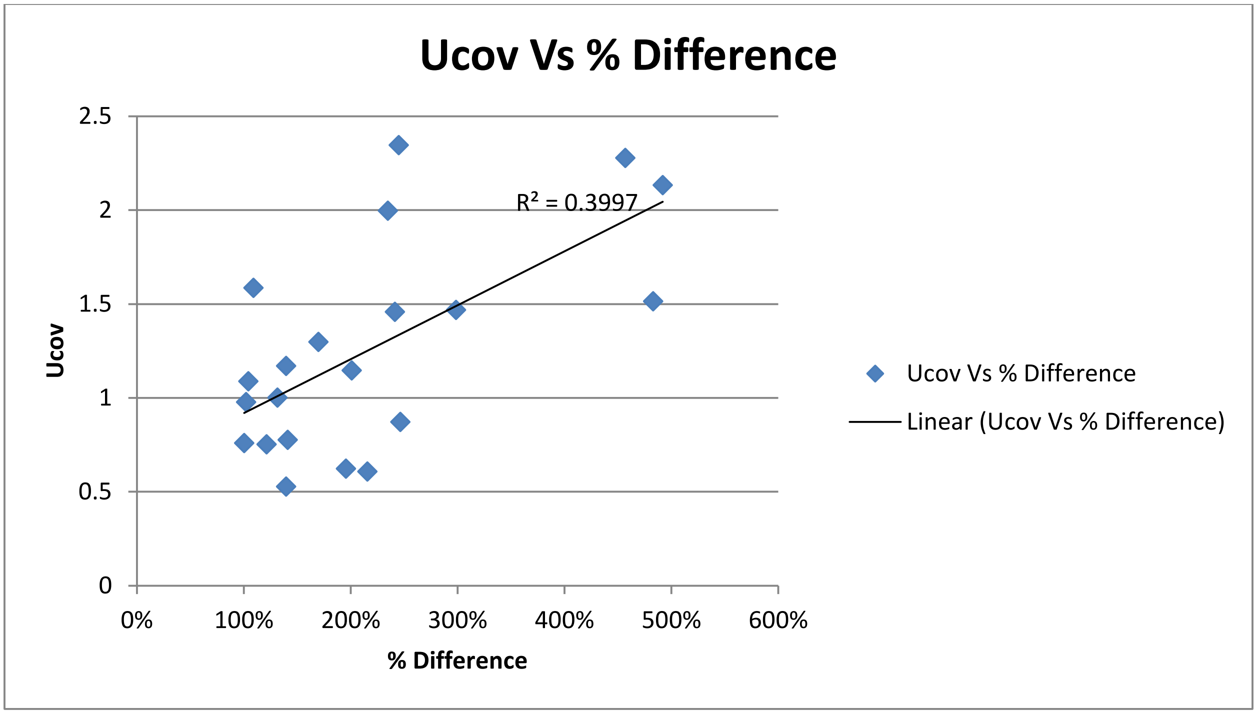


Figure 36 Comparison between % Difference and Usage C_v.

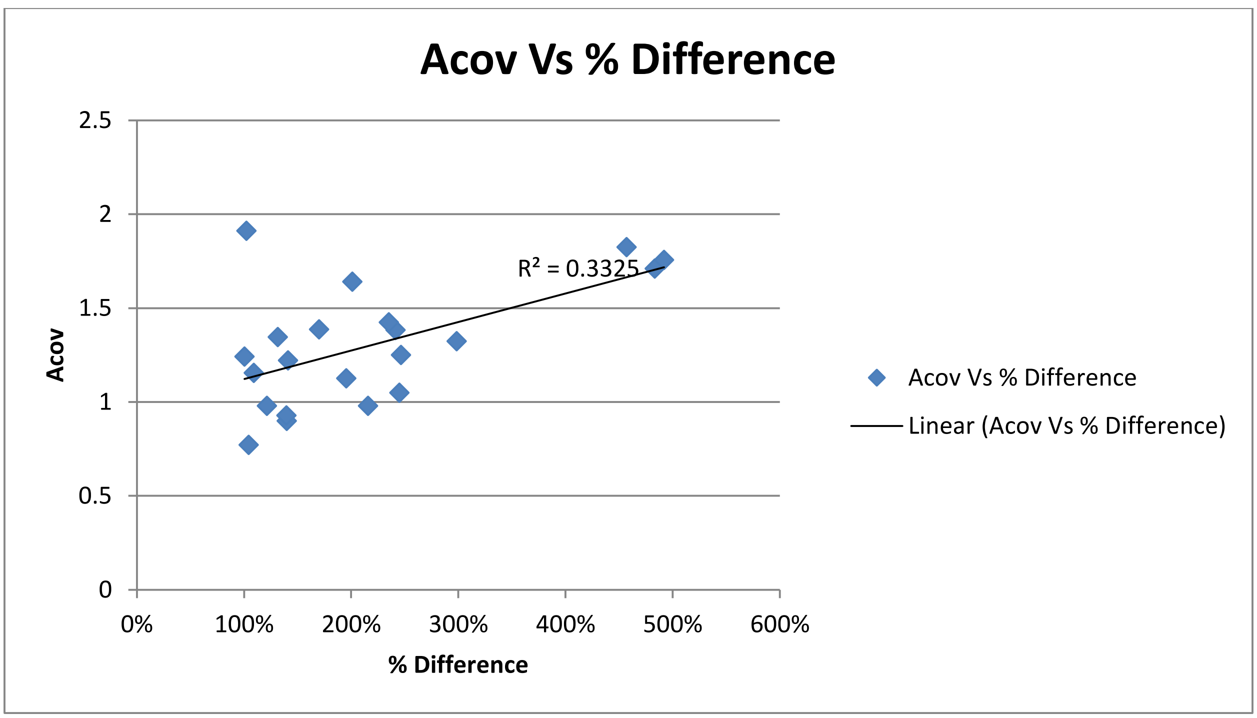


Figure 37 Comparison between % Difference and Arrival C_v.

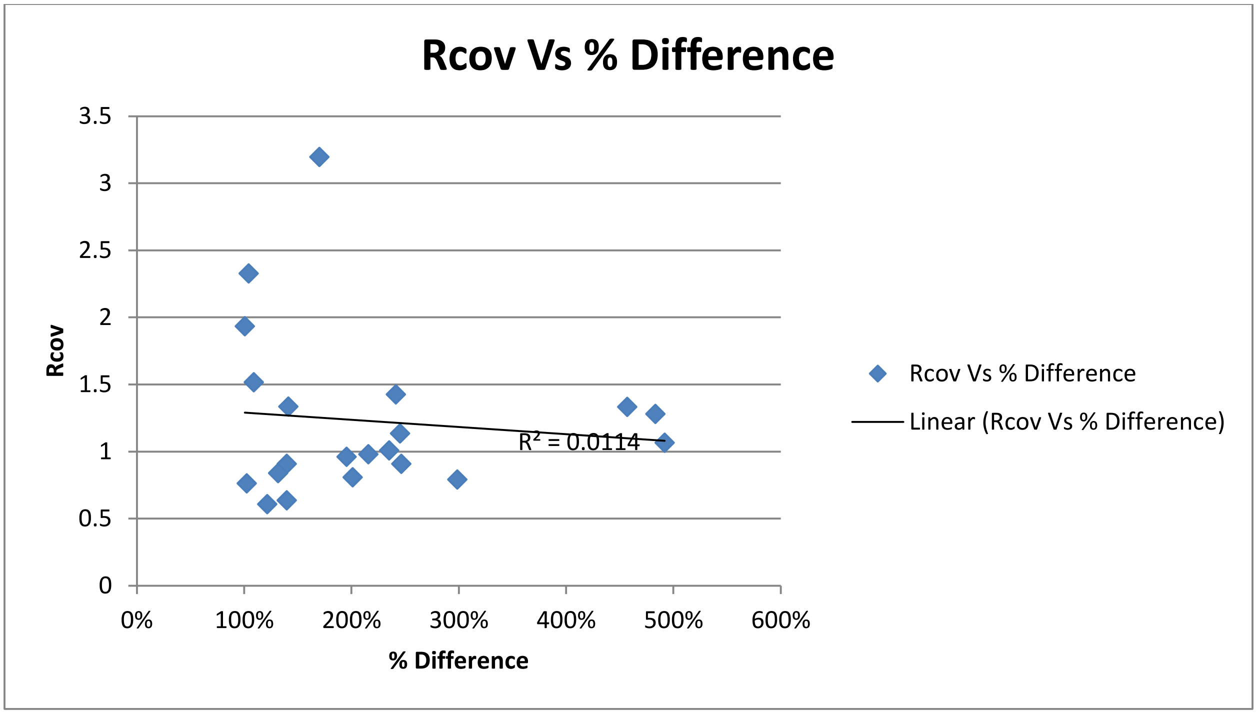


Figure 38 Comparison between % Difference and Arrival C_v.

The graphs above shows a possible relationship from a visual examination to the percentage difference especially UC_v and AC_v. This discovery suggests that if the C_v for these three variables can be determined it may be possible derive a statistical model that will provide coefficients/constants in place of the original Safety factor term.

4.5 Fleet Size Model Derivation

Given that the gap in percentage difference of $N = D/T$ and the optimised simulation models results may be explained through other aspects of the data the following variables are derived and prepared for use in a statistical methodology known as stepwise linear regression.

Variables

Please note these variables are calculated for each individual route from the raw data extracted in the sponsor company.

1. Car - This variable is the raw Carrasco-Gallego fleet size estimation excluding the safety factors.($N = D/T$)
2. $Uavg$ - This is the average time calibration kits spent in the usage module.
3. $Ustdev$ - This is the standard deviation of the time calibration kits spent in the usage module.
4. UC_v - This is the coefficient of variation of the time calibration kits spent in the usage module.
5. $Ravg$ - This is the average time calibration kits spent in the regeneration step.
6. $Rstdev$ - This is the standard deviation of the time calibration kits spent in the regeneration step.
7. RC_v - This is the coefficient of variation of the time calibration kits spent in the regeneration step.
8. $Aavg$ - This is the average interarrival times calibration kits where demanded by the modules.
9. $Astdev$ - This is the standard deviation of interarrival times calibration kits where demanded by the modules.
10. AC_v - This is the coefficient of variation of interarrival times calibration kits where demanded by the modules.

In this analysis the optimised simulation fleet size result, 'Opt' is classified as 'Y' the estimated **dependent** variable. The 10 variables defined above are the **independent variables** that will be entered into the model. Using the statistical software R, a backward elimination approach was used in the stepwise regression. This means that all variables are included in the analysis from the very start and based on a statistical significance test will be eliminated 1 by 1 until only significant features remain.

```
> car.lm = lm(opt~ car+Uavg+Ustdev+Ucov+Ravg+Rstdev+Rcov+Aavg+Astdev+Acov)
> summary (car.lm)

Call:
lm(formula = opt ~ car + Uavg + Ustdev + Ucov + Ravg + Rstdev +
    Rcov + Aavg + Astdev + Acov)

Residuals:
    Min      1Q  Median      3Q     Max
-2.9442 -0.3671 -0.2013  0.2660  2.9596

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.386914   6.488321   0.522   0.6130
car          1.673581   0.225173   7.432 2.23e-05 ***
Uavg        -0.002969   0.023459  -0.127   0.9018
Ustdev       0.003982   0.020149   0.198   0.8473
Ucov        -1.175332   1.442573  -0.815   0.4342
Ravg        -0.243028   0.244071  -0.996   0.3429
Rstdev       0.326780   0.267989   1.219   0.2507
Rcov        -2.994298   3.251018  -0.921   0.3787
Aavg         0.164055   0.247896   0.662   0.5231
Astdev      -0.256356   0.220509  -1.163   0.2720
Acov         6.750429   3.567022   1.892   0.0877 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.843 on 10 degrees of freedom
Multiple R-squared:  0.9819,    Adjusted R-squared:  0.9637
F-statistic:  54.1 on 10 and 10 DF,  p-value: 2.335e-07
```

Figure 39 Regression analysis example in R

As can be seen in Figure 39, above, a linear regression analysis was conducted in R with the following statement:

$$car8.lm = lm(opt\sim car + Uavg + Ustdev + Ucov + Ravg + Rstdev + Rcov + Scov + Aavg + Astdev + Acov)$$

The aim of is to predict Opt the dependent variable using the 10 independent variables. The main body of results show the significance of these variables when being used to predict the Opt. The first line termed the intercept (Constant) has a coefficient of 3.39, which on its own is a meaningless number unless it's possible to have zero values as appropriate numbers in the independent variables which in this case it's not.

In the following 10 lines which run from car to $Acov$ the key piece of information is in the last column which is the t statistic and in here any number below 0.05 is defined as statistically significant when aiming to explain the variability in the dependent variable Opt. As can be seen from the analysis the only variable in this run that is significant is car with the remaining variables showing as > 0.05 and so not significant.

In the backward elimination process the next step is to define that variable which is the least significant and remove it from the analysis. Least significant is the variable with the t value furthest away from 0.05. In this case that variable is $Uavg$ with a significance of 0.9018. The analysis was rerun with this variable excluded and the process repeated until there were only significant terms left in the model (see Figure 40).

```
> car.lm = lm(opt~ car+Acov)
> summary (car.lm)

Call:
lm(formula = opt ~ car + Acov)

Residuals:
    Min      1Q  Median      3Q     Max
-3.1262 -1.0549 -0.0605  0.3422  4.5018

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.52516    1.73634   0.302  0.76578
car          1.71636    0.07252  23.666 5.18e-15 ***
Acov         3.90567    1.23170   3.171  0.00529 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.78 on 18 degrees of freedom
Multiple R-squared:  0.9695,    Adjusted R-squared:  0.9662
F-statistic: 286.5 on 2 and 18 DF,  p-value: 2.252e-14
```

Figure 40 Final results from R linear regression analysis.

On completion of the backward elimination stepwise regression analysis two variables remained, 'car' which is the kernel of the Carrasco-Gallego formula $N = D/T$ and $Acov$ which is the coefficient of variation of the interarrival times that the calibration kits are demanded by the modules. Both results are statistically significant (5.18e-15 and 0.00529, respectively). The other key piece of information contained in this R output is the 'Adjusted R-squared' number which is a measure of how much of the variability in Opt is described when using these two variables. In this analysis car and $Acov$ can describe 96.62% of the variability seen in Opt which is quite high and a good indication that the model will be accurate in its prediction. The regression equation is given in Equation 12 below and Figure 41 shows the performance of this prediction equation versus the optimised simulation results and the raw $N = D/T$ formula results. Direct observation of Figure 41 shows the performance of the regression prediction equation is superior to the raw formula and is a reasonable prediction of the optimised simulation results.

$$Opt = 0.52516 + 1.71636(Car) + 3.90567(Acov)$$

Equation 12

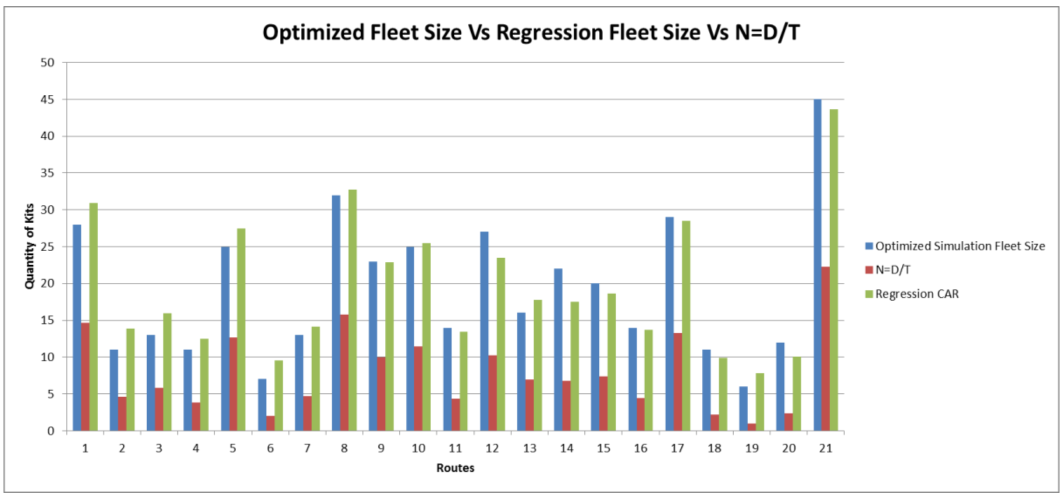


Figure 41: Optimised Simulation Fleet Size Vs Regression prediction Vs N=D/T

Model Robustness

Given that a prediction model with a high 'R squared' value has been developed for predicting Opt and which has been validated as a good measure of the real world the question becomes how robust is the model when applied to data it hasn't seen before? In the analysis above the model has been derived using 100% of the data, hence, we need to test for over fitting which would suggest that the model is not generalisable/applicable in the real world. As a means for ensuring robustness, a statistical method known as 'cross validation' can be applied. Cross validation is conducted by creating two groups of data from the dataset. One group is termed the training group (and is usually the larger group) while the other is termed the testing group.

The aim is derive a model using the data in the training group and determine how well it predicts the independent variable when tested with the new data in the testing group to which it has not be previously exposed. In the dataset used in this research there were 21 different routes which act as the cohort of data points. Using R, a script was written to conduct a 1,000 cross validation exercise; Figure 42 shows the commented code to detail how it works.

Cross Validation script rev3 - Notepad

File Edit Format View Help

```
rm(list=ls(all=TRUE))
cars=read.delim(file.choose())
attach(cars)
i <- 1 # This is the variable that will store the while loop
total<- data.frame() # declaring data.frame that variables will be stored in, empty brackets define no set columns or rows.
while(i<=1000){ # loop until i hits 1000 e.g. 1000 cross validation
newidx<- cars[order(runif(21)),] # randomly orders the 21 subjects
y<- newidx[1:14,] # picks the Training(66.6%) subjects
z<- newidx[15:21,] # picks the Test (33.3%) subjects
attach(y)
cars.lr1=lm(opt~ car+Acov) #trains the specified model against the first 66.6%
detach(y)
attach(z)
d1<- data.frame(predictions=predict(cars.lr1, newdata=z, type="response")) # tests the model using the trained coefficients against the other 7,
d2<- data.frame(route) # ID is stored in data frame d2
d3<- data.frame(opt)# Falls history is stored in dataframe d3
d4<- cbind(d1,d2,d3) # d1,d2,d3 columns are joined
detach(z)
total<- rbind(total, d4)# original empty data frame is joined to the d4
i<- i+1 # variable i increase by 1 and returns to top of loop signified by {
}
write.csv(total, file="cars8.csv")
```

Figure 42 Cross Validation Script

In the script above the 21 data points were defined into 2 groups; a training group which consisted of 66.6% (14) data points from the dataset and a testing group which is made up of the remaining 33.3.% (7). The script defines that the 21 data points will be randomly shuffled before this split is made. The first 14 will be used to define the model intercept and coefficients using those variables which were defined as statistically significant i.e. ***cars.lr1=lm(opt~ car+AC_v)***. Once this model has been generated it is tested on the remaining 7 data points; implying that the $Acov$ and car values of these 7 data points are inputted into the model derived using the 14 data points and this generates a predicted value for Opt which is then stored in 'cars8.csv' and saved for review. This was repeated for 1000 replications the resulting output being a .csv file with 7,000 lines of Opt values and their predicted values as per the process above. The 1000 replications were chosen as a big enough arbitrary number in order to test that the derived linear regression model was not over fitted and was indeed generalizable against unseen data. The output from such a file looks like that shown in Figure 43.

ID	predictions	Test Group	opt
1	29.5215234	1	28
2	11.79414604	2	11
3	14.40858157	3	13
4	10.69109038	4	11
5	26.09844647	5	25
6	7.842844816	6	7
7	12.79759421	7	13
8	32.23905157	8	32
9	22.29729886	9	23
10	24.96760933	10	25

Figure 43 Cross Validation output extract

In order to test results of the cross validation technique we created a 95% confidence interval from the 7,000 predicted rows. The aim was to understand whether this interval would successfully contain the 'actual' average optimized result of the same 7000 rows.

The 95% confidence interval was calculated using the equation outlined below:

$$\bar{x} \pm 1.96 \frac{\sigma}{\sqrt{n}}$$

Equation 13

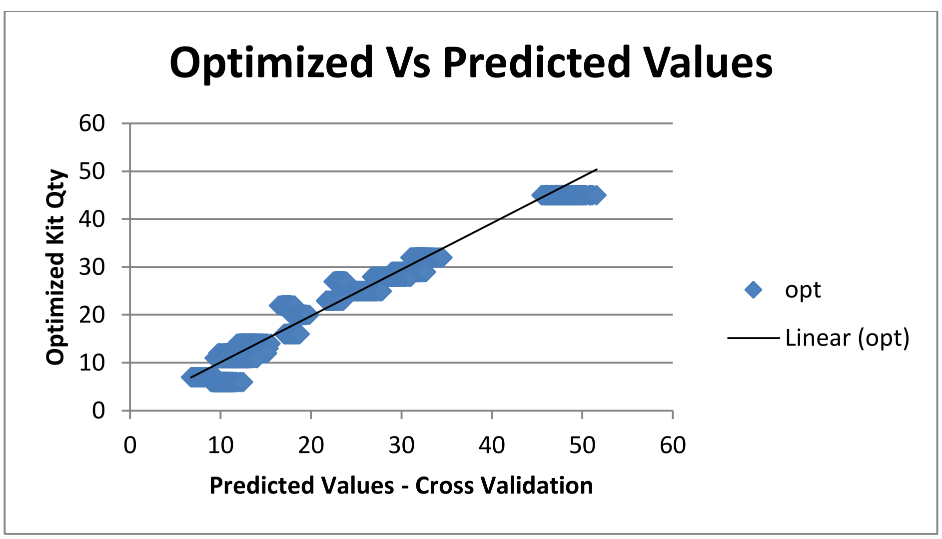


Figure 44 Actual Optimized Vs Cross Validated Predictions

The lower bound of the 95% confidence interval predicted results was 19.16 kits, the upper bound was 19.61 Kits. The actual optimized kit value was 19.18 which falls within our 95% confidence interval demonstrating that our model is indeed accurate and robust.

The aim of the research presented throughout this document has been to provide a model that is generalizable to the problem of fleet sizing for RAs. As this research was conducted within one organisation, a company operating in the electronic devices and information technology sector, a natural question is whether or not this model is only applicable to the industry in which it was derived. It has been shown in the literature survey presented in Chapter 2 that the problem of fleet size calculations for RAs is prevalent across a huge variety of industry.

To answer this question a second case study was obtained from an organisation in the Medical Devices & Technology sector (hereinafter referred to as the MedTech dataset) which was a fleet sizing problem that was directly applicable to the research in question. In this new dataset there were 13 different routes with three data inputs as per the previous research example.

1. Interarrival time - This is the variable that measures time between demand signals.
2. Usage - This variable represents the time spent in use.
3. Regeneration - This variable represents the time spent in regenerating the article and making it ready for re-use.

As before, the necessary validations and verifications of the model and its input data were conducted to ensure that the model was built right and the right model was built. Upon completion of this data validation a set of optimisation results for each of the 13 routes with their equivalent Carrasco-Gallego calculations minus the safety factors ($N = D/T$) were obtained. The results of this are presented in Figure 45 below.

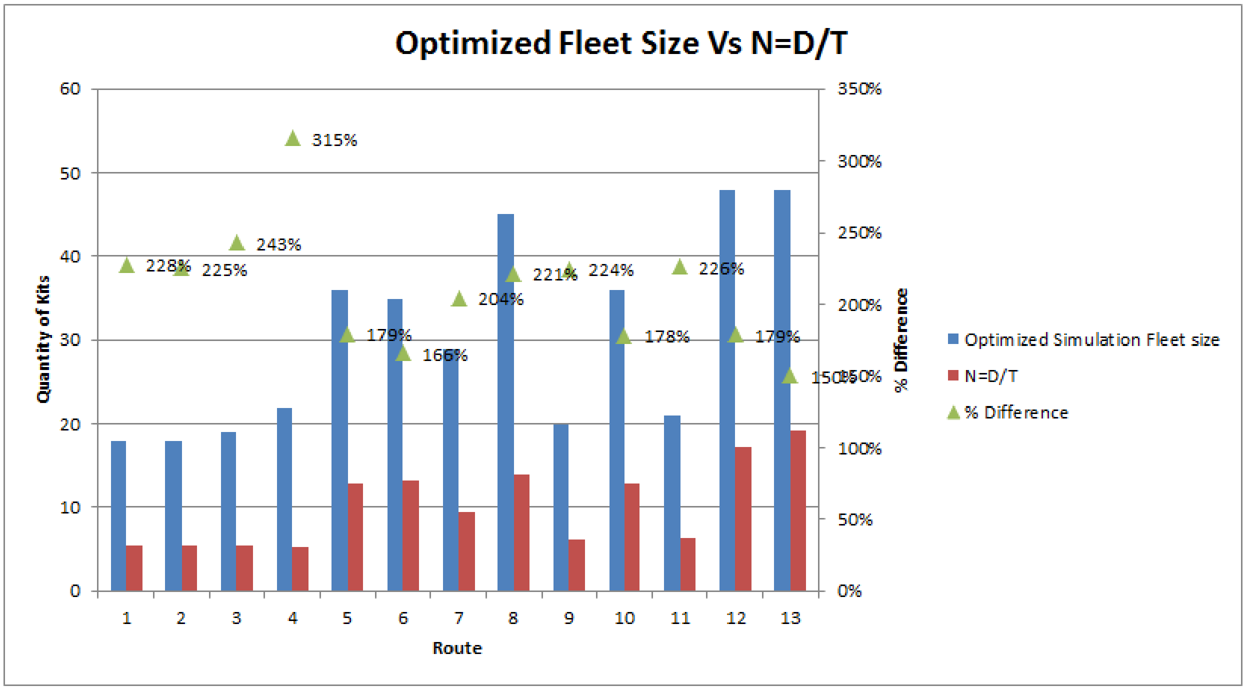


Figure 45 Comparison between Fleet Size Calculation Vs N=D/T

As can be seen from Figure 45, when comparing the optimised fleet size calculation against the $N = D/T$ Carrasco-Gallego formula the difference between the results are also highly variable ranging from a 150% difference to 315%.The purpose of this exercise is to demonstrate how well the formula derived from the original dataset performs when applied in a different industry. Therefore, the next step was to take the formula and insert the appropriate variables in order to derive new stock levels. The purpose of this is to test, if the analyst can't or doesn't want to spend time to generate an optimised simulation model for this new dataset in order to determine the appropriate fleet size, would the model derived in another industry perform when applied 'blindly' to this new dataset. Recall that the expectation is that it 'should' perform well given the cross validation result unless there is an industry related bias in effect that hasn't been accounted for in the original analysis.

In addition to applying the model derived from the original dataset a regression model was derived on 100% of the MedTech dataset involving no cross validation. As can be seen from the R extract in Figure 46 below these variables are appropriate when aiming to describe the variability in the optimised simulation fleet size calculation with an adjusted R squared value of 98.77%. The regression model developed based on the MedTech dataset is given in Equation 14.

```
Call:
lm(formula = Opt ~ Car + Acov)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.9506 -0.9494 -0.3526  1.2168  1.3600 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -6.2115     2.4833  -2.501  0.03137 *  
Car           1.4834     0.1709   8.678 5.74e-06 ***
Acov          9.6584     1.7635   5.477  0.00027 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.291 on 10 degrees of freedom
Multiple R-squared:  0.9897,    Adjusted R-squared:  0.9877 
F-statistic: 482.1 on 2 and 10 DF,  p-value: 1.14e-10
```

Figure 46 Regression model output

$$Opt = -6.2115 + 1.4835(Car) + 9.6584(Acov)$$

Equation 14

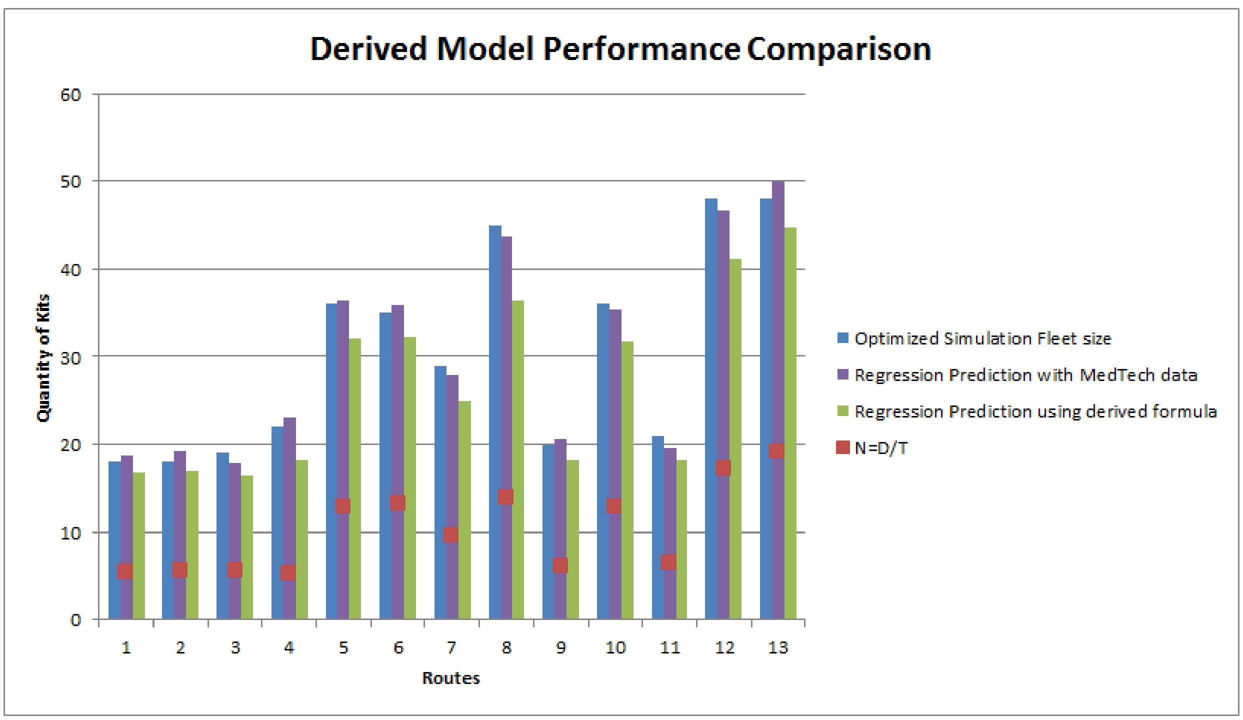


Figure 47 Comparison between Fleet Size Calculation Vs N=D/T Vs Derived formula Vs Regression MedTech

As can be seen from Figure 47, above, both regression models (Equation 12 and Equation 14) are tracking the optimised simulation fleet size values. The newly derived model (Equation 14) has obviously the greater accuracy. However, the main purpose here was to test whether the model proposed in Equation 12 is robust when applied to a new dataset from a different industrial sector. From examining the performance of this model on this dataset, it was determined that the absolute percentage difference between the model predicted kit quantity for Opt and the optimised simulation model kit quantities for Opt was 11.53%. This corresponds to an accuracy rate of 88.47% for the original model when applied to the MedTech dataset. In summary the accuracy of the original derived model has held when applying it to cross industry data showing its robustness and value as a potential fleet size predictor for reusable articles.

CHAPTER 5: DISCUSSION

5.1 Summary of Results

The original intent of this research was to investigate whether it would be possible to replicate the output of an advanced analytical model such as optimised simulation modelling through the use of a structurally simpler analytical equivalent that would be generalizable, robust and hence reduce the time to generate accurate fleets size calculations for reusable articles in a closed loop supply chain. As stated previously such advanced analytical techniques are out of reach for fleet size managers in industry due to lack of time, data and expertise in many instances.

In order to fully understand the problem a research methodology known as *'triangulation'* was incorporated and within that grouping the approach known as *'between methods'* was applied to this research. The idea behind such a methodology is to use two or more distinct methods that are congruent and yield comparable results when examining the same dimension of a research problem. In this research study there was access to ERP data (quantitative) and user experience (qualitative); utilising these sources a quantitative analysis on the data was conducted looking at the process flow, mapping the routes, examining the times that kits spent in areas, characterising the behaviour regarding the moving of kits through areas etc. and a comparison was conducted against a qualitative survey which posed questions of system experts regarding the issues with the current process and where they saw the main problems.

One of the main issues to arise from the qualitative research was the mismanagement of the calibration kit process this was raised time and time again when comparing this feedback against the quantitative analysis scenarios were discovered where kits were mismanaged; examples such as kits being used but not being processed (logged) into the module were evident in many routes and caused a lack of visibility to the kit management group of the actual quantity of available kits and so provided false signals on usage and in many cases resulted in delays and in worst case scenarios calibration kit purchases based on the pressure not to stop the line.

While kit mismanagement was a problem that inflated the quantity of kits in the system, of more interest to this study was understanding the system that was being used to determine kit quantities. In order to do this the calibration kit decision engine (CKDE), which was a newly incorporated methodology to control the quantity of kits in the process and allow for easier management, was reviewed. The 'Calibration Kit Decision Engine' was an online tool that ranked calibration kit routes based on their Days of Inventory (DOI) in the system, previously given in Equation 2 but given again here in Equation 15 for convenience

$$\boldsymbol{DOI} = \frac{\boldsymbol{Good\ inventory}}{\boldsymbol{usage\ rate}} - \boldsymbol{time\ to\ replenish}$$

Equation 15

DOI could be defined as a measure of how many 'good' kits are available for use. Once an appropriate DOI could be agreed upon this tool highlighted those routes that had extremely high DOI which suggested over stocking and resulted in actions to remove and, hence, reduce stock on these routes. However, the formula did not account for variability in usage (apart from a rudimentary rule of thumb to take the greatest usage of 4 or 30 days) or replenishment time which was hard coded into the system as a static number. This practice resulted in stock levels that remained suboptimal with lots of room for improvement.

As a means to test the performance of the current system an optimised simulation model was developed for the routes deemed as being significant from a usage perspective; this was an iterative process that included the engagement of all subject matter experts and included rigorous validation and verification of the models. The results of the comparison validated initial feelings that the current system was suboptimal by demonstrating a potential further 21% reduction of the number of kits on the routes analysed would be possible (see Figure 34).

In order to test the hypothesis that it would be possible to generate a robust analytical model for RA fleet sizing the literature was reviewed to determine appropriate fleet size calculation methodologies for reusable articles. From this review process the Carrasco-Gallego formula was selected as offering the most potential. After a comparison of the formula against the optimised simulation results it was obvious that there was no possibility for a constant safety factor to be inserted into the Carrasco-Gallego formula based on the variability in deltas between the optimised simulation model calculations and the calculation of the raw formula ($N = D/T$). This result lead to taking the approach to develop a regression model utilising all variables that were available to see if an analytical model could be developed that replicated the optimised simulation results. The regression model given in Equation 12 was derived and, with the application of a cross validation technique and a 95% confidence interval, successfully predicted the fleet size when compared to that of the validated optimised simulation model (see Figure 41). In order to demonstrate the robustness of the regression model in a broader environment it was tested on a dataset from the MedTech industry. The results showed an accuracy rating of 88.47% and pointed to a model that could be generalized in a different industry sector (see Figure 47).

5.2 Results Interpretation

The model derived from this analysis attempts to predict the optimised simulation results for reusable article fleet size determination utilising independent variables $N = D/T$ which is the kernel of the Carrasco-Gallego model and the coefficient of variation of the interarrival rate, $Acov$. It is possible to infer characterisation of the model through analysis of the coefficients assigned to the independent variables. As can be seen in Figure 48 below there is a positive linear relationship between the optimised fleet size and $N = D/T$. It can be derived from the formula (Equation 12) that for every unit increase of N there will be an increase in the fleet size by a factor of 1.72.

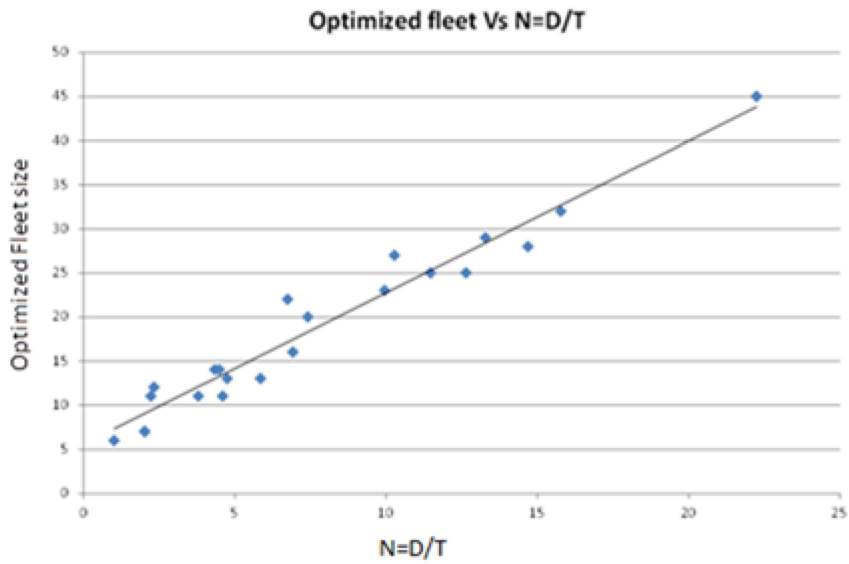


Figure 48 Optimised Fleet Vs N=D/T

Considering the Carrasco-Gallego formula it can be seen that the inclusion of the term that accounted for the ratio of average demand in a given time period, t, and the average amount of turns a reusable article can perform in the same time period, t, is an excellent predictor of fleet size determination. However when $N = D/T$ calculations were plotted against the optimised simulation results (Figure 35) it was shown that the gap between the two is highly variable. Hence, the inclusion of a safety factor that takes account of the cycle time variation and demand variation is required.

The stepwise regression modelling approach resulted in the elimination of all but one of the variables tested, other that $N = D/T$. The other independent variable that was statistically significant from the cohort of data was the coefficient of variation of the interarrival rate, $Acov$. Figure 49 below shows the relationship between the gap between the optimised fleet size and $N = \frac{D}{T} \times 1.72$ plotted against $Acov$.

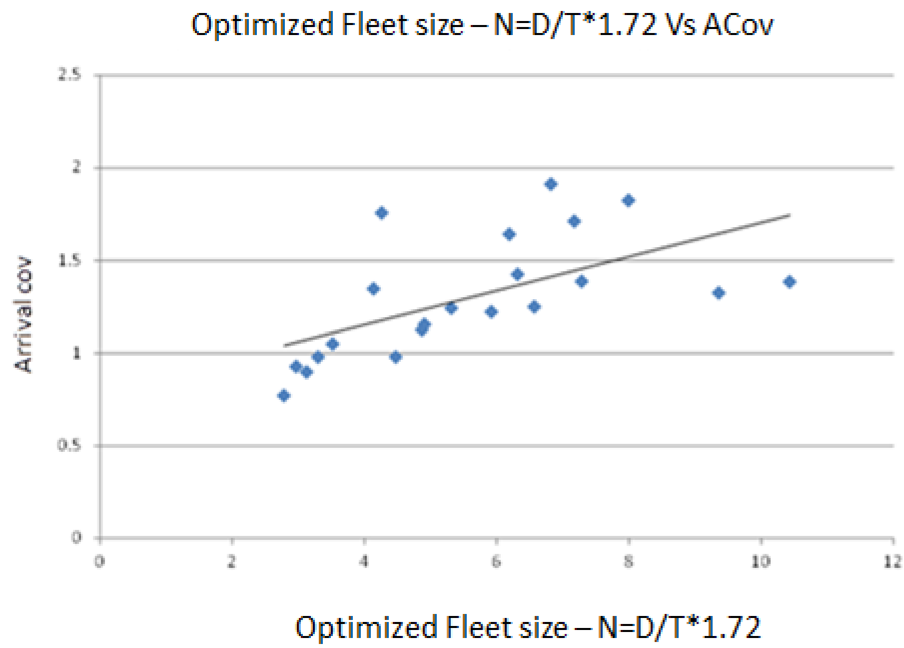


Figure 49 Optimised Simulation Fleet Size - ($N = \frac{D}{T} \times 1.72$) Vs $ACov$

The coefficient associated with $Acov$ is 3.9 which suggests that the higher the interarrival rate variability the larger the fleet size requirement is, hence, a route with $Acov$ of 1.77 versus one with 0.80 will require approximately 4 units more than its counterpart. The intercept is meaningless in this equation as there is no possibility of having a zero measure for $N = D/T$ or $Acov$.

5.3 Hypothesis - Proven /Disproven?

The initial hypothesis was to test the statement that fleet size quantities developed as part of an optimised simulation model can be replicated adequately with a generalizable analytical model thus enabling fleet size managers to benefit from the application of advanced analytics through an easily applicable analytical model. Breaking this hypothesis into its main parts enables analysis of whether the hypothesis was proven or disproven.

Part 1: highlights that the results from an optimised simulation model can be '**replicated adequately**'.

Part 2: states that it is achieved using a '**generalizable analytical model**'.

Part 3: details that it should be '**easily applicable**'.

To understand whether the results from the optimised simulation model are replicated adequately the output from the original regression model analysis must be revisited (see Figure 41). In this model the adjusted R-squared value is 0.9662 which points to the fact that 96.62% of the variability witnessed in the optimised simulation results is explained with the model proposed; this formula was then applied to another dataset in a different industry where an adjusted R-squared value of 0.9877 was obtained again highlighting that the model proposed is explaining 98.77% of the variability in the new dataset. Such results prove that part 1 of the Hypothesis is met and that that the results from an optimised simulation model can be '**replicated adequately**'.

Part 2 of the Hypothesis states that a '**generalizable analytical model**' is developed as part of the research. In order to test whether the model is 'generalizable' a cross validation technique was incorporated to test whether the model will hold up in an environment of unseen data. The output from this cross validation exercise demonstrated that the true optimized kit quantity fell within the 95% CI of predicted values. However, in order to test the robustness of the model further it was applied to a new dataset in the MedTech industry resulting in an accuracy of 88.47% when comparing optimized and predicted kit quantities. Such results provide evidence that part 2 of the hypothesis is met and that the model developed is **'generalizable analytical model'**.

Finally, Part 3 of the hypothesis suggests that the model is **'easily applicable'**. This analytical model requires the user to have access to factory systems in order to gather data on its reusable articles regarding cycle time and demand interarrival time stamps. This data will undergo very basic descriptive data analysis such as querying averages and standard deviations hence the user will need to have a basic understanding of excel and its data analysis functions. The analytical model which can easily be inserted in an excel spreadsheet requires the user to simply input the findings and press return. Such functionality provides evidence that part 3 of the Hypothesis is met and that the model developed is **'easily applicable'.**

Given the above, it is therefore offered that the central hypothesis to this research that fleet size quantities developed as part of an optimised simulation model can be replicated adequately with a generalizable analytical model thus enabling fleet size managers to benefit from the application of advanced analytics through an easily applicable analytical model has been proven.

5.4 Comparison with Previous research

When considering previous related studies, Carrasco-Gallego's body of work represents the most in depth and comprehensive research in the area of management of closed loop supply chains for reusable articles. In her research she identifies five main problems when managing reusable articles one of which is defining the fleet size dimension. This is a problem for reusable articles from a customer satisfaction perspective and tied up capital. If the fleet size is not sufficiently large the system will not be able to meet demand, resulting in unhappy customers and lost business. However, fleet size that is larger than is required to satisfy customer demands will result in unnecessarily tying up capital in stock where it could be used elsewhere to earn value for the organisation and its shareholder.

To address this issue Carrasco-Gallego put forward a following formula that accounts for average demand (D) during time period t, average number of times (T) a fleet item is used during time t and incorporates a safety factor to account for variability in demand (Sd) and cycle time (Sct). The model that is developed in this research largely corroborates with the Carrasco-Gallego formula in that the terms in the derived cross validated regression model include the D/T term (Average Demand/Average number of times fleet item is used). There is also a term that accounts for the variability in demand similar to the 'Sd' term in the original formula however rather than a factor this research has replaced 'Sd' with a scaled value that accounts for the Cov in interarrival rates. The only deviation from the original formula is that no cycle time term showed up as being statistically significant. However, such a deviation could be due to the dataset being analysed and so may warrant further investigation.

5.5 Conclusion

The study was setup initially to explore whether it was possible to take an advanced analytical methodology such as optimised simulation and develop a structurally simpler model to replicate such results. This type of idea is not new as was shown in the literature review where we see comparable studies in the areas of AGV fleet size determination. However, its application in the area of reusable articles as defined by Carrasco-Gallego is new. Reusable articles by their definition are an important mechanism for companies to embrace into the future when we understand the finiteness of our natural resources and, as shown, in the literature the perception of a 'green' or carbon footprint aware company can have positive knock on financial benefits for companies also.

For these reasons, the study sought to prove the hypothesis that fleet size quantities developed as part of an optimised simulation model can be replicated adequately with a generalizable analytical model thus enabling fleet size managers to benefit from the application of advanced analytics through an easily applicable analytical model.

As highlighted in section 5.3 the main constituent parts of the hypothesis were met. The theoretical implications of this work add to the body of research regarding the replication of advanced analytical analysis using structurally simpler analytical models. More importantly, however, the specific application to the area of Reusable Articles provides a methodology that now corroborates and advances the current methodology for fleet size determination.

The model, although showing positive results from an accuracy and robustness perspective, is limited by the maximum and minimum of fleet size requirements borne from the data on which it is being trained. This means that the model in its current form would not be robust beyond these boundaries; for example the maximum fleet size in the trained data was 45 suggesting that if it were to be applied to a process where 200 items were required it may perform poorly given that it has never been exposed to such data.

In the Carrasco-Gallego body of work there were many case studies used to test theories. In order to develop this area of research further more case studies are required to test the model with varying levels of cycle time, interarrival variability and fleet size requirements. The model in question was developed using 10 variables that were derived from the raw data; the derivation and inclusion of additional terms in the model could improve the accuracy and especially around the cycle time given its lack of inclusion in the current formula.

Finally, as shown in other studies the marrying of advanced analytical models with structurally simpler formulae can work. The output from this research shows that it is possible to take optimised simulation results and develop a regression model that is accurate and robust with a cross section of industries. The main benefit from this study, however, is that through this work the ability to determine fleet size determination in the area of reusable articles has been advanced which will enable companies and industries to embrace a greener way of doing business and in turn aid the longevity of our finite resources.

REFERENCES

[1] D. W. Johnson, “Standardizing and improving test wafer processes: inventory optimization and a days of inventory pull system”, *Masters Thesis, MIT, USA*, 2009. (retrieved from http://dspace.mit.edu/handle/1721.1/53091)

[2] R. Carrasco-Gallego, E. Ponce-Cueto, and R. Dekker, “A framework for closed-loop supply chains of reusable articles” *Econometric Institute*, Technical Report Number EI 2009-21, pp. 1–40, 2009.

[3] European Commission, “Integrated Product Policy,”, 2012 (retrieved from http://ec.europa.eu/environment/ipp/index_en.htm).

[4] Ernst and Young and the Science Policy Research Unit at Sussex University, "Integrated Product Policy, a report for the European Commission DGXI",1998,

[5] R. G. Ingalls, “The Value of Simulation in Modeling Supply Chains,” *In proceedings of the 1998 Winter Simulation Conference*, D.J. Medeiros, E.F. Watson, J.S. Carson and M.S. Manivannan, editors; pp. 1371–1375, 1998.

[6] E. Koenigsberg, “Cyclic Queue Models of Fleet Operations.”, *Operations Research,* vol. 24, no. 3, pp. 516-529, 1976.

[7] D. Roy, J. Sebastian, and W. P. No, “Fleet Sizing for Transporters with Seasonal Demands", *International Journal of Automation and Logistics*, vol. 1, no. 1, pp. 1–11, 2013.

[8] M. Ji and J. Xia, “Analysis of vehicle requirements in a general automated guided vehicle system based transportation system,” *Computers & Industrial Engineering.*, vol. 59, no. 4, pp. 544–551, Nov. 2010.

[9] P.-C. Hung and F.-H. Liu, “Estimation of the Fleet Size for a Multi-load Automated Guided,” *In Proceedings of National Science Council: Physical Science and Engineering*, vol. 25, no. 4, pp. 244–253, 2001.

[10] S. Rajotia, K. Shanker, and L. J. Batra, “Determination of optimal AGV fleet size for an FMS", *International Journal of Production Research*, vol. 36, no. 5, pp. 1177-1198, 1998.

[11] M. Turnquist, “A Model for Fleet Sizing and Vehicle allocation”, *Transportation Science*, vol. 25, no. 1, pp. 19-45, 1991.

[12] L. Bryson, “Brewers Do you know where your kegs are?” *The New Brewer*, 2005 (retrieved from http://www.beertown.org).

[13] R. Carrasco-Gallego and E. Ponce-Cueto, "A management model for closed-loop supply chains of reusable articles : proposing solutions," I*n Proceedings of the 4th International Conference on Industrial Engineering and Industrial Management XIV Congreso de Ingeniería de Organización,* Donostia- San Sebastián , September 8th -10th 2010, pp. 1795–1804, 2010.

[14] N. Byrne, P. Liston, J. Geraghty, and P. Young, "The potential role of open source discrete event simulation software in the manufacturing sector," *In Proceedings of the Operational Research Society Simulation Workshop 2012 (SW12)*, B.Tjahjono, C. Heavey, S. Onggo, and D-J. van der Zee, eds., pp. 117-126, 2012

[15] M. Better, F. Glover, and G. Kochenberger, "Simulation Optimization : Improving decisions under uncertainty." *Breakthroughs in Decision Science and Risk Analysis* (ed. by Cox L. A.). Willey, New York, 2014

[16] D. Gilmore, "Supply Chain Optimization versus Simulation", Supply Chain Digest, May 31st 2007. (retrieved from: http://www.scdigest.com/assets/FirstThoughts/07-05-31.php)

[17] Q. Wang, "A discrete event modelling approach for supply chain simulation," *International. Journal of Simulation Modeling.*, vol. 7, no. 3, pp. 124–134, Sep. 2008.

[18] Y. Chang and H. Makatsoris, "Supply chain modeling using simulation", I*nternational Journal of Simulation*, Vol. 2 No. 1, pp. 24-30, 2001

[19] K.-H. Chang, a-L. Chang, and C.-Y. Kuo, "A simulation-based framework for multi-objective vehicle fleet sizing of automated material handling systems: an empirical study," *Journal of. Simulation*, vol. 8, no. 4, pp. 271–280, May 2014.

[20] T. D. Jick, "Mixing Qualitative and Quantitative Methods : Triangulation in Action", *Administrative Science Quarterly*, Vol. 24, No. 4, Qualitative Methodology (Dec., 1979), pp. 602-611, 1979.

[21] T.H. Naylor, M. Finger, J.L. McKenney, W.E. Schrank and C.C. Holt, " Verification of Computer Simulation Models", *Management Science*, vol. 14, no. 2, pp. B92-B106, Oct 1967.

[22] J. Manget, C. Roche and F. Münnich, "Capturing the Green Advantage for Consumer Companies" *The Boston Consulting Group*, Jan. 2009 (retrived from: https://www.bcg.com/documents/file15407.pdf)

[23] J.W.Osborne and A. Overbay. "The power of outliers (and why researchers should always check for them)",. *Practical Assessment, Research & Evaluation*, vol. 9, no. 6, 2004 (retrieved from http://PAREonline.net/getvn.asp?v=9&n=6).

[24] J.I. Maletic and A. Marcus, "Data Cleansing: Beyond Integrity Checking", *in Proceedings of the Conference on Information Quality (IQ2000)*, Massachusetts Institute of Technology, Boston, MA, USA, pp. 200-209, October 20-22, 2000

APPENDIX A – MODEL DETAILS FOR REVISION 1 OF THE SIMULATION MODEL

Table 6 Model Component Details

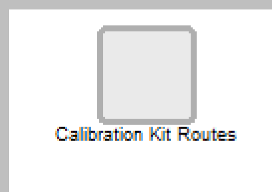
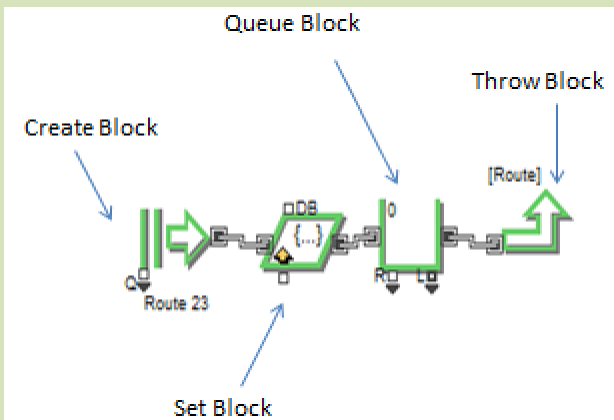
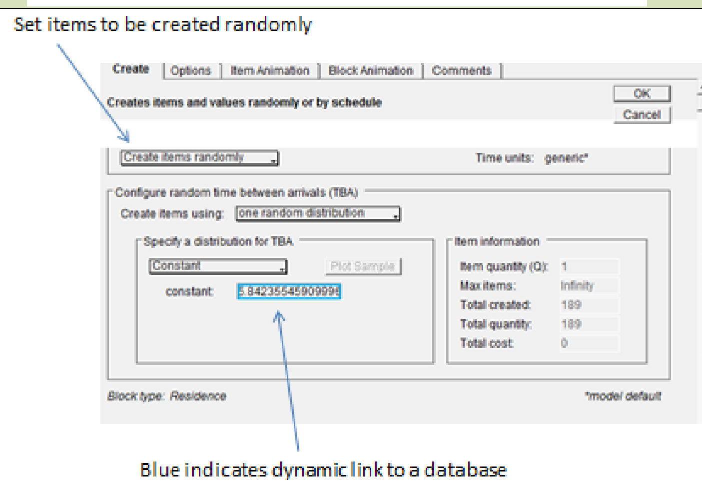
Name	Component	Function
Demand Hierarchical Block		The function of the Calibration Kit route hierarchical block is to group the different routes within the bounds of this research.
Route Process Flow		This flow of components sets the demand characteristics for each route and assigns a specific attribute.
Create Block		In this block we set the criteria for assigning appropriate demand distribution

Table 7 (Continued) Model Component Details

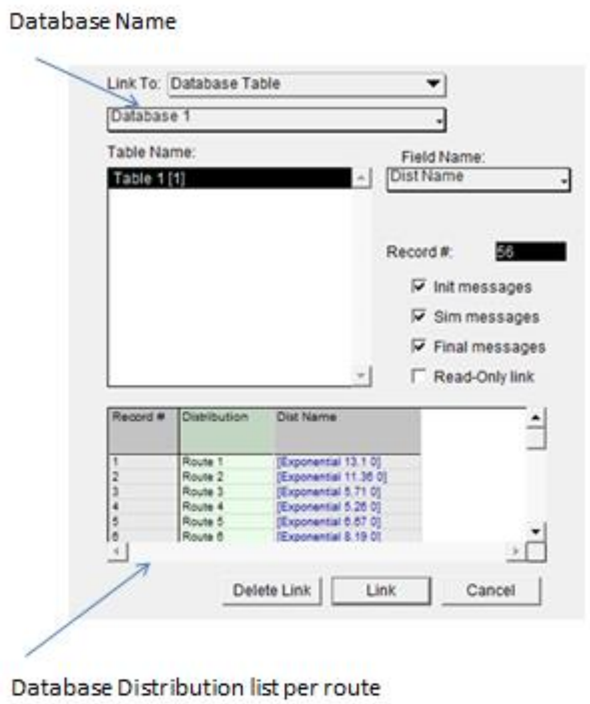
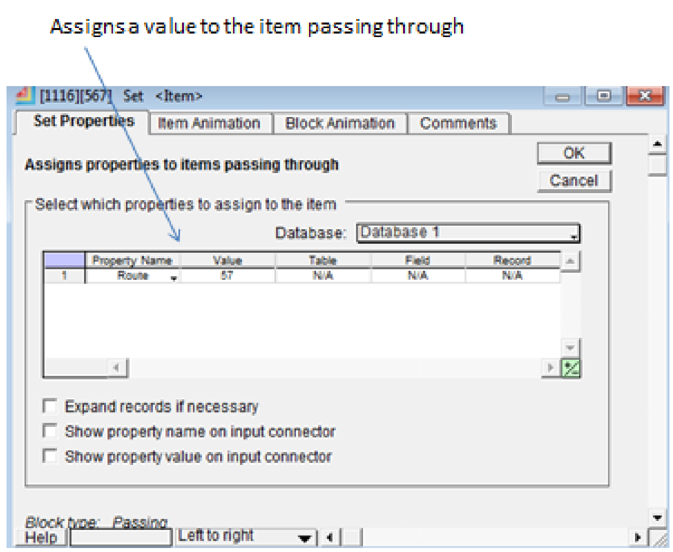
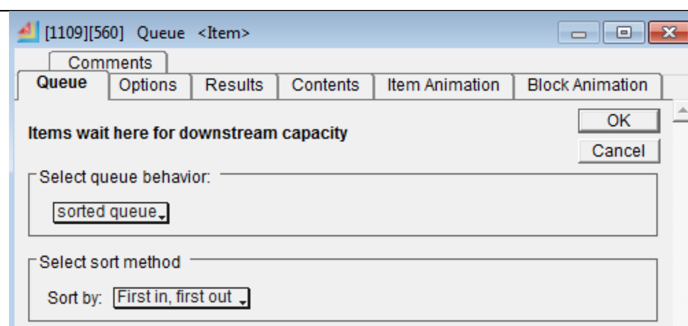
Name	Component	Function
Create Block – Dynamic Link screen		This screen shows the dynamic link to 'Database 1' which is where we store the demand distributions for each route.
Set Block		In this block we want to assign a unique property to the item passing through so as we can route it appropriately
Queue Block		This block stores the items and is a mandatory component before a 'Throw Block'

Table 7 (Continued) Model Component Details

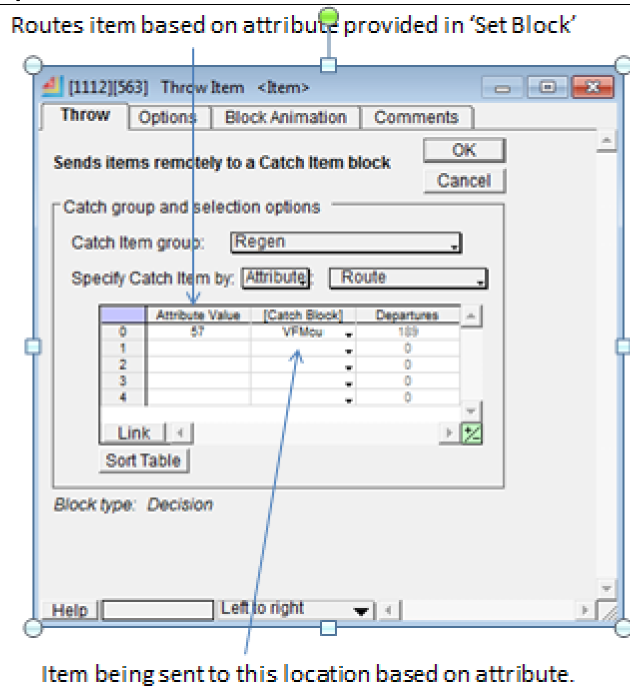
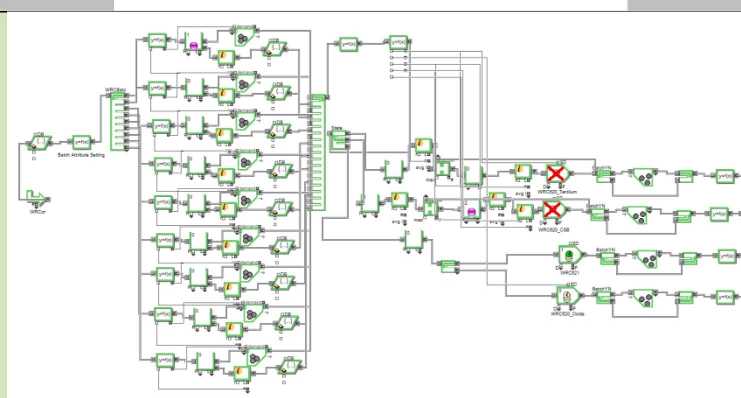
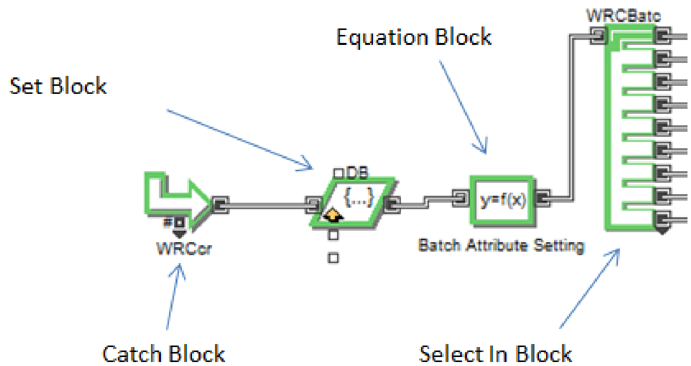
Name	Component	Function
Throw Block		The function of this component is to route the item based on a specific set attribute.
Clean Hierarchical Block		This hierarchical block houses each of the entities in the clean process flow and allows for run rule logic design
WRCcr Block		This block is responsible for representing the run rules that existed within the WRCcr entity regarding the cleaning of Calibration Kits

Table 7 (Continued) Model Component Details

Name	**Component**	**Function**
WRCcr - Catch and Batch attribute setting section.		In this section of the model the **'Catch Block'** catches the items being 'thrown' from the 'Demand hierarchical block'. The **'Set Block'** assigns a batch attribute of 1 which will be modified depending on its batch status further down the line. The **'Equation Block**' assigns a batch attribute depending on their 'Route ID' only certain routes can be batched together. The **'Select In Block'** assigns the item to a specific route dependent on the batch ID

Equation Block Code	if(Route==3 OR Route==4 OR Route==5 OR Route==6) {
	WRCBatch=1;
	} else if (Route==19 OR Route==20) {
	WRCBatch=2;
	} else if (Route==21 OR Route==22 OR Route==23 OR Route==24) {
	WRCBatch=3;
	} else if (Route==25 OR Route==26 OR Route==121 OR Route==122 OR Route==127 OR Route==128 OR Route==129) {
	WRCBatch=4;
	} else if (Route==27 OR Route==28 OR Route==29 OR Route==30 OR Route==125) {
	WRCBatch=5;
	} else if (Route==37 OR Route==38) {
	WRCBatch=6;
	} else if (Route==52) {
	WRCBatch=7;
	} else if (Route==53 OR Route==54) {
	WRCBatch=8;
	} else if (Route==126) {
	WRCBatch=9;
	} else {
	WRCBatch=0;
	}
		Code for batching on different routes.

Table 7 (Continued) Model Component Details

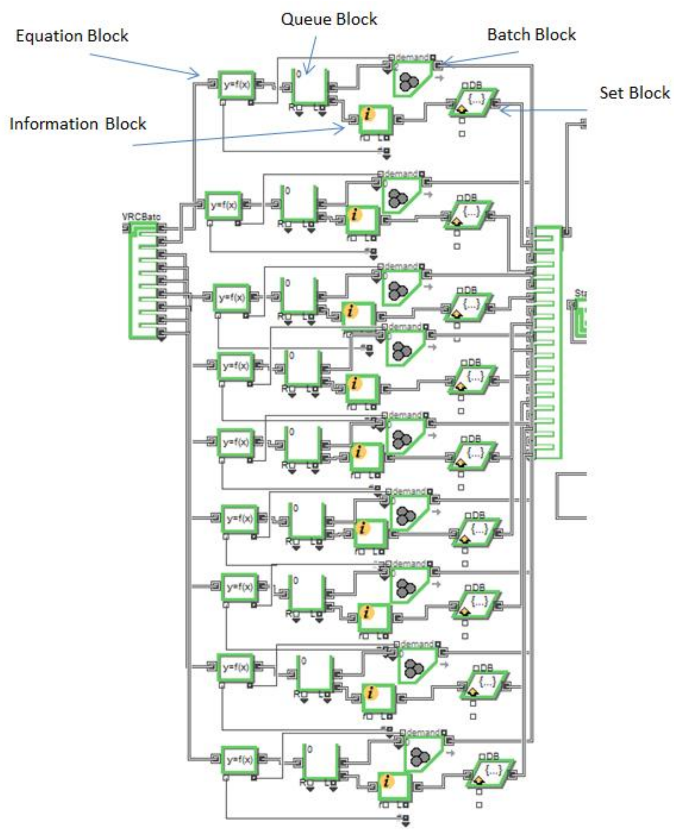
Name	Component	Function
WRCcr – Batch Section		In this section of the model the item is sent to one of the 9 different routes by the 'Select in Block' as identified in the previous section. The '**Equation Block'** monitors the quantity of items that has passed through it and activates the batching block when required. The '**Equation Block'** also monitors those items that have passed through but have been reneged due to wait time. The **Queue Block** holds the items until a batch can be made however if after a period of time an equivalent item has not arrived the item will be processed forward on its own or 'reneged' as is known in the Queue Block. The **Batch Block** waits on a signal from the equation block which indicates when we there are 2 items capable of being batched. Lastly the **Set Block** is responsible changing the batch attribute on those items that were reneged to a value that indicates no batching took place.

Table 7 (Continued) Model Component Details

<table>
<tr><th>Name</th><th>Component</th><th>Function</th></tr>
<tr><td>Equation Block Code</td><td>
count=count+1;

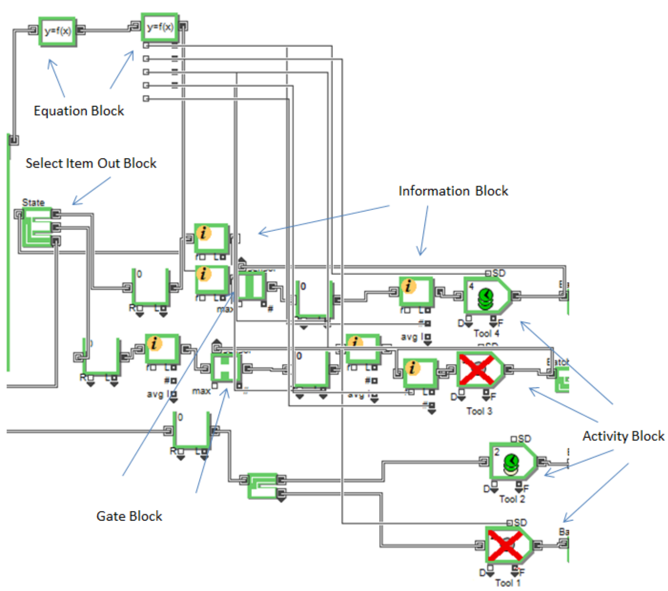
if ((count Mod 2)>0){   Monitors odd or even

outCon0=0;   if odd, value will be greater than 0 hence send ‘0’ to demand signal of batch block e.g. don’t turn on.

} else if (inCon0 > renege){   If item passes through ‘Information block’ inCon0 will be higher than ‘renege’ variable and so indicate that item that passed through is no longer in queue and so batching option is off

count = count-1;   Reset Count

renege= renege+1;   Make Renege counter the same as inCon0
}else {
outCon0 =1;   Send ‘1’ to demand signal of batch block, e.g. turn on and batch 2 items.

}
</td><td>Code for sending demand signal to Batch Block.</td></tr>
<tr><td>WRCcr-Product flow section.</td><td>


</td><td>In this section of the model we are designing the logic of how the kits flow through the tool. The 2 ‘Equation Blocks’ assign specific run states to the different routes and control their release as required; they also determine when the ‘Activity Blocks’ are shut down for maintenance / re-pour. The ‘Gate Block’ controls the amount of kits that can sit in the queue an process area of the tool. The ‘Activity Block’ provides run time details on how long the batches of kits take to process.</td></tr>
</table>

Table 7 (Continued) Model Component Details

<table>
<tr><th>Name</th><th>Component</th><th>Function</th></tr>
<tr><td>Equation Code 1</td><td><pre>
if(WRCBatch==1) {
        State=2; // State 2
} else if (WRCBatch==7 OR WRCBatch==9) {
        State=1; // State 1
} else if (WRCBatch==2 OR WRCBatch==3 OR WRCBatch==4
OR WRCBatch==5 OR WRCBatch==6 OR WRCBatch==8) {
        State=3; // State 3 Everything else
} else {
State=0;
}
</pre></td><td>Code for assigning batch states to different routes to enable routing.</td></tr>
<tr><td>Equation Code 2</td><td><pre>
if (state1q >3) // setting limit at 4 state1 kits when state will change from
state3 to state1
  state1=0; // shut down signal on state1 state is removed once queue hits 4
state1 kits
else
  state1=1;
if (state2q >4) // setting limit at 5 state2 kits when state will change from
state3 to state2
  state2=0; // shut down signal on state2 state is removed once queue hits 5
state2 kits
else
 state2=1;

if (state1q>3 OR state2q >4)
  state3 = 1; // shut down signal on state3 state is sent once queue hits 5 state2
kits
else
  state3=0;
if(state1outs2 == state1outs AND state1outs >1 AND state2q>2 AND
state2outs<5)
   state2=0;
if(state1outs2 ==state1outs AND state1outs >1 AND state2q>2 AND
state2outs<5)
  state3=1;
if ((state1q >3) OR (state2outs>4) OR (state2outs<5 AND state2==1))   //
setting limit at 4 state1 kits when state will change from state3 to state1
 reset=1; // shut down signal on state1 state is removed once queue hits 4
state1 kits
else
 reset=0;
</pre></td><td>Code for controlling batch quantities to different tools and determining the shutdown timings.</td></tr>
</table>

Table 7 (Continued) Model Component Details

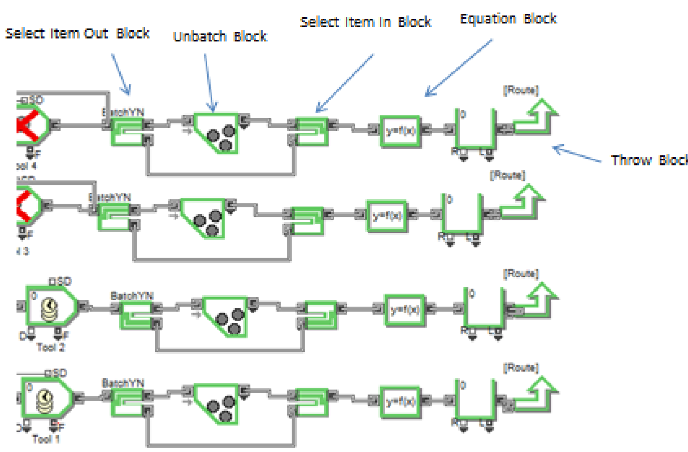
Name	Component	Function
WRCcr – Un-batching section and route flow determination.		In this section of the model we unbatch the kits to their unique entities. The **'Select Item Out Block'** takes the batching state that was assigned in previous sections. Those that have not been batched get funneled past the '**Un-batch Block';** batched items go through the '**Un-batch Block'** where they are split back to their unique entity status. The '**Select Item in Block'** simply takes kits from multiple sources and feeds back to a single flow. The kits then get processed through an '**Equation Block'** where they get assigned new route codes based on where they've been; for example some routes have the same process step twice in the same route; this is a way of monitoring qty of times through this operation. After this the '**Throw Block'** determines where they're going next on the process flow.

Table 7 (Continued) Model Component Details

Name	Component	Function

Equation Code	`if (Route ==21 OR Route==121 OR Route==22 OR Route==122 OR Route==25 OR Route==125 OR Route==27 OR Route==127 OR Route ==28 OR Route==128 OR Route==29 OR Route==129)`
	`    Route = Route+100;`
	`else`
	`    Route = Route;`
		This equation modifies the route of items that have been through an operation in order to track where in the process they have been.

APPENDIX B – MODEL DETAILS FOR REVISION 2 OF THE SIMULATION MODEL

Table 7 Model Component Details for Revision 2

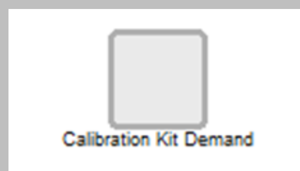
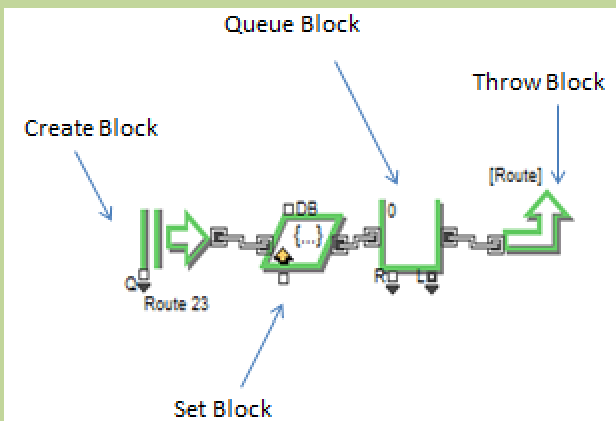
Name	Component	Function
Demand Hierarchical Block		The function of the Calibration Kit Demand hierarchical block is to group the different routes within the bounds of this research.
Route Process Flow		This flow of components sets the demand characteristics for each route and assigns a specific attribute.

Table 8 (Continued) Model Component Details for Revision 2

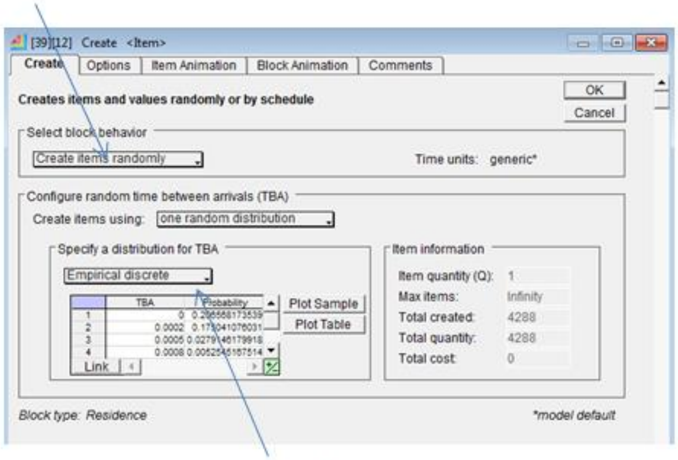
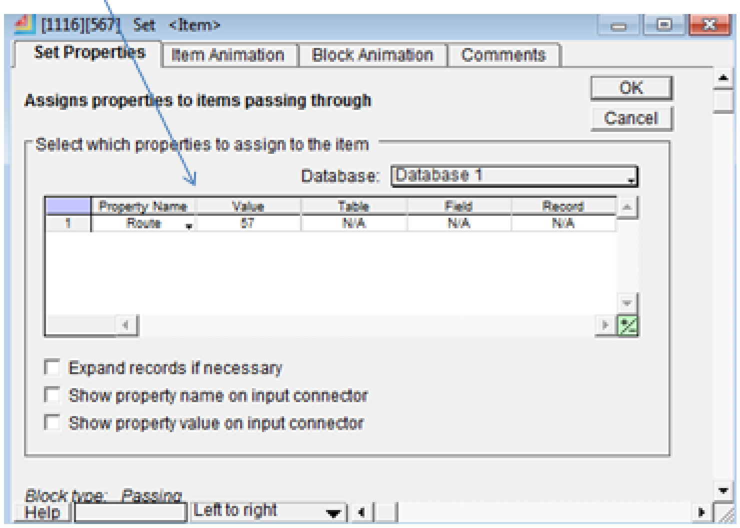
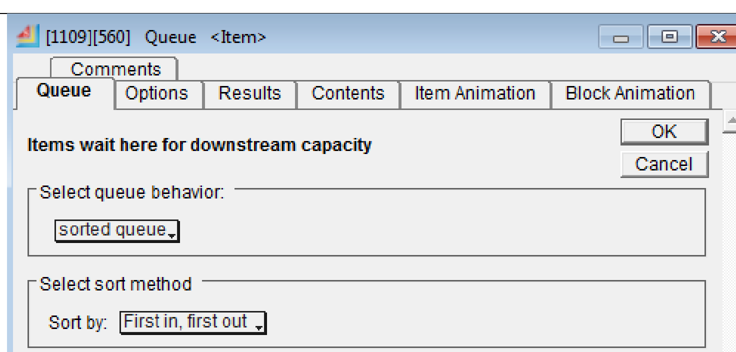
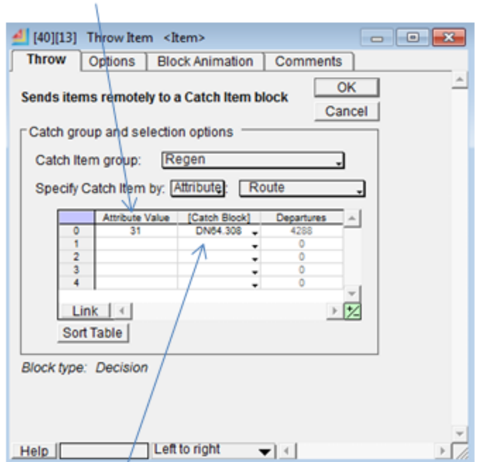
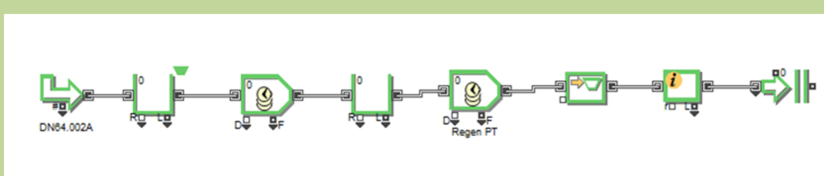
Create Block	Sets Items to be created randomly  Setting filter to accept an empirical discrete distribution.	In this block we set the criteria for assigning appropriate demand distribution
Set Block	Assigns a value to the item passing through  	In this block we want to assign a unique property to the item passing through so as we can route it appropriately
Queue Block	 	This block stores the items and is a mandatory component before a 'Throw Block'

Table 8 (Continued) Model Component Details for Revision 2

Throw Block	Routes Item based upon attribute provided in 'Set Block'  Item sent to this location based on attribute	The function of this component is to route the item based on a specific set attribute.
Use and Clean Hierarchical Block		The function of the Calibration Kit Use and Clean hierarchical block is to group the different routes within the bounds of this research.
Route Process Flow		This process flow represents the stochastic lead time of a calibration kit through the usage module and clean process of it

		respective route.

Table 8 (Continued) Model Component Details for Revision 2

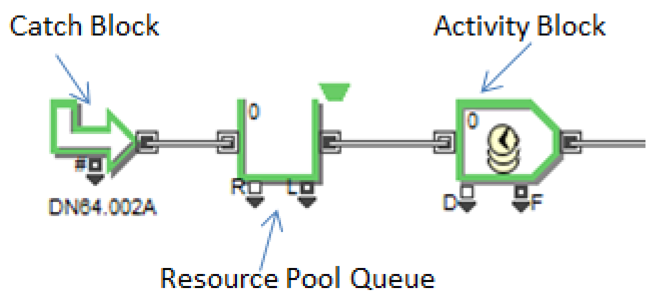
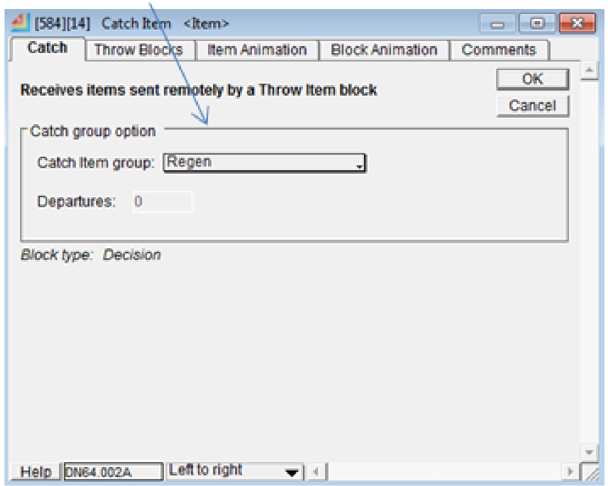
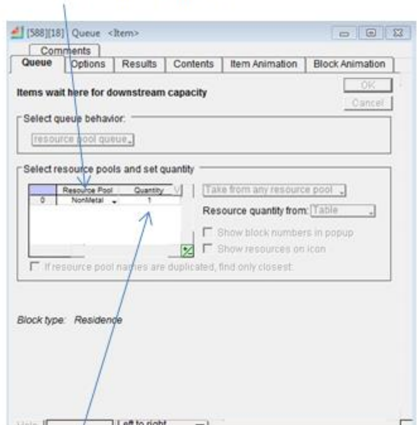
Use section of the Process flow		This flow of components represents the time delay experienced when a Calibration Kit being utilized by the module.
Catch Block	Specifies the name with which this catch item is associated with  The name of the Catch Block	The function of this block is to catch items being thrown from Throw Block within the Demand Hierarchical block.
Resource Pool Queue	Name of pool from which the Calibration Kit is going to be pulled  The Quantity to be removed from the Resource pool upon receiving signal.	This block simulates the activity of pulling a Calibration Kit from stock for use.

Table 8 (Continued) Model Component Details for Revision 2

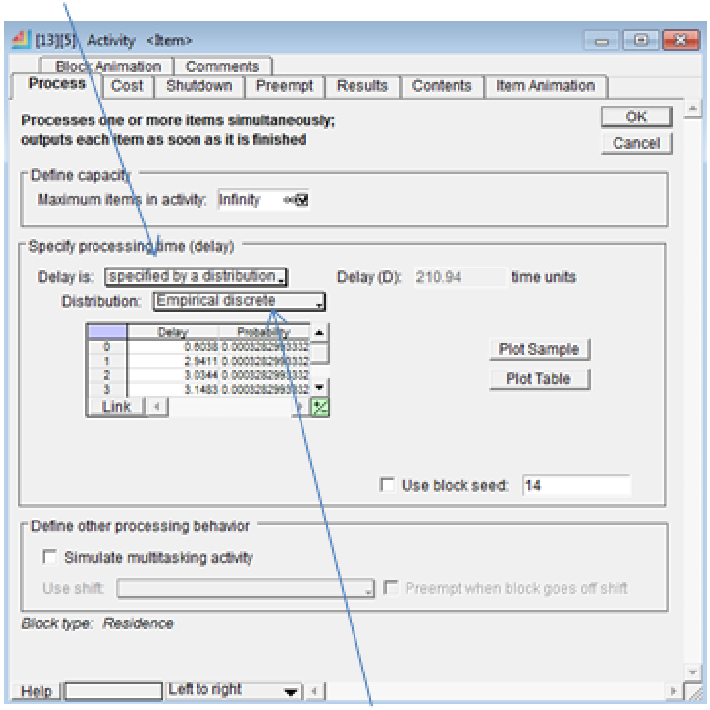
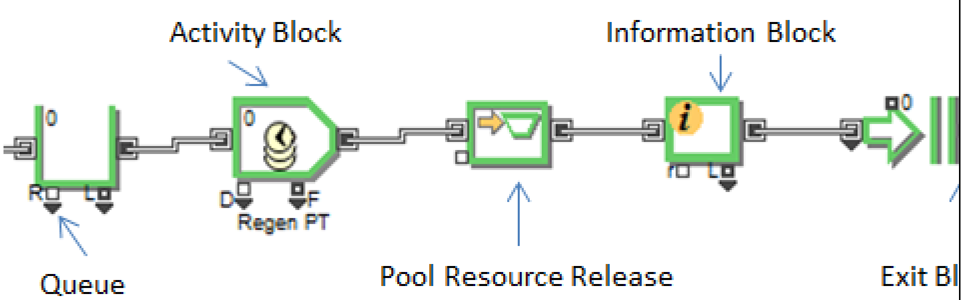
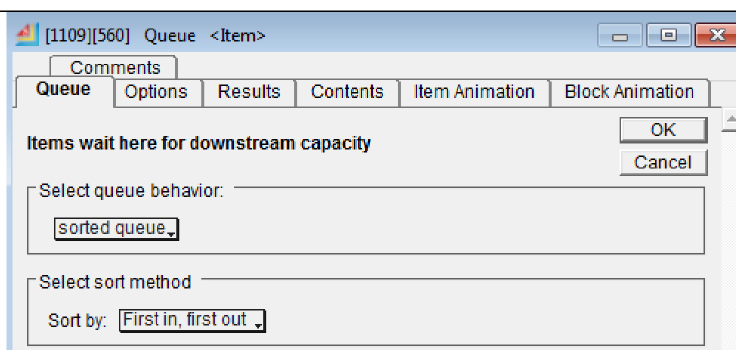
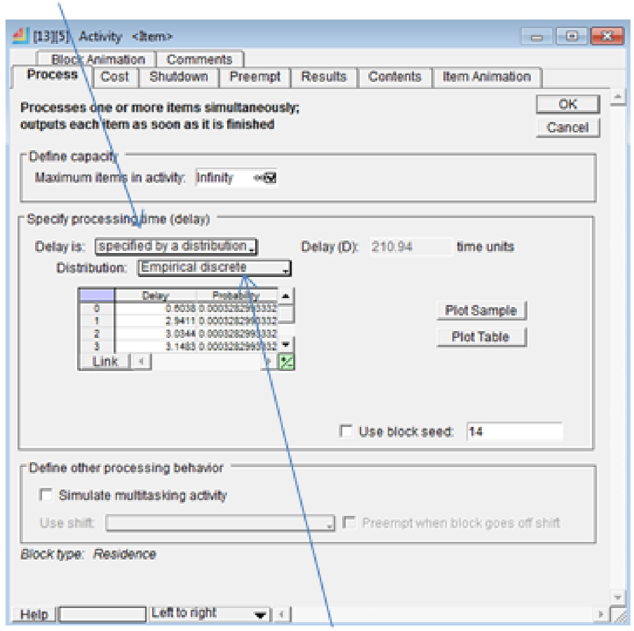
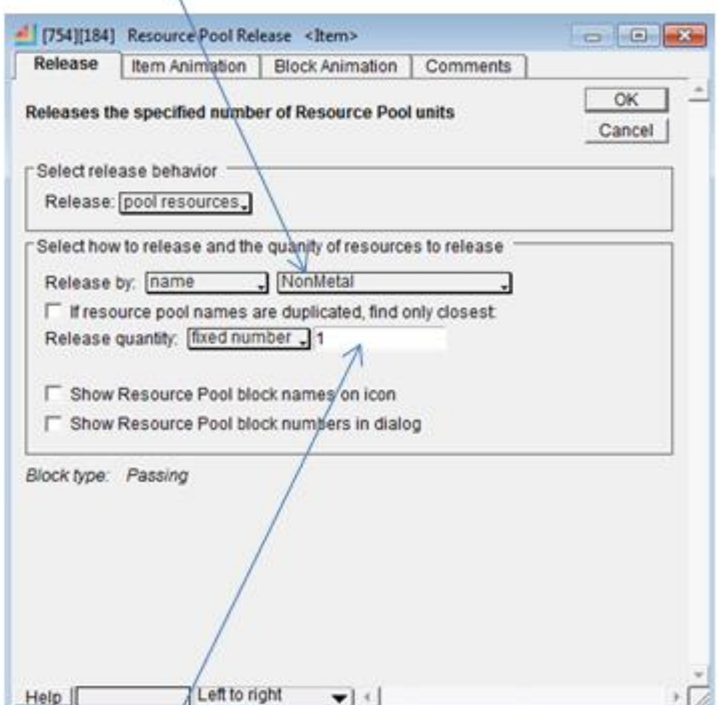
<table>
<tr>
<td>Activity Block</td>
<td>Sets Items to be delayed by a distribution

Setting filter to accept an empirical discrete distribution.</td>
<td>This component of the simulation model replicates the delay experienced by the calibration kit through its Usage stage.</td>
</tr>
<tr>
<td>Clean section of the Process flow</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Queue Block</td>
<td></td>
<td>This block stores the items and is a mandatory component before an 'Activity Block'</td>
</tr>
</table>

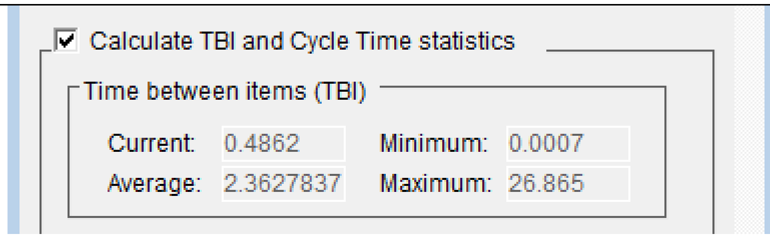
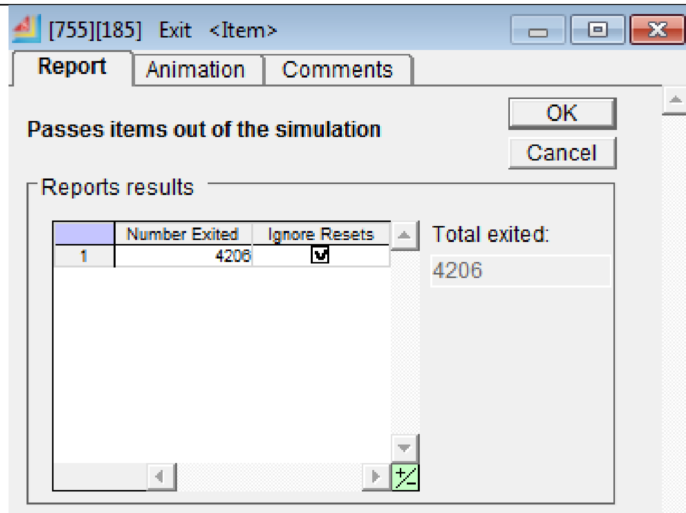
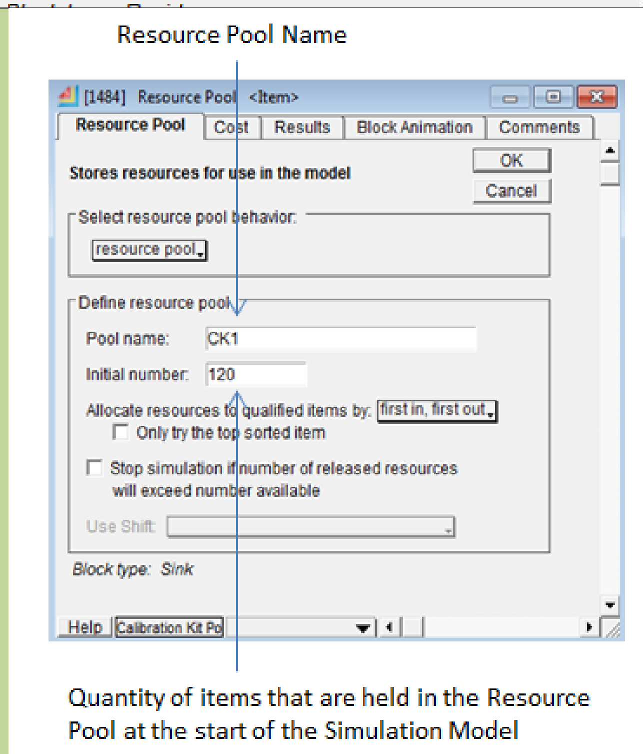
Table 8 (Continued) Model Component Details for Revision 2

<table>
<tr>
<td>Activity Block</td>
<td>Sets Items to be delayed by a distribution


Setting filter to accept an empirical discrete distribution.</td>
<td>This component of the simulation model replicates the delay experienced by the calibration kit through its Clean stage.</td>
</tr>
<tr>
<td>Pool Resource Release</td>
<td>Name of the Resource pool to release items back to.


Quantity of resources to release to the pool.</td>
<td>This component of the model releases the calibration kit back to the Resource pool from which it came.</td>
</tr>
</table>

Table 8 (Continued) Model Component Details for Revision 2

Information Block		This component is utilized to measure output from the model.
Exit Block		This component removes the demand signal from the process flow.
Resource Pool		This Block is responsible for holding the Calibration Kits, releasing them and accepting them post clean.

APPENDIX C – OPTIMISER DETAILS

Table 8 Details of the Optimiser Block included in the model

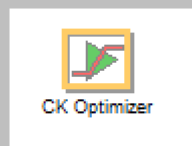
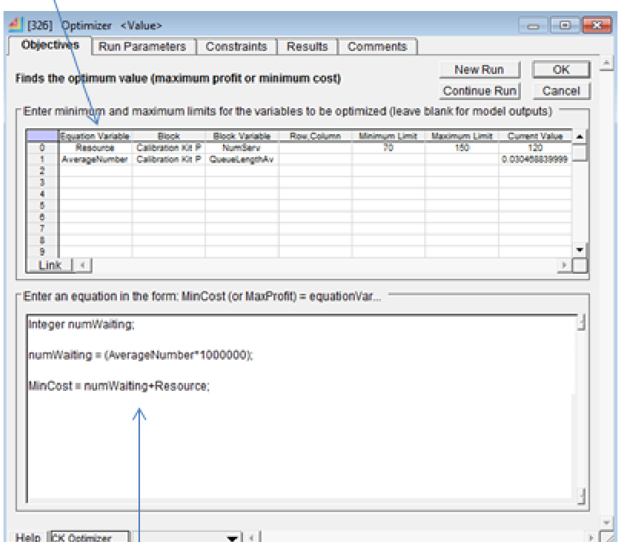
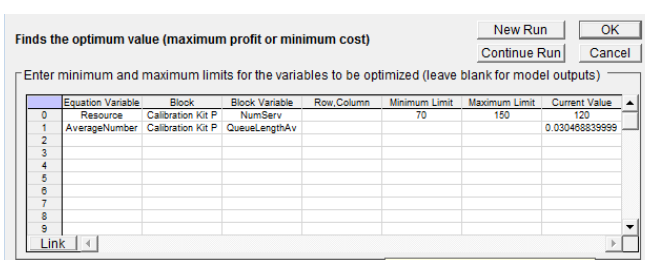
Name	Component	Function
Optimizer Block		This block contains the functionality to sit on top of a discrete event simulation model and provide an optimised solution within current constraints.
Objectives and equation tab	Variables for use in optimization equation  Equation for determining optimized safety stock levels	This is kernel of the block which determines the objectives of the optimizer through identification of the variables and outlining of the equation.
Variables		In this equation we are defining 2 variables for the optimization model. The 'Resource' variable is an input that is fed into the Resource Pool Block in the Simulation model. As part of the design we have defined arbitrary min and max boundaries for this input. The second variable known as Average Number is taken as an output from the Resource Pool Results Tab which monitors the average number of requests waiting in the queue.

Table 9 (Continued) Details of the Optimiser Block included in the model

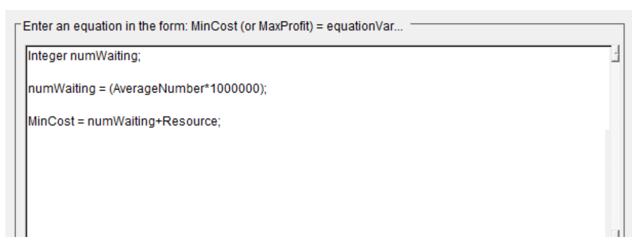
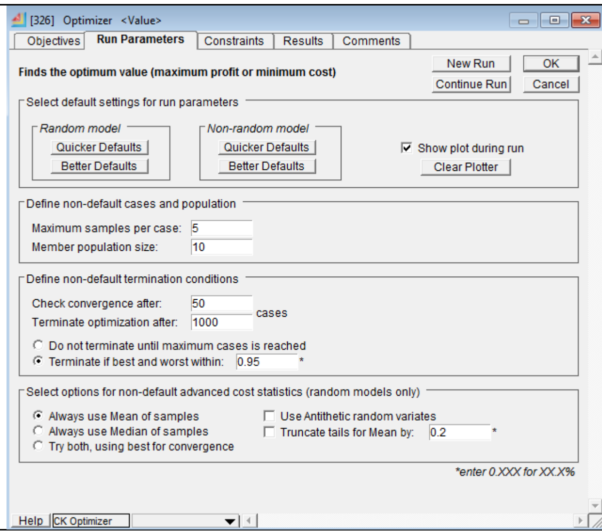
Equation		In order to run an optimization model we need to define the linear programming equation. In the equation we firstly define an Integer variable called 'numWaiting'. We then assign a formula to this variable which takes the average queue qty for requests in the Resource Pool called 'AverageNumber' and Multiply it by 1 million. We take this variable and insert it in the 'MinCost' equation whose goal is to minimize the formula using the identified inputs and within the run parameters. The other term in this formula include the 'Resource' qty that is an input into the resource pool at the start of the simulation run which defines our starting kit qty. The equation should function like so: Any time during the model run that there is an occasion where we don't have enough stock and cause a queue of any number. By multiplying 'AverageNumber' by a million we magnify the effect so as when we try and minimize the equation the model will, assuming our min and max constraints are set appropriately, always reject any scenario that has caused a queue of any size and we will be left with only those scenarios whose resource number references the actual stock quantity that was used.

Table 9 (Continued) Details of the Optimiser Block included in the model

Run Parameters for the Optimizer		These parameters outline the boundaries of the optimization run.

APPENDIX D – ROLES AND RESPONSIBILITIES IN THE CALIBRATION KIT DECISION ENGINE PROCESS

MT Calibration kit Coordinator Roles and responsibilities.

1. Ensure at the Start of Shift that inventory of Calibration kits is sufficient for the monitors due.
2. Monitor inventory levels in the Functional Area to ensure used kits are proc'd out and old kits do not build up.
3. Provide incoming shift with a clear passdown and information on Calibration kit availability.
4. Meet regularly with Engineering to review performance/ issues/ Areas for improvement.
5. They are the first point of contact on shift in the Functional area for all Calibration kit related issues.
6. Disposition and flagging of Kits on hold on their routes.
7. Identify and removal of Ghost kits from the system.
8. Co-ordinate Emergency Starts.

9. Train all other MT's on correct procedures and disciplines with respect to the use of calibration kit 's.
10. Become a source of Knowledge for all other MT's and supervisors on calibration kit related matters.
11. Provide support to engineering on calibration kit related experimentation.

MT Calibration kit Coordinator's supervisor roles and responsibilities.

1. Sign off on Emergency Starts
2. Embed the calibration kit Coordinator role as part of the Core Job.
3. Ensure that the expectations outlined are reviewed and discussed during 1:1's.
4. Ensure that the calibration kit Coordinator performance is recognised at review period.
5. Ensure that the calibration kit Co-ordinator is provided with the Time to carry out his roles and responsibilities and is given the time to complete the proposed training.
6. Encourage the calibration kit Co-ordinator to roll out training or calibration kit Updates to all of the MT's in the functional Area at staff meetings or cluster meetings.

Shift Manager's roles and responsibilities.

1. Ensure that there is a Full Matrix of calibration kit coordinators for the Shift in place at all times.
2. Ensure that calibration kit Availability and Management is an agenda item at Start of Shift, mid shift and end of shift meetings.
3. Calibration kit capability, management and execution are part of every Supervisors Expectation plan.
4. Ensure that all calibration kit Coordinators are given the opportunity to attend the proposed training and any supplementary training that is needed.

APPENDIX E – QUALITATIVE FEEDBACK

Feedback Interviewee 1 (I1)
• The main focus for I1 was to ensure the clean process meets factory demands from a calibration kit perspective and causes no impact to factory output. • This needs to be done using a minimum amount of Calibration kits. At the time of the interview calibration kits outnumbered production by 5 times. • A statement was made about the calibration kit process as being equivalent to a Mini-Factory. • Tools logged into a down state for wait Calibration kit provide the main metric for calibration kit area performance. • Cycle time is being analysed for entire flow however breakdowns between Clean area and queue and process cycle times are not being monitored.
Feedback Interviewee 2 (I2)
• I2 is working with sister companies on Calibration kit issues and so has a unique view and opinion on how things work. He wanted to ensure that whatever methodology was devised on this technology could be transferred to other technologies down the road. He highlighted his desire for it to be simple, if it becomes overly complicated and complex it won't be used and would become difficult to maintain. His initial feeling was that he had worked in this area for the last 3-4 years and the level of complexity was really high…..he had spent the last 2 years trying to simplify the process and take an abstract view of it so as it became manageable sacrificing some accuracy e.g. 80% accurate Vs a load of complexity for 90-95%. • The current system devised by I2 calculates calibration kit usage in the different areas by taking 30 day and 4 day averages which I will go into more detail in follow on sections. I2 feels that this gives him an accuracy which right now he's happy with. • I2 is definitely interested in how the variability of usage and clean could be incorporated into a methodology. The current system tries to dynamically understand usage by taking a long and short term view however the clean time is currently a static hard coded figure which is not dynamic and hence doesn't represent reality. • He suggests that I should be looking at any methodology from an operation perspective rather than a route perspective…after all when the clean area are processing kits they don't batch by route they batch by operation and many different routes contain the same operation. • I2 states that once a calibration kit is passed through Clean it's no different than any other calibration kit coming out of Clean however due to route restrictions calibration

kit's have to remain on their route and so according to him unnecessary constraints are being placed on the system.

- I2 wants the final methodology to be as generic as possible and easily transferrable to the next technology and possibly sister companies worldwide. I2 would like any derived methodology to take this Calibration kit process and provide the users with a platform that represents its logic and to allow experimentation in all aspects of the system such as reducing variability in process times, queue times, batching, wip management rules, bagging opportunities, priority strategies etc.

Feedback Interviewee 3 (I3)

- I3 felt that the module areas management of the Calibration kits is a key concern when it comes to the Calibration kit process.
- I3 demonstrated this fact by showing a Calibration kit route that was highlighted as priority 1, e.g. needs to be processed through the Clean area as quickly as possible, and through the "Days at Operation" column showed that Calibration kits had been left to accumulate for a period of time and then processed through to Clean in one go leaving a short fall in the module area and pressure on the clean area to get processed.
- I3 states that this mismanagement leads to tools going into 'Wait CK' status which is one of the key metrics with which the Calibration kit process is measured by.
- Regarding a methodology I3 stated that anything that would heighten the Calibration kit module owner's education regarding Calibration kit management would be of benefit.

Feedback Interviewee 4 (I4)

- I4 stated that there are times that the Clean area gets 'dumped on' with a large quantity of Calibration kits with the expectation of a 'miracle' to get the kits back to their area as quickly as possible.
- I4 states that a constant flow from the modules would be of great benefit as it would ensure that the Clean area always had capacity and that areas would not be going down for 'Wait CK'.
- I4 went through a daily report that detailed why areas were going into 'Wait CK'. Over a 1 month period 74% of down time in the 'Wait CK' status was due to 'Poor CK Management'.

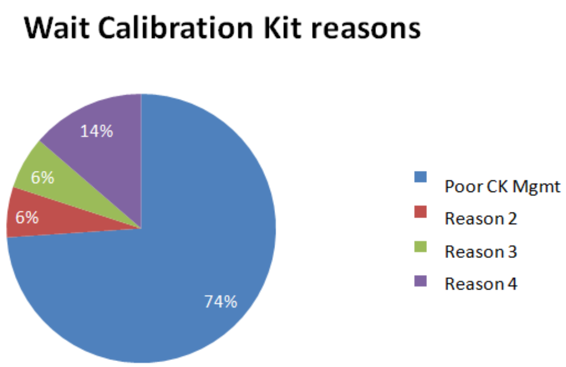


Figure 50. % of time spent by tools in 'Wait CK' and their respective reasons

- I4 states that some areas operate using Calibration kit tracking, this system automatically is able to test (PRE status) for kits that are appropriate for their purpose. This differentiates areas through their visibility of the quality of calibration kit's available to them.

Feedback Interviewee 5 (I5)

- I5 speaks of how they can get dumped on with kits; this is largely caused by the lack of calibration kit management according to I5. I5 spoke of how there may be 1 calibration kit owner per tool area however this causes issues as this person is on shift and so is only available for half the week and may not look at the calibration kit situation until near the end of his shift.
- I5 speaks of the fact that they only look at the CT for their own area, e.g. Clean area 1 looking at Clean area 1 cycle time and Clean area 2 only looking at Clean area 2 etc; CT for the entire process flow is not monitored. This can reduce visibility for Modules on when they send Calibration kits to clean as there is no guide on how long it takes to get back to the module. I5 suspect's reasons for this may be due to the fact that that some of the tools involved in the Clean process are not within Clean control and are reliant to compete with production kits for tool time. Secondly Calibration kits cycle time is largely dictated by their priority assignment which determines how quickly they are run through the process.
- I5 highlights that rules governing the days of inventory calculation are hard coded and have shown on some occasions to cause inventory build up on certain routes due to rules that are no longer mirror reality.
- Avoiding 'Wait CK' downtime is 'king' according to I5. Focus for everyone is to ensure a module does not go down for 'Wait CK' which can result in the purchase of new kits's for mismanaged routes which in the long run results in routes having more inventory than required.

Feedback Interviewee 6 (I6)

- I6 used an interesting analogy when describing the main issues in the Calibration kit process.

• He stated; When it comes to gases, chemicals, spare parts MT's view these consumables as somebody would view their electricity, gas or water, has to be used that's that….however when it comes to calibration kits modules view these like MT's would view their income….needs to be minded, they own it, they're going to save it. This has been seen to drive mismanagement of the calibration kit process and so results in inventory build. • I6 stated that not all areas use Calibration kit tracking as they prefer to manually manage the kits in order to take advantage of the cycling capabilities of used calibration kit's.
Feedback Interviewee 7 (I7)
• I7 sees that the main issues regarding the mismanagement of the Calibration kit process is due to the fact that not all areas are managed by the Calibration kit tracking system. • I7 would like to see the removal of the manual process and let the Calibration kit tracking system run the process. • I7 would be really interested in understanding how a developed methodology for optimised Calibration kit fleet size could be incorporated into the Calibration kit tracking system.

APPENDIX F – RUN RULES

Tool1

This machine can take eight kits at a time, i.e. can have eight kits on these tools in one go. The kits are loaded in batches of two. They're not constrained by route but the operation needs to be the same. Tool1 has to run operations in a specific order which is made up of these three states; State 1 (Operation X or Operation Y (4 batches (8 Kits) then replaces the cleaning agent in the machine), State 2 (Operation Z, 5 batches (10 Kits) then replaces cleaning agent in the machine) and State 3 (all other operations). Preventative Maintenance procedures are time and counter based.

Tool2

This machine can be loaded with five kits at a time. Not constrained by route or operation.

- Operation 'L' runs with Operation 'M', One 'L' operation kit is always run with 4'M' operation kits this is a process requirement.

- Operation ‘L’ also runs with Operation ‘O’ (no constraint on number of ‘O’)
- Operation ‘P’ or Operation ‘Q’ never run with another operation.

Tool3

This fleet contains only 1 machine and 1 operation.

The machine can only take one kit at a time with a 3 to 4 minute delay between the output of the last kit and the input of the next kit.

Tool4

This fleet of machines takes one kit at a time, no cascading was evident apart from very rare occasions where a kit can be loaded on 2 minutes before the last kit finishes. For the simulation model it was safe to assume that the kits run one at a time.

Tool5

The process times are determined by routes and operations; for example two routes can have the same operation yet they have different process times. There are two load ports on Tool 5, which allows for cascading of kits. So for example a kit on route 5 on operation ‘C’ when run takes 1.39 hours, a second kit is loaded 10 minutes after the first one however because the second kit has been loaded whilst the tool is working on kit 1 the process time appears a lot longer e.g 2.47 hours. Taking 1.39 hours as the time it takes to process the kit not in cascade mode and calculate the gain by cascading the kits i.e. running the second kit right up behind the first one we're looking at a saving of approximately 7 minutes per kit, so for example cascading 8 kits will have a process saving of approximately 49 minutes on the 7 kits after the first kit.

Tool7

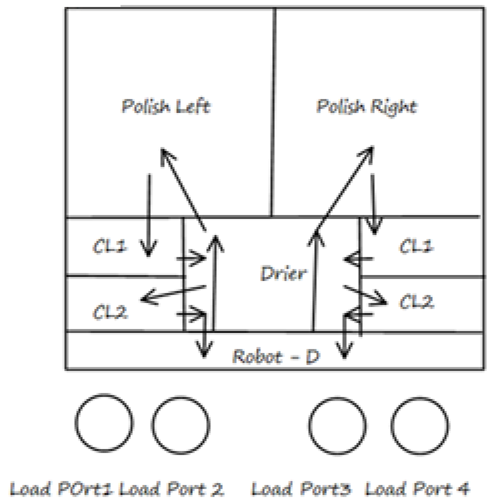


Figure 51 Visual Diagram of kit flow in Tool5

Figure 20, depicts the operation of this machine. The dirty holders containing the used kit sits on Load Port 1 (LP1) and Load Port 3 (LP3), the empty holder which takes the cleaned kit goes on Load Port 2 (LP2) and Load Port 4 (LP4). The first kit is taken in and uses both polish left and polish right. The way it works is kit 1 sitting on LP1 has a component taken in by robot into the drier; this component then goes into the Polish left. The next component from kit 1 is then taken into the drier and then goes to Polish right. When the components are finished in the Polish section the robot takes them and places them in clean 1 the robot then takes them out and places them in clean 2, after this step the robot places the component in the clean holder. This process also happens on the right hand side. Once the 19th component from kit 1 is back in the clean holder, the robot will start taking components from the second kit as one of the polish sections will be free, e.g. (1 component in POL right, CL1R, CL2R, CL1L and CL2L but POL left should be free).

One of the routes for operation 7215 is different because the kit is restricted to operating on one side of the Polish tool, e.g. the components can only run on Pol Left, hence increasing the time for each kit to get through. This route is only run on Tool 5a.

Tool6

Kits can be batched in two's. The operation needs to be the same for both kits, however, it's not constrained by route type. The machine can take a max of four pairs in one go.

Tool7

Kits are batched in two's and are not constrained by route but they are by operation. The machine can take a max of eight kits in one go.

Tool8

Kits are batched in two's and are not constrained by route but they are by operation. The machine can take a max of eight kits in one go.

Tool9

The machine is a cascade tool with two load ports. Two kits can be loaded at the same time, however, the second kit will sit in the load port until the first kit has all its components taken into the tool.

Tool10

This machine batches two kits at a time and can have eight kits running on the machine at any time. The kit needs to be at the same operation, however, the route does not have to be the same.

Tool11

This machine allows kits to be cascaded. There is one operation; however there appears to be different process times for different routes. Kits that are cascaded are showing a 10% saving in process time.

Tool12

This fleet of machines takes one kit at a time, no cascading evident apart from very rare occasions where a kit can be loaded on two minutes before the previous kit finishes. For this analysis assume that the kits run one at a time.