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Optimal Maintenance Resources Allocation Using Automated Simulation-based Optimisation and Data Management

Optimale Allokation von Wartungsressourcen durch den Einsatz von automatisierter simulationsbasierter Optimierung und Datenmanagement

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Abstract: This paper introduces a Streamlined Modelling and Decision Support (StreaMod) approach in which input data management, simulation model generation/update and simulation-based optimisation are synergistically integrated into a largely automated process. The aim of this automated process is to support decision making related to the optimal maintenance resources allocation that could improve the performance of production/logistic systems. The basic novelty of the StreaMod optimisation methodology lies on the formulation of an optimal maintenance allocation problem of a production/logistic system into a bi-objective optimisation problem, so that optimal resources/changes to improve the throughput of the system can be sought in a single optimisation run. The successful application of this methodology in a real-world automotive factory will also be addressed in this paper.

1 Introduction

Global industry, especially the automotive sector, is constantly challenged towards reduced lead times in product realisation projects and increased efficiency in existing operations. Virtual production development tools are of great importance to address these challenges. The use of simulation with the purpose to improve maintenance operations and, thus, increase equipment availability and Overall Equipment Effectiveness (OEE), is a common industrial practice nowadays. Nevertheless, although simulation is commonly used as a performance evaluation tool in industry, to identify the bottleneck of a production system is still not a trivial task. For example, in a recent study at an automotive manufacturer, it was revealed that no

employee (operators, maintenance personal, system developers, and production managers included) was able to point out the current constraint (bottleneck) of their system (Andersson and Danielsson 2013). In the literature, there are various methods for detecting both momentary and steady-state bottlenecks. These include utilisation of machines (Hopp and Spearman 2000), blocking and starving patterns (Kuo et al. 1996), data-driven approach (Li 2009), shifting bottleneck detection (Roser et al. 2001), multiple bottlenecks (Aneja and Punnen 1999) as well as a method based on inter-departure time and failure cycle data (Sengupta et al. 2008). Nevertheless, all of these existing methods suffer from the same deficiency: even if the overall constraint of the system can be identified down to a specific workstation or machine in the system, there is not enough information provided for determining what improvement action(s) has to be taken. These improvement actions can be in form of reducing processing time, e.g., through new tooling. But in many cases, they are related to improving the availability of the workstation. As maintenance is the process that keeps a workstation operational and reduces the variability and failure in its operational availability (Malakooti 2014), improvement actions can therefore be related to how maintenance resources are allocated. For instance, to increase the availability of the system through preventive maintenance to ensure a process to stay operational (i.e. increase Mean-Time-To-Failure/MTTF) and/or effective breakdown maintenance to reduce its down-time. While these improvement actions can be purely technological, e.g. through investing condition-based maintenance, they can also be related to elevating the capability of the maintanence personell through training. Therefore, to identify and improve the bottleneck of a system can be formulated into an optimal maintenance resources allocation problem, which in turn can be solved as an optimisation problem.

The aim of this paper is to introduce a simulation-based optimisation methodology for solving the above-said optimal maintenance resources allocation problem. By using simulation to model the behaviour of the production/logistic system, optimisation can be carried out to predict where the right improvement actions can be put in order to optimally improve the performance of the entire system. It has been observed that the development of a simulation model as well as the input data analysis and update could be too time-consuming, prohibiting the interest of using simulation and hence the optimisation method for decision support in industry. Therefore, the StreaMod (Strealined Modelling) application framework is introduced so that automated data management, automated model generation and the above-said simulation-based optimisation are integrated to provide a 'streamlined' decision support system for production and maintenance engineers. The rest of the paper is organised as follows: Section 2 is about the theory of applying for multi-objective optimisation for optimal maintenance resources allocation, illustrated by a real-world, motivating example in Section 3. Section 4 provides details of the StreaMod framework and why it is so important for decision-making support in industry. Conclusions and current work are given in Section 5.

2 Theory

In principle, improving any system is a kind of multi-objective optimisation (MOO) problems because there are almost always some constraints that restrain the total investment/budget and resources that can be put to the improvement. Interestingly,

to our best knowledge, bottleneck improvement has not been studied adequately within the context of MOO. Consider an MOO problem in its general mathematical form:

$$\text{Minimise/Maximise } f_m(\boldsymbol{x}), \qquad m = 1,2,\dots,M \tag{1}$$

Subject to $g_j(\boldsymbol{x}) \geq 0, h_k(\boldsymbol{x}) = 0, \quad j = 1,2,\dots,J; k = 1,2,\dots,K$

With respect to $\boldsymbol{x} = (x_1, x_2, \dots, x_N)^T$, where $x_i^L \leq x_i \leq x_i^U$ and $i = 1,2,\dots N$.

Here, $f_m(\boldsymbol{x})$ represents the $M \geq 2$ objectives, which can be minimised and maximised with $\boldsymbol{x} \in$ R N as a solution vector (or simply solution), consisted of N decision variables within their respective lower bounds (x_i^L) and upper bounds (x_i^U), which maps a solution in the decision space to the objective space as fi : R N → R M. These solutions also have to satisfy the inequality constraints, $g_j(\boldsymbol{x})$, and equality constraints $h_k(\boldsymbol{x})$. In many MOO applications, where the objectives $f_m(\boldsymbol{x})$ are in conflict with each other, finding a single best optimal solution is impossible because improving one objective would deteriorate the others. This gives rise to the concept of Pareto-optimality, describing the set of optimal solutions which are the best trade-offs with respect to $f_m(\boldsymbol{x})$. In order to determine such a set of optimal solutions, popularly known as Pareto-optimal solutions, the concept of dominance is commonly used by many MOO algorithms:

Definition 1: A solution $\boldsymbol{x_1}$ is said to dominate the other solution $\boldsymbol{x_2}$, if both of the following two conditions hold true:

1. The solution $\boldsymbol{x_1}$ is no worse than $\boldsymbol{x_2}$ in all M objectives. So without loss of generality, if we consider a problem of minimising all $f_m(\boldsymbol{x})$ objectives, then $f_m(\boldsymbol{x_1}) \leq f_m(\boldsymbol{x_2})$, $\forall\ m = 1,2, \dots, M$.
2. The solution $\boldsymbol{x_1}$ is strictly better than $\boldsymbol{x_2}$ in at least one objective, i.e. $\exists\ j \in (1,2,\dots,M)$ such that $f_j(\boldsymbol{x_1}) < f_j(\boldsymbol{x_2})$.

The basic idea proposed in (Pehrsson et al. 2011) was based on an observation that many decision-making situations in production system improvement projects can be effectively formulated into an MOO problem. While the primary objective is usually related to a key performance measure, such as system throughput (TH) or cycle time, the novelty of our approach is on formulating the investments needed to improve various attributes of the system as a summation function to represent the second objective of the MOO problem. For example, if the production system throughput, TH is the primary objective for the improvement so that $f_1(\boldsymbol{x})$=maximise(TH), then we can define the total number of changes, i.e. improvement actions, as minimise($f_2(\boldsymbol{x})$) in the MOO problem. In this paper, we consider three types of discrete, two-level parameters that can either be set to the system's original value or to a value representing an improvement action: workstation cycle times (C), workstation availability (A), and workstation mean down time (D). In other words, mathematically, the second objective in the MOO problem can be represented by the summation function if there are totally N workstations:

$$f_2(x) = \min\left(\sum_{i=1}^{N} \hat{A}_i + \sum_{i=1}^{N} \hat{C}_i + \sum_{i=1}^{N} \hat{D}_i\right) \tag{2}$$

where:

$\hat{A}_i = 0$, if availability of workstation *i* is not improved and remains to be β_i, or;

$\hat{A}_i = 1$, if availability of workstation *i* is improved (increased) from β_i to $\hat{\beta}_i$.

$\hat{C}_i = 0$, if cycle time of workstation *i* is not improved and remains to be α_i, or;

$\hat{C}_i = 1$, if cycle time of workstation *i* is reduced from α_i to $\hat{\alpha}_i$.

Similarly, $\hat{D}_i = 0$, if the mean down time of workstation *i* is not improved and remains to be γ_i, or; $\hat{D}_i = 1$, if mean down time of workstation *i* is improved (reduced) from γ_i to $\hat{\gamma}_i$.

In this way, the second objective function is a discrete function that varies in the range [0, 3*N*], because the maximum number of changes can only be 3*N*. Figure 1 illustrates this bi-objective problem in a graphical way, showing how the Pareto-optimal solutions in the objective space can be used for supporting the decision making in choosing the optimal (minimal) changes to improve the system to achieve the target throughput (e.g., the throughput TH_t in fig. 1).

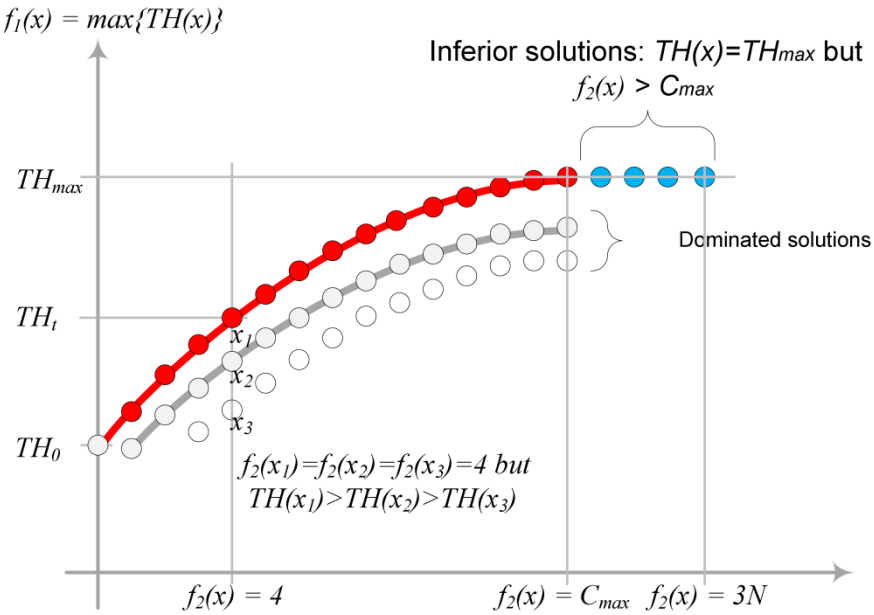

Figure 1: *MOO results for decision making of system improvement.*

3 A Motivating Industrial Application

This section addresses how a real-world improvement project was solved by MOO which effectively identified the exact areas of optimal improvements in production

and maintenance parameters to reach the desired target condition. The complex production line is an automotive component machining line that includes multiple parallel sections, portal cranes, machining centres and assembly stations which conduct multiple operations. Apart from some maintenance issues that affect the machine availabilities, tens of variants have to be processed in the line and variations in the weekly volume contribute to the high variability of the system. The crucial issue of the company was the poor production capacity of this line, far below the required capacity to keep up production, which made it the "bottleneck" of the entire plant. An improvement project was in order but given the size, complexity and variability of the line, it was believed to be extremely hard to locate where and what to improve, let alone the effect of performing the improvements, if only traditional simulation tool had been used. And it was obvious that not a single, but multiple improvement actions had to be made in order to achieve the targeted throughput level demanded by the management of the company. The engineers in charge decided to build a simulation model. Several versions had been developed but the latest complete model as shown in figure 2 was built in FACTS Analyzer (Ng et al. 2007). The rapid modelling, easy to learn and use features of FACTS Analyzer has endowed the possibility for the engineers to build/update simulation models for their own production lines.

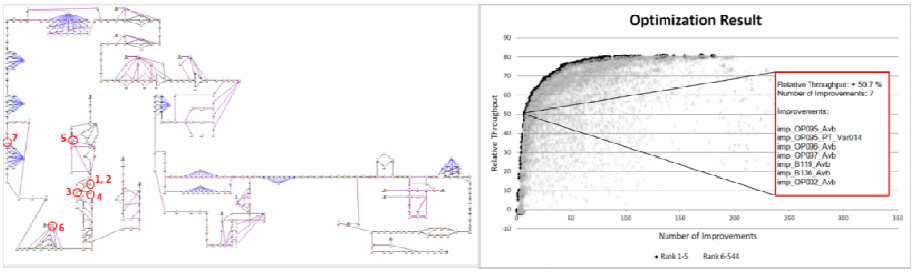

Figure 2: *The simulation model and MOO results from a real-world production system improvement project.*

When the model was completed and validated, the project manager called upon all production and maintenance engineers in charge of the production line together in some workshops in order to propose all possible improvement options, including reduced processing times (per variant where applicable), increased availabilities, and reduced mean times to repair (MTTR). The levels of the improvement (from the original value) are varied between different work-stations. Table 1 lists the number of improvement variables of each type and also the range of the improvements of that type, e.g. the processing time reduction ranges from only 0.2 % for one station to 41.8 % for another station. That summed up to be 464 improvement alternatives represented in the optimisation problem as binary Multiple Choice Set (MCS) variables, for more detail see (Bernedixen and Ng 2014).

Table 1: *Number of decision variables and the range for their improvements*

Number of variables of this type	*Number of variables*	*Range (min-max)*
Processing time	317	-0.2% to -41.8%
Availability	82	+0.1% to +23.8%
MTTR	65	-5.5% to -92.1%

The optimisation results, in form of Pareto front, showing the optimal trade-offs between minimising the number of improvement actions and maximising throughput generated in the project using the well-known NSGA-II algorithm (Deb et al. 2002) are also shown in the data plot in figure 2. In order to conceal the real figure of the company, here only relative throughput, expressed as relative change in percent from the original state (i.e. no improvements), is displayed. It can be seen that the optimal improvement actions found in the optimisation could improve the system substantially up to 80 % and a significant improvement (about 50 %) can already be reached with only seven improvements, as indicated in the data plot in figure 2. These seven areas of improvement are labelled in the snapshot of the model and note that four of them are centred around one single production area. These optimisation results actually surprised the production engineers as they had believed that the major problematic areas that should be improved and prioritised were somewhere else. With further engineering/maintenance investigations on how to achieve the optimal improvement actions, subsequent decision making was made largely based on this set of optimisation results plus more simulation runs to verify the final decisions before implementations. The engineering team also concluded that the optimisation results also greatly facilitated their discussions and cooperation as well as supported their decision making when compared with only traditional lean methods and tools had been used. Nevertheless, the most daunting task identified in the project which yet to be solved if the same method has to be used for other lines, was data collection for updating the input data of the model. As a matter of fact, data collection alone is a critical issue in any simulation modelling project and an automated process to collect and update the model data is badly needed if such an optimisation method has to be used in a regular (weekly) basis to continuously improve the performance of complex production system.

4 StreaMod: System Framework

As hinted above, a major challenge for increasing the use of virtual tools for the purpose of increasing the efficiency of existing production system is to reduce the often extensive lead times of simulation studies. There is also a need to increase the usability of these tools especially among production and maintenance engineers. A current Swedish research project called StreaMod is addressing these challenges by building a framework for automated connection of input data collection and analysis, simulation model generation, and optimisation.

Most previous research in the area has been directed towards increasing efficiency of the separate activities of the simulation modelling procedure, e.g. input data

management, model generation, and output analysis. These efforts have, for example, resulted in software solutions such as the GDM-Tool (for automated input data management) and FACTS Analyzer (for efficient model building and optimisation). Nevertheless, to reach the desired lead-time in simulation studies, these steps need to be fully integrated.

4.1 StreaMod Purpose and Aim

Based on the challenges outlined above, the purpose of the StreaMod framework is to enable more facts-based decisions in production development related to lean operations and plant design. This will be reached through dramatic reductions of the times used in both data collection, modelling, and generation of decision support. Such a new type of decision support system is also necessary to turn today's substantial system losses into a potential for improved economic and ecologic sustainability.

Advanced analysis of production data, in combination with simulation model building and optimisation, can provide both detailed and visual input to continuous improvements as well as conceptual design. A key component for such decision support system is dramatically reduced time from data collection through model building and optimisation. Improved interfaces and user focus is also necessary to facilitate dissemination among production and maintenance engineers. A major challenge is to provide the necessary technical solutions and to combine them with manual work procedures making the results generic in terms of different organisational structures.

In order to fulfil the purpose, the specific aims of the StreaMod framework are:

- Reduce lead-time for simulation of production flows to <24h response time, including data collection, model building, optimisation, and improvement suggestions.
- Proven identification of improvement potential never detected by analytical analysis, resulting in 10% increased throughput at our demo-lines.
- Extended user base among production and maintenance engineers and more frequent use of modelling techniques in production systems analysis.
- Increase the amount of quality assured data compared to current assumptions and guesses.

4.2 Framework Components

The StreaMod framework is divided into several integrated components. The decision support system is the "user interface" providing a set of automated analyses for the targeted production and maintenance engineers. Further, the components for efficient input data management, model generation and optimisation are integrated using a solution based on Intelligent Data Points (IDP). There is also a component providing manual work procedures, mainly for assuring high quality of input data and for complementing missing parts of raw data.

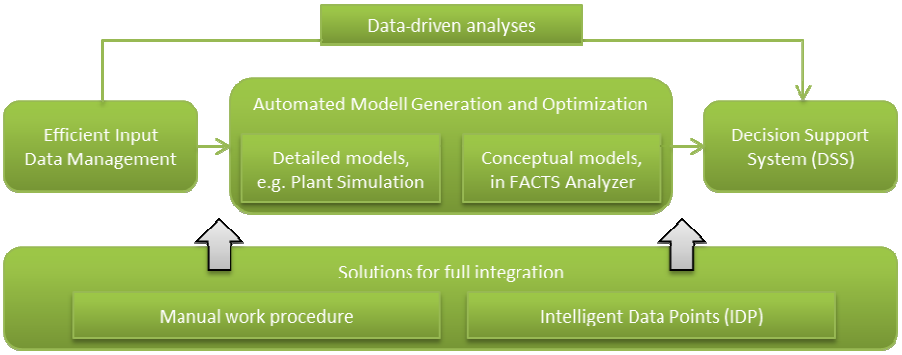

Figure 3: *StreaMod framework*

4.2.1 Decision Support System

This component provides a decision support system (DSS) that can be used to support high-quality decision making in production systems design and improvement in industry. Apart from the common features in an ordinary DSS, like visualisation, scenario development, user interaction, database and knowledge-base management, the uniqueness of the new DSS is built on the concept of integrating data-driven analyses, simulation, optimisation and data mining technologies within a unified framework. An aim is to show how production constraints and corresponding improvement proposals as shown in Section 2-3 can be generated as daily reports automatically using the simulation model generated for real-world projects. In order to generate valid improvement proposals automatically, the simulation models must also be generated automatically.

4.2.2 Efficient Input Data Management

This component increases the applicability of simulation and optimisation as well as purely data-driven approaches by reducing the time-consumption for collecting and preparing the necessary input data. Correct input data is crucial for facts-based decision support using any detailed analysis method, specifically when considering dynamic aspects of production systems. The procedure of managing this data is currently a major contributor for extensive lead-times of simulation studies due to the vast amount of samples required. Hence, this is a common reason for companies to renounce these powerful approaches in favour of less detailed and precise methods. This is specifically problematic in operational phases when answers are expected in just days or hours.

A crucial capability is to automatically combine and integrate data from major PLM systems (e.g. SIEMENS' Teamcenter) with local data sources (e.g. systems for real-time collection of downtimes and cycle times). This is necessary for both simulation and data-driven analyses. The development of automated input data management is based on prior research on the GDM-Tool (Skoogh et al. 2012).

4.2.3 Automated Model Generation and Optimisation

This component provides the required automated model generation and optimisation algorithms for the DSS as exemplified earlier in this paper. The concept of auto-

mated model generation was first explored and successfully demonstrated in FACTS Analyzer, but unlike the technology introduced in FACTS that a detailed model (e.g. Siemens Plant Simulation) can be generated and subsequently extended from a simple line specification, the StreaMod framework requires exploring the technology to generate simulation models from the automated data management system in an on-line basis. Another major challenge is on how the automated model generation can seamlessly support the automated optimisation required by the DSS.

4.2.4 Integrated Data Management and Model Generation

The integration of previously explained components is enabled by the automated, seamless model generation based on IDP. IDP is used for automating the connection between model generation and data collection/processing using data intelligence, i.e. data will be automatically requested by recognising model entities and finding related data and information from global and local sources online. Automated import of model entities and logics from PLM system is also provided through IDP – i.e. customised IDPs that connect to PLM entities. The integration of FACTS and the GDM-Tool is then realised by a standard format for sharing information between these data and modelling applications.

4.2.5 Integrating Work Procedure

This component describes a general work procedure for integrating data sources and simulation model with a focus on identifying and quality assuring available data and completing unavailable data with manual gathering. One important example is instructions specifying responsibility and frequency for updating sources production data. Despite the focus on data sources and gathering, the work procedure aims to cover all parts of the information chain of the StreaMod framework, e.g. including instructions on the use of the DSS. The major challenges are to turn the existing, general approach, into practical work procedures similar to project management models. Furthermore, the work procedure has to be adaptable to the different organisational structures exemplified by major automotive companies as well for Small and Medium-sized Enterprises (SMEs) and clients to consultancy firms.

5 Conclusions and Current Work

This paper has introduced how optimal maintenance allocation can be formulated into a bi-objective optimisation problem in order to improve bottleneck of production systems. As a matter of fact, by formulating a bottleneck improvement into an MOO and then generate an optimal efficient solution set is only part of a complete solution because various issues, including computationally expensiveness; incorporating preference of decision maker, if any; the analysis of the factors which contribute to the best trade-offs, as well as automated input data collection and update for the simulation model, are equally important. The last issue is addressed in this paper as a key objective of the StreaMod project in Sweden. The StreaMod framework is now being implemented in this industrial-based project, aiming at a complete system prototype for the try-out in Swedish automotive industry.

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