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Sensemaking support system (S^3) for manufacturing process improvement

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Production management teams often face unfamiliar situations where each team member must understand new phenomena individually before the team can make mutually understandable and acceptable decisions. Contradicting subjective judgments can distort the group's decision-making process because team members understand situations differently and are generally prone to behavioural biases. This paper presents the development of a sensemaking support system (S^3,S cube) for selecting improvement projects in a complex,small-volume batch production system of a premium car manufacturer. All phases of the sensemaking process are facilitated by making various sources of information available to a team of managers and experts to reduce conflicts regarding the selection of improvement projects. S^3 is based on a lens model which combines judgments of the management team with discrete event simulation and provides visual representations of the differences and misjudgements related to various improvement options. The results – that can easily be generalised to many similar settings – indicate different understanding and lack of coherence within the management team which prevents them from defining mutually acceptable actions. This is countered with the creation of an action proposal,summarising and visualising causal relationships,and connecting them to improvement options to improve performance of the production system.

Keywords: sensemaking support system; lens model; manufacturing process improvement; automotive industry; discrete event simulation; judgment analysis

1. Introduction

Based on a true story, Norman Maclean's (1992) book *Young Men and Fire* describes the events of a deadly fire disaster happening in Montana when several fire jumpers were dropped to deal with a small wildfire that they expected to have under control within a short timeframe and would not impact a surface area larger than 100 acres. Unique characteristics of the terrain, unknown to the firefighters, however, caused the fire to increase rapidly and turn towards their direction, which did not make sense to them and served as the basis for Weick's (1993) analysis about their sensemaking processes during the incident. Surprised by the turn of events they failed to communicate properly because everybody had a different understanding of what was happening, and all responded differently to this dire situation. They failed to formulate a mutually accepted action plan and, in the end, almost all the first responders died or suffered major injuries and the fire spread upon an area of 4,500 acres.

A similar situation, albeit not as catastrophic, was observed by the authors within a small-volume job shop production system of an automotive OEM and serves as an example of the applicability of Weick's sensemaking framework in operations management. Managers, assigned to deal with stagnating manufacturing performance, initially were inclined to use the methods they were familiar with from large-scale production. However, none of the improvement projects initiated led to significant performance gains, which did not make sense for management, and the 'fire' kept spreading endangering the survival of the business unit. Managers needed to find different explanations for situations at the new production system. Many failed and still made decisions based on old misconceptions because they expected to be able to work in the same way in the small-scale production system and that the same measures and actions would lead to the same results based on their own individual experiences. This led to two problems. First, decisions made in the old mind-set were generally counter-productive or sub-optimal because of the different characteristics of the production system, and second, decisions clashed with those of other managers and led to conflicts or at least missing support and understanding from their colleagues.

After several years and several failed attempts to improve specific parts of the production system, like material tracking and reduction of work-in-progress materials, or preventive machine maintenance, management realised that they would need

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a different approach to develop action plans for future improvement activities at the business unit. The question was how to aid managers within their sensemaking process in this unfamiliar situation to reduce distortions in a team's decision-making process due to subjective and biased decision-making methods of individuals.

In this paper, a sensemaking support system (S^3, S cube) is introduced to help management to make sense of a new and not very well understood production system and to define proper improvement activities based on Six Sigma and continuous process improvement, or Kaizen. A lens model methodology (Castellan 1972; Cooksey 1996) is used to contrast cause-and-effect relationships between different input variables, or cues, and manufacturing throughput time for all weekly production orders. The results of a discrete event simulation (DES) model are compared to the results of a judgment analysis questionnaire, measuring how the same cues are perceived by management. S^3 uses the results of DES to visualise cause-and-effect relationships based on a regression analysis to create, label and categorise cues to determine inputs and transformations. This creation and labelling of cues (please note that we use the word 'cue' synonymously with the inputs of the simulation analysis and the choices given in the judgment tasks) is one integral part of the sensemaking framework. We then perform a judgment analysis based on a questionnaire to develop a visual representation of the judgments of the management team. This facilitates further steps of the sensemaking process, namely the interpretation of cues by individual managers and their communication to form a mutually accepted action plan. The goal is to make differences and similarities of perceived and measured resource-performance linkages visible to the management team and support their sensemaking process.

The following exploratory case study showcases an application of S^3 within the production system to aid sensemaking and define actions for efficient and effective improvement of processes to reduce manufacturing throughput time – a competitive priority of the production system. The production system is characterised by high complexity, causal ambiguity and a general lack of holistic insight into the system, which makes it difficult to identify and assess improvement projects efficiently. A major problem of the business unit was that the production system grew at a rapid pace, but processes and control systems did not grow alongside to cope with increased dynamics and complexity. There was a lack of employee training, missing preventive equipment maintenance (TPM), the quality management system needed an upgrade; all while the overall value stream had to be improved as well. All major processes had to be analysed, improved and aligned with the overall strategy of the unit, but there were not enough resources to do it simultaneously. An efficient, effective, and mutually agreeable action plan was needed to prevent wrong prioritisation, misalignment of different departments and misunderstanding between people of different functional areas to improve the most important processes to increase manufacturing performance.

The remainder of this paper is organised as follows. Section 2 gives an overview about the literature on continual improvement, sensemaking and the lens model. Section 3 describes how the lens model can be used facilitate sensemaking when it is unclear which actions should be taken to improve specific processes for increased manufacturing performance. Section 4 describes the environmental system and the main variables (cues) and processes that influence the performance of the production system in terms of throughput time reduction. The simulation model and the judgment analysis are described in section 5 and the results and findings are discussed in section 6.

2. Literature review

Continual improvement in manufacturing is still a highly relevant topic (Li, Papadopoulos, and Zhang 2016) and many factors are important when making decisions regarding improvement projects in organisations. In general, the commitment and active participation of management, a long-term plan, and the application of tools and techniques are critical for the success of any lean programme (Netland 2016). Careful planning of lean and continual improvement actions is highly important because misalignment or missing strategies can have a severe impact on the success of a lean programme (McLean, Antony, and Dahlgaard 2015) and the stress levels of people on the shop floor (Stimek and Grima 2019). Knol et al. (2018) found that especially for advanced lean enterprises, leadership is a critical success factor when organisations start to manage more different improvement projects with increased complexity.

All this means that management needs a very detailed and precise plan to manage several improvement projects in alignment with the company strategy and the support of the shop floor levels of the organisation. Consequently, if managers find it hard to make sense of new situations in a different and less well-known production system, and their decisions are not aligned towards a common goal, it becomes very difficult to achieve the desired results. Managers often tend to fall back on subjective decision-making methods and heuristics which can be detrimental to the overall selection process of improvement activities. Kirkham et al. (2014) found in their study that almost 90% of the large organisations analysed were almost always successful when solely applying objective methods, while less than 70% reported the same results when combining objective and subjective methods. The S^3 can detect subjective misalignments based on the results of objective analyses and improve group decision making by reducing subjectivity and biased judgments.

The S³ provides managers crucial information about their environment and their own judgments to aid them in their sensemaking processes when entering new and unfamiliar systems. Maitlis (2005, 64) defines sensemaking as 'process of social construction in which individuals attempt to interpret and explain sets of cues from their environments [. . .] sensemaking allows people to deal with uncertainty and ambiguity by creating rational accounts of the world that enable action'. Most authors define several steps within the sensemaking process. We use five key activities as summarised by Seidel et al. (2018) for our study. Sensemaking starts with chaos (Weick, Sutcliffe, and Obstfeld 2005) and a trigger event (Weick 1995) characterised by disruptive ambiguity and outcome uncertainty which usually leads to a situation when nothing seems to make sense. Maitlis and Christianson (2014) define several triggers. First, triggers can be the results of unexpected events that disrupt people's understanding of the world in a significant way for them to question their ability to understand the environment in which the event took place, for example, the realisation that a fire is not behaving as expected. Also, organisational crises as a result of significant exogenous forces or questioning of self-identity can act as triggers. Furthermore, planned change interventions which are anticipated and planned by organisations to change organisational identities and processes can trigger sensemaking.

At the second step, people begin to construct intersubjective meaning by noticing and bracketing cues which might have caused the trigger event to occur. For example, when process improvement activities do not bring the desired results people start questioning their understanding of cause-and-effect relationships and begin to look for possible input factors and explanations for the failed intervention. Managers in our production system expected to use the same, familiar methodologies that always worked based on their previous experiences and sooner or later realised that this was not the case (trigger event). They needed to look for different inputs and different processes to improve and communicate their intentions with their colleagues to find a mutually acceptable action plan. This search for different cues is difficult and complex and could be improved with a support system to create sense in a planned and guided process.

The third step in the sensemaking process is the labelling and categorising of newly found cues to form diverging opinions and knowledge for new and ambiguous phenomena. Experiences must be labelled and categorised to put them into new perspectives. This means that sensemaking is retrospective and experiences are compared to previous observations (Weick, Sutcliffe, and Obstfeld 2005). A DES can be used to define cues, label them and put them into categories when selecting the input parameters for the simulation and regression analysis.

The fourth step, after the sensemaking has been triggered, cues are identified, and labelled, is about presumption and action. People start to anticipate outcomes based on latest experiences and cue inputs in this new environment and begin to act in different ways to create more inputs. In other words, the actions they take are the inputs for further cue generation, interpretation and labelling, thus, resulting in a continuous sensemaking processes. The DES can be used in this context to create further information to predict outcomes, in this case for manufacturing throughput times, in the real environment based on the results of the regression analysis. People can then act based on their new knowledge and incrementally increase their level of understanding for new phenomena. The difference between decision making and sensemaking is that in sensemaking the broader conceptual framework in which the decision-making environment is formed. Decisions are only part of the process to create cues to further promote future sensemaking.

The final step in the process is about the social aspect of sensemaking and it is accomplished through discussions to formulate a common view of new phenomena. This includes the knowledge and judgments of all the people involved in the sensemaking process and forms an organisational view of things in a new setting. S^3 facilitates this process by visualising the cue selection process and judgments of individuals and compare them to their peers. It calculates weights for each cue given by the preferences of participants of the judgment analysis and serves as the basis of discussion of differences and similarities. If a group of people, in this case the management team, can find mutually understandable and acceptable outcomes of their combined sensemaking processes, decisions can be taken, which ultimately lead to action and the creation of further inputs for the sensemaking process. The lens model unites all the previously mentioned steps by visualising the results of the DES based on the identification, labelling and categorising of cues and by providing information about potential outcomes for ambiguous situations. It furthermore visualises the judgments of people to be compared with the results of the judgment analyses of all participants to each other and to the results of the DES as a basis for communication and action.

The lens model has been used for various applications to visualise judgments and support sensemaking processes of managers for complex judgment tasks or behavioural analyses. Dhir (1987) used the lens model to understand consumer behaviour in the hospitality industry and found that consumers are not fully aware about their own judgments and preferences – for example, due to preference uncertainty and attribute conflict (Fischer, Luce, and Jia 2000). The lens model provides a representation of their judgments and helps restaurant managers to better understand and adapt to individual customer preferences. Other applications are found in healthcare (Thompson et al. 2005), where the lens model is used to analyse decision processes about a patient's status in critical care, or in education (Haigh, Ell, and Mackisack 2013), where it is used to improve judgments about teacher's readiness to teach. It is also used as a judgment capturing tool to give insights into production strategy and policies (Ebert, Rude, and Cecil 1985).

The lens model is based on Brunswik's (1952) work and a tool of social judgment theory. The reason why it is preferred over tools from other theories is its strongly descriptive approach. It facilitates recommendations solely based on the decision maker's own judgments. Dhir (2001) compared this theory to various other theories (decision theory, multi-attribute utility theory, analytic hierarchy process, information integration theory, etc.) in a manufacturing setting and concluded that social judgment theory and the lens model can be best used to develop judgment and decision aids because of its descriptive nature to obtain an unfiltered model of individual judgment processes. Most other theories mentioned, on the other hand, are highly prescriptive and indicate how rational decision should be made or why they are made which is not the purpose of this study.

3. Integrating the lens model into a continuous improvement process

Figure 1 depicts a typical univariate lens model in a stochastic environment. The distal variable or criterion variable Y_e is the dependent factor in the environment or ecology to be judged by the decision makers. In this paper, it is manufacturing throughput time, or the time to produce all weekly production orders for a given product mix, which is influenced by independent factors (x_k), or cues. The left side of the model depicts the true state of the ecological system, or how the distal variable will behave based on the inputs. The right side describes how decision makers use the cue information to make judgments about the true state of the system. Their judgment Y_s is then compared with the true state Y_e to calculate the correlation between their estimates and the true state, which is called *response validity*, or *achievement index*, $r_\alpha = r\ Y_e\ Y_s$. This gives an indication about the performance of the decision makers and their ability to understand how the criterion will behave under different conditions.

In a stochastic environment, however, the true state must be predicted using some sort of model. In this research, it is a simulation model based on the processes and value stream of the production system. $\hat{Y}_e$ is the predicted criterion variable and the environmental predictability can be calculated ($R_e = r\ Y_e\ \hat{Y}_e$) with throughput time as the dependent variable and the cues as the independent variables. The same process is applied on the right side of the lens model to analyse how judges are utilising different cues with the help of a questionnaire. R_s is the consistency of the judge's cue utilisation based on different cue input profiles, that is, how coherent is their assessment of cues towards the distal variable ($R_s = r\ Y_s\ \hat{Y}_s$). The correlation between the predicted ecological state and the predicted judgments is called the *matching index* $r_m = r\ \hat{Y}_\mathrm{e}\ \hat{Y}_\mathrm{s}$, or how similar the expected judgments are, compared to the expected environmental state.

To visualise judgment processes, it is important to calculate the weight of each input variable given by the judgments of the management team by using a non-additive model of polynomial form (see appendix) as described in Hammond et al. (1975, 281–282) and Cooksey (1996, 178–180). They use algebraic transformation of the regression model and separate

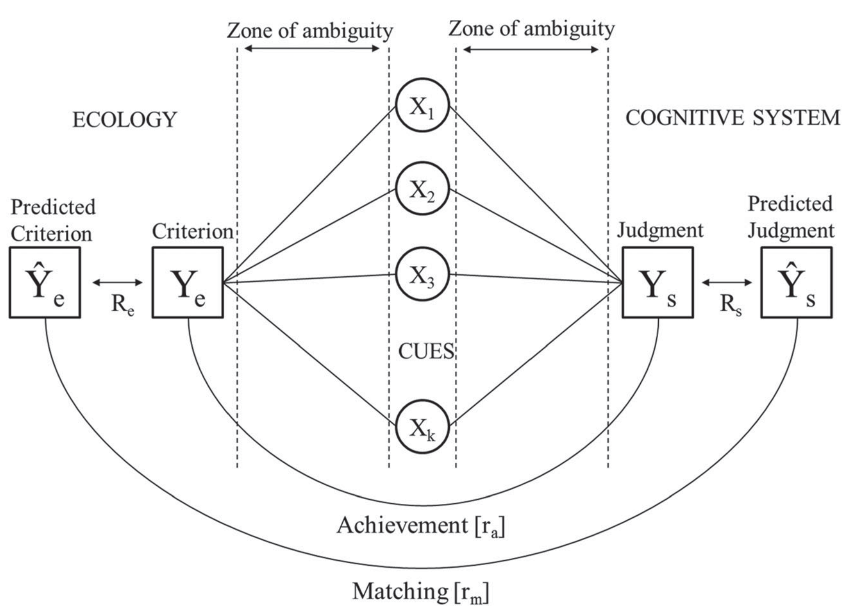

Figure 1. Univariate lens model. Source: Authors representation of Cooksey (1996) and Castellan (1992).

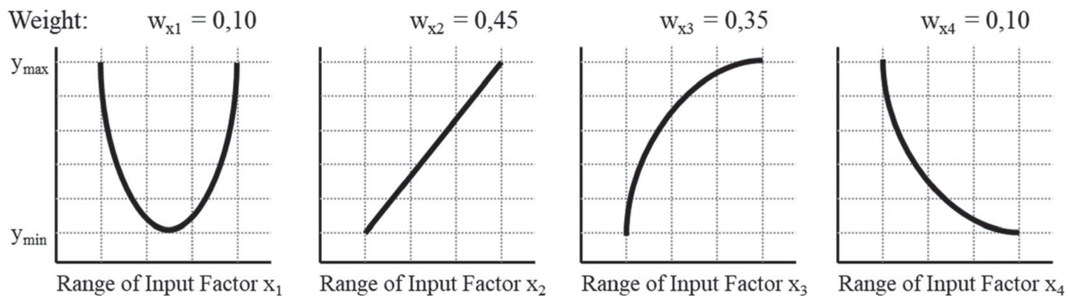

Figure 2. Illustrative example of visualising weights and function forms.
Source: Authors representation of Dhir (2001).

weight and function form for each cue to visualisze the results of all judgments. The method is called '*range method*' and the results give an indication about the preferences of individuals based on their judgments. The highest weight represents the highest preference of the judge towards a cue factor with function forms showcasing judgments related to higher and lower performance levels, respectively (Figure 2). This method visualises how managers are using uncertain and intersubstitutable cue information in causally ambiguous situations based on their judgments. The same method can be applied to visualise the regression results of the data generated by the DES. Weights and function forms are computed for both, the DES and the judgment analysis, and is the foundation of S^3 to make decisions regarding the selection of improvement activities for different processes.

Previous research has shown that process performance can be significantly improved by the adequate use of continuous improvement methods (Hahn, Doganaksoy, and Hoerl 2000). However, it also shows that there is no guarantee that any kind of operational excellence can be achieved if certain factors are not available to generate the desired outputs (McLean, Antony, and Dahlgaard 2015). The success of improvement projects depends on the experience of team members and their abilities to identify and solve problems (Easton and Rosenzweig 2012). Companies are sometimes spending billions of dollars for process improvement (Swink and Jacobs 2012) and it is critical to ensure proper allocation of scarce and expensive resources. The management of a production system needs a holistic understanding about causal relationships between all processes within the system to be able to properly identify the most beneficial improvement projects. Too many projects without enough capacity increase the risk of failure for all projects and can be a reason why Six Sigma or Kaizen do not yield the desired returns (McLean, Antony, and Dahlgaard 2015). S^3, introduced in this paper, is used to guide an improvement process to select the most beneficial improvement projects to increase performance based on competitive priorities by following a stepwise approach adapted from Dhir (2001).

(1) *A trigger event initiates a sensemaking process about a criterion variable* which is ambiguous in terms of resource-performance linkages, in this case, manufacturing throughput time and its influencing factors.
(2) *Define, label and categorise* what factors influence this variable in terms of management judgments and for building the model of a system. Different key performance indicators (KPIs) and related process improvement options were selected as cues to analyse their impact on throughput time within the system. All KPIs selected for this analysis could potentially be improved to reduce throughput time by initiating an improvement process. However, due to high expenses and limited resources, it was necessary to decide and mutually agree upon the priority of process improvement options.
(3) *Calculate and visualise* weights and function forms (Figure 2) as perceived by the management team and based on the results of DES. The questionnaire is used to analyse judgments of the management team. The key question was how the management team, based on their experiences and knowledge, utilises KPIs as cues within their cognitive systems to make decisions regarding throughput time improvements. For the left side of the lens model, DES is used to predict throughput time reduction within the production system when different processes and KPIs are improved.
(4) *Use the results and analyse how decision makers utilise cues compared to each other and to the DES*. The results of both analyses, from the environmental system and the cognitive systems, are visualised to make both results comparable to be discussed within the sensemaking process. The overall weights and function forms can be determined for each cue to select the most important KPIs and processes for improvement. Also, differences and similarities (matching index) can be assessed and discussed to make a mutually acceptable decision and to mitigate subjective influences of individuals.

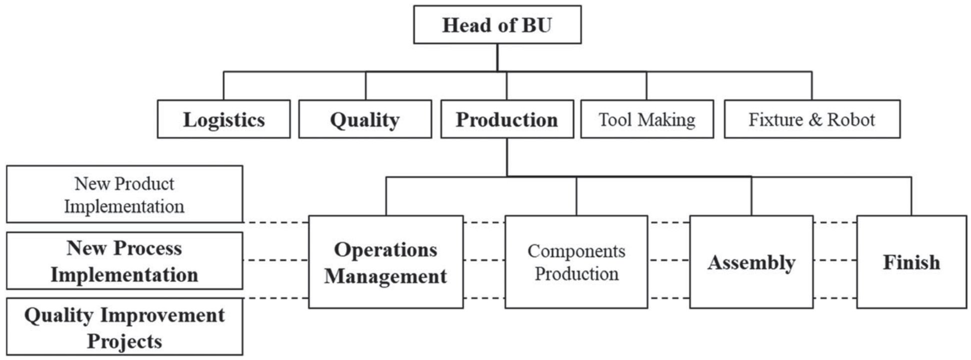

Figure 3. Organisational structure of the business unit (BU).

4. System design and variables

4.1. Production System overview and value stream

The production system consists of three departments that contain all production processes from metal disc to final assembly of all core products like doors, side panels, roofs, bonnets and hatches for premium sports cars. The first department is the component production, where metal components are pressed, and laser cut out of aluminium or stainless-steel discs. The second department contains all the assembly processes where the final assemblies are put together from two to five main-components. The third department is called 'finish' and it is responsible to ensure proper quality of the final product. This department is also the bottleneck of the system based on the results of the DES and has the highest utilisation rate of all processes. There is also an Operations Management department within the small-volume production segment, responsible for launching new projects and to ensure continuous smooth operations of all running projects throughout their life cycle. In addition to the small-volume batch production segment, the business unit contains four other segments, which are: quality management, logistics, fixture construction and tool making. Also, many projects are running at the same time, like new product implementation into the existing production equipment, improvement projects for existing processes, and implementation of new processes, which creates a matrix structure of the organisation as depicted in Figure 3.

In this complex environment of many interconnected processes and projects, the head of the unit must allocate resources properly to all ongoing projects. The key-actors and decision makers of the management team, including project managers, are coming from the highlighted departments (bold text in Figure 3), and those are the ones who will be included in the judgment analysis. Projects can be managed by production ramp-up managers for new product implementation, industrial engineering for quality and process improvement projects, and production system planners for new process implementation. With a lack of control and signalling tools as well as feedback loops, it was critical for the top-management of the business unit to rely on mutual understanding, joint decision-making and unified actions to reach the unit's goals based on a collectively developed action proposal.

The production system is simulated from the components supermarket to the finished goods inventory. The value stream design, as depicted in Figure 4, is focused on ensuring a stable and balanced material flow between each supermarket based on the theory of Swift, Even Flow (Schmenner and Swink 1998; Schmenner 2015). This is also the basis of the DES and the judgment analysis.

4.2. Inputs (Cues), improvement options and performance levels

Five KPIs were defined as cues with help of and inputs from the management team. Each input is connected to a reaction process to improve KPIs if they are not satisfactory. If so, a specific process improvement option is selected to bring the KPI back into the desired range by improving the appertaining reaction process. Management could decide where to intervene and how much resources should be invested into a process improvement option, which results in different performance levels for all reaction processes and ultimately different ranges of KPIs. The higher the investments into improvement activities for a process, the higher the performance level of the reaction process and the better the range for the input variable will be, which, in turn, will influence throughput times. Performance levels and expected values of each cue, as depicted in the complete list of cues in the appendix, were defined with the current measurements within the production system and feedback from management about what was 'normal', or what could be achieved for a 'good/bad' week. For example, machine down time for the average level was defined by log files coming from the maintenance department. The upper and lower values for all the other levels were then defined by the management team and cross-checked with past log files. The

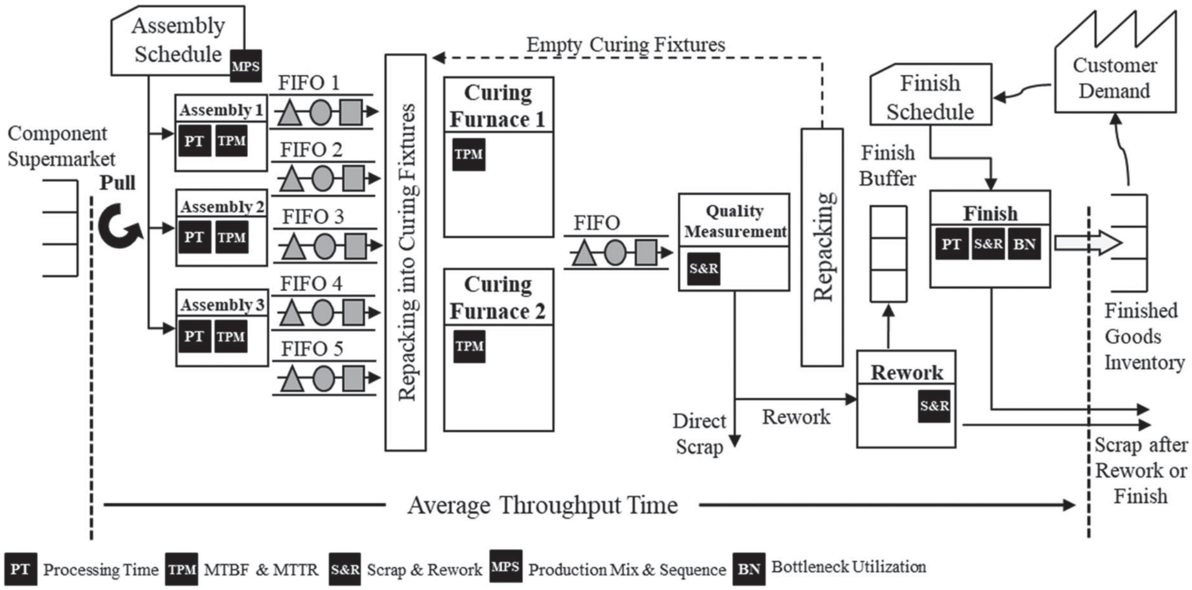

Figure 4. Value stream of the production system.

following is a list of the five KPIs to be considered in the lens model analysis with their specific reaction processes and performance levels.

Cue 1: Processing Time Variability and Training (Level 1–7): Processing time variability based on varying worker performance for manual tasks was the first KPI to be considered in the analysis and was selected by the production department of the production system. Workers were not fully trained for all manufacturing processes according to the defined standards, did not have the required qualification profiles, and lacked understanding of basic process improvement methods. Therefore, the project team concluded that a reaction process called 'training' would be the most appropriate to improve this KPI as learning and training is a major tool to reduce process variability (Zantek, Wright, and Plante 2002). Training only influences processes with a significant amount of manual operations, which can be found in the assembly systems and the finish department marked with 'PT' in Figure 4. The range of the KPI is determined by the distribution of tact times for the completion of one product and is dependent on the performance level of the training process. The higher the performance level of the training process, the lower the dispersion (or spread) and the overall completion time of manual tasks will be until they reach the defined, standardised processing times with high reliability.

Cue 2: Mean Time Before Failure (MTBF), Mean Time To Repair (MTTR) and Total Productive Maintenance (TPM) (Level 1–7): Machine processing times at the assembly systems and curing furnaces cannot deviate much, but machines can have unplanned downtime, therefore, MTBF and MTTR can be defined as another set of indicators (again required by the production department to be included in the analysis). The underlying concept of those measures is total productive maintenance (TPM), introduced by Nakajima (1988), which is used as the reaction process for the MTBF and MTTR indicators. The right maintenance policy is critical to maintain high levels of availability and performance at an optimal cost level and has become a significant profit contributor in modern production systems (Faccio et al. 2014). Again, high performance levels of the TPM reaction process tend to improve related KPIs and has an impact on overall throughput times of the system.

Cue 3: Scrap, Rework Rates and Problem Solving (Level 1–7): If product quality is not within the given range, a problem-solving process is triggered to deal with quality problems. Scrap and rework mostly result from changing part quality discovered at the quality measurement, rework and finish departments (see 'S&R' marks in Figure 4). A problem-solving team of experts and engineers is needed to improve the quality of products and processes. A high-performance level can only be achieved with enough investments into quality analysis and improvement to deal with complex problems. It is then possible to sustainably and efficiently reduce scrap and rework rates and ultimately improve throughput rates and throughput times (Johnson 2003) with a sophisticated problem-solving process. This process was selected by the quality department of the production system and all KPIs were critical for the managers of this department.

Cue 4: Production Mix, Sequence and Master Production Scheduling (Level 1–4): Master production scheduling (MPS) based on the manufacturing planning and control framework by Vollmann et al. (2004) is the process for the fourth input: production mix and sequence, as requested by the logistics department. It aims to create an assembly schedule to achieve an optimal product mix and sequence for the assembly stations to ensure proper replenishment and inventory levels at the finish buffer. Based on Jonsson and Ivert (2015), the balancing between capacity and demand is used to define performance levels for the MPS. A very low performance level of the MPS process means that the production sequence and mix are completely random and unbalanced, which results in long throughput times. No demand or capacity restrictions are considered at this level and the production plan is not capable of balancing both factors due to a sub-optimal MPS. The basic production plans for all higher levels of this reaction process, from levels two to four, is based on an optimised MPS considering capacity, demand, sequence and product mix issues. Nevertheless, as analyses within the production system have shown, there were up to ten deviations per week from the production plans due to planning errors, from a total of 25 production orders every week. The performance levels of the MPS process are therefore based on the number of deviations of the production plan compared to the optimised plan to analyse the effect of bad planning on average throughput time. This means that for a level four process, there is no deviation from the optimised MPS. The lower levels were then simulated by changing the sequence of the production plan for up to ten production orders to deviate from the optimal MPS based on real examples experienced at the production system. Planning errors due to low performance levels are introduced artificially and randomly to simulate different levels of planning performance.

Cue 5: Bottleneck Utilisation and Business Process Optimisation (Level 1–4): The fifth cue is the bottleneck's processing time compared to the processing time of the second slowest process, or, the difference of utilisation levels of the two processing units with the highest utilizations (Hopp 2011). Business process optimisation of the bottleneck was used as a reaction process to achieve balanced and improved flows of materials as requested by the operations management department. Sophisticated process optimisation will accurately analyse potential bottlenecks and ensure a balanced production based on the concepts of Drum, Buffer, and Rope (Goldratt and Fox 1986) or the theory of Swift, Even Flow (Schmenner and Swink 1998; Schmenner 2015). With low performance levels, processing times and utilisation levels will vary, causing the whole production system to suffer from unbalanced process design due to a lack of focus on the bottleneck. The finish department was identified to be the bottleneck process under normal circumstances with an average utilisation of over 80%. The process with the second-highest utilisation was the curing furnace with only about 60% of utilisation for all weekly production orders, given the product mix used for the DES. Shift models, worker cross-training, dedicated machines for special product families, or different routing options can help to balance the throughput time for each process as shown in Johnson (2003). A mix of worker cross-training with more finish stations, an increase in capacity, as well as improvements in processing times were used to optimise the bottleneck process towards utilisation rates like those of the curing process.

Each of the main inputs of the model has an impact on the overall throughput time of the production system in terms of supply chain management (Hopp 2011), manufacturing throughput times (Johnson 2003), or other capacity, variability and inventory trade-offs within process management (Klassen and Menor 2007). Therefore, these five KPIs are used as input factors (cues) for the lens model application as depicted in Figure 1. Filho and Uzsoy (2014) use a similar set of input variables for their simulation analysis of cycle time in a flow shop. The reduction of variation due to quality, quantity and timing is also a critical factor in the theory of Swift, Even Flow (Schmenner 2015), with the other factor being throughput time.

5. Simulation model and judgment analysis

Each cue of the lens model is divided into certain performance levels on an ordinal scale representing different ranges of values for each KPI. Different scenarios of production system configurations were created to obtain the input data for the questionnaire and the DES. This was done by randomly assigning performance levels to each cue, based on viable and concerted ranges, to create different production system profiles with varying strengths and weaknesses based on the cues with higher or lower performance levels, respectively. 20 input profiles were created randomly to simulate trade-offs and present them to the management team for the judgment analysis. The set of profiles was checked for plausibility, variety of profiles, and orthogonality. Where necessary new profiles were created randomly to replace unsatisfactory ones. At the end, the Pearson product-moment correlation coefficient was used to calculate the correlation between all pairs of factors to test for orthogonality of the input profiles. The highest correlation was found at $r = -0.368$ between factors three and four. The t-value for the highest correlated pair was 1.677, which lies under the critical t-value of 1.734 at 0.1 level of significance for 18 degrees of freedom. This means that there is no significant correlation between all pairs, thus making the profiles orthogonal. All scenarios (input profiles) were simulated for 25 runs to obtain a data set for throughput times from the DES. Management was asked to rate the same profiles in the questionnaire to obtain their judgments for the same scenarios and the cues they mostly utilised to make their decisions.

The judgment analysis was conducted to develop a pictorial representation of the expert's mental models to be compared with the results of the simulation model. The judges are members of the management team, from production and logistics department, but also production system planners, process engineers and other members of the business unit with in-depth

Table 1. List of participants and functions (*Top Decision Makers).

Group	Code	Name	Function	Age	Exp.[a]	In BU	Edu.[b]
Group 1	TOPMGR1	Top-Manag. 1*	Head of BU	45–50	2–4	2–4	Eng. + IE
Top-Management &	NPIMGR1	New Proc. Implement. Manag. 1	Project Head	55 +	12 +	2–4	Eng.
Innovation	NPIMGR2	New Proc. Implement. Manag. 2	Project Supervisor	30–35	4–6	6–8	Eng.
Group 2	PROMGR1	Production Manag. 1	Head of Production	40–45	4–6	< 2	Eng.
Production	PROMGR2	Production Manag. 2*	Head of Production	40–45	< 2	8–10	Eng.
Management	PROMGR3	Production Manag. 3	Line Manager	45–50	10–12	2–4	Eng.
Group 3	LOGMGR1	Logistics Manag. 1*	Head of Logistics	40–45	2–4	2–4	Business
Logistics Management	LOGMGR2	Logistics Manag. 2	Line Manager	35–40	< 2	4–6	Logistics
	LOGMGR3	Logistics Manag. 3	Project Supervisor	25–30	< 2	2–4	Logistics
Group 4	QUAMGR1	Quality Manag. 1	Line Manager	35–40	< 2	2–4	Eng.
Quality Improvement	PRIMGR1	Proc. Improv. Manag. 1	Project Supervisor	30–35	4–6	4–6	IE
	PRIMGR2	Proc. Improv. Manag. 2	Project Supervisor	35–40	2–4	< 2	IE

[a]Work experience (number of years in current function and level).
[b]All with master's degree in Engineering (Eng.), Industrial Engineering (IE), Business or Logistics.

knowledge of the production system, who decide on how to run the system in terms of improved throughput times. 17 experts were identified, who were qualified to participate in the survey – of whom twelve completed the questionnaire under the guidance of the authors. Five people were considered as the top decision makers with the highest level of involvement in making decisions, of whom four responded to the questionnaire (asterisk in Table 1). Consequently, we are confident that all relevant characteristics of the problem domain were captured.

Each expert received the same questionnaire with the set of 20 different input profiles and was asked to rate each profile and its expected performance regarding throughput times from a scale from 1 to 20, with 1 meaning that the expert is estimating very long (bad) throughout times and 20 meaning that the expert is estimating a significant reduction of throughput times. Each profile was presented to the participants in form of a 'profile card' (Table 2), so they could rearrange the cards and have a better overview over the whole set of profiles. 20 profiles represented the upper limit participants could handle in terms of complexity and time to complete the questionnaire, so this number was selected by the authors. The most important information on the cards were the different performance levels for each process and KPI. The ranges and an additional description were also visible, and the list of all ranges was given to the participants as well (appendix). Before the actual rating of the input profiles, an a priori assessment was conducted, and the participant could assign a total of 100 points to each of the five processes to represent their preferences before the actual judgment analysis. The comparison of the a priori assessment with the actual judgment analysis gives an indication about the consistency of the judges and the difference between a simple assessment and a causally ambiguous judgment task.

The weights and function form, as judged by each member of the management team, could be calculated based on the ratings of each profile and the regression model. Performance levels for each cue were the independent variables and profile ratings the dependent. The results gave a visual representation of the cognitive system of the judges and the mutual preference of the management team to be compared with the results of the DES. The DES was modelled after the value stream design of the production system with all process steps, master product data (bill of materials) and routing based on Figure 4, using the Tecnomatix Plant Simulation software by Siemens. All input profiles were modelled, and 25 simulation runs were executed for each profile to acquire a large enough sample size for the regression analysis to calculate weights and function forms for the environmental system. The average throughput time over the whole product mix was the output of the simulation and the dependent variable of the regression analysis to assess the impact of performance level changes of each cue on throughput time. All input profiles could be simulated by changing the levels of each parameter in the simulation, for example, processing time variability, unplanned machine down time, and various production schedules. The production at the assembly stations was simulated based on the assembly schedule with the previously defined ranges for processing times. A specially coded logic in Tecnomatix Plant Simulation for the repacking stations and the curing furnace was applied to simulate the selection of the next batch to be cured at the furnaces based on the arrival from the FIFO-lines and the availability of curing fixtures. Scrap and rework rates were applied before and after the finish stations and at the rework station. A higher quantity of products had to be produced to compensate for quality losses affecting the overall manufacturing throughput times of the system. Twelve finish stations were simulated individually based on the finish schedule taking parts from the finish buffer with an initial starting level of WIP materials. Machine down breaks were also simulated randomly based on the probability of a break down and the average duration. A TPM break in the middle of the week was set to simulate TPM times defined by the performance levels of the TPM cue.

Table 2. Input profile with judgment y_{ij} in form of a 'Profile Card'.

	Main Process (Cue)	Indicators (KPIs)	Performance Level [x_{jk}]	Range			Description
j1	Process Training	Processing Time Variability (in %)	Level 2 – Low	105% of EV	Expected Value	180% of EV	Start of basic training for employees. They can almost reach target in best case (105% of EV), but still miss target by a lot (+80%)
				MTBF	**TPM Time per Week**	**MTTR**	
	TPM	TPM per Week; MTBF; MTTR (all in hours)	Level 1 – Very Low	2	0	1.3	No weekly TPM. Regular unplanned down time (every 2 h) and long repair time (1.3 h) – 60.6% Availability
				Scrap ± %	**Rework** ± %	**Scrap after Rework**	
	Quality Problem Solving	Scrap; Rework; Scrap after Rework (Compared to base rates in %)	Level 2 – Low	+20	+35	+35	All rates increased. Quality is getting worse due to lack of efficient 'Quality Problem Solving' process (9,2% Total Scrap)
				Sequence and Number of Changes in Schedule			
	Manufacturing Planning and Control	Sequence (Number of Changes in Schedule)	Level 4 – Very High	Optimised production schedule, sequence and execution			All 25 weekly production orders are executed as planned and in the optimal sequence – no changes needed
				Bottleneck Optimisation (BN)			
	Bottleneck Improvement	Improvement of Bottleneck (BN) (Reduction of BN gap in %)	Level 3 – High	The bottleneck gap is reduced by 60%			Gap between the BN and the process with second-higest utilisation is reduced by 60%.
		Based on the performance levels, I estimate the average throughput time to be: Scale from 1–20: 20 = expected very short (good) throughput time; 1 = throughput time is very long (bad)					15 [yij]

The results were validated by comparison with real-life data and by following each part through the value stream as modelled in the simulation. Furthermore, the simulation was used to plan and validate processes of the real shop floor of the production system in a different project. Other outputs of the simulation were the log files of each process, which product type was processed when and where, and the number of parts/containers coming into each station and out of it. The functioning of the simulation model could be validated with the help of the log files and the real-life data.

The cue performance levels for each cue as independent variables and the average throughput time as dependent variable were then used as input data to conduct curvilinear regression analysis for testing the fit of the regression model of throughput time. To compare the results of each profile, the production system was simulated for one week of production (seven days) without a warm-up period to better reflect the changes of the dependent variable for each profile. The regression model captured the dependence of the output variable with a relatively high degree of accuracy, with an adjusted R-square of .935 (see appendix for more details), with most of the input variables being significant at the 0.01 level. The regression model of the DES was visualised in the same way than the regression models for each judge based on the results of the questionnaire to obtain weights and function forms of all cues and to compare both sides of the lens model.

6. Comparing the results on both sides of the lens model

6.1. Judgment analysis – weights, function form and causal relationship

The judgment analysis was performed to explore judgment patterns and subjective preferences of each team member based on their knowledge and experience. The management team was divided into four functional groups: (1) Top-management and process innovators, (2) production management, (3) logistics management, (4) quality improvement, with each group containing three members.

The first group included the head of the business unit (TOPMGR1) and the two most important project managers (NPIMGR1/2), responsible to manage the re-engineering and implementation of all new processes. Two of the top decision makers are based in this group and both were foreign expats; appointed and sent to the business unit by the headquarters of the corporation – the top-manager for a longer period and the project manager for the duration of the project. Both had been working at the business unit for more than two years when the judgment analysis was conducted. The second group consisted of the former head of production (PROMGR1), with a lot of experience coming from the foreign headquarters as well; and the current head of production (PROMGR2), who was relatively new at this position, but also a top decision maker and a local manager within the business unit for a long time. Together with a third production line manager, this group was responsible for the training, TPM and scrap and rework KPIs, as well as the overall functioning the production system. The third group consisted of two logistics managers with LOGMGR1 being the head of the logistics department and the only local female top decision maker of the management team. These two were the only managers from the same group with relatively similar judgments and were responsible for the production planning and training processes. The last group included a quality manager and two process improvement coordinators responsible for improving product and process quality. This group had no top decision maker, but all members were heavily involved in defining and implementing improvement projects with a focus on scrap and rework, bottleneck improvement and training.

The weights and function forms were computed based on the judgments of each manager as depicted in Figure 5a-d. The results within the groups indicate that there was a general lack of agreement within each group and within the whole team. Only a few pairs of managers had similar judgments and they came from different functional areas and different groups. The results also indicate that the participants relied on different cues for their judgments. It was not possible for the management team to identify a single most important cue for throughput time of the production system due to linkage ambiguity within the systems and within their judgments. Although all participants were experienced managers, familiar with the production system, and routinely made decisions regarding improvement activities, there was a general lack of agreement and common understanding. Many managers were biased towards the process which is most critical in their functional role, for example, scrap and rework for the quality manager – QUAMGR1.

A lack of focus on specific cues made it very difficult to rate profiles consistently based on the a priori assessment, which resulted in substantial differences between the weights of the a priori results and the actual judgment analysis. Those, who clearly prioritised one or two cues, generally could achieve higher consistency with their a priori assessment, because they only focused on specific cues when rating the profiles which made it easier to cope with the complexity of the judgment task. One reason for high variance was, most likely, the absence of a clear and holistic manufacturing policy to align decision making of all managers. This also resulted in judgment errors for some managers and they misjudged some profiles which caused high deviations from their a priori assessment; see LOGMGR2 for the TPM cue, for example. Misjudgements, or overlooking of alternatives can always happen in complex judgment and decision tasks and this method can detect, and point towards them, to re-evaluate some alternatives.

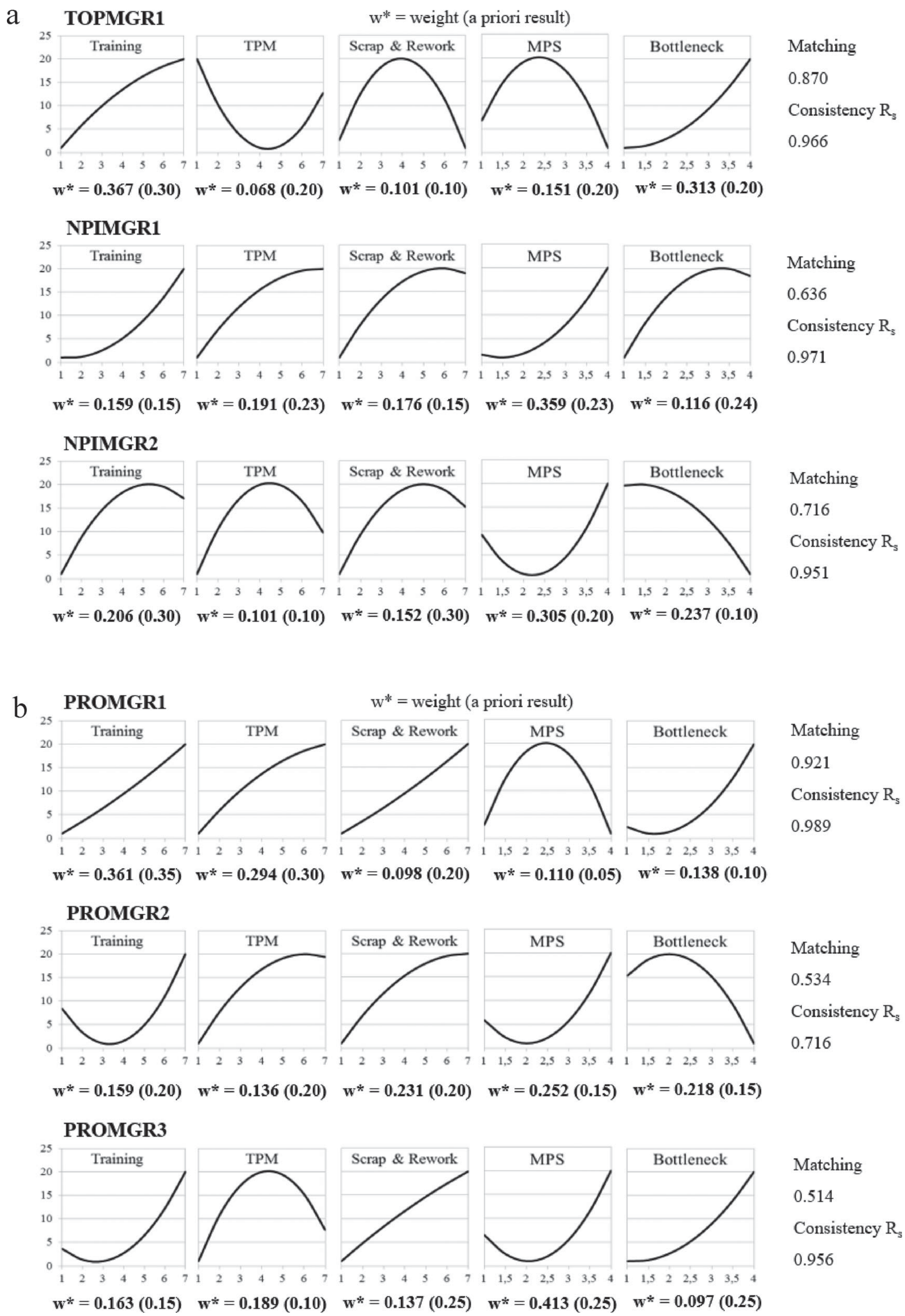

Figure 5. (a) Weights and function forms of group 1, top-management and innovators. (b) Weights and function forms of group 2, production management. (c) Weights and function forms of group 3, logistics management. (d) Weights and function forms of group 4, quality improvement.

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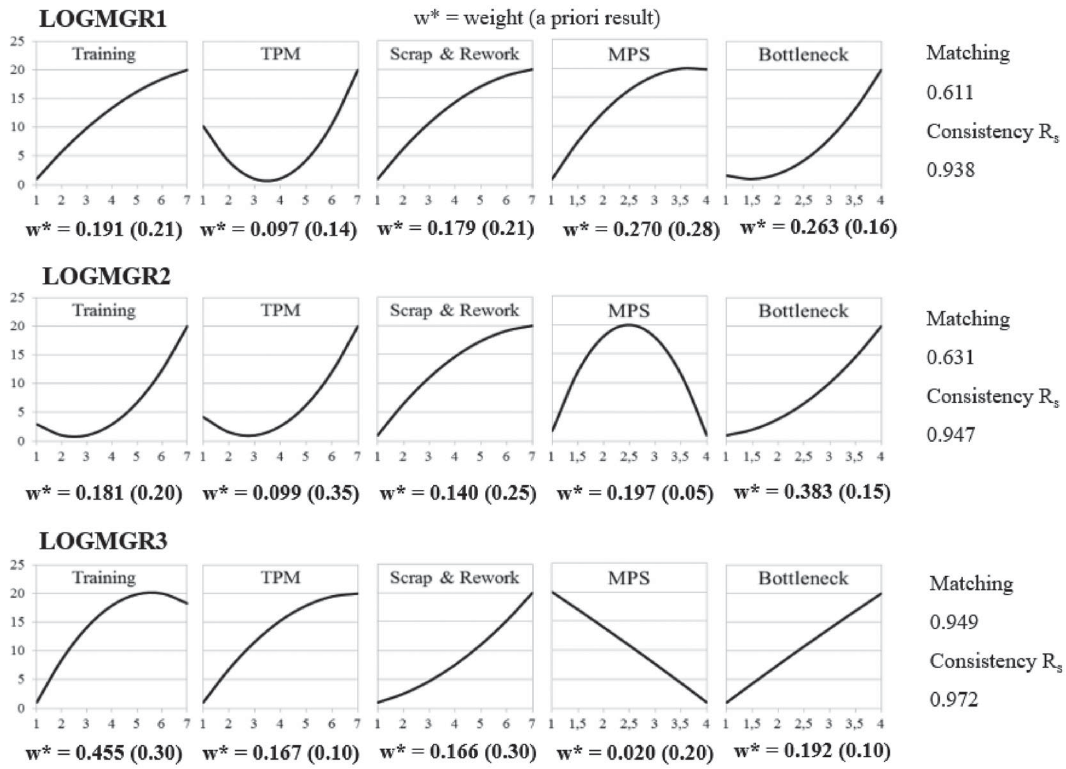

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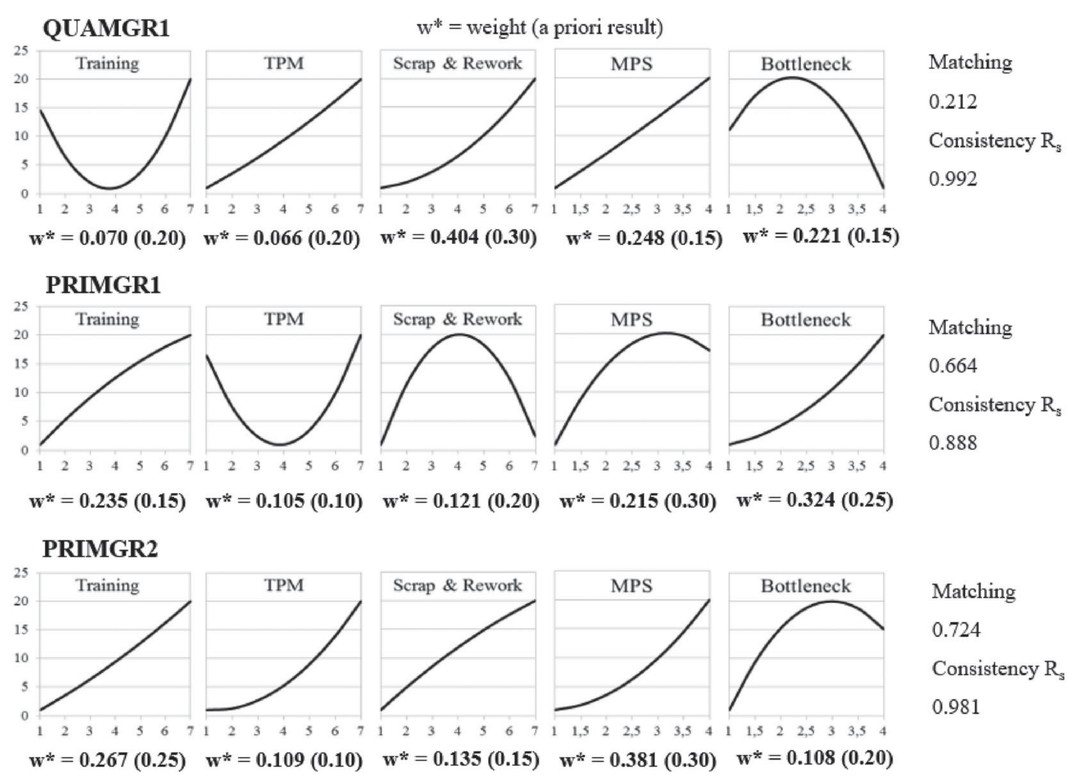

Figure 5. Continued.

Table 3. Judgment analysis for the management team (*Top Decision Makers).

	A Priori Assessment					Judgment Analysis				
Name	Training	TPM	Scrap&RW	MPS	Bottleneck	Training	TPM	Scrap&RW	MPS	Bottleneck
TOPMGR1	0.3	0.2	0.1	0.2	0.2	0.37	0.07	0.10	0.15	0.31
NPIMGR1	0.15	0.23	0.15	0.23	0.24	0.16	0.19	0.18	0.36	0.12
NPIMGR2	0.3	0.1	0.3	0.2	0.1	0.21	0.10	0.15	0.30	0.24
PROMGR1	0.35	0.3	0.2	0.05	0.1	0.36	0.29	0.10	0.11	0.14
PROMGR2	0.2	0.2	0.2	0.15	0.25	0.16	0.14	0.23	0.26	0.22
PROMGR3	0.15	0.1	0.25	0.25	0.25	0.16	0.19	0.14	0.41	0.10
LOGMGR1	0.21	0.14	0.21	0.28	0.16	0.19	0.10	0.18	0.27	0.26
LOGMGR2	0.2	0.35	0.25	0.05	0.15	0.18	0.10	0.14	0.20	0.38
LOGMGR3	0.3	0.1	0.3	0.2	0.1	0.46	0.17	0.17	0.02	0.19
QUAMGR1	0.2	0.2	0.3	0.15	0.15	0.07	0.07	0.40	0.25	0.21
PRIMGR1	0.15	0.1	0.2	0.3	0.25	0.23	0.10	0.12	0.22	0.32
PRIMGR2	0.25	0.1	0.15	0.3	0.2	0.27	0.11	0.14	0.38	0.11
	Mean					Mean				
	0.231	0.169	0.236	0.193	0.171	0.229	0.136	0.176	0.242	0.217
	Std. Deviation					Std. Deviation				
	0.064	0.087	0.050	0.089	0.060	0.104	0.063	0.083	0.111	0.086
	Coefficient of Variation					Coefficient of Variation				
	0.275	0.518	0.210	0.459	0.349	0.456	0.460	0.473	0.459	0.398

Function forms also play an important role in the judgment analysis as they depict the changes of perception of managers for different cue levels. It is important to note, however, that the function form should always be considered in relation to the weight because of the characteristics of the range method. The range method always calculates the graph between the minimum and maximum judgments over the whole range of cues and the weights are separated from the function form. A function form of a cue with a lower weight should not be emphasised as much as one with a higher weight because of the higher impact of the latter. Some of the function forms are strictly negative linear, which could mean that the participant thought of that cue as highly negative for throughput time, for example the MPS cue for LOGMGR3. The reason for that is that the manager completely disregarded this specific cue in favour of other inputs, which resulted in a very low weight of .02 for the MPS process. Other managers, however, also had negative function forms with high weights for some cues, which means that they truly had a negative perception about specific cues in terms of throughput time reduction.

Table 3 summarises all results for the whole management team. This showcases the general lack of consensus among the management team with no clear priorities among the variables as every manager chooses to rely on different cues. The aggregate group preference lies in the MPS process with only a minor lead over the training process and bottleneck optimisation for the judgment analysis. The team seems to agree only on the TPM process to be the least relevant process for throughput time, which is somehow counter-intuitive. The only explanation by the authors is that TPM is the least appealing and intuitive process among all cues so the participants sub-consciously devalued the impact of this input on throughput time. The equipment was also relatively new, which led to assumptions that there would not be as much unplanned downtime as initially simulated. In the a priori assessment it came in last in terms of relative weights as well, but not by the same margin as was the case in the judgment analysis and there were outliers in both assessments. Scrap and rework had a relatively low weight as well, because of the nature of the small-volume batch production system, characterised by a low quantity of high-value products being produced. In this case, the influence of scrap and rework is higher on quality costs than on throughput times which is intuitive and was also reflected in the judgments of the management team.

The results in this analysis are consistent with the findings of Dhir (2001), where participants had substantial differences in their initial judgments, however, they could at least agree upon the two most important factors with a significant margin in a deterministic judgment problem. In our study, however, managers even within the same area had substantial differences in their judgments and a high degree of linkage ambiguity can be observed, even within a relatively homogeneous group.

6.2. Simulation – weights, function form and causal relationship

The weight and function forms for the simulation analysis were computed in the same way as the results of the judgment analysis. All profiles were rated based on the averages of throughput times from 25 simulation runs with the best profile

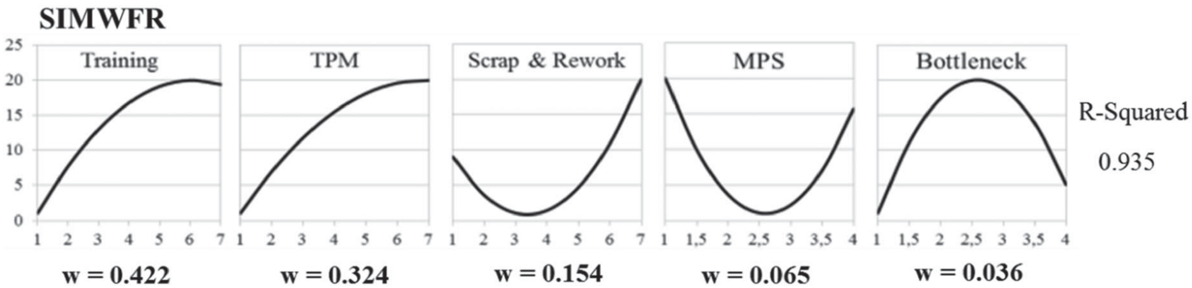

Figure 6. Weights and function forms based on simulation results.

getting 20 points and the worst one point. The ratings were then used like the results of an additional judge in the judgment analysis, and function forms and weights were calculated accordingly. Figure 6 shows the results of the 'quasi judgment analysis' based on the simulation results to create a picture for the left side of the lens model.

The simulation results decisively showcased the impact of the variables on throughput time for the environmental system on the left side of the lens model. Employee training was the most important factor for throughput time improvements because of the wide range of the input variable (see appendix). In the worst case, workers performed manual processes with only half the speed compared to the defined standards, while in the best case they could even improve on old standardised processing times with decentralised improvement on the operative level. This spread was a clear indication that employee training was critical for fast and stable processing of production orders, especially, because the modifier also affected bottleneck processing times at the finish department which is 100% manual and relies heavily on training. A unit-wide training programme was the most promising decision to enable employees to improve their processes autonomously with good knowledge in standardised work and improvement methods.

The second-most important process according to the simulation analysis was TPM to reduce unplanned machine downtime and further decrease the variability on the shop floor. This process only affected automated process of the assembly systems and furnaces with relatively lower capacity utilisation levels compared to the finish department. However, long downtime significantly affected the proper flow of products through the value stream and, at a certain level, the upstream processes could not supply the finish department efficiently. At low levels of the TPM process, the bottleneck shifted to the furnace process because the TPM modifier for automated processes did not affect the finish department. Machine breakdown occurred randomly and with varying impact on the system based on the current state of production and the duration of the downtime period. Manufacturing planning and control with the development of an improved MPS to optimise the sequence and flow of parts through the system had almost no effect on throughput times due to high WIP inventory which decreased the sensitivity of the system to a varying product mix and sequence. It was far more important to produce each order effectively than to plan and optimise the sequence of orders due to high variability in other processes. The least important process was bottleneck optimisation because it was also overshadowed by other processes with higher variability.

Furthermore, improvements at the finish department became meaningless when the bottleneck shifted to the furnace process due to a bad TPM process, which affected only furnace, but not the finish department. High unplanned downtime reduced protective capacity at the non-bottleneck workstations and caused increased bottleneck shiftiness, which confirms the finding of Craighead, Patterson, and Fredendall (2001) that bottleneck shiftiness can be reduced by placing more protective capacity before and after the bottleneck. This questions the TOC (Goldratt and Fox 1986) that a continuous improvement process should always focus on the bottleneck, and improvement of non-bottleneck resources is wasted, which is also supported by Filho and Uzsoy (2014). They find that smaller improvements at all workstations had almost the same effect on cycle time as a large improvement activity at the bottleneck workstation, which is confirmed by our analysis.

6.3. Comparison of results and development of an action proposal

Both sides of the lens model have been analysed and visualised in the same way and can now be compared to find sources of agreement and disagreement for better communication within the sensemaking process. The ladder graph of Figure 7 shows the weights for all factors as calculated for the simulation analysis and the judgment analysis of the management team. The indifference of the management team can be seen on the right side and they could not mutually agree on a single-most important cue with a significant margin. The simulation on the other hand generated clear results to focus on a specific factor with the highest potential for improvement of throughput time and therefore, the average matching index was relatively low.

The training process was a clear winner for the simulation analysis and the management team agreed at least to some extent by giving this factor the second-highest weight, despite the large absolute difference in weights between both sides

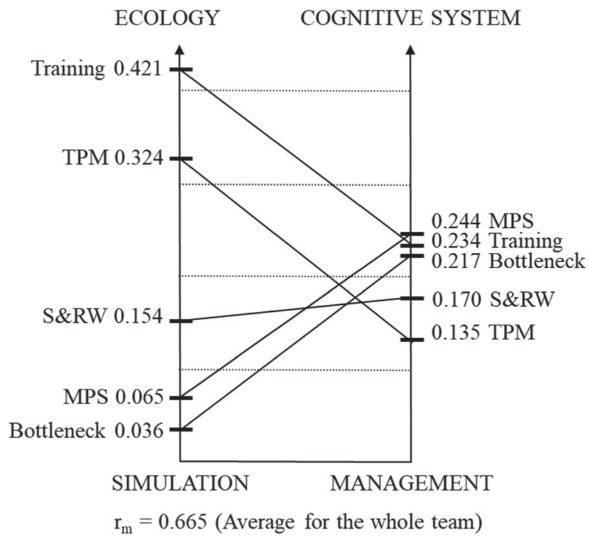

Figure 7. Comparison of weights between simulation and judgment analysis.

of the lens model. Scrap and rework were relatively even on both sides of the lens model but ranked differently. MPS and bottleneck processes did not influence the dependent variable as much due to the aforementioned reasons, however, the management team had them ranked in the top group of subjectively more relevant processes. While there might be various reasons for disagreement – attribute conflict and preference uncertainty (Fischer, Luce, and Jia 2000) for example – it shows that no clear causal relationship can be identified among the management team for the environmental system and only a few managers had some agreement with the simulation results as seen in Figure 8. The graph shows the weights for each factor for the three closest managers compared to the simulation; all three managers overvalued the bottleneck factor to the detriment of TPM. The goal of the lens model is to unfold these differences and make them visible for the management team to improve their group decision making.

The differences in the weights for the TPM process were the most interesting, because they accurately reflected the real dynamics within the production system as observed by the authors. Only one participant, namely PROMGR1, weighted this

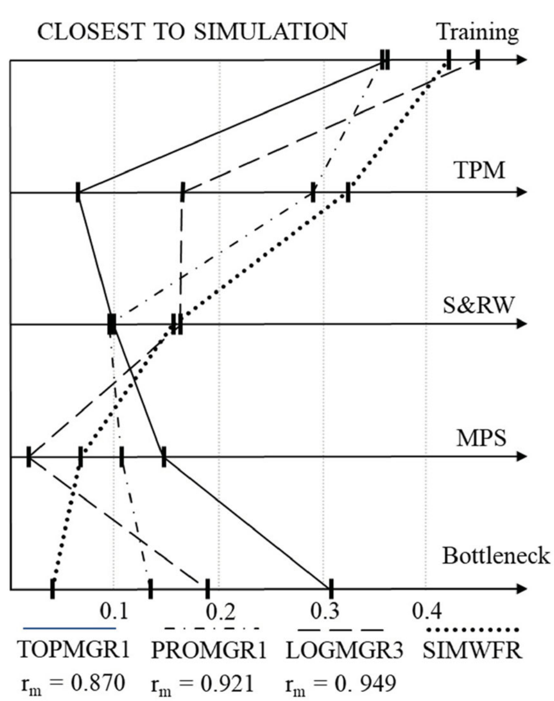

Figure 8. Highest agreement based on matching index and weights.

factor above 0.2 in the judgment analysis, who was indeed the one who tried to initiate an improvement project for the TPM process during this research project. This process improvement activity, however, was never implemented due to a lack of support of the other managers and there was no mutually acceptable action proposal.

Action proposals support a causal link between a course of action and its consequences and can be used to justify how certain solutions, based on theoretical research and models, lead to an anticipated and desired outcome on the process-level of a production system (White 2016). Friend and Hickling (2005) point out that OM interventions and models rarely solve organisational problems directly and if they were to be relevant and useful for practitioners, they need to be embedded in action proposals, or commitment packages. This method can be used in combination with the lens model methodology, because action is an integral part of the sensemaking framework (Weick, Sutcliffe, and Obstfeld 2005).

A commitment package, as developed by Friend and Hickling (2005), is an action proposal that defines a set of immediate actions and future decisions to achieve incremental progress in a continuous planning process. It defines what actions must be taken immediately, or if more exploration is necessary based on time and uncertainty of the decision areas. This means that some decisions should only be made if uncertainty is below a certain level and if there is not enough time for further explorations. It also leaves future decision space for deferred choices and contingency planning if there is still enough time to analyse further choices or to reduce uncertainty by doing more research, as depicted in Table 4. Note, that this is only one isolated concept out of the whole framework to assist decision makers in a continuous planning process but is an excellent tool to summarise the results of the lens model. It can also be used synergistically with continuous improvement cycles based on Six Sigma or Lean and is designed to work in environments with high uncertainty and causal ambiguity where judgments are needed for decision making.

An immediate action that should be taken based on this study is to initiate a training programme to improve manual processes and to reduce processing variability caused by assembly and finish workers. Stable and improved processing times had to be the number one priority of the business unit, however three of the four top decision makers (Table 3) viewed it not as a top priority according to the weights given in the judgment analysis. The lens model made these deviations transparent and specific managers could adjust their cognitive system by progressing in their sensemaking processes to adapt cue utilisation for this specific problem. It is fair to assume that these misconceptions of key decision makers within the production system prevented actions to improve this critical input. With the help of the information generated by the lens model specific people could be convinced and the action was finally implemented through an extensive production preparation process where all manual processes were trained, improved and standardised. This continuous improvement cycle was the new main priority for the unit and a clear focus for resource allocation. Allocation of resources into improvement of TPM and master production scheduling, on the other hand, was deferred and required further investigation, data collection and analysis. Those were the two processes where the management team deviated from the DES and at least one side valued it as a top-priority and the other mostly neglected it. This makes both processes good candidates for further explorations and differed choices in Table 4, as it is obvious that no consensual decision could be made based on the lens model analysis. In

Table 4. Commitment package, or action proposal based on the lens model results.

	Immediate Decisions		Future Decision Space	
Decision Area	Actions	Explorations	Deferred Choices	Contingency Planning
Training	Initiate training programme for process learning and improvement methods	–	–	If training programme is unsuccessful, revise process standards
TPM	–	Analyze current unplanned down time and MTBF/MTTR	Improve TPM processes and methods	If management judgment was correct, do not weight TPM as high
Scrap & Rework	–	–	–	Analyze again in next lens model analysis
MPS	–	Verify if it is a bad MPS or lack of execution?	Create an improved MPS and sequence of orders	If management judgment was correct, improve MPS
Bottleneck	–	–	–	Analyze again in next lens model analysis

Source: Authors representation of Friend and Hickling (2005).

this case the continuous improvement cycle starts again with a 'plan' or 'define' stage in a future period and no resources should be deployed without a clear understanding about the potential benefits of those processes.

No resources were assigned to bottleneck optimisation since it was the lowest ranked in the top group for the management team and the lowest overall in the DES. The quality solving process to reduce scrap and rework was also not a priority in terms of throughput time. Resources were allocated accordingly, with the majority going into the execution of immediate actions, and the rest could be invested into further analysis of other important factors that required more information. This ensured efficient and effective selection of improvement projects based on measurable indicators and management judgments. Relying on one source would potentially have led to a different allocation of resources without an exact classification of actions for each decision area.

Management generally trusted the results of the simulation analysis and accepted the action plan after pointing out the differences between the DES and their judgment analysis. They were involved right from the beginning of the analysis and the creation of the DES and could easily interpret the results of the judgment analysis to adjust their mental model. This way we could minimise subjective influences based on objective results and create a mutually acceptable action proposal.

7. Conclusion and future research directions

There are many reasons why managers cannot or do not want to understand objective quantitative analyses. For example, complexity can create a gap between the model builder's insights and a manager's understanding of its results, as explained by Dhir (2001). Another point is that people are not particularly good at explaining the reasoning behind their judgments, which prevents effective communication and understanding between individuals. Dietvorst, Simmons, and Massey (2015) found algorithm aversion, or a lack of trust into results of quantitative analyses if people have had bad experiences in the past. All these factors influence managers to still rely on their own subjective methods because they believe to already know the most important factor for improvement (Kirkham et al. 2014). The lens model confronts managers with their biases which is why it is so important that the analysis from the lens model method is purely descriptive to analyse factors deep within an individual's cognitive system.

The S^3 developed in this paper is not focused on decision-making based on precise mathematical calculations, but rather serves as a sensemaking tool to bring the management team closer together and empower them to define mutually acceptable actions to move forward and improve the production system. After a trigger event, a criterion variable (e.g. manufacturing throughput time, or behaviour of wildfires in certain terrains) is defined to be the centre point of the sensemaking process and the lens model analysis. The DES helps to define, label and categorise inputs and generate insights into potential future states of the system and form presumption about the environment. Then the judgement analysis visualises cognitive patterns of the management team and their preferences for cue utilisation and rankings as a basis for communication. We exposed differences and similarities as a basis for communication and discussion to bring the management team closer together and facilitate exchange of ideas and knowledge. The action plan generated by combining both analyses is the foundation for future steps to create even more sense when the sensemaking process is repeated. In this ongoing process of sensemaking, action generates more inputs that can be included in future lens model analyses. That way knowledge and understanding can be continuously increased to make more sense of complex processes within the production system. More cycles in the sensemaking process are necessary to define, label and categorise different, and potentially better, cues and use the results of previous communication to integrate them into better models and create better action plans as the sensemaking process goes on, which is the goal for future research.

This method is valuable even for production systems without extensive data collection and can be easily implemented. Various other objective methods, for example pareto analysis, structural equation modelling, etc., can be used on the left side of the lens model to predict the true state of a system and can be compared with the judgment analysis on the right side to yield the same results. Future research can implement this method to test results of objective scientific methods and bring them into closer relation to the judgments of managers affected by this analysis. Another crucial part, left for future research, would be to test the effects of the cognitive analysis with the lens model methodology in comparison to just a 'regular' scientific intervention. This would empirically strengthen many ideas of behavioural OM/OR and the benefits of including the human factor in applied research in our field. In a broader sense, if we put academics fighting for rigour on one side and the practitioners living in the world of relevance on the other, our paper is an attempt to bridge the gap between the two groups. We hope that it will be followed by many.

The lens model methodology includes managers into the sensemaking process and valuable insights can be gathered by making all judgments available to top management. This was also observed by King and Zeithaml (2001) who reported a high interest of top-managers regarding the perception of their colleagues and middle managers about resource-performance linkages, which was also the case in this research because managers want to understand what their colleagues think. They found that the transfer and collaborative exploitation of resources could lead to increased firm performance; this is why this research aims to make this information available for the management team to improve mutual understanding. It shows that integrated information from the DES and the judgments of management can be used to create holistic and accepted action proposals to increase the relevance of OM interventions for practical applications. Samson and Whybark (1998) and Vastag (2000) emphasise focusing on soft issues and organisational capabilities to outperform competitors due to better decision making and usage of manufacturing inputs, investments and choices. The sensemaking framework is one way to improve decision making within the production system and to help management acting in an organised, coherent way.

Kirkham et al. (2014) provide an excellent literature review of improvement project prioritisation and conclude that limited empirical research has been conducted to understand improvement project selection processes. They find that objective prioritisation methods, especially in a Six Sigma context, generally lead to better results, compared to subjective ones. We try to analyse and combine both methods to help to fill the gap in the literature and to create a deeper understanding of managerial sensemaking processes and the prioritisation of improvement projects. A lot of research has been conducted on the best way to improve a production system, Goldratt and Fox (1986), or Ferdows and De Meyer (1990), to name just two, but ultimately it depends on the judgment and the alignment of the decision makers to go in the same direction and work together to achieve common goals of the production system. Production systems, supply chains or service providers are, after all, complex social systems, where behaviour of individuals, groups, or whole organisations is the central driver of operations and performance (Gino and Pisano 2008).

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Supplemental data

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