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# Life Cycle Costs of a Paediatric Prosthetic Knee

## Final Report

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# Contents

## List of Figures

## List of Tables

# Executive Summary

Engineering a product for optimal reliability at minimal life cycle costs (LCC) has been a challenging aspect to nearly all industries. Uncertainties complicate control over these costs, with many LCC models having been developed to determine the optimal design.

This project aims to find the best reliability level for a low-cost paediatric prosthetic knee (PPK) under development by the Council for Scientific and Industrial Research (CSIR) and minimise its LCC. An agent based simulation in combination with system dynamics techniques is utilised to reach this goal. A pilot version of the agent based model is compared with an analytical Monte Carlo simulation in order to validate the use of the agent based simulation. The LCC are especially important, as the CSIR do not intend to make a profit from the PPK and all costs will be attributed to research and development. A mathematical expression capable of predicting the time to failure based on user patterns is developed, which will assist prosthetists and parents with future financial planning for the eventuality of a failure.

What is to be learnt from this project is the important link and interaction between reliability and product performance, culminating in its LCC. The end-beneficiaries are essentially the children who will receive a well-designed product to use and improve their lives. Future low-cost prosthetic products may also be able to use this combined modelling approach and minimise their expenses.

# *Chapter 1*

# Introduction

## 1.1 Background on the Paediatric Prosthetic Knee

Paediatric prosthetics are based on simplicity and dependability. Components must fit the child's developmental phase, supporting his / her capabilities and life activities. A completely functional prosthesis will assist the child in their development and adaptations as an amputee (Oglesby and Tablada, 1992) . Lower limb prosthetic products have come a long way in becoming sophisticated to support the life activities of child amputees and enhance their quality of life. There are a variety of paediatric prosthetics knee (PPK) products on the market.   They are mainly categorized according to articulation types they offer. These range from simple single-axis models to complex ones with polycentric multi-bar linkages, hydraulic swing phase controls, foot rotations, extension assist mechanisms and robotics. They allow children to do a multitude of functions, also assisting them in their gait and ease of use (Andrysek et al., 2004).

The primary challenge has now shifted from improving the functional and mechanical capabilities of the prosthesis to the availability and accessibility thereof. The main reason behind inaccessibility is not only the high manufacturing and distribution costs, but also the uncertainty with regards to future life cycle expenses (Kickham and Nowlan, 2014). South Africa's resource constrained public health system cannot provide all child amputees with the required prosthesis, and not all medical insurers are prepared to fund expensive prosthesis over a long period of time.

Stanford University, in conjunction with the Bhagwan Mahaveer Viklang Sahayata Samti (BMVSS) organisation in India, have developed the Stanford-Jaipur knee to provide a low-cost option to resource-poor patients. Time magazine has named this product as one of the 50 best inventions of 2009 (Samti, 2013). Figure 1 illustrates a child using the Jaipur knee.

Figure 1: A child walking with the Jaipur knee (Greig, 2009)

It would seem that the Jaipur knee will be able to fill the demand for PPK's in South Africa; however it was found after evaluation that this product would not be able to stand up to the harsher African conditions. The CSIR has therefore decided to develop a low-cost PPK to be manufactured and distributed locally, with the requirement for higher durability to suit for the African conditions and children's high activity levels.

The Jaipur knee is made from oil impregnated nylon (Samti, 2013) with yield strength between 55 and 83 MPa (Callister and Rethwisch, 2011). Materials such as steel, titanium and aluminium alloys have been traditionally used in prosthetic manufacturing. Some carbon-fibre limbs have also been developed (Uellendahl, 1998). These materials have got much higher yield strengths than that of nylon, making them more durable for the use in prosthetics. The design team is implementing steel and aluminium alloys in their design, as it is much less costly than titanium and carbon fibre composites (Callister and Rethwisch, 2011) and they have easy access to these materials. With the product in the early stages of development, the design is still open to changes.

## 1.2 About This Project

There are four main areas where Industrial Engineering can make a positive difference in the costs, quality and availability of prosthetic products, as outlined by Zhang and Wang (2014):

1. Optimisation of manufacturing processes
2. Incorporating ergonomics into the design
3. Optimising the supply chain
4. Providing testable predictors with regards to LCC for medical insurers

This project is focused on the fourth area: to launch an investigation into the expected life cycle costs (LCC) associated with the supply and use of the PPK under development. These costs are subject to uncertainty, and are significant in the delivery of the PPK.

The knee prosthesis has the following basic components (Zhang and Wang, 2014):

- Knee joint
- Pylon (functioning as the lower leg)
- Foot
- Custom made socket, which is the main interface between the residual limb and the mechanical knee

Figure 2 shows a basic knee prosthesis (Orthrotics, 2012).


**Figure 2: A basic knee prosthesis (McCleve Prosthetics and Orthotics, 2012)**

The scope of this project is limited to the mechanical knee only, consisting of the knee joint, the pylon and the foot. The socket component is excluded, as it is subject to other factors outside the field proposed for this study.

The CSIR is the designer and will be the manufacturer and main distributor of the prosthetic knee joint. The joint will be assembled together with standardised pylon and foot components to make up the mechanical knee. The expected demand for the PPK will influence the production rate of the joint, as well as the order rate of the pylon and foot. Currently, the CSIR is estimating an initial production of 1800 joint units in 2016. Demand from new fittings is expected to be between 1 and 5 units per week based on feedback from prosthetists in industry who are involved with paediatric knee fittings. Table 1 is breakdown of the current costs.

Table 1: Cost Summary

| Activity | Costs (in Rand value) |
|---|---|
| **Design** | 3 060 000 |
| **Manufacturing (per knee joint)** | 3700 |
| **Selling price (1st time)** | 2400 |
| **Warranty Price** | 3400 |
| **Validation** | 700 000 |

The selling price is payable when the child receives a PPK for the first time. Any replacements afterwards will incur the warranty price. The manufacturing costs remain the same for both new units and those replaced. The warranty costs constitute the difference between the manufacturing price and the warranty price – i.e. R 300.

## 1.3 Needs Requirement

Uncertainty with regards to future demand as well as associated LCC has prompted the following questions:

1. What are the associated LCC over 5 years?
2. What is the expected demand, i.e. how many units will be replaced and manufactured over the course of the project?
3. What effective design changes can be made to reduce the LCC, i.e. what is the optimal design policy?
4. When will a child require a replacement?

The answers to the questions will all have significant influences on decisions taken during the development of the PPK, before it is put out to market. Ultimately, the aim is to minimise the LCC associated with the PPK. The results will assist the CSIR in design, production and delivery planning. This information can also be of benefit to the public and private health care industries, medical insurers as well as investors who wish to support the prosthetic project. The government has in recent times announced its plans for the National Health Insurance scheme, known as NHI, with the objective of providing access to quality health care to all South Africans (Matsoso and Fryatt, 2013). The results can assist the government in providing enough financial assistance towards an amputee's continuous health and prosthetic requirements.

## 1.4 Project Approach

This project will attempt to answer the questions posted in a systematic process. This process is outlined in the following steps:

1. Conduct a literature review to explore and investigate the fields of product development, LCC and solution methods applicable to these areas
2. Outline the life cycle of the PPK as a system and identify major factors affecting the costs
3. Develop the method to calculate LCC
4. Verify and validate the method
5. Link product development and LCC in monetary terms, using the selected solution method
6. Optimise the design in terms of its development and minimum LCC

7. Deliver the solution and results to the CSIR.

A preliminary literature review identified Monte Carlo (MC), Agent Based Simulation (ABS) and System Dynamics (SD) modelling as viable tools to solve product development problems (Fang and Zhaodong, 2015, Maisenbachera et al., 2014). This project will be utilising the functionalities of ABS and the SD library in Anylogic software, making use of parameters and variables identified in Step 2. A MC simulation will be run using the statistical programming language R, in order to compare the results with that of the ABS. The ultimate aim is to find the optimised level of development and minimising LCC. Variables to be used include the following:

- Design variables
- Selling and Warranty price
- Manufacturing parameters
- Human factors
- Economic factors

Modification in design variables will drive the simulation, as all future events depend on how the product was designed. The model will be tracing the effects of these changes and the associated costs. Verifying and validating the model is an important step as to determine the credibility of the results, to support the decision making process to be undertaken by the CSIR development team. The selling and warranty price will be lower than the production costs; this deficit is assigned to Research and Development (R & D), adding to the importance of these decisions.

# Chapter 2

# Literature Review

This review investigates the relation between product development and LCC, as well as exploring simulation as a technique to mathematically express this link. Systems thinking is applied to demonstrate the life cycle of a product as a system, with each phase representing a component of the system influencing the next phase.

Several articles, conference proceedings and academic books were consulted to complete the review and find evidence to support the utility of LCC during product development. The collected works also explored the various simulation methods used to compute LCC. From this evidence base, a feasible simulation method to be used in this project was found, and is presented in Chapter 3.

## 2.1 Product Development and Life Cycle Factors

The life cycle of a product is characterised by four main phases, namely (Yuling et al., 2009):

- Design
- Manufacturing / Production
- Service / Operational use
- Retirement

### 2.1.1 Design

A product is designed and manufactured to fill a void in the market and must meet customers and consumer requirements. The design and manufacturing stages are often jointly referred to as the development phase. It is during this phase that the product quality, and hence its future performance, is determined. The process of synchronized engineering by a multidisciplinary team of engineers has proven to improve the quality of products (Levin and Kalal, 2003). However, this phase is challenged by uncertainties with product performance in the future. An over-engineered product will consume company resources and not find its use amongst consumers. The reverse side also holds true, as a poorly developed product will not satisfy the ever increasing knowledgeable customers' demand for quality. To solve this problem, Levin and Kalal (2003) suggested that the concurrent engineering process be extended to the entire life cycle of a product.

A product's faults or future failures can be summarised by the term dependability, which constitutes its reliability, availability, maintainability, quality and safety (Kleyner and Sandborn, 2008). The dependability of a product is determined during its development, and is proportionally linked to its performance during service. Poor dependability will result in poor performance, while a highly dependable product will perform to its expectations. Designing a product while taking its entire life cycle into account will benefit both the developing company and the consumer.

Of the several functional requirements (FR) that a prosthetic product must meet, security in its performance is most important. The prosthesis must support any physical activity performed by the user. It must be robust, resilient and reliable (Soares and Rebelo, 2014). Design of the PPK depends on the FR's of children and parents. These include ease of use, steadiness, fatigue- and falling factors. The requirements surmise to overall dependability of the knee, as well as being affordable (Andrysek et al., 2004). This brings to mind an important consideration that must be taken into account: the number of replacements required until the child has reached adulthood. It is therefore important for designers to keep this thought in mind, as each replacement incurs costs. Designing with awareness of failure rates will influence the demand for replacements later on.

### 2.1.2 Manufacturing

As mentioned the manufacturing of a product is synchronised with its design. Prototype testing and revisiting of manufacturing methods will contribute to a higher quality product. Prosthetic products require quality surface finishes, fine tolerances and conservation of material strength. Computer numerical control (CNC) machining, laser cutting, 3D-printing and moulding are used in the manufacturing of prosthetics and medical devices (Groover, 2013). The CSIR has decided to make use of CNC methods, as materials required for the 3D-printing of medical devices are too expensive, and laser cutting will not be sufficient. However, as the technology will become more affordable in future, the CSIR plans to incorporate 3D-printing into the manufacturing process.

### 2.1.3 Service

The service phase starts once the product has been put out to market. The performance and quality of a product during its service stage is determined by the preceding phases, namely design and manufacturing. A product's reliability during operation depends on the design and the environment in which it will be operating (Matsuyama et al., 2014). Availability of a product plays an important role during this phase. Consumers will become frustrated with extended downtime of systems or unavailability for use of a product, as it results in losses and inconveniences. In order to maintain a product's availability for use during this phase, manufacturers must be able to repair or replace a product still under warranty (Kleyner and Sandborn, 2008).

Production volumes are therefore determined by both new product sales and warranty claims. A product with a longer mean time to failure (MTTF) will require a smaller amount replacements or repairs than a less reliable product. A link is therefore made between dependability and product replacement demand. The CSIR developed a policy to fully replace a failed component rather than repair it, thereby lowering logistical supply chain expenses. This is also referred to in the literature as the repair-by-replacement concept, and directly impacts the spare part inventory required to fill the demand (Öner et al., 2010). Availability of the product can be delayed if the spare parts are not readily available, an event the CSIR would want to avoid.

### 2.1.4 Retirement

Once the demand for a product has declined or the product has become outdated, a company must decide on retiring the product and replacing it with a new, more advanced product (Levin and Kalal, 2003). The CSIR did not impose a time for the product to retire, but will consider to renew or improve the product once new technology becomes available that can contribute to making the product more affordable. The remaining units, if any, will be stored for future use, as there will always be a demand.

## 2.2 Product Reliability and Life Cycle Costs

Reliability and availability of a product have remarkable influences on the LCC of the product. The end-user will typically decide upon a product based on its LCC (Yuling et al., 2009). However, the reliability and MTTF of a product or component are subjected to uncertainty, and hence the LCC are also uncertain (Levin and Kalal, 2003). This complicates control over LCC of a product.

Life cycle costs are a function of development (design and manufacturing) and warranty (or replacement) costs. These costs form a relationship in such that a higher reliability will increase development cost, while decreasing the warranty costs. However, a point will come where the development cost exceeds the replacement costs, becoming infeasible for both producer and end-user. Their sum is graphed as a U-shaped curve, as illustrated in Figure 3. The minimised LCC is found on the lowest point on the total costs curve (Kleyner and Sandborn, 2008), which is the point of indifference for development and replacements. This trade-off between investment in reliability and warranty expenses is an important step in the product development process (Öner et al., 2010).

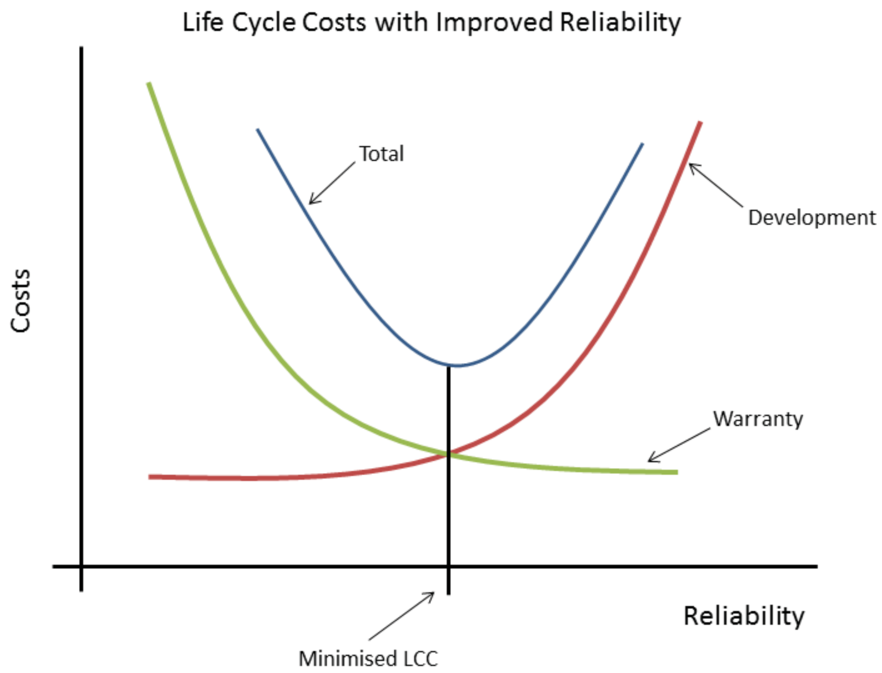


Figure 3: Development versus Warranty Costs with Improved Reliability (Kleyner and Sandborn, 2008)

The service phase is the longest of the four phases, accounting for between 50 – 60% of the total LCC. Design and production cost accounts for 10% and 20-30% respectively (Yuling et al., 2009). Costs to make changes to the design or fix mistakes is lower to recover during the design and manufacturing phase than the service phase (Nasar and Kamrani, 2007), and the amount of control over the product's features decreases (Chao, 2010). Figure 4 graphs the costs associated with each phase, linking it with the amount of control over the product changes during each phase.

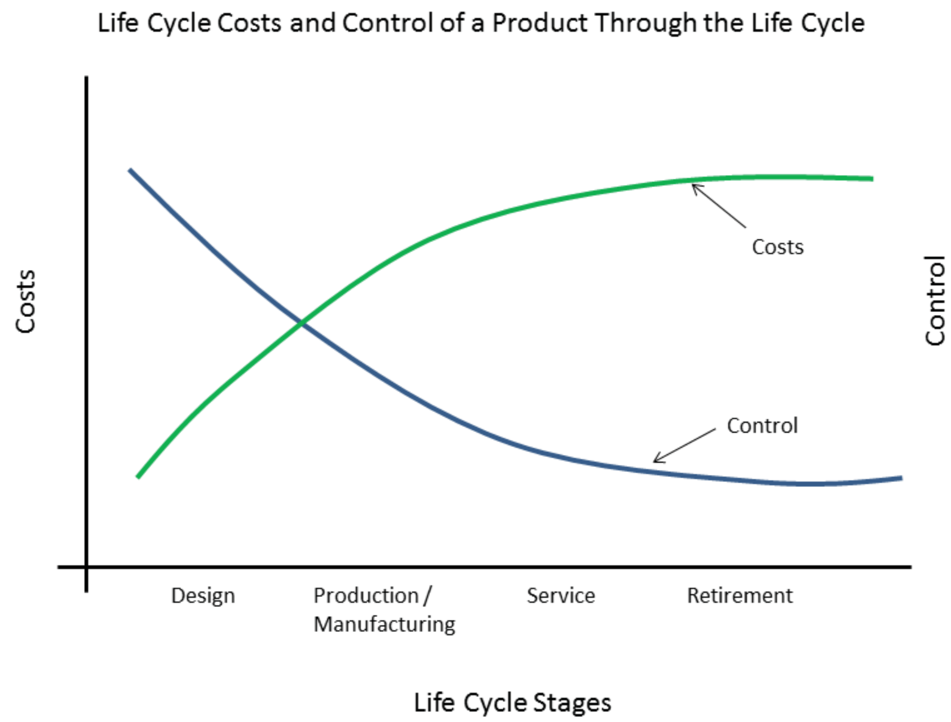


Figure 4: Life Cycle Costs and Control (Chao, 2010)

It would therefore be ideal to make changes to the product during the development phase, as well as deciding on the reliability level to design for. Reducing the failure rate will have a significant impact on LCC. In an experiment on failure rate reduction of aviation equipment, substantial savings in LCC were observed. This is graphically depicted in Figure 5 (Fang and Zhaodong, 2015).

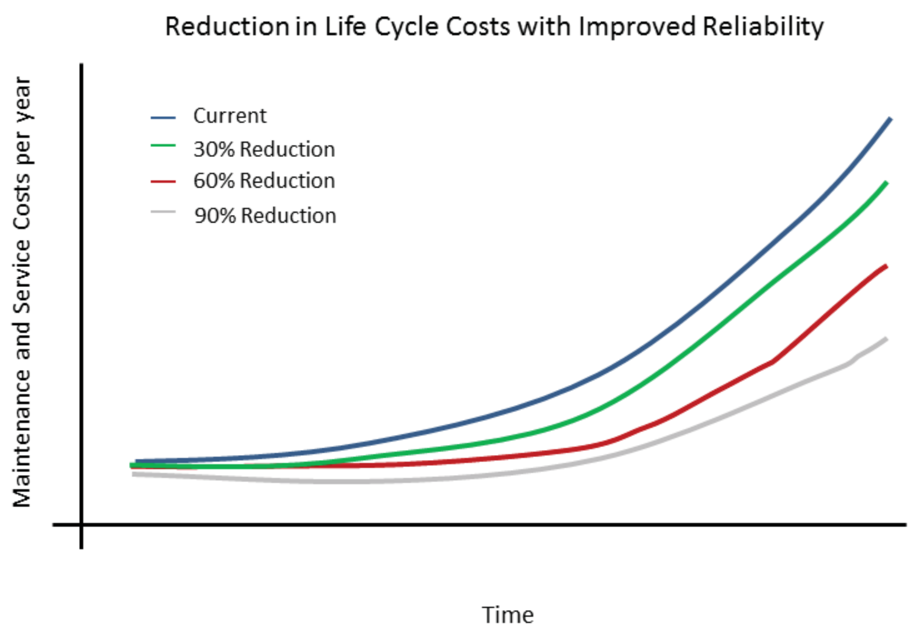


Figure 5: Reduction in Failure Rate and Decreases in Life Cycle Costs (Fang and Zhaodong, 2015)

Many researchers have developed costing models for products still under development or undergoing design changes, in order to find the optimal reliability level and hence minimising LCC. These include Monte Carlo-, SD- and ABM simulation methods and will be discussed in this document. Being able to estimate the warranty expenses within a known degree of uncertainty, provides the developer with an engineering and competitive advantage in the market (Kleyner and Sandborn, 2008). Prosthetic products are subject to minimum standards (Soares and Rebelo, 2014), thereby already allocating an amount of investment to secure reliability and performance. The CSIR can however exceed this minimum level of quality, trading it off with future warranty expenses.

## 2.3 Life Cycle Cost Estimation

Cost estimation from an engineering perspective is done by using engineering judgment, quantitative principles and techniques to solve costing problems and improve control over project expenses. Since it is an estimate, this approach provides decision makers with an acceptable range within which the costs will fall (Nasar and Kamrani, 2007).

### 2.3.1 Cost Estimation Categories

Three categories of cost estimation have been outlined by Nasar and Kamrani (2007), namely:

- *Screening*
  This category assists the decision maker in which direction to go, or whether it will be beneficial to accept the project.
- *Budgetary*
  This category extends into more detail for cost allocation.
- *Definitive*
  The estimation is much more accurate than the previous categories and takes a longer amount of time to reach a decision.

This project will deliver the screening cost estimate for the PPK, and assist the developers on the way forward. Applying LCC methods, these costs will be found within a certain degree of certainty.

### 2.3.2 Life Cycle Costing Methods

Various quantitative life cycle costing methods (LCCM) have been developed to estimate LCC within the mentioned categories. These include, but are not limited to the following (Nasar and Kamrani, 2007):

- Opinion estimates by experts
- Conference estimation
- Comparison
- Unit estimates
- Cost and time relationship
- Power law and sizing model
- Probabilistic
- Simulation

Due to the uncertainties and future elements involved in the product development arena, attention is given to the Probabilistic, Cost and Time Relationship and Simulation methods.

- *Cost and Time Relationship*

The same amount of money will have a different value at various points in time, due to inflation. Life cycle costing necessitates the calculation of future maintenance, repair and warranty costs with respect to the time value of money. The expected future cash outflow is converted to its present value using inflation as a discount factor before an investment is made (Dhillon, 2013). The net present value of a project or a new product will assist the decision makers in whether it is a viable investment to pursue. This method will grant the CSIR the opportunity to evaluate the total future warranty and R & D costs of the PPK in terms of today's value, assisting them in determining the way forward.

- *Probabilistic*

Full or partial use of probability methods can be applied as a LCCM. Probability is used to predict the possibility of an occurrence of a risk factor. The anticipated value of such a risk occurring is then used to estimate costs (Nasar and Kamrani, 2007). However, a realistic distribution must be used to determine the lifetime of a system or product, in order to warrant the probabilities of failure do not exceed some tolerable level (Tobias, 2013).

As the LCC is linked to a product's reliability, probability methods used in reliability engineering are applicable to this project. The following statistical distributions are most generally used (Montgomery and Runger, 2011):

- Exponential
- Erlang
- Gamma
- Weibull

All these distributions are concerned with finding the MTTF and probabilities of a failure in a certain opportunity frame. Where the exponential random variable describes the interval until a first count is obtained in a Poisson process, the Erlang and Gamma distributions are concerned with the length until the $r^{th}$ counts come about in a Poisson process. They are applicable in stand-by systems where more than one component must fail before the system has failed – i.e. r components must fail to constitute a system failure (Montgomery and Runger, 2011).

The Weibull distribution is used to model the time to failure in electrical and mechanical components and physical systems, where the failure rate can either increase or decrease with time or remain constant (Montgomery and Runger, 2011). This failure rate is linked to the mode of failure, which can be categorised as an infant mortality, random or wear out. Most mechanical failures are either in the random or wear out category (Schop, 2008). Mechanical parts are subjected to varying loads over time. A component that was designed to withstand a certain static load, may fail earlier when placed under a dynamic load. The flexibility of the Weibull distribution makes provision for this change in failure rates linked with periodical loads (Tobias, 2013).

There are different Weibull probability functions, of which the 2-parameter function is mentioned here. There are two main parameters: the shape β and characteristic life or scale parameter δ. These parameters are obtained from the experimental output data during validation testing and plotting it onto a Weibull graph. It can take on the features of another distribution, based on the value of β. The probability density function (pdf) for the random variable X of the 2-parameter Weibull distribution is as follows:

$$f(x) = \frac{\beta}{\delta}\left(\frac{x}{\delta}\right)^{\beta-1} e^{-\left(\frac{x}{\delta}\right)^{\beta}} \quad for\ x > 0;\ \beta > 0;\ \delta > 0 \qquad (2.1)$$

It can be derived from this function that with $\beta = 1$, the Weibull distribution reduces to the exponential distribution in the random failure mode category with its rate parameter $\lambda = 1/\delta$. A β-value of between 1 and 4 falls within the early wear out category, whereas a β-value beyond 4 is categorised as old-age rapid wear out. The β-value is also referred to as the slope on the Weibull plot. The characteristics of the Weibull distribution means that a steeper slope implies a smaller variation of the times to failure, as units will fail within a short period of each other (Schop, 2008).

A case study presented at the PLOT Seminar demonstrated the effective use of the Weibull distribution in finding failure probabilities for steering links in 18-wheeler trucks. The β-value of 3.26 implied wear out as failure mode. The results were then used to predict the time of failure and how many failures there would be. Subsequent planning could be done to prepare for the eventuality and counteractive steps was taken to solve the design issues (Schop, 2008). Another case study presented in the Engineering Statistics Handbook illustrates the Weibull distribution's use in the fatigue life testing of Aluminium strips that were subjected to periodical loadings. It proved to be the best representation of the failure times of the strips (Tobias, 2013).

As the PPK is a mechanical product exposed to dynamic loading, the Weibull distribution is considered to be the most applicable probability method. Once test data are obtained from the CSIR, it can be fitted onto 2-parameter Weibull plot to determine the parameters. These parameters will serve as input for random variable generation in the simulation models.

The failure rate of the PPK is measured in number of steps up to failure, i.e. one failure in x amount of steps. Incorporating the number of steps an average child amputee takes per day, the opportunity frame can be approximated to time in days – i.e. the number of days up to failure. Once a failure occurs in the future, the costs of a replacement is calculated using the time value of money and added to the total expenses.

- *Simulation*

A computer-generated model is made of the real product, system or project. The virtual product is taken through its life phases by use of probabilistic algorithms. During each phase, the associated costs are calculated using the time value of money and added to the total LCC (Nasar and Kamrani, 2007). The output data is an estimate of the future LCC, which is compared with the initial investment required to calculate the expected payoffs. The simulation will also deliver results in terms of time of failures based on each child's activity level. This can aid parents and medical insurers to be financially prepared, having an estimate of the time frame at which the child will require a replacement for the knee.

## 2.4 Systems Thinking and Simulation Modelling

The model must be sufficiently complex to capture the salient features, but also simple enough to make the simulation tractable. It must maintain a balance between the most important details and simplicity.

### 2.4.1 Thinking in Systems

A system can be defined as a co-dependent group of subjects creating a united behavioural pattern. The outcomes of such a behavioural pattern are called events. Applying systems thinking, the system's behaviour is determined by its inherent structure. Although the behaviour of a system creates certain events, problems cannot be solved if only the behavioural pattern is addressed. A higher degree of leverage over the problem is found when changing the inner structure of a system (Kirkwood, 1998). Figure 6 illustrates this concept.

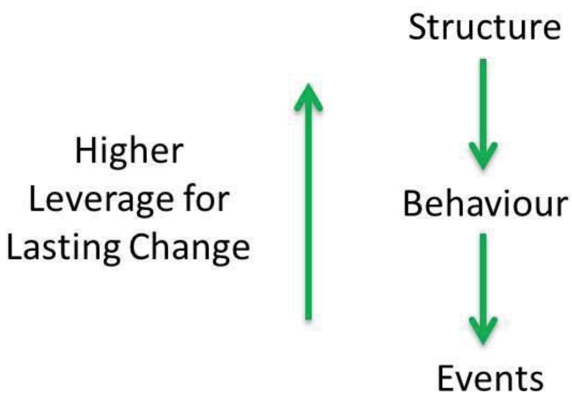


Figure 6: Leverage over Problem Solving in a System

Changes in the structure of a process will result in changes in behaviour or generate a behavioural pattern, in the end creating events as outcomes. The outcomes can provide support to foundational decisions that must be taken, or what to expect from the system in the future (Kirkwood, 1998). Knowing what behavioural pattern a system will display, the future risks or rewards may be identified. This identification will aid in correct planning for such behaviour, or develop mechanisms to mitigate risks.

In a product development environment, the life cycle can also be viewed as a system, as each phase influences the following one. The product's performance (behaviour) during its operational stage depends on how it was designed (its' structure), with the event being a failure of that product at a certain point in the future. This failure will incur a replacement cost, which will start adding up as more products fail. The escalating costs can be seen as the outcome or the event in the system.

### 2.4.2 The Paediatric Prosthetic Knee's System

The notion is to trade-off the costs of changes during design and manufacturing (or development), with warranty or replacement costs incurred during the long-term service phase. All the costs are influenced by inflation as the system moves through time. The selling and warranty price are lower than the manufacturing costs. The deficit is attributed to R & D. Figure 7 illustrates the system of the PPK, with its input parameters and output variables.

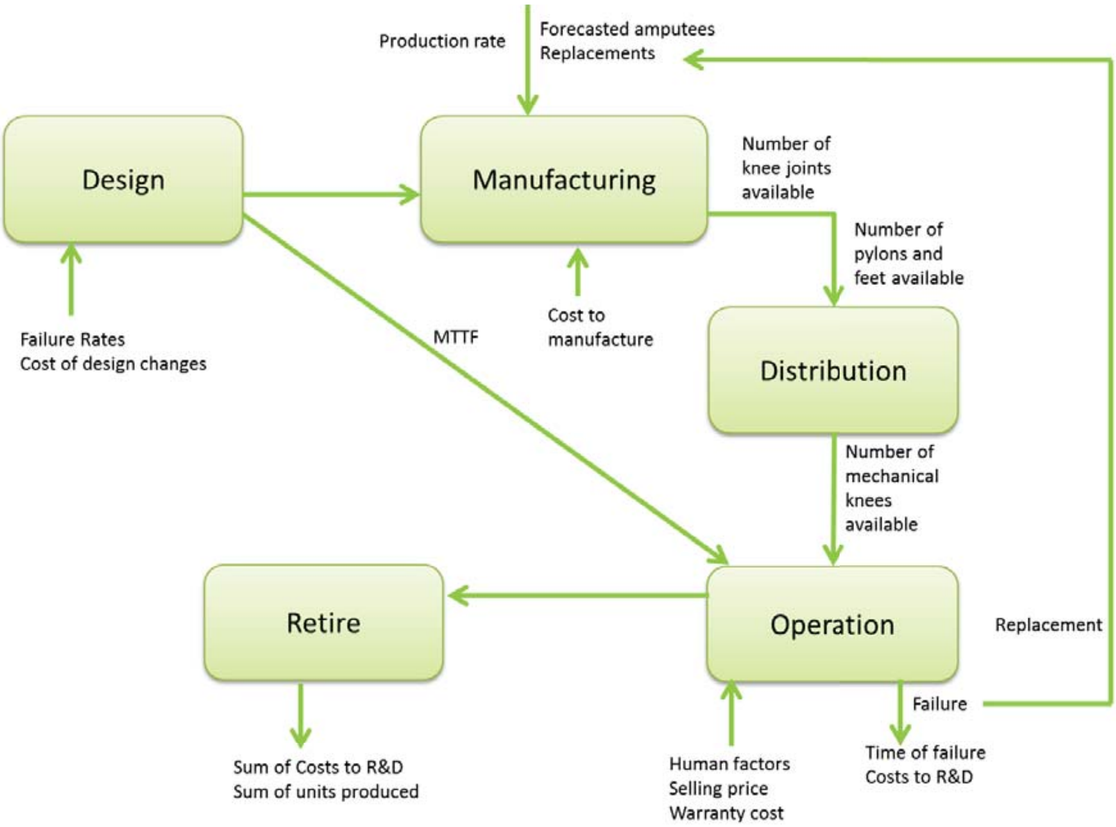


**Figure 7: The Life Cycle of the PPK with Input and Output at each stage**

Outcomes that will vary during the service phase for varying failure rates are as follows:

- Time elapsed between replacements of components (i.e. MTTF)
- Number of replacements
- Total service costs associated with replacements, also referred to as warranty costs
- Opportunity costs to R & D
- Production rates per year

*Production Rate*

The production rate is determined by new child amputees that require a knee and the replacements due to failure. The inventory policy is of importance, as it will determine the amount of stock to be ordered from the manufacturer. Demand for a single unit may arise at any given time, complicating the determination of a reorder point. In such cases, the continuous review policy is recommended (Winston, 2004). This policy uses two parameters to determine the order size – minimum allowable stock level, denoted by $s$, and the maximum level, $S$. They are combined into a single notation, $(s, S)$.

An order is placed when the actual stock level is equal or less than *s.* The size of the order raises the stock level to the maximum, *S*. Stock is released to users until the inventory again reaches or falls below *s*.

*Human Factors*

The human factors play an important role in the failure of a part. A typical child amputee falls in the K-4 level of activity, as per the Medicare Functional Classification Level. This implies an activity level of 2500 – 5000 steps per day onto the prosthesis (Rosenbaum-Chou et al., 2014). The steps taken per day by a child is thereby linked to the time of failure, as the failure rate is expressed as one failure in x amount of steps. The weight of a child plays an important role due to the 45 kg weight limitation placed on the knee joint. Once the child exceeds this weight, he / she are no longer a candidate for use of the PPK, and will be allocated to an adult prosthetic knee. If the unit is still in an acceptable condition, it will be allocated to another child.

*The System's Expected Behaviour*

Referring back to Figure 3, the system is expected to display two main behavioural patterns. The first will follow the upward curve, representing higher development costs as the product is improved. The second will be that of warranty costs on the downward curve, decreasing as the reliability is improved. At some ideal point, the lowest point on the combined U-curve would be found, which will represent the optimum reliability level to design for. Behavioural patterns for both R & D costs and production rates are expected to follow an upward trend as time progresses, while that of MTTF will follow an upward tendency as the product becomes more reliable and a downward trend for the total number of warranties issued. Figure 8 illustrates the expected behaviour of the system.

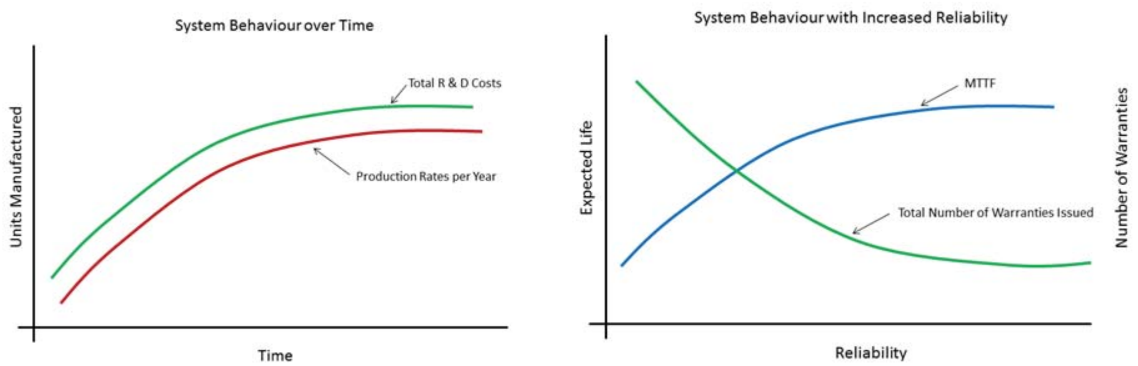


**Figure 8: Expected Behaviour of the System in terms of Time and Reliability**

### 2.4.3 Simulation Modelling of Systems

Simulation modelling is defined by Robinson (2014) as the experimentation of an operation or system as it advances through time. The purpose is to better comprehend the process and identify possible areas of improvement. The system's behaviour can be controlled by adjusting its parameters, in essence its structure, of which the event outcomes can be measured. Simulation incorporates the inherent variability, interconnectedness and intricacy of a system to represent the real world problem as close as possible (Robinson, 2014). It is essentially an extended laboratory in which experiments can be done on a non-existing system, or when real-life tests become too expensive and risky.

Simulation models range from being simple and modest in order to understand the overall system, to very complex models to support high-level decision making. To distinguish between them, three modes of simulation practice have been identified by Robinson (2014), namely:

- Software Engineering
- Process of Organisational Change
- Facilitation

The process of organisational change is most applicable in the product development environment, as the main purpose of such a model is to understand the problem and find a solution for it. Decision making time is short and financial investment lower; therefore models are small-scaled in comparison with software engineering. It takes a few months to complete and must provide a solution for a single decision (Robinson, 2014). The CSIR will base their decision with regards to the reliability level on the screening cost estimate, delivered as the final output of the simulation model.

Operational simulation has been found supportive in the early design phase of a new product. It enables the developers to investigate and test the design concepts in a generic operational environment (Schumann et al., 2011). The authors indicated two main ways in which the simulation model aided the development of a new Unmanned Aviation Vehicle (UAV). It was first used as an optimisation tool in the product's operational environment and secondly, it provided feedback with regards to product characteristics such as allowable future costs.

The credibility of any simulation model must be established before the final decision is taken. A sensitivity analysis, verification and validation of the model must be completed. Sensitivity analysis will account for the effect of uncertainties on the output of the model and is an important step to establish which input parameters dominate the model's behaviour (Raychaudhuri, 2008). Verification links the conceptual model with the numerical model, and asks the question – is the computerised model doing what the conceptual model says it must? Validation deals with the relationship between reality and the numerical model, asking whether the computerised model adequately represent the real world (Oberkampf and Roy, 2010).

Summarising, sensitivity analysis evaluates the robustness of the simulation, while verification and validation determines the usefulness of the model. Both these methods determine the credibility of the model, and play a vital role during decision making.

## 2.5 Simulation Modelling Methods

Simulation modelling methods can be static in nature, or dynamic. Static models are time-independent, where-as dynamic models depends on time. A static model deals with a system in fixed states, taking snapshots of the system's state at a particular time. It does not deal with how the system evolved to reach such a state. Dynamic modelling, however, is concerned with the continuous variation in output of a system as time progresses to reach a particular state, and how it transfers between states (El-Haik and Al-Aomar, 2006).

Four key simulation methods have been identified by Robinson (2014), namely:

- Monte Carlo
- Discrete Event
- System Dynamics
- Agent Based Modelling

These four methods are discussed in the following paragraphs.

### 2.5.1 Monte Carlo

This method of simulation modelling is independent of time, i.e. it is static. Monte Carlo simulation uses recurrent random sampling from a certain distribution, to generate input parameters. Each set of output data is linked to a set of input parameters. Monte Carlo simulation has many uses, including in reliability engineering. In this field, it estimates the time frame in which a component might fail with a certain probability. This method is then used to evaluate product development and LCC of the part or the system (Raychaudhuri, 2008).

Kleyner and Sandborn (2008) used MC techniques to simulate the relationship between reliability, product validation and life cycle costing for electronic components in the automotive industry. The aim was to minimise the LCC, based on uncertainties in reliability. One disadvantage of the MC simulation is that it only provided answers for the current costs, not including the time value of money. It is however, a simpler method than ABM and SD modelling. The net present value can still be calculated by applying the time value of money to the MC simulation output.

### 2.5.2 Discrete Event

Discrete event simulation (DES) captures objects that go through a sequence of queues and modification or service events at definite points in time. They have mainly been used in the manufacturing sector to simulate production processes, however this method of modelling has been extended to the service sector as well (Robinson and Tako, 2010). This method have also been employed in supply chain management, as a product moves from raw material right up to delivery at the retailer or consumer (Anylogic, 2014). Discrete event simulation can be employed in product development to represent the manufacturing and delivery phases, where production and delivery rates will be the main input variables using the continuous review policy as described earlier.

### 2.5.3 System Dynamics

System dynamics (SD) modelling is often used to illustrate the performance of a system or a process over time. It makes use of the cause-effect principle and causal loop diagrams. The cause-effect principle is born from the search process for the root cause of a problematic event. The cause of one event may in itself be the event caused by a preceding event. In this way, an analyst can continue indefinitely trying to find the root cause of the final event. Applying systems thinking, a cause for the event and its preceding behavioural pattern must be found within the system's structure (Kirkwood, 1998).

Causal loops are a graphical representation of the cause-effects taking place within a system, and can be classified as either being a closed or open loop. Closed loops result from an entity indirectly influencing itself (Kirkwood, 1998). He uses the example of an inventory problem. Inventory is influenced by production and shipment. Production will cause an increase in inventory levels, while shipments will decrease it. When inventory reaches a desired level, production rates may be lowered or shipments will be scheduled to move the inventory out. In this way, the level of inventory indirectly influences itself. Summarising, production rate adds to the inventory levels (positive end), while the shipment decreases the inventory level (negative). Such a loop is called a feedback loop. Open loops on the other hand, do not incorporate the feedback component. Kirkwood (1998) indicates that the open loop cause-effect analysis do not fully evaluate the result of an action on the system. Figure 9 is an illustration of a causal loop diagram based on the inventory problem.

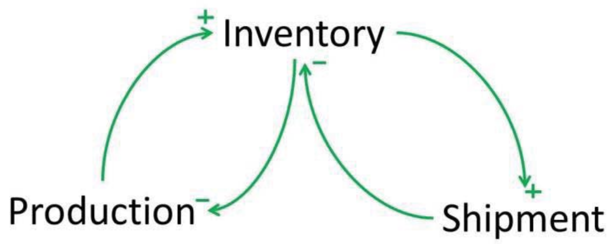


**Figure 9: Simple Causal-loop Diagram for the Inventory Problem**

The escalating warranty costs in a product's life cycle system can be seen as the outcome or the event in that system. Product reliability and warranty costs influence each other in such that as warranty costs increases beyond a desired level, a re-design of the product's reliability will be considered. A more reliable product will incur less warranty costs. In this way, warranty costs have indirectly influenced itself, forming a closed feedback loop. This is illustrated in Figure 10.

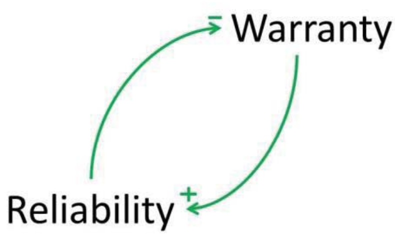


**Figure 10: Causal-loop for Warranty and Reliability**

System Dynamics modelling is more concerned with high level activities and strategic planning. The day-to-day complex detail of operations is aggregated into quantitative entities without their individual properties (Osgood, 2009). For example, the aggregate rate of coal transported on a conveyor to a depot is 1000 kg / hour, without stating where each kilogram came from. This high level modelling can be used to ease cost calculation. Using dynamic variables, the various in- and outflow rates of a financial entity can be combined, thereby simplifying the calculation.

This principle is useful in reliability engineering for the calculation of LCC. All the warranty or maintenance expenses over a certain period are aggregated into a rate equation. The costs consequently increase as a function of time, not directly due to individual warranty or maintenance events. System dynamics have been used to determine corrective maintenance costs of aviation equipment (Fang and Zhaodong, 2015). The reliability parameters were adjusted to find the optimal design policy – i.e. where the reliability costs and maintenance costs strike a balance. The effect of changes in failure rates on maintenance and LCC were analysed to provide support for decision makers.

This modelling type can incorporate the probabilistic and time value of money methods into an aggregated calculation of warranty and R & D costs for the PPK. These costs can be traded off with that of the development costs of the PPK, in order to find the lowest point on the combined U-curve (refer to Figure 3).

### 2.5.4 Agent Based Modelling

Agent based modelling (ABM), also referred to as agent based simulation (ABS), have become a powerful tool in the simulation environment. It is a bottom-up approach where system components are represented as entities capable of making independent judgments. The entities are referred to as agents with individual set of rules or behaviours (Macal and North, 2010). By modelling each individually and per interaction, the full effect of their behaviour on the system can be captured. Figure 11 explains the interactions (Macal and North, 2010).

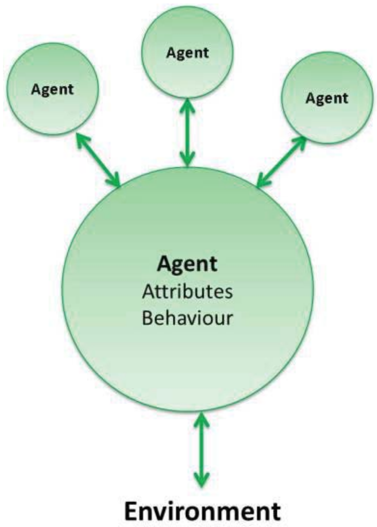


Figure 11: Agent Based Modelling Structure (Macal and North, 2010)

Railsback and Grimm (2011) define an ABM as a model that addresses problems concerned with the rise or emergence of behaviour. The system's dynamics become apparent as the individual agents making up that system interact with each other and the environment. The agents can also modify their own behaviour, based on the state of the system or the environment. Agent based modelling can therefore answer two questions (Railsback and Grimm, 2011):

1. What is the impact on a system based on the individuals actions and
2. What is the impact on the individuals based on how the system behaves?

The ability to look at both the individual and the system as a whole is why ABS finds applications in a wide array of fields. This range from the physical, biological, social, engineering and management sciences (Macal and North, 2010). A single agent can contain System Dynamics and Discrete Event models in its own structure (Anylogic, 2015), enabling an ABM to represent complex problems in these fields that mathematical models purely based on formulas, cannot. This is because an ABM can include important processes that is simply too complex to model using pure mathematics (Railsback and Grimm, 2011).

For product development, an ABS can deliver insight into the associations between development and service or performance of the product. Each end-user will display unique patterns of use of the product. The product's behaviour will also vary, due to uncertainties in the inherent reliability and availability. This interaction between user and product can therefore be modelled using ABS.

Agent based simulation's applicability in product-service systems, where the end-user pays for the functionality of the product, has been found useful in creating sustainable products and promoting customer satisfaction (Maisenbachera et al., 2014). The computer software program Anylogic (2014) illustrates an example simulation of a product's life cycle by representing the phases as states making up the system, of which the parameters can be changed. They have also developed an illustration model in the maintenance of wind farming equipment. A failure of a wind turbine initiates repair responses, demanding resource allocation of repair equipment. Due to the individualistic structure of the various entities with regards to failure rate of turbines, availability of resources and location of a wind turbine in the sea, the interactions that occur between the entities results in emergence of operational behaviour that would not otherwise be visible. Stakeholders can consequently make informed decisions during early operational planning for maintenance practices.

Agent based modelling in Anylogic was used in optimising the design of a new development in the civil aerospace industry (Schumann et al., 2011). The design of the product, a Search-and-Rescue UAV, was partly based on the results of an operational simulation model. The output of the model delivered parameters such as fuel used, maintenance, repair and erosion of airframes. This output information was used to subsequently value the product design and optimise it. This model illustrates the applicability of ABM in the product development setting, and proved to be a valuable asset during decision making.

For this project, a unique pattern of use of the PPK will emerge as the number of steps taken per day and growth rate of each child vary. An ABM can incorporate this variability into each entity and link it to the failure rate of the PPK, thereby conveying the time of failure in days or months as an output. As it is dynamic modelling method, the time value of money can easily be implemented using the appropriate discount factor. The model will be able to track the child's growth, and remove the entity from the simulation once they have reached the weight limit.

## 2.6 Conclusion

The literature provided illustrations of a relationship between a product's development features and its LCC. Little information in this regard was found specifically linked to prosthetic products. However, by defining prosthesis as a mechanical device, the link between its reliability and LCC can be made.

Life cycle costing methods must be applied in the correct context. Due to the uncertainties involved, the probabilistic and simulation methods are applicable to this project. Focus was placed on the Weibull distribution for the probabilistic failure modelling of mechanical components. The time-money relationship is also important, and will be incorporated into the model.

Simulation modelling has demonstrated to be a viable way of determining expected LCC of products and systems. Monte Carlo simulation was most often in reliability engineering. For this project, the feedback loop technique will be employed to demonstrate systems thinking and where to balance the development and warranty costs until the optimal reliability level is found at the minimised LCC. The actions of the agents in the ABM will bring about the changes in the PPK's life cycle system's structure and behaviour; finally calculating the demand for replacements and minimising the LCC.

As the ABM approach to product development is still fairly novel, a MC simulation will be implemented and the cost results compared with that of a pilot ABM in order to validate the ABS method. The success of this project is not limited to the decision support delivered to the CSIR. This project will also provide another case study where ABM was applied in the product development environment and reliability engineering.

# Chapter 3

# Method

## 3.1 Solution Process

The solution process consists of:

1. Constructing a feedback loop diagram
2. Testing a pilot ABM versus an analytical MC simulation
3. Optimising the reliability level using an extended ABS
4. Repeated simulation runs to find the mean value of the minimised LCC at the optimal reliability level
5. Regression Analysis to find a mathematical expression for the prediction of time of failure

Recall that LCC are a function of development (design and manufacturing) and warranty (or replacement) costs. Thereby, a more reliable product may have higher developing costs, but will have lower warranty costs. On the other hand, a less reliable product may incur lower development costs but will have higher warranty costs (refer to Figure 3). All the LCC associated with the PPK will be attributed to R & D. The development team must find the balance between development and warranty expenses.

The feedback loop diagram from the System Dynamics approach is depicted in Figure 12, with two loops:

1. An inner loop with links between expected life and design costs
2. An outer loop formed between expected life and warranty costs

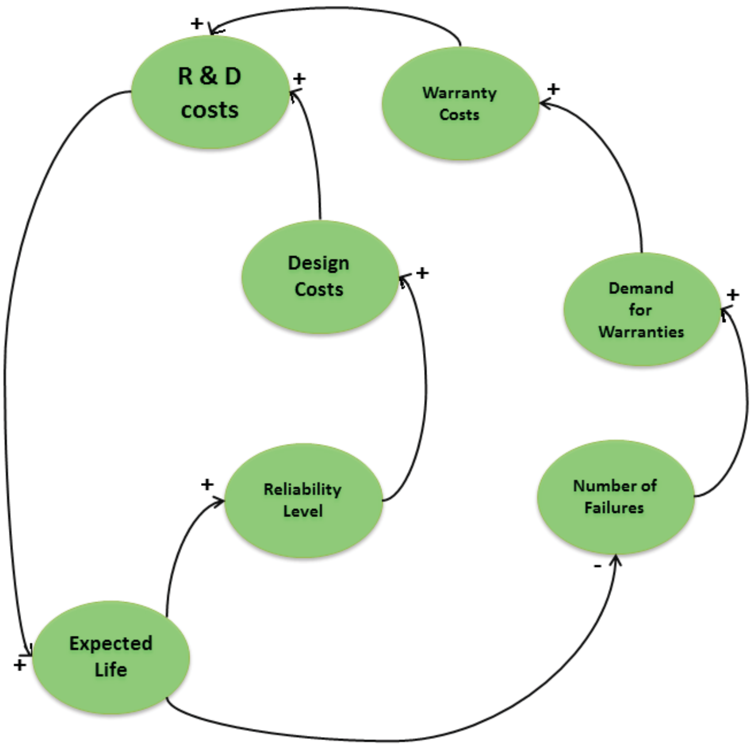


Figure 12: Feedback Loop Diagram between R & D costs and Expected Life

On the outer loop, linking with warranties, a balancing loop is formed. This means as expected life is increased fewer failures will occur and lower the demand for warranties. The costs associated with warranties are lowered, resulting in a decrease in LCC attributed to R & D. Along the inner loop, a longer expected life will improve the reliability level and increase the design costs, which will add to the R & D costs. This higher investment in R & D will lead to an increase in expected life. These two loops are traded off until the optimal reliability level is found, where the LCC are minimised.

## 3.2 Conceptual Model

The conceptual model explains the logic and mathematical calculations that are to be used in the simulation models. The LCC model explains the sequence of events for the calculations.

### 3.2.1 The Life Cycle Costs Model

Figure 13 gives an overview of the model on how the LCC are calculated in the simulation models.

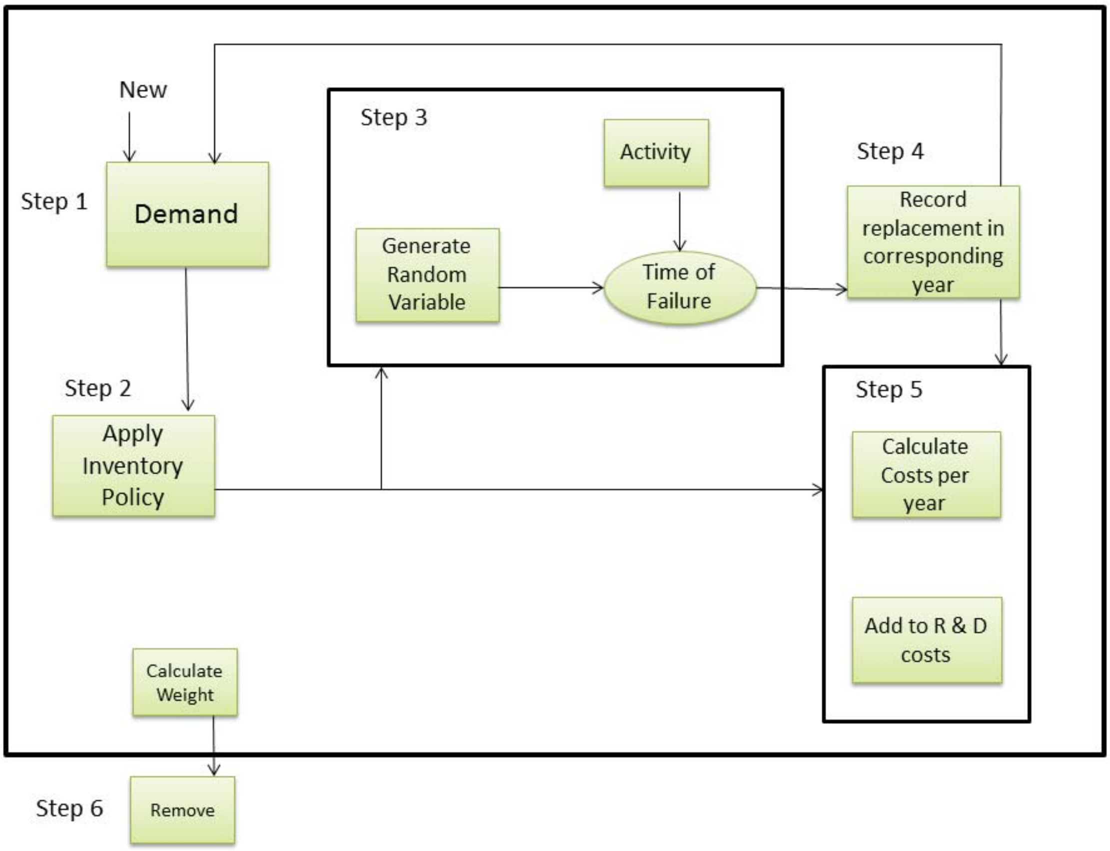


Figure 13: Model Diagram for LCC Calculation

Starting at Step 1, a demand is initially generated from all 1st time users. In Step 2, the inventory policy is applied. This policy dictates how many units must be manufactured to maintain a minimum stock level available to the users. The manufacturing costs are calculated each time a batch is delivered using Step 5. Step 3 generates a random Weibull variable for the unit supplied to a child. The child's physical activity (i.e. number of steps taken per day) is used to determine the time of failure. Once a unit has failed, it is recorded in Step 4 where the replacement is added to the associated year. A request for a replacement adds to the demand and the process is repeated from Step 1. New child amputees are added at a certain rate each week, thereby also generating demand. They then follow the same process as those already in the system. However, the pilot ABM and the MC will only execute steps 3 to 5, as it does not simulate the ongoing use-replace cycle nor does it add new amputees to the model.

After the warranty replacement is recorded, Step 5 calculates the warranty costs for the associated year. The manufacturing, sales and warranty costs are all added to the R & D costs. Step 6 is only completed when the entity has reached the weight limit. This entity is removed and plays no further part in the model. Again, this step only applies to the extended ABM.

### 3.2.2 Variables and Output

The output of the model is as follows:

- Future values of yearly LCC for 5 years
- Total value of the LCC after 5 years
- Number of units manufactured, replaced and sold for each year
- A cash flow diagram tracking each year's expenses

To deliver the output, the following input parameters are required:

- Design
  - Expected life of the knee joint, δ
  - Shape parameter, β
  - Costs of improved design and component quality
- Production
  - Entry rate of new users
  - Selling and warranty price
  - Manufacturing costs
- Human Factors
  - Child growth rate in weight (varies over time and within each child)
  - Activity level (steps taken per day)
- Economic
  - Inflation

Table 2 summarises the variable assignments.

Table 2: Operator Assignments

| Symbol | Assigned value |
|---|---|
| β | Shape parameter for Weibull distribution |
| δ | Expected life (in number of steps) of the PPK |
| $RV_w$ | Random variable from Weibull distribution |
| $M_n$ | Total number of units manufactured for year n (both new and those for replacements) |
| $W_n$ | Total number of warranty replacements for year n |
| $S_n$ | Total number of units sold new in year n |
| $P_w$ | Present warranty price |
| $P_m$ | Present manufacturing costs |
| $P_s$ | Present sales price |
| $F_n$ | Future LCC of year n |
| $PV_D$ | Present value of design costs |
| $PV_V$ | Present value of validation costs |
| $R$ | Total number of replacements required over lifetime of PPK |
| $LCC_P$ | Total Present Value of the LCC |
| $K$ | Total number of children in the model |
| $A_t$ | Activity level (number of steps taken on day t) |
| $i$ | Inflation (constant at 4.7%, for August 2015 (Taborda, 2015)) |
| $h_k$ | Weight of child k in kilogram |
| $a_k$ | Age of child k in months |
| $c_j$ | Growth percentile curve j, with j ϵ (1, 9) |
| $r_k$ | Counting factor of replacements for child k |

### 3.2.3 Failure Modelling

The Weibull distribution is used to model the failure of mechanical components subjected to variable and dynamic loads (Tobias, 2013). The PPK will undergo such loading as the user steps onto the unit. A random variable from the Weibull distribution with shape parameter β and expected life δ is generated:

$$RV_W \sim Weibull(\beta, \delta) \qquad (3.1)$$

The activity level, $A_t$, is uniformly distributed between 2500 and 5000. For each passing day t, the steps are summed until the total number of steps equals or surpasses the random variable, and a failure occurs at day T.

Therefore, a failure will occur when:

$$\sum_{t=1}^{T} A_t \geq RV_W \qquad (3.2)$$

The counting variable $r_k$ increases with one for that child. The summative value R is the total number of replacements over the life time of the PPK project. It is expressed as:

$$R = \sum_1^K r_k \qquad (3.3)$$

A child receives a replacement unit, and a new random variable is generated. The process is repeated for as long as the child is in the system or until the simulation period has stopped at 5 years.

### 3.2.4 Manufacturing, Sales and Replacements

The variables $M_n$, $S_n$ and $W_n$ are set at 0 at the start of each year. The variable $W_n$ keeps track of the number of replacements and is increased with one each time a unit fails, irrespective of which child entity it originated from. The units sold to new amputees, $S_n$, is a rate with a uniform distribution of between 1 and 5 units per week. The number of units manufactured, $M_n$, is dependent on the demand from both warranties and new sales.

### 3.2.5 Cost calculations

Future LCC, $F_n$, is a function of the number of units manufactured, replaced and sold as new for the year n. The unit is sold at a loss – this loss is to be included in the LCC

$$F_n = (M_n P_m + W_n(P_m - P_w) - S_n P_s) \times (1 + i)^n \qquad (3.4)$$

The present worth of the total LCC over the 5 year period, $LCC_p$, is a function of design and validation costs and the future LCC costs for each year.

$$LCC_P = PV_V + PV_D + \sum_{n=1}^{5} \frac{F_n}{(i+1)^n} \qquad (3.5)$$

It's this value that is the objective function which is to be minimised in the ABM. The minimised value will be a function of the optimum reliability level, i.e. expected life δ, of the unit.

These calculations will be repeated for different failure rates, to determine the optimal reliability level – i.e. the lowest point on the combined U-curve, as explained in Figure 3. The lead engineer estimates an increase of R 250 000 in development costs for every three month extension in expected life.

### 3.2.6 Human Factors

The weight of children is normally distributed for each age interval. Growth charts were developed by the Centre for Disease Control in the United States and transformed to fit onto percentile curves from the 3% up to 97%, nine in total (Kuczmarski RJ et al., 2002). See Figures 14 and 15 for the charts for both male and female children as constructed by the CDC. The percentile curves are different for each. The child's weight is a function of a percentile curve $c_j$ and their age, $a_k$, on the x-axis of the chart.

$$h_k = f(a_k, c_j), \;\; j \in (1,9) \qquad (3.6)$$

A random gender, starting age and percentile curve will be assigned to each child entity. They will remain on the specific percentile curve for the rest of their life. Once they have reached the weight limit, the entity will be removed from the simulation.

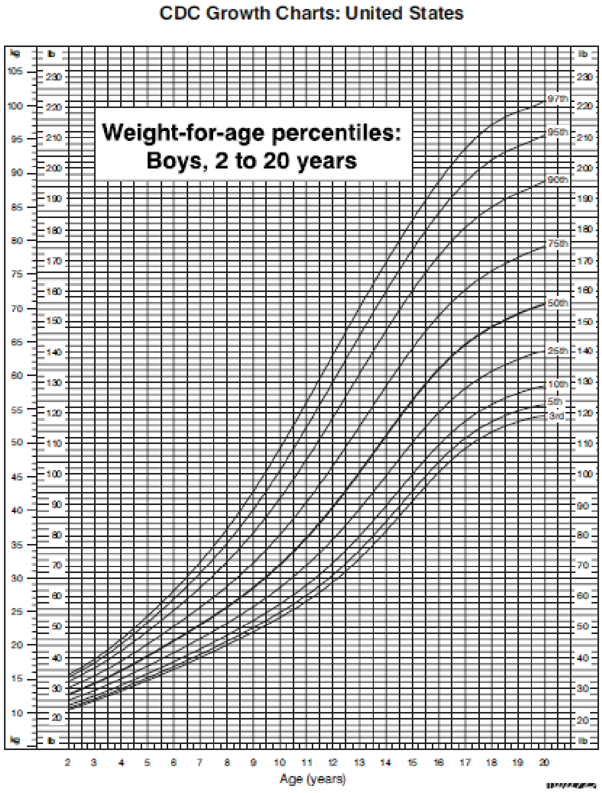


Figure 14: Growth Chart for Males: 2 to 20 years (Kuczmarski RJ et al., 2002)

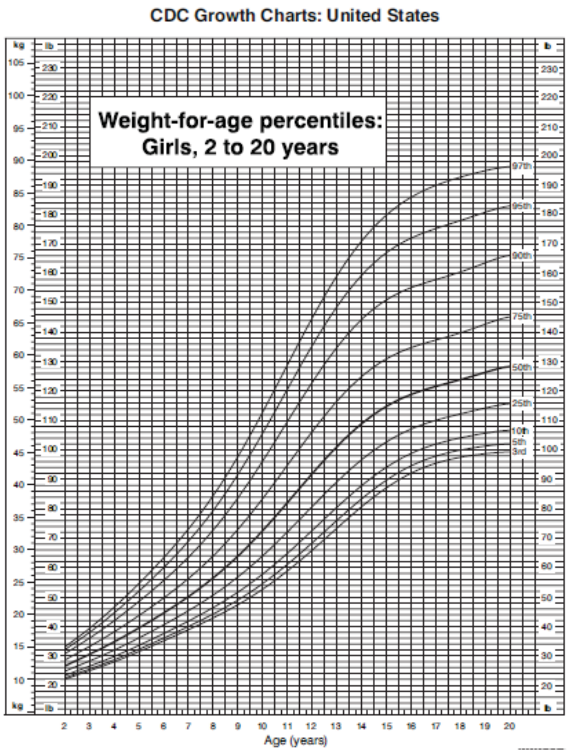


Figure 15: Growth Chart for Females: 2 to 20 years (Kuczmarski RJ et al., 2002)

### 3.2.7 Assumptions

The models will make the following assumptions:

- Inflation remain constant over 5 years
- No other increases in manufacturing costs
- The PPK is used for its intended purposes

The units have not yet gone through the quality tests for their reliability performance, due to delays at the CSIR's manufacturing facilities. The lead engineer decided to make use of scenarios to model the life cycle of the PPK project. The minimum required expected life for prosthetic knees is set at 3 000 000 step cycles (ISO, 2006). This will also serve as the initial assumed expected life, $\delta$, of the units. A failure below this level will constitute a sub-standard product which will not be allowed to proceed to manufacturing. For the shape parameter, the lead engineer decided to use $\beta = 2$, to simulate failure of mechanical units due to wear out (Schop, 2008). These Weibull parameters are subject to change at a later stage.

### 3.2.8 Constraints and Limitations

Data related to child growth in South Africa are scarce and incomplete. Tables by the CDC are used, but were developed in the US and revised in 2000. Although there are charts developed by the World Health Organisation (WHO), these only go up to 24 months of age. The CDC's data tables and charts are prescribed by the WHO to measure child development from this age on (Wei, 2000) which will therefore also be used as input into this project's model.

There is limited available data on child amputees in South Africa. Historic demand figures from prostheses supplying units to children are used as estimates by the developers of the PPK for the rate of new arrivals and subsequent new sales.

## 3.3 Numerical Model

Four models were completed for this project to answer the research questions in Chapter 1. They are as follows:

1. A pilot ABM in Anylogic
2. Monte Carlo (MC) simulation using R
3. Extended ABM in Anylogic
4. Regression model to determine MTTF for activity levels in R

Models (1) and (2) are basic reliability models. The pilot ABM was constructed to simplify functions and to perform basic testing on concepts that is to be contained in the extended ABM. Its results are also compared to the results of the analytical MC simulation. This is to ensure that the calculations and logic of the ABM model are correctly executed. The extended ABM will be based on the pilot version; however it will continue the use – replace cycle for a period of 5 years. It is essentially a repetition of a MC simulation, but with each new unit starting its life at a different time. The regression model must determine the expected time of failure for fixed activity levels. It will make use of the MC simulation for time to failure data, but stop short of cost calculations.

### 3.3.1 The Basic Pilot Agent Based Model and the Monte Carlo Simulation

*Pilot ABM*

The Pilot ABM completes Steps 3 to 5 from the LCC calculation model. It follows an initial number of units through their life up to failure and records the time of failure, adds it to the counting variables and determine the warranty costs for the associated year. The model consists of two agents – Main and Unit. The Unit agent has a state chart with two possible states – in-use and failed. The in-use state is re-entered every day to add to the number of steps. The transition condition is when the total steps surpass the random Weibull variable generated at start-up for each unit entity, as per Step 3 of the LCC model and equation 3.2. Figure 16 illustrates the interaction between the Main and Unit entities, together with the steps from the LCC model.

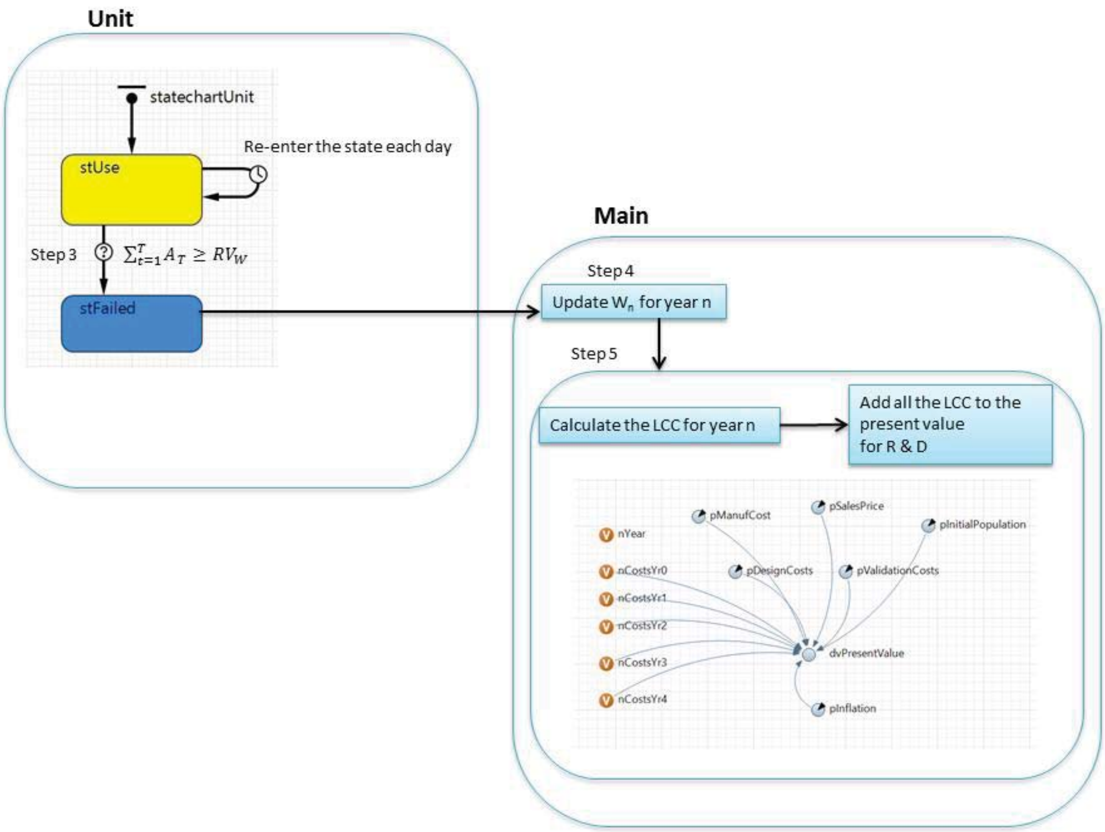


**Figure 16: Interaction between Unit and Main Agents in the pilot ABM**

In the Main agent, arrays are used update the number of warranties, $W_n$, for each year, after it has been determined that a unit has failed. This is Step 4. A dynamic variable is used to calculate the yearly costs, as per equation 3.4. All costs are then added to the present value for R & D in the dynamic variable, as per equation 3.5. This constitutes the final Step 5 of the process.

*Monte Carlo*

The aim of the MC simulation is to confirm the output from the Pilot ABM. It will sample from the same Weibull distribution with set input parameters, calculate time of failures and perform the necessary cost calculations.

The Monte Carlo simulation in R applies a failure function for each unit, using the activity level, i.e. $A_t$, as input. A random Weibull variable is generated at the start of the function, which is the number of steps at which the unit will fail. The code is then repeated to increment the total steps, until the failure condition is satisfied, as per equation 3.2. For each passing day, the counting variable for days up to failure is increased with one. The function breaks when the total steps surpass the random variable, and the data are collected into an array.

The pseudo-code is as follows:

{Create the empty arrays for data collection

Set the random Weibull variable

Set the total steps and days to failure to 0

*Repeat:*

*Generate new daily steps-value*

*Add this daily steps to the total steps*

*Count the days to failure*

*Stop:* when the total steps taken are greater or equal to the random variable

*Collect the total steps and time of failure into arrays*

End the function

Perform cost calculations over the arrays

Repeat the experiment

Perform statistical analysis

End the simulation

}

The time of failure in days are stored into another array to calculate the year (as an integer) in which the failure took place. Cost calculations are then applied to each entry using a for-loop across the year array and storing it into separate cost arrays. Finally, this experiment is repeated in order to bin the results of each replication to calculate the means, standard deviations and draw histograms of the LCC output. The times to failure in days and steps, associated year and costs are delivered in a data frame as output.

The output of these two models is compared to determine the applicability of an ABM in reliability engineering.

### 3.3.2 Extended Agent Based Model in Anylogic

This is an extension of the pilot Anylogic model, and is more complicated. The continuous cycle of receive-and-replacement of units is to be captured in this model, as well as taking the growth factor and addition of entities as time progresses, into account.

Four agents were created in this model to capture the complex behaviour of the system:

- Main
- Child
- Supply
- Statistics

*Interactions between agents*

Figure 17 depicts the interaction between the agents, as well as the step completions from the LCC model in Figure 13.

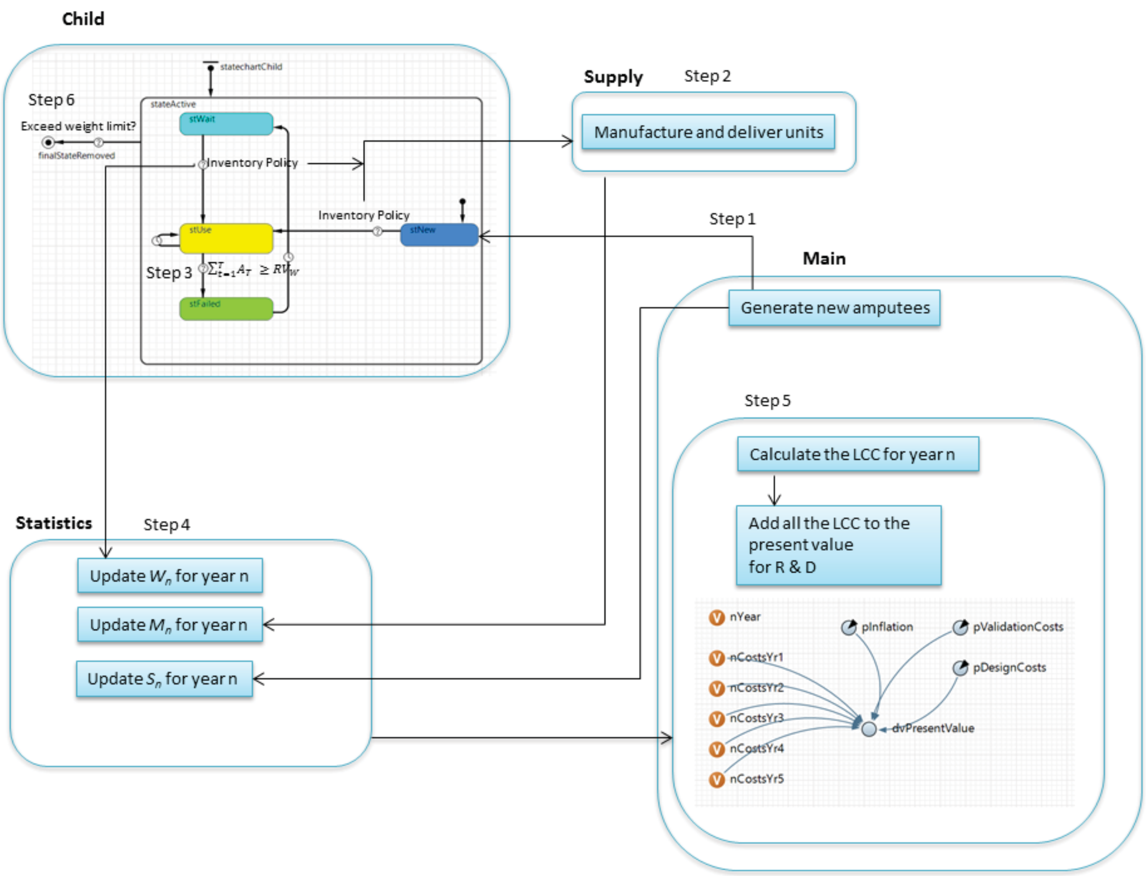


Figure 17: Interactions between Agents for the Extended ABM

The Child agent's state chart is more complicated than that of the unit for the pilot ABM. Each generated child entity, which is done in the Main agent, starts in the New state. It can transition to Use once a unit is available by applying the inventory policy, as per Step 2, in the Supply agent. When a unit has failed, the state returns to waiting for a replacement unit. The inventory policy is applied and once a child receives the replacement, the warranty variables are updated in the Stats agent for that year. A new random variable is generated for the next cycle (Step 3). Steps and days up to failure are reset to 0 for each repeat of the cycle. In this way, the use-fail-replace cycle is continued. When a child has reached the weight limit, they transition out of the Active state to be removed from the simulation (Step 6 from the LCC model).

The Supply agent must also update the number of units manufactured in the Stats agent, each time a batch is delivered. The Main agent has much the same functions as the pilot version. However, it uses the counting variables from the Statistics agent to do the yearly LCC calculations, as per step 5 from the LCC model.

*Minimisation of LCC*

The main aim of this model is to minimise the total present value of PPK project, with the objective function being as follows:

$$\min(z) = PV_V + PV_D + \sum_{n=1}^{5} \frac{F_n}{(i+1)^n} \qquad (3.7)$$

The independent variables are the yearly future LCC, $F_n$ and the fixed development costs, namely design, $PV_D$ and validation $PV_V$. Recall that the yearly future LCC are a function of the number of units manufactured, replaced or sold as new for that particular year. Referring to Figure 3, the increase in developmental costs is traded off against the future LCC for an array of reliability levels, until the minimum present value is found. This minimum value is calculated at the optimal reliability level, or expected life, δ. This model is to be used to optimise the design, rendering the knee both dependable and affordable.

In Anylogic, the Optimisation functionality is utilised to minimise the LCC. It essentially iterates through the range of expected life values and calculates the costs for each level. It finally delivers the expected life for the lowest total LCC value. Once the optimised expected life has been found, the simulation is to be replicated 50 times at this value using the Parameter Variation of Anylogic. This final experiment then delivers the means, standard deviations and confidence intervals of the minimised LCC output.

*Input for the Model*

As mentioned before, the development or design costs increase with R 250 000 for every three month extension in expected life of the unit. The 3 month extension is converted to number of steps. The lead engineer decided to only look at two extension intervals. Table 3 contains the input parameters for the model.

Table 3: Input Parameters for the Extended ABM

| Parameter | Value |
|---|---|
| **Expected Life Intervals (δ)** | Total Development Costs (R) |
| **3000 000 – 3 337 500** | 3 740 000 |
| **3 337 501 – 3 675 000** | 3 990 000 |
| **Shape parameter β** | 2 |
| **Manufacturing costs** | R 3700 |
| **Warranty price** | R 3400 |
| **Initial sales price** | R 2400 |
| **Inflation** | 4.7 % |
| **Arrival rate of new amputees** | ~Uniform(1, 5) per week |
| **Activity level in steps** | ~Uniform(2500, 5000) |
| **Starting age in months** | ~Uniform(24.5, 120.5) |
| **Growth curve** | ~Uniform(1, 9) |
| **Continuous Review Inventory Policy (s,S)** | (20, 50) |

The only values to change during the experiment are that of the expected life and the development costs. All other parameters remain constant. The arrival rate of new amputees as well as starting ages are based on feedback from prosthetists in industry. The activity level in number of steps per day is based on the K-4 level of activity for amputees, as per the Medicare Functional Classification Level (Rosenbaum-Chou et al., 2014). Inflation rate of August 2015 is used (Taborda, 2015). The growth curve is randomly selected from the child growth tables developed by the Centre for Disease Control (Kuczmarski RJ et al., 2002). The inventory policy figures for both *s* and *S* were an arbitrary choice, as no inventory related decision has been made.

### 3.3.3 Regression Model for Activity Levels

A regression analysis is performed to explore the relationship between the activity level and time to failure of the PPK. In the simulation models, randomness is not only attributed to a single variable (the Weibull for the PPK's reliability), but also the varying activity levels of the users. By using the activity level as a known input value rather than a random variable, a more exact prediction on the mean time to failure can be simulated. In this model, the activity level will be the independent variable and the time to failure the dependent (or response) variable.

The profile that the output data points will take on the scatter plot (time to failure versus activity level) will determine the type of regression to be performed, i.e. linear, exponential etc. A function is generated of the regression line, which may be used to mathematically predict the time of failure. In a linear regression model, the response variable, Y, is dependent on the variable x, by the straight-line relationship (Montgomery and Runger, 2011):

$$Y = \alpha_0 + \alpha_1 x \qquad (3.8)$$

The uniform distribution of the activity levels from the pure MC simulation is replaced with fixed values between 500 and 5000, so that the model can be pushed to its extremes. Table 4 contains the input parameters to be used in the MC simulation to obtain the time to failure data.

Table 4: Input Parameters for the Regression Model

| Variable | Value |
|---|---|
| **Shape parameter, β** | 2 |
| **Expected Life, δ** | 3 000 000 (ISO, 2006) |
| **Activity sequence in steps** | Min = 500<br>Max = 5000<br>Increment by 100 |

The rational of the output function of the regression model is therefore to give the prostheses and users an indication of when a unit will fail, based on a fixed activity level, x. This may assist them in the timing of replacements and to be financially prepared for the eventuality of a failure.

## 3.4 Model Validation

The experiments of the simulation models must investigate the influence of changing variables in the models on the final outcomes. The system's behaviour will become more apparent as sensitivity of the outcomes to certain variables becomes visible. Due to the randomness and uncertainty in the failure modelling of mechanical units, the final answers to the research questions will be delivered as a range and not just a single figure.

In this experiment, the LCC are delivered using a single Weibull distribution, with input parameters as set out in Table 5:

Table 5: Input for Basic Reliability Experiments

| Variable | Value |
|---|---|
| **Shape parameter, β** | 2 |
| **Expected Life, δ** | 3 000 000 (ISO, 2006) |
| **Number of initial units** | 1800 |

The pilot ABM and a pure analytical Monte Carlo simulation, as described in Section 3.3.1, perform this experiment. The means, standard deviations and confidence intervals of the output are compared in the final results, as a way to substantiate the applicability of an ABM in reliability engineering. The experiment stops once all the units have failed. This experiment is limited as it does not display the behaviour of the repair-by-replacement cycle as found in the extended ABM.

Results from 100 replications of these experiments have shown consistency in the outputs between the pilot ABM and the Monte Carlo simulation. At an expected life of 3 000 000 steps, it was found that most units failed within the 1$^{st}$ two years of operation, peaking during the 2$^{nd}$ year. The following table contains the values for the outputs:

Table 6: Outputs from Pilot ABM and MC simulations

| Variable | Output |
| --- | --- |
| **Warranties in year 1 (units)** | ABM: 349<br>MC: 354 |
| **Warranties in year 2 (units)** | ABM: 675<br>MC: 646 |
| **Total Warranty Costs in year 1 (in Rand)** | ABM: 101 900<br>MC: 105 100 |
| **Total Warranty Costs in year 2 (in Rand)** | ABM: 216 630<br>MC: 202 850 |
| **Mean of the Present Value of LCC (in Rand)** | ABM: 6 617 090<br>MC: 6 617 357 |
| **Standard Deviation of Present Value of LCC (in Rand)** | ABM: 931.8<br>MC: 877.7 |
| **5th percentile (from MC) of LCC (in Rand)** | 6 615 800 |
| **95th percentile (from MC) of LCC (in Rand)** | 6 618 800 |

The histogram constructed from the MC simulation is displayed in Figure 18, showing both the mean and 5th and 95th percentiles.

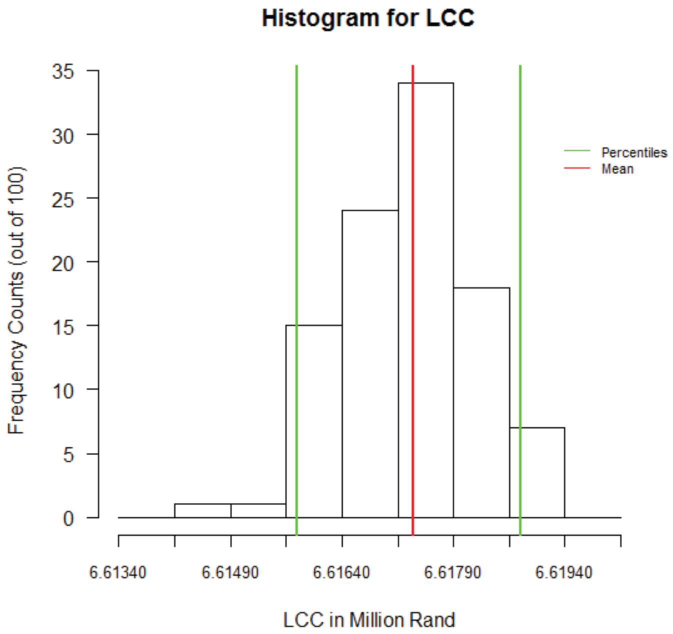


Figure 18: Histogram for the LCC output from the MC simulation

The similar results indicate that an ABM can be used to determine LCC of mechanical units. The basic principles, logic and concepts contained in the pilot ABM simulation have therefore been confirmed to be reliable and fit for use. The extended ABM will now make use of these concepts to further the experiment to answer the research questions. The basic reliability models' final output for the LCC has been verified by manual calculations performed on the yearly manufacturing-, warranty and sales data from randomly selected simulation runs.

# *Chapter 4*

# Results

The output from the various models provided useful information that can be used to answer the research questions posted in Chapter 1:

1. What are the associated LCC over 5 years?
2. What is the expected demand, i.e. how many units will be manufactured and replaced over the course of the project?
3. What effective design changes can be made to reduce the LCC, i.e. what is the optimal design policy?
4. When will a child require a replacement?

## 4.1 Results

### 4.1.1 Optimisation of Design and Life Cycle Costs

This experiment must answer questions 1 to 3 from the research questions. The LCC was minimised at the expected life of 3 675 000 steps, at a minimum total LCC of R 8 294 800. The output from repeated simulation runs at this reliability level is tabulated in Table 7.

Table 7: Output from the Optimisation Experiment

| Variable | Mean | Standard Deviation |
|---|---|---|
| **Total Value (TV) of LCC in Rand** | 8 428 000 | 46 246 |
| **Yearly costs (R):** | | |
| **Year 1** | 2 872 000 | 38 081 |
| **Year 2** | 429 600 | 60 051 |
| **Year 3** | 492 800 | 55 237 |
| **Year 4** | 525 700 | 63 494 |
| **Year 5** | 548 030 | 57 602 |
| **Warranties issued:** | | |
| **Year 1** | 236.7 | 15.24 |
| **Year 2** | 606.5 | 22.12 |
| **Year 3** | 772.1 | 25.89 |
| **Year 4** | 792.4 | 25.84 |
| **Year 5** | 777.8 | 26.46 |
| **Units Manufactured:** | | |
| **Year 1** | 2227 | 20.35 |
| **Year 2** | 764.5 | 27.73 |
| **Year 3** | 927 | 30.19 |
| **Year 4** | 948.6 | 33.14 |
| **Year 5** | 932.5 | 33.05 |
| **Sales over 5 years** | 2580 | 24.84 |

The frequency histogram of the total LCC is presented in Figure 19, with the 5$^{th}$ and 95$^{th}$ percentiles shown.

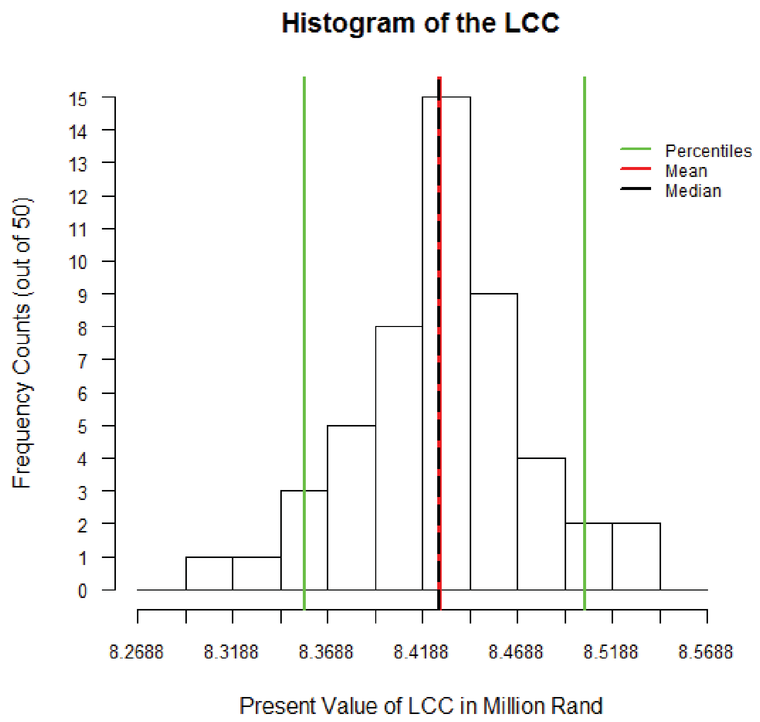


Figure 19: Frequency Histogram of the Present Value of the LCC for the PPK

The associated percentiles of the LCC are outlined in Table 8.

Table 8: Percentiles for the LCC

| Minimum | 5% | 25% | 50% | 75% | 95% | Maximum |
|---|---|---|---|---|---|---|
| 8 294 800 | 8 356 900 | 8 403 700 | 8 427 400 | 8 452 500 | 8 504 800 | 8 530 700 |

The median is slightly smaller than the mean, almost coinciding with the difference only R 600. The histogram is therefore judged to be symmetrical. The 95% confidence interval estimate for the true value of the mean total LCC was calculated as:

$$8\,415\,180 \ \leq \mu_{LCC} \leq 8\,444\,020 \qquad (3.10)$$

### 4.1.2 Regression Analysis Experiment

This experiment is based upon the regression model as described in Section 3.3.3. It will answer Question 4 from the research objectives. Three weighted regressions using the standard deviations were performed, namely:

1. Linear
2. Exponential
3. Hyperbolic

The output summaries from the regression analyses are shown in Table 9. The scatter plot, together with the fitted lines and error bars, are shown in Figure 20. The linear transform of the hyperbole is inserted onto the figure. The error bar indicates the spread of 1 standard deviation from the mean value for each activity level.

Table 9: Output from the Regression Analysis

| Linear Model | | |
|---|---|---|
| | **Value** | **p-value** |
| Intercept | 3280 | $2 \times 10^{-16}$ |
| Independent Variable | -0.682 | 5.43e-12 |
| $R^2$-value | 0.6642 | |
| 95 % Confidence Interval | **Lower** | **Upper** |
| Intercept | 2830 | 3730 |
| Slope | -0.829 | -0.535 |
| Function | $Y = 3280 - 0.682x$ | |

| Exponential Model | | |
|---|---|---|
| | **Value** | **p-value** |
| Intercept | 7.834 | $2 \times 10^{-16}$ |
| Independent Variable | $-3.292 \times 10^{-4}$ | $2 \times 10^{-16}$ |
| $R^2$-value | 0.929 | |
| 95 % Confidence Interval | **Lower** | **Upper** |
| Intercept | 7.727 | 7.942 |
| Slope | $-3.57 \times 10^{-4}$ | $-3.015 \times 10^{-4}$ |
| Function | Linear transform: $\ln Y = 7.834 - 3.292 \times 10^{-4}\, x$<br>Exponential form: $Y = 2525e^{-3.292 \times 10^{-4} x}$ | |

| Hyperbolic Model | | |
|---|---|---|
| | **Value** | **p-value** |
| Intercept | -12.28 | 0.399 |
| Independent Variable | 2 686 600 | 2e-16 |
| $R^2$-value | 0.9882 | |
| 95 % Confidence Interval | **Lower** | **Upper** |
| Intercept | -41.35 | 16.8 |
| Independent Variable | 2 597 400 | 2 775 800 |
| Function | $Y = \frac{2\,686\,600}{x}$ | |

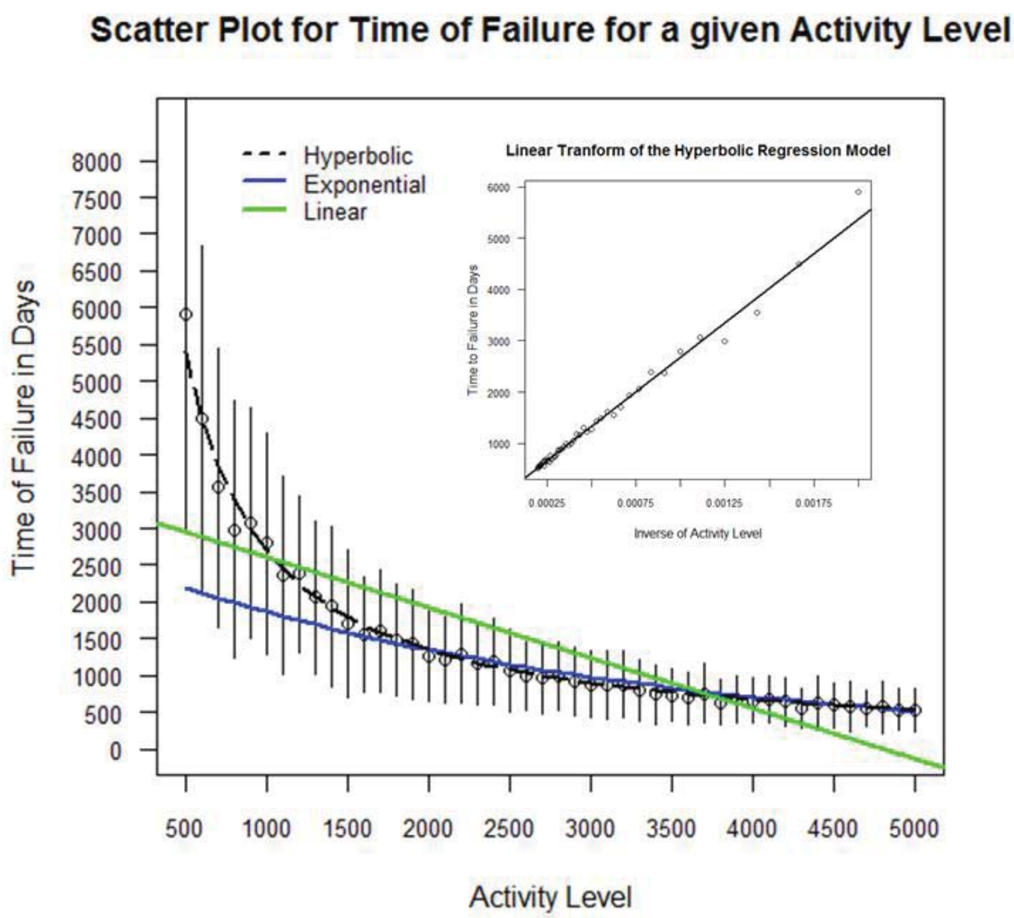


Figure 20: Scatter Plot and Fitted Lines for the Regression Models

## 4.2 Results from Sensitivity Analysis

Four parameters are identified to use for a sensitivity analysis, namely:

- Shape parameter, β
- Scale parameter, δ
- Warranty price
- Sales prices

A higher shape parameter will influence the variability in failure times. An increase in the expected life will improve the reliability and failures will occur at a later stage. Both these parameters will impact the number of warranties issued during a particular year. Increases in both the warranty and sales prices will narrow the gap between income from sales and warranties and the manufacturing costs. The sensitivity analysis is done by changing one value at a time.

### 4.2.1 Effect of Increase Shape Parameter on Life Cycle Costs

Increase in the β-value, i.e. from 2 to 4 and 6, while keeping all the other parameters as per the optimised model, resulted in the changes in output formulated in Table 10.

Table 10: Model Output for Increases in β-values and Expected Life of 3 675 000

| Output Variables | Original β = 2 | β = 4 (100% increase) | | β = 6 (200% increase) | |
|---|---|---|---|---|---|
| | Original Value | New Value | Percentage Change | Change in Value | Percentage Change |
| **Total LCC in Rand** | 8 428 000 | 8 320 000 | -1.278 | 8 267 570 | -1.9002 |
| **Yearly costs (R):** | | | | | |
| Year 1 | 2 872 000 | 2 807 600 | -2.25 | 2 797 749 | -2.593 |
| Year 2 | 429 600 | 364 600 | -15.13 | 308 969 | -28.085 |
| Year 3 | 492 800 | 565 600 | 14.76 | 639 920 | 29.843 |
| Year 4 | 525 700 | 490 470 | -6.709 | 414 438 | -21.171 |
| Year 5 | 548 030 | 521 995 | -4.751 | 529 838 | -3.3197 |
| **Warranties issued:** | | | | | |
| Year 1 | | | | | |
| Year 2 | 236.7 | 35.08 | -85.18 | 4.7 | -98.014 |
| Year 3 | 606.5 | 428 | -29.43 | 264.3 | -56.421 |
| Year 4 | 772.1 | 951.4 | 23.23 | 1182.4 | 53.151 |
| Year 5 | 792.4 | 686.5 | -13.36 | 469.34 | -40.767 |
| | 777.8 | 715.9 | -7.968 | 715.74 | -7.9836 |
| **Units Manufactured:** | | | | | |
| Year 1 | | | | | |
| Year 2 | 2227 | 2026 | -9.046 | 1995.1 | -10.437 |
| Year 3 | 764.5 | 585.3 | -23.44 | 419.12 | -45.174 |
| Year 4 | 927 | 1109 | 19.6 | 1338 | 44.348 |
| Year 5 | 948.6 | 841.3 | -11.31 | 624.96 | -34.118 |
| | 932.5 | 871.1 | -6.582 | 872.96 | -6.383 |

### 4.2.2 Effect of Increase in Expected Life on Life Cycle Costs

The δ-value was increased with from 3 675 000 to 4 593 750 (25% increase) and to 5 512 500 (50% increase), while maintaining β = 2. The results are shown in Table 11.

Table 11: Model Output for Increases in Expected Life and Shape Parameter of 2

| Output Value | Original at δ = 3 675 000 | New Value at δ = 4 593 750 (25% increase) | Change (%) | New Value at δ = 5 512 500 (50% increase) | Change (%) |
|---|---|---|---|---|---|
| Total LCC in Rand | 8 428 000 | 8 183 200 | -2.901 | 8 022 300 | -4.811 |
| Yearly costs (R): | | | | | |
| Year 1 | 2 872 000 | 2 846 700 | -0.8899 | 2 828 900 | -1.509 |
| Year 2 | 429 600 | 365 000 | -15.04 | 316 800 | -26.26 |
| Year 3 | 492 800 | 433 380 | -12.06 | 385 800 | -21.71 |
| Year 4 | 525 700 | 470 000 | -10.6 | 417 680 | -20.55 |
| Year 5 | 548 030 | 468 800 | -14.45 | 449 900 | -17.91 |
| Warranties issued | | | | | |
| Year 1 | 236.7 | 152 | -35.74 | 107 | -54.77 |
| Year 2 | 606.5 | 419.8 | -30.77 | 298.1 | -50.84 |
| Year 3 | 772.1 | 569.7 | -26.21 | 432 | -43.93 |
| Year 4 | 792.4 | 617.2 | -22.1 | 489.1 | -38.27 |
| Year 5 | 777.8 | 623.4 | -19.86 | 505.6 | -35 |
| Units Manufactured | | | | | |
| Year 1 | 2227 | 2144 | -3.73 | 2097 | -5.873 |
| Year 2 | 764.5 | 577.8 | -24.41 | 452 | -40.88 |
| Year 3 | 927 | 727.9 | -21.47 | 589 | -36.45 |
| Year 4 | 948.6 | 773.1 | -18.5 | 646.7 | -31.83 |
| Year 5 | 932.5 | 774.4 | -16.95 | 662.2 | -28.99 |

### 4.2.3 Combined Effect of Increased Scale and Shape Parameters

Combinations of increased expected life and shape parameters delivered the output as per Tables 12 and 13.

*Keeping δ = 4 593 750 and increasing β to 4 and 6.*

**Table 12: Model Output for Expected Life of 4 593 750 and Increases in Shape Parameter**

| Output Variables | Original<br>β = 2<br>δ = 3 675 000 | β = 4<br>(100% increase)<br>δ = 4 593 750 | | β = 6<br>(200% increase)<br>δ = 4 593 750 | |
|---|---|---|---|---|---|
| | Original Value | New Value | Change (%) | New Value | Change (%) |
| **Total LCC in Rand** | 8 428 000 | 8 086 300 | -4.051 | 8 029 000 | -4.731 |
| **Yearly costs (R):** | | | | | |
| Year 1 | 2 872 000 | 2 805 200 | -2.335 | 2 793 300 | -2.749 |
| Year 2 | 429 600 | 2 77 100 | -35.51 | 238 600 | -44.47 |
| Year 3 | 492 800 | 452 800 | -8.131 | 439 200 | -10.88 |
| Year 4 | 525 700 | 515 600 | -1.926 | 577 340 | 9.815 |
| Year 5 | 548 030 | 428 700 | -21.78 | 365 300 | -33.34 |
| **Warranties issued:** | | | | | |
| Year 1 | 236.7 | 13.68 | -94.22 | 1.26 | -99.47 |
| Year 2 | 606.5 | 191.3 | -68.46 | 71.02 | -88.29 |
| Year 3 | 772.1 | 607.6 | -21.3 | 587.1 | -23.96 |
| Year 4 | 792.4 | 738.7 | -6.777 | 914.7 | 15.44 |
| Year 5 | 777.8 | 507.3 | -34.78 | 310.7 | -60.06 |
| **Units Manufactured:** | | | | | |
| Year 1 | 2227 | 2005 | -9.992 | 1991 | -10.63 |
| Year 2 | 764.5 | 346 | -54.74 | 224.4 | -70.64 |
| Year 3 | 927 | 768.2 | -17.12 | 744 | -19.73 |
| Year 4 | 948.6 | 895.9 | -5.556 | 1070 | 12.75 |
| Year 5 | 932.5 | 660.9 | -29.12 | 464.4 | -50.2 |

*Keeping δ = 5 512 500 and increasing β to 4 and 6.*

Table 13: Model Output Expected Life of 5 512 500 and Increases in Shape Parameter

| Output Variables | Original<br>β = 2<br>δ = 3 675 000 | β = 4<br>(100% increase)<br>δ = 5 512 500 | | β = 6<br>(200% increase)<br>δ = 5 512 500 | |
|---|---|---|---|---|---|
| | Original Value | New Value | Change (%) | New Value | Change (%) |
| **Total LCC in Rand** | 8 428 000 | 7 935 700 | -5.838 | 7 953 800 | -5.624 |
| **Yearly costs (R):** | | | | | |
| Year 1 | 2 872 000 | 2 794 200 | -2.716 | 2 800 200 | -2.507 |
| Year 2 | 429 600 | 245 780 | -42.79 | 224 960 | -47.64 |
| Year 3 | 492 800 | 358 670 | -27.22 | 324 080 | -34.24 |
| Year 4 | 525 700 | 453 000 | -13.84 | 497 900 | -5.298 |
| Year 5 | 548 030 | 457 000 | -16.6 | 487 340 | -11.07 |
| **Warranties issued:** | | | | | |
| Year 1 | 236.7 | 6.56 | -97.23 | 0.24 | -99.9 |
| Year 2 | 606.5 | 96.1 | -84.15 | 24.38 | -95.98 |
| Year 3 | 772.1 | 344.3 | -55.4 | 230.3 | -70.17 |
| Year 4 | 792.4 | 601.9 | -24.04 | 728.7 | -8.029 |
| Year 5 | 777.8 | 552.8 | -28.93 | 607.6 | -21.89 |
| **Units Manufactured:** | | | | | |
| Year 1 | 2227 | 1994 | -10.47 | 1992 | -10.58 |
| Year 2 | 764.5 | 249.9 | -67.32 | 177.9 | -76.72 |
| Year 3 | 927 | 500.3 | -46.02 | 390 | -57.93 |
| Year 4 | 948.6 | 755.8 | -20.33 | 884.1 | -6.797 |
| Year 5 | 932.5 | 706.2 | -24.27 | 763.8 | -18.09 |

### 4.2.4 Effect of Change in the Cost Structure

*Increase in Warranty Price*

The warranty price was increased from R 3400 to R 3500, i.e. a 2.9% increase. The rest of the cost structure remained the same as per the original model.

Table 14: Total and Yearly Life Cycle Costs output for Increased Warranty Price

| Output Value | Original Price of R3400 | Warranty price of R 3500 | Change (%) |
|---|---|---|---|
| Total LCC in Rand | 8 428 000 | 8 109 840 | -3.772 |
| Yearly costs (R): | | | |
| Year 1 | 2 872 000 | 2 839 426 | -1.142 |
| Year 2 | 429 600 | 356 930 | -16.92 |
| Year 3 | 492 800 | 408 477 | -17.12 |
| Year 4 | 525 700 | 433 035 | -17.63 |
| Year 5 | 548 030 | 460 500 | -15.97 |

*Increase in Sales Price*

A 50% increase in the sales price, i.e. form the original R 2400 to R 3600, showed the changes in Table 15. The rest of the cost structure remained the same as per the original model.

Table 15: Total and Yearly Life Cycle Costs output for Increased in Sales Price

| Output Value | Original Price of R 2400 | New Value Sales Price of R 3600 | Change (%) |
|---|---|---|---|
| Total LCC in Rand | 8 428 000 | 5 330 000 | -36.76 |
| Yearly costs (R): | | | |
| Year 1 | 2 872 000 | 412 834 | -85.63 |
| Year 2 | 429 600 | 223 168 | -48.06 |
| Year 3 | 492 800 | 277 188 | -43.76 |
| Year 4 | 525 700 | 302 877 | -42.39 |
| Year 5 | 548 030 | 312 704 | -42.94 |

*Combined Effect of Change in Cost Structure*

The sales price was increased with 50% to R3600, but the warranty price was decreased with 10% to R 3060.

Table 16: Total and Yearly Life Cycle Costs output for the Combined Changes in Cost Structure

| Output Value | Original Prices: Sales: R 2400 Warranty R 3400 | New Value Sales Price: R 3600 Warranty Price: R 3060 | Change (%) |
|---|---|---|---|
| Total LCC in Rand | 8 428 000 | 6 414 500 | -23.88 |
| Yearly costs (R): | | | |
| Year 1 | 2 872 000 | 512 300 | -82.16 |
| Year 2 | 429 600 | 430 300 | 0.1436 |
| Year 3 | 492 800 | 589 500 | 19.62 |
| Year 4 | 525 700 | 607 900 | 15.63 |
| Year 5 | 548 030 | 658 100 | 20.08 |

### 4.2.5 Effect of Increased β-value on Regression Models

Table 17 contains the output of the regression models for the higher β-values.

Table 17: Regression Model Changes for Increased Shape Parameter

| | Linear Model | | |
|---|---|---|---|
| | Original Output β = 2 | β = 4 | β = 6 |
| $R^2$-value | 0.664 | 0.680 | 0.692 |
| Function | $Y = 3280 - 0.682x$ | $Y = 3331 - 0.690x$ | $Y = 3381 - 0.0.696x$ |
| | **Exponential Model** | | |
| | β = 2 | β = 4 | β = 6 |
| $R^2$-value | 0.929 | 0.945 | 0.945 |
| Function (Exponential form) | $Y = 2525e^{-3.292 \times 10^{-4}x}$ | $Y = 2597e^{-3.285 \times 10^{-4}x}$ | $Y = 2631e^{-3.231 \times 10^{-4}x}$ |
| | **Hyperbolic Model** | | |
| | β = 2 | β = 4 | β = 6 |
| $R^2$-value | 0.988 | 0.997 | 0.999 |
| Function | $Y = \frac{2\,686\,600}{x}$ | $Y = \frac{2\,738\,000}{x}$ | $Y = \frac{2\,765\,000}{x}$ |

## 4.3 Discussion

The results proved to be of value to the engineering team at the CSIR and have answered all four the research questions.

### 4.3.1 Design Optimisation and LCC

The main aim of this experiment was to optimise the design – i.e. to decide on the best reliability level at the lowest LCC. Also, it had to indicate the expected demand for replacements and new sales over the 5 year period. This directly impacts the number of units to be manufactured, and therefore also the LCC.

*Present Value of the LCC and Design Optimisation*

The extended ABM simulation in Anylogic optimised the design at an expected life of 3 675 000 steps for a shape parameter of 2. At this reliability level, the minimised LCC are R 8 294 800. However, this is the minimum costs that were obtained only once. It is therefore unrealistic to expect the real costs to be true to this value. It is more important to know what the mean LCC at this reliability level would be over the 5 year period.

The simulation provided a mean LCC of R 8 428 000 and a maximum of R 8 530 700. This is a total range of R 235 900 from minimum to maximum and is 0.28% of the mean. Referring to the symmetrical nature of the histogram (see Figure 19), the LCC may be considered as distributed normally and expressed as:

$$LCC \sim N(8\,428\,000, 46\,246^2)$$

The small spread of the data, the standard deviation being only 0.55 % of the mean value, implies that the data is reliable to use to predict the LCC with some probability. The 5th percentile indicates that there is a 5% probability of the LCC being equal or below R 8 356 900, with the 95th percentile indicating a 5% probability of LCC being greater or equal to R 8 504 800.

*Expected Demand and Yearly LCC*

For production data, the number of units manufactured and those replaced (the warranties) seems to stabilise during year 3, as can also be seen in Figure 21. The high number of units manufactured in year 1 is due to the start-up of the project, where each entity received a new unit. Thereafter, the manufacturing and warranties tend to move towards each other and then maintain a balance.

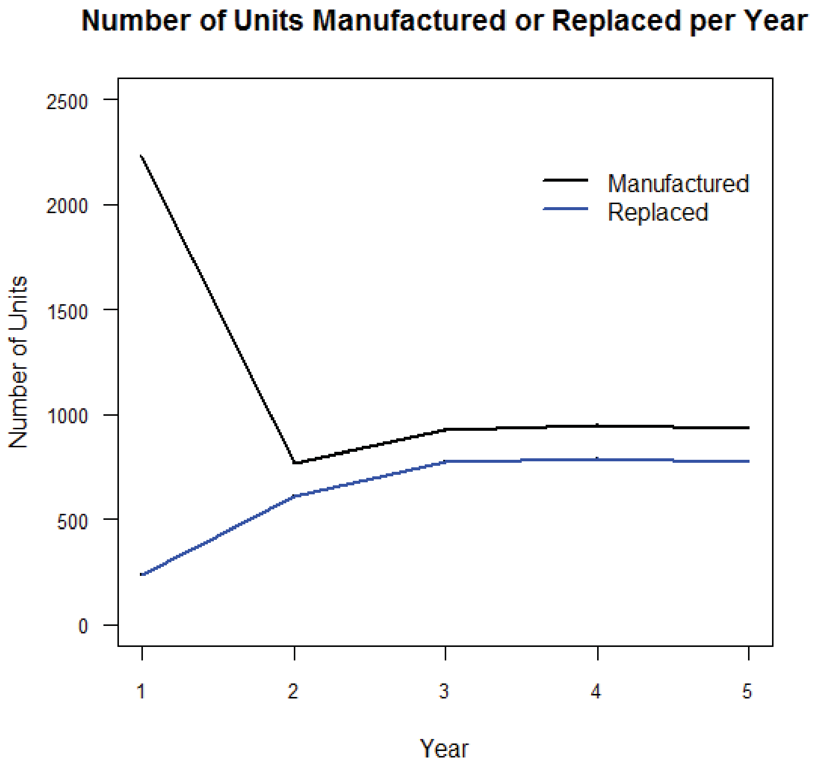


Figure 21: The Manufactured and Replaced Units over 5 years

From the graph it is evident that warranties make up a large proportion of the manufactured units. Over the course of 5 years, a mean total of 4000 units were manufactured and 780 sold as new, excluding the initial 1800 units manufactured and sold at the beginning. A mean total of 3186 warranties were issued. This implies that 79.7% of manufactured units were allotted as warranties, with only 20.3% attributed to new sales. These figures are indicative that the quality of the PPK must be revised, as nearly 4 times as many units are replaced than sold new. Figure 22 is a bar plot of these figures.

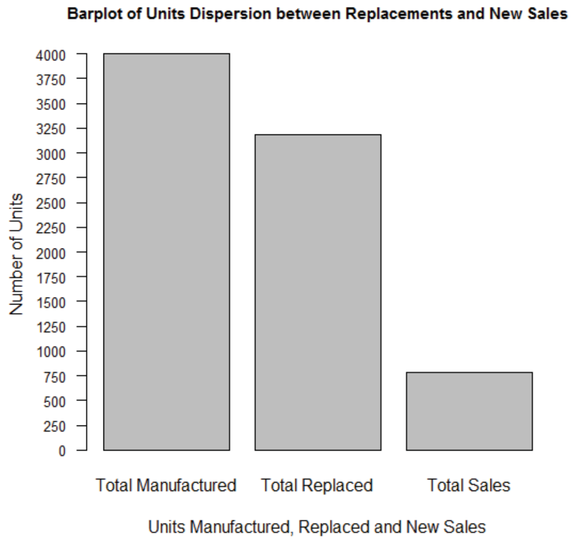


Figure 22: Bar plot for Dispersion of Demand

The yearly cash flow diagram (not drawn to scale) in Figure 23 indicates a high costs during the first year, mostly accredited to the initial manufacturing volume. The LCC for year 2 is then lower, after which there is a steady rise in future values, mostly attributed to the effect of inflation.

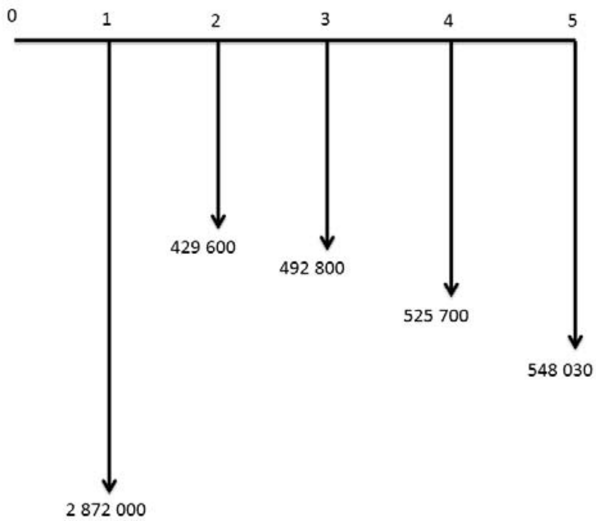


Figure 23: Yearly Cash Flow of Future Costs

### 4.3.2 Impact of Changes in Design Parameters on the Life Cycle Costs

*Increased β-value and Maintaining δ = 3 675 000*

The greatest reduction for the total LCC is observed for the β-value of 6 at 1.9%. The only positive changes, i.e. increase in figures, are observed for year 3 as shown in the tornado diagrams in Figure 24.

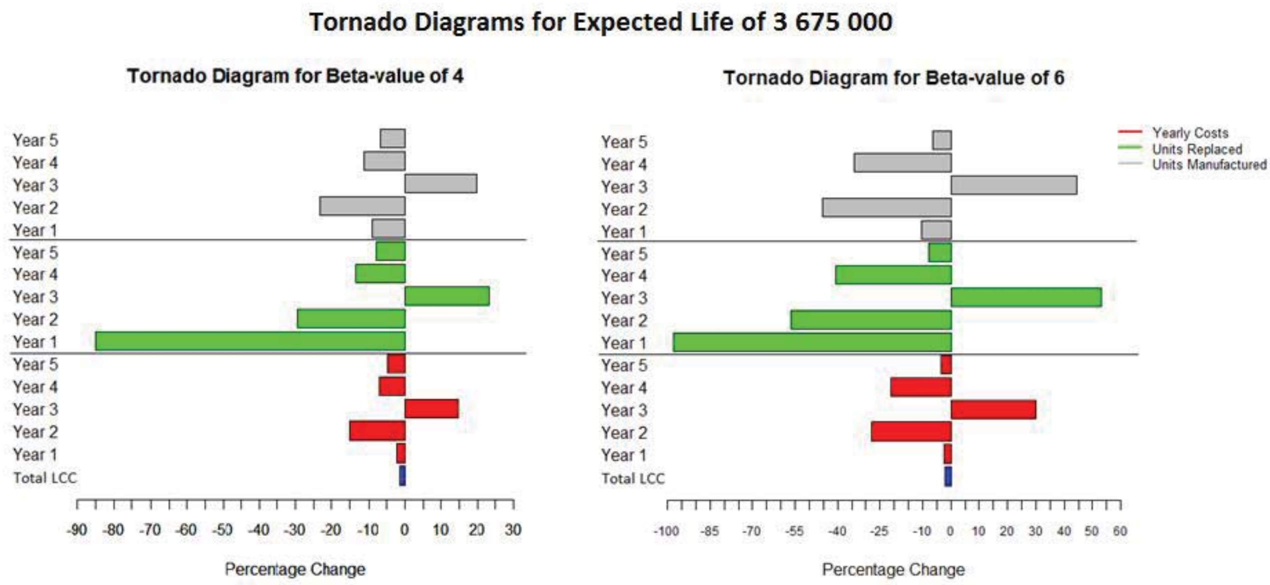


Figure 24: Tornado Diagrams for Increased Shape Parameters and Expected Life of 3 675 000

The higher β-value concentrated the spread of failures around the 3rd year, explaining the increases in warranties issued when compared to the original β-value. The costs also increased for this year, due to the higher number of warranties issued and units manufactured. The number of warranties issued during the 3rd year for the β-value of 6 is larger than that of the β-value of 4. This supports the notion that the increase in the shape parameter narrows the spread of failure times, although the MTTF remained the same.

Another prevalent change for the increases in the β-values is seen in the decrease in the number of warranties issued during the 1st year, although this is not significantly reflected in the year's costs. Recall that the number of sales is highest for the 1st year, which accounts for the largest part expenses for that year.

*Increased Expected Life (δ) and Maintaining β = 2*

The greatest change in LCC is observed for a δ-value of 5 512 500 at a 4.81% decrease from the original value. Figure 25 shows the tornado diagrams for the two increases in the expected life values.

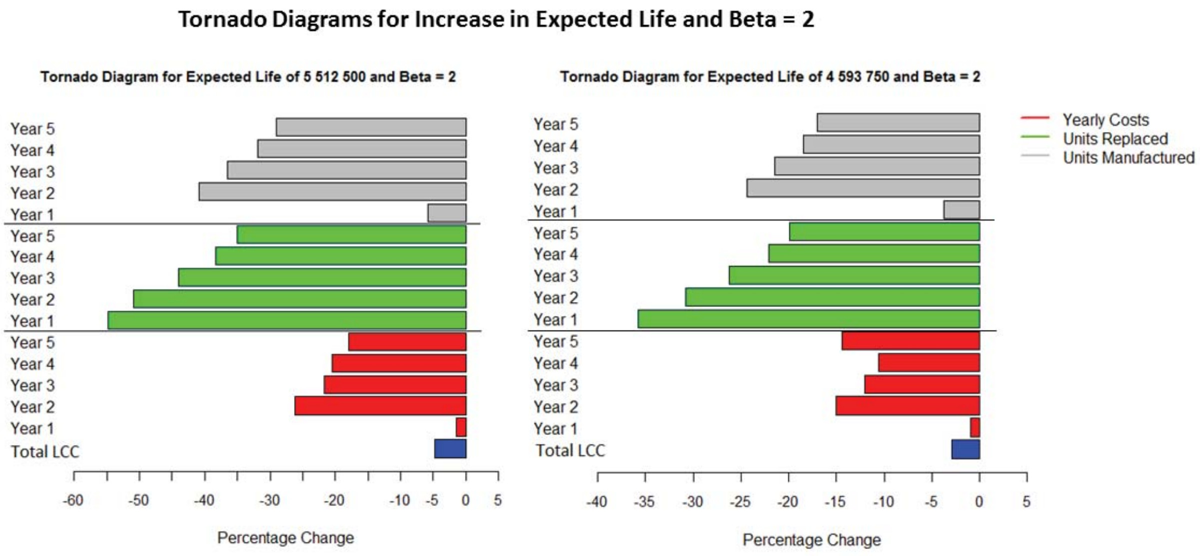


Figure 25: Tornado Diagrams for Increases in Expected Life with Shape Parameter Constant at 2

The number of warranties issued for each year decreased due to the improved reliability level, with the most reduction seen during the 1st two years. All the yearly costs have therefore also been reduced. However, the spread of failure times has remained much the same as the β-value was unchanged.

*Combined Effect of Increased δ- and β-values*

Figure 26 contains the tornado diagrams for the effects on outcomes for the combination of parameter changes. The increases in δ-values resulted in major reductions of warranties issued during the 1st three years. The only positive changes are for warranties issued during the 4th year for the δ-value of 4 593 500 and β-value of 6. The number of warranties issued peaks during the 4th year for all the combinations. However, for the β-value of 6, more units failed in the 4th year when compared to the β-value of 4 for both the δ-levels.

This pattern is also reflected in the decreased yearly costs for all combinations, with the exception of the increase in costs for the 4th year for a δ-value of 4 593 500 and β-value of 6. Overall, the total LCC is reduced the most at 5.838% for the combination of δ = 5 512 500 and β = 4. The different total LCC values for the changed parameters are plotted onto a single graph in Figure 27.

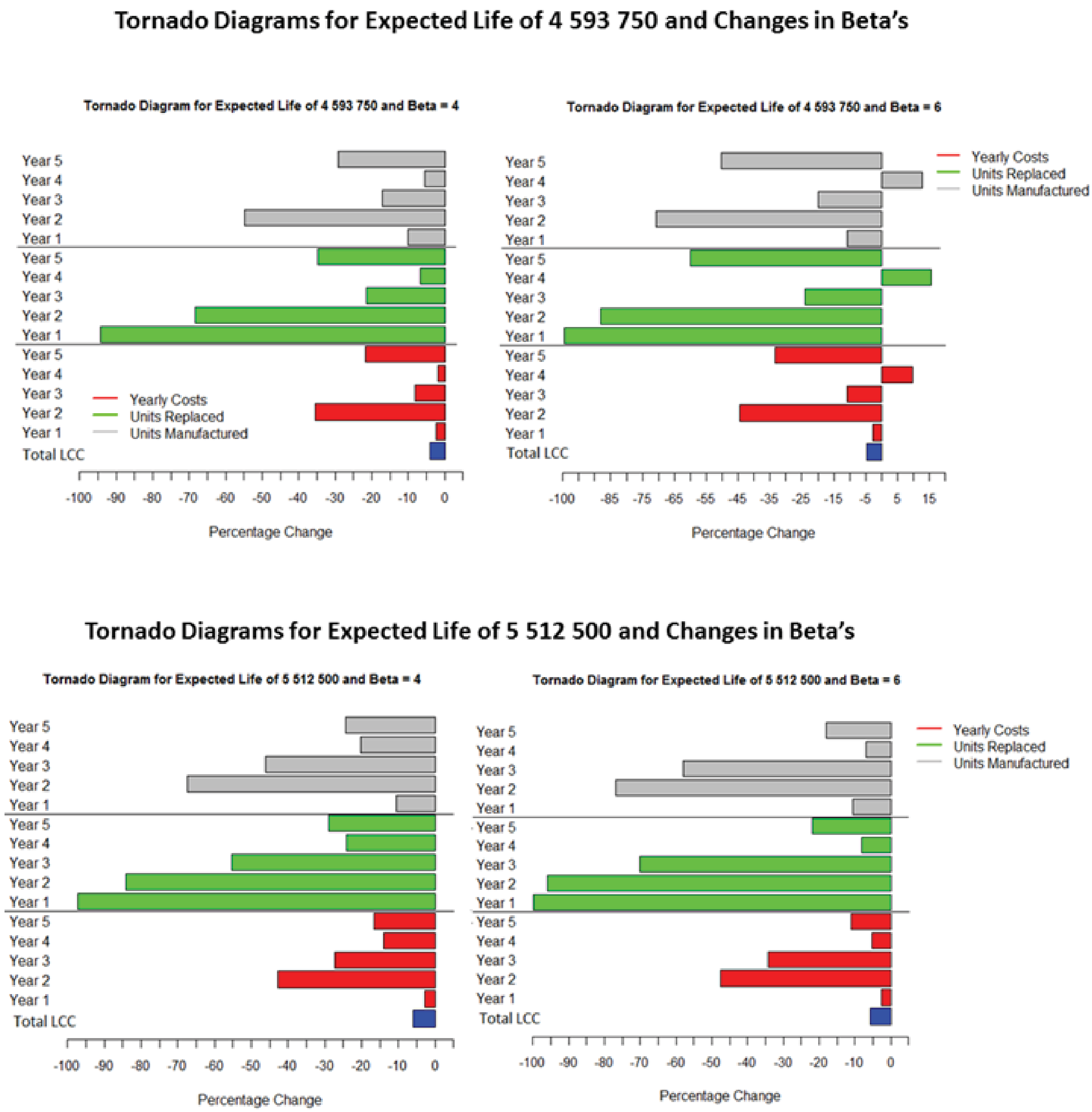


**Figure 26: Tornado Diagrams for Combined Effects of Weibull Parameter Changes**

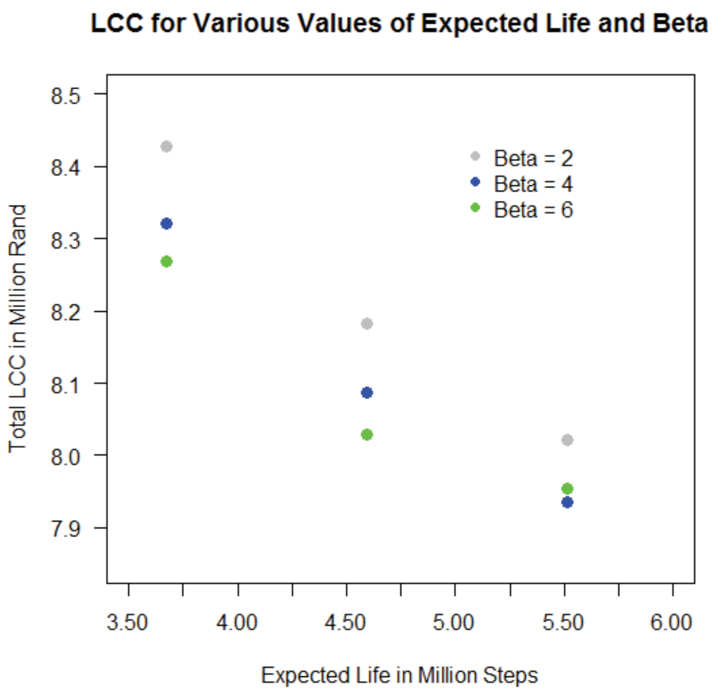


Figure 27: Life Cycle Costs for Combinations of the Weibull Parameters

*Increase in Warranty Price and Maintaining all other Parameters*

The total LCC decreased by 3.77% at a higher warranty price of R 3500. This is a lesser change than what was brought on by the combined increases in δ- and β-values. The tornado diagram for this parameter change is shown in Figure 28.

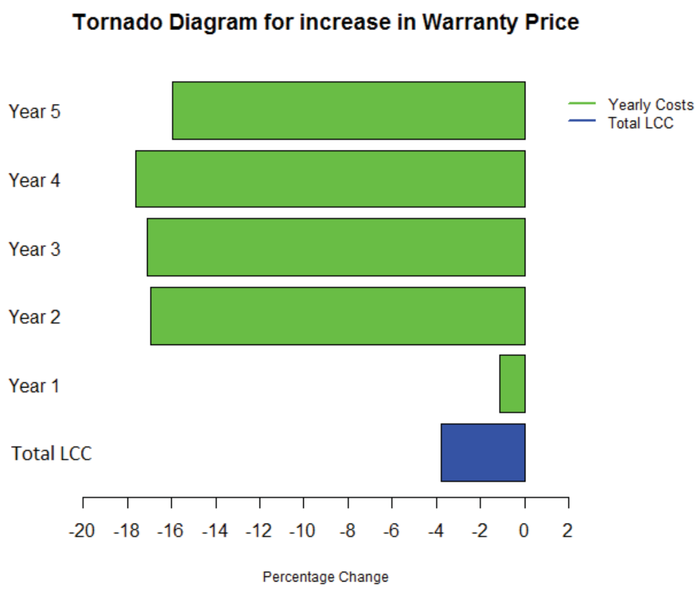


Figure 28: Tornado Diagram for Increased Warranty Price

*Increase in Sales Price and Maintaining all other Parameters*

The 50% increase in sales price resulted in a 36.76% lowering in the total LCC. This is by far the most significant reduction when compared to the other parameters. The tornado diagram is shown in Figure 29.

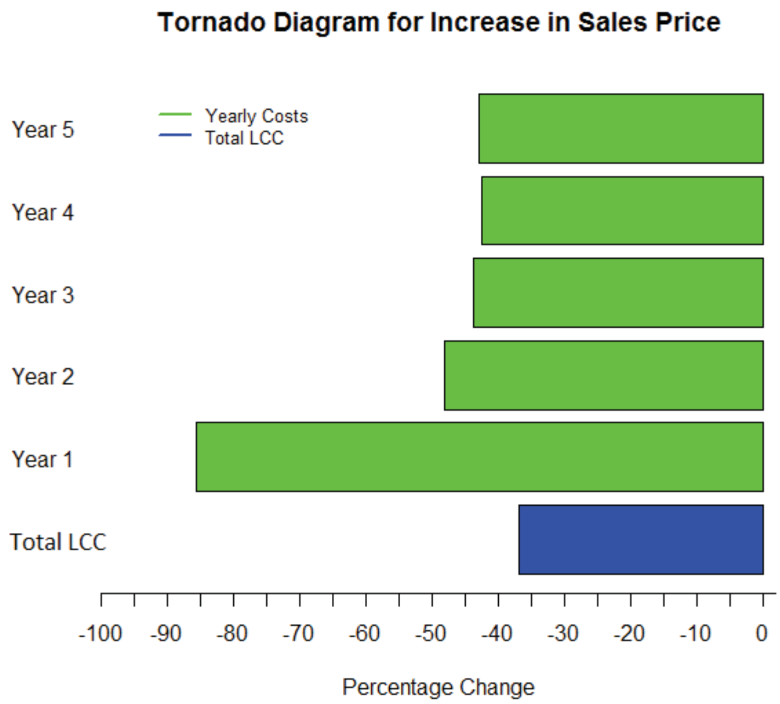


Figure 29: Tornado Diagram for Increased Sales Price

*Combined Effect of Changes in Cost Structure*

The increase in sales price allowed for a reduction in the warranty price, this combination also led to a reduction of the total LCC. The most significant change is observed for the costs of the 1st year. This is attributed to the sales being highest in this year. For the rest of the time, the warranties issued far exceed the number of sales, which would explain the increases in yearly costs for the next 4 years. Figure 30 shows the tornado diagram for the combined changes.

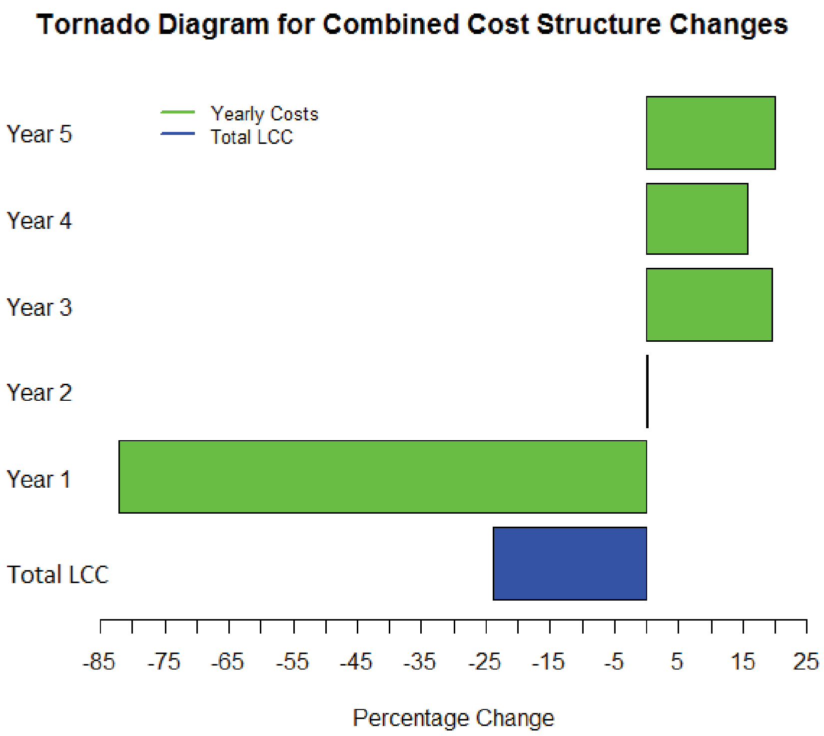


**Figure 30: Tornado Diagram for Combined Changes in Cost Structure**

*Conclusion*

The LCC – output is more sensitive to the increases in δ-values than increases in β-values. This is due to the improved reliability level, implicating fewer failures and thereby a lowering in total warranty costs. However, the spread of warranties issued over 5 years is more affected by changes in β than increases in expected life. The most significant reduction in LCC is due to the increase in sales price alone; however this vast improvement allowed for a decrease in the warranty price. This combination resulted in the second highest reduction in total LCC. Further changes to the prices in this fashion can be tested to find an acceptable cost structure.

### 4.3.3 Regression Models

The main purpose of these models is to predict the time of failure, based on the activity level of the user. The models provided did deliver good results to a certain extent, but is limited in its use due to large standard deviations observed in the data.

Of the three models generated, the hyperbolic function has the highest correlation coefficient, indicating that 98.8% of the variability in the output is attributed to the function. The null-hypothesis, i.e. slope's value is equal to zero, may be rejected. The generated function in Table 6 is therefore accepted. The hyperbolic line on the scatter graph (Figure 20) also matches the data points on the plot best. The insert on Figure 20 shows the linear transform of the hyperbolic function. The inverse of the activity levels are on the x-axis. The data points are closely scattered around the straight line.

The exponential function has the 2nd highest correlation coefficient with the variability of the model assigned to the function 92.9% of the time. The null-hypothesis, i.e. that both the intercept's and the slope's values are zero, may be rejected and the function in Table 6 be accepted. Further inspection of the fitted lines on the scatter plot in Figure 20 shows that the exponential line closely matches the data points from a 1000 steps and onwards, albeit not as close as the hyperbolic line.

The linear model produced the lowest correlation. This indicates a poor fit, with only meagre accuracy in prediction. It is also evident from the scatter plot that this function will not accurately predict the time to failure. This function will not be used.

It must be noted that large standard deviations were observed for the time to failure, for each activity level (from 500 steps up to 5000). The mean of the standard deviations is 730. This equals to two years. A large deviation from the mean such as this may render the functions undependable to use to predict the time of failure.

Referring to the characteristics of the Weibull distribution, a steeper slope (the shape parameter, β) implies a smaller variation of the times to failure and more predictable results (Schop, 2008). The variation seen in the times of failure from this simulation may be the result of the less steep slope, i.e. the β-value of 2, which places the PPK within the early wear-out category of mechanical failure. Figure 31 generically illustrates this concept.

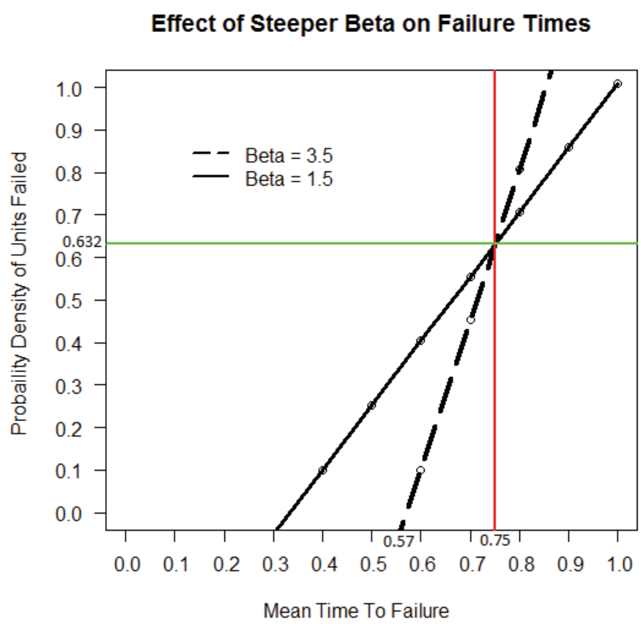


Figure 31: Effect of the Shape Parameter on Spread of Failure Times

On the steeper gradient (β = 3.5), the difference between 0 failures and reaching 63.2% of failures is 0.18 time units (the intercept with the red line). On the line with the gradient of β = 1.5, the failures up to the 63.2% mark are more dispersed at 0.45 time units. The steeper gradient results in failures being close together, thereby predicting the time of failure is within a smaller window. However, a higher β-value does not imply a shorter MTTF, as both these cases display a MTTF of 0.75 time units. Therefore, to obtain more accurate forecasting of times to failure, it is advised to improve the design to obtain a higher β-value, preferably greater than 4 as well as a longer expected life. This will place the PPK within the old-age rapid wear-out category (Schop, 2008), and make predictions for time of failure more accurate.

Should the development team decide to still use the regression models, it is advised to use the Hyperbolic function to forecast the time of failure, albeit with caution due to the large standard deviations observed.

### 4.3.4 Impact of Changes of the Parameters on the Regression Models

The fitted lines are redrawn on Figure 32 and illustrate how the standard error bars are reduced for the higher β-values. The top plot is that of the original β-value of 2. Predictions of failure times by the functions are now within a smaller window and therefore more accurate. This explains the increase in the correlation coefficients for all the models. However, the hyperbolic function still has the highest $R^2$-coefficient and remains the selected model to predict failure times.

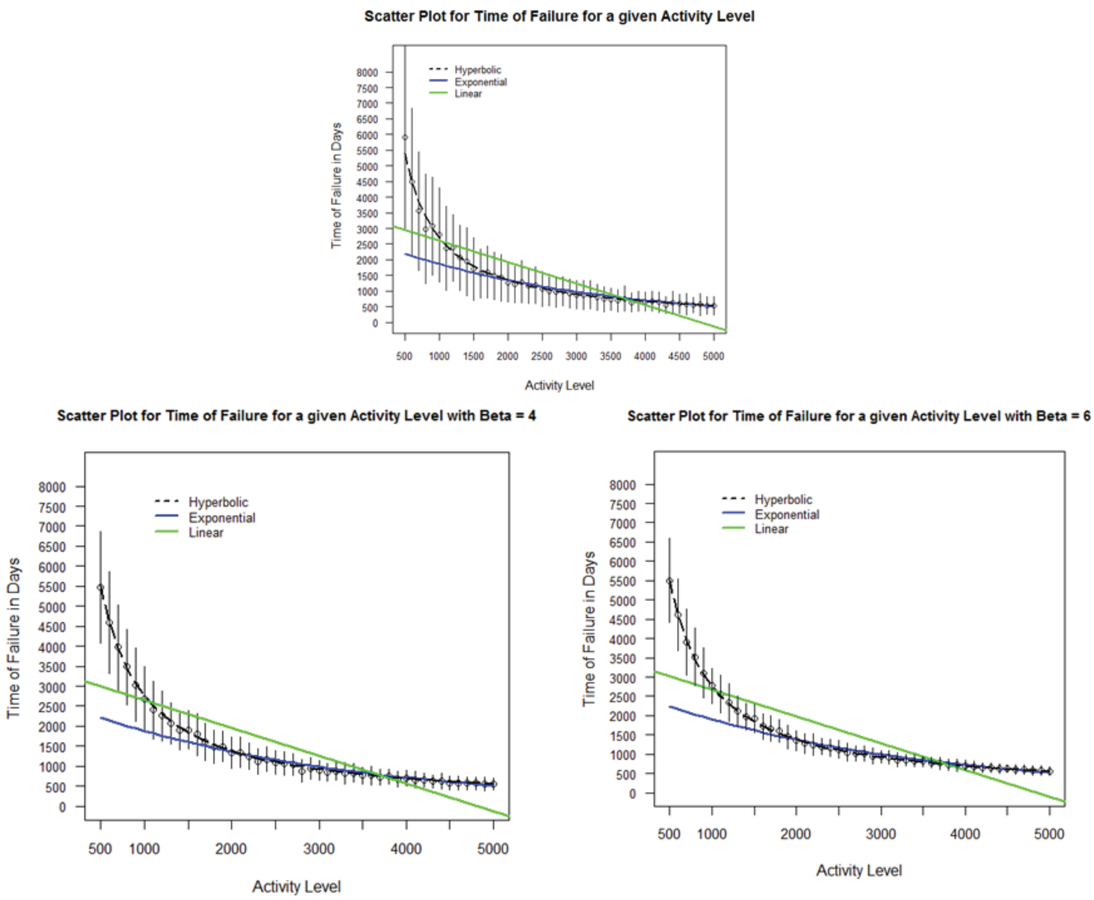


Figure 32: Scatter Plots for Increases in Shape Parameter

## 4.4 Validation: Implications for the Real World

The simulation models exhibited the anticipated behaviour with the change in input parameters. With extended expected life the demand for replacements decreased and a subsequent lowering of yearly costs ensued, resulting in the dropping of the total LCC. With higher shape parameters the replacements occurred closer together as the spread of failures across the 5 year period was decreased, also resulting in lower LCC. For the regression models, the correlation coefficients of the functions improved and the standard error bars were reduced in size for the higher β-values, at the same expected life.

This project delivered testable predictors with regards to LCC that can now be used by the development team to partly optimise the design and value the PPK. The products' overall reliability must be improved to lower the LCC, as well as a change in the cost structure. Parents and medical insurers will benefit from the findings and be empowered to improve their financial planning for a child's continued use of the PPK.

# Chapter 5

## *Conclusion*

The final outcome of this project provided beneficial insight into the behaviour of the system of the PPK in terms of its yearly and total LCC, as well as expected demand. As the PPK project is still in the early stages of development, it assisted the development team to gain an overall picture of what to expect from the system with its current parameters. The screening cost estimate affords the CSIR with a foundation to decide on the way forward in developing the product optimally.

The lead engineer of the PPK has expressed more interest in the tools or models themselves than what the final answers were. This is due to the PPK being a new product with no historical data to work from. The models are developed to be flexible enough to change the parameters once real reliability testing and operational data becomes available. In future, these parameters can be used as input to the simulations in order to deliver the relevant results. The development of an algorithm to predict time to failure for the varying activity levels can also be continued, using the hyperbolic regression model as a starting point.

This project made use of agent based modelling in reliability engineering and product development. It provided an example of how useful and valid an ABM can be to test design features, and optimise the value of the product.

*"Industrial Engineers cannot replace life before amputation, but improving prosthetic design and manufacturing can better the lives of today's amputees"*

(Zhang and Wang, 2014)

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# Appendix A: Abbreviations

| | |
|---|---|
| **ABM** | Agent Based Model |
| **ABS** | Agent Based Simulation |
| **CSIR** | Council for Scientific and Industrial Research |
| **LCC** | Life Cycle Costs |
| **MC** | Monte Carlo |
| **MTTF** | Mean Time to Failure |
| **PPK** | Paediatric Prosthetic Knee |
| **R & D** | Research and Development |
| **SD** | System Dynamics |