Msc Thesis Industrial Design Engineering

Deriving adequate insights in HMLV manufacturing

Galina Veldkamp*[a]

[a] Department of Design, Production and Management, University of Twente, Enschede, The Netherlands

Abstract

Making adequate decisions in high-mix, low-volume (HMLV) environments is difficult due to the interplay of influential factors affecting data points required to obtain insights. To be able to make adequate decisions, data-driven insights are required, based on data points from both company data systems such as ERP/MES and IoT devices. This study highlights the challenges and proposes a systematic approach using these data points to create objective indicators, which are used within a subjective perspective to obtain an insight. Guidelines are offered to enhance predictability and robustness while focussing on the interplay of influential factors and perspectives steering the outcome. Next to these factors, the complexity of manufacturing companies involves production processes which must meet all characteristics for the engendering of tailored (both new and repetitive) product order, the use of various machinery, equipment, and tools with different levels of automation and multiple stakeholders with a broad range in disciplines and skills. A case study on Overall Equipment Effectiveness (OEE) and one about a data-based dashboard verify the approach, emphasizing a holistic understanding of indicators, potential consequences of perspectives, the used data and influential factors to foster informed, stable and adequate insights for decision-making across manufacturing processes.

Keywords: Manufacturing; HMLV; (K)PI; Predictability; Case-based research

1. Introduction

In high-tech industries, complex products require collaboration among manufacturers. Original Equipment Manufacturers (OEMs) oversee intricate assembly, relying on specialized suppliers for components. The resulting supply network involves strategic outsourcing for co-development, knowledge exchange, and quality management. This culminates in high-mix, low-volume (HMLV) manufacturing strategies, characterised by high precision, complexity, and bespoke nature, tailored to meet the requirements in the overall supply chain.

Manufacturing involves value-adding processes such as production, process planning, production planning, and shop floor control [1]. It requires the use of various machinery, equipment, and tools with different levels of automation. The production environment must meet all characteristics for the engendering of tailored (both new and repetitive) product orders in the supply network. This asserts that control, planning and optimisation paradigms are required that go beyond the inveterate working methods in job-shop or mass-production environments. Moreover, the involvement of multiple stakeholders that cover a broad range of disciplines, subjective and objective perspectives, and skills, make the HMLV scope demanding.

As the basis for informed decision-making, (Key) Performance Indicators ((K)PI) are often used to summarise or represent the operational performance of a company. These (K)PIs are habitually based on a variety of data sources/points across business operations, ranging from, for example, ERP, PDM, and MES systems to machine status and sensor data.

Despite the assimilated use of (K)PIs in industry, the intricate relations between the many inputs that influence indicators do not inherently enable or improve decision-making. This is due to the fact that the actual insights required for adequate decision-making cannot stem from sheer data values alone, but also depend on the perspective and other influential factors. Therefore, it is imperative to recognise that indicators merely provide a transient snapshot of a pre-determined selection of the company's state.

This research aims to establish a systematic basis for informed decision-making in HMLV manufacturing environments, in both theory and a case study, with the use of:

- Data point(s): objective data collected from company systems or machines/sensors.
- Indicator(s): consist of at least one data point, or they can be aggregated data points.
- Perspective(s): the view of a stakeholder within a company.
- Insight(s): the summarized information from indicator(s) and perspective(s) required for a specific decision.

Information about the used definition producing, manufacturing and machining is provided in Appendix 11.1.

2. Approach

To facilitate purposeful, adequate, effective, and efficient decision-making, indicators should ensue from historical and current data, based on what predictive models can be made. Such data analytics aims to capture i) what happened, ii) why it happened, iii) what will/might happen, and iv) how can we make it happen best under which circumstances. (Additional explanation about data analytics can be found in Appendix 11.2.). Based on these steps, the aim becomes to align potential futures with envisaged circumstances [2]. For adequate data analysis, i) data collected from machines and sensors and ii) company data from systems used by the company (ERP, PDM, CAD, etc.) are required.

In literature, there are already many theoretical approaches available [3,4]. However, in the industrial context of the research, the observation has been that, all too often, the theoretical models insufficiently align with, or do not even do justice to the idiosyncrasies and unpredictabilities of day-today realities at shop floors (e.g. [5,6]). This is especially true for approaches that are process-oriented rather than emerge from the information/data that is available in the company [7]. For this reason, this research project does not aim to impose theory on reality, but rather aims to use existing approaches as mere guidelines to establish adequate reasoning and structure rooted in operations in HMLV environments. Consequently, a more bottom-up approach is called for, and this typically starts with data generated on the shop floor.

Data collected from machines and sensors has a timestamped character and aims to capture (series of) data values related to individual sources like sensors or machine status. As such, this data is often referred to as 'Internet of Things' (IoT) data, more information about this topic is stated in Appendix 11.3. In the context of production environments, it therefore represents operational and technical status information on (groups of) assets. IoT data requires contextualisation and interpretation, covering

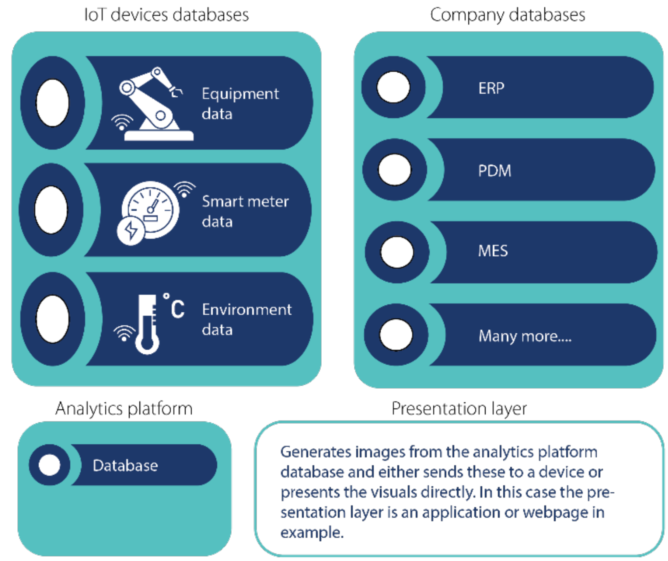

Fig. 2. Data processing in a manufacturing environment.

i) registration, ii) transmission, iii) data processing, iv) data visualisation, and v) data analysis. Therefore, the data itself is usually not directly fit for determining indicators or for decision-making.

The company data represents the primary processes in a company. Because this data, and the systems that represent it, are ingrained in many applications and processes in the company, the flexibility and adaptability of these systems is extremely low (Fig. 1. [8]). This, for example, implies that for decision-making that is agile, not pre-established, or involves different interfaces to the data, a direct link to information systems is insufficient or too intransigent. Therefore, decision-making often requires a representation or visualisation of the data that, in addition to sheer company data, also requires additional processing or analytics. As this is separate from existing information systems, a specific analytics database and presentation functionality are introduced here (see Fig. 2).

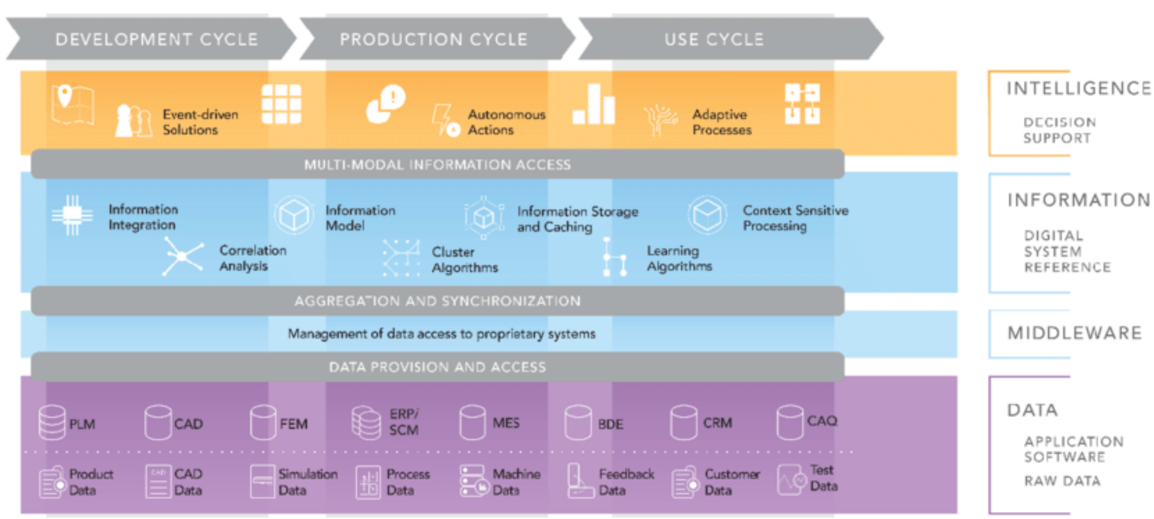

Fig. 1. Advanced manufacturing landscape [8].

Whereas execution steps in data analytics often receive the most attention, HMLV environments must prioritise the preparatory and consequential steps. Firstly, the ground for doing something is important – especially with respect to the envisaged goal (doing the right things). Secondly, potential consequences of a decision might positively or negatively influence the judgement on actually executing a decision.

In this, the preparatory steps address, for example, the identification of what data would contribute to the indicators used in decision-making, as well as where and how that data can be obtained in effective and efficient manners with adequate certainty. With that, the scope of data-informed decision trajectories exceeds the mere technicalities. Fig. 3 represents the overall scope of data analytics for adequate decisions in HMVL environments.

Two feedback loops are implemented in the approach, one during the decision phase to ensure that the goal can be met while not (overly) influencing other insights. The other feedback loop connects the predictive and diagnostic phases to foster the adequate evaluation of considerations, reasons, causes, and rationale in both governing foresighting and in enhancing diagnostics (approaches).

During the approach, four aspects should be kept in mind, which are relevant for the IoT process: things, data, people, process [9]. However, these are rephrased, to be relevant for the decision-making approach in its entirety. More information about these four aspects can be found in Appendix 11.4.

1. Things: IoT devices, which preferably have their own unique identifier to enable traceability of data.
2. Information: creating useful information from the collected data.
3. Communication: to enable effective and efficient use of data and process flows, clear communication is useful; different stakeholders need to collaborate and determine how to interpret data and what to do next.
4. Process: the strategic and tactical approach that relates to establishing who (or what) needs which information when.

Chapter 3 and 4 will elaborate on the first two steps of the approach from Fig. 3 how to start and how to prepare the data, while chapter 5 will address the influential factors that affect the indicators, rendering them susceptible to fluctuations, as input for the third step modelling & investigating.

3. Realizing meaningful insights

A generalized approach is provided on how to start obtaining valuable insights on which decisions can be based, the first step from Fig. 3. An initial plan should be clear before collecting data and getting lost in the process. Before starting, the following things should be defined: what is the goal, which (K)PIs are needed to have enough information to be able to draw a decision, which data is needed for these insights and where can the data be found. Rather than using company dependent (K)PIs, the generalized term indicator will be used. In example, the (K)PI ‘A customer satisfaction of 90%’ will be rephrased as the indicator ‘Customer satisfaction’.

These indicators can be formulated on three different aggregation levels:

1. Strategic indicators: focus on the vision and mission of a company on long term.
2. Tactical indicators: translate the strategic focus into tangible actions on a medium term.
3. Operational indicators: execute the activities and maintain alignment with both strategic and tactical levels on short term.

The indicators are used to steer decisions, but the consequences of these decisions regarding their effect on other indicators and their dependence is often left out of scope.

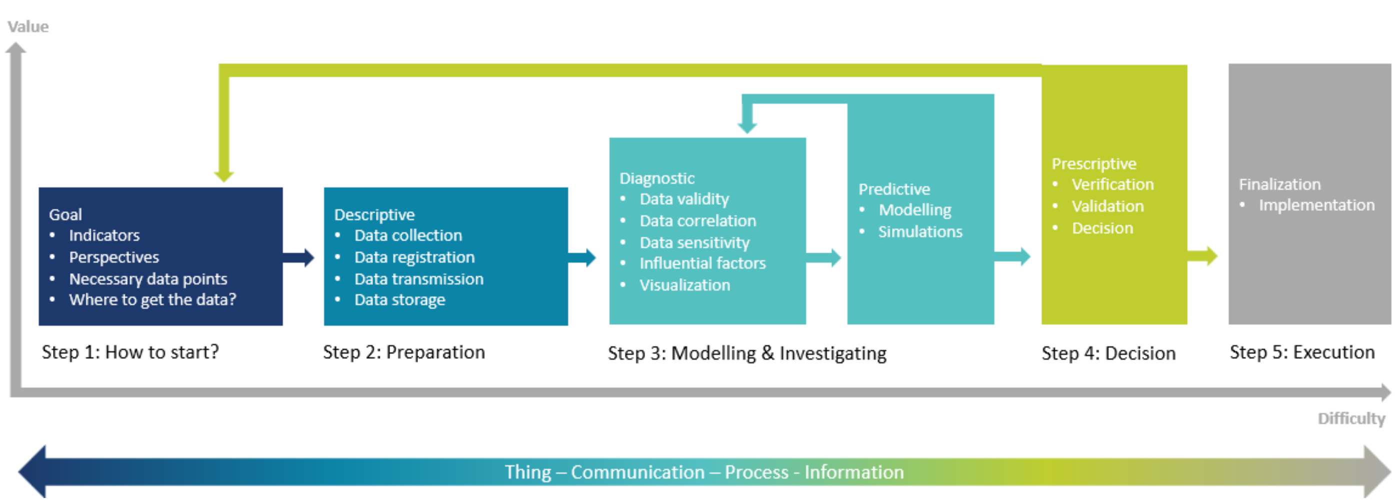

Fig. 3. Proposed approach how to obtain valuable insights.

Fig. 4 shows these influences, providing an underpinning for the positioning and structuring of indicators.

The first row represents the indicator, which essentially define the *'What is the required knowledge?'* aspects. Upon clarifying this indicator, the focus will shift to determining *'What should be measured?'* represented by the squares in the second row, while those in the last row signify the specific information that is required. Where all green squares represent IoT data and blue squares indicate company data. This approach leads to a strategic alignment between the indicators pursued and the overarching goals of the organization.

The indicator '*Company production productivity*' is represented in the first column of Fig. 4., the strategic aggregation level. In the second column, the tactical aggregation level is displayed, which usually needs to be calculated or measured, in example the OEE (Overall Equipment Effectiveness). The OEE is also part of the *'What should be measured'* of a strategical indicator. While the indicator quality machine on the operational aggregation level supports both the tactical as well as the strategic indicator.

3.1. Perspective

Stakeholders have different objectives, responsibilities and interests, depending on the organizational chart of a company and therefore also different perspectives on all aggregation levels.

Where perspectives can require the same type of indicator for decision-making, this inherently implies that decision-making in one perspective has (unintended) consequences for activities and decision-making in other perspectives. Therefore, a holistic overview that transcends departmental silos and fosters a cross-functional view is required.

A precondition for such an overview is a sufficient understanding of the (relation between the) different perspectives. By considering the broader organisational context, one can anticipate how acting upon one indicator might impact others and avoid potential negative consequences. In example, the decision in purchasing a cheaper material is beneficial for the costs indicator in a sales perspective, but it might result in more rejected products, negatively influencing the indicator machine quality useful for the quality engineers' perspective.

3.2. Vertical and horizontal relations

When making decisions based on strategic indicators within a perspective, understanding the operational and tactical aspects of an organization help improve the understanding of the implications of the decision-making process. These are considered vertical relations.

The interplay between perspectives within an aggregation level is considered as horizontal relation. The execution of a decision based on one indicator can affect other indicators on the same aggregation level. For example, from a management board perspective, the indicator company production productivity is obtained and a decision is made to increase the machine power, to increase the value of the company production productivity. This decision can result in more products, influencing the other strategical indicators profit margin and revenue growth as well. Appendix 11.5. can be consulted for a clarifying visualization.

4. Preparation phase

When it is known which information is needed, the data can be collected, registered, transmitted and stored as mentioned in the second step of Fig. 3. The integration of both company and IoT data is needed, where the latter could lack availability at first.

In a manufacturing environment, the amount of collected data is big due to both the company data and life status of IoT devices, the data type is of a wide variety, and the collection happens at a very high speed in little time. Due to these factors, big data in a manufacturing environment is also referred to as Industrial Big Data. To prevent an unnecessary amount of data and getting lost of the needed information, it is beneficial to have some guidelines set up before collecting data.

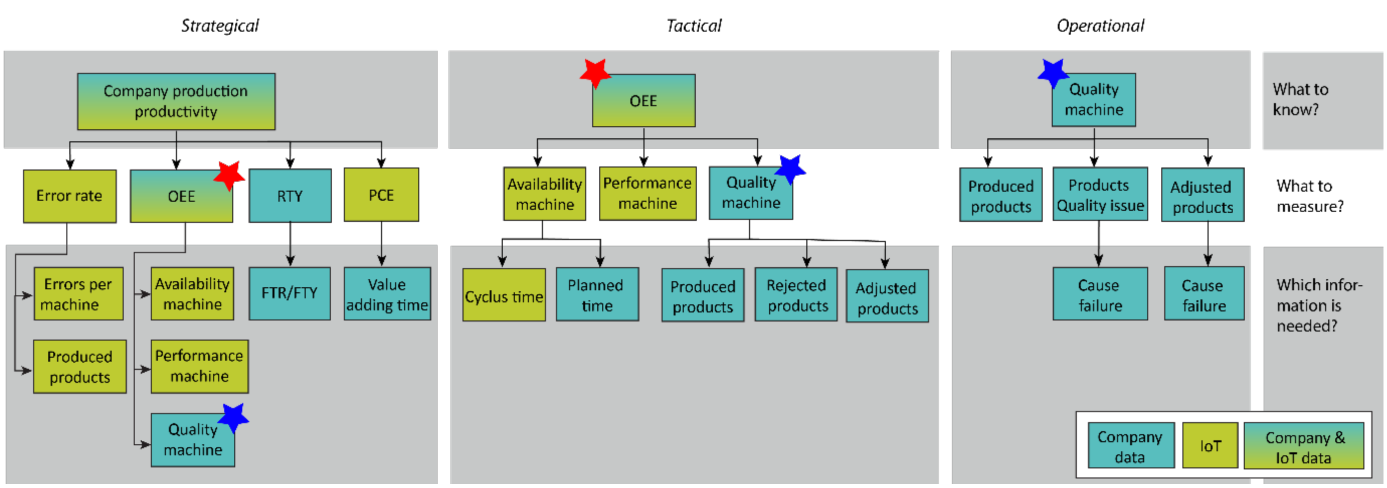

Fig. 4. Dependencies of indicators of one perspective.

Before beginning data collection, it is important to establish several parameters, such as the frequency and accuracy of data registration, the adaptability of these, and the duration and longevity of the data repository. The frequency and accuracy of data recording are crucial as they determine the volume of data generated and subsequently influence the requirements for data storage capacity. It is also relevant to determine the time lag between implementing a decision and observing its impact in the collected data. Additionally, it is important to clearly define the temporal scope of data collection, including whether data needs to be gathered continuously throughout the day, exclusively on weekends, or during specific time frames. The shelf life of data is determined by stakeholder requirements, the significance and objectives of the data collection effort, and the duration for which the data should be retained. In some cases, clients may stipulate that specific datasets are to be preserved for extended periods.

If there are any changes in the objectives that affect data accuracy, the chosen data registration method of a company should be assessed if it remains compatible. The evaluation of the feasibility of improving the frequency and accuracy of data collection is necessary. Therefore, all data should be traceable with the use of a unique identifier, a structured display and IT architecture to allow for the integration of information [10].

5. Modelling and investigating phase

In the third step of the approach in Fig. 3, modelling and investigation phase, insights are derived from the collected indicators (objective) with a perspective (subjective).

In a manufacturing environment, numerous factors have a significant influence on the manufacturing process affecting the to be collected data points, and therefore impact the indicators. An Ishikawa, or Fishbone, diagram can be used as a guide to identify these influential factors. This is a tool for conducting root-cause analysis, available in various formats.

Two formats are used, the 6M and 8P diagram, as the 6M is more tactical, calculated information, and IoT related, while the 8P is based merely on company data. The 6M is mostly used to find a quality root-cause looking at six different factors: manpower, method, machine, mother nature, material, and measurements. Where 8P is used when looking into services or administration and covers price, people, place/plant, procedures, promotion, processes, product, policies.

Both are related to each other and some additional factors, such as safety and supplier are considered forming a new diagram represented in Fig. 5. These factors are divided into three groups since not all factors are measurable and objective, resulting in: measurable (objective), semi-measurable (both objective and subjective) and non-measurable (subjective).

Measurable factors are objective data that can be included in a database, such as the temperature and humidity in the environment. Semi-measurable factors are both objective and subjective, making them more difficult to measure and digitize. For example, the quality of work instructions and procedures depends on perspective of the reader. The content on the other side is objective. Finally, the subjective influential factors, which are non-measurable and not part of a database. In example, human influence is significant because an individual's discipline impacts many data points.

To obtain adequate insights, it is necessary to determine which influential factors influence the indicators and therefore should be taken into account. Fig. 5. can be used as guideline on what factors to consider. Based on this, for example what-if scenarios and simulations of potential futures can be used to create foresights of the relations between the influential factors and the evolvement of the company environment.

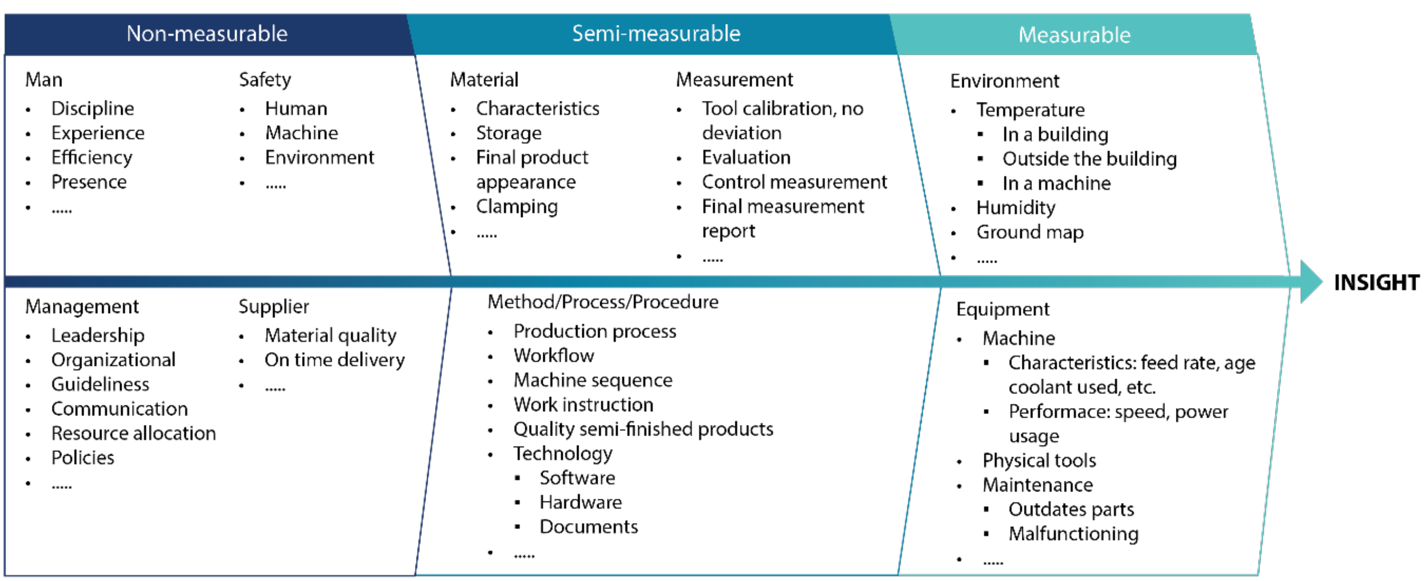

Fig. 5. Ishikawa influential factors.

6. OEE case study

To verify the approach depicted in Fig. 3, a case study is performed for a HMLV contract manufacturer, NTS Hengelo. Appendix 11.6. provides more information about the company. In this case study the first two phases of the approach, *'How to start?'* and the *'Preparation phase'*, and the use of the combined Ishikawa diagram (6M and 8P) as a guide to identify influential factors have been assessed.

Indicators have been acquired by interviewing stakeholders within the company. The question *'What is the required insight?'* has been summarize into '*What is the company production productivity?'* on a strategic aggregation level. The underlying goal is to know the company's production productivity when machines operate at their maximal performance.

Calculating the productivity can be done with the use of tactical indicators: productivity of a machine (OEE), productivity of people (looking at work instructions), productivity of the process (Process Cycle Efficiency), and more. For this case study the focus will be on only the OEE, to verify the approach in a limited yet realistic setting. OEE is defined as a percentage representing the productivity of a machine compared to the ideal machine. It consists of three elements representing operational indicators and is calculated by eq.1:

$$OEE = Availability \times Performance \times Quality \qquad (1)$$

Each of the elements in eq.1 in itself is a calculated component, consisting of data points, as stated in eq.2.

$$OEE = \frac{operation\ time}{planned\ production\ time} \times \frac{ideal\ cycle\ time}{operational\ time} \times \frac{\sum Products_{FTR}}{\sum Products} \qquad (2)$$

Elaborated information about data points behind the formula can be found in appendix 11.7. From eq.2, it becomes apparent that both machine data and company data are required. The operation time and performance can be obtained from the machine, while the planned production time and amount of FTR stems from company data. FTR is First Time Right and refers to all products, which are correctly produced the first time.

6.1. Case study observations

Step 1 – How to start:

- Stakeholder interviews provide an indication on the different perspectives and different organizational levels, but also provide an understanding of the interrelations between and within the aggregational levels.
- Perspectives vary in significance (see section 3.1) across different stakeholders and organizational positions. In example, the operational indicator machine quality is necessary for the calculation of OEE. Simultaneously, machine quality is a tactical indicator for the maintenance department, to represent their performance.

Step 2 –Preparation:

- Data collection, registration, transmission, and storage was already available for the required company data. However, within the company, IoT data of the operation time, and the performance, is not yet available.
- Clearer guidelines for data management, as mentioned in chapter 4, in a HMLV environment are needed, including frequency of measurement and connectivity methods.

Step 3 – Modelling and investigation:

- Determining the OEE depends on factors beyond the entities in eq.2. This includes, for example, the impact of human efficiency and restraints on both availability and quality. Also, external factors like temperature, humidity, or logistics may affect operational abilities of a machine.
- To enhance insight accuracy, simply adding more data points for indicators isn't sufficient. Emphasis should be on variables with a high sensitivity: showing substantial impact variations with minor input changes. Fig 6. represents on the left panel different variables which might affect OEE, and on the right a close up as readable example. These variables differ per use and represent data points and influential factors.

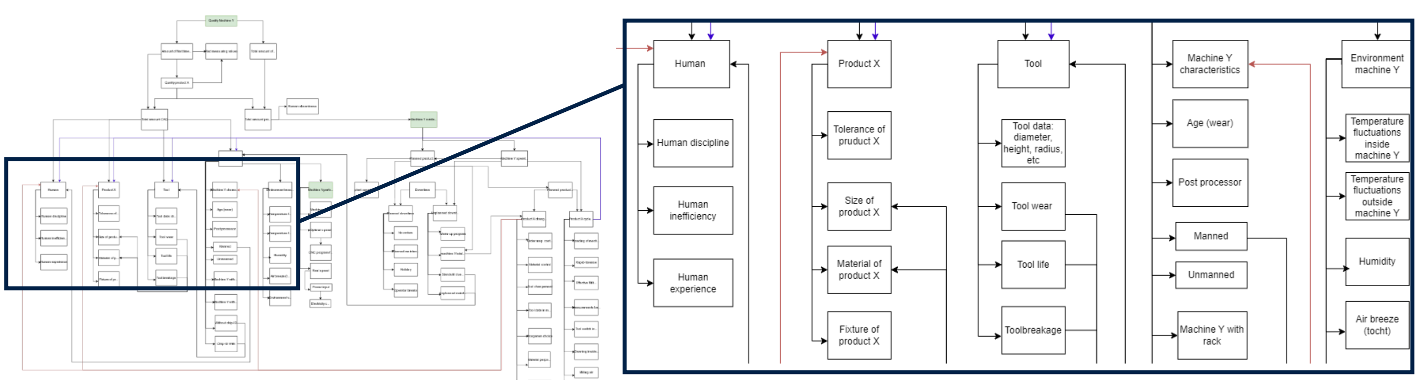

Fig. 6. OEE variables.

While no OEE percentage is obtained, the study emerges that indeed the myriad mutual relations between the factors do influence each other and the calculation significantly, and sometimes disproportionally, necessitating the relevance of the modelling and investigation efforts in Step 3 of Fig. 3. The case study maps part of the HMLV with the use of data points, indicators, insights and perspectives. The first two steps of the approach and the use of the combined Ishikawa diagram (6M and 8P) as a guide to identify influential factors are verified.

For future research about OEE in a HMLV environment, it is advised to use MEE, machine equipment effectiveness. This is similar to OEE consisting of availability, performance and quality, but with changes to better suit the HMLV environment. The MEE uses a modified optimal cycle time for the performance, which includes small stops such as in-process measuring and inspection [11]. On top of that, the quality does not focus on FTR, but on the economic value of the production time and costs of concessions, rework and scrap [11].

7. Additional case study (S)QLTC dashboard

While working on the OEE case study, another case study was introduced: the (S)QLTC dashboard, (Safety), Quality, Logistics, Technology and Costs. These objectives were represented in a visual, seen in Fig. 7. and used by the company to encourage the operators to follow the planning.

After evaluation two mistakes emerged. Firstly, the interpretation and definition of the data request did not meet the data provisioning. Secondly, the underlying goal was not defined and influential factors were left out of scope.

1. Examples of inconsistent data definition and interpretation:

a. The costs showcases the total amount of incorrect product costs. For a HMLV manufacturer, these costs are based on three categories: i) rework, ii) scrap, and iii) concession: products with a deviation but accepted by the customer. The company uses a formula and estimations to calculate the costs and therefore the dashboard should mention that the costs indicative.

b. For the logistic part, the availability was used. However, this is not the availability of the OEE. Operation time for availability is 'planned production – downtime loss'. The availability from the dashboard on the other hand did not subtract the downtime, changeover time. Therefore, the dashboard should either not refer to availability to prevent confusion or use the correct data. Moreover, the used data point for operation time is not representable for a real life situation. Some operators book the amount of provided hours instead of the spent hours and sometimes multiple hours are booked at the end of the week or forgotten to be registered.

2. Example neglected initial goal and influential factor:

a. During discussion, the goal of the dashboard appeared to be 'following the planning' because it is believed that following the planning will result in an on time delivery and therefore makes the customer happy who provides money. However, following a planning is not met with showcasing a dashboard and having no actions following. The goal was initially made because operators deviate from the provided planning. If this is good or not can be discussed, but the operators already know they do not meet the plan realisation and changing the planning is not allowed. With the logistics part of the dashboard the operators will only be assigned negatively and shown what they already know. However, 'man' is one of the influential factors and very important. If the operators are not motivated, the production can be negatively affected.

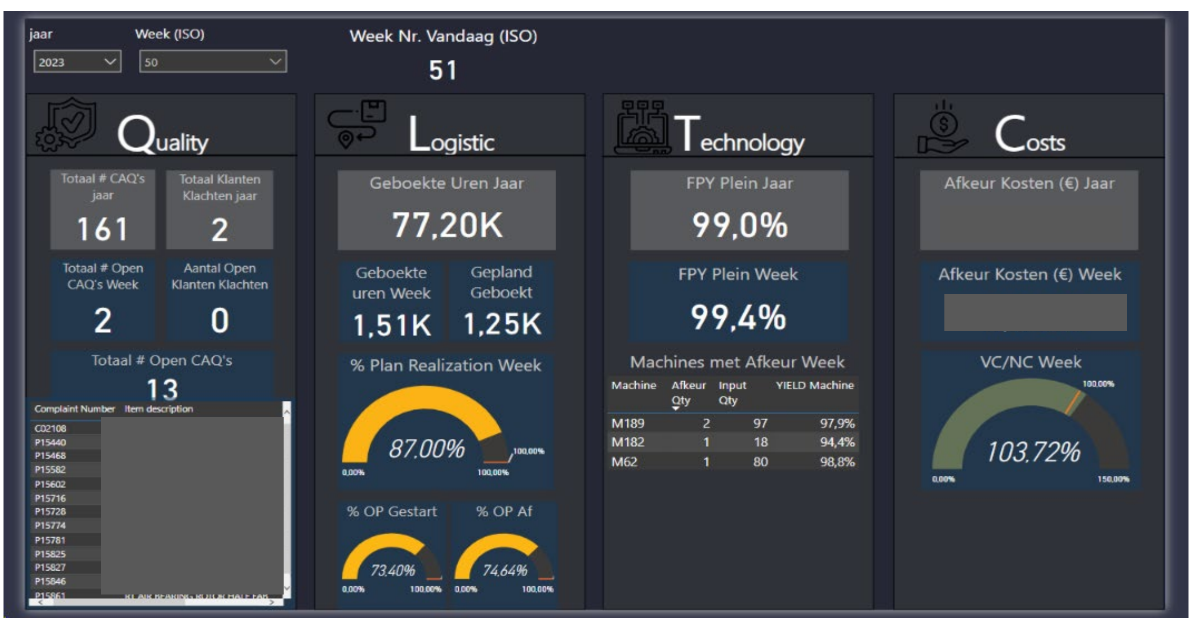

Fig.7. (S)QLTC Dashboard.

7.1. Improvements based on the proposed approach

If the proposed approach of Fig.3. would be taken into account it can be stated that the creation of the dashboard focussed mainly on the third and fourth step 'Modelling & investigating, and Decision'. The first mistake of inconsistent data definition and interpretation could have been prevented by taking the first step of the approach into account: *'How to start?'*. This would also partially prevent the second mistake of a neglected initial goal. On top of that, the influential factors from step 3 should have been taken into account to prevent potential negative consequences.

Based on the initial goal, following the planning, a new goal is formulated: on time delivery, OTD. An advice is made how to create the logistic part of the dashboard while following the approach from Fig. 3. However, the second step is not discussed while all required data was available.

Step 1 – How to start:

- First there will be looked into required indicators and necessary data points to obtain an insight as explained in chapter 3. Insight in OTD can be achieved with the indicator: 'plan realisation', which can be measured by dividing the amount of produced products with the planned products. This information can be found in an ERP system. The indicator can be observed from multiple perspectives as managers focus on a plan realisation for a product and area planners or operators focus on their production step.

Step 3 - Modelling & Investigating

- Once the data is collected, influential factors should be looked into as shown in Fig. 5. from chapter 5. These factors can influence the data point: amount of produced products. Especially man is important as operators work with the machines and influence the efficiency of the process and might affect the product quality. In discussion with the team leader, planner and some operators of the turning area, it was decided to model three images for the plan realisation to keep everyone motivated and satisfied, see Fig. 8.

Step 4 – Decision

- It should be investigated and tested if the proposed representation works and other additional influential factors should be looked into and their sensitivity before a decision can be made.

Step 5 – Execution

- If the new representation is used to obtain insight in the indicator plan realisation, actions should be taken. If the insight shows a plan realisation of 50%, the cause should be known why a product is not produced and actions should be taken and divided to prevent this from happening.

7.2. Importance of the executing step

The final step execution might seem very obvious, but is also rapidly overlooked. It appears that due to the company workflow insights are obtained, while no actions are taken afterwards, thus the current situation will not change. This is a problem which appeared more than once. In example, there already was a document about plan realisation with reasons why a product is not produced, but nothing was done with the information.

Another example is an optimization process about power usage. The power usage of all machines is monitored and represented in multiple charts. Differences in usage between machines are shown and it shows a power usage on days the machines should not be producing, but no actions were taken. Again only step three from the approach in Fig. 3. Preparation & Modelling was performed.

To conclude, there is an urge to start with step 3 and 4. However, it is important to take a step back and look at the goal, indicators, insights, perspective and data to prevent inconsistent data definition/interpretation and neglecting the initial goal. Once an insight is obtained and reflected if the decision would be suitable, step 5, Execution, should be performed: actions should be divided and acted upon to make a difference.

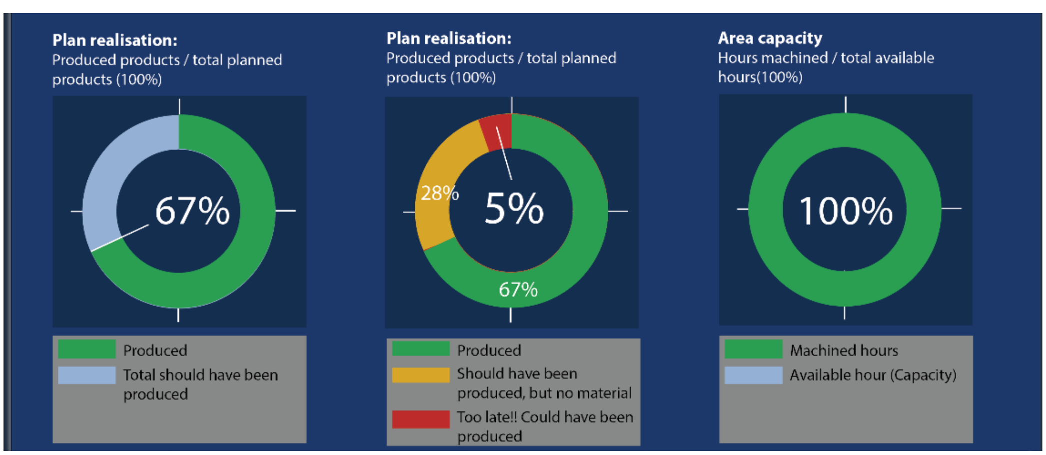

Fig. 8. New logistic visual for (S)QLTC dashboard.

8. Concluding remarks

Often, theoretical models cannot do justice to the operational reality on shop floors of HMLV companies. The increasing complexity of such shop floors calls for a reorientation on the role of decision-making; from seeing decisions as part of a workflow, a shift is proposed to root decision-making in data that adequately depicts the operational reality. This research contributes to that by focusing on insights as the archetypical indicator(s) and perspective(s) required for a specific decision. This results in an approach (see Fig. 3 effectively focuses on the information that is available for decision-making.

While many organizations focus on the visualization of data, (step 3 of the approach), the approach and case studies highlight the importance of interrelating decision-making (processes) to the myriad, interrelated, uncertain, and even uncharted factors and values that determine the outcome of such decisions.

The approach does also not only has a feed-forward character, during the case studies it was clear that the content of the first steps require and benefit from activities related to the subsequent step – or even from what-if scenarios envisaging more future steps. Such feedback loops do not only improve the decision-making at hand but are also certainly instrumental in advancing the way in which the initial steps are performed.

The (S)QLTC case study especially enhances the need for a reflection after a decision is made to prevent forgetting the initial goal, looking into the affect of influential factors, perspectives, and it confirms the need of an execution step. The OEE case study verified the importance of the first two steps and the influential factors.

The approach prevents being "data rich, yet insight poor" and involves aligning aggregation levels, perspectives, information provision, and workflows. Within HMLV manufacturing, many of these aspects have volatile information which can be used effectively and efficiently when facilitated by communication in a way that addresses its intended recipients, the format of dissemination, responsibilities, and the protocols for information storage and retrieval.

Appendix 11.8. provides some information about a potential communication tool (11.8.2.) and organizational structures (11.8.1.) to create a structured work flow.

Although the initial phases and feedback loops of the proposed approach have been verified, it is necessary to further define the pre-operational conditions, context, and sensitivity of factors to improve the predictability and robustness of the manufacturing process in HMLV settings.

9. Future research

The preparatory phases did yield an intricate and extensive network of factors and dependencies that call for categorial modelling and scrutiny. Future research must address the modelling in step 3, emphasizing that this serves as a crucial tool for decision-making. Considering the influential factors identified, their correlation and sensitivity with respect to the data points should be investigated. Once this is known, efforts can be made to stabilize or control their sensitivity for an adequate insight. Moreover, the effect of a decision on indicators should be investigated to prevent unwanted consequences. Appendix 11.9. is an additional case study providing a method on how to determine sensitivity with the use of a digital model.

Next, the integration of this approach into organizational practices, its impact on information management, and the adaptation or implementation of information systems need to be explored, and the technological capabilities required for operational data processing and storage need to be assessed.

Additional research should focus on the guidelines for data management, as mentioned in the preparation phase, chapter 4. These guidelines differ per insight and company, but can be more elaborated, advices can be provided regarding different situations, or comparison lists with pros and cons can be made.

Finally, the approach can be verified across the modelling and investigation, decision-making, and execution phases, with each step subject to rigorous validation.

10. References

[1] Segreto, T., Teti, R. Manufacturing; In: *CIRP Encyclopedia of Production Engineering*; (Laperrière, L., Reinhart, G.); p. 1-5. Berlin, Heidelberg. Springer, 2016.

[2] Nassehi, A., Colledani, M., Kádár, B., Lutters, E.; CIRP Annals; *Daydreaming factories*, 2022, Volume 71-2, p. 671-692.

[3] ElMaraghy, H., Monostori, L., Schuh, G., ElMaraghy, W.; CIRP Annals; *Evolution and future of manufacturing systems*, 2021, Volume 70-2, p. 635- 658.

[4] Tolio, T., Monostori, L., Váncza, J., Sauer, O.; CIRP Annals; Platform-based manufacturing, 2023, Volume 72-2, p. 697-723.

[5] Nigischer, C., Reiterer, F., Bougain, S., Grafinger, M.; Procedia CIRP; *Finding the proper level of detail to achieve sufficient model fidelity using FlexSim: An industrial use case*, 2023, Volume 119, p. 1240-1245.

[6] Kober, C., Algan, B., Fette, M., Wulfsberg, J.; Procedia CIRP; *Relations of Digital Twin Fidelity and Benefits: A Design-to-Value Approach*, 2023, Volume 119, p. 809-815.

[7] Damgrave, R., Slot, M., Van Der Worp, L., Lutter, E.; Procedia CIRP; *A digital twinning reference model to facilitate multi-stakeholder decision-making*, 2023, Volume 119, p. 315-320.

[8] Slot, M., Fraikin, M., Damgrave, R., Lutter, E.; Procedia CIRP; *Digital infrastructures as the basis for implementing digital twinning*, 2022, Volume 109, p. 568-573.

[9] Firouzi, F., Farahani, B., Weinberger, M., DePace, G., Aliee, F.S.; IoT Fundamentals: Definitions, Architectures, Challenged, and Promises , In: *Intelligent Internet of Things*; (Firouzi, F., Chakrabarty, K., Nassif, S.); p. 3-50. Cham, Springer Nature Switzerland AG., 2020.

[10] Uiterweerd, E. *Improving information traceability in high-tech Contract manufacturing environments*, 2023.

[11] Juan M. Jauregui Becker, Jesper Borst, Abele van der Veen; CIRP Annals; *Improving the overall equipment effectiveness in high-mix-low-volume manufacturing environments*, 2015, Volume 64 (1), p. 419-422.

Appendices

11.1. Production, manufacturing & machining

To create a product, producing, manufacturing and machining are commonly used terms. However, they have many definitions, which are not set in stone. Some use manufacturing and producing as synonyms, while these are not. To provide clearances, each term is described how they are used within this thesis. Manufacturing is the biggest system, production is a process and machining is a process step.

Machining is a process where a machine removes material to obtain the required product. This can be milling, drilling, turning, grinding, EDM, etc. A machining process is part of production and manufacturing.

Producing is the entire process of physically making a product. This can be converting raw materials or semi-finished products into the desired product. It covers both the producing of parts and assembling to create the final product, but excludes the design phase, planning and controlling production [1].

Manufacturing is the bigger system as it covers all functions and activities directly contributing to creating products [2]. Production is part of manufacturing, but next to the physical process, manufacturing also covers managerial and organizational functions. Manufacturing includes the value adding processes of production, process planning, production planning and control [2]. It involves people with a broad range of discipline and skills, variety of machinery, equipment and tools with various levels of automation. Automation in manufacturing is a broad topic covering activities as industry 4.0, Internet of Things, computer aided process planning, industrial robots and more. Some include the design phase as well because a product can be designed for manufacturing taking production and planning into account. However, in this thesis, the design phase is excluded from manufacturing as it is assumed to have received a finished design, but an additional design review is included in manufacturing.

Within contract manufacturers, different processes exists, among which are build-to-print (BTP) and build-to-print+ (BTP+). To enable a fast start, the customer delivers all drawings and information needed to manufacture the product: BTP. However, sometimes extra effort is required from the manufacturer because the customer requests a final design review. The customer provides their technical product documentation (TPD), and the manufacturer verifies the feasibility of tolerances, assesses the optimal production method, check the producibility on available machines, and ensures compliance with customer standards. This additional design review constitutes BTP+ and is considered part of manufacturing, as the design already exists.

11.2. Data analytics

Data analytics can improve businesses performance by optimizing their process with the use of historical data and real-time information. The data analytics process consists of four stages: descriptive, diagnostic, predictive and prescriptive, shown in Fig. 9. Each next stage is more complex due to the uncertainty of the analytics.

Descriptive analysis provides hindsight of a process and is based on historical data, such as the costs made in a year, or a dashboard on the work floor with a number of produced products. Often key metrics and measures are used by companies to reflect on their performance of the past week or month to learn from and obtain insight into their future possibilities.

Diagnostic analysis focuses on the present and provides insight into the current situation looking at relations of data and why they are related. The variety of data is the diversity of different data and can be obtained from withing the company or external. When data is affected by other data they are correlated, which can be a positive correlation or a negative correlation. In general, the diagnostic analysis looks at what is important and why with the use of root cause-analysis, data discovery, data mining, drill down and correlation [3].

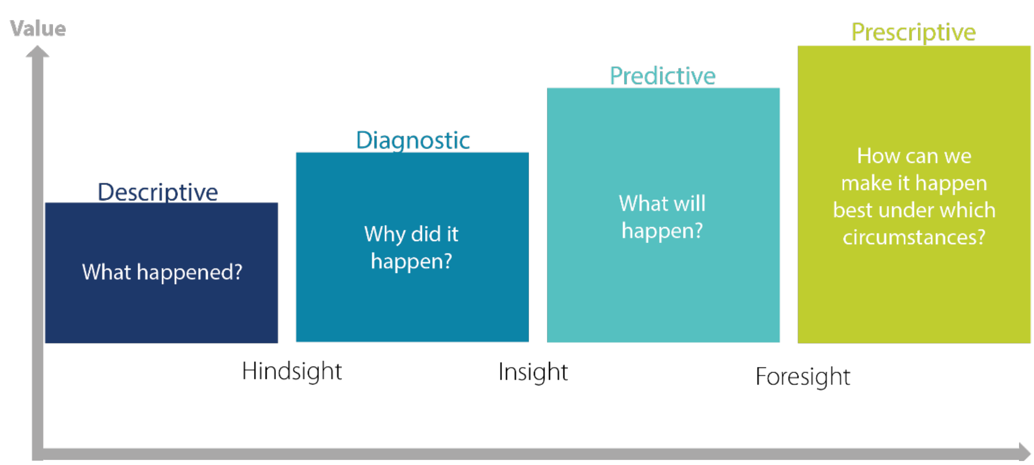

Fig. 9. Data analytics phases.

Predictive analysis is more complex because it looks at the future and how one variable affects others if it changes: sensitivity. If many data points are greatly affected or dependent on one variable, then this variable is very sensitive. The predictive analysis looks at what will happen while taking the current insights and historical data into account. Tools among which Artificial Intelligence (AI) and Machine Learning (ML) can also provide insight into how data is going to evolve.

Prescriptive analysis helps make choices which choices are available and under which circumstances is which choice the best with the use of simulations and prediction models. AI is also very helpful as support.

11.3. Internet Of Things

IoT, is not a physical thing, it is more a process about data. It covers the process of devices which can sense and transfer their data to the internet and/or other devices for data processing at high speed, which can among others be analysed and visualized to obtain new insights. IoT is very elaborate and contains many steps, but to provide a basic overview Fig. 10. Is shown with five basic steps regarding IoT for a manufacturing environment.

The first step is data registration focussing on which data is needed from which 'thing' and how to measure the data. Within a production environment many IoT data can be collected in different ways. Information about energy consumption can be monitored with a smart meter. The environmental data temperature, humidity and air quality can be measured with specific devices and a machine has both sensors measuring data and a memory with data such as the speed or number of errors.

When the data is monitored it should be transferred from the measuring device to another device or the internet. The monitoring device passes the data to a gateway with the use of a connectivity method such as Wi-Fi/ethernet/Bluetooth/LP WAN. Next, the data gets transferred from the gateway to a cloud, server or other storage location with a connectivity method. A firewall can be added to the gateway to protect the data by controlling all incoming and outgoing data and to filter the data if wanted to prevent storing too much data.

In the storage, the data is processed, it will be manipulated, classified and sorted into readable information. To store the data on-premises or in the cloud depends on multiple decisions among which investment, the goal, data security, quantity and quality.

With the collected historical and current data, visualizations can be made. An analytics platform collects the necessary information from different databases whereafter a presentation layer creates the required visual. This presentation layer either sends the visuals to a screen, laptop, tablet, phone, or it is an application or webpage itself showcasing the visuals.

Finally, with the use of visuals and raw data, a data analysis can be made looking at the future. Predicting what is going to happen with the use of models or simulations.

Fig. 10. represents the five process steps of IoT. Between each step a connectivity method is needed to enable the transmission of the data through the process. However, the choice for this method depends on different factors and differs therefore per company and required insight. Some factors are the amount of data, the precision, transporting data to one side, or bi-directional. Transporting in one direction is for example a temperature sensor in a room which status is represented in a visual and with bi-directional an operator can directly send a signal to the machine with their computer to use more cooling fluid when the visual shows a too high temperature.

11.4. Things, People, Data, Process

During the approach from chapter 2, four aspects should be kept in mind: things, information, communication and process. These four are rephrased and based on the initial factors: things, data, people and process, which should be taken into account during an IoT process [4]. While these factors were also important for obtaining an insight and data analytics, the factors were used and rephrased to fit the proposed approach. To be able to obtain adequate decisions, it is important to have these factors clear and stable before and during the approach.

The content of the factors will be explained: things, people & communication, data & information, process.

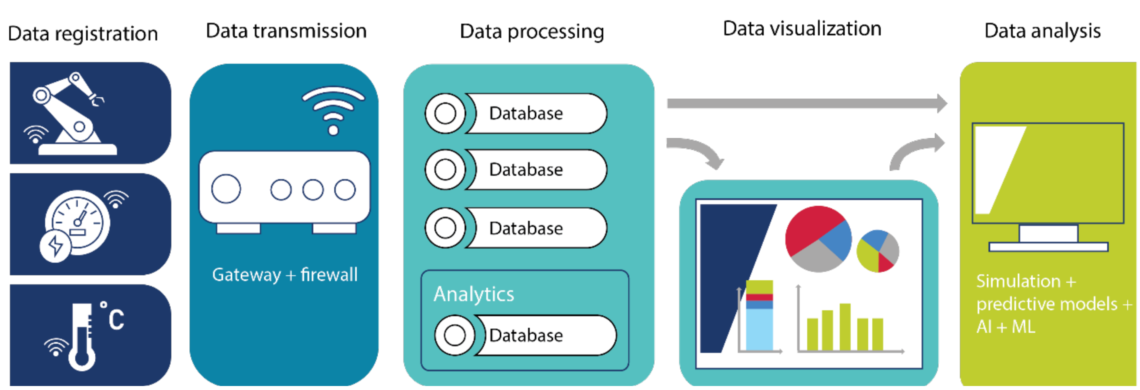

Fig. 10. Data processing in a manufacturing company.

Things are all the objects which can make the connection to the network or other devices and are referred to as IoT devices. Each device should have its own unique identifier to know where the data comes from. A sensor for example can be an IoT device when it measures the temperature in the room, but it can also be an embedded IoT device in another IoT device. When it measures the temperature in a machine, the data from the sensor is part of the machine data thus within that unique identifier.

The data and information component is about creating useful information based on collected data. This includes controlling all data to see if it is valid and reliable, if assumptions are needed to use the data and if the data is accurate and/or precise. All these factors also influence the storage and processing of the data. On top of that, before collecting data it should be known which data is needed, how precise it is collected, at which frequency and where and how long should it be stored.

However, the most important thing to have stabilized are people and communication. It is not the data from the devices that optimize a company, but people their actions what they do with the data. Data is used to make predictions and suggest optimization steps. However, to achieve this, communication is very important and different stakeholders need to determine together how to interpret data and what further steps to take.

To know who should collaborate and who needs information, the process is very important. The process covers the research process from a higher perspective and focusses on who (or what) needs which information when.

11.5. Horizontal and vertical indicator relations

Fig. 11. is created to clarify the horizontal and vertical relations as explained in chapter 3.2. The top squares are strategic indicators. From a management board perspective, the indicator company production productivity is obtained and a decision is made to increase the machine performance. This decision can result in more products, influencing the other strategical indicators profit margin and revenue growth as well because more products means more sales.

A vertical relation example is the dependency of one indicator on other detail levels. The company production productivity can be calculated by OEE, which is dependent on availability, performance and quality. Sometimes one indicator within an aggregation level even depends on another aggregation level. The strategic indicator company production productivity is depend on the OEE, which can be a tactical indicator on its own.

11.6. NTS Hengelo

In high-tech industries, increasingly complex products often cannot be entirely produced in-house, leading to business-to-business sales where specialised companies, known as Original Equipment Manufacturers (OEMs), create precise and complex components for more intricate products. OEMs outsource intricate parts to contract manufacturers, who produce highly specific, unique parts not sold to other clients. These contract manufacturers handle high-mix, low-volume, high-precision, and high-complexity production.

NTS Hengelo, formerly NTS Norma, is a contract manufacturer based in Hengelo, the Netherlands, and part of the NTS group, which includes twelve sites. They have 65+ years of experience and approximate 470 employees. NTS Hengelo specialises in ultra-precision manufacturing and cleanroom assembly, serving high-tech markets and supplying various OEMs in the semiconductor, analytical, and health industries.

All projects at NTS Hengelo are divided into three phases: sales, new product introduction (NPI), and volume. The company adopts a BTP and BTP+ approach, detailed in Appendix 11.1.

The sales phase begins with a customer order request, resulting in a business case and quotation. Upon customer acceptance, the project enters the NPI phase, where technical product specifications are verified, and the process design is created, tested, and finalised. The NPI phase concludes with prototype production and, if successful, a pilot series. The project then transitions to the volume phase when processes are under control. In this phase, production capacity is scaled up, and products are manufactured according to verified processes and specifications [5]. To avoid confusion with mass production, the produced products will be referred to as repetitive.

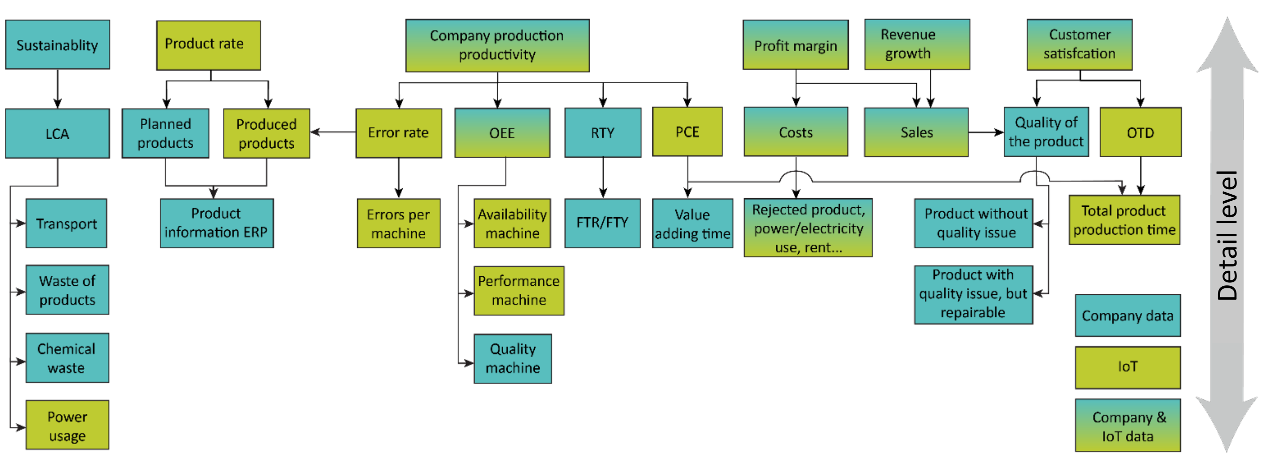

Fig. 9. Indicators horizontal and vertical relations.

11.7. OEE variables

The OEE is already partially explained in chapter 6. However, the provided equations are not complete yet as the objects also depend on data points and lack some background information. Therefore availability, performance and quality are explained into more detail.

11.7.1. Availability: operation time / planned production time

Fig 12. Shows and summary of all necessary information to be able to calculate the availability.

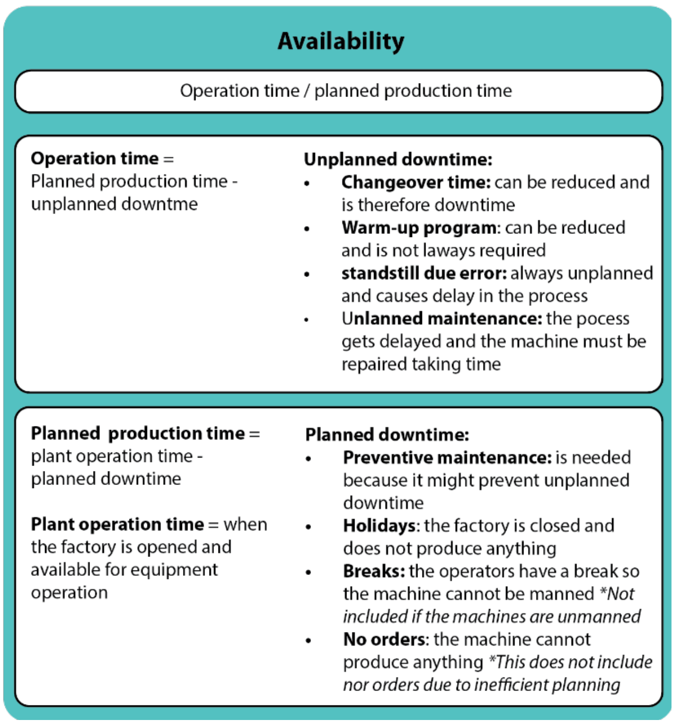

Fig. 12. Summary of availability information for OEE.

11.7.2. Quality: good produced / total produced products

There are two options for good produced products, within the customers' requirements. Firstly, first time right (FTR) includes only products that are correct the first time they are produced. Secondly, good products, includes all products that are not scrap, but they require repairs or additional quality control.

To obtain the number of correctly produced products for the company, Computer-aided quality, CAQ, documents are looked at. When a product has a deviation, a CAQ is made, whereafter a quality control process is followed. A Quality engineer will eventually decide if the deviation can be repaired or if the product should be rejected. If a product did not obtain a CAQ, the quality is FTR. However, if it did get a CAQ the products quality can still be sufficient, a good product.

It is advised to use FTR because if a CAQ is made the product will delay the process thus the quality is not optimal. Both options are summarize in a visuals in Fig. 13.

However, this data is for NTS (and other companies) not always 100% reliable because some products have abbreviations, during measurements, but their production is continued based on expertise of an operator and team leader. To have a correct FTR, the products should have neither a CAQ nor abbreviations.

Fig. 13. Summary of quality information for OEE.

11.7.3. Performance: ideal cycle time / operation time

The performance can be based on two things, speed or multiplicity. Based on speed a comparison is made between the ideal speed in time and the operating speed in time. The ideal time to create a (semi-finished) product is the ideal operation time. This time is based on the real cycle time of a product from which machine wear, substandard materials, misfeeds, operator inefficiency are subtracted.

When looking at multiplicity, one can consider two options. Either look at the multiplicity of a machine, for example, a machine has 24 holes for injection moulding, but only uses 23 due to malfunction. The performance will be 23/24 = 82.7%. Or the multiplicity of the processor, the computer shows how much percentage of the processer is used, but this is usually extremely low. For NTS the performance will be based on speed, a visual with the required information is shown in Fig. 14.

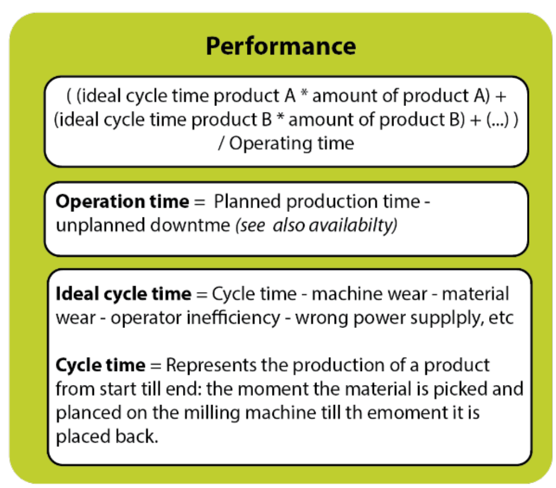

Fig. 14. Summary of performance information for OEE.

11.8. Company internal communication

To enhance the productivity of the manufacturing process, the communication process should be clear. Everyone must know their responsibilities, what to deliver, in which format, who to communicate to, and who to ask for help or feedback.

In a manufacturing environment there can be multiple teams such as functional teams consisting of employees with similar functions, or cross-functional teams with different disciplines. The team structure relies on the organizational structure, which is dependent on the company size, geographical location, and the goal. Chapter 11.8.1 and 11.8.2. provide an example of a good organizational structure and communication tool to insure the quality, processes and goals of a company.

11.8.1. Organizational structure

All companies have their own organizational structure, with each benefits and disadvantages. The organizational structure can, for example, be hierarchical, functional, matrix, process-based, product-focussed, or project-focussed. Which structure is best depends on factors such as the company's goal, type of company, and vision. In a HMLV contract manufacturing environment, multiple products are made as well repetitive as new, different diverse departments can be found and a high product quality is required, while the products are complex and have a high accuracy. Resulting in the need for a strong and clear process and obvious communication. Therefore, the following benefits and disadvantages apply to the organizational structures.

A hierarchical structure is useful when a decision should be made, one person is accountable and it is clear who to report to. However, the amount of layers might influence the reaction speed. When a decision is made, it should cross all layers before an operator can implement the change and react. On top of that, a strong workflow is required to prevent misinterpretation when information is forwarded.

Something else to take into account is the choice for the type of manager. A manager is often a leader of a team, they divide the tasks in a team, host meetings with other managers to keep an overview, and make decisions. However, a manager as leader is not always specialized themselves, making it harder to make a decision as they are dependent on their team for necessary information, and the manager cannot fully support the team with their work tasks. To prevent this, a manager can be one of the team, someone who is both a leader and also carries out part of the work. This makes decision-making more judicious as the team leader has the required knowledge, is more involved and in case of lower man capacity, the team leader can support the team.

To enhance fast decision-making, a hierarchical structure with fewer levels can be beneficial, a flat structure. This structure has often three levels: employees, managers, and directors. Due to the fewer levels, fewer people are involved, resulting in a more rapid decision-making and execution process. Therefore, it enhances productivity and provides more autonomy to employees, which can be motivational.

Both flat and hierarchical structures can be functional organized. All employees below a manager have a similar function and form a team: sales, marketing, ME, PDM, etc. Working in a team with the same knowledge area stimulates and facilitates discussions and providing feedback, while the team members are well acquainted and are often stationed at the same location. Asking different teams for input and communicating with them is not always structured and is either performed on own initiative or via the manager, which can be negatively as direct input and feedback is required.

To solve the communication lack or inconsistency between teams, a project based team can be made. Project teams are assembled based on a project, manufacturing a (new) product, and consist of people with different expertise to enable discussion and decision-making while ensuring all necessary knowledge is present. These teams can differ in size during a project, because not all expertise is needed along the time span of a project. This team structure can be very useful for contract manufacturers, while they have many departments involved during manufacturing, and create as well processes for new products and optimize processes of repetitive products.

All these different structures can be combined into a matrix. A matrix structure consist of a hierarchical functional structure (vertical in Fig.15.) and project teams consisting of members from different functional teams (horizontal rows in Fig.15.). This structure enhances communication within functional teams as well as project teams, enabling better decision-making while integrating different perspectives in a project. However, within this structure a conflict can arise between the project manager and the functional manager. Therefore, it should be clear beforehand who makes which decisions. In example, the functional manager can decide who of their team works on which project.

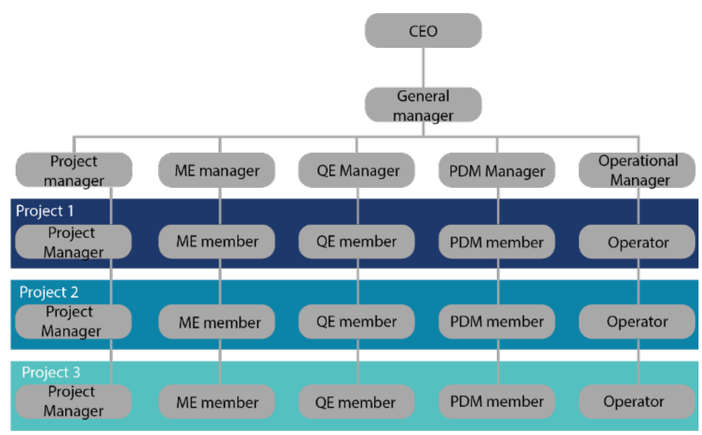

Fig.15. Organizational structure: matrix.

On top of that, it would be useful if the functional manager is one of the team. They should not only manage, but also work on a project, or have their own tasks within the department. The project manager on the other hand can be one of the team or only manage. The project manager can guide multiple projects and only be an active member of one, or only manage. They should guide the team, keep an overview, mediate in decision-making and ensure everyone who is engaged is informed. This matrix structure is a bit more complex as a project team member must report to their functional manager as well as the project manager, but with clear communication guidelines, it can motivate people, enhance productivity, and increase efficiency.

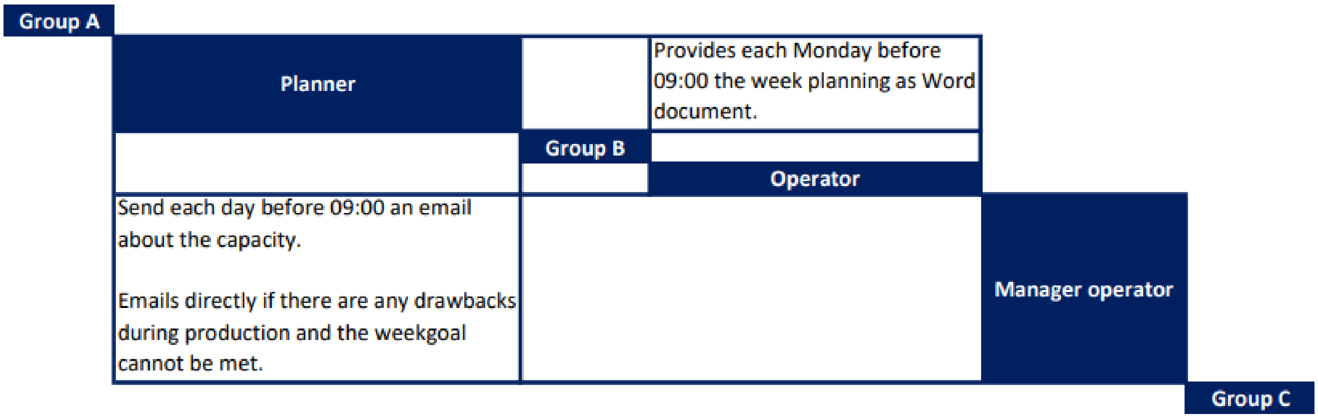

Fig. 16. N2-diagram example with different teams.

Depending on the amount of projects, it might be beneficial to have a 'head' project manager guiding all project managers and make sure everything is one track. Otherwise, the general manager can fulfil this function.

11.8.2. Communication tool

To enhance an efficient workflow, some general communication rules should be clear: where to find information, in which format should it be stored, who should be informed, who can be asked for feedback and who is responsible for what during a project.

Before the start of a project, all members should agree with the working formats and on which location all the information will be stored, which both depend on the company and project. This clarity is needed to enable an efficient process and prevent storing information in two different formats on multiple places.

Different tools can be used to visualize who to communicate to, or from who to receive information. Their effectiveness depends on the company and how they are used. One tool, which can be used for complex systems, such as a HMLV environment, is the technical tool, N2-diagram. A N2-diagram is usually used for systems engineering to visualize functional and physical interfaces by showing the inputs and outputs for very complex systems.

This can also be applied for complex communication within a team or between teams. In the N2 diagram all departments or functions can be represented, with their output and input, which can be as elaborated as required.

The output can be a general description of the information, or additionally add when it should happen, in which format, how often, etc. An example is shown in Fig. 16. The diagonal represents the different groups, vertical connections are outputs and vertical inputs. In Fig.16., the planner provides each Monday before 09:00 the week planning as Word document to the operator. The manager operator emails the planner about the capacity based on man availability each day before 09:00 and emails directly if there are drawbacks during production and the goal cannot be met.

The N2-diagram provides insight in the communication between groups, but it does not look at who is responsible to complete a task, who is accountable when something goes wrong, or who can be asked for help. To clarify who has which role a RA(S)CI metric is made. A RA(S)CI metric is based on five different roles in a group:

- R, responsible: the responsible person should perform an assigned task and when finished inform the informed.
- A, accountable: the accountable is often an employee with a higher rank as they control the resources and keep an eye on the project.
- (S), supportive: provides assistance to the responsible.
- C, consulted: gives advice to the responsible.
- I, informed: all who need to be informed during the project.

When using a RA(S)CI it should be kept in mind that not all roles are always required, roles can be performed by multiple persons and not all persons need a role. An example is shown in table 1.

Table 1. RA(S)CI metric.

	Manager A	Person A	Person B	Person C
Task 1.	A	R	S	C
Task 2.	A	I	R	
Task 3.	A	I	R	I
Task 3.	A & R	I	I	I

Within in a RA(S)CI metric, it is not directly clear from who to obtain certain information and how much to inform someone. Send them all information or only provide a summary on the status of a task. The N2-diagram on the other hand lacks the information who is responsible or accountable during a project.

Therefore, the proposal is made to combine both tools. A N2-diagram as the basis, but next to the output a role should be specified, shown in Fig.17. which can be found on the next page.

Additionally, the N2-diagram can be broadened, in example, when taking IoT into account, not only persons provide input, but also machines or databases. Adding these to the diagram clarifies immediately where all information can be found.

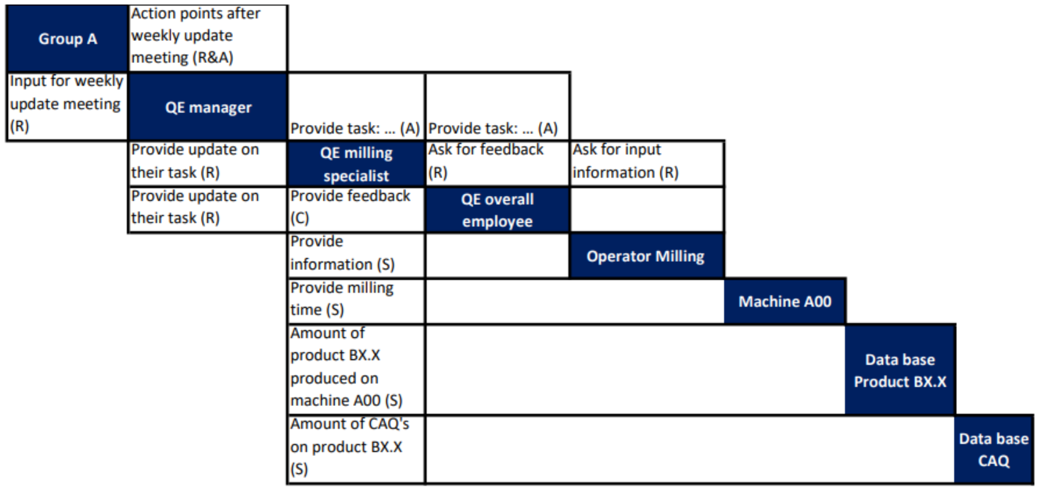

Fig. 17. Combination of N2-diagram and RA(S)CI.

11.9. Modelling sensitivity

Measuring sensitivity and correlation can be done in multiple ways, but it has been chosen to investigate the use of a digital model, which is often used for predictive analysis. The predictive and diagnostic analyses represent (parts of) reality and should be scalable and capable of handling large volumes of data. To enable analysis, decision-making and control for a defined objective and scope, manufacturers can create a fit-for-purpose digital representation of their production systems and processes using collected data and information [6].

This digital representation is known as a Digital Twin, DT, and has multiple definitions, but refers to a copy of a physical space in a virtual space, which enables the possibility to rapidly perform tests and different scenarios. The DT depends in general on three factors: application, context and viewpoint [6]. Application determines if the information from the twin should be life or offline and which information is required, viewpoint refers to the twin itself (a product, system or process), and context is how the DT provides information.

To test the sensitivity of influential factors, a representation of the production process (viewpoint) can be made with offline data (application) and depending on the factor, the result might be a visual, dashboard within the software or an excel list with data (context). However to test the effect of decisions or factors, the production process does not have to be 100 percent similar. In a very complex environment, HMLV, it is almost impossible to create an identical twin of a process. Therefore, multiple twins might be needed, or irrelevant aspects can be left out of scope.

"There is a common view that simulation, and in particular discrete event-based simulation, DES, provides the most efficient set of tools for analyzing the complex impact of decisions which are related both to the static structure and dynamic behavior of a production system [7]." To test if the sensitivity of factors can be determined with a DT of the production, the DES software Tecnomatix, plant simulation from Siemens is used.

11.9.1. Modelling results

Within plant simulation a test set-up is made consisting of five machines and five products, shown in Fig. 18. The products: A1, B2, C3, D4, and E5 have different routings, and cyclus and set-up times. This information is automatically written in a datatable because it is connected to an excel file, which is downloaded from an ERP system. If a change is made in the excel file, the plant simulation datatable can be refreshed and updated.

The workcenters, WC, are represented in frames, with a Station (the machine/workplace) and Enter and Exit buffer. The Enter buffer receives the products, where the Exit buffer sends the products to the next WC according the provided routing.

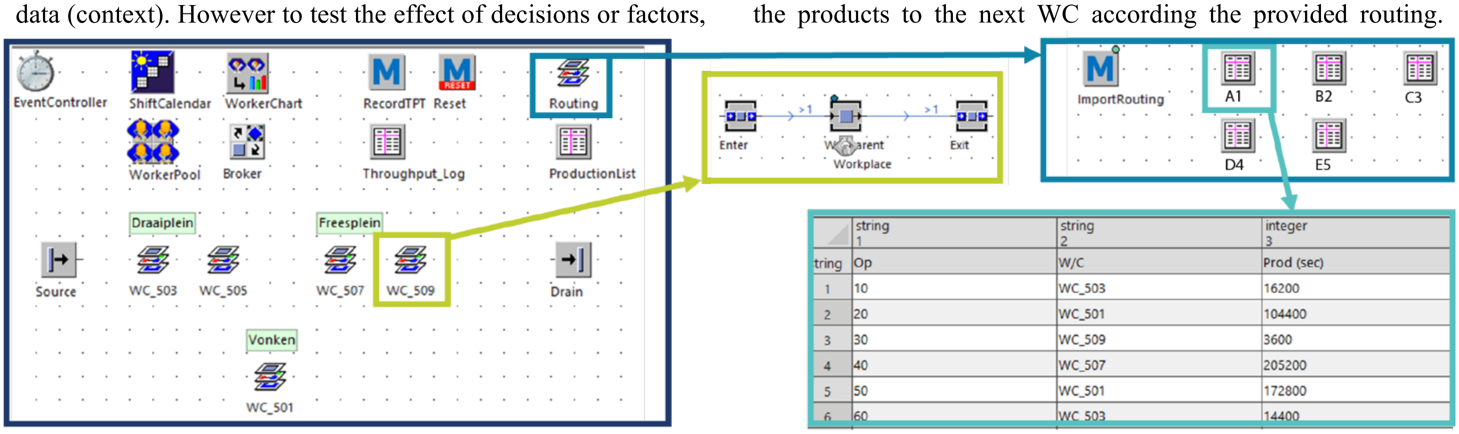

Fig. 18. Plant simulation HMLV test set-up.

Between the buffers and station, assembly stations, robot arms, workers, or other stations can be added as required.

The Source generates products and the Drain shows statistics about the produced parts. A method reads and writes the throughput in a Datatable colom, which can be exported automatically to excel when reset.

It is proven that changes in machine availability, failure rate or operator efficiency influence the measured outputs. The research: Data analytics-based decision support workflow for high-mix low-volume production systems, also used a DES model to perform a sensitivity analysis and proved the effectivenss [6]. Nonetheless in a different setting and aproach, but it can be stated that a DT can be used to measure sensitivity.

11.10. References used in the Appendices

[1] Alexopoulos, K., Makris, S., Chryssolouris, G.. Production; In: *CIRP Encyclopedia of Production Engineering*; p. 1-5. Berlin, Heidelberg. Springer, 2018.

[2] Segreto, T., Teti, R. Manufacturing; In: *CIRP Encyclopedia of Production Engineering*; (Laperrière, L., Reinhart, G.); p. 1-5. Berlin, Heidelberg. Springer, 2016.

[3] Balali, F., Nouri, J., Nasiri, A., Zhao, T.; Data Analytics. In: *Data Intensive Industrial Asset Management*. P. 105-113. Cham, Springer. 2020.

[4] Firouzi, F., Farahani, B., Weinberger, M., DePace, G., Aliee, F.S.; IoT Fundamentals: Definitions, Architectures, Challenged, and Promises. In: *Intelligent Internet of Things*; (Firouzi, F., Chakrabarty, K., Nassif, S. (eds)); p. 3-50. Cham, Springer. 2020.

[5] Uiterweerd, E. *Improving information traceability in high-tech Contract manufacturing environments*, 2023.

[6] Shao, G., & Helu, M.; Framework for a digital Twin in Manufacturing: Scope and requirements; *Manufacturing Letters*, 2020, 24, p. 105-107.

[7] Gödri, I., Kardos, C., Pfeiffer, A., & Váncza, J. Data analytics-based decision support workflow for high-mix low-volume production systems.; In: *CIRP Annals – Manufacturing Technology*; 2019, 68(1), p. 471-474.