MODELLING HUMAN VARIATION IN ASSEMBLY LINE MODELS

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ABSTRACT:
Discrete event simulation models allow engineers to understand and predict the behaviour of manufacturing systems. A standard way of taking workers into account is to model them as resources not considering any person, organisational or environmental influences. Worker behaviour differs notably between people, tasks and systems which has an impact on the individual processing times and in the end on the output of the manufacturing system. Ignoring this fact causes inaccuracy in the results from the simulation model, especially when modelling systems with highly manual work content, such as assembly lines. The paper describes the ongoing research of investigating the importance of incorporating human performance variation models into manufacturing system simulation models.

Keywords: Manufacturing System Design, Discrete Event Simulation, Human Variation Modelling

1 INTRODUCTION

In 1907, Henry Ford announced his goal for the Ford Motor Company: to create "a motor car for the great multitude." [1]. At that time, automobiles were expensive, custom-made machines. Ford realised he would need a more efficient way to produce the car in order to lower the price. He and his team looked at other industries and found four principles that would further their goal: interchangeable parts, continuous flow, division of labour and reducing wasted effort. In 1913, after more than five years of development and tuning, the principles came together in the first moving assembly line ever used for large-scale manufacturing. Ford produced cars at a record-breaking rate.

An assembly line is a set of sequential workstations, typically connected by a continuous material handling system [2]. On first view common assembly lines look quite simple because tasks are done in a sequential order but in reality these assembly lines are quite complex and non-deterministic constructs due to variations in processing times and breakdowns of various types. These breakdowns can be caused by failure of machinery or conveyors, but they might also be due to temporary unavailability of workers or due to operations that take an unusually long time.

Discrete Event Simulation (DES) models allow engineers to understand and predict the behaviour of such time variant dynamic systems. A standard way of taking workers into account is to model them as resources [3, 4] not considering any person, organisational or environmental influences. But worker behaviour differs notably between people, tasks and systems which has an impact on the individual processing times and in the end on the output of the manufacturing system [5].

The paper describes the ongoing research of investigating the importance of incorporating Human Performance (HP) variation models into manufacturing system simulation models. Section 2 looks at manufacturing simulation and its current limitations. The research aim, objectives and research method used are explained in section 3. To test the impact that HP variation modelling has on the manufacturing system simulation output, a simulation model of an existing engine assembly line with the capability of representing HP variation through distributions has been built. In section 4 the model construction and data collection are described. Section 5 describes the experiments undertaken with the simulation model and discusses the results obtained from the simulation runs. Finally section 6 lists the conclusions drawn from the experiments and gives an outlook of future work planned for this project.

2 BACKGROUND

Since the early 1960's simulation has been used by manufacturing system designers on the one hand to better understand some observed real world phenomena and on the other hand for advice and decision support [6]. DES is now a standard tool used in the design and implementation of different automotive manufacturing [7]. Law & Kelton [8] define DES in the following way: "DES concerns the modelling of a system as it evolves over time by representation in which the state variables change instantaneously at separate points in time. These points in time are the ones at which an event occurs and which may change the state of a system".

Due to the complexity of real systems, system models can only be restricted copies of a real system. They are simplifications and abstractions of the real world. "Simplification entails the stripping away of unimportant details or the assumption of simpler relationships [9] e.g. assumption of linear relationships. "An abstraction comprises or concentrates in itself the essential qualities or behaviours of a thing but not necessarily in the same form or detail as in the original" [9].

There are common observations that are made when a simulation study is conducted:

First, a gap is likely to exist between the performance predictions of a system model and the performance of the real system (see Figure 2.1). System models compared to real world systems tend to represent the real world too optimistically. This phenomenon is related to the aspects of simplification and abstraction mentioned in the previous paragraph.

Figure 2.1 Gap between simulation performance prediction and real system performance

Second, the magnitude of variation of the system output between the manual assembly line models and the real world assembly lines is significantly higher than the variation of the output between automated machining line models and real world machining lines. It is assumed that this is partly due to the common practice of considering the worker as a deterministic resource.

This leads to the hypothesis that by modelling the worker resource more accurately it is possible to reduce the difference in performance prediction that exists between assembly line models and machining line models. This includes consideration of the variation in activity time and error rate due to task, person, physical environment and organisational factors.

3 RESEARCH PROBLEM AND METHOD

3.1 RESEARCH PROBLEM

This research paper is concerned with testing the part of the hypothesis mentioned above, which is related to consideration of the variation in activity times. The aim is to investigate how different empirical models of human variation influence the behaviour of the system simulation model.

There are two main objectives for conducting the investigation: to test how more realistic representation of human variation might influence the gap and to test the variations when different groups of workers are considered.

Due to the nature of the tests that need to be conducted the following simplification of the system simulation model seems to be reasonable without influencing the meaningfulness of the results: that not the whole manufacturing system has to be considered. Therefore no absolute comparisons between the output of the simulation and the real world production figures can be made. It is only legitimate to compare the results of the test runs in a relative fashion.

3.2 METHOD

The method employed to investigate the issues mentioned in the aim and objectives is outlined in Figure 3.1. After the experimental design two different kind of models have to be built: the manufacturing system DES model and the models that represent the activity time histograms of the workers' activity times. The system model has to be evaluated and possibly refined. This is not necessary for the activity time histograms as they are built purely from empirically collected data. Once all models are built they will be combined into one model which serves as the test model. Tests will be executed and the results analysed. After this has taken place the part of the hypothesis under consideration can either be accepted or rejected.

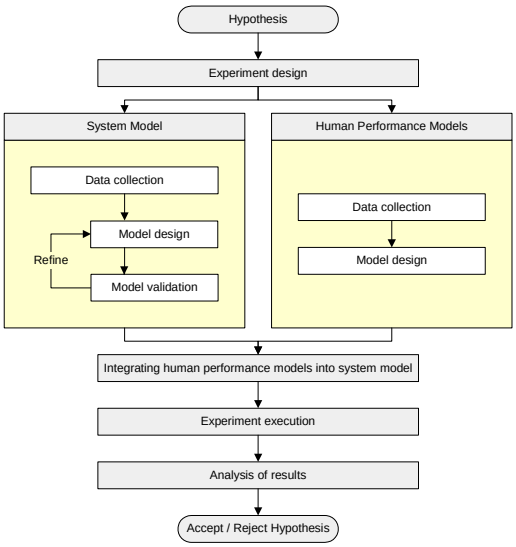

Fig 3.1 Schematic of the research approach

4 MODEL DESIGN

4.1 SYSTEM MODEL DESIGN

The manufacturing system that has been chosen for the simulation study is a section of the final assembly of an automotive engine assembly line in the UK. Engine parts from five sub assembly lines arrive at this final assembly line at different places, are assembled with other parts into a working engine. Three different, but from an assembly point of view, similar types of engine are assembled at the line, depending on the weekly demand for the specific engine types.

Figure 4.1 shows the conceptual model of the line section that has been used for designing the simulation model. The split into five sections is only for display purposes. In reality all sections are directly linked to previous sections. The numbered boxes represent the different workstations: 26 manual and four machining places. The same numbers in two boxes indicates that one operator works at two places. The complete final assembly line consists of 110 workstations. The dark unnumbered boxes represent turntables and bridges. Arrows show the positions of switches where engines can be stopped, either automatically by the control system or manually by the operators.

It has been found that during the period of the data collection the data for the production per hour varies considerably, depending on short-term and long-term problems. For the experiments a period of production has been chosen where there were minimal disruptions.

4.2 HP VARIATION MODEL DESIGN

One of the pitfalls that has been identified by Law & Kelton [8] which can undermine a simulation study is concerned with simulation input modelling: Replacing the input probability distributions by its perceived mean might produce completely erroneous simulation results. The variability of the probability distributions, rather than just their means, has a significant effect on the queue lengths in most queuing type systems and needs to be used as a source of randomness. A second point to take into account is the shape of the distribution. Normal input distributions are commonly used but are rarely appropriate to model a source of randomness such as service times [10].

Therefore the approach used for this paper to consider variations of worker activity times within a manufacturing system simulation model is to use histograms built from empirical data replacing the commonly used mean values derived from time studies. This overcomes both limitations mentioned in the previous paragraph.

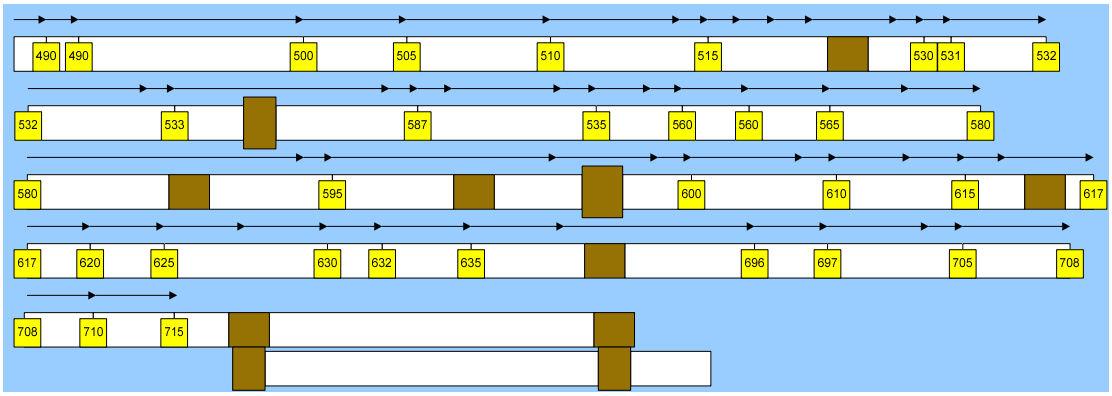

Figure 4.1 Conceptual model of final assembly line section under consideration for the study

On the one hand histograms are used to represent the mean values. On the other hand statistically valid amount of empirical data is used to derive the histograms so the shape of the distribution does not have to be defined by the system modeller.

The HP data have been collected over a period of 12 weeks at ten different workstations and include 2.000.000 data points representing the activity times of assembly line workers. 60 activity time frequency distributions have been designed from the data pool considering the ten workstations for two different crews at three different shifts. More sophisticated consideration e.g. hourly distributions instead of shift distributions are planned in future work.

The simulation model itself includes an algorithm for changing the proportion of the distributions depending on the given work standard activity time. Figure 4.2 shows an example of such a frequency distribution. The workstation where the data was collected had a planned activity time of 22 sec. for one work cycle. If this distribution is used for modelling a workstation with a longer activity time it will be stretched; if the planned activity time is shorter it will be shorten.

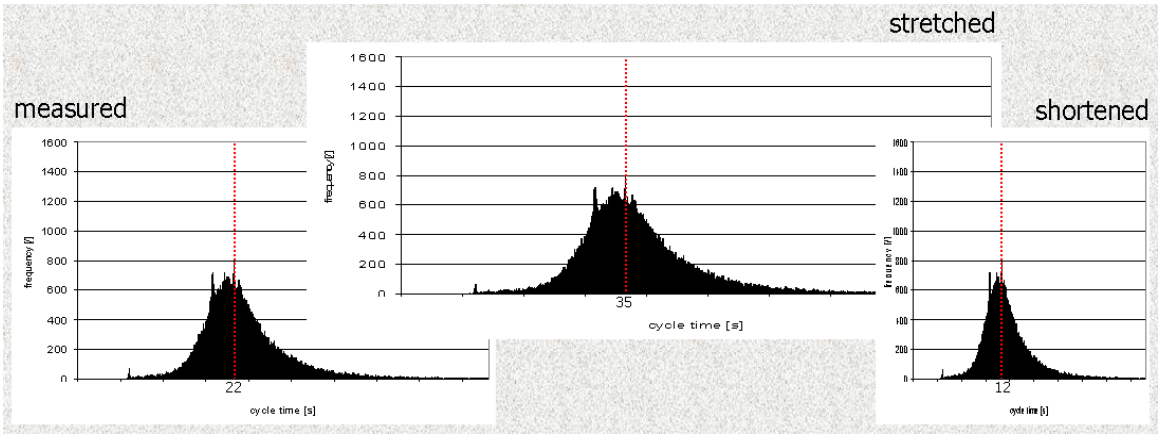

Figure 4.2 Adaptation of frequency distributions for different activity times

5 EXPERIMENTATION AND RESULTS

The objective of the first set of experiments is to help to identify the effect that specific shapes of frequency distributions have on the system behaviour. Therefore the same distribution shape, one out of the ten available ones, has been used for all workers during a series of experiments. 40 series of experiments were conducted considering the ten different tasks for the following four crew set-ups: both crews alternating after each shift, first crew only, second crew only and mean value of both crews.

For all experiments an infinite amount of engines was used as input and the output showed the maximum production rate possible for each shift.

Conditions for each single experiment:

- Warm-up period: 24 hours
- Single test run: 20 days (60 shifts)
- Repetition: ten times using different random numbers

Therefore 400 simulation runs have been completed. The following three diagrams show some of the results.

Figure 5.1 on the next page shows the results of all ten tasks distributions in comparison, alternating the crew after each shift.

The target output for the system is 991 engines per shift, defined in the work standard for this production line. The line marked "ws" in the diagram represents the results when the deterministic work standard times are used during the simulation run. The peaks are due to simulating machine breakdowns. The line marked "real" represents the real output of the system during a smooth running period.

The simulation model predicts that the system is capable to produce nearly the amount of engines that is required from the work standard. Due to machine breakdowns it is 4% below the target. Reality looks a bit different. Here the output is 28% below target.

When discussing these results, however the main limitations of the system model predictability capabilities mentioned in section 3.1 should not be forgotten i.e. not considering the full line and not considering the slow feed from the feeder lines. Looking at the simulation runs for activity time distribution no. 1-10 it can be seen that the frequency distributions have a different impact on the output per shift although they are all built from empirical data.

One interesting phenomena which was the motivation for the next set of experiments is the fact that some of the frequency distributions for the same task differ notably between the two crews. The experiment looks in detail at the frequency distributions of one particular task.

Figure 5.2 shows the empirical frequency distribution of that task for both crews. These distributions also show evidence that different people have different working strategies. The first peak indicates that people work in batches - they walk down the line to do their job and then release a series of engines at the same time. Then they can have a break before they start the next series. The second peak represents the standard working procedure.

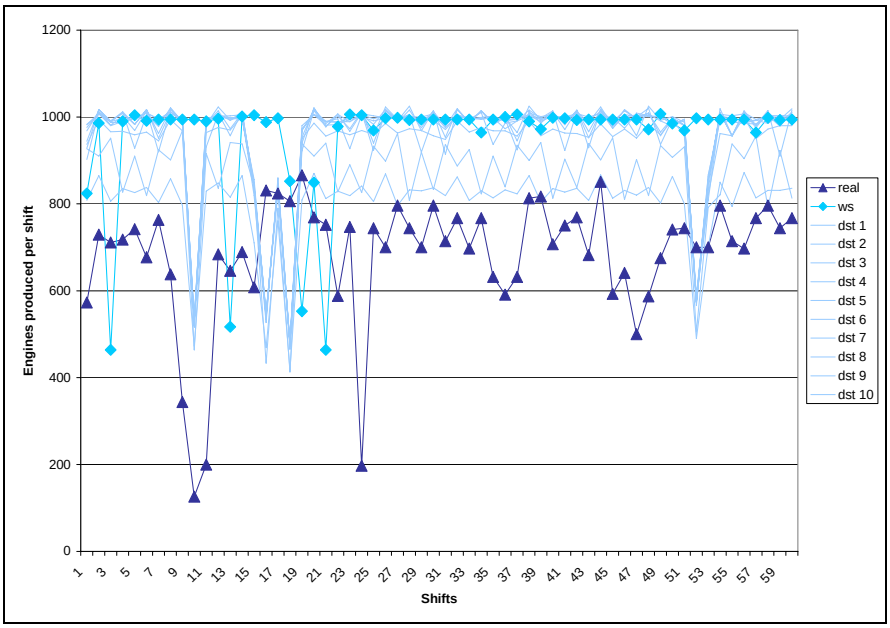

Figure 5.1 Engine production per shift for: 20 days, ten differen tasks, alternating crews

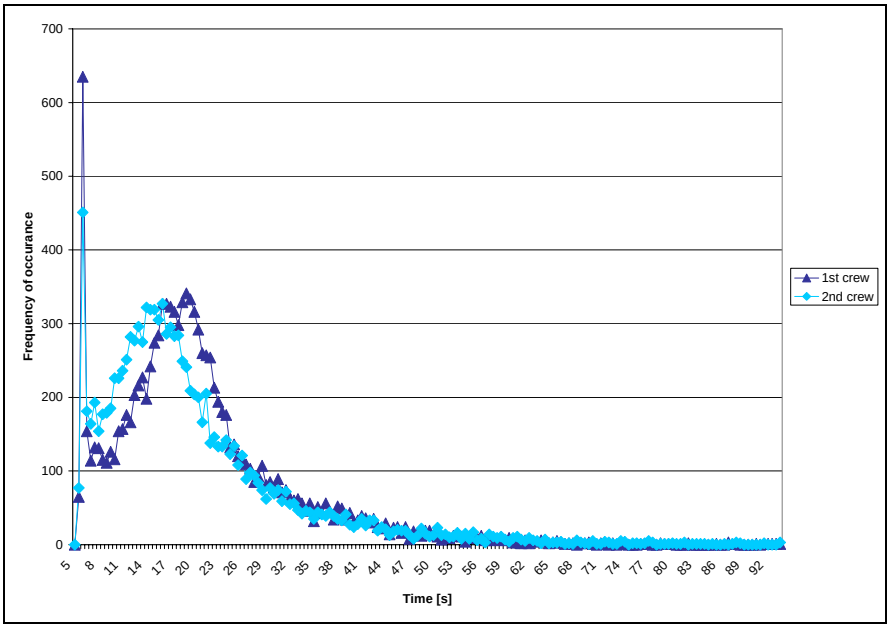

Figure 5.2 Frequency distribution example

When using these distributions in the experiment the results differ notably. Figure 5.3 shows the effect that the differences in the frequency distributions between the crews have on the simulation output.

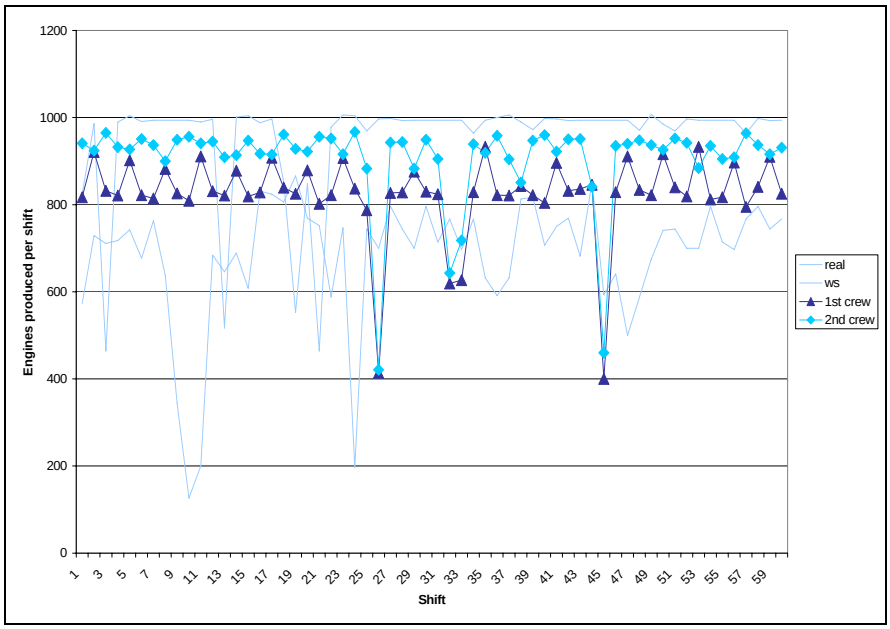

Figure 5.3 Engine production per shift for: 20 days, specific task, both crews separated

As mentioned before the operators are doing the same job but the difference between both crews over a period of 20 days is 9%. This observation suggests that manufacturing system designers have to consider the differences between individual workers as well as workgroups when simulating manufacturing systems.

6 CONCLUSION AND FUTURE WORK

This paper has described the design of a simulation model with enhanced capabilities of taking human variation into account. The models for representing human variation were developed by using empirical activity time data collected over a period of 12 weeks.

The experiments have shown that considering these variations in the system simulation models can influence the output of the system simulation model notably, depending on the shape of the distribution being used. The experiments have also shown that even for the same task conducted by two different crews the output can be significantly different.

So far representative HP modelling in the form of activity time frequency distributions, has been used to represent the changes in human performance over time. Another approach to deal with HPM would be to employ HP modelling. First trials with using predictive HP modelling in the context of manufacturing system design have been conducted by Mason [11] using micro models for modelling influences of age, circadian rhythm, and time since sleep on workers performance. Other predictive techniques which are successfully used in the social science to represent behaviour, e.g. multi agent systems [12], have not yet been adapted into the field of manufacturing system design for this purpose.

The next steps of this project will be to remove some of the simplifications in the system simulation model mentioned in section 3.1. Therefore the model will be expanded to cover the whole final assembly line (closed loop consideration) which includes models of disruptions caused by slow feed from the feeder lines.

This will enable better information to be retrieved about how much of the difference between the simulation model predicted output and the real world production output can be accounted for by human variation as it allows absolute comparison of simulation output and real world production data.

Due to the way in which the data for the activity time frequency distribution has been collected, data about the break taking behaviour of the workers can also be extracted. This data can be represented with frequency distributions as well and used in a similar way to the activity time data to simulate variations in start and duration of breaks.

Following this, more sophisticated ways of modelling the performance of workers using predictive HP modelling techniques are planned. The short-term plan is to explore the effectiveness of modelling dependability of workers by the use of rule based AI and fuzzy sets. In the long term it is planned to investigate the capabilities of using multi-agent based modelling for a dynamic representation of workers and workgroups [13].

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AUTHOR BIOGRAPHIES

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JOHN LADBROOK has worked for Ford Motor Company since 1968 where his current position is Simulation Technical Specialist. In 1998 after 4 years research into modeling breakdowns he gained a M. Phil. (Eng.) at the University of Birmingham where he has lectured on a part time basis since 1996. In his time at Ford he has served his apprenticeship, worked in Thames Foundry Quality Control before training to be an Industrial Engineer. Since 1982 he has used and promoted the use of Discrete Event Simulation. In this role he has been responsible for sponsoring many projects with various universities this resulted in an appointment as a Fellow with Cranfield University in 2001 He is also Chair of the Witness Automotive Special Interest Group. Current areas of research and collaborations are:- With Lanner and Luminova - enabling Manufacturing Engineers with out time and skills to build simulation models in normal 2D and Virtually. With Cranfield University – Researching the feasibility of modeling the effect that people and the environment have on Production Output. With Warwick and Aston University looking at the effect of Human Decision making and the inclusion of AI in simulation.