A Framework for the Provision of Online Discrete Event Simulation for Operational Decision Support in Complex Manufacturing Environments

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Declaration

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

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Abstract

The engineering body of knowledge contains an array of methodologies and techniques to address the effectiveness and efficiency of operational activities within a manufacturing environment. One such example is simulation modelling, a powerful analytical tool that can potentially be valuable in assisting decision makers, managers and engineers to gauge improvement opportunities and achieve process advancements. However, the cost of ownership for simulation models is not insignificant even for large multinationals, this stems from the requirements for specialist skills in simulation software, model development, data mining and statistical analysis.

Simulation projects typically require a large investment to develop and usually are used-once-and-thrown-away. To reuse the model, it would require repeating a large portion of the development cycle. In order for simulation modelling to achieve wider recognition as a decision support tool there is a necessity to reduce the cost of model maintainability, promote reusability, increase flexibility and improve user friendliness.

The research proposed framework intends to achieve four goals.

i.) Improve and advance the deployment and maintenance requirements of simulation projects in comparison to traditional methods.

ii.) Integrate automation into model deployment phase of a simulation projects. Thus, allowing unique user-specified simulation models to be generated by automatically extracting and manipulating data from factory databases.

iii.) Enforce a strong documentation technique to achieve interoperability and re-traceability of project progress, therefore permitting programme code or even entire models to be reused and utilised in future projects.

iv.) Advance user friendliness and acceptance towards simulation modelling. Reducing the expertise required to conduct simulation studies will improve the programming exercise image associated with typical simulation studies.

This framework assists in developing customised simulation modules. These modules facilitate automated online rapid development of reconfigurable, flexible, self-maintaining simulation models, aiming to deliver tailored analysis to support real-time operational decision making.

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Nomenclature

Block	Simulation Block
DES	Discrete Event Simulation
HLA	High Level Architecture
Items	Machine or Lot item in the simulation model
Kanban	A buffer concept related to lean and just-in-time (JIT) production
Machine	Tool or Workstation
Machine-Set	Toolset or Work Centre
Macro	A single instruction that expands automatically into a set of instructions to perform a particular task.
MES	Manufacturing Executive System: An information technology system that manages manufacturing operations in factories.
Monitor Loop	Studied production line section
MTBF	Mean Time between Failures
MTTR	Mean Time to Repair
On-loop	Serial flow through studied production section
Skip Rate	Production Sampling Rate

Chapter 1 Introduction

1.1 Research Motivation

Stiff competition in today's business environment has forced managers to establish strategies in order to increase their company's competitive advantage. Decision support tools are intended to work in harmony with the organisational business aims and strategic goals to assist the decision making process.

Modern manufacturing systems such as those found in the high-technology semiconductor manufacturing, bio-pharmaceutical and electronics industries are very complex systems to manage and control. In the semiconductor environment, for example, this complexity arises from a combination of several factors such as number of processing steps (often in excess of 500), re-entrant product flows, machine-product dedications and complex preventative maintenance programmes among others. Such systems cannot be managed through the application of simple rules of thumb. They require the application of models of the system to support the decision making process and often a single model is incapable of supporting all decision scenarios. For instance a model required to support supply-chain management decisions often represents a manufacturing system as a black-box with determinable input and output performances. Such a model could not be employed to support a factory production planner. This would require a much more detailed representation of the factory dynamics.

In practice the real picture is usually quite different from textbook illustrations. These force engineers to adapt their learned knowledge and apply it to the varying challenges they face on a daily basis. One such challenge encountered was the primary motivation for this research. The following case study conducted by research colleagues at the university investigated the relationship between particular quality risk performance measures. Management involved on the project initiated the request to continue further investigation. Traditional methodology used during that project was not capable in achieving the response rapidity required in such fast paced flexible manufacturing system.

1.2 Case Study – Preceding Risk Assessment Project

The preceding project [1] targeted the development of a prediction model for both the number of un-sampled items between successive samples and the time between two successive samples in a multi-product, multi-stage highly parallel, flexible manufacturing system, with a deterministic sampling strategy implemented in one production step [2].

The motivation for the initial project stemmed from a desire by the management team to obtain a better understanding of the trade-offs between production and yield decision making, particularly with respect to line speed (cycle-time) and the number of lots at risk between inspections.

1.2.1 System

The production section studied here can be considered a segment of a wider flexible production system. The system consists of numerous production and inspection stations. Each production station can perform a set of processes at different stages of fabrication. An inspection station measures feature characteristics of the parts produced at the upstream production stations and ensures quality compliance.

1.2.2 Products

The product produced is a thin slice of semiconductor material, such as a silicon crystal, used in the fabrication of integrated circuits. To produce, the product undergoes a number of fabrication process steps such as ion implantation, etching, deposition of various materials, and photolithographic patterning [3].

A number of different product families are produced in the studied system. Each product does not necessarily visit all the stations in the segment. Only a few product types cascade through the segment stations in a serial fashion. These products enter the first processing station, visit all the stations and exit the system at the last station within the segment. For these types of products and the production segment of interest, the system layout can be considered a serial production line. Other products cross the segment at a particular station and follow a different route through the system in a parallel manner, with a prospect of revisiting the segment at the same or any different station during their production cycle. Hence, the project was dealing with a highly flexible production facility with complicated scheduling directive and intricate routing practice.

1.2.3 Machines

Each station consists of several machines that operate in a parallel manner. Each machine has an independent behaviour, with several machines able to process more than one item simultaneously. The maximum number of items a machine can process in parallel varies depending on the type of station. The machines are error-prone and subject to diverse failure modes. Machines are regularly shut down for preventive maintenance. The rate of recurrence for preventive maintenance depends on the stations. Different modes of preventive maintenance are implemented in the system, for example daily, weekly, monthly, etc. Each station has an upstream buffer from which machines within the station can select their next production items. There is no structured queuing discipline employed in order to regulate the departure of the items from each buffer.

1.2.4 Defect Screening

Two serial product types flowing through the studied segment were considered for screening. The inspection strategy implemented on the production line is based on a sampling frequency. Generally the most critical and value adding station in the segment is the station for making sampling decisions. It is here that a particular operation is chosen as the decision point. A sampling frequency is determined for each product type so that every given number of items of a given product type is flagged for sampling. The decision is made only on the product types which follow a serial path through the segment. Furthermore, the inspection station does handle additional products arriving from other production routes and need to be accounted for in the study.

During the aforementioned project a simulation model of the system was developed using ImaginThat ExtendSim (Ver.6) simulation software. The model was run to simulate 6,000 production hours including a 1,500 hour warm-up period. Five replications, repetitions of the model run, were conducted each time an experimental scenario was investigated. Data outputs were averaged across the five replications on an event-by-event basis, providing a population of about 3,000 samples behind each reported statistic. The model was validated against historical data from the real system and management at the facility verified that the model results were credible.

1.2.5 Validation

The prediction model was validated using simulation results under different operating conditions and its robustness has been tested by varying the type of flow through the stations in the simulation model. In all cases tested, the model has presented very low percentage errors both for the number of un-sampled items and for the time between samples.

1.2.6 Project Outcomes

Feedback was positive from the prior project and management was interested in expanding their study to cover other segments of their production facility. However, this represented a new problem for the research group. It was possible to duplicate and conduct the same research on a different section of the fabrication facility, but that would have entailed a time consuming process of data collection, data analysis, and a labour intensive model building activity to reconstruct the entire project.

1.3 Research Investigation and Main Objectives

The project just described took close to an entire year to complete, with model construction and validation taking several months [2]. This was not feasible nor acceptable in the fast changing, ultra-modern and time critical operating environment being studied. The conclusion of the above research instigated the need for developing a framework to allow for a rapid model construction and execution module. In order to allow investigation of other segments, as management were keen to do, the process of developing, validating and deploying the model could not be repeated in a timely and cost effective manner. This implied a need for a framework that can enable customised rapid model development and deployment, while ensuring coherent validity.

Given the expense and time involved in developing any simulation model, online models cannot be “use-once then throw away” models. They must, therefore, be maintained on an on-going basis. A current challenge to simulation today is the absence of a framework for enabling current, synchronised factory models and the automated building of simulation models from factory databases [4]. The literature on online simulation is sparse; however, the development and maintenance of such models should be possible today owing to the vast amount of data that is collected and maintained by modern shop-floor data collection systems and advances in computer technology [4]. The key aim of this research is to develop and test such a framework, enabling organisations to provide simulation-based decision support for operational decisions.

The framework developed contributed towards enabling automated online decision support by infusing automation to facilitate reusability, modularity and documentation to help achieve faster development, smarter deployment and sustained maintainability to simulation projects. As a result, better return on investment and reduced cost of ownership of simulation studies is attained.

1.3.1 Research Strategy

The research timeframe was a three-year period. An in-depth review of the literature in the area of discrete event simulation, simulation based decision making support, data and information quality and representation and other related fields was conducted. A framework for the development and maintenance of the simulation model was developed over a period of eighteen months. The sponsoring organisation was willing to provide limited access to their factory databases. A pilot study to produce simulation models was developed with the organisation to test the simulation modelling framework to determine and improve its capabilities over a period of twelve months. The period in which the pilot study was conducted partially overlapped the period for the framework development. The final six months was reserved for refining the framework and completion of the thesis write-up.

1.4 Thesis Structure

Given the motivation for the research, the initial objective was to research relevant past work to help develop a general knowledge of simulation modelling literature available aiding in the development of the proposed framework. The remainder of this chapter outlines the structure of the thesis by summarising the main topics discussed and developed in the succeeding chapters.

Chapter 2 – Literature Review

This chapter provides a detailed review of the literature on the subject of simulation modelling and a number of topics involved in the construction of the framework introduced in Chapter 3. The simulation section includes an evaluation of practised project methodologies, prior examples of simulation implementation and challenges facing the wider used of simulation in the industry.

Chapter 3 – Research Framework

The proposed framework is introduced and a detailed description is given to the contained fundamentals within the framework. This chapter highlight the added advantage of the element involved and how each can contribute to automated simulation studies.

Chapter 4 – Pilot Simulation Development

A comprehensive exploration of the pilot project that developed a flexible simulation module using the proposed framework presented in Chapter 3 can be followed, with further exploration to varied techniques incorporated into the simulation study to facilitate flexible simulation-based decision support.

Chapter 5 – Testing and Experimentation

This chapter presents experiments used to evaluate the validity and responsiveness of the developed pilot simulation in comparison to the results attained in the case study described earlier in Chapter 1.

Chapters *6 – Discussion and Conclusion*

These chapters provide a summary of the thesis, highlighting results achieved and outlines issues for further consideration.

Chapter 2 Literature Review

2.1 Introduction

In the past, modelling techniques have supported practitioners in analysing and studying complex problems in a wide variety of topics: physical systems, chemical experiments, social interaction, among others. Several tools have emerged to assist such analysis. Analytical methods allowed people to challenge these problems, facilitating the advancement of science and technology [5].

Recently, a number of modern complex systems have evolved that cannot be studied with standard techniques. In such areas, computers have aided to progress problem solving through the use of simulations. Simulations permit the users to experiment with a virtual system, permitting changes be made to the system or its testing conditions, allowing to find solutions to rapid changing problems [6].

In order to present the proposed framework, the literature review chapter is intended to familiarise the reader with the subject of simulation modelling and the commonly used procedure for conducting a successful simulation study.

2.2 Studying a system

In its simplest form, a system is an assembly of components, linked collectively in an organised manner [7], and separated from its surroundings by a boundary as illustrated in Figure 2-1. A system can be described and categorised in the way it transforms inputs into outputs [7].

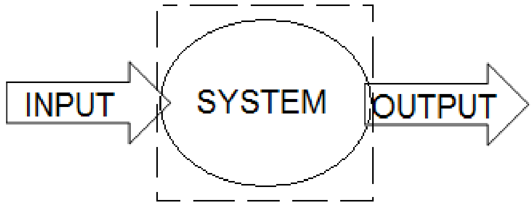

Figure 2-1: A System Paradigm

The aim of studying a system is to gain an insight into the association among its various components or to forecast performance outcomes under certain conditions of interest. There are two ways one can study a system; either by experimenting with the actual system, or by representing the system by a model and experimenting on the model. Furthermore, there are two types of models one can create; physical models can be reproduced to replicate the actual system and then experiments can be carried out on them to investigate the systems behaviour. Else, mathematical models can be built to represent the system being studied using a set of mathematical equations corresponding to the varying factors of interest. These mathematical models are solved using two techniques, analytical solution, or simulation [8]. Figure 2-2 below summarises ways of studying a system.

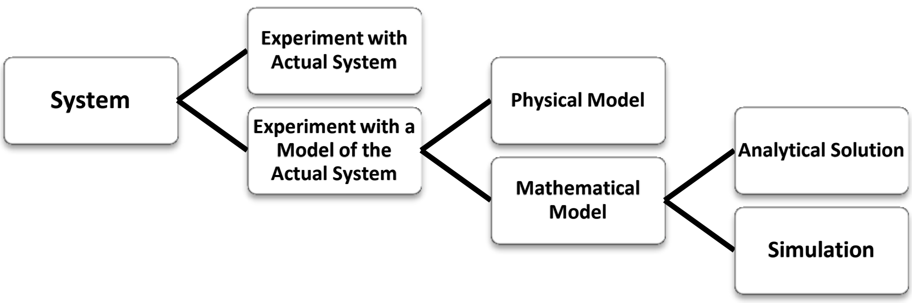

Figure 2-2: Ways to study a system. [8]

2.3 Modelling

Generally, a model is used to symbolise or represent a system on which it is based. It is possible to have a physical model, for example, architects commonly make miniature models of their proposed building designs to help them convey their ideas to their clients. In other cases, when feasible, these physical models may even be to scale and used directly for testing. However, a conceptual model may only be drawn on paper, displayed on a screen, described in words, or even just imagined. Models are used to help explore and comprehend the subject they represent [9].

At times it is required to communicate a logical model. A logical model is a sort of interpretation representing a situation where a particular statement is true. These can be divided into two categories; mathematical models where the model function is to represent concepts, or scientific models which attempt to represent physical objects and factual relationships [10].

Mathematical models can take many forms, including but not limited to dynamical systems, statistical models, or differential equations models. These and other types of models can overlap, within a given model, involving a variety of abstract structures.

A scientific model is an abstract view of reality [11]. It represents objects, event, and physical processes in a logical manner. The aim of modelling is to construct a formal system of which reality is interpreted. The surrounding environment is an interpretation (or model) of these sciences, as held true by scientific law to the observer [9].

In modelling, certain properties of the system are represented as variables [12]. The actual model is a set of functions that describe the relationship between the variables. The value of the variables can be represented using real or integer numbers, Boolean values or strings.

Analysing the behaviour of a system to understand how to control or optimise the outcome is a common task for engineers [13, 14]. This can be achieved with the use of modelling. Engineers can hypothetically compose a model to describe how a system could work, and also try and estimate how certain events would affect the system [15]. Likewise, in system control, engineers can research different control variations by the use of simulations to investigate such things as production yield rate, kanban size or resource usage.

2.4 Simulation

"A simulation is the implementation of a model over time. A simulation brings a model to life and shows how a particular object or phenomenon will behave. It is useful for testing, analysis or training where real-world systems or concepts can be represented by a model." [16]

Simulation is a crucial problem-solving methodology for finding solutions to numerous types of problems. Simulation can be defined as the imitation or replication of the operation of a real-world process or facility over time [8, 13, 15, 17-19]. The process or facility being studied is usually referred to as a system. A simulation model is used to represent a system, that is characterised to be a collection of entities that interact together to accomplish some logical goal [20].

Simulation is used to describe and analyse the behaviour of these systems, to help answer "what if" questions and aid its design [21]. In addition, simulation can take that a step further by potentially becoming a proactive decision support tool that can answer "what now" questions as well [21]. Both existing and conceptual systems can be modelled and investigated by simulation [17].

Simulations are often used to analyse systems that are too complicated to manipulate using analytic methods [18]. Simulation models use computers to deal with the vast amounts of numerical calculations involved in order to assess a system over a period of time. As the models are run, data is collected to facilitate the study of the model's true characteristics.

A series of examples demonstrating the application of simulation in real world situations is listed below [8, 20, 22]:

- Manufacturing systems designing and analysing.
- Military weapon systems or logistics evaluation.
- Communication networks requirements and protocols.
- Computer system hardware and software requirements.
- Designing and operating transportation systems.
- Evaluating service organizations such as call centres, hospitals, and fast-food.
- Reengineering of business processes.
- Determining ordering polices for an inventory system.
- Analysing economic or financial systems.

Simulation has been gaining a great amount of attention, especially over the past three decades [18]. This is partly due to the Winter Simulation Conference (WSC), which attracts around 600 practitioners from academia to industry every year, which groups together an international forum for disseminating advances in the field of system simulation.

The majority of large scale systems studied using simulation models tend to be complex in nature and writing lines of code and developing computer programs to execute them can be an intricate task [15]. Despite the advancements in the available software products, users still require training and a high standard of simulation experience to avail of their full potential.

A time-consuming computation period is sometimes required to process simulation models. However, with the continuous advances in computer processors and increasingly intelligent programming languages, this issue has become negligible in comparison to computers from past eras. Computers, nowadays, are faster and also a great deal cheaper in comparison to 15 years ago. The majority of the time now is spent on the development and validation procedures rather than the simulation execution [18].

There has been an unfortunate impression in the past that building simulations is a computer programming exercise. As a result, many simulation studies have been composed of heuristic model building, coding and a single model execution to obtain the answers [17]. The attitude of neglecting the important issues of developing a valid and properly coded model to draw conclusions about the system of interest, has led to erroneous findings being drawn from simulation studies in the past [23]. It is inevitable that this will occur in the future, which resulted in the development of frameworks to serve as a methodology that allows users to follow a systematic recipe to compile a coherent and valid simulation study [24].

2.4.1 Different Types of Simulation

Banks et al. [25] makes a distinction between three types of simulation model characteristics:

- Static or dynamic
- Deterministic or stochastic
- Discrete or continuous

In a static system the model is not dependent on time, meaning that it represents the system at any point in time. A dynamic model represents a system that changes over time. A deterministic model is one where the output measures can be precisely determined as long as the input measures are known while a stochastic model has one or more random input variables, thus generating random outputs. A discrete model is one where the variables change only at a distinct point in time, causing the system to change in some way whereas continuous models change constantly over time.

Simulations are used to explore systems of interest. These systems consist of numerous entities that operate and interrelate to accomplish some logical interactions. The state of these systems can be described by a collection of variables that relay its status at a particular point in time, relative to the study objectives.

Systems can be categorised into two types, *Discrete and Continuous*. Discrete systems are described by variables that instantaneously change status at distinct points in time (*example the number of customers in the bank)*. On the other hand, continuous systems have continually changing variables with respect to time (*in the example of a travelling car both position and velocity are continuously changing)*. In some instances, there is a third type of system, a combinational hybrid consisting of both discrete and continuous systems that can be studied by simulation, but these are not common. The type of simulation modelling used in this thesis is Discrete Event Simulation and in this regard is the main focus of the reviewed literature.

2.4.2 Discrete Event Simulation

The majority of the models surveyed in this literature review and similarly in this research are Discrete Event Simulations (DES). DES involves the modelling of a system as it develops with time, but only at isolated points during the running of the model do the state variables actually change. This means that the system can only change at a finite number of points during the simulation run time period. These isolated occurrences are defined as *Events* [19].

DES activities or events are governed by the *Simulation clock*. The simulation clock is the variable in a simulation model that gives the current value of simulated time. However, this variable does not increase in fixed increments of equal size, but rather is dependent on event occurrences. The simulation clock advances to the next event at each increase. The simulation clock is usually initialised at zero, unless specified otherwise, with the time occurrence of future events pre-determined.

2.4.3 Steps in a Simulation Study

A number of cases are found in literature to assess the phases of the simulation process, while others concentrate on particular sections. Those include; [4, 13, 26-35]. When conducting a simulation study, good practice dictates having a paradigm structure in place before commencing a project [19, 28-30, 36-38]. The objective of these structures is to organise the procedure in which a simulation study is conducted. Pursuing a tested and proven structure when conducting a simulation study can help avoid overlooking critical model building aspects and the need of continued review.

In order to conduct a scientifically coherent study and translate a real system into a simulation model, a number of assumptions need to be made to represent how the system works [30, 39]. This is done because it is very difficult to replicate all the factors that are involved in a real system. It is also worth noting that it is important to only simulate what is required to fulfil the objectives of the study. Any attempt to emulate beyond what is necessary is a waste of resources, such as time, effort and particularly cost [35, 40].

Many of these authors (Balci, Banks, Law, Robinson amongst others) [4, 8, 25, 29, 35, 36] have demonstrated an individual view on how a simulation study should be carried out and a structural breakdown of the different elements involved. Simulation textbooks typically recommend that a ten (Law and Kelton) [41] to twelve (Banks) [17] step process is followed in the development of simulation models. However, the majority of peers display derivative roots to the subject pioneers. Law and Kelton [41] suggest following the steps illustrated in Figure 2-3 in order to conduct an ideal simulation study.

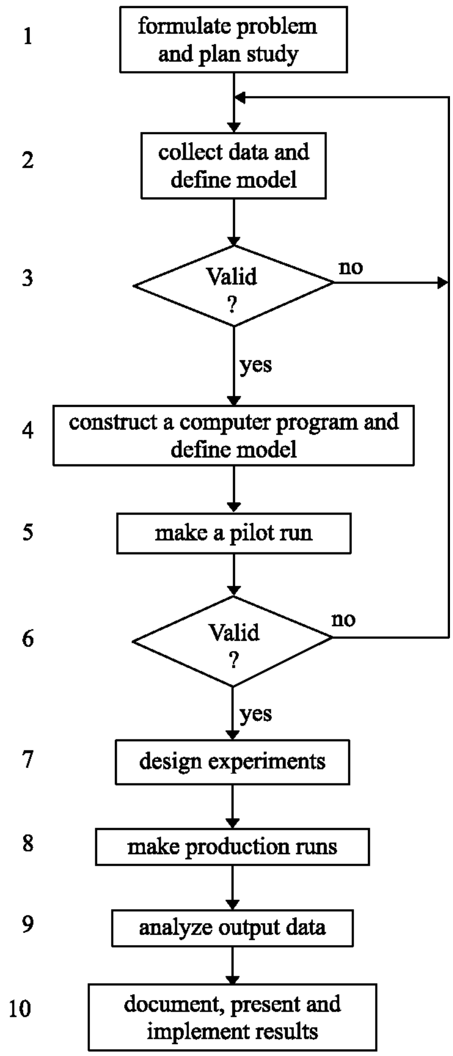

Figure 2-3: Steps in a Simulation Study [8]

1. **Formulate Problem and Plan Study:**

   The initiation of any study usually begins when a problem of interest is identified by a management group. If approved, the study starts with one or more kick-off meetings that involve attendance from the project manager, simulation analysts, and other parties involved in the area of the system being studied, also known as Subject-Matter Experts (SMEs) [42].

The first step in a simulation study involves defining the overall objective of the study and determining specific questions to be answered [30, 35]. The project is further defined by setting the time frame, scope and system configurations to be modelled. Standard performance measures used to evaluate the efficiency of the new system configurations must also be defined.

2. **Collect Data and Define Model:**

Collecting data involves gathering information on the system layout and operating procedure. It is not sufficient to get the information from a single operator from the system (if a system exists), as sometimes he/she may have inaccurate information. Data should always be collected rather than taking information from operating procedure manuals as they may not be formalised or may be out-dated. Collecting data allows for specifying model parameters and defining input probability distributions.

Information collected and model suppositions made throughout the project should be acknowledged in an *"Assumption Document"* that is updated on regular bases. This will be valuable when attempting to verify and validate the conceptual model being built. Furthermore, the interaction between managers and other key project-related personnel should be maintained on a regular basis. This will help regulate the study and calibrate the level of model detail. The model detail is dependent on a number of factors such as project objectives, data availability, data credibility, opinions of senior project participants and most vitally the time and money constraints that have been placed on the study.

3. **Validation (1):**

   Is the conceptual model valid? The next step entails performing a structured walk-through of the conceptual model using the assumptions document. Conducting this in front of project participants helps to validate that the correct model assumptions were made. Validating the concept ensures that queries can be addressed before commencing with the coding to avoid any significant reprogramming at later stages.

4. **Construct a Computer Program and Verify:**

   Here the model code is written in a programming language or built using a simulation software package. The benefit of using existing programming languages are twofold: the availability of the software in the market, and the various sections of code used in previous studies can be recycled in the current project to save time and unnecessary error proofing. The use of dedicated simulation software reduces programming time and results in a lower project cost. Once the model is built, time should be spent to debug and verify the compiled simulation computer program.

5. **Make Pilot Runs:**

   This step involves making pilot test runs that will be used for validations in the following step.

6. **Validation (2):**

   Is the programmed model valid? If the real system exists, then a comparison of the simulations behaviour can be made to historical data of the real system. Regardless, the simulation analyst and experts involved, such as management and system coordinators, should review the built model for correctness. The use of sensitivity analysis should help determine what model features have considerable impact on performance measures and, thus, have to be modelled with additional care.

7. **Design Experiments**

Each planned run of the simulation model needs to be considered and certain factors specified before moving into the experimentation phase. The run duration and repletion period needs to be decided to facilitate the construction of confidence intervals. A warm-up period is generally mandatory if the system being modelled is a factory representation or similar scenario requiring the system to have a certain loading of products. This is required as most models usually start empty unless otherwise specified.

8. **Make Production Run**

Specified system configurations of interest are emulated by running the simulation and recording the output.

9. **Analyse Output Data**

There are two main objectives from analysing the simulation results. First, it allows for determining the performance of certain system configurations that were put to the test. Second, possible comparisons of altered system configurations can be done once mutually relative performance measures are derived.

10. **Document, Present and Use Results**

An important part of any study, including simulation studies, is documentation and record keeping of the study and the results concluded. A detailed account of the

"Assumptions Document", along with the computer programme (simulation) should be recorded and documented in case further use is required. The findings and study results should also be thoroughly documented as reference to them may be needed within current or future projects.

Personnel involved in the project should consider using visual mediums when presenting the project to managers and other staff involved who may not be familiar with all aspects of simulation modelling. This can increase the credibility of the model and help management buy into simulation; it is worthwhile discussing the building and validation steps conducted in the process of constructing the simulation model. This is important, as participants backing and full managerial supports are equally essential for successful project outcomes [43]. Without full management backing and support, simulation projects can result in lost effort and wasted resources.

2.4.4 Advantages of Simulation

Real-life systems tend to be complex, entailing stochastic elements that cannot be precisely expressed using mathematical equations. Therefore, a tool such as simulation may be an option to help investigate such problem types [13, 35, 44].

Simulation can allow the performance of an existing or conceptual system under projected operating conditions to be estimated at a lower cost than actually rebuilding the system and conducting experiments. Comparison of alternatives such as system designs, or operating policies, can be investigated using simulation to aid decision making to meet specific requirements [28].

Simulation studies have an agile grasp on the time element. Elongated timeframe studies to investigate economic system behaviour can be studied alongside lightning incidents. Simulation allows shortening the prior and expanding on the latter to facilitate investigations to further our understanding. This comes along with the added benefit of being able to experiment in a controlled environment, which may be very difficult to manage when examining real systems [13].

2.4.5 Disadvantages and Pitfalls of Simulation

Simulation models require resources such as time, specialised expertise and capital investment to develop and deploy, making simulation a second alternative to traditional management tools [45]. As many of the inputs in simulation models are based on random distributions, this consequently causes the output of stochastic simulation models to only represent an estimate or sample of the model's true characteristics [46]. As a result, if a validated analytical model of the system to be studied is accessible or can be easily developed, it will generally be preferable over a simulation model.

Validating a model is of great importance. Results may sometimes appear corresponding and correct for a certain scenario, but without proper validation, the study will provide no effective information about the actual system behaviour [47]. In some studies however, both simulation and analytic models might be useful. In particular, simulation can be used to ensure the validity of assumptions made in an analytic model. Conversely, an analytic model can suggest reasonable alternatives to investigate in a simulation study.

There are many pitfalls that can cause simulation studies to fail. This can vary widely, depending on what aspect of the simulation steps guideline was not thoroughly followed [48]. From the start of a simulation project, it is crucial to establish a well-defined set of study objectives [49, 50]. Failing to set out on the right course will inevitably result in rogue answers, or require intensive restructuring and reprogramming at later stages. This also includes the level of model detail: shortage of detail will not suffice for a valid model; and vice-versa extra detail will consume time, money and resources with no added gain [35, 49].

Management involvement on a continuous basis is vital [51]. It is a common pitfall when management only establish the initiation of the project and take a backseat awaiting results. Their involvement is needed throughout the course of the study and when implementing the changes that need to take place [43]. This removes the possibility of management misunderstanding the simulation concepts. Management will be reluctant to support any study where they have not been involved or where they might not have full understanding of what is involved [46].

The modelling team, who build the simulations, must consist of participants that have strong background knowledge in simulation methodology and statistics along with SME's and management [49, 50]. This will avoid frequent pitfalls that occur by treating the study as a computer programming exercise, help in selecting an appropriate simulation software package, and aid the validation of collected data about the system being studied [48].

Care should be given when selecting a simulation software package because many claim ease of use and requiring little technical competence [46]. Selecting the right software is critical; the users must understand how information is handled by the programme. Depending on the coding language, the programme may not interpret data the same way the user expects. Therefore, a programming expert on the project team can interpret and verify the software proficiency.

Animation should not be used as a tool to validate a system model [48]. Random inputs can be seen as another pitfall as developers may perhaps use arbitrary distributions, such as normal or uniform, to fit curves using just mean and standard deviation, instead of accounting correctly for sources of randomness in the actual system [52]. Similarly, taking the results from a single replication and treating the output statistics as the "true answer" to the system's actual behaviour or comparing different system designs on the basis of one replication can be a drawback [50].

2.4.6 Online and Real-Time Simulation

The concepts of *Online* and *Real-Time* simulation are critical aspects of this thesis, but there are conflicting definitions in the literature to what each author considers Online and Real-time simulation. To avoid confusion, it is necessary to provide a definition for the purpose of this research. Online simulation is used here to describe a simulation model that is connected to the actual system being simulated in one form or another [53, 54]. Information about the fabrication facility can be extracted through direct sensors on the machinery or by access to a Manufacturing Execution System (MES). Real-Time simulation is defined as retrieving an answer from the simulation model in a short, if not immediate, time period [4].

In this regard, online real-time simulation-based problem solving capability means that if the status of the factory changes unexpectedly, the simulation can be run instantaneously to decide on an appropriate action [4]. Due to the need for prompt responses to certain types of problems dealt with in manufacturing, model-building and data collection times must be relatively short [17, 22]. In terms of decision making, the simulation based solution time required for operational problems is considerably less than the time necessary for traditional approaches of tactical and strategic problems [55]. However, an emphasis on providing accurate results is still important for the results to be accepted.

Complicated planning, scheduling, and control problems found in complex manufacturing systems have sparked interest in simulation as an online tool. By tradition, simulation has been used for long-term planning or design and models are shelved and rarely used again once their intended plans or designs have been finalised. An online simulation model, however, is intended for continuous use during daily manufacturing. The dynamic and random nature of a production facility requires online simulation to adapt and have higher flexibility in comparison to traditional, off-line simulations. Advancements in both modelling approaches and simulation language development have facilitated the field of online simulation [56, 57]. There is a need for representation of problems and decision making within complex manufacturing systems so that a real-time simulation model can be efficiently constructed. This would mean that online simulation should also have a distinct separation between decision-making and the physical characteristics of the system being simulated [57].

El-Maraghy et al. [58] present's a novel framework for online simulation and control using an approach which integrates optimisation and simulation techniques. The methodology proposed provides an integrated environment for the production manager for online control using optimisation and simulation techniques. This framework incorporates two powerful features; firstly, the ability to provide optimal or near-optimal initial schedules and secondly, the ability to efficiently reschedule when a disturbance occurs on the shop floor [58]. The challenge in this work is to combine optimisation techniques and simulation in an interactive way, with the purpose of utilising the advantages offered by each approach.

Online simulation is a modern control strategy to assist management in the short-term decision making process in current active systems. With the added complexity of today's systems, an increased demand is placed on the efficiency of the decision support tools used. The majority of mainstream simulation projects are conducted offline, and the simulation models are no longer utilised once a decision is made [4, 53, 59]. Online systems are different from traditional data processing systems in that they are constrained by certain non-functional requirements [60]. An efficient simulation of an online system requires a model that satisfies both simulation objectives and timing constraints [60]. This refers to the simulation model being able to acquire sufficient new data while initialising the simulation and deliver results in a time period that is found acceptable by the simulator.

Online simulations are part of a simulation application in which the simulation model is connected to the real system being simulated [54], with emphasis on delivering results within a certain time period to be current and effective. A typical application for online simulation is proactive decision support for manufacturing scheduling problems [21, 53, 61-63]. This scheduling practice is also known as real-time scheduling, as feedback or decisions to reschedule are rapidly formulated.

Linking the data from a real system with an online simulation model is one of the fundamental tasks in online simulation [59]. When initialising the simulation, the model is required to reproduce the conditions of the real system. The reliability of the available data is vital for online simulation applications. Manufacturing Executive Systems (MES), data depots and factory databases are generally the main source of information for solving scheduling problems in manufacturing systems. However, Fowler and Rose [4] point out that a principal problem is the availability of up to date and correct data from these resources. Even other applications of online simulation; such as street traffic and pedestrian flow studies, face difficulties in acquiring initialisation data, and the collected data may not be reliable either [64]. Successful application of online simulation requires initialising the models with adequate accuracy, however longer forecasting periods diminishes the initialisation sufficiency [4, 65, 66].

2.5 Simulation Challenges

A number of authors [4, 34, 67-69] have attempted to highlight the challenges facing simulation in the manufacturing industry. Fowler and Rose's identified challenges [4] specifically have received over 70 citations to date and considered the best deduced summary [70].

Managing and controlling modern manufacturing systems such as semiconductor fabrication facilities is very complex. The complexity arises from a combination of factors involved in the production of these sophisticated integrated circuits. To understand the multifaceted interactions of all elements involved is outside the capacity of commonly deployed analytical techniques [4].

The term “cost of ownership” is used to describe the total cost of the initial simulation project and the additional financial cost it will require upholding the model validity throughout its useful lifespan. Simulation modelling can represent the complexity of these systems and account for the stochastic behaviour inherent in manufacturing [13]. However, the cost of ownership of such models is high considering the effort and expertise required each time a new model is developed. Additionally long term maintenance of models may require repeating a large portion of the development cycle as the underlying production system evolves over time [4].

A paper published by Fowler and Rose [4] revised the current position of simulation technology and deduced *four grand challenges* restraining the advancement of modelling and simulation use in current and future decision support opportunities. The challenges exposed were as follows: (i) an order of magnitude reduction in problem-solving cycles is needed, (ii) the development of real-time, simulation-based problem-solving capability, (iii) the need for true plug-and-play interoperability of simulations and supporting software and (iv) convincing management to sponsor modelling and simulation projects instead of, or in addition to, traditionally used improvement methods such as lean manufacturing and six-sigma.

2.5.1 Reduction in Problem Solving Time

Designing, collecting data, building, executing, and analysing a simulation model to support a manufacturing decision making is a time consuming process. This results in projects being rushed at key stages where more time would have improved the quality and possible outcomes of the study.

Drastic overhaul of the entire simulation study process is overpowering and perhaps impractical, for instance Law and Kelton's [8] ten stage process that took years of practical experience and knowledge to achieve. Advising practitioners to work faster will de-motive instead of encourage reducing problem solving time [71]. Opportunities lie in advising users to work smarter at finding means to improve these methods rather than rushing them. In advancing the methodology and striving for minute reductions in the time and effort required at each of the different phases of the simulation process, the combined efforts will result in a substantial overall improvement [72, 73].

2.5.2 Development of Real-Time Simulation Based Problem Solving Capability

Generally simulation models are used in individual projects for tactical and strategic decision making support. Simulation is often used to seek the advantages of purchasing extra equipment, or assess planned changes in material flow control. Building these simulation models from scratch entails substantial effort [25]. In many cases, these models are shelved after the project is completed and never used again. Even though this is true, there remains a high return on investment from many traditional simulation projects [30].

Using simulation to approach operational (real-time) decisions in a manufacturing setting has had little coverage in literature. However, modern shop-floor information systems are collecting more data than ever before, and with the advancements in simulation software capabilities [33], this may facilitate the development of real-time simulation models.

In this context, real-time, simulation-based problem solving capability means that if the status of the factory changes unexpectedly, the simulation can be run near instantaneously to decide on the appropriate action. The capability to generate a set of simulations to see what might happen for any scenario of the decision to be made, could be extremely beneficial since these decisions have a major influence on the performance of the whole system.

A prompt response to certain types of problems dealt with in manufacturing, a reduction in model-building and data collection times is required [6]. In particular, the simulation based solution time requirements for operational problems are considerably more hostile (*shorter*) than for traditional approaches. However, providing accurate results is still important for the results to be accepted. Fowler and Rose [4] present two ways to realise online real-time simulation capabilities:

• Using a simulation model that is permanently running and corresponding to the factory and

• Automated model building from the factory databases.

The first option of having a permanently engaged, synchronised factory model comes with an array of constraints and concerns. The main problem for this approach is the availability and integrity of the data from the MES [59] (for example SAP, Oracle and QAD Inc.).

It is common to have more than one database used to collect shop-floor information when dealing with large fabrication facilities. This is due to databases evolving and growing over time, and sometimes new databases are introduced to handle new machinery software that may be incompatible with older databases at the facility. Additionally, the time lag issue must be considered when querying the database for real-time information as data uploaded to the simulation might not always be current [4].

The data collection, processing and transfer capabilities of the tools range from very basic to highly sophisticated. Without a standardised format it will be very difficult to build a model that will synchronise with all database systems involved. The problem is further complicated as the market for such a flexible simulation software package is very limited

[74]. If the above obstacles are overcome the live model could be used when a facility situation occurs. Users can simulate possible actions to resolve their situation by experimenting on a clone simulation of the manufacturing facility however the cloned model must be validated first.

The second option is to have an on-demand, automatically generated factory model overcoming the absence of real-time simulation software capability. Instead of generating a clone from the factory simulation model that requires synchronising, the engineers can generate a model on demand directly from the factory database. The factory database requirements for this setup will remain, but simulation software and computation requirements will have reduced sophistication [4].

This scenario requires an application that retrieves current factory data from the databases and then transforms it into a simulation model. A considerable amount of factory data describing the toolsets and their properties, the product mix and product routings amongst other information is necessary to build a model due to distribution fitting, processing time and inter-arrival of products to name but a few. It may take considerably longer time to retrieve and process the information to finish the model building process. As a result, this approach is less suited for time-critical decisions in which the simulation results have to be available a short time after the occurrence of the crisis. Nevertheless, this will still consume far less time than starting a project from inception when trying to build a new model. Timeframes for such a type of simulation should be capable to return an answer within an hour [4].

2.5.3 True Plug-and-Play Interoperability of Simulations and Supporting Software

Standardised simulation architecture is required for allowing the use of simulation to become more accessible [59]. As more studies are conducted on various segments of manufacturing facilities, it will increasingly be more important that these systems are able to communicate and share information between each other and surrounding environment. Fowler [4] suggested the use of High-Level-Architecture (HLA) as a potential solution. HLA is a general-purpose architecture for simulation reuse and interoperability [75].

Using HLA simulations can interact to other simulations regardless of the computing platforms that they are run from. Communication between simulations is managed by a Run-Time infrastructure [75]. The simulation software community has been slow in adapting the HLA concept in their products and this can be appointed to the lack of understanding of HLA capability [4]. Numerous attempts are evident in literature to create such interoperability in the field [14, 76, 77]. Whether they were successful or not, the need is evident for this type of functionality as analysts strive to interlink their projects and allow for a new spectrum of plug-and-play simulation software to emerge.

2.5.4 Greater Acceptance of Modelling and Simulation Modelling

Simulation is just one of several options available for manufacturing system design and improvement advances that are accessible to management for possible execution. Other approaches include Lean Manufacturing, Six Sigma, Just-In-Time Manufacturing and Total Quality Management among many others. The simulation analyst should not try to convince management that simulation is better than these techniques [51]. Simulation, on its own, does not improve the performance of a manufacturing system. It is by using these models; specific questions can be answered about ways to change the system to identify improvements. Simulation analysts should try to encourage management that simulation is a complementary tool to the other approaches mentioned above and that it can be used to gauge the potential improvements that can be made to the system when the other approaches are deployed.

2.5.5 Summary of Challenges

The challenges facing simulation are clearly defined and solution opportunities are proposed. These challenges are stated in an extremely general format and more investigation into each obstacle is required to see where opportunities exist in resolving them. It is evident that simulation modelling possesses the advantage that many decision support tools can gain from.

Literature presents a wide selection of improvement tools and techniques that organisations have availed of for a long time. However, simulation can be used as a complementary tool to filter through these apparatus to indicate the resulting benefits of using each individual one, without having to actually agitate the real system by trial and error, which further enforces the need for a tool such as simulation.

An additional challenge exposed is expediting the delay at which simulation solutions can be delivered highlighting the issue of the long problem solving time associated with simulation studies. To surmount this challenge lean ethics can bear a solution. Revamping the entire process of simulation study guidelines will be a drastic measure, but concentrating on little improvements at each of the stages involved in the simulation study will predictably accumulate to a noticeable improvement.

The remaining two challenges are standardisation and technology related. The interoperability issue can only be achieved once a benchmark simulation language is exercised across the board of simulation practitioners. The HLA did attempt to achieve this but has not gained enough exposure to cause an impact; furthermore, no solution has yet been implemented in the HLA specification to correct this concern. Technical limitations have been a hindering factor to real-time simulation compatibility; however this factor has become less significant with modern computational capabilities. Interaction with company databases has improved, and as today's manufacturing plants are storing more manufacturing data than ever before, this is increasing the possibility that information required for simulation is already being recorded and just needs the right filtering to be imported into a simulation software package.

2.6 Analysing Discrete Event Simulation Modelling Activities

In the manufacturing industry DES is implemented in a small proportion of cases where it will possibly give considerable value [22]. According to Banks [22], the complexity of the tool itself is the primary obstacle to the broad deployment of DES technology. Furthermore, simulation modelling is seen as a time consuming and expensive gadget by prospective users in industry [8, 25, 44]. Despite the unenthusiastic attitudes towards simulation, it is a vital decision making tool capable of presenting the complexity often experienced at manufacturing facilities. Simulation is a flexible tool and the prospective areas of application in manufacturing industry include a wide variety of cases; examples range from operative planning support, system analysis and system design [78, 79].

When attempting to tackle issues relating to manufacturing process design using traditional design methods, only static capacity analysis can be carried out. To manage the system complexity and the dynamics of material flow, the employment of simulation is needed. The aim should be to integrate simulation at an early development stage as a design support tool and to verify design stages continuously during the development of the system [35, 44, 45, 80]. In contrast to frequent situations where simulation is used to validate the capacity and properties of an already finished system design developed using traditional methods.

Many conditions encountered at one manufacturing facility can be categorised as common among different fabrication facilities in the industry [81]. However, it is always difficult to introduce the implementation of modern technologies into existing organisations. This is further complicated by involving a consultant group from outside the organisation to assist in the process [45, 55].

The weak link in this situation is that management considers simulation to be a technical obstacle. Technology will be a hurdle in this case, but it is also accompanied by two further components. The methodology and organisational aspects should also be considered on the pursuit to overcome barriers and obstacles on how to introduce simulation effectively. Klingstam [82] suggests that it takes one part of technology, 10 parts of methodology and 100 parts of organisation to handle the implementation of new technology. In many simulation case studies, the attitude in the approach towards the new technology may be a decisive factor [6].

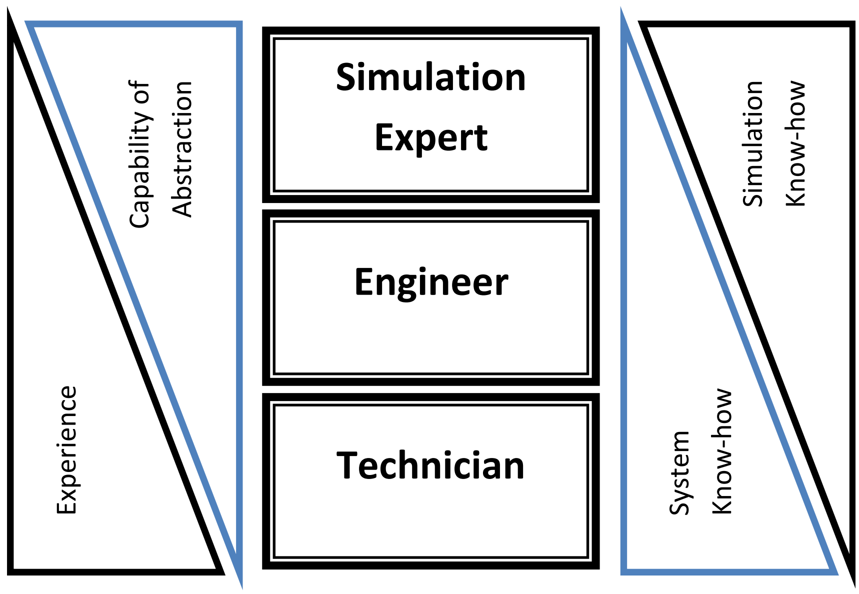

Figure 2-4: Participant input to simulation study [33]**.**

Unlike a number of attempts to systemise the modelling process [33], the approach illustrated in Figure 2-4 emphasises the collaboration between simulation expert, engineer, technician and factors that sustain the integration between system and simulation know-how in the design process. While DES modelling is basically a complex and iterative process, it must contain a great deal of creativity for problem solving and collaborative processes that involve both system and simulation know-how. In conclusion, one must remember that DES is a virtual and complex representation of mathematical modelling.

2.7 Automation

Automation is the use of both control systems and information technology in order to reduce the need for human intervention. Automation can be seen as the next evolutionary step from mechanisation in industrial terms. Mechanisation offers human operators the machinery to boost their standard physical strength (less requirement for powerful personnel), whereas automation reduced the human involvement further by supplying machines with sensors and artificial logic to carry out their functions [83].

There are various advantages and disadvantages to automation. Replacing human operators by automated machines can have a vast advantage to increasing productivity, efficiency and effectiveness. Both mechanical and mathematical operations can be performed considerably faster than if done manually by humans [84]. Automation enables the performance of tasks at a rate beyond human capability. The accuracy achieved by automation is far superior to man-made potentials. Automation can also be availed of in hazardous environments where humans cannot survive, such areas include: extreme high/low temperatures, deep underwater, vacuum or high radiation.

Nevertheless there is also a downside to consider in regards to automation. The fact remains that automation is generally expensive and the associated initial high cost involved must be studied to justify the investment, it is dependent of the quantity produced in the long run to rationalise the high setup cost [85]. Technology applies another restriction to automation, advancements have improved the situation exponentially over the past decades, but certain operation cannot be automated. This can be due to the nature of the operation requiring human interaction that cannot yet be automated, or due to complex intricacy that automation cannot yet achieve [83].

2.7.1 Attempts at Automating Simulation

Automation, in terms of simulation, is used in areas where large amounts of repetitive formatting or computations are involved and may be carried out by a computer programming code. This saves time and abolishes human error. The intricacy of automating a process or procedure involves considering all possible outcomes and accounting for each as this will provide the logic behind the programme coding. This research thesis attempts to automate the simulation study procedure and investigates past efforts to achieve a standalone automated simulation package. After searching the body of academic knowledge no evidence was found to support a complete end-to-end success; however, numerous attempts at automating partial sections of the simulation study provided a valuable learning curve.

Balci [86] and later Balci and Nance [87, 88] proposed an automated simulation paradigm which they termed “Simulation Modelling Development Environment” (SMDE). A series of further related publications report their attempts to develop the key features and functionalities of the SMDE [36, 37, 87-89].

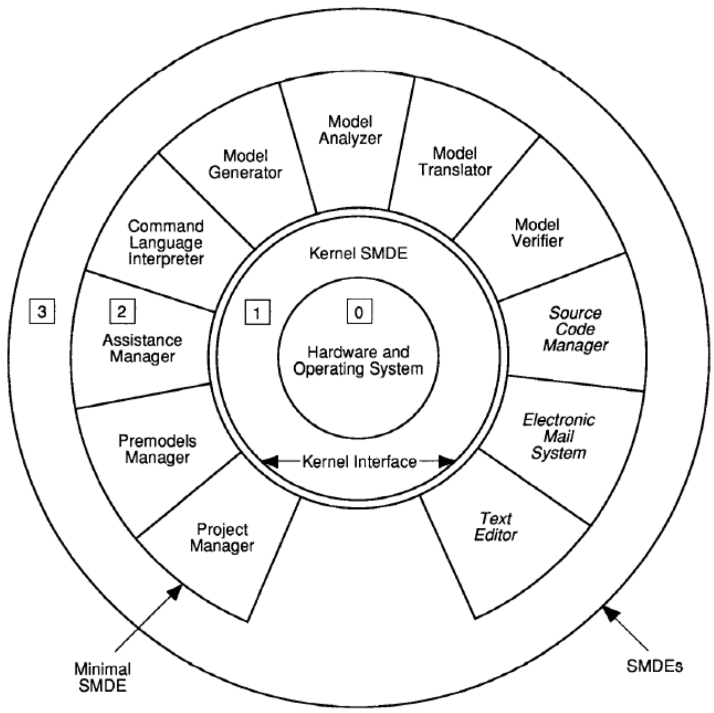

Figure 2-5: Simulation Model Development Environment Architecture [36]

The SMDE project, outlined in Figure 2-5 above, was aiming to pave the future of simulation application in the industry. Balci and Nance believed in the need for automated support in simulation model development. Their work spanned the entire range of the simulation project starting at hardware and operating system and followed by the Kernel interface which provides a standard communication protocol and a uniform set of interface definitions. SMDE contained simulation modelling and software communication tools along with completed interface and user interaction points [87, 88].

The main research aim of SMDE project was to incorporate a comprehensive collection of computer-based tools to: (i) offer cost-effective, integrated and automated support of model development throughout the model life cycle, (ii) improve the model quality by successfully assisting in the quality assurance of the model, (iii) considerably increase efficiency and productivity of the project team and (iv) significantly decrease the model development time [36].

The project faced major obstruction to achieving these aims back in the 1980's, largely due to lack of computer capability and high cost of computer hardware. Balci and Nance [87, 88] were correct in predicting that the price of computers would continue to decline and that processing capabilities continue to rise. One must note that when the SMDE project was outlined, simulation projects where carried out quite differently than nowadays. Simulation algorithms used today, handled in the background of a simulation package, were once the simulation analyst's job to encode and programme. There have been major breakthroughs in simulation software that have emerged into the commercial market over the past two decades. Balci and Nance [36] do state that this framework was not achievable at the time of writing, but insisted that the outlined structure of the SMDE would still hold with advancements in computing and simulation knowledge. The automation-based paradigm did accomplish success within the context of a very restricted problem domain; however, the paradigm became extremely difficult to realise in domain-independent cases. Nevertheless, Balci and Nance [36] remained positive that the challenge can be met with continuous development to their prototype, which later deviated towards concentrating on visual simulation support [37].

Another automated simulation attempt was carried out by McNally and Heavey [55] to construct a desktop-based simulation resource. Expanding on work carried out by Geraghty and Heavey [90] they concluded on two main points for their project: (i) manufacturing systems are complex and experience continuous change and simulation is a very important decision tool for management to efficiently operate these systems and (ii) how simulation is currently implemented mitigates against simulation being used on an on-going basis by manufacturing companies. McNally and Heavey [55] recognised that the complexity of the simulation packages available and the mainstream way of constructing simulation was a major obstacle to achieving a maintainable simulation resource.

Market available simulation software is quite intricate for users with no prior simulation knowledge or expertise to use or modify [78]. Likewise the way simulation studies are conducted is aimed at tackling strategic (long term) decision support rather than operational or tactical (short term). This can be related to simulation study projects requiring long periods of system familiarisation, data mining and model construction that can take 4 to 6 months, making them inadequate to handle short term decisions [55]. A common occurrence in these types of projects is that simulation experts/consultants are acquired by the company conducting the simulation for the duration of the study. The models built in these projects generally get shelved soon after the initial study is complete. There are a number of reasons for this for example once the initial study is complete, the findings can cause such a significant change to the company's layout that the built simulation model is no longer representative of the new structure. The information and data in the model may require regular updating but more commonly it is that the internal staff at the company may not have the knowledge or expertise to re-modify the simulation model to adapt the new company configuration [55].

McNally and Heavey [55] did construct a desktop based simulation resource. They reduced the model maintenance requirements, however, they could not predict and anticipate all the possible structural changes required to the model in the future. For example, small changes in the operating procedure at the company could result in requiring major re-coding of the simulation model. This would not present a problem if the model was developed by an in-house employee, but in most cases this is not the situation due to feasibility factors such as costs associated employing a full time simulation developer or training internal staff. Furthermore, the lack of standardisation in current model development practice and documentation adds further difficulty to allowing personnel, other than the actual expert that developed the module, to take over the model maintenance.

The simulation model developed during the McNally and Heavy [55] project was partially successful, a detailed, highly customised model was developed that linked with the production planning system. The model was deployed and provided useful results to the company. However, long-term sustainability of the simulation model within the company was uncertain, primarily due to difficulties in maintaining the model.

Al-Durgham and Barghash [91] proposed a Simulation Application Framework for Manufacturing (SAFM). The framework highlights the relationship between different decision areas in manufacturing and makes the concept of using simulation to support decision making more methodical. The foundation of the framework is based solely on reviewed literature. Al-Durgham and Barghash [91] propose the framework's main components to be; manufacturing strategies, layout, material handling, scheduling and manufacturing processes and resources. In the SAFM, managerial policy and precedence is the guiding trigger and organiser to the use of simulation in manufacturing. They advocate that all the major steps in the use of simulation for supporting manufacturing where included in the SAFM.

A novel online simulation framework for multi-resource constrained flexible manufacturing systems is presented by El-Maraghy et al. [58]. The framework foundation is a combination of optimisation and simulation techniques. Optimisation procedures are used for initial off-line scheduling and online rescheduling using Petri nets, genetic algorithms and dispatching rules. A range of performance measures such as minimising the make-span and the average flow time where incorporated. Arena (simulation software), MS Access and MS Visual C/C++ were used in the implementation of this framework.

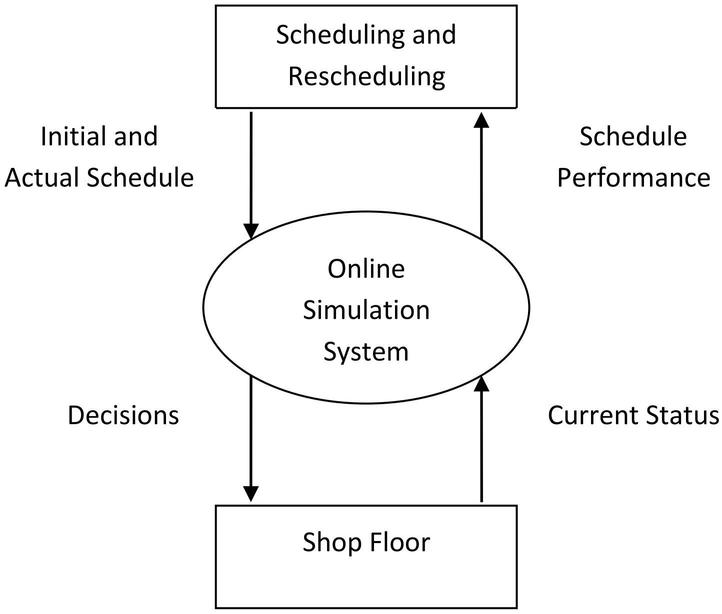

Figure 2-6: A General Framework of Online Simulation [58]

The proposed methodology was intended to provide an integrated environment for the production manager for online control using optimisation and simulation techniques. This framework integrates two powerful features: (i) the ability to provide optimal or near-optimal initial schedules and (ii) the ability to efficiently reschedule when a disturbance occurs on the production line. Figure 2-6 above displays a general design of an on-line integrated simulation system [57]. The simulation model runs parallel to the real system in order to keep track of its current status and feeds back to the scheduling utility if rescheduling is necessary. A key issue in this framework regards the response time of the rescheduling algorithms, specifically as a disturbance in the model occurs. The prospective benefits of El-Maraghy's [58] research are significant to the manufacturing sector, as simulation and control techniques will hold a direct impact on productivity, profitability and production costs.

Hoad et al. [47] conducted a further automation attempt. The project produced a plug-in to support simulation software rather than a standalone package. It provides the user with three vital tools to assist in conducting a viable simulation analysis. (i) Warm-up analyser;

to facilitate the user in allowing sufficient time to elapse in order to avoid any bias initiation data to effect the performance measures. (ii) Replication calculator; to allow for a sufficient number of replications to be carried out ensuring enough data points are collected to achieve a set precision in the output point estimators. (ii) Single run analyser; defines a satisfactory run length for single run simulation models.

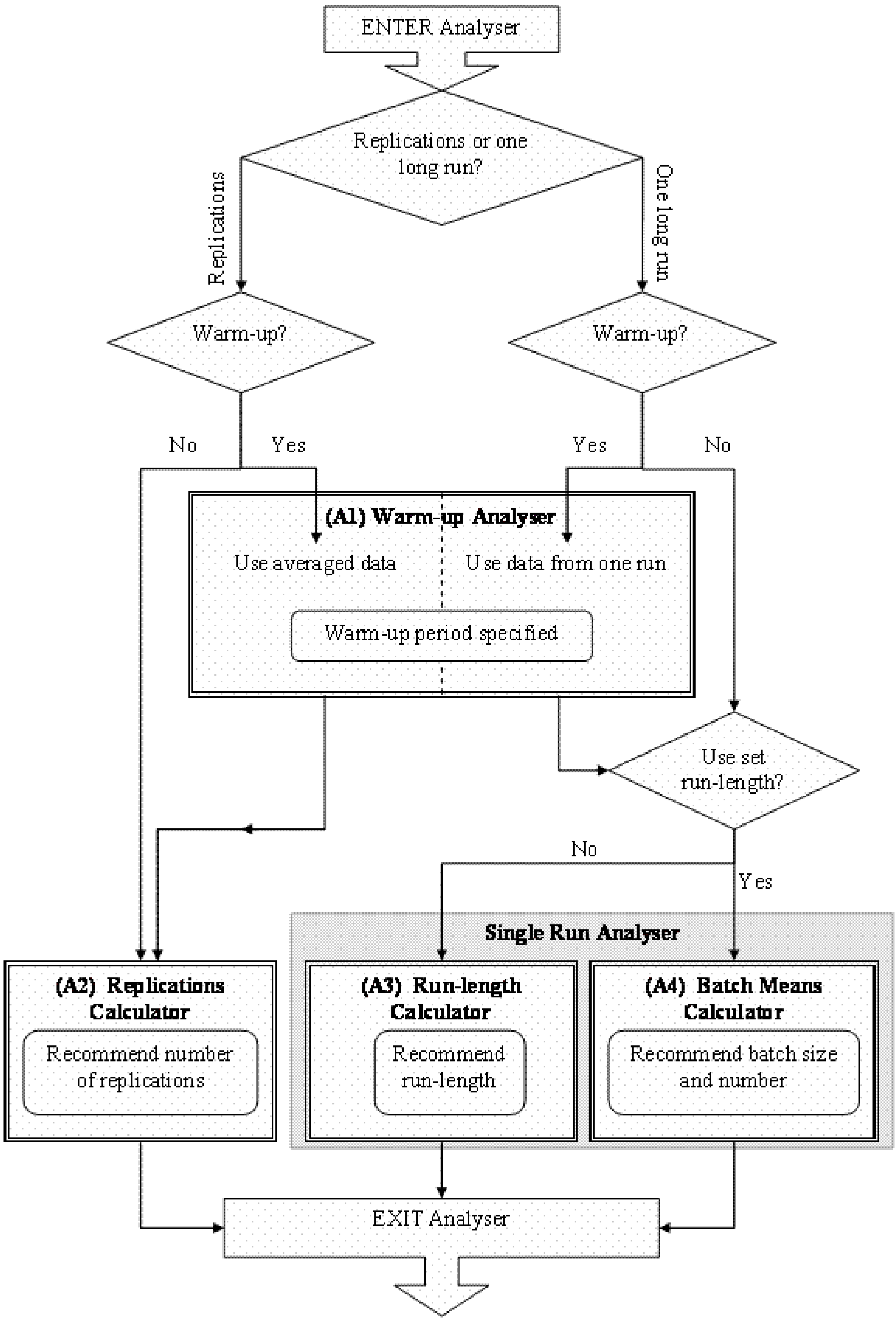

Figure 2-7: Overview of the Automated Analysis Procedure [47]

Hoad et al. [47] created an automated simulation output analyser in order to estimate the mean and variance of output data. Two key issues are resolved with this package assuring accuracy of performance estimates obtained from running a single scenario simulation model. Firstly it considers the removal of any initialization bias during a simulation run and secondly, it ensures that enough output data is produced to obtain an accurate estimate of performance. The approach outlined in Figure 2-7 above has been implemented into the Simul8 simulation software package.

2.8 Documentation (Setting a Standard)

Various techniques and methods are available to project managers and simulation modellers in order to document information regarding a simulation study. The offered range is vast and includes, but is not limited to meeting minutes, Petri Nets and IDEF.

An industry wide standard has not yet been established for data and information gathering, however, each of the tools and methods that are available have distinct merits [92]. When building a simulation model the system characteristics have to be captured in precise detail. The chosen method should certify that the simulation model and its outputs are constructive and functional to the project objectives and eventual vendor. Validation and verification stages are required to deem the built model as credible. Strong documenting from start to finish will help facilitate a smooth validation and verification process. Furthermore, high-quality precise documentation permits this but also may prolong the simulation model shelf-life, and possible reuse of parts or whole sections of the model in further and future studies [42].

2.8.1 Written or Visual: Which information is better?

Documented information is generally stored in either a written or visual format. At the outset of a simulation study emphasis is placed on meetings between the project manager, simulation analyst and the SME's to discuss the system being represented.

It is useful to attain written documentation during a meeting however using the same method to document say the material flow through a production line for a manufacturer would not be as efficient. It would be more logical to represent such a complex line by a diagram or a series of diagrams. This example demonstrates that neither visual nor text based documenting techniques alone are sufficient to represent the information that needs capturing in a simulation study. Noteworthy information can be overlooked if the volume of the text-based information captured is rather large but on the other hand relying merely on visual data in creating a simulation model, can lead to precise details being ignored [50].

2.8.2 Formal or Descriptive Methods

Heavey and Ryan [42] divide the methods and tools of information documenting into two categories; formal and descriptive. Formal methods are defined as having a formal basis and contain several software implementations. Examples of formal methods include (i) Petri Nets (ii) EDPC (Event Driven Process Chains) (iii) DEVS (Discrete Event System Specification). Descriptive methods have little or no formal basis and are mainly software implementations; these include (i) IDEF (Integrated Definition for Function Modelling) (ii) Role Activity Diagrams (iii) UML (Unified Modelling Language) State Charts and Activity Diagrams. These exemplars only correspond to a small sample of the vast range available. Once a tool or method is selected it is important to assess the benefits against time requirements in an information gathering context.

Table 2-1: Main Characteristics of Evaluation [42]

Characteristics	**Description**
Communication	The ability of the method to communicate system information, especially to non-experts.
State	The ability of the method to model state changes in a system.
Information	The ability of the method to model information flow in a system.
Resources	The ability of the method to model resources used in a system.
Benching	The ability of the method to model the complex branching logic.
Elaboration	The ability of the method to allow elaboration of the system descriptions.

Heavey and Ryan [42] derived Table 2-1 listing characteristics for evaluating documentation techniques. Whilst some methods outclass in certain areas, they lack in others. Heavey and Ryan [42] state that 'a very important task in a simulation project is requirements gathering and conceptual model development' and concluded that the industry is falling short in benchmarking a documentation standard specific for simulation. Although documentation tools from other fields are satisfactory, gaps remain because the tools are not specifically developed to support simulation.

2.9 Frameworks

The dictionary definition of a framework is *'A structure composed of parts fitted together, especially, one designed to support or encloses something; as, the framework of a house, a basic system or structure around which something is built'* [93].

In terms of simulation, a framework can be defined as: '*a conceptual model based on diverse fields of science and technology, synthesising tools' or methods' diverse area of applications, relating them together and directing towards achieving the objectives of the system*' [91].

The purpose of a framework is to facilitate working with complex technologies. A framework combines together several discrete components into a more meaningful entity [7]. In terms of simulation modelling, following a framework will assist in developing uniform code which can be used by various members of a project team, even if they were not involved in writing the code. It encourages project teams to work in a centric manner that will produce fewer development errors and a more flexible application to an organised process building [94]. A framework is a set of general and prefabricated guidance flowcharts that developers can use, extend or customize for specific targeted solutions. Frameworks are built from a collection of knowledge so both the design and application of the framework may be reused [91].

It is necessary for a project team to carry out an assignment using a verified framework as a guide, as without confined or dictated directions the end result will usually resemble a mixture of different approaches and styles that combines the participant's pool of knowledge and expertise. This results in a lack of consistency, making it difficult to debug, challenging to maintain and in addition complex to further develop. The experience is generally a long-winded learning curve, not feasible to repeat with each new project [94].

A framework that enforces a methodology will help each participant to manage and preserve their project data and avoid duplicating others work. The outcomes resulting from a framework guided project are generally easy to debug, straightforward to maintain and relatively flexible accommodating further development [7, 94].

2.10 Literature Review Summary

Simulation allows users to experiment with a virtual system, permitting alterations to the system or its testing conditions, to find solutions to rapidly changing problems [6]. The simulation literature advocates that simulation models be developed using a 10 [8] or 12 [25] step process. In this regard, such approaches leave much work and creative responsibility to the simulation analyst.

Developing a simulation model becomes an art as much as a science. Simulation models are often developed from scratch, so the individual analyst plays a significant role in shaping and configuring the model generated. These approaches leave little opportunity for the analyst to build upon the work of others since each simulation is built as a customised solution to a distinctive predicament.

2.10.1 Standard Simulation Project Shortcomings and Requirements for an Automated Simulation Study Framework

Simulation models require scores of resources to develop and deploy meaning that it is not always the first option. Input data from manufacturing applications, for example from a machine sensor or from a MES, is often in an unsuitable format for simulation, hence data must be abstracted, re-formatted and/or translated into a form that can be transferred into simulation software. Substantial effort and time is required to accomplish this, but with computer technology advancements these processes can soon be automated. One must anticipate the diversity of retrieved information when extracting data for use in the simulation model.

Validation and verification are two essential procedures that have to be carried out during a simulation project. These procedures are largely facilitated by good quality project documentation. There is no benchmark standard advised by the available simulation frameworks in literature and no means of verifying that worthy documentation has been achieved until perhaps too late. This emphasises the need for a standard of record keeping to be established in order to help make the validation and verification process more straightforward.

The diverse knowledge base of participants in a simulation project team plays a vital role on the outcome. Alongside the participation of simulation analyst, management and SMEs, there is a further demand that requires them not only to work on the project but also work harmoniously together. It is the combined knowledge of all involved that will provide the advantage to the study. In the surveyed literature, there is high importance on team collaboration and strong emphasis on continuous management involvement and support.

Finally, the variety of simulation software packages currently available in the market is huge, and many claim to be the solution to any simulation need. This is another example where standardisation could benefit the simulation industry. Having dozens of differentiated simulation languages in practice makes inter-compatibility between different platforms more complicated. Simulation software is never easy and straight forward nor is conducting a simulation study, it requires time and practice to adapt and learn like any other skill. To achieve plug-and-play interoperability in simulation unifying the coding language is a necessary step. Simulation modelling opportunities lie in allowing, for example, projects from various sections of a factory to be inter-connected in order to simulate a supply chain of the factory. This could be done without having to remodel the entire subsections to reconstruct under a solitary model. This is not yet available, but with today's computer capabilities and current advancements, it should not be impossible. HLA might be an overlooked solution.

2.11 Thesis Hypothesis (Online Simulation-based Decision Support Framework)

Fowler and Rose [4] put forward four challenges that are restricting the use of modelling and simulation in current decision support opportunities. The challenges exposed were the following;

i.) Reduction in Problem Solving Cycle;

ii.) Development of Real-Time Simulation-Based Problem-Solving Capability;

iii.) True Plug-and-Play Interoperability of Simulations and Supporting Software; and

iv.) Greater Acceptance of Modelling and Simulation within Industry.

The hypothesis is to experiment on these challenges and attempt to provide solutions and try to develop novel ideas to help advance the concept. This is done by the proposed Online Simulation-based Decision Support (OSDS) framework that targets to deliver real-time problem solving capability, reduce the problem solving cycle, and facilitate a wider acceptance of simulation modelling in the industry. This is achieved by integrating a number of decisive novel tools into the simulation toolbox. To realise real-time problem solving, online simulation is practiced. In order to reduce the problem solving cycle, automation is introduced were possible. To facilitate user acceptance, the user is separated from the complex simulation software environment.

The OSDS framework aim is to develop modules that can by-pass the complications associated with simulation (i.e. data gathering and manipulation, model building and post simulation analysis) by standardising the process and by giving the end user all the necessary options in a more familiar and user-friendly context. Automation is the groundwork supporting the framework's essential pillars. The essential pillars of are modularity, documentation and re-usability.

This research presents a framework that can be used as a basis for developing a simulation module with reduced cost-of-ownership by significantly reducing the effort, time and expertise needed for simulation model deployment and maintenance. The purpose of a framework is to facilitate working with complex technologies. The full structure of the framework was not completed together, but rather in stages by gradually learning from prototype modules developed throughout the research period. This allowed pieces of the framework jigsaw to gradually merge together. The following chapter will present the proposed OSDS framework with examples and further detail on each aspect within the framework composite.

Chapter 3 Research Framework

3.1 Introduction to OSDS Framework

Given the expense involved and time spent developing a simulation model, models cannot be used once and then shelved. Even if the model achieved its intended purpose, a significant portion of the code can be recycled to use on other simulation projects, especially within a site or process specific projects.

A further time element to consider is the validity of the initialising model information, as time elapses the model can become out-dated. Models must therefore be maintained on an on-going basis to remain valid. However, with the vast amounts of data collected and maintained by modern shop-floor data collection systems [4] the development and maintenance of such models should be made possible and more accessible. The principal challenge to simulation today is the absence of a framework for enabling current, synchronised factory models and automated simulation building directly from factory data source without the need for end-user intervention.

The OSDS framework has the intentions to achieve four goals;

1. Improve and accelerate the deployment and maintenance requirement of simulation projects in comparison to using traditional methods, where typical simulation project would take 4-6 months reduced down to a couple of hours or less.
2. Integrating automation into simulation model development phase, can allow for models to be generated by automatically extracting and analysing data from the factory database (MES) to the user specification.

3. Robust documentation techniques to allow better interoperability and re-traceability of prior projects so that code portions or even entire models can be reused and utilised in future projects.
4. Improve the user friendliness of simulation projects. Reducing the end-user expertise required to conduct simulation studies will improve perception of simulation, and it will expectantly improve the programming exercise associated image of simulation studies.

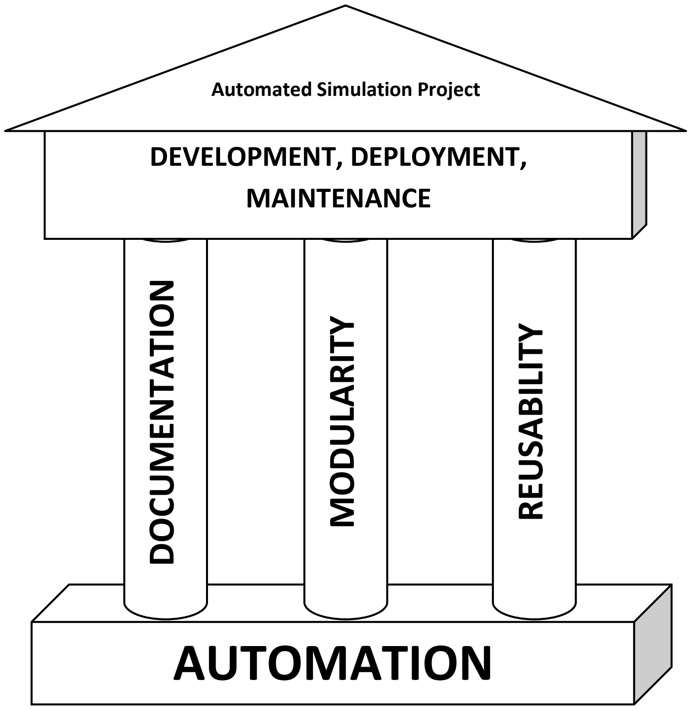

Figure 3-1: OSDS Framework

Figure 3-1 above presents an abstract overview of the framework. Each pillar was carefully exercised when deploying the framework to develop the prototype simulations. The framework encapsulates the entire process of data extraction, data analysis, model generation, execution and result analysis into distinct subdivisions within one project. Benchmarking the manufacturing structure to a standard-form provided standardisation and facilitated in automating the process. Having the module extract up-to-date information with every new run, allowed it to be current, self-maintaining and re-usable.

The remaining sections of the chapter will provide detailed description of the elements constituting the OSDS framework.

3.2 Simulation Projects (Development, Deployment and Maintenance)

In reviewing the literature, a number of simulation step proposals were covered in Section [2.4.3]. These ranged from Law and Kelton's 10 step guide to sound simulation [8], Banks's 12 step simulation study [25], Robinson and Bhatia's 4 phases of a simulation project [29], to others that could be considered slight deviations of these three. After covering a number of guides and reading their evaluations after implementation, it is difficult to find a project that adhered completely to their selected guide. Commonly found with each simulation project, participant's personal experience and intuition play a vital role in shaping the resulting simulation study. Eventually the final say is with the end-user to mix and match what steps to follow in order to conduct a good simulation study. Experienced users will be able to make their own judgement on succeeding steps at each point during the project.

Figure 3-2 below demonstrates the simulation steps that where found useful and comprehensive to cover a simulation study during this research. Each simulation study step is described in detail.

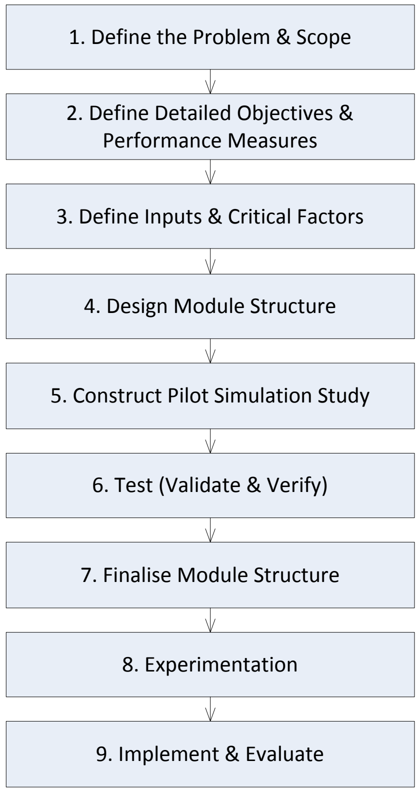

Figure 3-2: Framework Suggested Simulation Project Steps

1. **<u>Define the Problem and Scope:-</u>** It is usually the starting point of a simulation study, where management identify a problem of interest and initiates a kick-off meeting with key participants such as subject matter experts and simulation analysts to outline the project. Here the problem is presented to the project participants in a brainstorming format to further define the project issues, set a time frame, decide on a budget limit, and define team members and job roles.

2. **<u>Define detailed Objectives and Performance measures:-</u>** The objective indicates the issues to be answered by the simulation study and discuss system configurations to be implemented in the models. Project participants should also consider alternative methodologies besides simulation modelling. The project team classifies the performance measures to be used in evaluating the efficiency of the simulated system configuration.

3. **Define Inputs and Critical Factors:-** The objectives of the study have a large impact on the kind of information to be gathered and collected for the inputs to the simulation model. Input data also depends on the type of information required. It is not always necessary to physically collect new data; modern shop-floor information systems collect a large amount of data that can be used in simulations modelling the manufacturing environment. However, there are certain situations where new data needs to be gathered be it physically or through video monitoring. Examples include customer queue lengths at banks or supermarket tills, and car traffic queues at intersections.

4. **Design Model Structure:-** This portion of the simulation project is probably as much art as science. Although it is not possible to guarantee building a successful and representative model in every occasion, following proven guidelines will improve the likelihood. It is by abstracting the critical characteristics and subscribing to a list of carefully assessed assumptions that allow models to define the real system being simulated. However, it is recommended to begin with simplified models and then construct towards a greater complexity with added detail and specification.

5. **Construct Pilot Simulation Study/Model:-** Pilot runs are required to test the model validity. It is time consuming but essential to verify that the objectives and assumptions, agreed at earlier stages, have been incorporated into the constructed model. This will give the participants a model that can be tested and improved upon.

6. **Test (Validate and Verify):-** Validating comprises of determining if the simulation model is representative of the real system. The validation process is done by comparing model results to actual system behaviour. Using discrepancies to the system along with subject matter expert's support can assist to further progress the simulation model. This continues until the project leaders are satisfied with the model accuracy achieved. Verification is more towards the software carrying out the simulation. It authenticates that the algorithms and formulas being implemented in the simulation model are computed in a suitable fashion. There are many simulation packages (e.g. Simul8, ExtenSim, SimPy, Flexsim) and statistical software (StatFit, ExpertFit, MatLab, XLStat) available on the market. Statistical packages, specifically, tend to vary in the way they manipulate data especially when calculating or randomly generating distributions. It is ultimately the user's responsibility to ensure that the appropriate software is selected for the project.

7. **Finalise Module Structure:-** Learning from exposed mistakes and improvement opportunities during the pilot study can dramatically reshape the original model structure. Testing can also have an impact on the finalised shape of the study as it can influence the output evaluation, and final decision making.

8. **Experimentation:-** Once verified, validated and finalised, the project intended problem can be investigated by running experimentations using the simulation package. Specific system configurations of interest are emulated by running the simulation and recording the output. Analysing the outputs will give the resulting feedback.

9. **Implement and Evaluate:-** The success of the implementation is dependent on the accuracy of results obtained from the simulation. It is also contingent upon how thoroughly involved was the end user during the entire simulation project. If the model is comprehensible and easy to use, providing the ultimate user enough information regarding the model structure and its inputs, this would incline the likelihood of an enthusiastic implementation. On the other hand, if the project was conducted under poor communication and blurred assumptions, implementations would suffer negatively, regardless of simulation's validity. Once the implementation takes place based on the analysis of simulation results, the outcome and resulting consequences to the real system needs to be evaluated. This will aid in future improvements and developments to the simulation model, with the possibility to expand the work conducted to other areas.

3.3 Documentation

Documentation is vital for record keeping and validation purposes during a simulation study. It is essential to keep a record of all the significant events that take place during project team meetings and also at each participants individual work contribution. This allows for re-traceability, progress tracking and proves helpful during validation and verification procedures.

Simulation models are commonly shelved once the original project is completed because new users are unable to recalibrate or modify previous work or that conducted by others. This is due to lack of standard practice on code writing for a simulation modelling languages, as it is generally determined or reflective of the original programmer. Re-traceability is a major challenge when attempting to reuse simulation projects. Much depends on the simulation analyst, and how much detail they provide when writing each portions of simulation code. This will dictate how straightforward it will be for other to avail of his/her work in future projects.

A further aspect of data gathering and communicating information is related to the audience. When presenting to management, a detailed description of the simulation model's building blocks is unnecessary, but rather an abstract representation of the logic implemented by the model would be more suitable. In contrast, a greater level of detail is required when communicating with engineers, operators or other system experts in order to elicit their opinion on whether the model accurately reflects their understanding of how the system operates. To satisfy this aspect a documenting technique is required that has hierarchical levels of detail. The user should have the capability to minimise or expand the level of detail to cater for their particular communication needs.

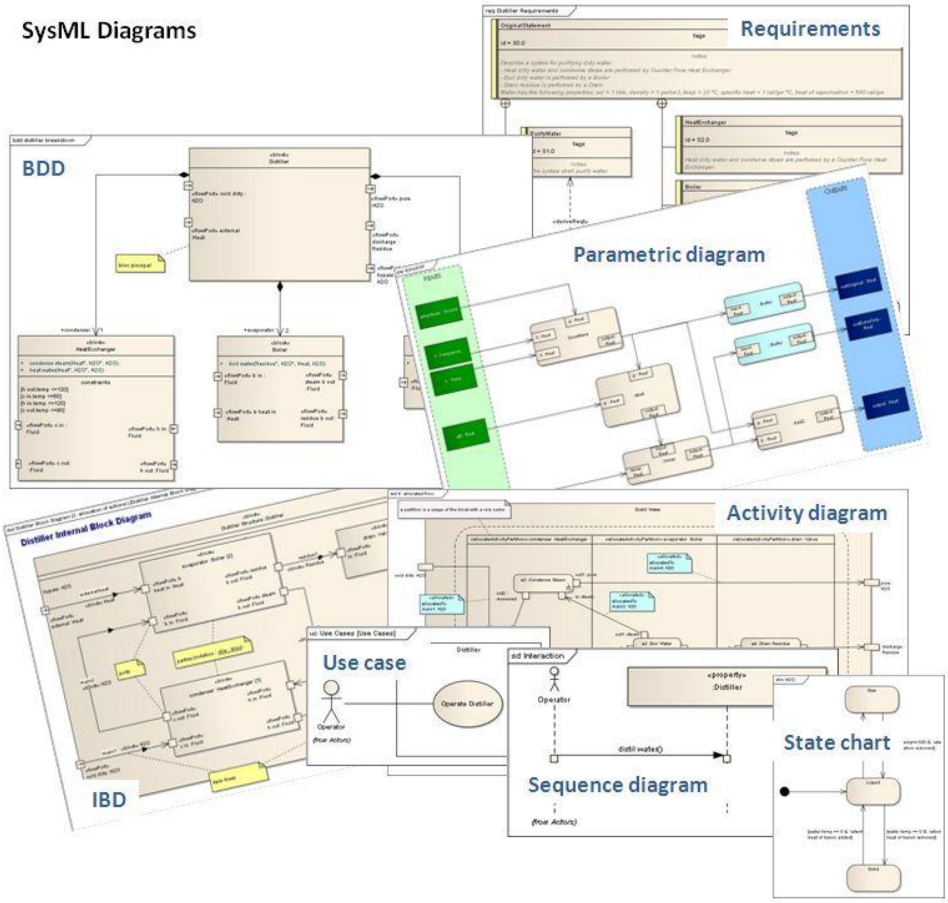

Figure 3-3: SysML Examples

A method that can display such characteristics is SysML. The name SysML is composed from Systems Modelling Language, a general purpose open-source modelling language for engineering application. SysML examples can be seen in [Figure 3-3]. SysML can support analysis, design, validation and verification of a wide variety of systems. SysML is an extension of the Unified Modelling Language (UML).

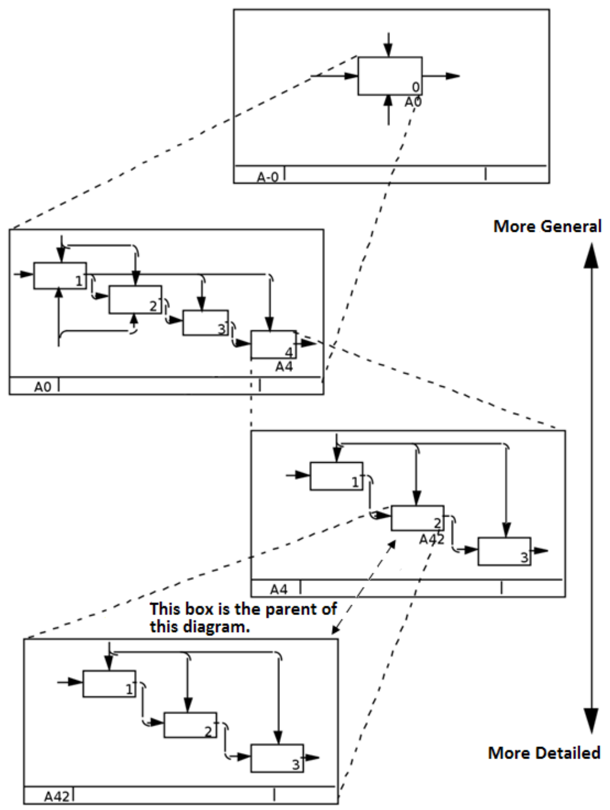

Figure 3-4: IDEF0 Example

Another method that has similar characteristics is IDEF0 (Integration Definition for Function Modelling) Figure 3-4. IDEF0 is a function modelling methodology for describing manufacturing functions. It presents a functional modelling language for analysing, developing, reengineering, and integrating systems and processes [95]. IDEF0 is part of the IDEF family of modelling languages in the field of software engineering, and is built on the functional modelling language Structured Analysis and Design Technique (SADT).

Simulation software SIMUL8 and Microsoft have worked together to integrate MS Visio and SIMUL8 as explained in Figure 3-5. Users are given the opportunity to develop and save flowchart in MS Visio and use SIMUL8 to open file and insert simulation data and work on measuring performance. Having both software supporting XML files, users of SIMUL8 and

MS Visio can work with either package on the same file simultaneously. The files are available to be re-opened by either package for further development. All MS Visio and SIMUL8 changes are maintained after editing. Using the one file on both packages allows the user to select the best package for the operation being performed.

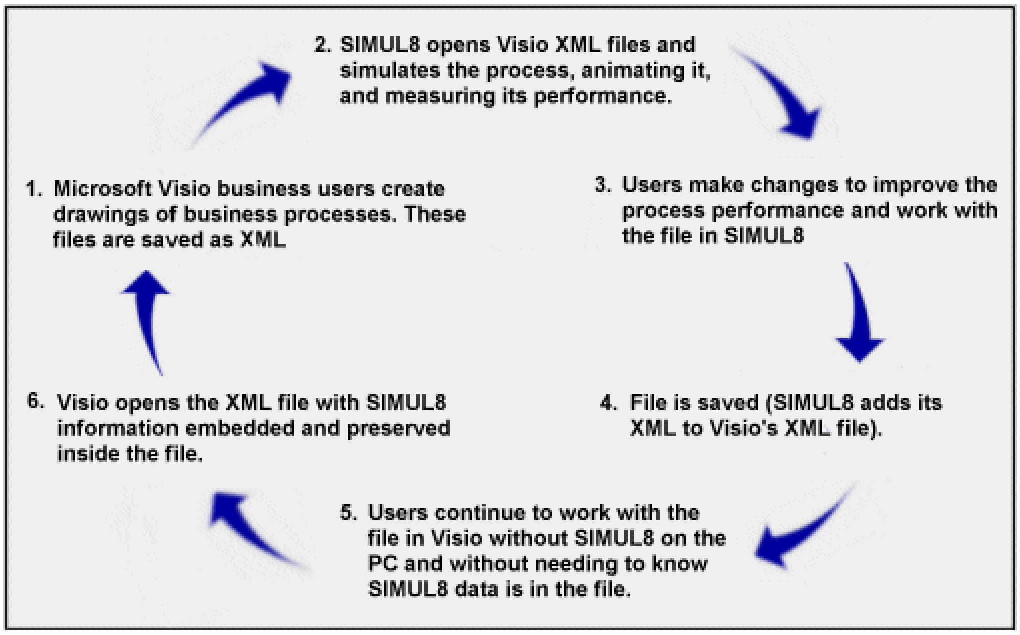

Figure 3-5: Visio and SIMUL8 Working Together [96]

Integrating a documentation method such a MS Visio flowchart into a simulation package could be a leap forward in modern simulation practice. Amalgamating the documentation phase directly into the simulation model building would possibly create a range of new simulation applications and facilitate enhanced accessibility to simulation modelling. This concept has been implemented in a joint project involving Simul8 and MS Visio and is currently available as an add-on. The package still experiences fluency issues, but will diminish with customer feedback and concentrated vendor usage. As further testing and user feedback will allow developers to repair and certainly enhance future revisions [96].

3.4 Modularity

Modularity can be defined as the use of individually distinct purposeful units, which will combine to form a functioning system. Modularity also describes the degree to which a structure's components maybe separated and recombined. An important aspect of this framework is modularity, as this segregates the different areas contained into a single automated simulation study. It allows separating the key elements, which are;

- Data extractions
- Data filtering and formatting (manipulation)
- Simulation
- Result analysis

These are the four phases of a simulation study run, once the framework is utilised to build a simulation module. The first step is for the module to extract raw data from information resources such as company database and/or machine sensors etc. This data gathered needs to be assessed and formulated into a compatible shape to import into the simulation model. Once the simulation is run, the results generated by the simulation model will require post simulation analysis, this can be done during the simulation as results are generated , or after the simulation is completed and the results are exported. Post simulation analysis deciphers the results to derive conclusions to assist the user in their decision making process.

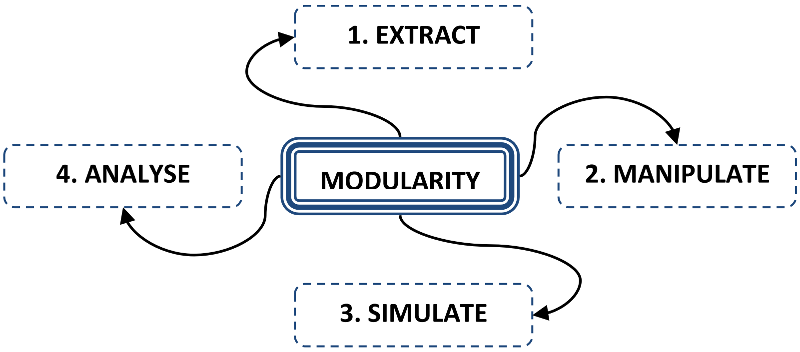

Figure 3-6: The Different Phases of Modularity in Simulation Projects

Attempting to build the entire study into one package is very complicated to achieve in a single attempt. It is more manageable to separate the four phases mentioned presented in Figure 3-6, and then challenge each phase individually. Hence, each macro is written to expand automatically into a set of instructions to perform a particular task, which can be individually tested on small portion of the simulation study. These macros are correlated together into a series of events that will perform a complete simulation study.

3.5 Re-usability

Simulation modelling is often used to represent the complexity inherent in manufacturing systems. However, the Cost-Of-Ownership (COO) of such models is high as they require considerable effort and expertise each time a new model is developed. Additionally long term maintenance of models may require repeating a large portion of the development cycle as the underlying production system evolves over time and input data is no longer up-to-date. The way to make the large investment worthwhile is by extending the model's useful shelf-life. This can be achieved by making these models re-usable and thereby distributing the cost over a longer period. Although the model may meet its objective which justifies the expenditure, a significant portion of the code can still be reused and utilised at subsequent simulation projects.

A simulation model can become obsolete when: the input data into the simulation model is from previous executions where they no longer correspond to current system statistics, or the representative system has evolved dramatically in shape and configuration that updating the inputs will not sufficiently reflect the system being modelled. Furthermore, developers require experience and expertise in simulation to update these models. Said experience may not be available among internal staff. Hence, the need to acquire the services of a consultant to carry out the maintenance procedure, which as stated previously is not a permanent solution, and will predictably, be repeated.

To achieve re-usability, it requires the simulation model to have instantaneous access to current data of the system being modelled. This can be referred to as an *online* simulation model covered in [Section 2.4.6], where the simulation is actually connected to the real system. Modern shop-floor information systems collect a large array of data, and with the improvements in simulation software packages, it should facilitate the development of simulation models that can access data when required and automatically update their input parameters. This will eliminate large portions of the development cycle that might be required in order to maintain or refurbish an old simulation model.

3.6 Automation

Automated manufacturing refers to the use of automation to produce products in a factory. The main advantage of automated manufacturing are: higher consistency and quality, reduce the lead times, simplification of production, reduce handling, improve work flow and increase the morale of workers when a good implementation of the automation is made. Automation advantages can be translated beyond manufacturing processes. Automation can be availed of in subsidiary areas to gain similar rewards of reduced lead time, higher accuracy and consistency. These areas include data gathering of shop-floor information, material handling, and production scheduling.

The OSDS framework demands to include automation as an integral part to simulation modelling. It is believed that automation can provide the capability of improved user accessibility and faster response time from the simulation module. Automation can take care of the time consuming process of data gathering and information mining in the background as the process is largely repetitive and automatable. If automation is properly implemented, it can facilitate manipulating input data and post simulation analysis, enabling long term model re-use and a more user-friendly environment that is (more) appealing to new practitioners. This concept gives new users the opportunity to customise previous models or expand on prior work, rather than starting with a blank canvas at each project. With the aid of automation, re-use can be made possible and allow for expanding the projects to a variety of areas within the organisation.

3.6.1 Standardisation

In order to accommodate automation into a procedure, one must standardise the method in such a way as to be able to anticipate all the possible inputs the system may encounter and prepare a logical output response. This is easier said than done. The intention of implementing standardisation to the system being modelled is to allow for the possibility of expanding the useful range of the simulation. For example, by standardising the interaction of a fabrication facility to just two types of items (tools and WIP/product/lot), this can allow for any partial section of the facility to be modelled, simply by supplying the simulation model a list of the tools involved, the rates of production of each product, and a list of operations linking those tools to their corresponding product list. The simulation can carry out a number of useful studies. These tests can include sampling rate policy, defect yield rating, and lead time assessment among many other customisable tests users can incorporate.

Building such models can highly complement reusability of simulation models, as the basic model structure can be used numerous times without requiring any maintenance. The only necessity is for the user to import data that reflects their objective study with every new implementation. Resulting in reduced cost of ownership and prolonging the shelf life of the simulation model. Furthermore, if the information gathering procedure can be linked to a database system containing the information, automating the extraction process of that data will result in a complete automated simulation study module.

The following chapter presents a simulation project performed using the framework to replicate the project introduced in the introduction chapter but with the advancements contributed by the developed framework. This will help demonstrate the strength and comprehensiveness of the framework.

Chapter 4 Pilot Simulation Development

4.1 Module Development using the OSDS Framework

The chapter covers a detailed outline of the pilot project development. In addition, it contains descriptions of the complications and difficulties that where encountered at various stages of the simulation project. During each portion of the module development, novel opportunity and areas of waste where exposed and learned from in the pursuit to accumulate the automated simulation enabled framework.

Simulation modelling is often used to represent the complexity of flexible manufacturing systems and account for the stochastic behaviour inherent in manufacturing. However, the cost of owning such models is high as they require considerable effort and expertise each time a new model is developed. Additionally long term maintenance of models may require repeating a large portion of the development cycle as the underlying production system evolves and advances over time.

The pilot project set out to accomplish delivering a module capable of decreasing the cost of ownership by significantly reducing the effort and expertise required for simulation project development, deployment and maintenance. Prior research activity (Case study - Chapter 1) regarding the use of simulation to understand the effectiveness of sampling policies provided the basis for this research. The previous study developed a simulation model of a defect monitor section and identified the key sources of information required to define the structure, stochastic behaviour, control parameters, and performance metrics. The model, however successful, could not be easily updated as the system advanced over time, reconfigured to reflect the evolved system or represent other monitor sections around the same facility.

4.2 Problem Definition

The focus of the pilot project is on the automated generation of a simulation model representing the current status of a discrete section of a production facility. The aim is to provide the capability to allow users to develop and conduct experiments on realistic models with minimal expertise in programming and simulation modelling. This setup, described in Figure 4-1, can also provide the user with the flexibility to allow reconfiguring a number of critical factors in order to assess their effect on the overall performance of the defect monitoring policy. Adding to this specification list is that this procedure should be executed and results achieved in the shortest possible time frame.

Points of interest include:

- Reduced cost of ownership
    - Running cost
    - Maintenance cost
- Extend shelf-life of simulation model (self-updating)
    - Current and introspective models
    - Online and up-to-date
- Infuse automation where possible
    - More rapidly simulation execution – real-time results
    - Suitable for low-simulation knowledge users
- Attempt to promote wider use of simulation modelling

The plan is to provide a support tool that is capable to rapidly develop and represent a model of a chosen monitoring segment at the facility, aiding to test different sampling policies for investigation.

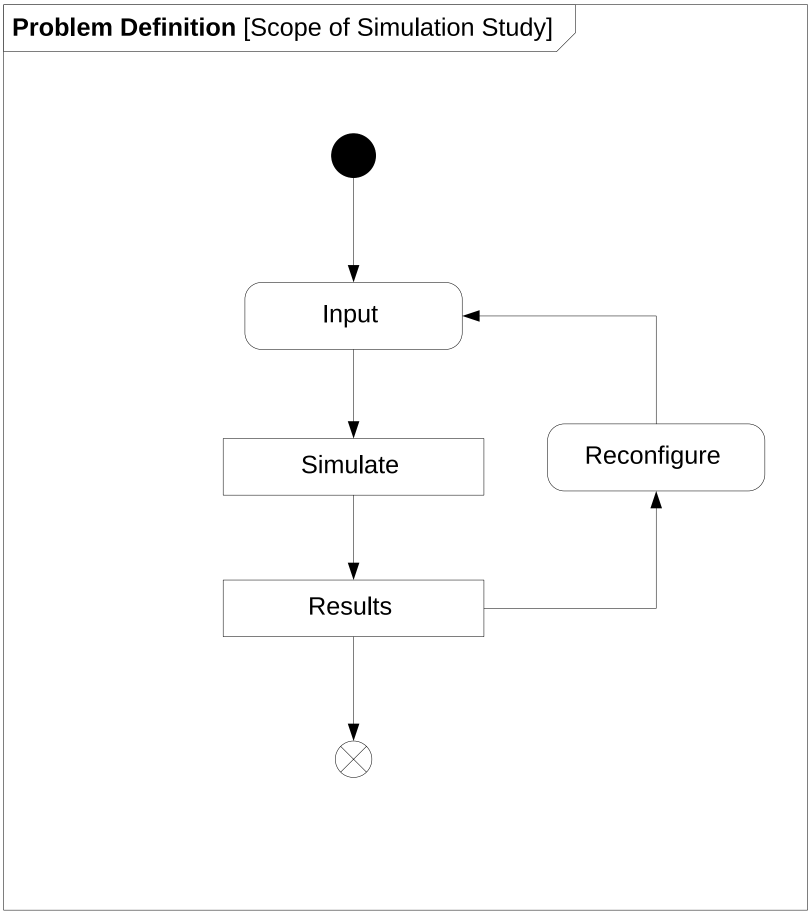

Figure 4-1: Project Outline

Due to simulation still being perceived as synonymous with the words complex or intricate, the aim is to automate, to the degree possible, every aspect involved in the simulation study, so that engineers with little or no simulation experience can benefit from the project by allowing them to conduct experiments and review results without having to interact with the actual simulation model. To facilitate this, MS Excel was chosen as a principal interface, first because most potential users have or are regular users of the Microsoft application, but more so, because of its vast computational capability.

MS Excel can assist in manipulating the information from the database and also analyse the results data returned from the simulation model. By strategically using automation to evaluate and interpret data involved in a simulation study, may possibly encourage and support promoting the further use of simulation modelling in the industry.

4.3 Performance Measures and Objectives

The objective of the pilot project is to assess the defect monitoring policy and its effect on the overall performance of the system. The two main performance measures taken into consideration here are *the number of lots* (WIP units/ batches) *between sampled measures,* and also *the time between two consecutive sampled lots*. Management and SME's assisting on the project put these two measures as the main priority in the study.

Other performance measures deduced from the simulation results can be added at a later stage into the analysis section, these may include among others, individual machine utilisation, over-all machine-set performance, yield rates and average machine queue sizes.

The intended outcome of this study was to derive a module that can assist the yield department in gauging the rate of output and defect confidence level in discrete sections of their production facility. The yield group has to deal with varied production issues that arise at the manufacturing facility. Product testing is essential and required, but simultaneously, the company needs to achieve a certain level of supply that is dictated by customer demand. In a perfect scenario, the company tests every item produced to ensure that customers never receive a defective product, but this is neither time-wise possible nor feasible. The yield department are required to assign a sampling rate that can accommodate the production time available and would deliver a satisfactory confidence margin to their supply. Therefore, yield management have to weigh their options between more frequent sampling against quicker throughput of the products as a trade-off.

4.3.1 Kick-off Meeting

The project started when the first initiation meeting took place to kick start the assignment. This meeting was attended by management at the plant, a number of yield engineers, research supervisors, and the research student performing the study. First order was to categorise what elements from the previous project needed to be flexible to achieve a fully adaptable model building module that can handle the diversity experienced at the fabrication plant being studied.

Table 4-1: Key Elements to Automate

1	Number of Operations – size of studied line segment (with a limit of 10 operations max.)
2	Number of Machines
3	Number of Products monitored (up to 5 max)
4	Machine capacity
5	Process Time (Distribution fitted)
6	Machine/Operation queue times (Distribution fitted)
7	Machine/Product/Lot ID (For tracking + assessment)
8	Sampling rate for each Product/Machine
9	Machine availability (MTTR/MTBF Distribution fitted)
10	Machine state (Type I or Type II errors)
11	Product volumes (Inter-arrival rates – Distribution fitted)
12	Simulation run length (Warm-up period + experiment)
13	Simulation stoppage rule
14	Extraction and manipulation of results

The categories that require flexibility are listed in Table 4-1 above, but a decision was made not to include all elements in the first revision of the module. The idea was to concentrate on a number of critical items that are essential and allowing subsidiary items to be investigated further and potentially included to the module at a later stage or subsequent revisions.

4.4 Simulation Inputs - Data Extraction

Every simulation model requires inputs to drive the simulation. To discover how the system would react, a simulation model calls for the initiating conditions that it will operate from in order to derive an outcome. In this case, the inputs are representing three categories of information. The first section of data the simulation model needs is a list of all the products involved and their attributes that comprise of product name, operating machine-set name and individual inter-arrival rate. The second section is describing the operations carried out by the system; the tabulated information includes the operation name/number, machine-set name where the operation takes place, and the processing duration in a distribution format. Finally, the third section is the list that describes the toolbox (Machines) available in the monitor loop being studied. The machine list gives details of the machine name and the machine-set it belongs to, along with planned and unplanned maintenance schedule.

The process of gathering information was simplified by the vast capability of the organisation’s comprehensive database system. All the required information, such as production logs and machine maintenance logs were available through the database. The process of extracting information was done by retrieving past history of the operations comprising the manufacturing segment being studied and manipulating the data in MS Excel to filter the required information for the simulation model. There is a large amount of work involved in conducting data extraction and this procedure is repeated at every simulation run and when a new line segment is chosen. Thus, the process became effusive but moreover repetitive and programmable, making the procedure suitable to automate.

The goal is to automate the development of simulation modules to study defect monitor modules at a fabrication facility. The aim is to allow for reconfiguration by the user to experiment with different scenarios and compare results. The end user will only interact through a MS Excel interface that will facilitate the extraction of previous manufacturing records directly from the manufacturer's database system. The retrieved information is used to compile statistics describing the line segment being investigated to assist in constructing a simulation model. Aiming to minimise the amount of data inputs required from the user, it was reduced to the bare minimum (to the developers knowledge). The user will only be required to enter the list of operation numbers that constitute a bound monitor loop at the facility. MS Excel macros will be triggered to drive the extraction of machine and lot information for those operations and conduct formulations to fit distributions and variable values required to generate the simulation model inputs.

The current factory configuration is taken as the default start setting at each execution of the simulation module, unless otherwise chosen by the user. This helps generates an up-to-date representative model, using the most recent eight weeks of production data, to demonstrate how the current facility will react to changes in the sampling procedure being tested. Eight weeks has shown to be a sufficient period to derive an accurate representative sample, however, the end user remains capable to extract a lengthier period if so required but face the possibility of longer computation time to process the data. Using this default setting will further assist in lengthening the modules shelf-life and ensure that most recent data is used when reviving simulation modules after a prolonged period of idle time.

4.4.1 How Does the Data Extraction Work?

The following section describes the sequence of data extraction and formalisation of input parameters for the simulation study. Two phases of data extraction take place within a single execution of the module. The first extraction exploit the user defined operations that define the studied manufacturing line segment, and comprises the complete list of machines and products flowing through this monitored line segment. The second extraction phase looks at retrieving a complete list of data describing all subsidiary products produced on the line segment.

1) The user enters the list of operations that constitute a monitor loop at the facility that they intend to study.
2) A MS Excel macro queries the studied line segment operations to the database to identify machine involved;
   a) This returns a list of machines that carry out the monitor loop operations.
3) Query both Lot History (Production Log) and Machine History (Machine Maintenance Log) on the list of machines returned from the above search, as described in Figure 4-2;
   a) Lot History provides;
      i) Processing Activity (Other operations carried out by machines involved)
      ii) Processing Times
      iii) Product Mix (Inter-arrival rates of serial products and cross-flow products)
      iv) Queuing + Transportation Times
   b) Machine History
      i) Scheduled/Unscheduled Preventive Maintenance
      ii) MTTR/MTBF Distribution
4) Merge Lot and Machine History to assess;
   a) Multiple Lot Loading (Product Tracking)
   b) Machine Status Events (Downtime History)

c) Machine Events Timeline

5) Final output of the extraction section are three tables constructed in MS Excel to completely describe the studied system inputs to use in the simulation model;

   a) Machine List

   b) Product List

   c) Operation List

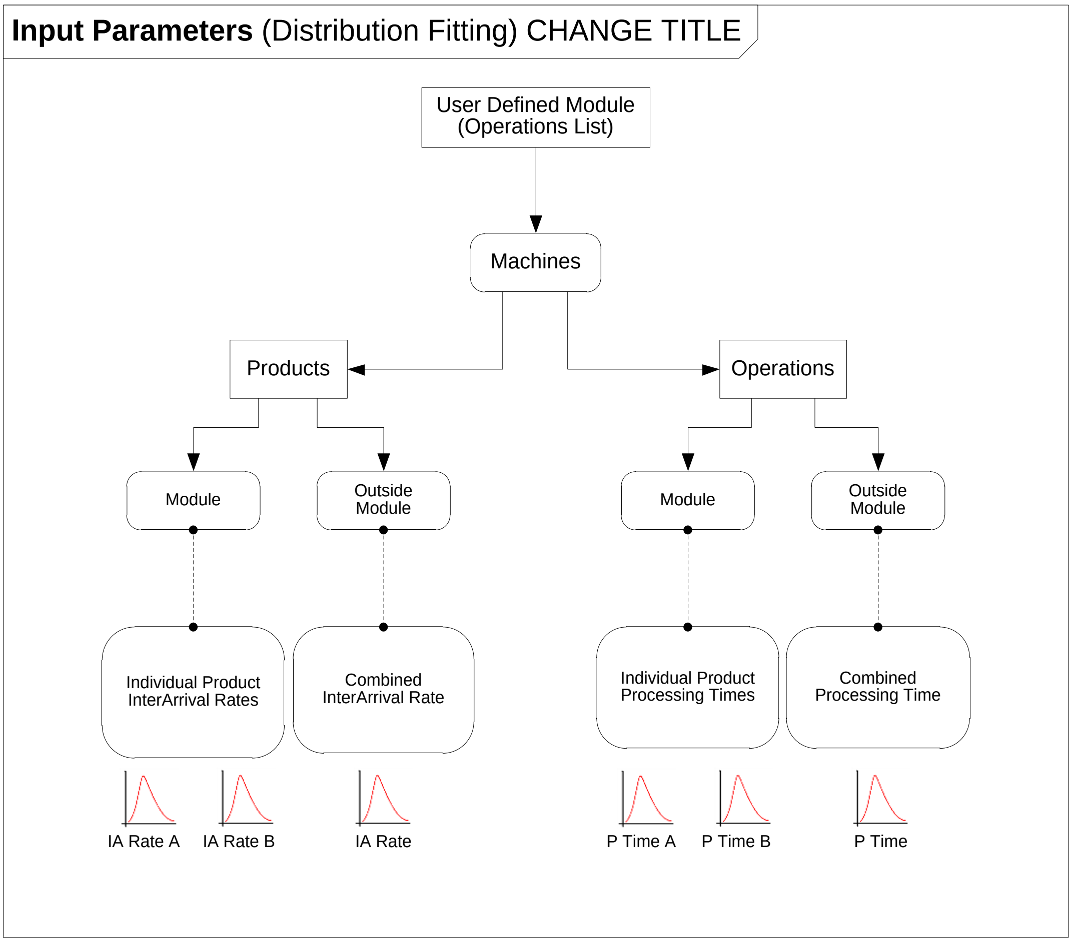

Figure 4-2: Input Parameter Fitting

4.4.2 Complications with Data Pull

The database used at this manufacturing complex has over a dozen individual logs that contain all sorts of production and inventory information among other transaction history that record all interaction occurring within the facility. On older production lines within the factory, operators perform barcode scans on lots to record database entries. This reduces the potential of human error in data entry, however, it is possible at times that wrong barcodes are scanned or product being processed prior to a scanned entry. This results with the following possible errors in the database history log;

- Duplicate entries
- Incomplete entries
- Missing entries
- Potential wrong entries

Part of the input analysis is filtering through the data and searching for these errors. It is a challenge to find a perfect source of data. Tests are required to confirm that the information being used to initiate a simulation model is free from inaccurate entries. At more modern factory lines, this issue less prominent, as the process is more automated and free from operator interaction. The loading and transportation of WIP/Lots is done by means of mechanised conveyor belts, ensuring a more reliable and accurate data recording system is adhered.

4.4.3 Data Analysis – Distribution Fitting

Common practice, in simulation studies and data analysis, is using statistical packages to formulate and fit distributions to sets of data. In some examples covered during the literature review, normal distribution curves are used to describe the processing time of machines and many other related characteristics. This was possibly done to simplify or expedite formulation time. However, the results are not very accurate in their presumptions and in real situations. Most occurrences in manufacturing setting would have a log-normal, as shown in Figure 4-4 rather than Figure 4-3, normal curve characteristic. For example, a distribution describing a machine that has a processing time of five minutes per unit would be unlikely to have a mean of five minutes with a normal distribution. It would be difficult for the machine to process products faster than the perceived processing time unless the setup is changed. Possible machine breakdown or other failures are more likely to delay rather than expedite the processing time. Therefore, a log-normal curve would be more accurate in describing the situation by starting the curve at the minimal point and using a positive skewness (The right curve tail is longer; the mass of the distribution is concentrated on the left of the curve, closer to the mean) to describe the processing time more accurately.

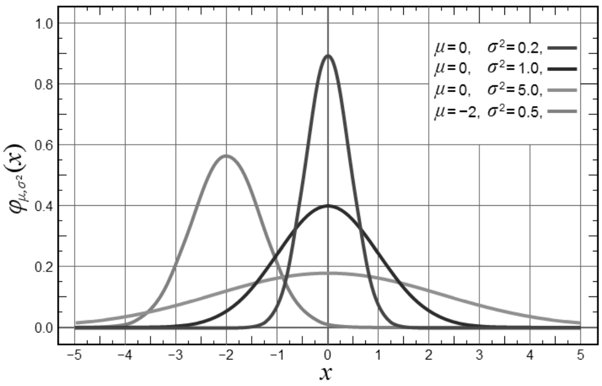

Figure 4-3: Example of Normal Curves [97]

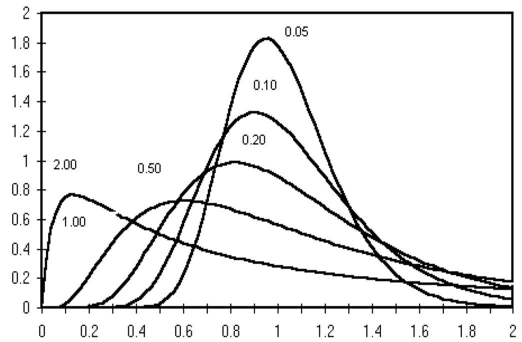

Figure 4-4: Example of Log-normal Curves [97]

In conclusion, distribution fitting and parameter estimation was largely executed using a method proposed by James Slifker and Samuel Shapiro [98]. This method utilises a family of log-normal curves to describe the data series. The reason behind this choice was due to the possibility of automating the procedure without the requirement of any additional statistical package to derive distributions, and after comprehensive background evaluation, no plausible grounds were found against using the method. Further details on distribution fitting can be found in [Section 4.7.1] below.

4.5 First Draft of Pilot Module

Commencing into the project, the research began investigating the model building blocks from the prior case study and attempting to dissect its building blocks to discover how each simulation block interconnected. This made apparent that the system is far more complicated than previously anticipated.

4.5.1 Early Complications

The flexibility of the system being studied is so miscellaneous, simple traditional techniques would not suffice. Each machine-set involved is comprised of a varied number of machines, and even though the machines are identical and able to perform the equivalent set of operations, it is not predominant that all the machines within a machine-set carry out that full list of operations. There are dedicated routing rules and diverse processing recipes to dictate what products are produced and on which machines. In addition to this complication, each machine can be performing up to a dozen operations. These may all represent the same procedure but for different products or for the same product at different stages during production. The assumption taken was to disregard the dedication principle, giving all machines within a given machine-set an equal probability. Previous project findings supported the assumption by demonstrating that machine dedication had no significant impact on overall machine loading or processing times.

A range of products flow through the studied flexible manufacturing system. Assessing the sample data supplied at the start of the project contained over a hundred different product codes. However, all these codes relate to about a dozen product types. The different coding was production floor related information rather than distinguishable products. This further confused the intentions of automating the process. Eventually the team agreed on a guideline that standardised the product codes, and grouped identical products together without any non-relevant associated information.

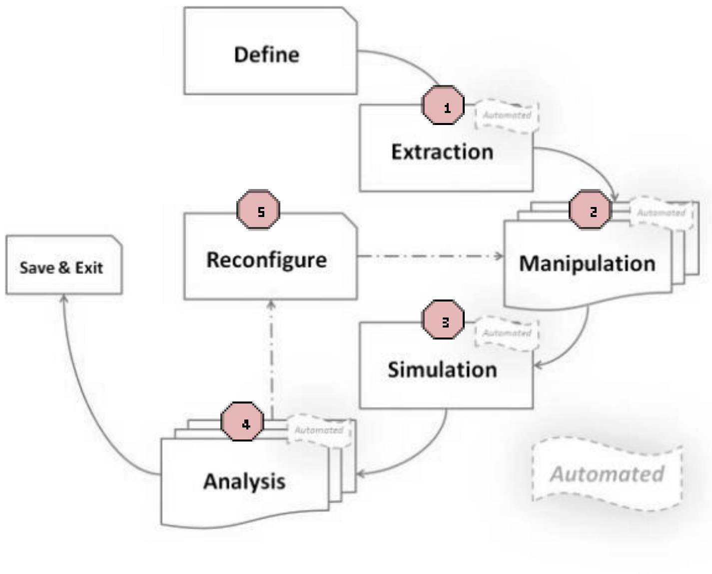

Figure 4-5 : Module Building Concept Diagram

To start, an outline diagram was drafted to identify the different stages of the module. Each section in the diagram above [Figure 4-5] is a different stage of the module building concept.

- **<u>Section 1:</u>** looks at the specification required from the user to initiate the start of the module. A list of the operations in the monitor loop to be studied is required. The user will also be able to set the time frame the Excel macro will extract from the factory database system.
- **<u>Section 2:</u>** is where a number of macros will run to manipulate the information extracted from the database and also formulate this information into a suitable tabulate format that can be exported to the simulation package (ImaginThat ExtendSim7).

- **Section 3:** will entail the importation of several tables of data that will allow the simulation package to build a representative model of the system, and run the simulation.
- **Section 4:** is the extraction of simulation results back into Excel, and running a different set of macros that will aid the assessment and tabulation of results into a form that the user can quickly identify with and interpret.
- **Section 5:** will be used if further investigation is required, where the used will assign new sampling policy to the different monitored products and rerunning the simulation to observe the resulting outcome.

In order to achieve the goal of providing a framework that would enable the automated development of a simulation model in response to a user-request the entities of the model, such as machines and queues, were not represented as physical resources within the model. Rather, both machines and lots are processed as items in the model that flow through the system in a logical manner. Figure 4-6 depicts an overview of this modelling approach. The approach has the principle advantage that the structure of the model (physical locations of resources such as machines and the relationships between them) does not have to be modified each time a user requests a model to be developed, only the appropriate database tables need to be modified to describe the system structure and relationships.

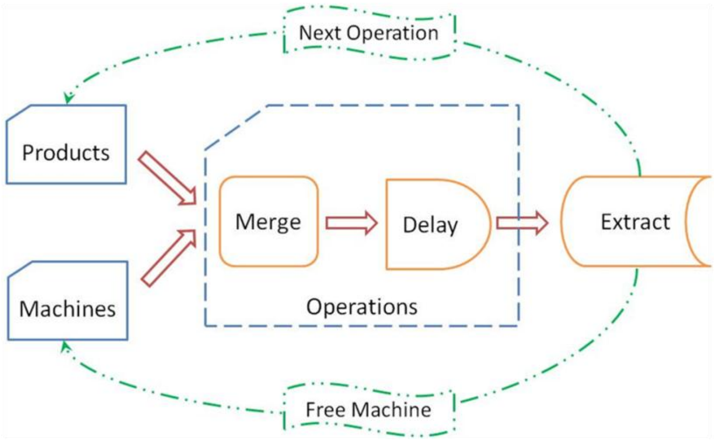

Figure 4-6: Outline of Simulation Model Concept

Using this concept, the simulation will represent lots (WIP), machines, as items. Lot and machine items will be generated to a devised inter-arrival rate and designated to operation queues to await merging. As a lot queues up, it searches for a machine item that is required to process that particular type of lot. These lots are merged and sent to an activity process where it will be delayed for a certain time period to represent the processing stage. The delay activity block, is a regular simulation activity block that can be used to represent a machining operation or any processing scenario. The activity block is set to have an infinite capacity and can process all the available jobs simultaneously with independent processing times and thus making it ideal for this purpose. Once the delay phase is completed, the process is reversed and the combined item is separated back into a machine item and a lot item. The machine item returns to join the queue of available machines, and the lot item is tested. Completed lot items at final operation, exit the system. Else, they are returned back to the lot queue to await subsequent processing operations.

4.5.2 Automating Data Analysis for Simulation Inputs

Automating the module proved more complex than previously anticipated. The diversity of products in the system studied produced a complex matrix. More than a dozen product families are produced at the plant. Each product group/family consists of a further dozen variations of that one product, hence, resulting is a multifaceted mix of products. However, the issue was simplified to facilitate the automation process by proposing three categories to characterise the product types. As illustrated in Figure 4-7 below, the categories are; On-Loop Products that are monitored, On-loop Products that do not get monitored, and Cross-Products that are not serial to the production sequence being studied, but still flow through the same machine sets and occupy production time that must be recognised.

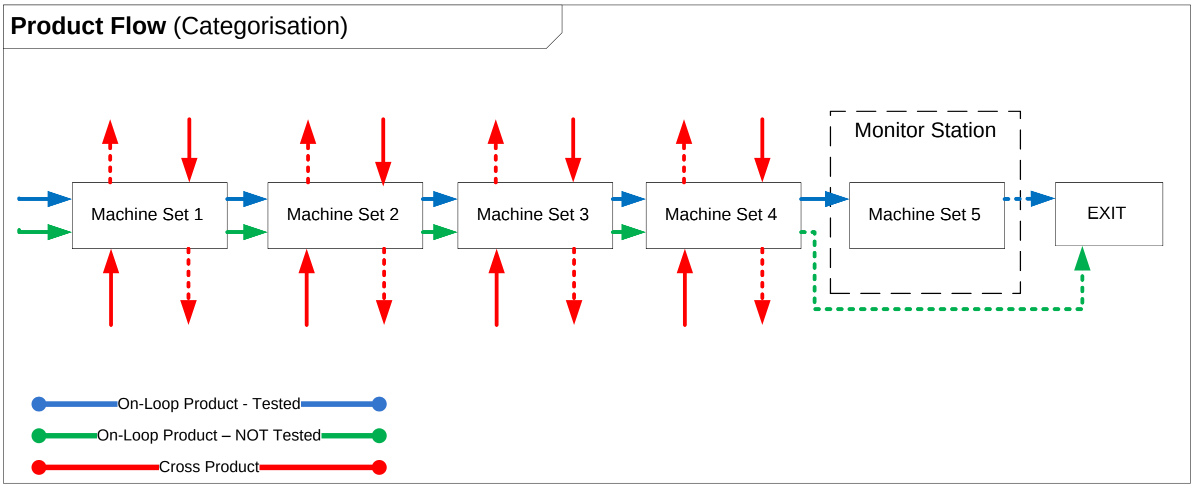

Figure 4-7: Product Type Categorisation

The initial MS Excel macro developed was designed to filter through each machine-set's log history in order of operation sequence and generate a list of all products that flow through all machine-sets within the monitored segment in a serial fashion and separate out the cross product. This will display a list of On-loop products for the user to select which he/she is interested in monitoring and enable them to specify the product sampling rate. The macros continue execution to complete the data pull manipulation. This includes the formulation of a set of tables that fully describe the production line segment being studied. Further details are discussed in the following section.

4.5.3 Tabulating Information

Three key sections of information are communicated to the simulation model.

1. Machines Table
2. Operations Table
3. Products Table

First, information about the machines involved in the monitor loop being studied need to be identified. Characteristics such as machine-set ID, machine ID, along with other data that will allow the simulation to represent the machines appropriately (see Figure 4-8). These include distributions for embodying the scheduled and unscheduled preventive maintenance. Second, is product data, this will include information about the number of products involved, and their inter-arrival rates, in company with sampling rate and whether the product is a cross product or a monitor loop product. Thirdly, an operation list is required, to provide the distributions describing the processing times. The fourth table labelled "Skip Table" is only to assist in counting the flow of monitored items within the simulation model, thus it does not add any specifications to the simulation model; as such it is an output of the simulation model as opposed to an input to it.

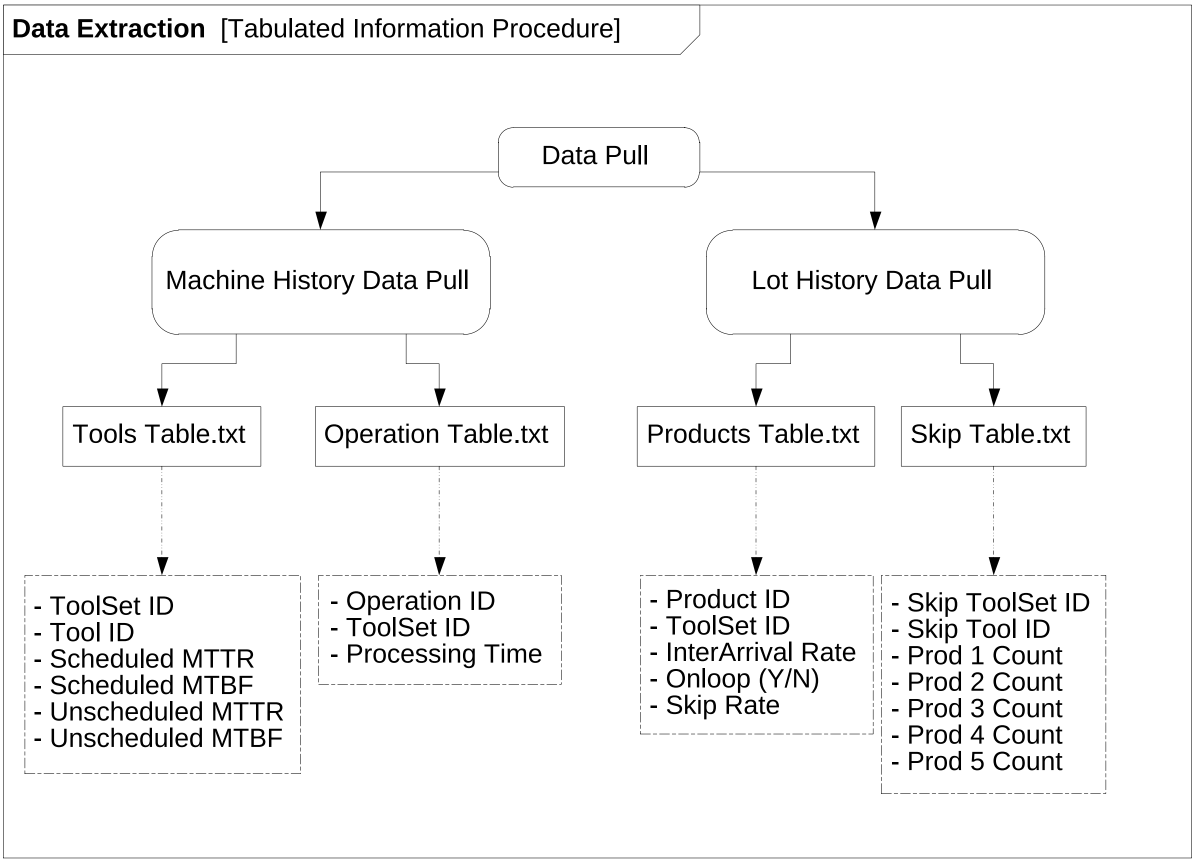

Figure 4-8: Tables Derived from Data Extraction

4.5.4 Assumption Sheet

An assumption sheet was composed to record any postulations made during the model building stages. Some assumptions where made to simplify the model structure, others to avoid extra unnecessary detail, as introducing any non-essential features into the model will only consume extra time and resources and would not aid the study any further than required.

The assumptions made are listed below.

- Cross products are batched per machine-set
- The model will allow for variable machine-set sizes
- Equal probability on demand within each machine-set
- Single lot processing is assumed on all machines

- All machines within a machine-set have the same characteristics
- Ignoring machine history for chambers, only considering actual machine status
- Combining all planned maintenance into one distribution
- Any Down Time > 2hr between failures should be ignored, as this means the first repair attempt did not solve the issue, or a wrong data entry into Data-Base – possible to ignore until later revisions of model. Down Time is defined as any time the machine is not available to process a lot. Down Time = Total Time – (Idle Time + Processing Time).
- Machines are only assessed after completing a processing step. (production or maintenance, i.e. machines cannot fail during processing)
- Skip Count is machine dependant rather than chamber dependant. When considering a multi-chamber machine, the monitor sampling count is done to the individual machine rather than to each individual chamber.
- The simulation model will assess and record each machine status after every process (being either production or maintenance). However, an equation block will assess the requirement for a Scheduled PM before an Unscheduled down.

4.6 Simulation Model Construction

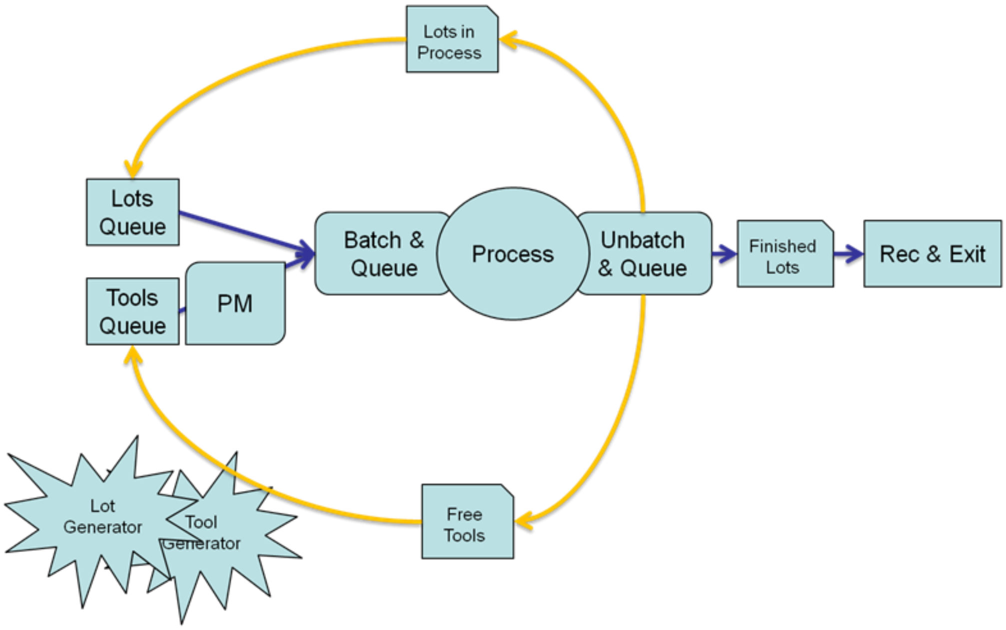

Figure 4-9: Simulation Model Concept

To start building the flexible simulation, a conceptual model was devised as in the diagram above [Figure 4-9]. When compiling the building blocks in the simulation package each section of the module outline are sketched into a logic flowchart [Figure 4-10] to assist in composing the model.

The basic concept of the model is that all machines involved at the line segment being studied are generated at the start of the simulation as items with certain characteristics, along with a continuous lot generator that will run throughout the simulation to generate lots with respect to the inter-arrival rates predefined for each product type. Both sets of items will queue at a merging block to amalgamate lots with suitable machines to proceed onto the processing stage.

Once the combined items are processed, which is represented by a delay equivalent to the duration of their processing time, they are separated back into their original states (lot item and a machine item). The machine item is recycled back into the model, however, after each processing iteration; the machine is examined to check if a maintenance procedure (scheduled or unscheduled) is due; if none is required, it is allowed back into the merging queue to await the following lot for processing.

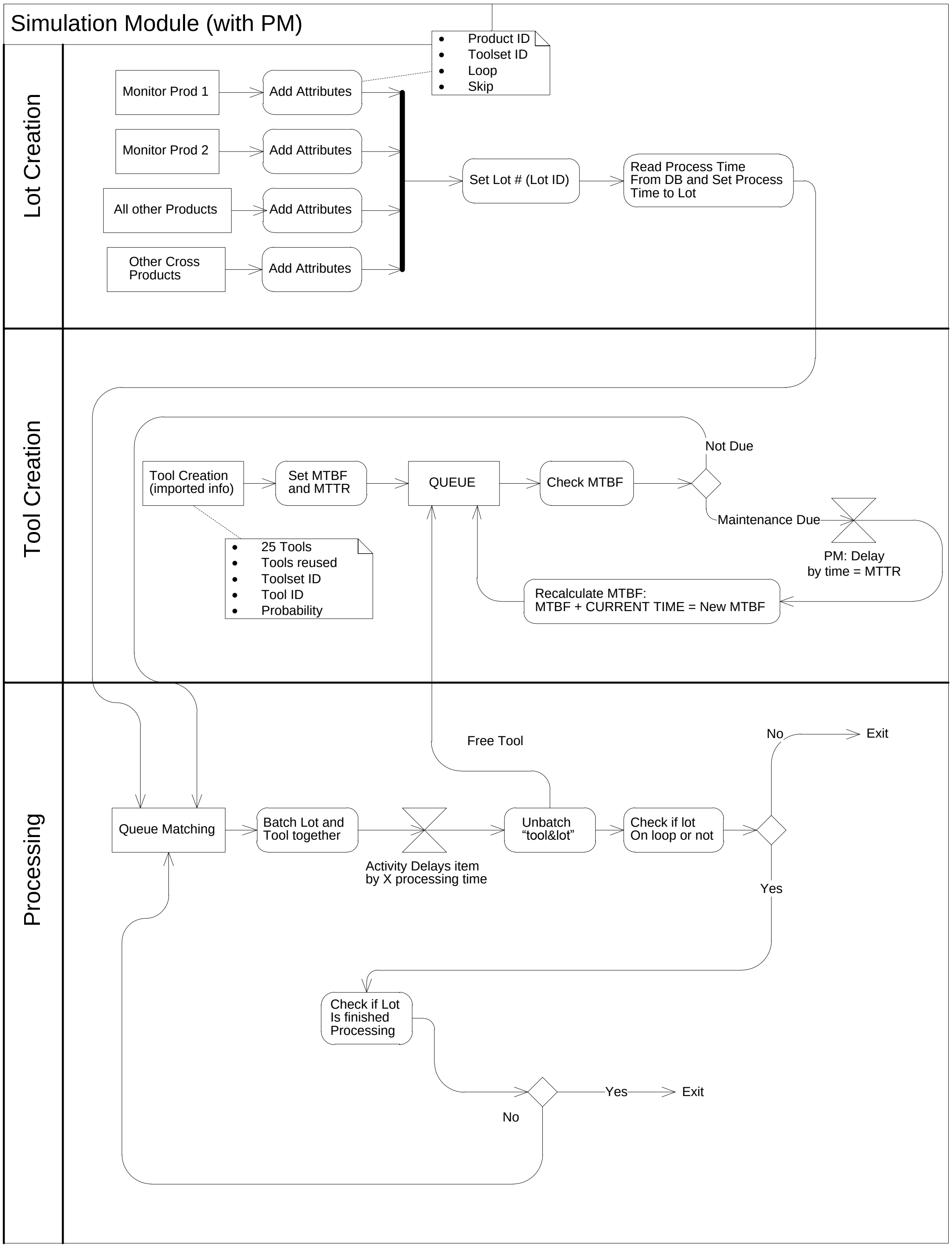

Figure 4-10: Flowchart of Simulation Model

The lot items are manipulated in a different way. As lot items detach from a machine item, the lot record is incremented to its successive operation phase. If the lot is at the last station, a control check is conducted to detect if the lot is due for testing station (end of monitor loop) which is dependent on the user defined sample rate policy. If lots are cross products or have completed their respective final step of processing, the lot item exits the simulation model.

Machine maintenance is scheduled to each machine item as they are created at the start of the simulation. The due date for machine maintenance is sampled from distributions fitted to each machine-set at the data processing stage. When machine items exit out from maintenance, a new sample is acquire for the subsequent scheduled downtime and recorded to the machine item before reintroducing the item back into the system. A drawback of this modelling concept in the simulation study is that machines are only rechecked (re-assessed) for failure or maintenance after fully completing a processing phase; being either production or maintenance and cannot fail during processing.

4.6.1 Model Descriptions

Progress on the *Lot Generation* was initially hindered with difficulties constructing a link between the Create Item block (in the simulation programme) and the list of various lot items (products) the model required to generate.

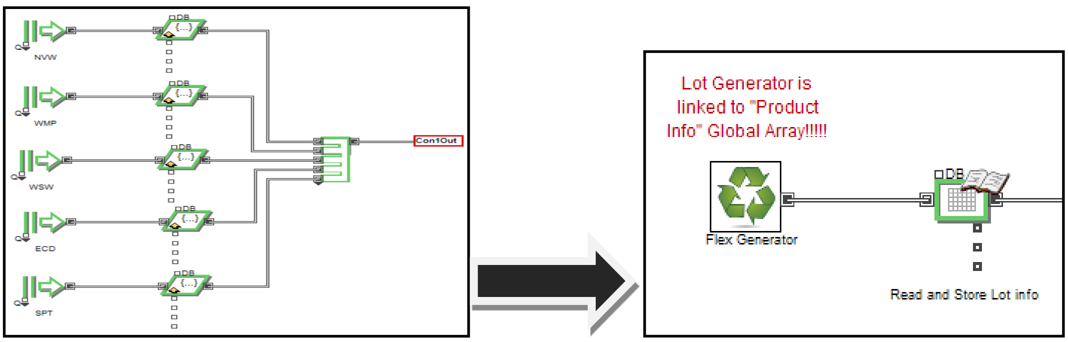

Figure 4-11 - Hardcode to Flexible Generator

Initially, the section was hard-coded with individual generators for each product type as shown for in

Figure 4-12, until a flexible generator was compiled to handle modification from an imported product table. The imported product table shown in Figure 4-13 contains information regarding the number of different products to create with their arrival characteristics expressed as a distribution.

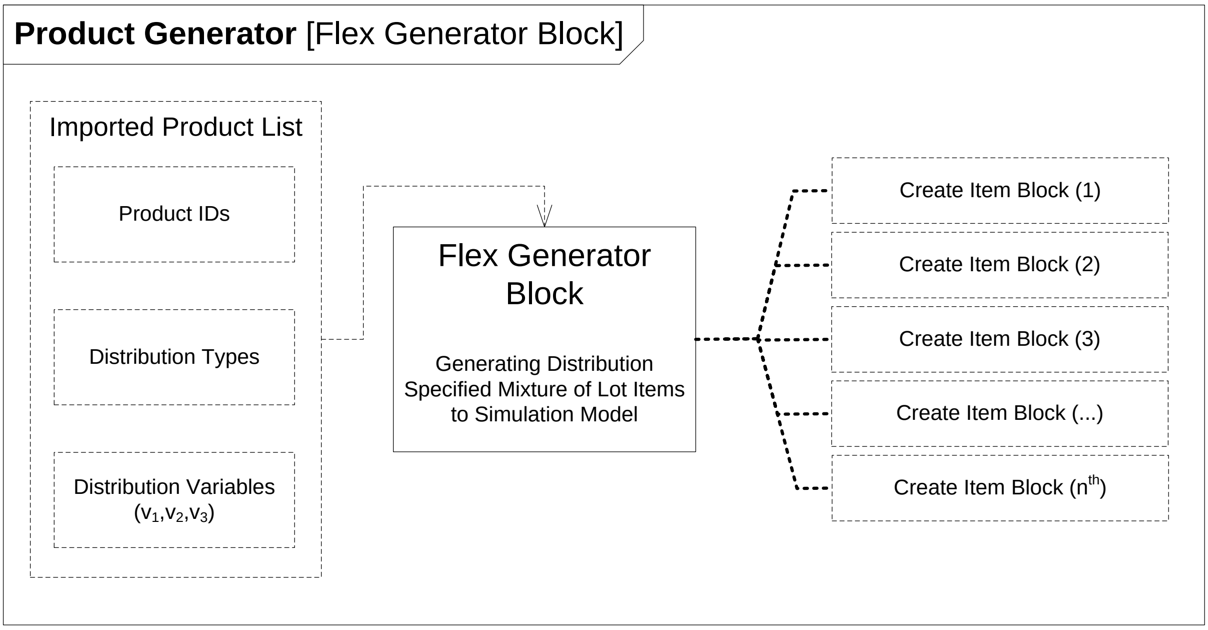

Figure 4-12: Flex Generator Block

	A	B	C	D	E
1	Distribution Type	Product Number	Variable 1	Variable 2	Variable 3
2	4	1	0.3517015	0	0
3	4	2	6.6409512	0	0
4	4	3	0.2857876	0	0
5	4	4	0.3132818	0	0
6	4	5	4.7835956	0	0
7	4	6	8.398284	0	0
8					

Figure 4-13: Sample Table from Item Generator

Machine Generation is a scheduled list of items to be created by a Create Item block at the start of the simulation. This was simpler than the *lots* generator, because all the machines are only generated once at the start of the simulation run as illustrated in Figure 4-14. All necessary attributes are assigned when the machine items are created. Each machine in the model is represented as an individual item. The initial MTBF and MTTR are read and assigned to the machine items.

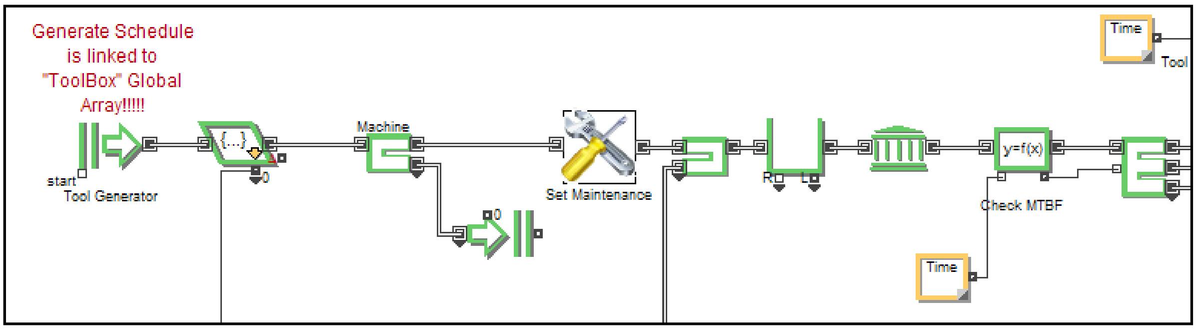

Figure 4-14 - Machine Generation

The machine generator information is imported to the simulation model in a similar format as with the lot generator, see Figure 4-15 below for illustration example.

Creat Time	Item Quantity	ToolSetID	ToolID	ToolChamber ID	Machine No.
0	1	1	1	1	1
0	1	1	2	1	2
0	1	2	1	1	3
0	1	2	1	2	4
0	1	2	1	3	5
0	1	3	1	1	6
0	1	3	2	1	7
0	1	4	1	1	8
0	1	8	1	1	15
0	1	8	1	2	16
0	1	8	2	1	17
0	1	9	1	1	18

Figure 4-15: Example ToolBox Table

Processing stage shown in Figure 4-16 involves *Machines* and *Lots* matched and batched into a processing queue. The two items are combined into a single unit that enters the activity for processing is completed. After processing the items are un-batched and released.

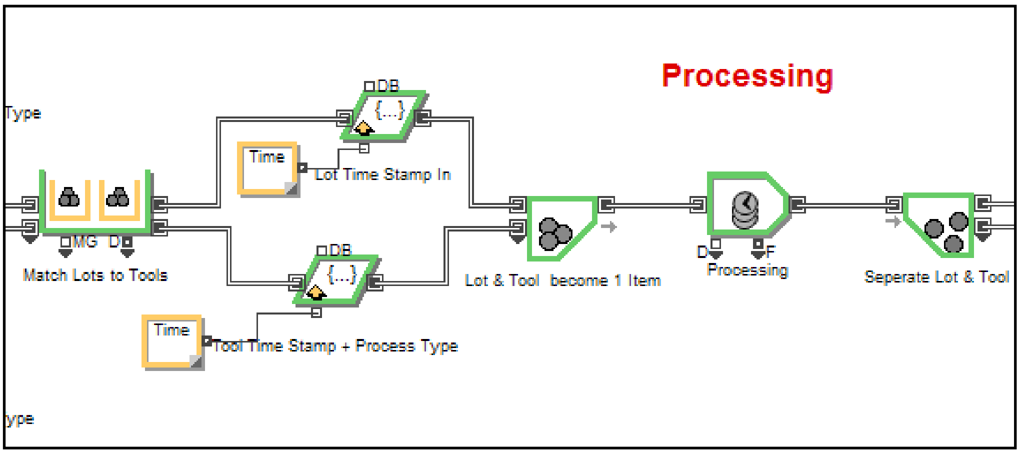

Figure 4-16 - Processing Stage

Lot Items Flow, presented in Figure 4-17, Lot items leaving the processing stage are initially checked for being on the monitor loop, if not, they are exited from the model (cross products). Subsequently they are checked if they have completed processing, if they have they exit the model, if not they are recycled to continue processing.

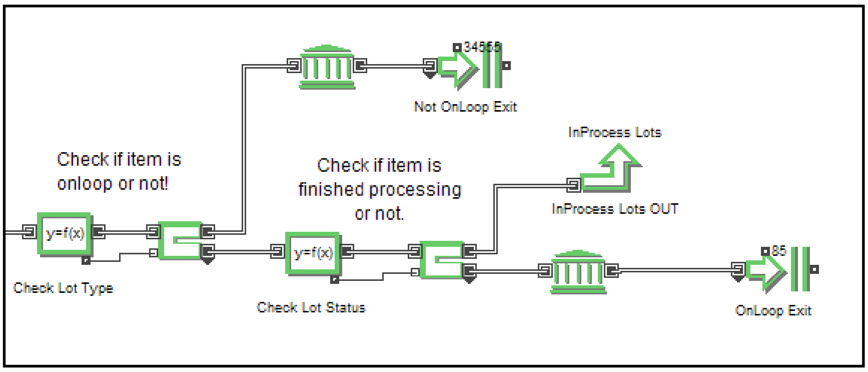

Figure 4-17 - Lot Flow

Maintenance Schedule, Figure 4-18, is checked every time a machine re-loops into the system; if a maintenance process is due, the machine item gets delayed in the PM section of the model for the duration of the maintenance procedure. Once completed the MTBF and MTTR get recalculated and stored in their respective attributes, which will be checked at the machines subsequent cycle.

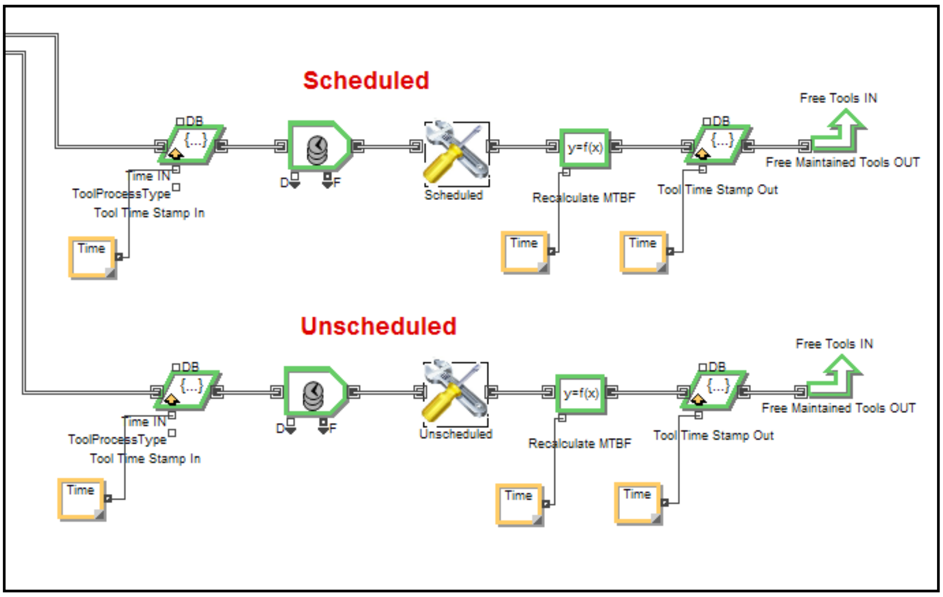

Figure 4-18: Modelling Preventative Maintenance and Unscheduled Downtime

The final outline, Figure 4-19, of the model resembles the model concept drafted [Figure 4-6] at the beginning of the model building exercise.

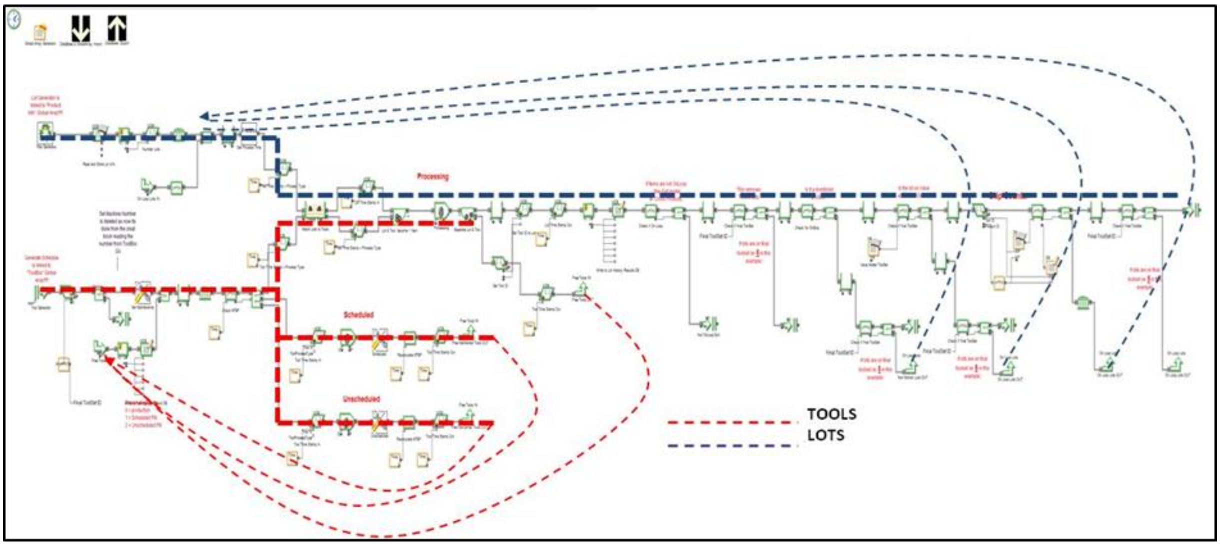

Figure 4-19: Simulation Model Outline

4.7 Experiment Apparatus

The research intended to construct a flexible automated simulation module. Reviewed literature did not provide much guidance as this concept is relatively new and previous attempts where on-off exemplars with no proper documentation or framework. Therefore, the project was based on a standard simulation model that would gradually be customised to permit incorporating features that would enable automation and integrate flexibility. This might not be the most appropriate way to achieving this, but even if this method proves uneventful, there is still a lot of knowledge to be gained for future projects. A number of techniques that have been utilised in this project are explained in more detail below. Simulation Model Outline

4.7.1 Distribution Fitting

In modelling and simulation of stochastic systems, a major problem is the selection of probability distributions that will adequately represent the input processes driving the simulation model [26, 65, 66, 99, 100]. Statisticians are often faced with the problem of summarising a set of data by means of mathematical function which will fit the data and also allow them to obtain estimates of percentiles [98, 101]. A common practice is the use of flexible family of distributions to accomplish this, often a family with four parameters being chosen [98].

Several approaches can be taken to choosing and fitting distributions for use as simulation model inputs [52]. These approaches include parametric modelling, empirical distributions, and use of flexible distributional families, of which the Johnson family is one example. Using slightly stronger assumptions one can construct general families of distributions, including the Johnson transition family [98], Pearson [102], and Schmeiser-Deutsch [103], among others. In contrast to the parametric approach, members of these families are considered useful approximations, and not necessarily the "true" distribution that generated the data [103 -104].

(Johnson Curve Percentile Fitting)

After reviewing different literature, it was concluded that there is no single fitting method or fitting criterion that is uniformly superior in all cases; different applications may require different statistical machines to yield appropriate model inputs [65]. In this section, the attention is focused on the Johnson translation family, which consists of three distributions whose variants can be transformed into normal variants. For completeness the normal distribution is treated as a fourth member of the family. The general form of the transformation is: $z = \gamma + \eta\ k_i(x; \lambda, \epsilon)$

The three distributions are the lognormal (S_L), bound (S_B), and unbound (S_U). The system proposed by Johnson contains three families of distributions which are generated by transformations of the form:

$$z = \gamma + \eta\ k_i(x; \lambda, \epsilon)$$

4-1

Where z is a standard normal variable and $k_i(x; \lambda, \epsilon)$ are chosen to cover a wide range of possible shapes. Johnson's distribution suggested the following functions:

$$S_U :$$
$$\rightarrow k_1(x; \lambda, \varepsilon) = \sinh^{-1}\left(\frac{x - \varepsilon}{\lambda}\right)$$

4-2

$$S_B:$$
$$\rightarrow k_2(x;\lambda,\varepsilon) = \ln\left(\frac{x-\varepsilon}{\lambda+\varepsilon-x}\right)$$

4-3

$$S_L:$$
$$\rightarrow k_3(x;\lambda,\varepsilon) = \ln\left(\frac{x-\varepsilon}{\lambda}\right)$$

4-4

In using the Johnson system, the first step is to determine which of the three families should be used. The usual procedure is to compute the sample estimates of the standardised moments, and choose the distribution according to which of the two regions the computed points fall into. Major shortcomings of this procedure are:

1. The moment estimators are greatly affected by outliers;
2. The variances of the estimates of the third and fourth moments are quite high;
3. The estimates of these moments are highly biased for small samples.

The variable x_n denotes the percentile value of the dataset. The equations for the selection procedure and parameter estimation are as follows;

$$m = x_{3z} - x_z$$
$$n = x_{-z} - x_{-3z}$$
$$p = x_z - x_{-z}$$

(4-5)

The z value; should be motivated by the number of data points. In general, for moderate-sized data sets (>30), a value of z less than 1.0 would be chosen. A choice of z of 1.0 or higher would make it difficult to estimate the percentile points corresponding to $\pm 3z$. However, the larger the number of observations will allow for a larger value of z that can be selected. Furthermore, examination of the standardised moment plane can help define the proper choice of model when $\frac{mn}{p^2}$ is close to one. For example, if the moments lie within the S_B region and $\frac{mn}{p^2} > 1$ for a particular choice of percentiles, this is an indication the S_L distribution should be considered [105].

$$\frac{mn}{p^2}\begin{Bmatrix} >1 \Rightarrow S_U \\ <1 \Rightarrow S_B \\ =1 \Rightarrow S_L \end{Bmatrix} \tag{4-6}$$

In the solution of the equations, it leads to the dependence of the parameters γ and Є as functions of the two remaining parameters, λ and η [105]. By incorporating four highly flexible families of distributions (lognormal, unbound, bound and normal families), the Johnson system can fit any distribution up to its first four moments; and in practice the Johnson system has been used successfully in a wide variety of disciplines [99].

Tadikamalla and Johnson [105] show how simple form solutions are obtainable by taking symmetric percentiles with $P_3 = 1 - P_2$; and $P_4 = 1 - P_1$. Further ingenious methods derived by Bukac [107], Mage [105], Slifker & Shapiro [98] and Wheeler [108] for S system distributions can be applied to L system distributions.

Even with using symmetrical percentile points to fit the Johnson curves the results seem encouraging. It can be seen that despite the substantial differences in the values of λ andγ, there is little difference between the curves fitted by percentile points and by moments. On the whole the errors using percentile points are slightly less than those using moments [107]. These estimators are of interest because of their simplicity and the light that they shed on the Johnson system. In practice they should provide good starting values for accurate iterative schemes, they are at least as good as moment estimators [108].

The key advantage of the Johnson translation system of probability distributions is its suppleness in approximating target distributions that take place in a variety of applications, making it a broad-spectrum apparatus for simulation inputs [65, 66]. Another smart feature of the Johnson system is that it can be extended easily to provide systems of multivariate distributions, and this property should allow for conveniently modelling dependencies among the inputs to a simulation [66]. The main disadvantage of the Johnson system is its analytical intractability.

For the purpose of this project data fitting software were avoided to ensure the rapidity and validity of distribution fittings. In certain cases, the reliability of the data fitted using a package like ExpertFit [52] or BestFit [108], or StatFit [109] may vary. Not to undermine these software packages and their capabilities, but rather to ensure the data is handled appropriately within the package. Hence, the decision was made to derive the distribution curves using percentiles and conduct all the calculations within MS Excel. This provided the added benefit of not including additional software (and cost, reducing cost for multiple software licences) to the module that could be avoided.

4.7.2 Machine Characteristics Representation

A diverse range of machines are used at manufacturing semiconductors. Attempting to simulate each of those machine types, the correct characteristics need to be incorporated into the simulation design in order to achieve a representative model. These machines include but not limited to the following types;

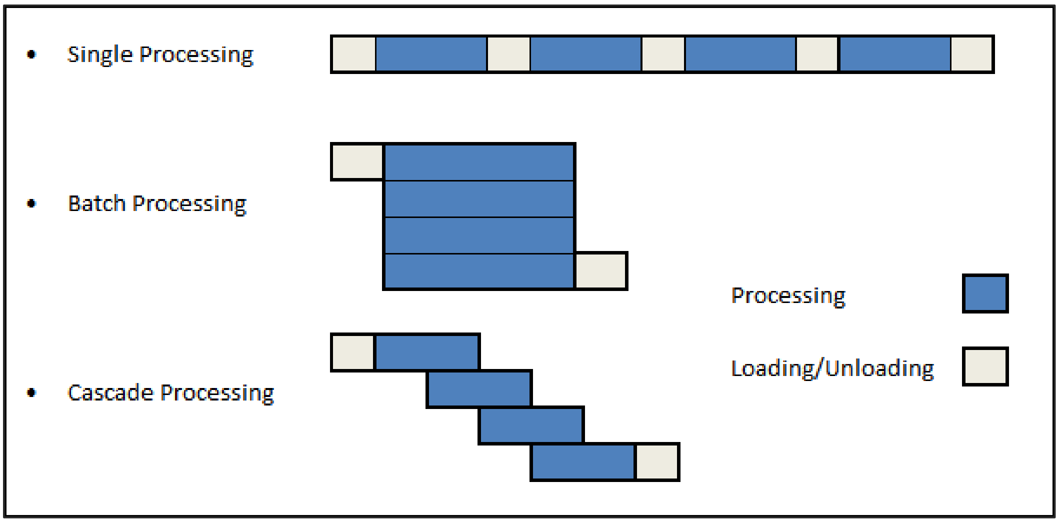

Figure 4-20: Example Machine Types

Single processing machines can only load/operate on one lot at a given time. Hence, the lot must complete processing and unload before a subsequent lot can be loaded. Batch processing allows lots requiring the same operation to be grouped or batched and processed simultaneously. In cascade processing, lots are overlapped (cascaded) through the machine with no specific operation changeover rules. Furthermore, batched cascade machines are similar to cascade processing machines, with the difference being that processing rules are applied; lots are formed up to an allowable batch size and cascaded through the machine for processing.

Initially this module handled all machines as single unit processing, as this was an assumption made in the kick-off meeting. However once the research commenced, tests have shown that the majority of the machines involved in the sample data given where multi chamber machines, and it was obvious from the results of the early simulation runs. Arrival rates and processing times calculated from the raw data initially reflected a different scenario to what was previously assumed. Due to assuming single lot processing, but running the simulation with demands of multi-lot batch production, it caused a gradually accumulating backlog of lots at each processing stage the longer the simulation was run. To resolve the issue, machines that consisted of multiple chambers were duplicated within the model to account for the processing capacity. This may affect the overall output synergy of the machine-set, but with a longer simulation run, the adverse effects should fade out.

There did not seem to be another solution as of yet to tackle this issue. Determining the chamber size of each machine was a further complication from just interrogating the raw data and the versatility of the machines operating within the flexible fabrication facility was not only vast and also inconsistent. For example; there are machines with four chambers. Those operate independently and are also loaded and processed individually from their counterparts in a cascading manner. Similar four chamber machines are combined into two twin chambers, which are loaded with two lots at each changeover, and varying in loading policy that dictates its waiting protocol.

As a consequence of using duplicate individual items to represent each multi-chambered machine, preventative maintenance will be executed in a different manner than how it actually occurs. Machines ordinarily get maintained as a single unit, rather than each chamber individually. Furthermore, a range of different breakdowns can occur in to these machines, but not necessarily all breakdowns will result with the workstation going offline. In certain cases, a four chambered machine can stay in production with one/two chambers being down. The situation is dependent on a number of reasons, for instance; a scheduled preventative maintenance is relatively soon, or the opportunity cost of shutting the machine down for repair is not feasible in comparison to running with lower capacity.

4.7.3 Warm-up Period

A warm-up period is necessary in a simulation study; otherwise the model would start empty throughout (no products at machines) whereas real factories more or less always start off with some WIP inventory. However there are certain situations where you would not need a warm-up time in a simulation run, this might occur when you are simulating a situation which starts empty on each day/shift, like a store, or a bank's cashier queue. In such circumstances it is advisable to separate off the results recorded during the early part of the shift from the results under peak conditions (e.g. lunch time rush!). This emphasises that assuming average performance conditions of an operation which never works under "average" conditions is probably pointless. Some simulation software packages contain a 'warm-up' assessment tool, during which results are either not collected, or can be separated after the simulation run.

A literature survey found 44 methods into the initial transient problem and methods for selecting a warm-up period [47]. The methods, with exception of Welch's method [110], experience limited use. Hoad et al. [47] concluded on three boundaries that appear to restrain the use of output analysis methods;

- Several methods found have been engaged to limited testing providing little confidence to their efficiency and general use.
- Other methods require a broad understanding of mathematical statistics and hence are difficult to employ, particularly for amateur simulation users.
- Furthermore, simulation software often lacks clarity in their implementation of these methods and users should heed the developer guide when applying.

One solution proposed to these problems is to implement an automated output analysis procedure within the simulation software [47]. This would overcome the problem of needing advanced statistical skills. Automation can be introduced either as complete automation that provides the user with the final answer, or as partial automation of the process by providing the user with guidance to interpret the outputs. The intention is to achieve a non-biased mean estimation of a simulation model outputs, with a non-biased estimate of the variance of that mean.

The module developed in the pilot project starts with an empty system and requires a warm-up period. The module mirrors the current status of the system in terms of the number of functioning tools involved and corresponsive inter-arrival frequency of product items. The Module used a predefined warm-up period of 1,500hrs (minimum recommendation of 450hr using the analyser) to satisfy compatible conditions against tested model. This was found satisfactory with the project participates and engineers facility, as little was known how the module would interact with the systems being studied beyond the initial testing monitor segment that was studied during development.

The decision was that a possible incorporation of an automated output analyser to estimate the length of warm-up period can be done at later revisions of the module. These can further improve the analysis process and remove possible initialisation prejudice from the simulation output data. The prospect is to integrate the MSER-5 warm-up method. MSER-5 is the MSER-m method using batches of 5 data points. This method was adapted from research work conducted by Hoad et al 2008 [47]. Their work has strong academic credentials and was also successfully implemented into Simul8 simulation software package.

The framework is moderately open to the type of warm-up analysis the users choses to integrate, but stresses to emphasise the importance of ensuring the validity of the analysis. The framework also requires the user to consider the trade-off between accuracy needed and time restrictions to possible longer computation and further coding to incorporate these algorithms within the simulation study module.

4.8 Simulation Control Panel

The simulation module is controlled from a simple, MS Excel-based, user interface. The simulation module requires the user to enter the operations list corresponding to the production segment they are intending to examine. The user is also required to define the machine capacity of each machine performing these operations (due to insufficient information about the machine capacity retrieved from the MES database) and define the value added step (e.g. operation 4 in the example below, Figure 4-21).

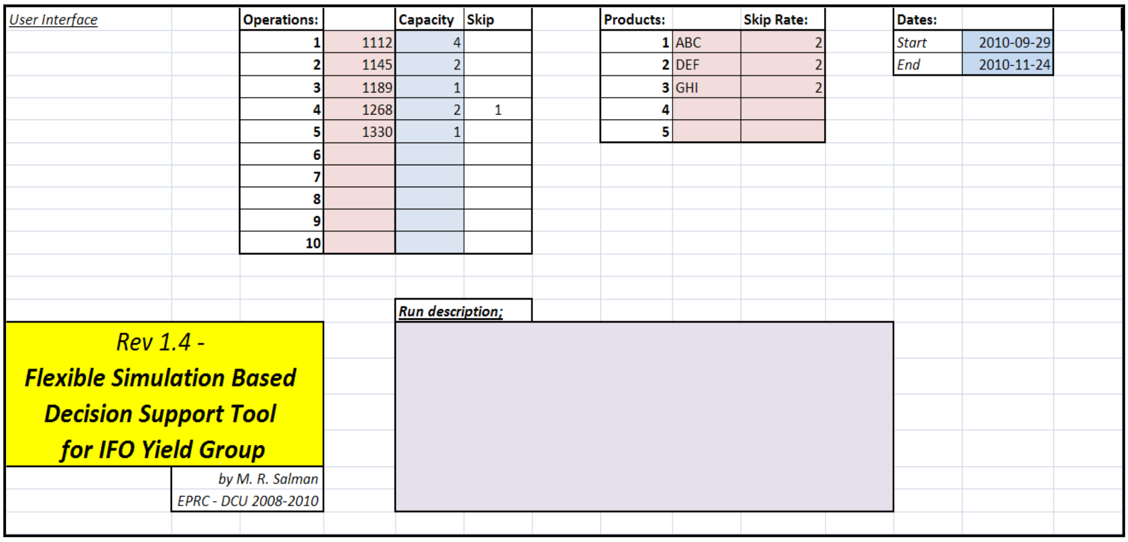

Figure 4-21- Module Control Interface (Master Console Sheet)

Once the user inputs are properly declared on the "master console", the simulation experiment can be started. A series of control buttons, as in Figure 4-22, allow for the user to carry out the required raw-data analysis, simulation and result analysis. The user will initially be able to control the commencement of each phase from the control panel individually. The process can be developed further into a single button, but for experimentation and debugging purposes, the procedures where kept separate. This will allow the user to complete the entire simulation study from start to finish by deploying a series of macros, without any direct interaction with the simulation software (ExtendSim7).

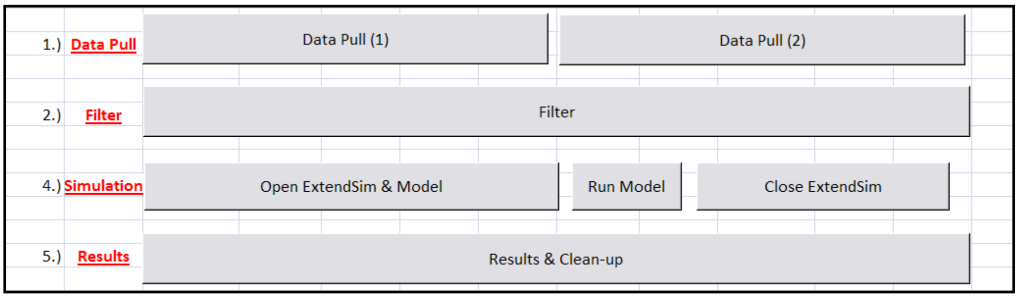

Figure 4-22 - Module Control Interface (Buttons Console)

4.9 Simulation Results

The requirement of this project was to study the effect of changing the sampling policy of certain products at different processing segments. Two tables of results are recorded during the simulation run. *Lot History* table records time entries for each lot as it flows through the system. Time stamps are recorded onto the lot item attributes at different phases and recorded to a result database at the end of each cycle around the model. This concludes with having a full list of records for each lot that has entered the system during the simulation. Similarly with machine items, information about the machine status and each process a machine conducts during the simulation is recorded in a comparable format as the information retrieved from the organisations database.

Two essential measures were the main concern to management when the project was initiated. *Number of Lots at Risk*; number of lots produced between two sampled lots (any product type produced) from the same machine at a value added step. And *Time between Samples*; exit time of a measured lot to the exit time of a proceeding measured lot from the same machine at a value added step. However, a number of other performance measures can be derived from the same set of result data, including a range of utilisation and performance measures for the machines. Table 4-2 & Table 4-3 below display two sample result tables outputted from the module.

Table 4-2: Lot Risk Assessment

		Number of Lots at Risk (Lots)				Time Between Samples (Hrs)			
ToolSet	Tool	Mean	Max	90%	95%	Mean	Max	90%	95%
1	1	54.49	296	97.60	139.70	72.18	363.32	137.05	189.86
1	2	50.71	243	118.20	148.70	70.69	365.37	151.73	219.08
1	3	52.08	217	121.40	140.20	69.44	293.92	162.90	175.39
1	4	39.51	202	80.00	95.20	53.34	252.10	119.71	143.98
ToolSet		**48.44**	**296**	**108.50**	**132.00**	**65.39**	**365.37**	**143.95**	**183.46**
2	1	77.76	371	158.80	188.60	88.18	414.45	176.11	219.42
2	2	64.05	425	132.70	173.30	72.36	482.70	144.48	193.09
2	3	92.16	236	188.60	224.10	104.98	281.43	213.80	255.02
2	4	80.56	390	159.80	210.75	91.25	444.74	182.38	234.95
2	5	73.51	311	137.80	155.00	83.72	366.30	156.50	178.03
ToolSet		**76.50**	**425**	**157.20**	**204.80**	**86.82**	**482.70**	**143.95**	**183.46**
3	1	59.13	253	114.80	165.80	52.63	220.62	104.84	146.31
3	2	93.50	390	218.40	280.30	82.39	331.75	188.22	255.25
3	3	97.45	311	255.00	293.00	86.42	271.75	222.71	247.09
3	4	75.38	295	179.00	208.50	67.01	278.17	158.13	180.10
ToolSet		**78.20**	**390**	**187.00**	**246.25**	**69.34**	**331.75**	**162.24**	**221.14**
4	1	12.86	65	25.40	30.70	60.48	759.25	123.83	151.35
4	2	13.16	45	28.60	33.40	53.59	278.32	126.90	175.68
4	3	11.97	55	22.00	29.15	45.93	231.69	114.00	141.19
ToolSet		**12.62**	**65**	**26.00**	**31.20**	**52.65**	**759.25**	**123.15**	**157.31**
5	1	71.72	163	134.10	150.00	97.29	228.78	183.66	203.00
5	2	70.50	208	109.00	134.20	95.05	309.61	154.65	183.69
5	3	74.82	179	128.00	150.80	99.70	247.35	167.27	198.85
5	4	64.76	165	116.60	134.90	87.83	232.48	159.50	193.59
5	5	66.04	153	114.00	125.00	90.66	197.96	163.94	171.28
ToolSet		**69.44**	**208**	**122.00**	**146.20**	**93.95**	**309.61**	**165.32**	**197.63**
6	1	39.43	164	92.20	102.10	78.63	329.47	179.32	206.78
6	2	40.46	165	99.00	134.90	78.53	322.98	193.31	280.20
6	3	35.81	159	81.40	105.00	70.36	301.00	165.60	212.89
6	4	36.28	201	73.50	112.55	71.96	402.73	141.49	235.19

Table 4-3: Machine Assessment

		5000 hr Run				
ToolSet	Tool	P Time	# of lots	M time	Utilisation	Lots/day
1	1	4578.08	3714	420.90	91.6%	17.8
1	2	4406.48	3627	592.69	88.1%	17.4
1	3	4524.72	3659	474.15	90.5%	17.6
1	4	4661.58	3772	336.67	93.2%	18.1
2	1	4776.43	4381	222.59	95.5%	21.0
2	2	4793.69	4403	205.39	95.9%	21.1
2	3	4794.34	4460	204.85	95.9%	21.4
2	4	4760.12	4379	237.97	95.2%	21.0
2	5	4767.01	4379	231.58	95.3%	21.0
3	1	3599.20	5661	110.23	72.0%	27.2
3	2	3573.53	5761	109.21	71.5%	27.7
3	3	3578.49	5661	126.46	71.6%	27.2
3	4	3604.15	5728	108.66	72.1%	27.5
4	1	2064.28	1298	576.75	41.3%	6.2
4	2	2118.32	1011	918.01	42.4%	4.9
4	3	1738.43	1289	958.29	34.8%	6.2
5	1	4501.87	3697	477.07	90.0%	17.7
5	2	4451.10	3631	537.23	89.0%	17.4
5	3	4629.01	3774	362.29	92.6%	18.1
5	4	4514.26	3695	478.09	90.3%	17.7
5	5	4475.00	3649	516.22	89.5%	17.5
6	1	1282.04	2524	21.77	25.6%	12.1
6	2	1324.85	2449	26.22	26.5%	11.8
6	3	1207.43	2592	19.94	24.1%	12.4
6	4	1175.87	2583	35.31	23.5%	12.4

4.10 Final Module Draft

The simulation module was completed, with all accessible stages built and debugged to the extent of the developer's knowledge. A complication hindering the full completion of the module is the restricted access to the organisation's database system. Using only a single sample set of data, it was difficult to gain a full understanding of the varying types and quality of information extracted for the database system. Every effort was given to ensure that the built module anticipates a wide array of possible data received and handles them appropriately. All aspects of the module, pending the initial data extraction protocol, have been comprehensively tested and are functioning in the approved manner. The complete processing steps involved in the module are outlined in Figure 4-23.

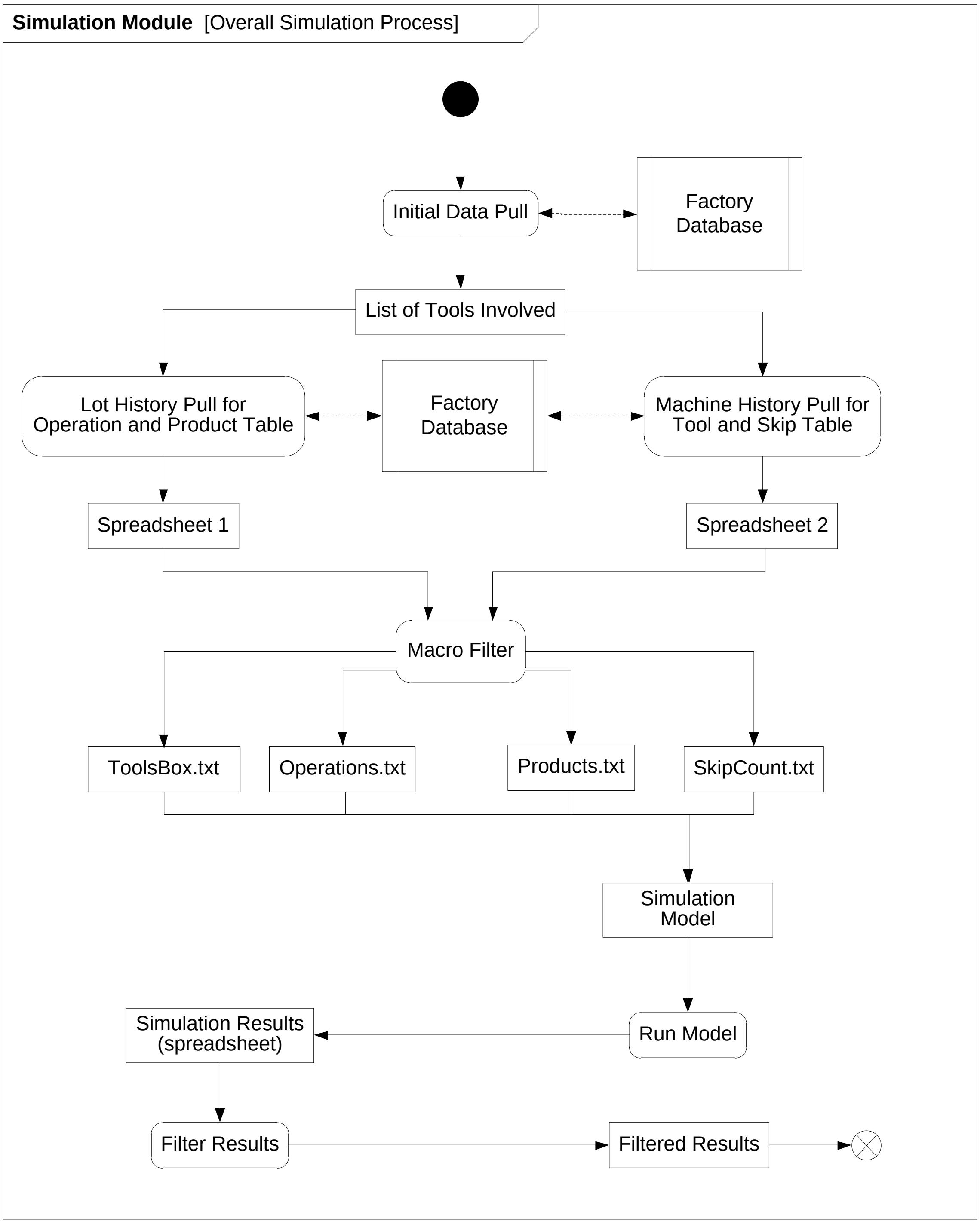

Figure 4-23: Overview of Completed Pilot Simulation Module

In Chapter 5, the automated simulation approach developed using the OSDS framework is tested. The following presents the experimentation and analysis conducted on the pilot project to assess its validity in comparison to results achieved in the case study described in Chapter 1 .

Chapter 5 Testing and Experimentation

5.1 Pilot Project Verification

Preliminary tests initiated the validation process to verify properties such as; Flexible Lot Generator Function, Machine Generator Function, Machine Maintenance Procedure, Matching Queue Function, Lot Routing Function Figure 5-1 and Skip Count Procedure Figure 5-2.

The Flexible Lot Generator and Machine Generator were tested to allow output evaluation to match input data and verify that information from both corresponded and that each generator is performing its precise function for varied sample inputs. Machine Maintenance was monitored over a number of runs to ensure that Machines where adequately removed and routed into repair when due for preventative maintenance, and that the machine is returned to the Processing route once maintenance is completed.

A vital key role of the flexible model concept used, is the function of the Matching Queue block. The Matching Queue is responsible for merging awaiting Lots with suitable Machines to begin processing. The Lots are queued in a FIFO manner for each Machine-Set type, therefore when a machine becomes available with an awaiting Lot, it will directly be merged and dispatched into processing. To assess, the model was run with smaller product varieties and this criteria was verified using visual inspection to the flow of the simulation model.

Using a flexible simulation concept brings a number of difficulties to the study. The simulation model needs the capability to handle unbounded lot quantities of diverse product types. Furthermore, the routing procedure is most critical when the lots complete processing and detach from the machines. The lot items have to be routed in an analytical manner to accurately represent the simulated system functions. Figure 5-1 describes the lot routing logic in a flowchart to show how the simulation model handles this task. The logic was tested by tracing the lot items flow using the production log outputted by the model for gauging lots cycle progression within the simulation run.

The skip count is correlated to the value added machine-set and the user assigned skip rate for that particular product. The Skip Counter responsibility is to maintain the sample count for the applicable product types. The Skip Table mentioned in section [Section 4.5.3] is used by the simulation model to keep the sum totals of sampled lots passing through the system. If the required count is reached, the product/lot item will be tagged for testing and the counter reset.

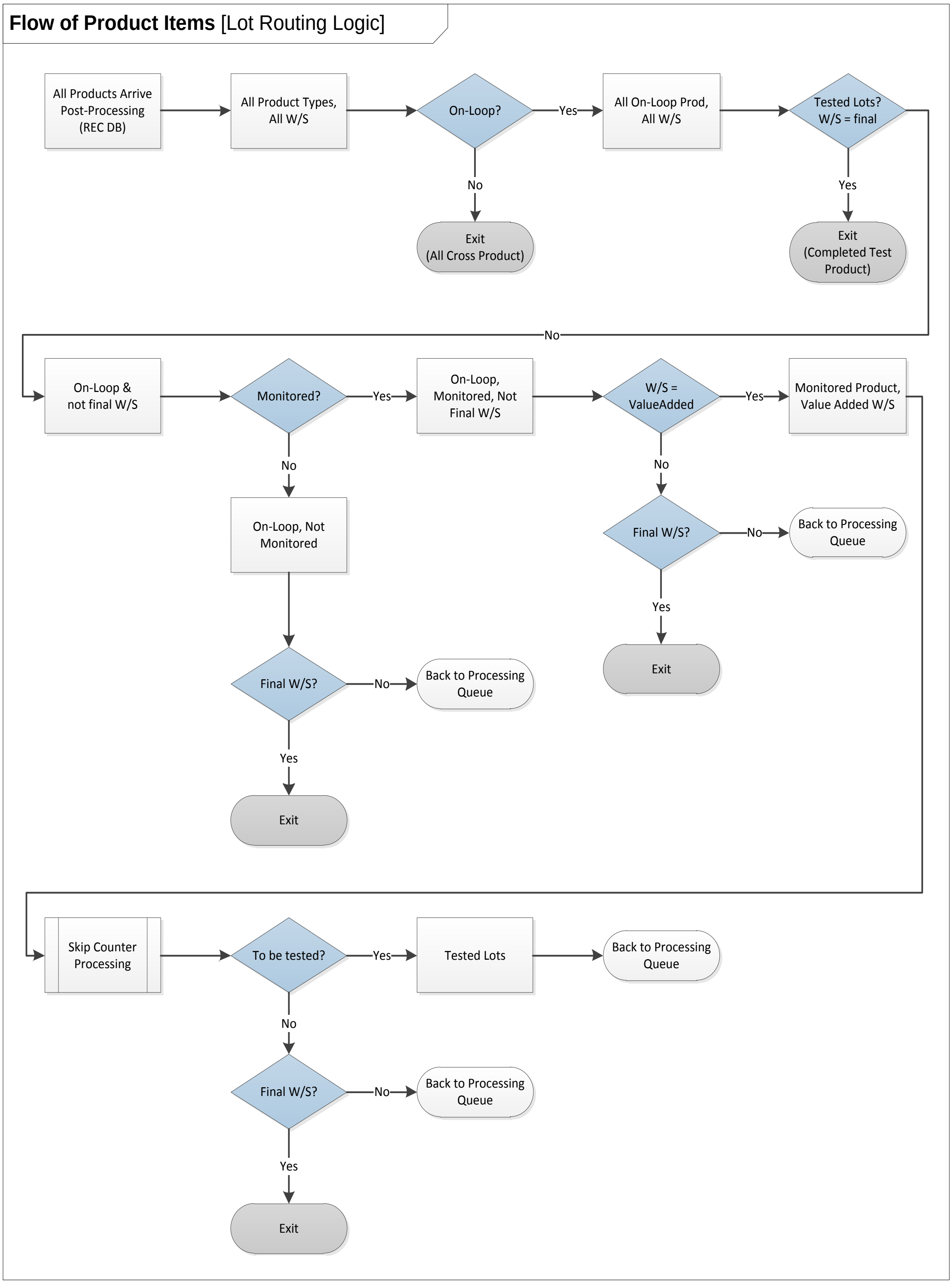

Figure 5-1: Lot Routing Logic Chart

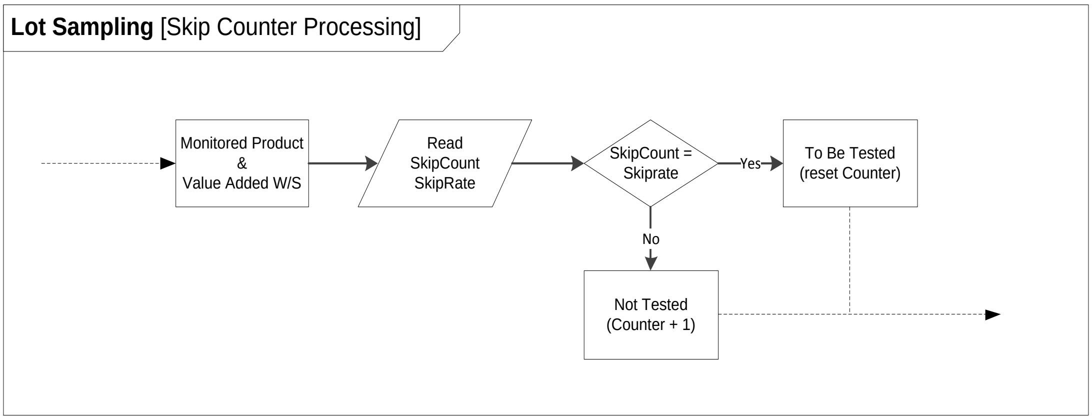

Figure 5-2: Skip Counter Logic Chart

5.2 Module Testing

To assess that the compiled module in the pilot project was of working order, a number of initial tests where required. Initial verification process took place to ensure that each individual section within the module performed its intended role and that the correct information is forwarded to the following phase of the simulation study. Due to having no direct access to the company's actual database system, it was difficult to evaluate the modules initial data extraction procedure. However, using a single set of sample data, the remaining phases of data manipulation, simulation and analysis could be tested and their functions verified.

The manipulation procedure involved screening the raw data received to identify the machines and products involved within a production segment being investigated. Characteristics for both machines and products are derived from the data to help create the simulation model inputs. The simulation model was composed to handle the tabulated information given by the preceding module phase. Errors in the simulation model are likely be caused by incorrectly formulated inputs, rather than simulation faults. The flexible simulation model concept is described in the development chapter [Chapter 4]. Results analysis is perhaps the final phase of the study if no further reconfiguration was required. Here the results from the simulation run will be analysed to assess the production segment being investigated. Along with standard machine utilisation and performance, the management was interested in a further two critical measures. The number of production lots at risk between two samples, and the time between two consecutive sampled lots.

A number of scenarios were tested and compared with Anna Rotondo's [1] hard-coded simulation model. This was possible as both projects where correlating to the exact same production segment studied using identical sample data. It was interesting to observe the swift changeover procedure when using this thesis's research approach in comparison to the traditional hard-coded simulation modelling method. Using the customised user interface, changing the sampled product range is easily done by typing the desired product acronym when prompted by the module during the data manipulation phase. The remaining stages are handled completely by the module. Traditionally in comparison, Anna would have to recalculate data statistics manually and modifying each simulation block to incorporate the changes to the model. This would take a substantial effort of a couple of hours and is very sensitive and prone to error if any step is overlooked.

Due to the assumption of categorising all machines involved as single-lot-processing machines, continuous WIP build-up occurred at a number of work stations within the simulation model. Prior to identifying the WIP issue, the assumption was employed but noted for re-assessing in future revisions. Once the root problem was identified, it could not be further ignored, as models generated by the module were not representative of the actual system being studied. The analysed production section and sample data used to construct the pilot project consisted of several workstations involving multi-chamber machines, and thus could not be handled appropriately in the module using the single-lot-processing machine assumption.

A solution was required to account for that difference. Adjusting or tweaking the input parameters to account for chamber capacity differences would result in complications further downstream where sampling occurs. Instead the decision was made to duplicate those machines to reflect the multiple chambers. This was convenient as it had no effect on the basic model structure, but rather required a small adjustment to the analysis procedure. Initially, duplicating the machines did not resolve the entire problem. Difficulty arose when analysing post-simulation results in separating the various chambers to assess machine utilisation. Hence to overcome this issue, each duplicate chamber needed a unique identifier to distinguish between them. The problem of multi-chambered machines was resolved using this addition, so that testing could commence on verifying the new concept.

5.2.1 Practical Experimentation On-site

Due to the fast-paced nature of the company, restructuring and personnel relocation occur on an on-going basis. As the research project spanned over three years, the number of participants involved in the project deteriorated gradually. Furthermore, additional restrictions where placed on researchers to protect the company's intellectual property. No direct access was available to the company database. However engineers that where involved in the project did manage to conduct trial experiments on the company's database system on behalf of the researcher.

Over a dozen runs where trialled on the initial studied line segment, along with preliminary testing of the module on newer segments within the fabrication facility. Simulation outputs from the runs conducted where not made available, but implementation statistics and feedback was related back. On average the time for simulation execution was relatively constant at approximately 15 seconds per 1000 hours of simulation. Yet the evaluation of results varied subject to the amount of information returned from the database. Depending on the segment being investigated, the number of machine-sets and machines in each set can vary, hence affecting the amount of information returned to the module from the company database. The amount of information generated within the simulation run of the module will also be affected. On average, a full run of the module took no more than 30 minutes to complete.

5.3 Experimentation and Results

No further access was given to new data samples for testing, little was available to conduct comprehensive scenario testing and validate the modules responsiveness and accuracy to production fluctuations at the facility. For that reason, the pilot module (Referred to as "R") is tested against results from the case study project (Referred to as "A") described in [Chapter 1]. This was possible because both projects used identical initial sample data, and so controlled runs were executed and results recorded for comparison.

Simulation model "A" was validated and deemed effective by project management and engineers while assessing the inspection policy. The assumption was made to accredit the module as valid if the results using the developed pilot project corresponded closely the results from the previously validated project model. The controlled test run inputs where derived using the same sample data to assign product arrival rates, sampling rates, and using similar capacity machine-sets to reserve fairness in objectivity. Furthermore, the same corresponding random seed numbers where used for both models to preserve fairness in pseudorandom numbers generated thought the simulation run.

The study consists of a small segment of a flexible manufacturing system with multiple product types, re-entrant flows, and multifaceted routing and scheduling sequences. From an operational prospective, the segment consists of a series of operations and consequently a number of production posts that are monitored by an inspection post. Each production post contains multiple duplicate machines capable of executing the same set of operations. Table 5-1 below lists the machine-sets involved in the model and number of machines contained within each set.

Table 5-1: Test Model Machine Configuration

Machine Centre	Number of Machines
M/C 1	4
M/C 2	5
M/C 3	4
M/C 4	3
M/C 5	5
M/C 6 (Monitor Station)	4

An assortment of serial and parallel product flow is experienced through the production segment investigated. Parallel flow products are considered cross-flow that acquire capacity at the machine-set but are not monitored in this production segment, thus consuming machine availability, but with no effect to the sampling. The serial flow products, referred to as On-loop products, are broken down into two types; Tested and none tested. These On-loop products progress in a sequential manner though the investigated production segment. Note that not all On-loop tested products actually get tested at the end monitoring station, but rather depending on the pre-assigned sampling rate are forwarded to the monitoring station.

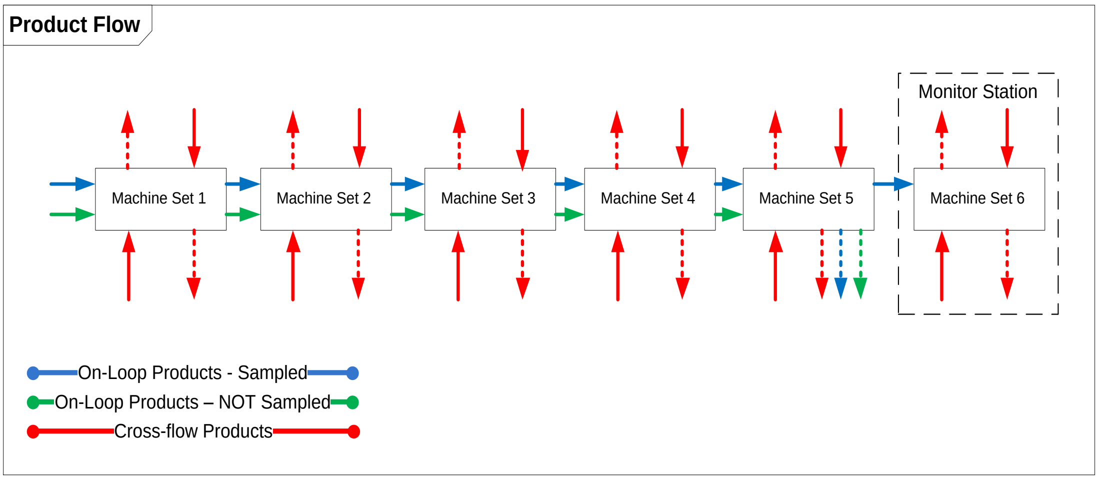

Figure 5-3: Simulation Model Product Flow (Case "R")

Scheduled preventive maintenance is implemented on machine with a time dependent frequency; shiftly-, daily- and weekly-based maintenance operations as observed in the real system. Furthermore, machines are shut-down for quality and operation failures that might happen arbitrarily. These are categorised as unscheduled preventive maintenance. The repair times for these machines are variable; therefore average durations are used depending on the type of occurring failure.

Model "A" has these characteristics incorporated into the model, with specific detail to for each machine-set and comprehensive breakdown of the scheduled preventive maintenance. In comparison, Model "R" is a more abstract interpretation, where all scheduled (shiftly, daily, weekly, monthly and so forth) preventive maintenance are grouped together, the same with unscheduled breakdowns.

In Model "A" two serial flow products across the segment and a single parallel cross flow was observed at each station. Model "A" incorporated non-tested serial flow products to be part of the cross flow. Further details on the line configuration and the operating condition are contained in Table 5-3 and Table 5-4. Information about processing time, inter-arrival time and availability of machines are provided in the form of the distribution shape modelling the historical data (for confidentiality reasons, numerical data are not shown).

Table 5-2: Distribution Key

Distribution Type	Distribution ID
Normal	1
Exponential	2
Log-Normal	3
Log-Logistic	4
Empirical	5
Johnson Bound	6
Johnson Unbound	7

Table 5-3: Case "R" Preventive Maintenance Used

Machine-Set	Scheduled		Unscheduled	
	MTBF	MTTR	MTBF	MTTR
M/C 1	6	6	6	6
M/C 2	7	7	7	6
M/C 3	6	7	6	6
M/C 4	6	7	7	6
M/C 5	6	6	6	6
M/C 6 (Monitor)	7	7	7	6

Table 5-4: Case "A" Preventive Maintenance Used

Machine-Set	Shiftly PM		Daily PM		Weekly PM		Unscheduled PM	
	MTBF	MTTR	MTBF	MTTR	MTBF	MTTR	MTBF	MTTR
M/C 1							2	2
M/C 2			1	5			2	2
M/C 3	3	5	3	5			2	5
M/C 4							5	2
M/C 5							2	2
M/C 6 (Monitor)					3	3	2	2

The investigation took part on a production segment of a complex flexible manufacturing system. The segment consisted of six machine-sets containing five production and one testing stages. The tested productions segment has over 30 varied types of products flowing through it in both serial and parallel manner. Sampling was carried out on two product types at a rate of 2:1 and 4:1 on product 1 and 2 respectively. Both products tested have a serial flow through the machine-sets of the monitored segment. The value added step where the sampling will be assessed from will be machine-set 5. Experimentation involved 10 repetitions, each consisting of 6000hr runs, which included a 1500hr warm-up period.

Result comparison was initially confined to total lot outputs from the various machine sets involved. The initial assessment was comparing total lot output from each of the models; also a more filtered approach was taken to assess the outputs of each machine set individually for tested products and other products involved. The other products include both serial flow products along with parallel flow cross products through the monitored production segment simulated. In addition, a sampling analysis was conducted to compare the validity of the screening proficiency of both model concepts.

5.3.1 Simulation Lot Outputs Assessment

The total output of products gives a general indication that both simulations are in synchronicity and the product flow is corresponsive. However, to truly assess the variability, the output of each machine centre within the monitored section needs to be examined individually. The result tables below [Table 5-5, Table 5-6, Table 5-7] show the outputs for total lots, monitored product lots, and other product lots respectively.

Minor variations in the results are expected, as each of the simulations handles the settings using a different concept. Concept "A" is a purpose built simulation model dedicated to simulate this specific production segment and contains vigorous detail of all the machines involved. Special attention was given to incorporate distinct characteristics for each machine and include lot routing, queuing and transportation between machine-sets. Concept "R" (Pilot Module) has a more flexible approach, with identical tool characteristics among each machine-set, standardised scheduled and unscheduled breakdown handling and a logic based lot routing dictated by the raw sample data.

One must also note that in case "A", input parameter calculation was done manually and tweaked by the developer in certain portions, whereas in case "R", parameters are automatically calculated and distributions fitted using a pre-set MS Excel macro without any user intermission other than indicating chosen sampling rate.

Table 5-5: Total Lot Outputs

Total Prod.		6000hr Run with 1500hr Warm-up									
	Run	1	2	3	4	5	6	7	8	9	10
M/C 1	A's	31208	31195	30932	30938	30957	31495	31574	31085	31208	31080
	R's	28951	28834	28928	29065	28935	28844	29289	28819	28775	28783
M/C 2	A's	13583	13750	13538	13756	13644	13803	13807	13469	13569	13923
	R's	23583	23289	23346	23827	23232	23137	23502	23223	23304	23337
M/C 3	A's	21369	21162	21271	21287	21307	21438	21278	21342	21392	21238
	R's	22938	22903	22955	22960	22897	22786	22945	23091	22964	23014
M/C 4	A's	4789	4846	4867	4762	4786	4986	4859	4656	4768	4837
	R's	5587	5640	5708	5750	5545	5666	5827	5612	5597	5598
M/C 5	A's	19379	19014	19400	19145	19311	19274	19491	19290	19162	19008
	R's	20489	20074	20141	20507	20146	20292	20176	20202	20234	20178
M/C 6	A's	9817	9895	9833	9932	9767	9721	9984	9737	9820	9971
	R's	9807	9785	9785	9813	9693	9680	9906	9829	9829	9756

Table 5-6: Prod 1&2 Lot Output (Monitored Product Types)

Products 1&2		6000hr Run with 1500hr Warm-up									
	Run	1	2	3	4	5	6	7	8	9	10
M/C 1 - 5	A's	2558	2580	2600	2546	2565	2699	2652	2501	2522	2609
	R's	2454	2552	2588	2591	2562	2549	2696	2562	2566	2596
M/C 6	A's	703	804	803	795	795	842	826	775	786	807
	R's	771	799	813	811	806	799	848	800	801	817

Table 5-7: Other Products Lot Output

Other Prod.		6000hr Run with 1500hr Warm-up									
	Run	1	2	3	4	5	6	7	8	9	10
M/C 1	A's	28650	28615	28332	28392	28392	28796	28922	28584	28686	28471
	R's	26497	26282	26340	26474	26373	26295	26593	26257	26209	26187
M/C 2	A's	11020	11170	10938	11210	11079	11104	11155	10968	11047	11314
	R's	21129	20737	20758	21236	20670	20588	20806	20661	20738	20741
M/C 3	A's	18806	18582	18671	18741	18742	18739	18626	18841	18870	18629
	R's	20484	20351	20367	20369	20335	20237	20249	20529	20398	20418
M/C 4	A's	2224	2266	2267	2216	2221	2287	2207	2155	2246	2228
	R's	3133	3088	3120	3159	2983	3117	3131	3050	3031	3002
M/C 5	A's	16814	16434	16800	16599	16746	16575	16839	16789	16640	16399
	R's	18035	17522	17553	17916	17584	17743	17480	17640	17668	17582
M/C 6	A's	9114	9091	9030	9137	8972	8879	9158	8962	9034	9164
	R's	9036	8986	8972	9002	8887	8881	9058	9029	9028	8939

From a visual inspection of the output summaries [Table 5-5, Table 5-6, Table 5-7], it is obvious that there is a large difference in the total outputs of the models achieved at M/C 2. From discussing these findings with management and line engineers at the facility it became apparent that workstations M/C 2 and M/C 3 are linked machine-sets. This means that the majority of the M/C 2 production volume (> 95%), irrespective of product type and manufacturing stage, is directly routed to M/C 3. This instates confidence in the model outputs from case ‘R’. Furthermore, as can be seen from Table 5-7, this insight from the discussion with management indicates that the distribution of inter-arrival times for the unmonitored flow (cross-products) at M/C 2 has not been accurately modelled in case ‘A’ and has in fact been particularly under-estimated.

Examining the output summaries in Table 5-6, of the machine-set for monitored lots, there is reasonable correspondence between both cases. Note that these experimental runs are conducted using the same random seed number for each corresponding runs of Case 'A' and 'R', hence making the output results directly comparable. This observation is further evidenced by Table 5-8, which reports the results of paired t-tests for the differences between the two cases for the output of the machine-sets with respect to monitored production flow. Since the confidence intervals for the differences between the cases contain zero, it can be concluded that there is no statistically significant difference between them. Furthermore, since the half-width of the confidence intervals are relatively small (largest half-width is 50.04 lots which is equivalent to one lot every four days) it is safe to assume that there is no evidence of a practically significant difference between them.

However, as can be observed from Table 5-7 and as is further evidenced by the paired t-test results reported in Table 5-9, there is a significant difference between the two cases in terms of the outputs from the machine-sets for the unmonitored flow. In all instances, with the exception of M/C 1 and the inspection station M/C 6, case "R" achieves a higher production throughput for the unmonitored flow. This may be due to fact that in case "R" some of the unmonitored production volume was identified as a serial flow through the entire segment and modelled as such; whereas in case "A" all unmonitored flow was represented by an inter-arrival time distribution at each machine-set and therefore treated as parallel cross-flow products.

Given that the objective for the study for which the model labelled case "A" was originally constructed to determine the risk of implementing a skip-lot sampling plan it is important now to determine whether this difference would impact significantly on the associated performance metrics. The performance metrics were mean number of lots between samples from a given machine in the sampling station (value-step) and the mean time between samples. This assessment is discussed in the next section [5.3.2].

Table 5-8: T-test Table 5-6 data series

	Half-Width	Lower Bound	Upper Bound
M/C 1-5	50.04	-37.74	62.34
M/C 6	13.85	-20.75	6.95

Table 5-9: T-test Table 5-7 data series

	Half-Width	Lower Bound	Upper Bound
M/C 1	145.34	2087.96	2378.64
M/C 2	158.33	-9864.23	-9547.57
M/C 3	67.56	-1716.56	-1581.44
M/C 4	46.83	-896.53	-802.87
M/C 5	161.22	-1170.02	-847.58
M/C 6	57.82	14.48	130.12

5.3.2 Simulation Lot Sampling Assessment

Having established a degree of credibility to the pilot simulation project, further investigation was possible by assessing the initial purpose of the pilot simulation module. The aim was to test the operating sampling policy, and assess the degree of confidence with a chosen sampling rate. Two measures were of significant interest to management at the plant, those are the number of lots between samples and time between samples. Simulation model "A" has been previously tested and validated to management's satisfaction. Thus, deriving consistent results for the overall sampling criteria, would give credibility to the responsiveness of case "R". The assessment was carried out on three randomly chosen runs (Run 2, 5 and 10) from the previous experimentation section [5.3.1]. A summary of the results obtained are presented in Table 5-10 and Table 5-11.

Purely from observation, certain assumptions made during case "R" composition are reflected through the results. Note how using identical machine characteristics and FIFO queuing rule has resulted with an even distribution of lots among the machines within the machine-set. In comparison to the wider fluctuations witnessed in case "A" between each machine, reflecting the unique characteristics given to each machine, along with the side-effects of having specific lot routing policies in place.

Table 5-10: Result Summary of Lots between Samples

		Lots Between Samples					
		M/C 5 Tool	**5.1**	**5.2**	**5.3**	**5.4**	**5.5**
Run 2	**A's**	**Min**	0	0	0	2	0
		Max	51	49	73	104	61
		Mean	**18.04**	**18.08**	**22.74**	**30.18**	**21.84**
	R's	**Min**	1	1	2	2	1
		Max	77	63	98	67	79
		Mean	**24.75**	**25.64**	**25.22**	**24.54**	**24.71**
Run 5	**A**	**Min**	1	0	0	0	0
		Max	59	64	65	84	92
		Mean	**17.64**	**17.41**	**23.87**	**29.02**	**26.65**
	R	**Min**	2	1	2	1	4
		Max	75	72	90	113	84
		Mean	**24.49**	**25.97**	**24.48**	**25.16**	**24.75**

Run 10	A	**Min**	0	0	0	0	1
		Max	58	64	72	99	108
		Mean	**17.49**	**16.76**	**24.65**	**30.40**	**21.82**
	R	**Min**	1	1	1	1	2
		Max	76	85	68	76	77
		Mean	**26.01**	**25.12**	**23.32**	**24.17**	**24.15**

Generally, a slight exaggeration can be noticed in the number of lots between measures for case "R" in comparison to case "A". The 2 ± 1 lot differences are relatively small when regarding a 23 lot overall mean. A rather collated result grouping can be seen in the Time between samples. The results show an approximate 27.5hrs mean duration between samples. Again fluctuations are present in case "A" results due to comprehensive production details, such as product transportation and routing, incorporated into the model.

Table 5-11: Result Summary of Time between Samples

		Time Between Samples (hrs.)					
		M/C 5 Tool	**5.1**	**5.2**	**5.3**	**5.4**	**5.5**
Run 2	A's	**Min**	0.03	0.67	0.02	2.00	0.49
		Max	72.65	63.64	85.37	139.57	73.75
		Mean	**21.20**	**22.33**	**28.20**	**39.13**	**25.90**
	R's	**Min**	0.81	0.41	1.73	1.93	0.18
		Max	79.65	87.90	99.54	83.57	86.69
		Mean	**27.50**	**28.45**	**29.06**	**27.27**	**27.72**

Run 5	A	Min	0.08	0.17	0.02	0.01	1.82
		Max	69.88	64.38	79.46	117.34	116.77
		Mean	**20.64**	**20.76**	**29.23**	**36.86**	**31.84**
	R	Min	1.47	1.66	2.01	1.42	4.18
		Max	95.21	82.02	111.51	158.49	108.61
		Mean	**26.76**	**29.17**	**27.29**	**27.88**	**28.33**

Run 10	A	Min	0.05	0.08	0.17	0.41	1.07
		Max	59.46	77.74	79.27	101.23	131.53
		Mean	**20.97**	**20.39**	**30.27**	**37.97**	**26.72**
	R	Min	1.54	0.71	1.16	1.18	1.36
		Max	96.72	106.81	79.38	64.43	90.40
		Mean	**29.03**	**28.29**	**26.15**	**25.82**	**27.65**

5.3.3 Experimentation Result Summary

The results seem encouraging in regards to the testing conducted. Comparable conclusions were achieved in respect to the performance measures of interest, reflecting the modules competence. Undoubtedly, further progresses can be done to enhance the rigidity of the module and generated models using the module. However, for the purpose of assessing the OSDS framework, experimental performance of the pilot project exceeded the project group's expectations in a number of areas. These range beyond achieving comparable results to prior projects, but rather in the elements of rapid module execution time, user friendliness and reconfiguration simplicity. The final chapter, Chapter 6 , will cover a detailed discussion to recapitulate on the OSDS framework proposed, the pilot study conducted and the overview conclusion of the thesis.

Chapter 6 Discussion and Conclusion

6.1 Introduction

The manufacturing industry has advanced significantly over the past century, prominently in the last 30 years due to progressions in information technology. Manufacturing facilities have evolved into intricate and complex systems to meet global demands. Those manufacturers need the capability to deliver a diversity of products to supply their international markets. To maintain competitive advantage, emphasis is placed on meeting necessary quantity, highest quality and deliver in the shortest lead time.

High capital investment is involved in building and sustaining high-tech flexible manufacturing systems. Controlling and maintaining the operation of these systems is a constant challenge for engineers. In order to maintain an innovative progress in the market, continuous research and development is essential. Experimenting on the actual system is not always an option due to the costs involved. Researchers and scientists build mathematical models to allow for experimentation with these systems. Attributable to the complexity involved in the modelled systems, the generated representations are outside simple analytical solution capability and require computer simulation to facilitate execution.

6.2 Simulation Modelling

The aim of studying a system is to gain an insight into how the various elements within a system collaborate in order to realise a logical objective. Engineers attempt to decode the system to enable forecasting and help in manipulating certain circumstances to achieve objective outcomes. Simulation modelling is used to study and analyse the behaviour of these systems. It can help answer “what if” questions in addition to “what now” questions as well. The benefit of simulation is that it can investigate both existing and conceptual systems.

Simulation projects require a large investment, simulation expertise and resources to develop, deploy and maintain. Commonly, simulation models are used once and shelved away once the project is completed. These projects have the potential to achieve outstanding system improvements resulting in changes to the studied system. To reuse, it would require repeating a large portion of the development cycle in order to update and revalidate the models to the new system configuration.

A number of frameworks are available in literature to assist practitioners to conduct simulation projects. Frameworks presented by authors such as Law and Kelton [8] or Banks [25] have been derived by subject experts using years of gathered simulation knowledge and experience in the field of simulation modelling. However, these frameworks have been developed in an excessively generalised outline to accommodate a vast range of potential simulation application. Practitioners have complete freedom when developing simulation models, making the process an art as much as a science.

Advancements in both simulation software and computer competency have radically improved simulation modelling capability. However, along these advancements new challenges have been exposed and identified restricting the future development of simulation application as a decision support tool.

6.2.1 Current Challenges in Complex Manufacturing

Fowler and Rose [4] identified four grand challenges that restrain the wider application of simulation modelling in current and future decision support opportunities throughout the manufacturing industry. The challenges were covered in detail in [Section 2.5].

All four challenges are interconnected. Real-time problem solving (ii) can only be achieved if a reduction in the problem solving cycle (i) is realised. Similarly, owing to the long problem solving cycle (i) associated with simulation projects there would possibly be greater acceptance to modelling and simulation in the industry (iv). Finally, the absence of a uniform simulation standard (iii) is no doubt the reason a lack of acceptance exists (iv). Attempting to resolve any of these challenges would be expected to result in progressions being done on another.

The surveyed literature introduces the challenges facing simulation and suggests possible resolution initiatives. It is evident that simulation modelling possesses the advantage that many current decision support tools can capitalise on. However, simulation can also be used as a complementary tool to network these apparatus and indicate the resulting benefits of using each individual one, without having to actually agitate the real system by trial and error. Prior to discussing further details on how these challenges where countered, it is more suitable to present the proposed framework and recap its resulting affects thereafter.

6.3 Online Simulation-based Decision Support Framework

The research intended to test these challenges by proposing a framework that will assist practitioners in developing flexible online simulation modules. These modules feature shorter deployment period, faster response capability and reduced need for simulation expertise to provide decision support in manufacturing environments.

The OSDS framework was developed over a two year research period. The framework has been derived from knowledge gained through simulation project participation and supported by the literature available. Different aspects within the framework have been incorporated from varied fields of study, not necessarily simulation modelling. This framework was designed by amalgamating diverse elements of varied fields of science and technology, relating them together and directing towards achieving the objectives of online decision support.

Automation is the underlying foundation of the OSDS framework. Implementing automation is challenging task, but any protocol, providing a defined logic is applied, can be automated. This holds true with an array of examples ranging from manufacturing assembly, telecommunication, traffic-control or food production, naming a few. In terms of simulation studies, a large proportion of repetitive data collecting procedures and post simulation analysis can benefit of the automation concept. The concept can be used as a method to improve the logical procedure for swifter and error-free information processing. The framework automation segment is based on the concept of allowing information technology to handle any analytical computations necessary, achieving results faster than by traditional means. Automation can be used in a number of areas within a simulation study. The key sections are listed below;

- Data Extraction
- Pre-Simulation Inputs Formulation
- Simulation Models Building
- Post-Simulation Result Analysis
- Evaluation Reports Construction

Data manipulating and information handling is a field of research on its own. However, for the objective of a simulation study, repetitive data protocols can be easily automated, provided a logical flow can be set to the procedure. Modern manufacturing facilities have a MES installed to record all interactions within the vicinity. These systems have a standardised format for recording data and other information, making the process further suitable for automating. In order to facilitate automation, three concepts need to be incorporated; *Documentation, Re-usability*, and *Modularity*.

A firm standard of documentation needs to be implemented. A good documentation technique will permit traceability of ideas and concepts used during a simulation project. Documenting model building and assumptions made throughout the development stages are critical to assist in validating and verifying simulation models. Further useful when utilising recycled work in future projects. Hierarchical documenting techniques have the additional advantage of providing different levels of detail, this compliment when relaying information to different target audience.

Factories evolve and change over time. Built simulation models go out-of-date soon after completion and become none reflective of the simulated system. Simulation models have a short shelf-life unless they are continuously maintained with up-to-date information. Re-usability is required for increased simulation lifespan and reduced model maintenance cost. The framework promotes online simulation modules to aid re-usability. Allowing the simulation direct access to the actual system or MES database, can provide enough information to self-update and sustain its relevance to the real system. Automating this data retrieval process can enable the re-usability and prolong the shelf-life of these models, justifying the added cost of automating.

Modularity is the final protocol that supports implementing automation. The simulation module can be segmented to individual partitions describing each phase of the study. Typical simulation studies can be broken into the following sections; Define, Extract, Manipulate, Build, Simulate and Analyse. This permits coding individual sections and helps interoperability when expanding on the work of others. Each segment can be remodelled individually to user specification without affecting the other sections in the study.

The automation promoting framework has further characteristics beside the pillars described above. The following section helps to explain the wider features automated decision support modules can provide to a simulation study.

6.4 Automated Decision Support Module

Simulation studies involve a complex process and although simulation software packages have significantly improved over the past two decades, the user friendliness is still absent. The finished decision support module requires minimal user interaction to conduct complete simulation studies. All that is required from the user is to enter the operation series of interest and execute the automated module. The diversity of possible entries at the factory where the project was conducted is vast. However, the system was standardised to allow automation to be implemented. This helped in setting a standard and assigning logic for the set of instructions executing the module.

The built simulation modules can be easily availed of by practitioners with minimal prior simulation knowledge. Using automation the aim was to by-pass complication by standardising the process and giving the end user all the necessary options in a more familiar context. Having the user interact with the simulation module through a tailored interface (customised MS Excel Workbook was used in pilot project, a programme used by most academics and practitioners on regular basis) does not only overcome intimidations of the complicated software package but also facilitating a smoother transition towards the use of simulation. All the possible reconfigurations that the user might need to conduct experiments are provided in a customised format. Automating the model construction and execution will facilitate a reduction in user time and effort in carrying out simulation studies. Up-to-date factory data is extracted with each new replication, diminishing maintenance and reusability issues of the past. New users can immediately start to experiment with simulation after familiarising themselves with a quick-start guide.

The user-friendly automated module will increase the user involvement. Allowing the user to build their own experiments will certainly encourage users to explore and investigate their system further. Furthermore, due to using a comprehensive documenting technique, experienced programmers are permitted to re-code any particular sections of the module to customise and cater for their own individual requirements.

6.4.1 Pilot Project vs. Case Study

The pilot module compiled in Chapter 4 has a number of advantages over the traditionally constructed simulation model in the case study presented in Chapter 1. The sample data used to derive the simulation inputs is the sole similarities between the two projects. The differences are pointed out bellow;

- A completely changed simulation modelling concept (modelling both machines and lots as items) using a flexible simulation model.
- Reduction in simulation model execution (over 50% decrease in computation time)
- Changing or reconfiguring monitored production segment would require a complete reassessment of the traditional model, in comparison to entering a new set of operations into the user interface.
- Complete module execution on new line sections (about 30 minutes) in comparison to weeks to recompile a new model from scratch.

Particular attention was given to the user interface. The proposed module framework emphasises the separation of the user from the simulation software. The pilot module distances the user from other phases of the simulation study; such as retrieving and capturing the factory data concerning the model. However, the user is still provided with enough flexibility to many experimental features (machine-set size, product mix, product volume and sampling rate among other) that can be altered during the experimentation. This is done by means of an MS Excel interface instead of direct interaction with the simulation software or the actual raw data. This concept significantly reduces the expertise/knowledge requirement of the end-user with simulation, with the intended purpose to assist in gaining a wider acceptance for future simulation modelling studies.

6.4.2 Pilot Module Feed Back

At the beginning, it was difficult to debug the initial data pull and have a stable link established with the organisations database system. The reason for this issue was due to constricted access to sensitive manufacturing intellectual property being extracted during implementation of the module. Therefore, testing was only possible by internal engineers to actually execute the full working module from start to finish. After establishing a stable access to the database and conducting preliminary test, few minor bugs where exposed and fixed on site.

Module updates where requested to accommodate the different user types (Standard-User/ Advanced-User). Further issue such as the simulation warm-up period has to be reassessed depending on the duration of the simulation run. The amount of data returned from the database is not predefined, as it depends on the user defined machine and the current machine operating capacity. This made it difficult to exactly judge the time span involved in processing the returned information, in order to manipulate the data for the simulation model execution.

Results feedback was positive, considering most of the variables controlling the simulation are based on sample distributions derived from a limited set of data. There is no assurance in that the returned measurements are accurate, but are rather indicators. The potential of this module lies in using the simulation as a guideline to suggest whether proposed changes to sampling policy and machine capacity will be beneficial or detrimental. No assurance that module outputs are exact, but rather a qualified support for decision making on a qualitative rather than quantitative compliance level. End-users must note that the module delivered is not a complete factory simulation, but rather a decision support tool. The outputs are only indicators and not 100% accurate, as they are purely based on a limited set of machine and lot history information extracted from the factory database. The module should be utilised as a complimentary addition to the numerous management tools used at the factory to control their production facility. It will allow for rapid real-time simulation feedback on system behaviour to different sampling strategies or machine capacity management can deploy. It can also gauge machine utilisation at the value adding stations chosen by the user and expose areas of waste and opportunity that management can capitalise on.

6.5 Novelty of Framework and Contribution

The proposed framework was designed and constructed by amalgamating assorted components of diverse fields of science and technology, relating them together and directing towards achieving the objectives of online simulation-based decision support.

A number of prior attempts at automating simulation modelling projects have been covered in the literature review. Surprisingly none of the authors made an effort to compile a structure to assist future studies, sharing recommendation and warning of pitfalls. The OSDS framework construction involved utilising and further developing achievements and failures of previous efforts from review literature and experience.

Utilising this framework will assist simulation project participants in composing simulation modules. These automated modules possess a number of elements that help in reducing the time of deployment and sustainability. Taking the pilot project as an example, the developed module was capable of:

1. Facilitate the reduction in simulation knowledge expertise required for conducting simulation studies. Customised MS Excel interface with simply identifiable reconfiguration options.

2. Increased re-usability and prolonged shelf-life to the compiled modules. New information is extracted from the company database with every execution, allowing the module to self-update.
3. Increased module flexibility due to process standardisation. A new operations list is all that is required to allow other sections of the facility to be investigated without having to repeat any portion of the development cycle. Reconfiguring machine-set size and product combinations can be modified through the interface without any interface to the simulation model.
4. Reduced computation time for executing simulations. Achieving a real-time response from the module within an acceptable period. A complete module implementation of data extraction, data manipulation, model execution and results analysis in less than 30 minutes.
5. Promoting simulation modelling as a tool to be used factory wide and not be restricted to simulation specialists. Customised interface promotes user friendliness and helps to encourage new uses experimenting with the module and expanding their system knowledge.

In summary, the study has progressed the deployment and maintenance procedure for simulation studies to achieve a reduction in time, effort and expertise required. The overall cost of ownership has contracted, as primary development can be distributed across the extended shelf-life of the re-usable, self-maintaining simulation project modules.

6.6 Recommendation for Further Research

Some avenues for further research are apparent. Firstly, further investigation is required to assess and possibly standardise data management procedure in simulation studies. Part of the developed module concentrated on extracting and manipulating data from a manufacturing executive system to construct simulation models and assess output results.

This information is critical for the validity of the compiled studies and must be given special attention. The procedure used to manipulate simulation results can benefit from improved filtering techniques to sort through the enormous sets of data returned from the simulation model. The methods incorporated into the developed module are adequate for time being, however could benefit with smarter handling to improve processing speed.

Secondly, the developed modules would benefit from incorporating supplementary details about the system being studied. Further research is needed to consider and weigh the benefits of fitting additional details into these modules versus the increased computation time. Issues encountered such as machine processing characteristics is a prime area to investigate. At current state, the module can only handle single lot processing machines. Duplicates are used to account for multi-chamber machines. However, additional machine types exist at the facility and may need to incorporate these machine types to better represent the system during simulation

Thirdly, the modularity promoted by the OSDS framework requires further research to define appropriate methods to store and archive these modules in libraries for sharing and future access. For example, data extraction or data analysis protocols can be extracted and imported into new projects as required.

Finally, the concept of flexible automated simulation can have a wider application than that limited to a manufacturing environment. Potential applications can arise in several fields where information describing the occurring events is accessible and maintained on a regular basis.

6.7 Conclusion

Cost of ownership for simulation based decision support is much more than the direct (quantifiable) costs such as software, hardware and training. It is driven by the skillset requirements for the project team or more often single modeller. This skillset includes:

- In-depth knowledge of the manufacturing system; the processes, inter-relationships, dynamics, influencers and metrics.
- Mathematical skills in the areas of Operational Research, Statistics and Probability.
- Computer programming skills, code writing, debugging and validation.
- Simulation abilities, familiarity with software package, but also skills in data preparation,
- Project Management skills, project scoping, tracking,
- Communication skills; in reporting progress and results, liaising with all stakeholders within the organisation from senior management to engineering and other specialists to operators and technicians.

Given this, the research aim of this thesis was to investigate how the COO of simulation based decision support for an organisation could be significantly reduced. To achieve this aim:

- This thesis proposed an Online Simulation-based Decision Support (OSDS) framework.
    - The absence of such a framework in the literature was an unexpected gap providing a major opportunity to contribute to the state-of-the-art.
- The framework has been developed, tested and discussed in this thesis in relation to theory and industrial application.
- The use of an existing simulation case study of a real industrial problem has demonstrated that the framework is capable of providing similar results to

traditional simulation approaches for principle performance metrics of interest to a decision maker.

  - The developed module allowed rapid real-time simulation feedback on system behaviour to different sampling strategies with minimal user interaction.
  - Due to the incorporated automation, further analysis is run simultaneously on the outputted data; this gauges utilisation of various machinery being simulated chosen by the user and expose areas of waste and opportunity that management can capitalise on.

The principle advantages of the OSDS framework over tradition simulation approaches arise from the elements of the framework itself:

- Automation is utilised to facilitate a reduction in the time, effort and user-knowledge required to develop simulation models. The framework assists in developing modules that include the acquisition of fresh data and post simulation outputs analysis of these simulation models within a statistical framework to design and conduct experiments.
- Documentation, in a standardised and structured format, assists in necessary record keeping and for validation purposes. It allows for users other than the developer to follow the steps that were taken to assemble the project and there by speed up the modelling process.
- Modularity is required in order to allow for each distinct section of the project to be developed and tested in segregation and later integrated into the overall simulation project. Modularity will also help in allowing certain segments such as data manipulation or post simulation analysis to be standardised and plugged-in into future projects.

- Re-usability of the developed models in the course of a simulation study is fundamental to ensuring prolonged usage of the modules and rationalise the cost investment required at times.
- Additionally, the 'developed' modules contain a flexible simulation structure that end-users are able to effortlessly conduct their experimentations through the MS Excel template interface without having to alter the structure of the model in ExtendSim, allowing different areas within the system (e.g other lines or segments) to be investigated without major redevelopment of model.

The aim of this thesis was to demonstrate that, with the aid modern technology and knowledge, it is possible to significantly reduce the COO of simulation based decision support.

- This thesis has proved the concept that COO of simulation based decision support can be significantly reduced through the adoption of the OSDS framework.
- The aim was not to provide a commercially viable/ready solution or product; however, the results of this research could guide and assist the development of further academic and commercial research on tools and approaches.

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