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From performance analysis to efficiency improvement strategy: A data-driven approach

An MDEA-based stepwise benchmarking framework in a dynamic supply chain setting

Contents

Management Summary

Data has become indispensable in today's society, likewise in business and industry. Utilizing data has become more and more important in the decision-making process. Accessing data in the correct matter such that companies can act upon it, could provide insights on the production performance and could unfold improvement strategies on the longer run. Accuracy of these planning parameters, such as production yields and required resources, is therefore essential in the era of continuously innovating industries with higher societal and governmental expectations and regulations regarding sustainability.
In the research conducted by Greijmans (2019), in collaboration with EyeOn, a framework is developed that could be implemented to gain insight on actual planning parameters, actual production performance and to present steps required to improve efficiency and sustainability in planning. In order to measure the performance of production processes over consecutive periods, a multi-period data envelopment analysis (MDEA) method is adapted and extended by benchmarking each inefficiently produced product in a stepwise fashion. These benchmark steps are then combined into a production efficiency improvement strategy for tactical planning.

On the road to lean factories and sustainable production

Despite the rapid disruptions in the field of information technology and data sciences, the applications are not yet widely introduced in supply chain optimization and planning processes. Large amounts of production, sales and delivery logs (production and planning data) are available, generated by continuously monitored production processes. Companies become more and more entangled in complex data systems with multiple information sources, and encounter difficulties of extracting adequate production figures. We could say that they operate in a 'data-rich yet information-poor' environment (Shang, Yang, Huang, & Lyu, 2014). These production figures, i.e. planning parameters, are essential for improving production performance in a highly dynamic supply chain. Performance may be improved by, for example, increasing productivity and minimizing used resources and produced waste. Intense competition, increased demand for customized products and shortened product life cycles has led to a range of production strategies, such as Industry 4.0. Industry 4.0 digitizes and integrates end-to-end processes with its supply chain partners and is based on smart factories, smart products and smart services through technologies such as the Internet of Things (IoT) (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014).

Providing insights on actual parameters for planners has a positive impact on costs; working capital is better allocated and revenue is increased as capacity and demand is better matched. It is not only in the interest of the company to improve productivity in order to increase market shares. Companies are nowadays more susceptible to changing environments than ever. The impact of industrial production on the environment has led to increasing awareness regarding global climate warming and environmental pollution. Because the consumption of non-renewable resources, such as petroleum and coal, increases, the industry needs to achieve high flexibility and efficiency as well as low energy consumption and cost (Wang, Li, & Zhang, 2016). With up-to-date planning parameters, planners can reduce waste (in all forms) by improved inventory levels and better resource allocation and transportation, such that the overall planning process is improved. Furthermore, having the data available on sustainability performance enables us to evaluate the impact of production on the environment and to develop steps leading to increased sustainability.

Integration of information technology (Industry 4.0) with information management is essential to obtain a certain level of agility (Wu, 2018). This is because organizations with agile supply chains are able to respond better to uncertainties and changes since they are better able to synchronize supply with demand through high responsiveness along the supply chain and convert changes into business opportunities (Swafford, Ghosh, & Murthy, 2008). The merging of manufacturing and warehousing systems with production plans and logistics is captured in cyber-physical systems (CPS), which enables so-called 'smart production'. Such smart factories require vertical integration of various components in a factory and networked manufacturing systems.

The implementation of smart factories combines smart objects with big data analytics. Smart objects are used for reconfiguration while big data analytics can provide global feedback and coordination to achieve high efficiency (Wang et al., 2016). Smart production features high interconnection between data management systems, mass data analytics and deep integration to sustain the planning feedback loop. Aside from having data available in the correct place and time, a translation of prior knowledge and human know-how into a knowledge base of various processes and rules must also be made in order to make rapid and appropriate decisions about complicated production processes (Li, 2016). Companies operating in such environments must adapt flexible production technologies, such as 'lean production' often used in agile manufacturing. Lean producers have the ability to respond quickly to customer demand by shifting between product models or between product lines (Kretschmer, Pfouga, Rulhoff, & Stjepandić, 2017). The essence of lean production is minimizing waste while ensuring quality. However, many companies experience difficulties in the integration of physical operations level and tactical planning level; they are not aligned in terms of data. As a result of this, tactical planning often does not reflect real situations on production level, let alone enables for lean production. Furthermore, in order to increase sustainability, manufacturers must know what the current level of sustainability is and what measures lead to a decrease of negative effects on the environment. In the work of Greijmans (2019), the aim is to provide an approach for data-driven decision-support for production planning to decrease waste and increase sustainability.

Disconnected supply chains

Due to highly dynamic environments, companies should constantly evaluate and revise production strategies (Dengler, Schönmann, Lohmann, & Reinhart, 2017). In order to do so, parameters on which production planning is based must match reality. Even better: tactical planning must be based on actual planning parameters resulting from real-time production and planning data. In order to include sustainability goals on a tactical level, companies should have insight into the actual performance of the production processes. Due to a lack of knowledge, two main problems arise with respect to the internal information flow within the planning process.

- **Disconnection**: production data is often available in large amounts but is often inconsistent and highly dispersed among multiple ERP (enterprise resource planning) platforms. Therefore, there is no general approach for outlier detection and estimation for missing parameters. Missing production parameters that are often estimated manually are among others:
    - lead times (from production, delivery or quality handling);
    - yields and waste percentages;
    - speed of works or outputs per shift.

As a result of this, the planning process is disconnected from the production process: there is no interaction between execution and planning, see Figure 1. Tactical planning is therefore difficult because of lack of visibility on the actual production process and its impact.

- **Sustainability:** data on sustainable aspects is often sparsely available or not monitored at all. Even if such data is available, there is no suitable approach to evaluate the sustainability performance of a production process including different kinds of aspects such as carbon dioxide emissions, water consumption, etc., without using conversions of these parameters into a single quantifiable unit (such as a monetary unit).

The first problem has a great impact on sales and operations planning (S&OP) within tactical planning. The essence of S&OP is matching supply with demand and deciding upon how much to produce for which customer, see Figure 2 for the different planning levels. Such decisions are often based on rough calculations based on manually estimated production parameters. Planning scenarios resulting from this are often far from efficient (in terms of sustainability) and could even be infeasible to achieve. Furthermore, if a company wants to increase sustainability, a strategy on tactical level is needed. But due to a lack of knowledge on sustainability performance, developing such a tactical plan is very difficult.

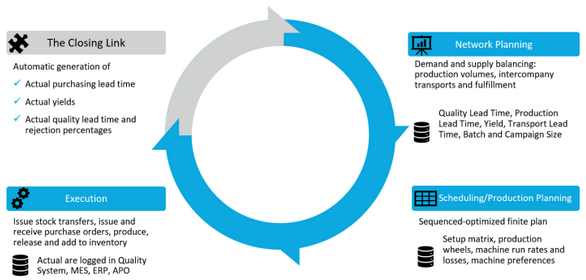


Figure 1 The closing link connects the production process with tactical planning

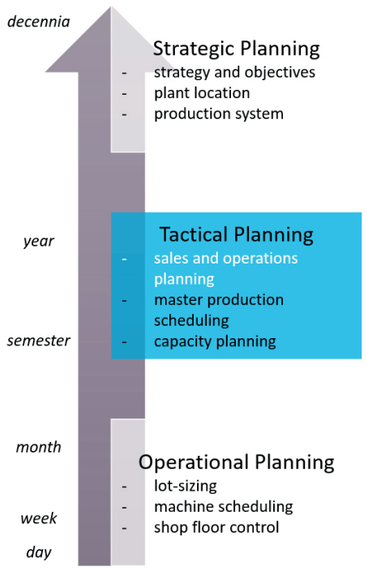


Figure 2 Different planning levels (Fleischmann & Meyr, 2003)

Data-driven S&OP

For enterprises to become agile and for S&OP match real-time situations, we introduce data-driven S&OP, in which S&OP decisions are made based on actual production parameters and thus reflect real-time situations, rather than intuition or personal experience. The challenge is incorporating planning and production data in the decision-making process in order to increase sustainable performance. Therefore, a framework was developed that supports decision-making on a tactical level by presenting an overall efficiency improvement strategy (Greijmans, 2019). Furthermore, with the framework, we can study the differences with the theoretical planning parameters compared to the actual, logged, planning parameters. In other words, how do the theoretical efficiency scores compare to the actual efficiency scores?

To capture the effect of using current – possibly inaccurate – parameters compared to actual logged parameters, we focus solely on the production performance evaluation. This performance evaluation of each product, comparing consumed resources with production output, could support S&OP decision-making and provide insights on how the production process and sustainability could be improved. A production process (input) has multiple types of attributes and can, therefore, include multiple types of unit measurements, especially when we include sustainability aspects such as carbon dioxide emissions, energy consumption and waste of resources. Since we do not know the exact relations of these production inputs and we cannot always express them in a monetary value, we propose data envelopment analysis (DEA) to compare performances to the production processes of multiple products. DEA is a data-oriented non-parametric method, developed by (Charnes, Cooper, & Rhodes, 1978) to assess the performance of a set of decision-making units (DMUs), with multiple inputs and outputs. By linear programming, DEA classifies DMUs either as efficient or inefficient by measuring the performance score of each DMU. In the developed framework, we treat every production process for each product as a separate DMU. Hence, each DMU consumes certain resources and yields certain gains; these are referred to as input and output factors. In this example, we focus on production process attributes such as production yields and the required production resources, see Figure 3 for the representation of a production process as a DMU. Additionally, environmental and operational attributes, such as water consumption and CO2 emissions in transportation, could be included in the analysis.

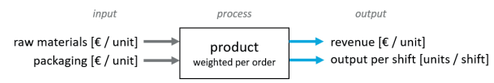


Figure 3 Production process represented as a Decision-Making Unit (DMU)

After the actual production parameters are extracted, we use multi-period DEA to evaluate the production performances of the produced products, for each evaluated period (on a yearly, quarterly and monthly basis). In order to close the link on the tactical planning level, we provide production improvement steps for the decision-makers, at a product level. These steps – referred to as benchmarking steps – relate to, not only to a single production factor, but all its production process attributes. By collecting this information, an overall strategy can be developed that provides steps needed to improve the entire production performance. Figure 4 summarizes the three steps within the framework. The blue squares indicate company input.

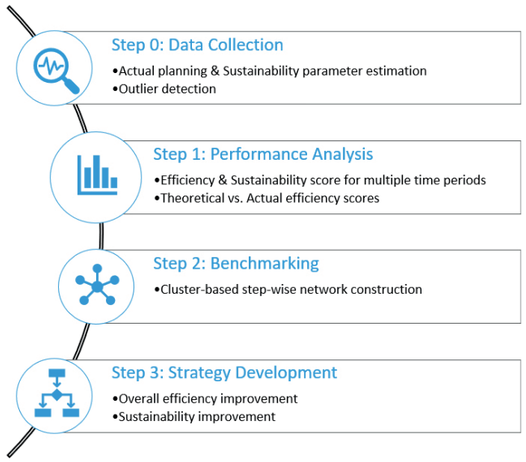
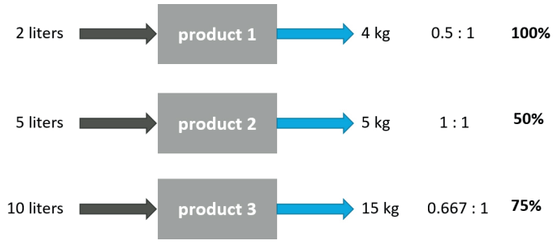


Figure 4 Framework for data-driven S&OP: An MDEA-based stepwise benchmarking framework

Intermezzo: Data Envelopment Analysis Examples

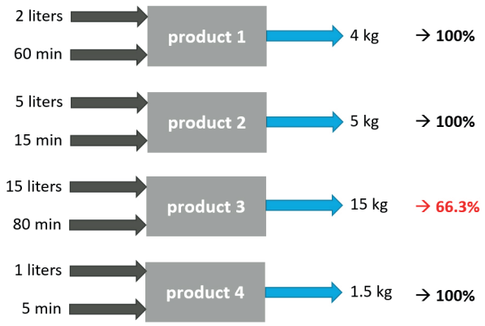
3 products with single input and output factors

By looking at the ratios of the input and output factors, we can reason that the first product is produced most efficiently, followed by the third product. The second product is produced less efficiently. In general: the lower the input factors (consumed resources) and the higher the output factors (production output), the higher the efficiency scores.



4 products with 2 input factors and 1 output factor

Using the same trick as before becomes more difficult if we add more products and more factors. We cannot simply calculate the ratios of input and output factors since we have two input factors and we do not have a simple conversion rule to express liters into minutes.



By applying the mathematical model (linear programming) below, we can calculate the efficiency scores. For this example, we can conclude that the third product is produced inefficiently as it scores lower than 100%. The other three products are produced relatively efficient (given this set of products and production factors).

For the set of DMUs J containing n products of which each product $j \in J$ consumes amount x_{ij} of input $i \in I$ and produces amount y_{rj} of output $r \in R$, the classical input-oriented DEA model is as follows:

$$
\begin{aligned}
\text{maximize} \quad & \sum_{r \in R} \mu_r y_{rj_0}, \\
\text{subject to} \quad & \sum_{r \in R} \mu_r y_{rj} - \sum_{i \in I} \nu_i x_{ij} \leq 0, && \forall j \in J, \\
& \sum_{i \in I} \nu_i x_{ij_0} = 1, && \forall i \in I, r \in R, \\
& \mu_r, \nu_i \geq 0 && \forall i \in I, r \in R,
\end{aligned}
$$

where μ_r and ν_i are virtual multipliers (decision variables) and represent the weights of input $i \in I$ and output $r \in R$ respectively. The efficiency score is calculated as follows:

$$E_{j_0} = \frac{\sum_{r \in R} \mu_r^* y_{rj}}{\sum_{i \in I} \nu_i^* x_{ij}}.$$

Example: results from an EyeOn customer

We used ERP data from an EyeOn customer. Via SQL queries and Python scripts, the data is collected, and the framework is programmed. The following sections describe the results.

Step 0: Data Collection

We collect both theoretical and actual planning parameters. The theoretical parameters are used in the planning process, while the actual planning parameters are acquired by processing production logs. Figure 5 shows some examples of how the theoretical yield parameters (blue lines) compare to the actual yield parameters (grey bars). Each bar indicates a single production order. For most products and for most production orders, the theoretical yield overestimates the actual yield. In other words, the number of products produced per shift is overestimated and planning with these parameters could, therefore, lead to infeasible production plans.

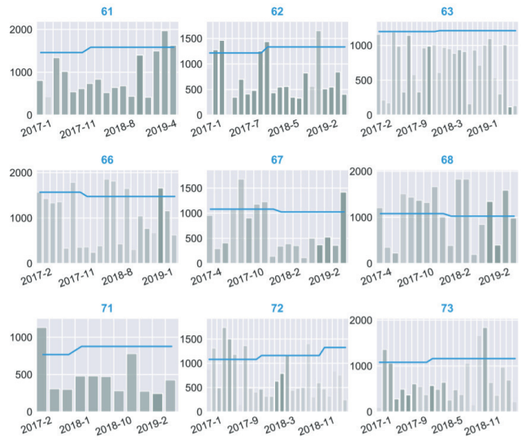


Figure 5 Examples of theoretical (line) vs. actual (bars) planning parameters of the yields

Step 1: Performance Analysis

By performing the performance analysis, we can compare the theoretical efficiency scores with the actual efficiency scores. Figure 6 shows how the actual efficiency scores (blue bars) compare to the theoretical efficiency scores (grey bars). For this set of products, we see that the theoretical efficiency scores are often higher than the actual efficiency scores. We also concluded that the scores are significantly different, as a result of the significantly different input and output production factors (from the data collection phase).

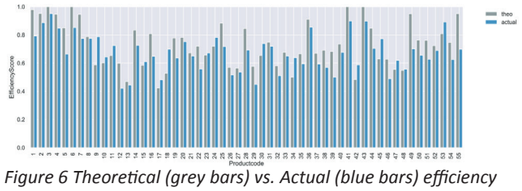


Figure 6 Theoretical (grey bars) vs. Actual (blue bars) efficiency scores

We proceed the framework with the actual production factors and actual efficiency scores. We can also calculate the efficiency scores per product group or production line, and per year, quarter or month. Figure 7 shows the distribution of efficiency scores for the products contained within different product groups (1 to 6). We can see that product groups 5 and 6 contain products that are evaluated with lower efficiency scores. The performance of these products is, therefore, lower compared to the products of the other production groups. The resources of these products must, therefore, be better allocated.

We also see that by decomposing the evaluated periods from a yearly to quarterly to monthly level, yields lower efficiency scores. This is because, on a yearly level, the production factors get averaged over a longer period, compared to, for example, on a monthly level. This smoothing effect vanishes if we evaluate the production processes more frequently. In particular, the model becomes more sensitive to outliers (extreme production factors), and as the model is fully data-driven, it is also sensitive to these outliers. Data quality and outlier detection is therefore extremely important for data-driven S&OP.

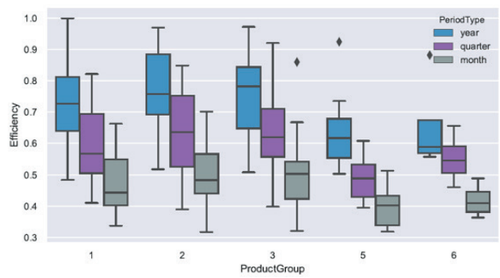


Figure 7 Actual efficiency scores per product group per year, quarter and month

Step 2: Benchmarking

We perform the benchmarking process for the inefficiently produced products (scores less than 100%). The benchmarking is done in a stepwise fashion; per product and per evaluated period, we collect the target products. This process is depicted in Figure 8; product 12 forms a target for product 46. If product 46 adjusts its input and output factors to a level of product 12, then product 46 benefits from a certain efficiency improvement. The thickness of the magnitude of production factor change.

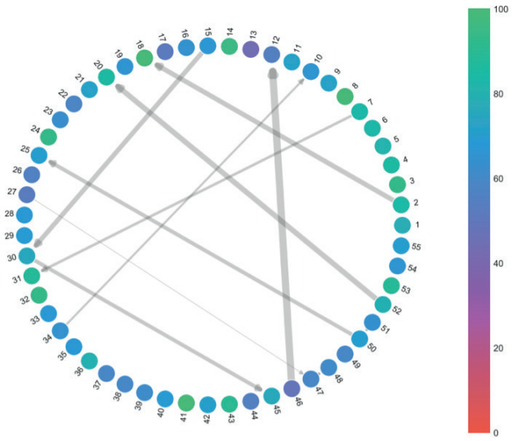


Figure 8 Nine benchmark steps

Furthermore, we also perform clustering; we only accept certain changes in production factors which we control with certain benchmark levels. The higher the benchmark level, the higher the difference between inefficient product and target product may be. From Figure 9 we can see that the higher the benchmark levels are, the higher efficiency improvements are obtained. The maximum efficiency improvement increases rapidly as the benchmark levels increase.

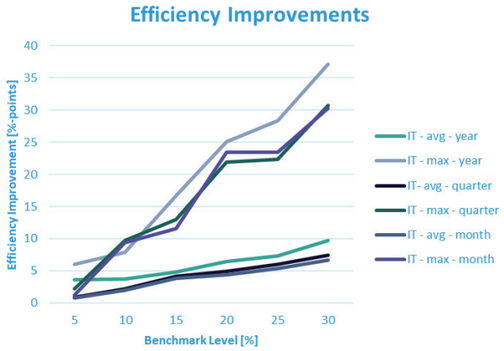


Figure 9 Average and maximum efficiency improvements per benchmark level

Step 3: Strategy Development

Finally, from the complete collection of benchmark steps (per product, per period and per benchmark level), we can deduct an overall efficiency improvement strategy. By the construction of a classification decision tree – by machine learning – we learn what measures lead to most efficiency improvements. Figure 10 shows an example of classification tree; increasing the selling price by 7% and up leads to most efficiency improvement (ΔE≥5%). The second most effective measure is to reduce the raw material costs with 1% and up. By constructing the decision tree for different subsets of products, we obtain even more specific measures leading to efficiency improvements.

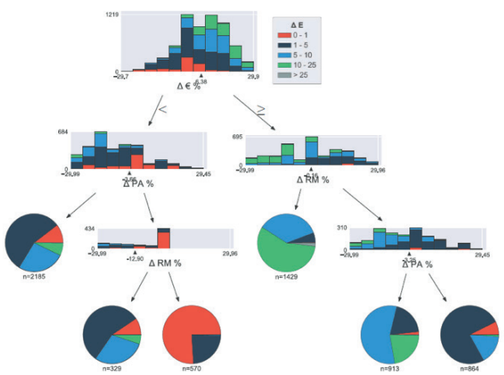


Figure 10 Example of a classification tree of the efficiency improvements

Conclusion

In this study, we have identified the problems regarding disconnected supply chains and have developed a framework that could support decision-making on a tactical level with the aim to close the planning loop. This closing of end-to-end planning processes is completely data driven. Data quality and completeness is therefore extremely important. If we start monitoring and measuring sustainability by smart sensing of production processes and IoT, we can establish a complete evaluation of the sustainability performance of a production process. From this performance analysis, we can develop an overall efficiency improvement strategy to the benefit of the entire production process and increase the sustainability of the entire manufacturing firm.

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