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DATA ANALYSIS FOR THE DECISION MAKING WITHIN EQUIPMENT EFFICIENCY CALCULATION MODELS

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Abstract: *Within the actual context dominated by a strong need to improve cost and competitiveness, manufacturing companies are looking into the options to increase operational efficiency to which the equipment effectiveness is a key driver. One of the most common indicators for the equipment performance measurement within manufacturing environment is OEE (Overall Equipment Effectiveness), this being broadly used within various industries. Since it was introduced, it was acknowledged that by setting up an OEE based performance measurement, the companies can quantify better the performance and by its structured approach can run more focused diagnosis and consequently can look into exact areas of improvement. While various methods are used to calculate the equipment efficiency, the loss analysis still stays at the traditional technical level. But the current transition to the Industry 4.0, which is increasingly embraced by the companies, is showing a tremendous Data usage and impact into the overall performance measurement. The Quality of Data may influence both system performance and, equally, the loss analysis and decision making. Starting by using the classic Nakajima model for OEE calculation and loss analysis applied within a case study, the authors extended the loss analysis beyond the traditional process and technical aspects to cover as well the data potential impact into the OEE losses. This is a starting point for further detailed study to develop loss analysis models having the Data as a starting point and to understand how decision making is influenced.*

Key words: *Equipment Efficiency, Decision Making, Data, Loss Analysis, Performance Measurement.*

1. INTRODUCTION

Overall Equipment Efficiency was introduced as a broad concept through Total Productive Maintenance large approach, Seiichi Nakajima having a strong signature on this model. Since it was introduced, many companies started to implement OEE based performance measurement to approach in a more structured way the equipment efficiency and various type of losses that may affect the overall result. By isolating the causes of loss through a standard model, the professionals involved in the process management can focus on the exact areas that need improvement and to define and implement the right measures.

The main types of loss described in the model are: equipment failures, set up and adjustments, minor stoppages, speed loss, defects. Companies that have this model implemented usually stop the loss analysis at this level with a higher or lower customization extend. One question that may be raised especially in current Industry 4.0 context is where the Data impact comes into the overall loss analysis as data is a key input in product, process and equipment design and performance. The purpose is to understand if traditional analysis can be extended to the data impact level and this article proposes to answer further to these questions.

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2. METHODOLOGY

To further answers to data loss related questions, few steps are addressed (Fig. 1).

Starting from summarizing the traditional APQ OEE calculation model and describing the six types of loss, this study presents few more detailed approaches based on data impact already [3], emphasized within prior studies [5], then is moving forward to describe the process failures modes, the relevant data caring elements and potential data failure modes with a case study.

2.1. OEE APQ Method

Traditional OEE calculation model states three main elements: Availability, Performance and Quality- reason why is broadly known as APQ method [1].

Within the manufacturing environment, the OEE calculation model starts from Calendar time, the overall hours considered within a certain company to run all activities. In example, within a manufacturing site with a three-shift implemented pattern and 5 working days in a week, each shift having 3 hours, the calendar time is 24 hours/ day, 120 hours per week.

Loading time represents the difference between calendar time and the amount of time considered for planned stoppages, in example for predictive maintenance.

Operating time is the difference between loading time and unplanned stops, for example caused by equipment failures or breakdown.

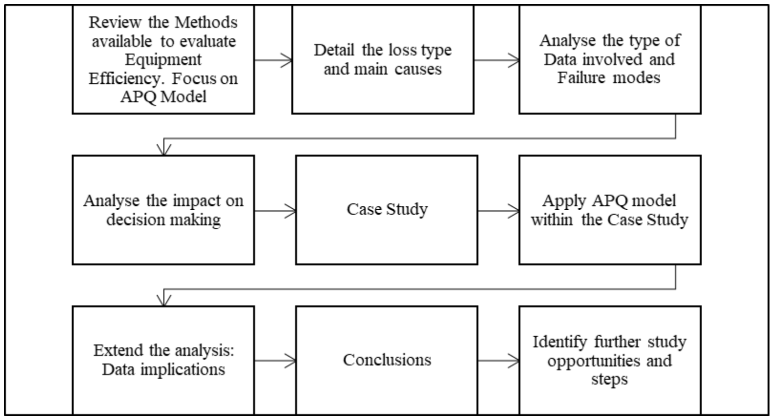

Fig. 1. Method Description.

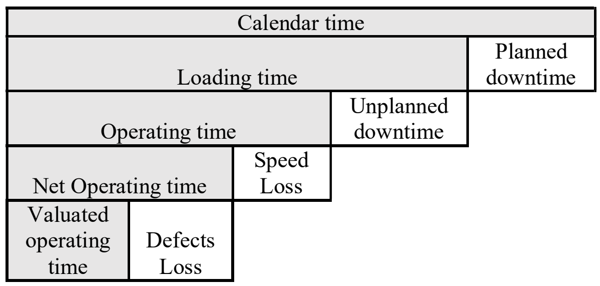

Fig. 2. OEE Elements and Losses.

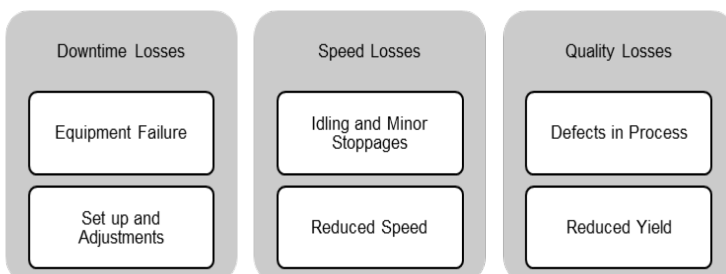

Fig. 3. Traditional Type of Losses.

The ration between Operating time and loading time, as a percentage, represent *Availability*, the first element of *OEE* calculation within APQ model:

$$Availability = \frac{Operating\ Time}{Loading\ Time} x\ 100$$

Net Operating time represents the difference between Operating time and minor stoppages unplanned, unplanned small adjustments, generically described by Nakajima as measuring the “maintenance of a given speed” over a given period (1).

Performance (*P* in APQ model) is the main indicator here, being measured as per formula:

$$Performance = \frac{Theoretical\ Cycle\ time\ \times Output}{Operating\ Time} x\ 100$$

Theoretical cycle time is often referred as ideal cycle time fixed as a standard to produce a certain item.

Quality element within the OEE calculation is the ratio between *Output* (good parts) and *Total output*:

$$Rate\ of\ Quality = \frac{Total\ Output - Defects}{Total\ Output} x\ 100$$

The *OEE* within the APQ model is represented by:

$$OEE = Availability \times Performance\ \times Quality$$

The Overall model according Nakajima approach [1] is described in Fig. 2.

2.2 Losses and Failure Modes

Within Nakajima model [1], there are mainly six types of losses identified (Fig. 3).

Many authors published various extended versions of these losses based on specific studies, approaching technical versus operational downtime [2], moving to the next level in disaggregating the categories and helping further to focus the attention and the corrective actions. Table 1 illustrates a more detailed loss breakdown and failure modes.

Once the companies implemented OEE based performance measurement system, the efforts to understand and fix the losses reached deeper root-causes and failure modes understanding, to which in the current study appears the question: where is the data and how can be linked tin the loss analysis?

2.3. Type of Data and Data Failure Modes

Having as a starting point the traditional type of losses and extended researches, the current study proposed to enlarge the failure modes analysis and to link OEE failure modes with various elements caring data.

Table 2 illustrates the failures modes that can drive Downtime loss with direct impact on Availability and their potential link with Data gaps. Equipment design failures and relevant specifications missing, maintainance plans not properly documented, instructions missing for the equipment validation, training plans not entirely documented and consequently not executed to secure the level of operators and engineering capabilities, quality documentation missing: all these are data caring elements and their failure may result into unplanned downtime with direct impact for Availability.

Speed Loss can be linked as well with various Data failure modes, Table 3. The overall OEE impact can be quantified into the Performance calculation element.

Data missing may cause poor bottleneck management, production line design failures with additional movement and handling, process design misses resulting in additional set up, lack of instructions: all these driving stoppages and cycle time outside the standard.

Quality loss can be as well associated to Data failures in the relevant documentation (Table 4).

Table 1

Losses Categories Breakdown and Failures Modes

Category	Elements	Failure Mode
Downtime Loss	Technical downtime: machines failure	Design Failure
		Training Failure
		Maintenance plan Failure
	Operational Downtime	Instructions Failure
		Training Failure
		Procedure execution Failure
	Quality related Downtime	Material, components or subassembly quality issues
Speed Loss	Small Stops	Bottleneck not managed
		Training Failure
		Environmental constraints
	Reduced Process Speed	Machines Layout Failure
		Process Balancing Failure
		Over- handling
		Machines design failure
Defects Loss	Scrap or/ and rework	Design Failure
		Material, components or subassembly quality issues
		Controls Failure

Table 2

Downtime Loss and Data Loss

Downtime Loss						
OEE Potential Failure Mode	**Design Failure**	**Maintenance Failure**	**Training Failure**	**Instructions Failure**	**Procedure execution Failure**	**Material, components or subassembly quality issues**
Data Potential Failure Modes	Drawing and specifications data not complete or not correct	Maintenance plans and procedures not complete or not correct	Data about required skills not complete or not correct	Standard documents: data missing or not correct	Data about failure modes and risk management not complete, not correct or not relevant	Quality Documentation data not complete or not correct
	Design validation instructions not complete or not correct	Spare parts inventory data not complete or not correct	Training Plans data not complete, not correct or not relevant			
			Training documents nor complete or not relevant			

Table 3

Speed Loss and Data Loss

Speed Loss						
OEE Potential Failure Mode	**Bottlenecks not managed**	**Environment constraints**	**Machine layout design failure**	**Process Balancing Failure**	**Over-handling**	**Machines design failure**
Data Potential Failure Modes	Process documentation data not complete or not correct	Risk Asessment data and response plans data not complete, correct or relevant	Simulation data not complete, correct or relevant	Simulation data not complete, correct or relevant	Process documentation data not complete or not correct	Drawing and specifications data not complete or not correct

Table 4

Quality Loss and Data Loss

Quality Loss			
OEE Potential Failure Mode	Design Failure	Material, components or subassembly quality issues	Controls Failure
Data Potential Failure Modes	Drawing and specifications data not complete or not correct	Design validation instructions not complete or not correct	Quality Documentation data not complete or not correct

Table 5

Data and Impact in Decisions Types

OEE Component	**Data influencing OEE**	**Decisions Category**
Availability	Drawing and specifications data	Design Management decisions
	Design validation instructions data	
	Maintenance plans and procedures	Maintenance Management decisions
	Spare parts inventory data	
	Data about required skills	Human Resources Management decisions
	Training Plans data	
	Standard work instructions documents	Production Management decisions
	Data about failure modes and risk management	
	Quality Documentation	Quality Management decisions
Performance	Process documentation data	Production Management decisions
	Environmental Risk Asessment data and response plans data	Risk Management decisions
	Layout simulation data	Production Management decisions
	Process Simulation data	Production Management decisions
	Demand Forecast data	Demand and Inventory Management decisions
	Drawing and specifications data	Design Management decisions
Quality	Drawing and specifications data	Design Management decisions
	Design validation instructions data	Design Management decisions
	Quality Documentation data	Quality Management decisions

One Key element is the product design and specifications for raw materials, sub-assemblies and finished goods.

Another key element within the process is the set of quality controls for raw materials, sub-components and finished goods. Data inconsistency in the procedures or across the process may result in defects.

A third element is a consistent risk assessment and response plan that must be embedded in all work instructions. If this is missing, while a negative event intervenes, there may be slow reaction and delay in re-setting the system back to the normal.

Data loss can be one contributor to the OEE, but as well one weak point in driving the adjustment decisions. As a next step this article proposes to cover the main type of decisions impacted by these failures.

2.4. Data Impact in Decision Making

Was concluded that within OEE model we can identify few levels of performance and losses. Equipment performance depends on the product design, manufacturing and supporting processes design, deployment plan and management actions including the adjustments required. All inputs are caring data to which data availability, reliability, comprehensiveness, relevance: are key. In all the phases impacting the OEE (design, deployment, adjustment): we take decisions.

Table 5 proposes to illustrate the link between data in this OEE context and various decisions.

Design decisions may refer to a product, an equipment or a process. They may be documented through drawings, specifications and procedures.

Validation decisions refer to the set of actions took for assessing if a product, equipment or process meet the specifications and overall standards.

Some process management decisions are involved in various areas interacting with OEE system:

- Maintenance Management decisions involve the choices to perform predictive, preventive or reactive maintainance actions to support the expected level availability. They include as well the spare parts inventory and replenishment policies.
- Inventory decisions involve all sets of actions to secure the levels of materials and subassemblies required to deliver the expected output at the required speed rate. Bottlenecks management is a key area of focus where a proper level of inventories must be set up to feed the bottlenecks.
- Skills Management provides the comprehensive list of expectations from all the participants within the production system to avoid operational failures. As well the proper level of trainings required and the journey to achieve the expected skills.
- Quality decisions secure the proper level of product and process specifications, controls and adjustments required as per the internal and industry standards.
- Production planning decisions connect the internal activities with the demand for various products, considering customer orders, inventory policies, capacity requirements and availability.

2.5. Example

In order to set up an example, few assumptions are taken.

A manufacturing unit has 3 shifts working pattern, each shift running 8 hours. Product A is planned to run during first shift on final assembly line F. One 30 minutes break is allowed during one shift. Four operators work on an assembly line.

At the beginning of the shift, 15 minutes are reserved for a daily meeting to review the plan and all operators are engaged.

Theoretical cycle time for one item is 2.8 minutes.

After producing the first 5 items, one operator discovers that insertion depth result is not good. Production stops for one hour to check component dimensions. A decision to adjust the equipment parameters is taken after and 20 minutes were spent to set up in orders to continue the process. Production restarted with new parameters and additional positioning sequence. At the shift end, 100 items were ready, out of which 92 are good.

Applying the traditional Nakajima model and further enhancements of this study (data potential causes), will calculate further the *OEE*, run the traditional loss analysis and then will apply data loss root cause analysis.

Planned downtime $Pdt = 15 + 30 = 45$ min,
Loading time $Lt = 480 – 45 = 435$ min,
Unplanned downtime $Udt = 60 + 20 = 80$ min,
Operating time $Ot = 435 – 80 = 355$ min,

OEE calculation resulted:

$$Availability = \frac{355}{435} x\ 100 = 82\%,$$

$$Performance = \frac{100x2.8}{355} x100 = 79\%,$$

$$Quality = \frac{92}{100} x100 = 92\%,$$

$$OEE = (0.82x\ 0.79x\ 0.92)x100 = 60\%.$$

As a first step the engineers perform a standard Root Cause Analysis focused on Downtime, Speed and Quality Loss, according traditional model, isolating the causes based on the information obtained from the process records, using various tools including Fishbone [6]. A deeper analysis is required to go to the Root Cause in direct connection with the data used as input for mainly process and product design. The findings show that in terms of design specification some key information (data) is missing and the specific level of controls were not included. Consequently, the first causes are Equipment Failure (Machines cause according Fishbone method) and Components Quality (Materials cause according Fishbone). Second Level Cause (Data Failure Analysis): missing specifications of specifications (Data Failure as was not available in the design phase). Table 6 highlights the data failure correspondence.

The main conclusion after extending the analysis to the Data failure was that the lack of specifications was the most impactful to the overall *OEE* result.

Table 5

Data Failure Analysis

Category	First Failure Level	Failure Mode	Second Failure level: Data Failure	OEE loss
Downtime	Machines failure	Design failure: machines	Specifications not complete and correct	18% availability
Speed Loss	Over Handling	Design failure: machines and process	Specifications and instructions not complete and correct	21% cycle time
Quality	Scrap/ Rework	Design failure: materials	Quality documentation for controls not complete	8% scrap

3. CONCLUSIONS AND POTENTIAL NEXT STEPS

Traditional approach stays as key baseline for OEE measurement and management, however within the loss and impact analysis the Data is a key player. With the new enhancements from Industry 4.0, the organizations can build *Data Loss Model* with all relevant input and impact levels to bring loss analysis and adjustments further in this area. Specific audits applied to the Data driving OEE performance model may help the companies to fix from the start any inconsistency that may impact later on the overall manufacturing process performance.

A good Data driven OEE model validated through a strong data audit system can not only support the manufacturing adjustments levels in case deviations occur, but can as well serve the upstream decisions. The main characteristics that a strong Data system must have are: Availability, Relevance, Comprehensiveness, Sustainability, Accuracy. These characteristics might be associated in future studies for OEE loss extended models and automated solutions to deliver data loss associated models may considerably help both design and execution decisional layers. These models may also support the companies to review the allocation of the resources differently during the overall process.

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