THE ROLE OF SIMULATION IN THE DEVELOPMENT OF INTELLIGENCE FOR FLEXIBLE MANUFACTURING SYSTEMS

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ABSTRACT

Discrete event simulation has been successfully employed as an analysis tool for predicting the effect changes have on existing and hypothetical systems. This insight allows for more informed appraisals of alternatives, greatly enhancing the planning function.

Simulation modelling allows microscopic analysis of complex system dynamics giving the intimate understanding required to maximise the efficiency of such systems. As well as being used to predict the future and explain the operation of complex processes, simulation models are also used in real-time control systems to provide decision support for automated (intelligent) decision makers.

Current research suggests that a combination of simulation and 'meta-heuristic' optimisation techniques applied to analytically intractable problems can yield optimal or near optimal solutions. This paper gives a brief review of the history of discrete event simulation and discusses the role of simulation modelling in the ever-changing manufacturing environment. It pays particular attention to the importance of simulation in intelligent, highly automated, flexible manufacturing systems. It details a case study in which a simulation model and an optimisation strategy are integrated as part of an intelligent decision maker. This application implements an adaptation of the Amherst – Karlsruhe model of an automated dynamic scheduling system.

KEYWORDS: (Simulation modelling, Dynamic Scheduling, FMS)

1. INTRODUCTION

The idea of manufacturing industries having to re-invent themselves is by no means a new concept. As markets globalise, pressure to sustain competitiveness has become more intense. Escalating labour costs in developed countries have forced companies to either increase levels of process automation, or relocate to more viable economic environments. Also, increased competition allows customers dictate specific requirements to manufacturers. Demand for high variability and low volume has been met by increasing levels of automation and implementing concepts such as Flexible Manufacturing Systems (FMS), and Computer Integrated Manufacturing (CIM).

As manufacturing facilities and their control systems increase in complexity, it becomes difficult if not impossible to optimise the design of, understanding of, and operating efficiency of these facilities, using conventional management techniques. To overcome this problem managers have turned to relatively new techniques such as Simulation modelling and Artificial Intelligence (AI). Simulation models are built to support the decision making process be it at a long term strategic level or real-time on the factory floor. Used in conjunction with AI technologies such as rule or knowledge-based expert systems, simulation can provide decision support in an automated decision making environment.

2 MODELLING OF SYSTEMS

2.1 Mathematical modelling

As human beings we continually strive to understand the dynamics of the world that surrounds us. Scientists ask questions in an attempt to unravel the mysteries of the physical world. Economists attempt to understand what influences financial and commercial markets. In order to understand the dynamics of any system, its behaviour must be studied in a variety of situations, under the effects of a variety of influences. In some instances it is possible to experiment using the physical system itself. However, in many cases it is impossible or impractical to do so.

> "A new system may not yet exist; it may be only in hypothetical form or at the design stage. Even if the system exists, it may be impractical to experiment with it. For example, it may not be wise or possible to double the unemployment rate to determine the effect of unemployment on inflation. In the case of a bank, reducing the number of tellers to study the effect on the length of waiting lines may infuriate the customers so greatly that they move their accounts to a competitor."

Banks et al (1996)

The alternative to experimenting using the actual system is to experiment using a model that mimics the behaviour of the system. In reality this representation is in the form of a mathematical expression that describes a direct relationship between the input variables and the resulting output. The basic modelling process is shown in Figure 1. The modelling process is not simply a case of formulating a mathematical model that accurately mimics a "real-life" system. The results of any particular experiment must be interpreted in order to infer what their significance is in terms of the real world.

Mathematical models can involve anything from simple linear equations to complex non-linear differential equations. Even the simplest "real-life" situations can be exposed to a complex interaction of both deterministic and stochastic variables. As a result, mathematical or analytical models rely heavily on the assumptions and simplifications upon which they are based. This is adequate under controlled experimental conditions, but when confronted with real-life scenarios, many mathematical models are rendered useless. For this reason, in complex situations such as the dynamic scheduling of an FMS, the development of a single global function that accurately describes the relationship between input variables and the system output becomes impossible without risking significant loss of model integrity. Invalidation of the model can result from over simplification of the problem.

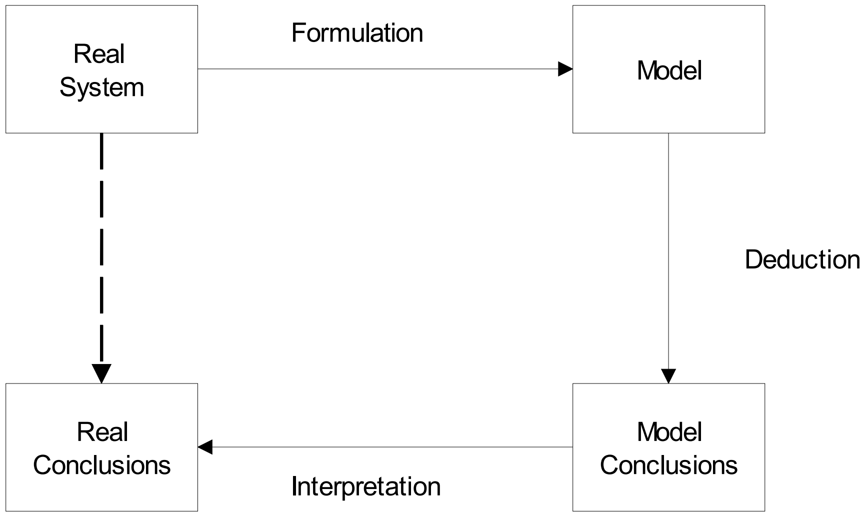

Figure 1, The Modelling Process, Ravindran et al (1987)

2.2 Simulation modelling

Simulation modelling is derived from a different approach to problem solving to its analytical counterpart. Traditional approaches tackle a problem in a single all-encompassing expression that attempts to incorporate even the most intricate and subtle relationships between variables. Simulation on the other-hand takes the view that large problems are really only a series of smaller problems that interact with one another. Therefore, if each of these sub-problems can be modelled mathematically then all that remains to complete the solution to the overall problem is to model the relationships between each of these sub-problems. Taha (1997) emphasises this point in a comparative description of simulation modelling and traditional mathematical modelling.

> "It differs from mathematical modelling in that the relationship between the input and output need not be stated explicitly. Instead, it breaks down the real system into (small) modules and then imitates the actual behaviour of the system by using logical relationships to link the modules together. Starting with the input module, the simulation computations move among the appropriate modules until the output result is realised."

Taha goes on to explain that one of the main advantages simulation modelling has over rigid mathematical systems is the flexibility that results from its simplicity, stating:

> "Simulation models are much more flexible in representing systems than their mathematical counterparts. The main reason for this flexibility is that simulation views the system at elemental level, whereas mathematical models tend to represent the system from a more global standpoint."

Taha (1997)

2.3 The New Emerging Role of Simulation in Manufacturing

Simulation, in addition to giving the user insight into how complex systems function and how variables interact with each other, provides the user with an informative approximation of "what-if" scenarios. To date much discussion has centred on using simulation to assist in supporting long-term strategic decisions. The success of simulation modelling in this role has however been mixed. In the past decade simulation modelling has taken on a new role providing analytical support to real-time decision makers. In the context of completely automated and flexible manufacturing systems, these decision makers are often AI components. Thus simulation models have become completely integrated as modules of automated control systems. McNally and Heavey (2002) describe this emerging niche.

> "Other researchers have been proposing the extension of simulation tools beyond a traditional design role (Dewhurst et al 2001, Kosturiak and Gregor 1999). With this approach the same model can be extended with control functions and interfaces with the environment (shop floor data collection systems and production planning and control databases) to support dynamic scheduling of production orders, capacity plans, labour allocations etc."

> "One area to emerge over the last decade has been the real time control and planning of manufacturing systems using computer simulation, especially in the area of flexible manufacturing systems… …the simulation model is linked to the controllers of the flexible manufacturing system. Real time activities primarily refer to daily operations that require efficient, timely, and adaptive responses to short-term planning, scheduling and execution problems."

3 MPECS – A MULTI-PASS EXPERT CONTROL SYSTEM FOR FMS CONTROL AND SCHEDULING

The MPECS model (Figure 2) of an automated manufacturing environment incorporates a simulation model in its design structure. This control architecture described by Wu (1989), combines expert system technology with a discrete event simulator. The dynamic control system uses the simulator as an evaluation tool in the decision making process. The scheduler contains the following key elements:

- An expert system to generate potential scheduling alternatives based on real-time shop information and scheduling knowledge.

- A simulation model, which is automatically generated by the control system to allow the system to evaluate alternative schedules based on the system performance (i.e. uses the simulation model as a source of feedback for system decision making).

- A decision structure that will update performance rules based on "simulation/system experience".

- A mechanism to affect the control on a variety of Flexible Manufacturing Cells.

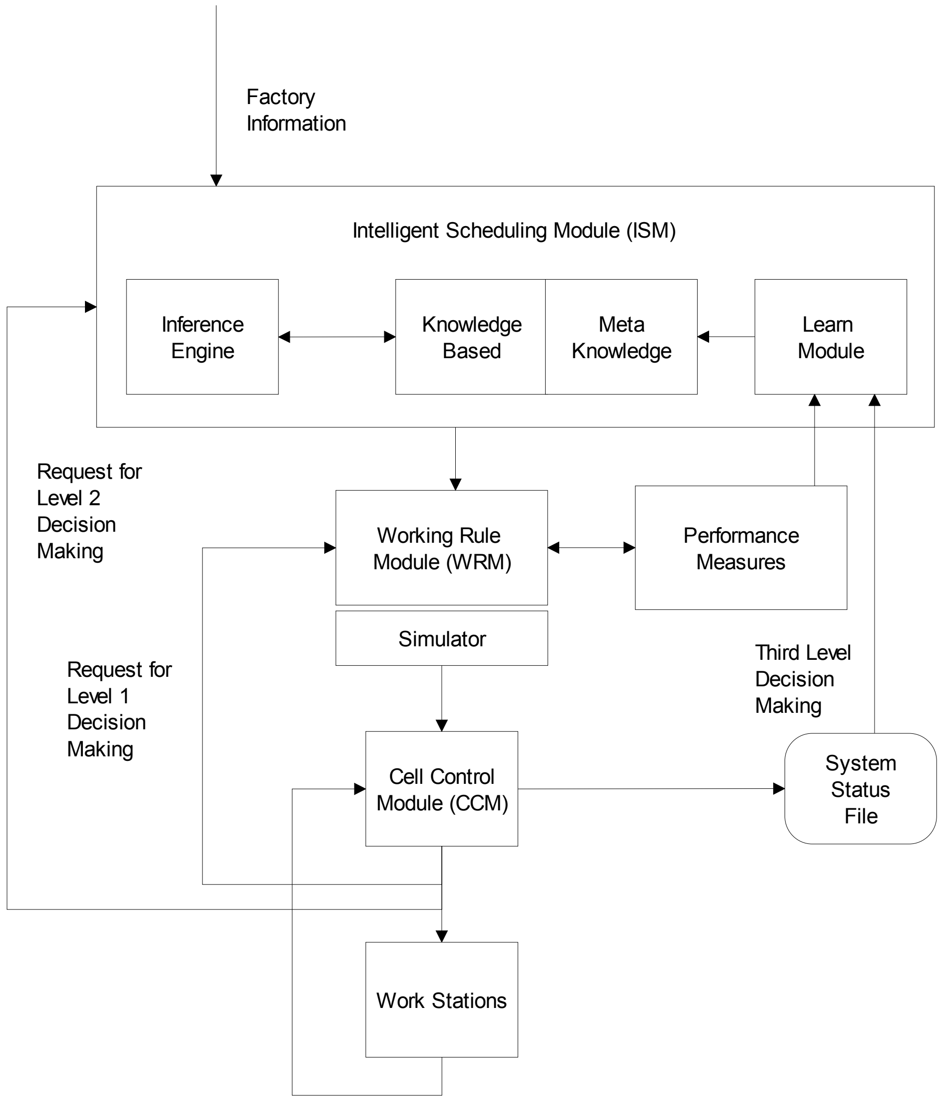

Figure 2, The General Scheme of MPECS, Wu (1989)

The main purpose of MPECS is to utilize the available data in a computerised manufacturing cell, create "good" strategies to guide the system, and generate real-time responses to make control decisions during system run-time. MPECS comprises three distinct modules, an intelligent scheduling module (ISM), a simulation model, and a cell control module (CCM).

- The arrival of new orders into the system or a request from a lower level control module to assist in handling some exception activates the ISM.
- Evaluates KB, which contains scheduling rules and principles as well as shop floor information.
- Applies inference procedures, ISM generates working rule module – contains current 'best' scheduling methods.

- These rules are sent to the simulator for further evaluation.
- Whenever a request is issued to make a decision for a predictable condition, the simulator is used to evaluate a set of alternatives.
- The 'best' schedule is sent to the cell control module for manufacture.

4 CASE STUDY – THE AMTLAB FMS DYNAMIC SCHEDULING SYSTEM

The Advanced Manufacturing Technology Laboratory (AMTLAB) group at Waterford Institute of Technology is a postgraduate research facility dedicated to the investigation and implementation of advanced manufacturing theories and technologies. One particular area that the group has concentrated on is the development of flexible manufacturing systems. The increase in complexity and subsequent introduction of automated decision-making has necessitated the development and integration of advanced control features such as the dynamic scheduling system currently being commissioned. This scheduling system is an adaptation of the Amherst-Karlsruhe dynamic scheduler, essentially containing the same key components as the MPECS system. The AMTLAB model (see Figure 3) does however include a number of distinguishing features, the most outstanding of which being the method it uses to generate the subset of "good quality" schedules from which it will select the "best" schedule.

Scheduling problems are notoriously difficult to solve. Scheduling tasks typically require a group of jobs to be arranged in an order that optimises some performance measure. Some examples of performance measure used are:

- The maximisation of resource utilisation in a manufacturing facility.
- The minimisation of total makespan or leadtime of a group of orders.
- The minimisation of number of jobs late or total lateness/tardiness.

In order to find the optimum schedule for a group of jobs or orders, ideally one would test all possible arrangements of these jobs. However, due to feasibility and time constraints this is rarely possible. To illustrate this point, take the example of a group of 10 jobs. This reasonably small problem has an extremely large solution set. These 10 jobs can be arranged in a total of 10 factorial (i.e. 3,628,800) unique configurations on a single machine. On 2 machines the same 10 jobs can be arranged $(10!)^2$ (approximately 13,168,000,000,000) different ways. For this reason, even when dealing with scheduling problems that are relatively small in magnitude, it is impractical to test all possible permutations and therefore it is difficult to find the optimum solution. Even if an optimal schedule is found, it may be impossible to know that it is in fact the optimum solution. This is the nature of NP hard combinatorial problems containing multiple nonlinearities and uncertainties. As with other approaches simulation is hampered by its inability to test more than a fraction of the solutions. Because it is impossible to test all solution permutations for most practical real-life systems, methods have been developed which isolate a subset of the entire solution set that contains predominately 'good quality' solutions. It may suffice to guarantee that a result will be very close to the optimum without guaranteeing optimality itself, in which case an approximation technique can be employed.

Approximation techniques range from the most basic of dispatching rules to sophisticated search algorithms. Dispatching rules or scheduling rules are a simple form of approximation technique. In many cases they are empirically based on 'rules of thumb' that have evolved through years of "hands-on" experience. The performance of each individual dispatching rule can vary substantially from problem to problem. Some examples of extremely simple yet effective rules include 'Earliest Due Date First' (used when attempting to minimise the total lateness or tardiness in the system), and 'Shortest Processing Time First' (used when attempting to minimise the make-span for a group of orders).

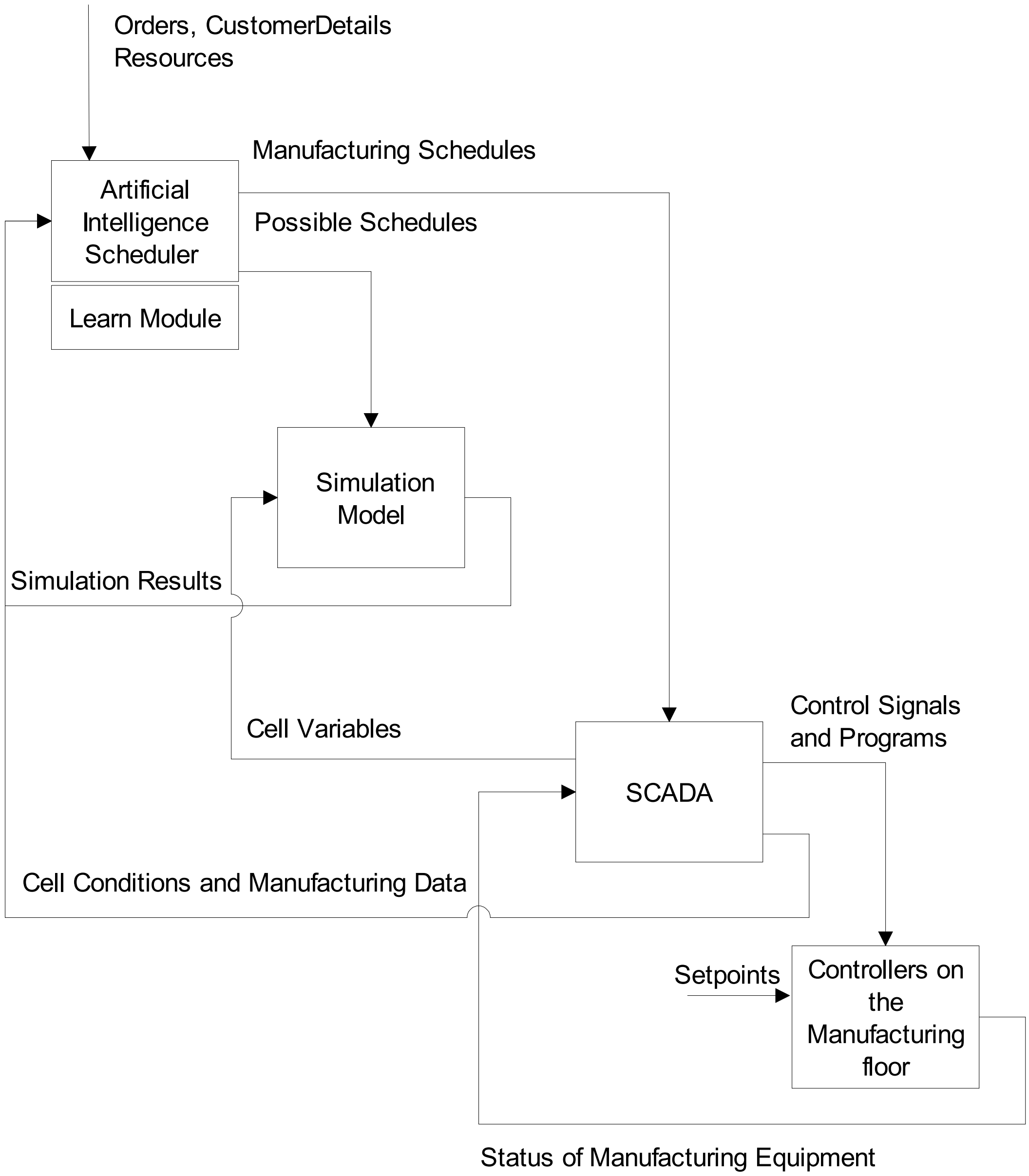

Figure 3, The AMTLAB Dynamic Scheduling System.

As part of the MPECS model, Wu (1989) describes the use of an intelligent module that selects the appropriate scheduling rule from a library of rules. These rules are tested using an integrated simulation model. Evaluation of the performance of each rule allows the intelligent module to accumulate knowledge of the system and to learn where and when to employ particular rules. The simulation model is an important part of the overall control system.

> "The major function of the simulation model is to evaluate control policies in a flexible manufacturing cell by examining the effect of the scheduling rules on an on-line test base."
>
> "Thus at the end of all simulation passes, the best scheduling rule that results from the simulation is applied to the physical manufacturing system. The basic principle behind the simulator is the use of a deterministic simulation as a short-term predictive tool for alternative control strategies in a manufacturing."

Wu (1989).

Rembold et al (1993) echo this concept in their description of the Amherst-Karslruhe dynamic scheduling system.

> "The heart of the system is a knowledge-based selector for scheduling methods and a library of logic scheduling algorithms. The system knows from a given order and manufacturing status which logic scheduling algorithms have to be used to obtain the desired manufacturing goal and to meet due dates."

This conventional approach to dynamic scheduling employs a variety of simple 'dispatching rules' or more sophisticated hybrid scheduling rules to decide which alternatives to evaluate. Most dispatching rules are "simple single pass priority dispatching rules….once a decision is arrived at by the operation of a rule, it is implemented without reconsideration of alternative courses of action." (King and Spachis 1980). The choice of rule is system dependent and often determined by the objective criteria. However, the performance of these rules can vary dramatically depending on the application. Therefore, a more sophisticated approach is required in order to guarantee more reliable solutions closer to the optimum.

Neighbourhood search techniques are launched from one or more starting points in the solution space and through a process of iterative improvement converge on a local optimum point. A typical solution space is depicted in Figure 4. It comprises a series of troughs that represent local optima (note: the objective in this case is to minimise the cost function). Before the search process can begin, an appropriate starting point must be selected. This starting point is typically determined using some heuristic such as a scheduling rule. Scheduling rules are complex hybrid formulations of several dispatching rule components. Each term is usually weighted to reflect its relative importance in the expression. There is a strong positive correlation between the objective or cost function being optimised and the scheduling rule used to determine the start point. As most cost functions incorporate the importance of the customer in their formulation, this factor is also built into the scheduling rule as another weighted factor. Earlier discussion highlighted the fact that a well-chosen dispatching rule will give a 'good' solution to the scheduling problem. The implication of this approach is that even the simplest search technique can do no worse than the dispatching rule used to generate its start point. Also, if there is time available before a decision is required, the opportunity should be taken to conduct additional searching of the solution space as this can only serve to improve the quality of the solution. In fact a good starting point is the safety net that advocates the use of any search technique irrespective of what it is.

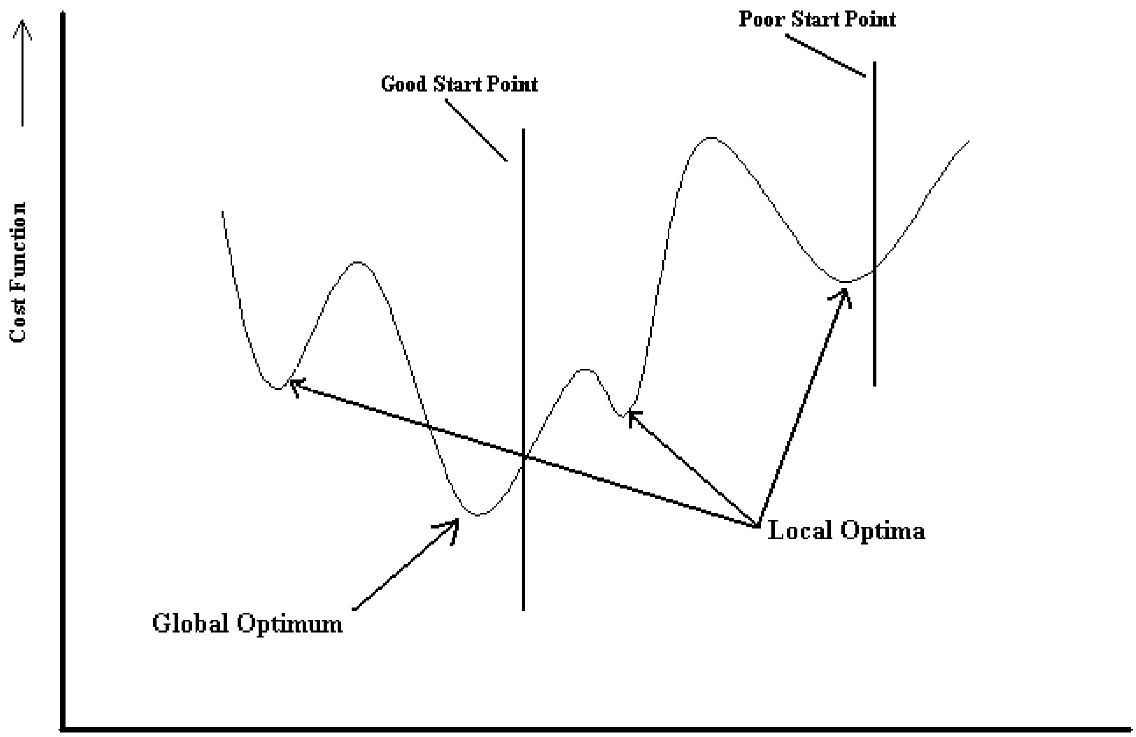

Figure 4, A Typical Solution Space

In addition to acting as a safety net, a starting point in all but the most advanced search techniques can be significant in determining the upper bound of a particular search. This ceiling effect can condemn some search techniques to sub optimal solutions from the outset. Figure 4 illustrates the difference between the result of using a good starting point and a poor starting point. Optimisation and approximation search processes have been likened to a hiker attempting to find the lowest (or highest) point in a series of undulating hills that are shrouded in a dense fog, subject to stringent time constraints. Unable to traverse the entire range, the hiker can only hypothesise about their immediate neighbourhood and by taking small steps downhill eventually arrive at the local minimum point. Short of searching the entire space there is no way of knowing whether any particular minimum point is the global optimum.

More advanced search techniques employ sophisticated techniques to avoid premature convergence and entrapment at local optimum points. Genetic Algorithm (GA) is a search technique analogous to the genetic evolution of species over time. By retaining 'good' portions of schedules and eliminating 'poorer' portions, GAs make iterative improvements to the objective function, evolving towards the optimum schedule. GAs avoid entrapment at local minimum points by incorporating a mutation strategy that causes the search to spontaneously jump from one neighbourhood to another. Another common search technique used is that of Simulated Annealing (SA). This technique is analogous to the annealing process used to relieve stresses in the heat-treatment of materials. Instead of employing a completely rigid strategy of only accepting schedules that yield improvement of the objective function, SA accepts some schedules that result in deterioration of the objective function, effectively allowing the search to cross into new search neighbourhoods by travelling "up-hill", eventually leading the search to the global optimum.

The AMTLAB dynamic scheduling system uses a combination of simulation and optimisation techniques to implement its search strategy. The simulation and optimisation communities have united under the banner of Simulation-Optimisation to tackle this type of problem. They are striving to develop more efficient ways of guiding a series of simulation trials towards the optimum.

> "Advances in the field of meta-heuristics – the domain of optimization that augments traditional mathematics with artificial intelligence and methods based on analogs to physical, biological or evolutionary processes – have led to the creation of a new approach that successfully integrates simulation and optimisation"
>
> Glover et al (1999)

The simulation model evaluates the tentative schedules generated by the search technique. This scheduling system incorporates an innovative search technique developed to meet the precise needs of the FMS dynamic scheduling system. The dynamic and complex nature of the system generally requires that decisions be made extremely quickly. Therefore the search technique must be capable of getting as close to the optimum as possible with a limited number of simulation runs. A simple yet effective strategy was devised that allows the search converge quickly on local optima. It also searches across the search space in order to prevent entrapment at sub-optimal points. Sufficient data is not yet available to validate the technique across a wide variety of situations and to conduct a comparative study with other techniques. However, the concept appears to be logically sound and initial tests have proved positive.

Order No.	Product	Qty	DueDate	No. Of Components
1	P1	48	8	432
2	P2	53	8	159
3	P1	37	16	333
4	P2	31	16	93
5	P2	30	24	90
6	P1	19	24	171
7	P1	54	32	486

Figure 5, Sample Group of Orders

As with other techniques the process begins with a group of jobs that must be scheduled in a manner that optimises the cost function. Each order is prioritised using a scheduling rule. To date no fixed rule has been chosen but tests have been carried out using 'Critical Ratio' and a combination of 'Earliest Due Date First' and 'Longest Processing Time First'. Figure 6 displays the results of all possible permutations of the 7 orders shown in figure 5. There are 5040 in total. Each of the 7 groups is a sub-division of the entire solution set representing all schedules starting with one particular order. The search technique makes an important distinction between static and dynamic scheduling. A static schedule is a list of start and completion times for each individual job on each machine. In a dynamic environment it is only necessary to establish which order must be launched into the manufacturing system next. Changes happen so frequently and so rapidly that scheduling far beyond the next job is of little value in the long-term.

The search technique must satisfy 2 principle objectives if it is to meet its ultimate goal of optimality. First of all it must ensure that it does not become trapped at a local optimum point. It achieves this by starting multiple searches in the neighbourhood of each local optimum. Each start point is generated from the initial list of prioritised jobs. Secondly the search must be capable of progressing quickly from this starting point towards each local optimum. Closer examination of the complete solution space depicted in Figure 6, reveals some interesting characteristics. Although more difficult to distinguish, the solution set comprises a series of troughs and peaks similar to that shown in Figure 4. Referring to Figure 6, each of the 7 groupings contains what are essentially the same schedules with one fundamental difference. Within in each group all of the schedules begin with the same job.

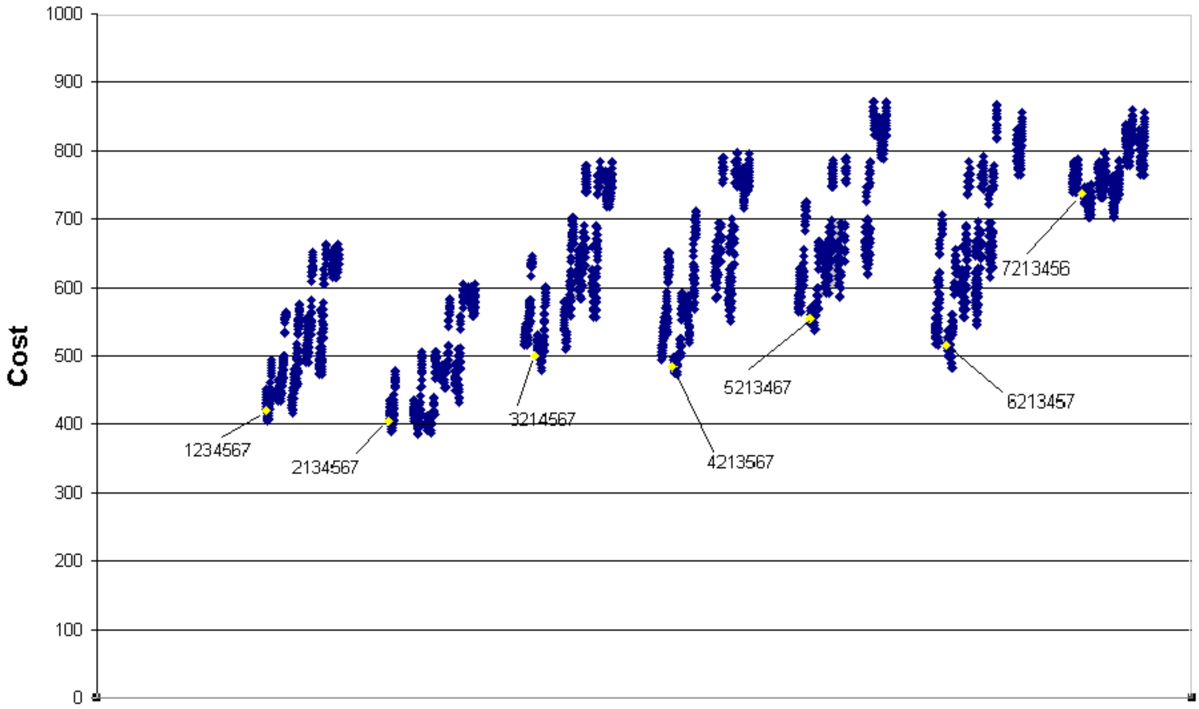

Figure 6, Complete Set of Schedule Permutations

The overall shifting of the each group's results can be directly attributed to the significance of the leading job (i.e. the only major difference between the groupings). The start point within each group is effectively a representative for the overall group. The relationship between each group is reasonably mirrored by the relationship between group representatives. Therefore by simulating each representative schedule, the search can quickly ascertain which group contains the optimum schedule or at worst a near optimum schedule. Isolation of the group containing the optimum is equivalent to isolating the next job to be launched because every schedule in the group starts with the same job. This job can then be launched. The procedure is then repeated within this group when a decision is required regarding subsequent job launches.

5 ADDITIONAL FEATURES

The simulation model is developed using a modelling software platform called Simul8. This object oriented code generator is user friendly and posses an impressive array of powerful modelling, coding and communication tools. These tools allow users from non-programming backgrounds to develop models incorporating sophisticated functionality. For example, the AMTLAB FMS simulation model is capable of changing itself dynamically to reflect changes in the FMS. If processing times change or machines breakdown then the model is programmed to dynamically recover. Other highly sophisticated management features have been incorporated in the model. Typically two simulation models are required to handle the exceptions that occur in the FMS. These models are saved at the critical points before an order is sent for manufacture and after this order is completely, effectively two snapshots of the system. While this order is being manufactured, the scheduling system is busy searching for the next order to launch. This order will start immediately after the first order. Therefore all simulation runs used to evaluate schedules must reflect this fact by using the simulation model that has been saved at the point in time when the first order is expected to complete manufacture. Should a breakdown occur in the middle of processing an order then the simulation model becomes invalid and the rescheduling of jobs is required. This is an extremely complex task. First of all the simulation model that was saved prior to the launch of the order in question must be opened. By comparing the work done and that remaining, the simulation model is "fast-forwarded" to the identical point where the breakdown occurred. The simulation model then dynamically modifies itself to reflect the fact that the FMS now has 1 less machine at its disposal. The system is then ready to continue.

6 CONCLUSIONS

As manufacturing systems become increasingly more complex, the role of simulation in helping to explain their operation is becoming evermore important. Simulation models allow us to ask "what-if" questions and make confident decisions as a result. Until recently simulation modelling was more "black-art" than science, now user-friendly modelling platforms such as Simul8 allow users to develop their own simulation models and with the aid of powerful communication tools embed these models in complex, automated, and intelligent control systems.

The versatility of simulation modelling has allowing it to explore new challenges easing comfortably into a variety of roles. Its marriage to optimisation and approximation search techniques has lead to the development of sophisticated yet practical and understandable systems that can take-on mammoth scheduling tasks. Even though many of these techniques are still in their infancy, promising results could have far reaching consequences for optimisation problems in other domains.

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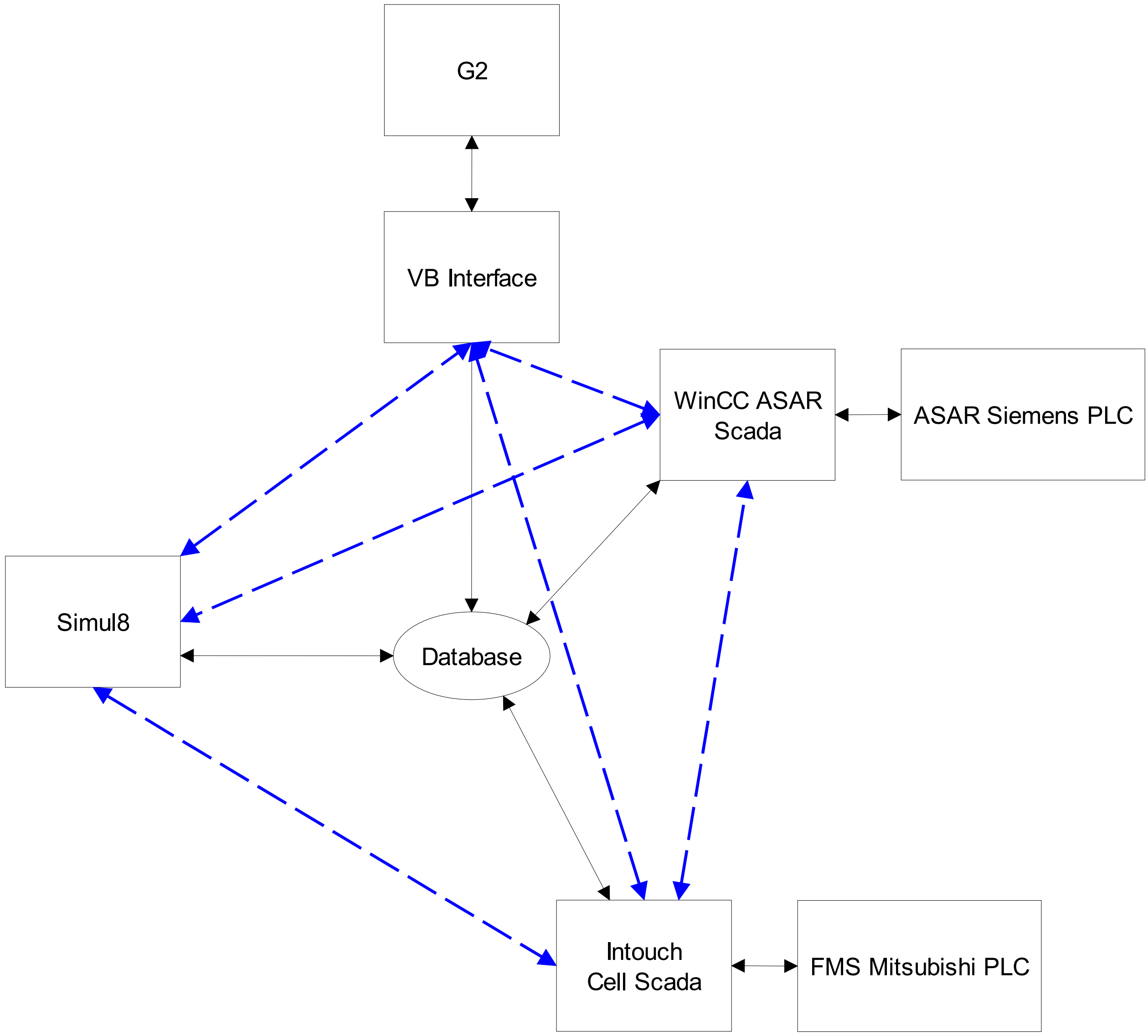
APPENDIX A



The AMTLAB Software Structure