Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

SIMULATION MODEL SIMPLIFICATION EXTENDED ABSTRACT.

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ABSTRACT

There is a need to use simplified simulation models to optimize production planning. However, the simplification is usually based on the gut feeling of experts who do not have time to analyze the various concepts in detail. In this research, a detailed analysis of the simulation model simplification by substituting operations for constant delays was performed under conditions close to the real world. A statistical model was developed to calculate the delay values. The simplification results based on the statistical model are compared with the results based on the detailed model. The experiments were carried out based on the MIMAC dataset 5 model.

1 INTRODUCTION

This research was inspired by one of the Winter Simulation Conference (WSC) 2019 reviewers who wrote: "my understanding is that the reduction approaches only work for a given workload..." and probably the same reviewer at WSC 2020 who wrote, "I am still not fully convinced that reduction approaches can work well." Therefore, this study considers the problem of building simplified simulation models in conditions close to real ones, i.e., when using a changing product mix. For this purpose, it is proposed to use a simplified (hybrid) model, in which a part of the tool sets is simulated in detail, and the other part is substituted for delays derived from a statistical model (metamodel). Usually, metamodels are used to replace the entire simulation model. The main feature of this investigation is the joint use of detailed simulation model elements and metamodel elements. If further developed, we believe that this approach will help to perform optimization based on such simplified models. This research's main contribution is that using the proposed statistical models does not lead to a significant deterioration in the accuracy of the simplified models compared to the simplified models based on the detailed model.

This study discusses the dynamic product mix and has the following goals (see Figure 1): 1) to describe the simulation model simplification approach, which uses a statistical model that predicts the behavior of a detailed model in the future (scenario α_2); 2) compare the results of the developed approach (α_2) with the baseline (scenario α_1 – using a detailed model to get information about its future behavior).

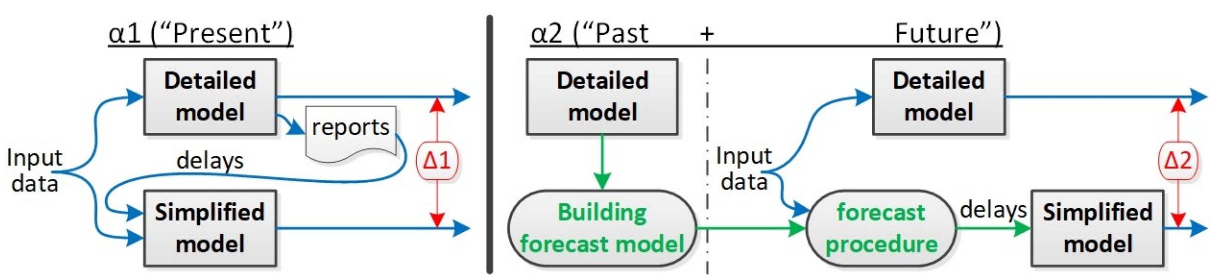

Figure 1: Two scenarios: α_1 ("Present") and α_2 ("Past + Future").

2 DESIGN OF EXPERIMENTS

To implement the experiments in this work, the previously developed automated experimental environment was used. This allowed to build graphs based on 6640 experiments to analyze simulation model simplification (five seeds for each experiment, the total sum of the simulation model runs is 33200). Each experiment represents the substitution of one tool set for a constant delay. Additionally, 14000 runs were performed to calculate delays (2000 for scenario α_1 and 12000 for scenario α_2). Because of the large volume of experiments, it was possible to carry out experiments only with the FIFO dispatching rule. For a detailed description of the design of the experiments, see (Stogniy and Scholl 2020). This section describes mainly the important additions.

In this study, we used the following sieve functions: $\zeta_1 = IDLE\%$; $\zeta_2 = IDLE\% + PROC\% - PROC\%(BS_{AVG} / BS_{MAX})$; $\zeta_3 = (100 - IDLE\%) / IDLE\#$; $\zeta_4 = QT_{AVG}$; $\zeta_5 = QT_{AVG} / PT_{AVG}$; $\zeta_6 = QL_{AVG}$; $\zeta_7 = QL_{AVG} / BS_{MAX}$; $\zeta_8 = CT_{SD}^{total}$; $\zeta_9 = CT_{SD}^{total} / CT_{AVG}^{total}$; and $\zeta_{10} = TH$. The following model statistics based on weekly standard model reports were used: *IDLE%/IDLE#* – the percent of time/the number of times a tool set entered the idle state; *PROC%* – the percent of time a tool set entered the processing state; BS_{AVG} – the average of batches processed (batch size); BS_{MAX} – the maximum quantity of pieces allowed in a batch; QT_{AVG} – the average time lots waited at the tool set (queue time); QL_{AVG} – the average number of pieces in front of the tool set (queue length); PT_{AVG} – the average of the lot processing time for the tool set; CT_{AVG} – the average lot cycle time for the tool set ($CT_{AVG} = PT_{AVG} + QT_{AVG}$); CT_{SD} – standard deviation of the cycle time for the tool set ($CT^2_{SD} = PT^2_{SD} + QT^2_{SD}$); TH – throughput for the tool set (Stogniy and Scholl 2020).

As in the previous paper, process step based delays (η_1) were also used. But instead of tool set based delays (η_2), its improved version, hybrid delays (η_3), was used:

$$\eta_3^X = \frac{RPT_X}{w.avg.RPT}\eta_2 = \frac{RPT_X \cdot \sum_i^n lot\_num_i}{\sum_i^n (RPT_i \cdot lot\_num_i)}\eta_2$$

where RPT_X is Raw Processing Time of X^{th} process step which belongs to the given tool set which has tool set based delay η_2; lot_num_i is the number of lots/week for i^{th} process step; n is the total number of process steps corresponding to the given tool set; *w.avg.RPT* is weighted average RPT. Since we consider a dynamic product mix, the delays were calculated for each week of model time.

3 CONCLUSIONS

In this research, we considered using a simplified simulation model under near-real-world conditions, i. e., when there is no information about the behavior of the detailed model in the future (scenario α_2). For this purpose, we created and described a forecasting model that can be used for any product mix. The key components of the forecasting model are initiating data, statistical approximation, and throughput evaluation. Using the proposed statistical models showed promising results in general. We also refined the way of using the previously developed accuracy measurements for the changing product mix scenario and described the effects that affect the accuracy of the simplified model: the lot cycle time mean shift and butterfly effect. Based on our experiments, we can conclude that applying utilization-based (ζ_2 and ζ_3) and queue length-based (ζ_6) sieve functions leads to acceptable accuracy using the forecasting model (α_2) for our case, the MIMAC 5 model. However, because of the lot cycle time mean shift influence on the accuracy of the simplified model, we cannot claim that for other simulation models, the same sieve functions will show good performance. On the other hand, we can almost certainly state that these effects (lot cycle time mean shift and butterfly effect) will appear for other models as well. The techniques and methods described in this study will allow future researchers to detect this fact in time.

REFERENCES

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