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USING EXPERIMENTAL DESIGN TO IMPROVE THE EFFICIENCY OF SIMULATION MODELING - A MANUFACTURING PERSPECTIVE

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ABSTRACT

Simulation models represent an abstraction of real life systems in terms of their components, parameters, and relationships. To obtain an acceptable understanding of any simulated system, experiments must be performed on their elements through representative simulation runs. Statistically designed experiments can be employed to improve the efficiency and effectiveness of experimentation with systems - real life or simulated. This technique coupled with simulation modeling provides a systematic and scientific approach to system analysis. At GM, designed experiments are used extensively as part of our simulation project methodology in many large scale projects. This has helped in both reducing the number of simulation runs needed to arrive at a given level of understanding of the system as well as providing a structure for the learning process. This paper discusses experimental design as part of the simulation modeling process from a manufacturing perspective.

1. INTRODUCTION

Design of experiments is a structured approach to problem solving using statistical concepts. A designed experiment is an active (as opposed to passive) approach to understanding any system through systematic and simultaneous manipulation of its variables. This concept, as well as the supporting statistical techniques, has been practised for some time. Statistical experimental design was invented in England by R.A. Fisher in the early 1920s. Fisher's factorial designs were used in the field of agriculture and were aimed at improving crop yields. Since then, designed experiments and related concepts have found extensive application in such fields as medicine, education, biology, engineering sciences, social sciences, and many other areas [Montgomery 1976].

Regardless of the field of application or the type of design chosen, the motives for conducting experiments can be categorized into two main classifications: a) to investigate the relationship of the response measure to the factors of study; and/or, b) to find the optimum settings for the independent factors that result in optimum system performance [Hunter and Naylor 1970]. While there exist other techniques for achieving the above objectives (e.g., regression techniques), a properly designed experiment provides the analyst with a systematic framework to ensure that the efficiency and effectiveness in both data gathering and data analysis are obtained. Efficiency is defined in terms of number of runs required to arrive at a conclusion and effectiveness refers to the accuracy in estimation of main effects and the ability in estimating interactions [Kleijnen 1989].

Furthermore, through simultaneous manipulation of experimental settings, interactions among two or more variables of the system can be identified. This is not attainable in the more traditional "one at a time" approach where only one factor is changed at any one time.

2. DESIGNED EXPERIMENTS AS PART OF THE PROJECT METHODOLOGY

The representation and description of many large scale and complex manufacturing setups can be achieved through simulation modeling. Simulation models describe systems in terms of their components, parameters, and relationships. Designed experiments provide a structured framework for understanding how a system is explained in terms of its elements.

Many issues that are addressed through design of experiments overlap or complement those that are typically dealt with in the simulation project methodology. Furthermore, for maximum effectiveness this framework must be phased over all stages of a typical simulation project. In the following discussion we deliberate on steps in such a process and how it has been applied in practice.

2.1 Forming a Project Team

The project team is formed as soon as it is determined that simulation is the appropriate tool for the study. Typically the team should be comprised of individuals from various departments and perspectives and from different levels of the organizational hierarchy. This ensures that a very thorough and complete view of the system is attained. In addition, the participation and commitment of various levels of the organization is ensured. As an example, project teams may be comprised of a process or industrial engineer who is familiar with the processes, a production supervisor, a production or area manager, a maintenance supervisor, and the simulation analyst. This exercise sets the stage for establishing proper objectives and identifying factors that can potentially influence the system.

2.2 Setting Objectives

One of the most important steps in a simulation project is stating a clear and complete purpose for the study. The objectives of a study determine which aspects of a system are to be studied and what work needs to be done. Stating objectives determines what information is needed and a designed experiment identifies how it can best be done. A designed experimental framework serves as a road map to help the project team remain focused on the purpose and how it can most efficiently be achieved.

2.3 Factor Selection and Screening

Two sets of factors must be identified. These are the dependent (in designed experiments this is also referred to as the response measure) and the independent variables of the study.

The choice of factors of any study depends on the objectives of the study. In many manufacturing settings the primary emphasis is on validating the system's design or performing what-if analysis with respect to the throughput of the system. With the implementation of synchronous manufacturing, a great deal of emphasis is also placed on reducing the work in process and the amount of time spent in the system.

Experimental designs tend to grow very rapidly as a result of the many possible combinations of the independent factors and their corresponding levels. This problem can be more pronounced when experimentation is performed through a simulation model since the analyst has control over the factors and their settings. The greater the number of variables, the more complicated the design becomes and/or effort (human and computer) is needed to adequately study their impact on the response variable (more on this is provided in the discussion of the design matrix). Failure to identify the magnitude of the task may delay project completion time and can be disastrous to the credibility of the simulation project.

From the brainstorming practices of all project team members, a manageable number of factors must be chosen to be included in the study. "Fish bone" or "cause and effect" diagrams can help to organize the factors. There are general guidelines in literature for choosing the independent variables [Overholt 1969], and statistical techniques for screening when too many factors are present [Kleijnen 1987]. In practice, past experience with similar systems and manufacturing "know-how" together with team synergy and focussed objectives play an important and effective role in determining the factors. Due to the large scope of many manufacturing models, other practical considerations and limitations (such as deadlines, computer time, etc.) can also influence the choice or number of factors.

2.3.1 *Importance of Interaction Effects*

Capturing the impact of factors of a study is one of the strengths of a designed experiment. This can be achieved in the "one factor at a time" approach only partially.

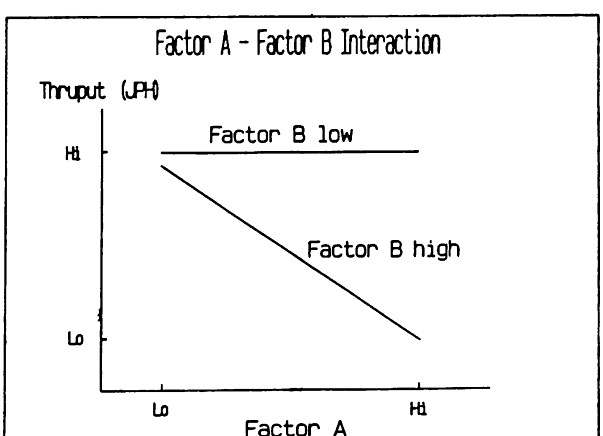

Figure 1. The interaction of Factor A and Factor B in a paint shop.

We emphasize the importance of this aspect of designed experiments through an example of one project which involved a car body paint system. The concern in this particular facility was whether it would be able to meet its production goals. The effects of a number of factors were of interest to the manufacturing plant because of their potential impact on the system's throughput. In particular the system was believed to be effected by changes in two of the variables of the study; Factor A and Factor B.

Upon analyzing the results from the experimental design the only significant effect was due to the interaction of Factor A and Factor B. When both Factor A and Factor B were at a high level the throughput of the system was significantly lower (see Figure-1).

When either Factor A or Factor B was considered individually, neither had a significant effect on the system throughput. If the "one at a time" approach to experimentation had been used in this situation the interaction might have been missed since both Factor A and Factor B would not have been simultaneously tested at their high levels.

2.4 Selection of Design Matrix

It is advisable to keep designs simple. Complex designs may not be understood by other project team members. Furthermore, data analysis for determining the important factors and building meta-models will be easier, less time consuming, and less prone to mistakes. Generally in simulation projects, the analyst has more flexibility in his/her choice of design to ensure that simplicity is maintained (e.g., have balanced designs).

Other considerations in the choice of an experimental design include the number of independent factors, potential interactions, and the levels for each factor. From the brainstorming and factor selection practices, if it is determined that interactions can not be ruled out, then it is best to leave them in. If all interactions are felt to be important then full factorial designs are appropriate. If some of those interactions are felt to be insignificant or non existent then a fractional factorial design can be employed to provide information on the remaining factors and interactions.

If a linear relationship is believed to exist between the dependent and any of the independent factors, then those factors can be set at two levels. If this can not be inferred beforehand for some factors or a non-linear relationship is suspected, then more than two levels of those factors should be considered.

2.5 Model Coding

Identifying the key factors to be used in the designed experiment is very useful for guiding the simulation analyst as to how much detail is required in the simulation model. The choice of variables and knowing exactly what forms of what-if analyses are expected, will also influence coding style. The model code can be built with the required flexibility in those areas where changes are to be incorporated.

2.6 Data Collection

Having determined the important factors and what level of detail to incorporate into the model, attention can be paid to the collection or estimation of the appropriate model input data.

2.7 Model Verification

Often verification is accomplished through sensitivity analysis. This implies changes in the input parameters and monitoring the reasonableness of the results [Banks and Carson 1984, Law and Kelton 1982]. The decision regarding the sensibility of the results can be better judged when simulation runs are conducted with consideration to a designed experiment.

Since many what-if scenarios are presented in the form of a design matrix, the analyst can choose those combinations of factor settings (e.g., paired testing or balanced observations) that can yield the necessary information. Integration of designed experiments into this phase of the project also encourages the analyst to ensure that all aspects of the model are correct and verified because a bug in the model could ruin the experimental design runs and require rerunning the experiments.

2.8 Model and Experimental Design Validation

Model assumptions are validated as part of the project team's discussions. In addition, as part of the design of experiments methodology many questions are raised and discussed that otherwise may have been omitted. The involvement and active participation of various levels of an organization in setting the objectives, selecting factors, etc. further adds to the face validity of the model and in general gives added credibility to the entire project.

As in the verification phase, as a result of the design of experiments, there is a greater incentive to ensure that the model is valid and that no rerunning of any of the experimental combinations will be required. Validation of model output is more easily accomplished under a designed framework rather than through an ad-hoc what-if analysis.

The same runs made for model validation can also contribute to validation of the design matrix itself. If reasonable or expected results are observed, it is likely that a proper design in terms of the factors of study and their interactions has been assumed. If on the other hand, unexpected results are obtained, the analyst can determine if a pattern exists and lead the team in identification of its source.

2.9 Output Analysis

Output analysis is accomplished with maximum efficiency as a result of making observations according to a statistically designed experiment. The purpose for this analysis can be classified into two main categories.

2.9.1 Identification of Significant Factors

One of the most important features of a designed experiment is that it enables the analyst to make use of statistical techniques. By making use of statistical methods, conclusions can be drawn on the existence of any relationships between the dependent and independent factors of the study. Analysis of Variance is performed to identify the sources of variation that are statistically significant in terms of the response measure of interest.

2.9.2 Metamodels and Prioritization of Improvement Initiatives

If the factors of a study are quantitative, regression models (metamodels) can be constructed which explain the dependent factor in terms of independent factors of the study. This relationship can help the analyst in determining which factors have a greater impact on the response variable. On the basis of this information, improvement efforts can be prioritized accordingly.

2.10 Conclusions

Simulation projects of manufacturing systems can result in significant savings. Results gain more acceptance when they are based on a systematic and thorough approach. There is more credibility and confidence in the conclusions because all possible combinations of importance are examined. The recommendations are much easier to justify because confirmation runs have validated the conclusions of the metamodels.

3. EXPERIENCE AT GENERAL MOTORS

At General Motors Corporation, designed experiments in general and Taguchi's contributions in particular have been extensively used for such purposes as quality improvement and product design for some time.

The application of designed experiments as part of our simulation methodology is relatively new. Over the past few years many simulation studies have been conducted that have utilized designed experiments to analyze large and complex systems. These highly automated systems involve a large number of machines, modern sophisticated material handling systems, and are employed in the high volume production of automotive related parts and assemblies. Without a systematic approach to problem definition and systems analysis, it is difficult or impossible to fully understand these systems. Designed experiments have provided the simulation methodology with such a framework for learning about the systems modeled. Furthermore, through designed experiments efficient output data analysis is achieved and has helped in the acceptance of the recommendations by management and engineers.

There exists a lot of overlap and common ground between simulation methodology and designed experiments - both in theory and practice. It has been our observation that the two complement each other very well throughout the entire project lifecycle. The project methodology that has been discussed in this paper has helped our simulation projects to remain focused on the objectives, identify important factors and evaluate their interactions, determine the required level of detail, assist in verification and validation phases, and build more credibility for the results and conclusions.

Our experience with manufacturing systems has been that for the most part little or no interactions of factors can be expected. Through the analyses of many diverse and complex environments, we have found some two factor interactions to be statistically significant. Interactions of three or more factors have rarely been found to be statistically significant. As a result, many of our experimental designs are based on fractional factorial design matrices. These designs are particularly attractive because one can estimate the effects of the key factors more efficiently (by pooling the interactions effects with the error term) with a fewer number of simulation runs.

While there are many advantages in applying designed experiments in simulation projects, in practice we have also recognized a number of considerations. Designed experiments can become large, complex, and time consuming. The more complicated the design and the subsequent analysis, the more the likelihood for human error in design or analysis. Furthermore, the value of the additional information must be weighed against the additional effort and time for data collection, model coding, and subsequent analysis [Hatami 1990].

Excessive analysis can also lead to over confidence in the results. One must never loose sight of the fact that the results and all the subsequent analysis are only as good as the data that has been included in the model.

We believe that for the maximum effectiveness, simulation and other forms of decision support must be made available to the people who are most familiar with the processes. This belief is shared by other groups in other industries as well [O'Loughlin et al. 1988; Tumay 1989]. Through transferring decision support tools to the plant floor engineer's level, a number of advantages are realized. For example, one of the greatest challenges to simulation analysts is to determine those significant characteristics of the system that need to be included in the model. Process experts know their systems best to make key assumptions and recognize the significant characteristics that must be included in the study. In line with that belief, our goal at General Motors is to transfer this tool and supporting techniques to the plant level engineers and system designers as much as possible. Design of experiments requires expertise and sufficient know-how in the field. The efficiency of this technique in data analysis is achieved at the expense of more complexity in designing of experiments and subsequent data analysis. Simulation modeling alone can be a daunting task for engineers who are not full time simulationists. Implementation of experimental design as part of this project methodology further complicates this form of analysis and further distances the part-time users from simulation.

4. CONCLUSIONS

The experience with the application of designed experiments as part of GM's project methodology has been very positive. Although this methodology is more time consuming and requires more effort, it is found to be very effective and efficient. Through team discussions and brainstorming, potentially important factors are identified upfront. This sets the level of model detail and data requirements. The simulation project always remains focused on the objectives, and the experimental design shows very clearly what further work needs to be done. The credibility of simulation projects is also increased by this exercise because of its thoroughness and scientific approach to factor selection and data analysis.

Through this methodology important factors and potential interactions are identified and priorities can be placed on improvement efforts. Recommendations are much more justifiable as confirmation runs on the simulation model are performed and results bear scientific significance.

In practice the fact remains, however, that designed experiments and simulation modeling require expertise and know-how. The acceptance of such tools and techniques by casual users (e.g., engineers with other responsibilities) in manufacturing facilities has not been wide-spread. Efforts are currently underway at GM to address organizational issues, educational and training requirements, and other considerations aimed at institutionalizing modeling techniques.

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