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Overall equipment effectiveness for additive manufacturing

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By

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Additive manufacturing is becoming a leading technology in the production of consumer parts. In order to compete with traditional methods which have had years to improve, additive systems must achieve a level of performance efficiency greater than it maintains today. While great effort is being expended to improve the printing time and add more systems level thinking to the problem, it is currently lacking a robust improvement methodology. To achieve the desired improvement, a technique from traditional manufacturing based on overall equipment effectiveness (OEE) is proposed. Overall additive manufacturing effectiveness (OAME) provides a methodology for enhancing this important emerging technology.

DEDICATION

For Anna, without whom none of this would be possible.

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The author would like to make special mention of Matthew Froehlich, who brought his knowledge and engineering prowess to bear in the development and implementation of OAME. Thank you for your friendship and assistance in working this and many other solutions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Additive manufacturing, “the process of joining materials to make parts from 3D model data layer upon layer” (Chergui, Hadj-Hamou, & Vignat, 2018), is leading the charge into the next wave of manufacturing. Though it has been around for many years it has recently increased in popularity due in large part to a reduction in the cost of three dimensional (3D) printing equipment (Chergui et al., 2018). Additionally, additive manufacturing provides many sustainability features including “complexity-for-free, tool-less manufacturing, and less-resource intensiveness” (Niaki, Torabi, & Nonino, 2019). These factors position additive manufacturing to drive the future of the manufacturing industry.

While a large portion of the industry is based on the historical rapid prototyping movement, which focuses on smaller scale 3D printing, many new applications for additive manufacturing are being explored across industries. Some examples are big area additive manufacturing (BAAM) which provides the opportunity to build outside of an oven (Roschli et al., 2019) and the increasing application of additive construction for concrete buildings (Diggs-McGee, Kreiger, Kreiger, & Case, 2019). The expanding use of these additive systems, coupled with the broad definition of manufacturing, are lending to the continued expansion and growth of the additive field.

In order to effectively compete in today's industrial marketplace, additive manufacturing must advance quickly through the progression of progress that traditional manufacturing methods have had years to work through. This is illustrated in additive manufacturing literature which points out that overall processing time is lengthy (Matilainen, Piili, Salminen, Syvänen, & Nyrhilä, 2014) and lacks system understanding and efficiency (Diggs-McGee et al., 2019). The method of improvement is being sought from a number of angles including the management of the process from a systems perspective (Eyers & Potter, 2017). Other efforts are focused on the component details such as improving the production speeds (Gusarov et al., 2018), or the monitoring of quality during the production process (Zhang, Liu, & Shin, 2019). An improvement tool which might otherwise be overlooked due to its association with traditional manufacturing, is the Overall Equipment Effectiveness (OEE) measurement which is part of the Total Productive Maintenance (TPM) movement of the 1980's.

With the increased use of additive manufacturing, it is very important to understand how equipment is functioning as it has a direct impact on the quality of products produced (Nakajima, 1988). TPM and OEE have provided "an essential strategy for continuous improvement" (Esmaeel, Zakuan, Jamal, & Taherdoost, 2018) in traditional manufacturing. This thesis proposes a transformation of the existing OEE calculation, which makes it applicable and effective in additive manufacturing environments. Overall Additive Manufacturing Effectiveness (OAME) will provide any additive manufacturing system the opportunity to improve, thrive, and develop world class efficiency.

CHAPTER II

LITERATURE REVIEW

2.1 OEE

Overall Equipment Effectiveness (OEE) is an equipment management tool developed by Seiichi Nakajima which provides the base measurement for which TPM is founded. The resulting OEE score, expressed as a percentage, is a calculation of "how the equipment is performing overall while it is being operated" (Hartman, 1992 p.52). This means that a clear picture can be drawn between how well the machine is being maintained and managed and its performance, thus providing insight into "the obstacles and wastes that are lowering the productivity rate" (Ahmed, 2013). Using OEE inside the greater TPM mindset has allowed companies to improve their equipment and in turn their factories (Hartman, 1992; Nakajima, 1988). This productivity improvement opportunity spans all types of products and processes including: automotive (Chand & Shirvani, 2000), impellers (Kumar, Mani, & Devraj, 2014), mining (Waqas, Tariq, Shahzad, Ali, & Saqib, 2015), printing (Moreira et al., 2018), tire production (Djatna & Munichputranto, 2015), urban transportation (Muñoz-Villamizar, Santos, Montoya-Torres, & Jaca, 2018), welding (Sivakumar & Manivel, 2019), and many others.

2.2 Foundations

At the foundational level, OEE is a system of tracking time at a piece of equipment. This is done through three measures - availability, performance, and quality. Managing equipment by time is an excellent way to understand what occurs during production of a product, as it accounts for everything that takes place. Tracking is done through the use of zero-based time accounting; meaning that all time that passes during the production process must be accounted for and categorized. This forces a greater understanding of the equipment and in turn increases the opportunity to improve it. All the time categories used in calculating an OEE score can be seen in Table 2.1

Table 2.1 Time Categories

Term	Definition
Calendar Time (T_C)	All time which passes over a set duration (day, week, month)
Not Scheduled (L_{NS})	Time which is planned for the machine to be idle (Non-working time such as weekend, holidays, off shifts)
Planned Downtime (L_{PD})	Time where machines are scheduled to receive maintenance
Planned Production Time (T_{PP})	Time planned for products to be produced
Unplanned Downtime (L_{UD})	Time lost due to unforeseen mechanical problems (machine related - breaks, faults, repairs, setup, adjustments, changeovers)
Available to Run (T_A)	Time where the machine is available to be run (not broken or delayed)
Minor Stops (L_{MS})	Machine or operator initiated stops under a certain defined duration. (usually 2 to 3 minutes)
Idle (L_E)	Time where the machine is stopped for no known issues
Speed Loss (L_S)	Time spent producing parts at a slower rate than programmed intent
Running Time (T_R)	Time required to produce parts as defined by the program.
Quality Loss (L_Q)	Time spent producing bad parts
Value Added Time (T_{VA})	Time spent producing good parts

2.3 Quality Measurement

While availability and performance are always defined in units of time it is important to define the units for the quality measurement and the implications for additive manufacturing. Throughout literature, quality is defined as either goods or time spent making goods (see Table 2.2). While even Nakajima (1988), uses goods to define quality, it has become acceptable to use time as the unit of measure (Sonmez, Testik, & Testik, 2018). Becker (2015), points out that by defining quality as time, the effort (in units of time) spent to rework a product can also be included in the calculation. Measuring in this way provides a greater systematic view of the product within the production process. This is important for our application within additive manufacturing, given its unique production method of layer-by-layer addition.

Table 2.2 Quality Measurement Unit

Quality as:	Source Literature
Time	(Andersson & Bellgran, 2015)
	(Foulloy, Clivillé, & Berrah, 2019)
	(Iranzadeh & Bagherzadeh, 2019)
	(Jauregui Becker, Borst, & Van Der Veen, 2015)
	(Sivakumar & Manivel, 2019)
	(Sonmez et al., 2018)
Goods	(Djatna & Munichputranto, 2015)
	(Djatna & Alitu, 2015)
	(Heng, Aiping, Liyun, & Moroni, 2019)
	(Mainea, Duta, Patic, & Caciula, 2010)
	(Moreira et al., 2018)
	(Mwanza & Mbohwa, 2015)
	(Nakajima, 1988)
	(Relkar & Nandurkar, 2012)
	(Singh, Shah, Gohil, & Shah, 2013)

Some additive processes today have the ability to produce final products at one hundred percent quality. This is not achieved through perfect manufacturing, but through in-production quality checks and rework. The additive process provides the opportunity to inspect, rework, or replace each layer to achieve a final product which, as a result, is free of defects. This is fantastic for manufacturers, since it means there are no more lost profits due to post-process scrap or reworked goods. However, the opportunity for losses within the manufacturing process still remain due to lost time on the machine for quality purposes.

Using the unit of time to measure quality in turn provides a way of measuring the time spent on quality items in process while still maintaining an overall final output of zero defects. To measure in this way, a transformation to the existing OEE calculation is proposed. The new formulation, Overall Additive Manufacturing Effectiveness, moves the quality measure from a stand-alone component to an integral part of the performance calculation, allowing OAME to be used in additive manufacturing with similar results to that of traditional manufacturing methods.

CHAPTER III

OVERALL EQUIPMENT EFFECTIVENESS

3.1 Calculation

To properly discuss the need for a new formulation of the OEE calculation, the traditional calculation will be reviewed and the associated shortcomings for additive manufacturing discussed. OEE is calculated by multiplying the components of availability, performance, and quality together. Figure 3.1, provides a visualization of the breakdown of time categories (defined in Table 2.1) needed to calculate the components and the overall OEE score.

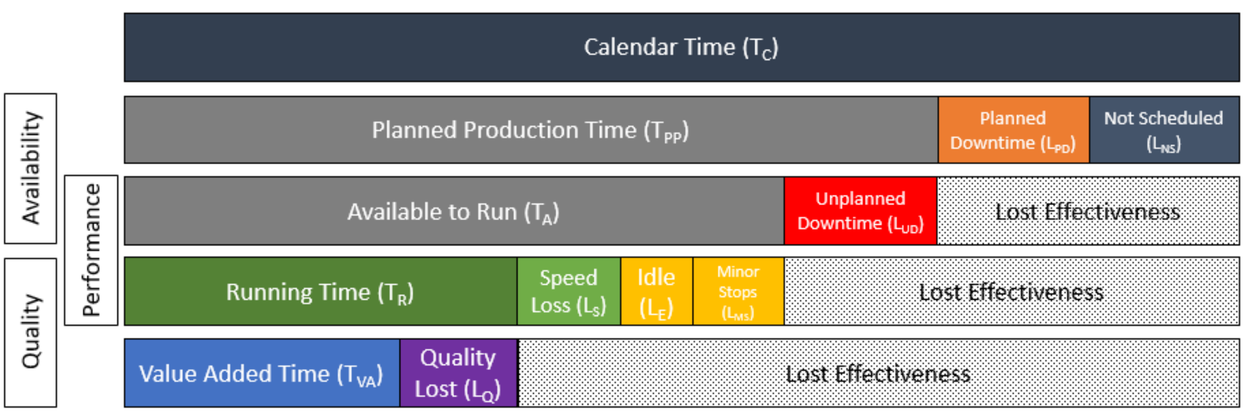

Figure 3.1 OEE

3.1.1 Availability

Availability is the time that the equipment is available for use. The calculation begins with all calendar time (T_C) fully accounted. The planned production time (T_{PP}) is derived from the calendar time less any time not scheduled to run (L_{NS}) and any planned downtimes (L_{PD}):

$$T_{PP} = T_C - L_{NS} - L_{PD} \qquad \text{(Eq.3.1)}$$

The time that is now available for the machine to run (T_A) can be accounted by reducing the planned production time (T_{PP}) by the unplanned downtime (L_{UD}):

$$T_A = T_{PP} - L_{UD} \qquad \text{(Eq.3.2)}$$

The availability can now be calculated by dividing the time available to run (T_A) by the planned production time (T_{PP}).

$$Availability = \frac{Available\ to\ Run\ (T_A)}{Planned\ Production\ Time\ (T_{PP})} \qquad \text{(Eq.2.3)}$$

3.1.2 Performance

The performance measures how well the machine is running inside the available time. To determine the performance of the system, the running time (T_R) has to first be calculated by removing the losses of speed (L_S), idleness (L_E), and minor stops (L_{MS}) from the time available to run (T_A):

$$T_R = T_A - L_S - L_E - L_{MS} \qquad \text{(Eq.3.3)}$$

While this is the correct representation for calculating running time (T_R) what is actually being solved for here are the losses since running time is a known value based on the programmed duration of the process. Running time (T_R) then is a function of the number of parts produced over the given calendar time multiplied by the programmed duration. This results in a known running and available time with the losses calculated in order to maintain zero-based time accounting. The running time (T_R) is divided by the time available to run (T_A), thus completing the performance portion of the OEE calculation.

$$Performance = \frac{Running\ Time\ (T_R)}{Availabile\ to\ Run\ (T_A)} \quad \text{(Eq.3.4)}$$

3.1.3 Quality

To determine the quality measure the value-added[1] time must be calculated. It is determined by removing the lost time due to producing defective parts (L_Q) from the running time (T_R):

$$T_{VA} = T_R - L_Q \quad \text{(Eq.3.5)}$$

To complete the quality calculation the value-added time (T_{VA}) is divided by the previously determined running time (T_R).

$$Quality = \frac{Value\ Added\ Time\ (T_{VA})}{Running\ Time\ (T_R)} \quad \text{(Eq.3.6)}$$

3.1.4 Summary

In conclusion, with all the necessary components gathered to calculate OEE, all that remains is to multiply them together. A detailed example of this entire process can be found in APPENDIX A.

$$OEE = Availability\ \times Performance\ \times Quality \quad \text{(Eq.3.7)}$$

3.2 Shortcomings

The OEE calculation is not conducive to real-time monitoring of the quality of a produced part. In a large majority of applications, parts cannot be determined to be within

[1] Value-Added: Time spent increasing the value of a product

specification until they reach their final form - when all processes have been completed. At this point the quality information has to be added back into the availability and performance dataset. This alignment of data requires time and effort which are not often surplus resources in a manufacturing environment.

When this quality measurement issue is considered in the context of additive manufacturing process, the problem can deepen. Additive processes have the ability to correct in-process defects during production, which could lead to defect-free parts at the end of the process.

$$T_{VA} = T_R - 0 \tag{Eq.3.8}$$

Thus, the quality portion of the calculation is held at 100%,

$$Quality = \frac{Value\ Added\ Time\ (T_{VA})}{Running\ Time\ (T_R)} = \frac{T_R}{T_R} = 1 \tag{Eq.3.9}$$

This creates a time gap in the OEE calculation because it does not have a way to track the time spent to inspect or rework the part. This results in the need for a new formulation to ensure an OEE score can be accurately calculated and improvements can be made.

CHAPTER IV

OVERAL ADDITIVE MANUFACTURING EFFECTIVENESS

4.1 Calculation

OAME seeks to provide an answer for the accounting of all time and provide additive manufacturing with a robust improvement methodology. The key component to the formulation is the movement of quality from a unique standalone component to a subset of the performance component, as seen in Figure 4.1.

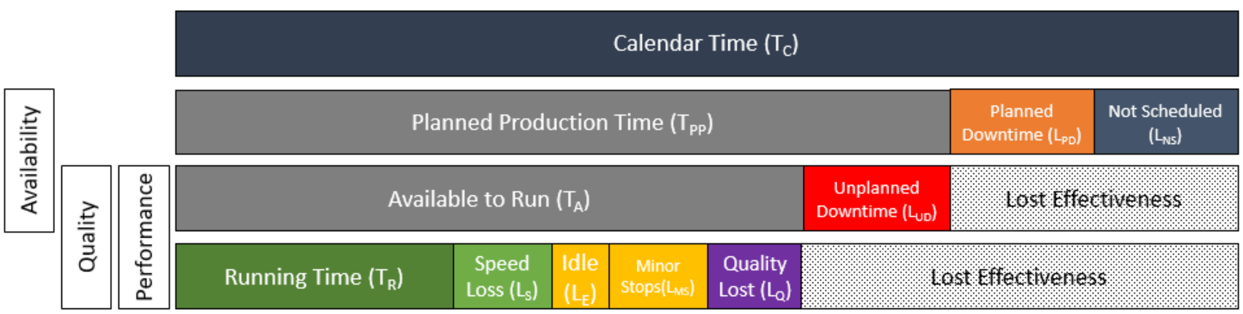

Figure 4.1 OAME

To move the quality component into the performance calculation, the final quality of all products needs to be within specification for every unit produced. This level of quality is ensured by the time spent on quality activities such as rework or inspection, redefining the quality loss category (L_Q). When quality is held at this level, the OAME calculation can be written as availability multiplied by performance.

$$OAME = Availability \times Performance \tag{Eq.10}$$

The higher-level components of availability and performance are still calculated in the same way; however, the factors that make up the performance calculation do change. The running time (T_R) is now reduced by an additional factor - quality loss (L_Q):

$$T_R = T_A - L_S - L_E - L_{MS} - L_Q \tag{Eq.11}$$

The quality loss category is now the time ensuring good parts are produced through the actions of inspection and rework. A detailed example of this calculation can be found in APPENDIX A.

4.2 Importance

While Figure 3.1 and Figure 4.1 may appear to illustrate the same information simply compressed into a single line, the definition of running time (T_R) will provide the additional proof of the need for OAME. Running time is defined as the "as-designed" time to complete a process (Nakajima, 1988, p.24). Today this is often the numerically controlled (NC) program run speed or program simulated time for a process. This means that the running time (T_R) is only the time in additive manufacturing where material is added to the designed product.

In the OEE calculation, quality is derived from the total running time reduced by the running time spent producing bad parts. Thus, the quality measurement is a subset or portion of running time. However, in OAME, quality is no longer defined as time spent producing bad parts but as time (not running time) ensuring the production of good parts; therefore, it is no longer a subset of running time but a degradation of the total amount of time available for running time. This is an important distinction in light of the running time definition for additive manufacturing.

If the OEE calculation is used, it results in a reporting of the time spent producing the part (running time) which is less than the time it is programmed to take. This creates uncategorical lost time rendering the OEE equation improvement methodology ineffective. By using OAME, the running time will match the programmed time and the quality losses will be deducted from the amount of available time (T_A) in which to run (T_R), there by maintaining the zero-based time accounting required to understand and improve the system. This change in how quality is represented provides additive manufacturing with a unique solution for its unique manufacturing process.

4.3 Solutions

Use of OAME also provides some additional solutions to the management of the quality data, since quality losses now occur during production and not after processing is complete. The quality data can be recorded live and in the same dataset as all the other captured data. This enables many more methods of data capture and provides opportunities to manage the system during the manufacturing time. This means that a quality problem can be detected and corrected earlier in the process thereby improving the future quality of the manufacture and potentially the overall throughput of the equipment.

CHAPTER V

CASE STUDY

5.1 Introduction

The OAME formulation was tested and proven during use as a methodology for improving the production system efficiency within an additive automation work cell. The motivation for this work was to provide the opportunity for increased throughput and maintenance and a reduction of demand for, and on, operators. All goals were achieved during the two-year examination period with work continuing past the conclusion of this study. The results of the work were a reduction in processing time by over 40 percent and an OAME score improvement of over 300 percent.

5.2 Production System

The robotic equipment used in this work cell, while automated during the value-added processes, expends a large portion of the production time on non-value added[2], but required, processes. This includes the time needed for quality inspections and reworking to the specifications that are required as part of the production process. Processing times in this work cell were highly variable. Additionally, being the bottleneck of the factory, the processes created blocking[3] and starving[4] problems in the following work cells. Due to the high variation and

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[2] Non-Value Added: Time spent on potentially necessary work but that does not add value to the final product
[3] Blocking: Receiving more product than is possible to process at a single time
[4] Starving: Receiving no product to process

manual work, the work cell operated twenty-four hours a day seven days a week. By the end of the study, the work cell operated a standard, eight-hour, three-shift, five-day weekly schedule.

5.3 Data Gathering

Gathering the data needed to perform the OAME calculations can be completely accomplished by hand, if required. Recording data in this way can create the potential for production losses if performed by the machine operator; however, the end benefits may outweigh these up-front losses. Other ways to gather the data are through the use of time studies (Puvanasvaran, Mei, & Alagendran, 2013), automatic machine data (Hedman, Subramaniyan, & Almström, 2016), or the development of an in-house solution (Singh et al., 2013). This case study began by using a combination of machine and operator-generated records. A secondary database software was used to gather both machine and operator information. To mitigate lost time for short stops, the minor stops category maximum was set at two and a half minutes (lowered to 2 minutes by study's end), which allowed operators to skip paperwork for these small periods of time. By the end of the study, all data was collected automatically into the database. The standardization gained and overall reduction of the need for operator input allowed the previously manual inputs to be coded into the database automatically and then verified by the operator during periods which would not inhibit production.

5.4 Reporting

As Foulloy et al., 2019, point out, the reason for reporting OEE is to provide a time-based answer to the question of what can be said of each day, week, and month. That is, with regards to performance, what is known today, from history, and expected in the future (Foulloy et al., 2019). In light of this, OAME reports were produced and published to the facility on a monthly basis and consisted of a complete work-cell summary as well as a by-machine summary. This time increment was chosen in order to gather a sufficient sample of products produced. When the duration of the ideal running time for a single product extends beyond a single day of production, as in this case, it is beneficial to choose a longer reporting period so that patterns and repetitive issues can emerge. These reports were used to help determine opportunities of improvement for management, personnel, and maintenance. Three additional OAME reports, by goods produced, weekly, and cumulative month - were also provided to the improvement team and were used to direct any reactive needs and determine if improvements were having an impact on the process.

5.5 Implementation

The benefit of using OAME is the ability to follow the traditional OEE implementation strategy - which is to implement TPM. In general, the phased approach presented by Hartman, 1992, was followed (see Table 5.1). While phase 3 is focused on the replacement of existing equipment, it does not have to be used exclusively for that purpose. In this case following similar steps, additional tools were added to the existing equipment system to increase robustness and reduce maintenance.

Table 5.1 Phased Approach

Phase	Step	Description
1 Improve	1	Determine existing equipment performance and availability
	2	Determine equipment condition
	3	Determine current maintenance (especially PM) performed on equipment
	4	Analyze equipment losses
	5	Develop (and rank) equipment improvement needs and opportunities
	6	Develop set-up or change-over improvement needs and opportunities
	7	Execute improvements as planned and scheduled
	8	Check results and continue as required
2 Maintain	1	Develop PM requirements for each machine
	2	Develop lubrication requirements for each machine
	3	Develop cleaning requirements for each machine
	4	Develop PM, lubrication and cleaning procedures
	5	Develop inspection procedure for each machine
	6	Develop the PM, lubrication, cleaning and inspection system, including all forms and controls
	7	Develop the PM manual
	8	Execute PM, cleaning and lubrication as planned and scheduled
	9	Check results and correct as required
3 Procure	1	Develop engineering specifications
	2	Get input from operators based on current equipment experience
	3	Get input from maintenance based on current equipment experience
	4	Eliminate past problems
	5	Design in new technology
	6	Design in diagnostics
	7	Design in maintainability (maintenance-free equipment)
	8	Start training (operational & maintenance) early
	9	Accept equipment only if it meets or exceeds specifications

In addition to the illustrated equipment focus, a similar course of action was taken with regard to the areas of management and personnel. By focusing on the entire system at one time, no individual group was blamed for being the problem, and as a result groups shared ideas more freely. While moving through the phases within each area, some steps were skipped and returned to at a later time. This provided flexibility to address the easiest improvement opportunities first and did not inhibit the overall progression. As highlighted in the last step of phases one and two, this is a learning process and may require several repetitions through each phase, both before and after moving to the next one, as the improvement journey continues.

5.6 Method

The key to achieving OAME improvement is by focusing on the loss categories. Within the TPM framework these are defined as the six big losses, as shown in Table 5.2 (Nakajima, 1988 p. 14). For this study, the terminology stayed with the previously defined terms from Table 2.1 (see Table 5.2 Column 3). By focusing on the loss categories, an accurate picture of where time has been spent can be drawn. This is the power of the OAME calculation - to define and facilitate understanding of issues which allows for the development of projects to address these loss issues (Muchiri & Pintelon, 2008).

Table 5.2 The Six Big Losses and the Relationship to Defined Terms

Loss	Definition	Related Term in Table 2.1
Equipment Failure	Breakdowns	Unplanned Downtime (L_{UD})
Setup and Adjustment	Ex: Exchange of die	Unplanned Downtime (L_{UD})
Idling and Minor Stops	Due to abnormal operation, work blockages	Idle (L_E) and Minor Stops (L_{MS})
Reduced Speed	Discrepancies between designed and actual speed	Speed Loss (L_S)
Process Defects	Due to scrap and quality defects	Quality (L_Q)
Reduced Yield	From startup to stable production	Quality (L_Q)

Columns 1 and 2 from Nakajima, 1988 p. 14; Column 3 shows relationship between the losses and the terms from Table 2.1

To achieve the needed improvement, a diversely skilled team was assembled with leadership's support. The represented functions were industrial engineering, information technology, maintenance, manufacturing engineering, production management, research engineering, operators, and quality engineering. The team members, in addition to working together for a majority of each day, met twice a week to discuss OAME results and improvement project status.

These improvement projects were developed through the analysis of time record details that make up the loss categories. By viewing each loss category individually, a pareto chart of the issues was developed. This is a common progression in literature and allowed the team to draw a vector of effort from the large amount of information derived from OAME loss data. Once projects were established, progress was tracked within the pareto charts to visualize the specific issue changes within the greater loss category. This maintained a positive team morale when the overall OAME score did not change due to an increase, equal to that of a reduction, which occurred in another time loss issue.

5.7 Improvement Progression

In a system with a large number of variables that are interconnected and highly variable within themselves, it became important to isolate issues as much as possible and work to correct them individually. Then as more control entered the system it became easier to determine the relationships among issues and to work toward driving process improvements to address them. Thus, this cyclical improvement approach continued as knowledge of the system developed. This is seen in Figure 5.1 where, even as overall reduction takes place, new categories are added.

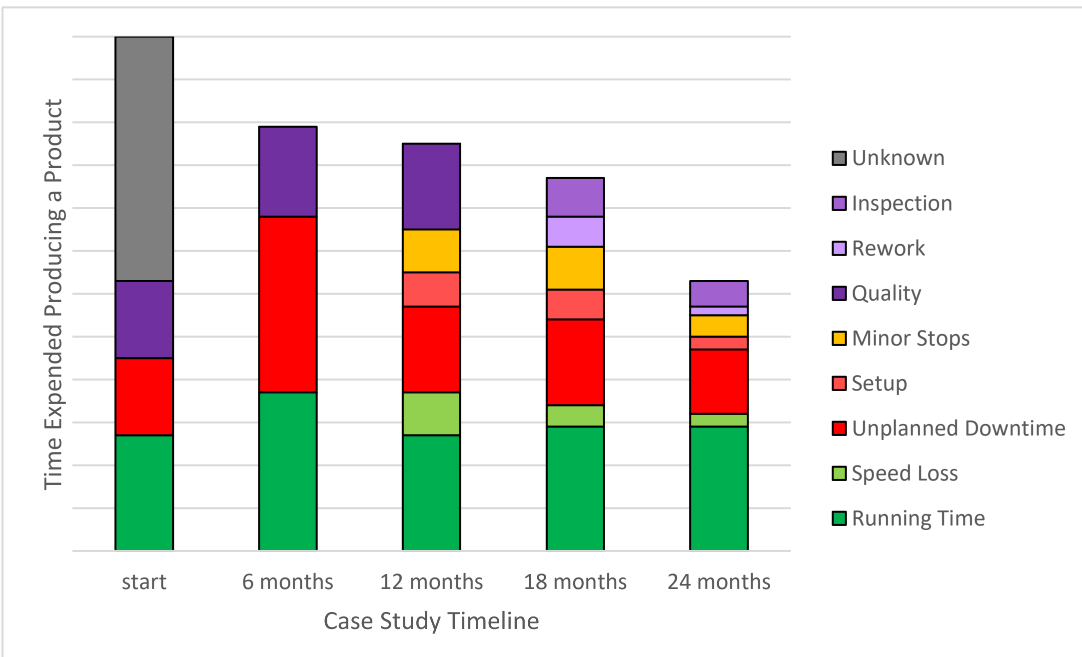

Figure 5.1 Improvement Progression

5.8 Solutions

The unplanned downtime was the largest loss category within the OAME score, and thus became the focus of the team's improvement efforts. The equipment used in this work cell generated thousands of codes in three types - notes, alerts, and faults - each with a severity rating of 1 to 5. Both the type and rating of each code would create an action on the part of the machine which ranged from no indication to stopping the machine. The large number and apparent randomness of when the machine would stop created confusion for the team, specifically the operators and maintenance personnel. This led to the ignoring of potential serious issues due to the abundance of non-issue codes. Thus, after a period of reviewing both commonly appearing codes and the full code list, a better code and rating system was developed. The improved system used only a small set of common codes and provided specific information in the code description. This created a system that was easier for the team to understand and act on quickly, especially when a stoppage occurred. Additionally, it helped with the grouping of detailed information within the unplanned downtime loss category which drove the projects.

As a result of this improved code system, when new issue codes appeared outside of the common set, corrections were much quicker. As an example, a potentially serious code appeared on one machine and was driving stops; however, no issues were found. After a short investigation period, it was discovered that the recently serviced air conditioner was blowing cold air on the sensor, causing it to fault. A simple redirection of the vent flanges removed the issue entirely. Without the new system in place, this code would have been lost in the mass of codes and could have plagued the machine for an extended period of time.

As the machine's codes were reduced, machine maintenance was able to be better targeted to the issue areas. The results of this improved preventative maintenance schedule, coupled with the replacement of some end-of-life-cycle components, led to a healthier machine. This, in turn, improved the first-pass quality of the machine and reduced the quality issues. This is the essence of what an OEE score drives in the TPM framework - to perform preventative off-line maintenance so that when equipment is running, it stays running, and at a high level of quality.

As the machine improvements reduced variability, observation and time studies produced a myriad of projects including speed loss reduction, standardization of work, raw material replacement, shift changeovers, training, and operational checklists. This provided ways to address the detailed drivers of several loss categories that within the database are not divisible, similar to the grouping of codes within the unplanned downtime category. For example, during one of the studies, the operator's use of the speed-control knob was noted as a potential area for improvement. The operators were constantly using the knob to better control the machine, which pointed to either a potential design issue or improper operator training. To improve the system, the capture of speed loss data was enabled, which resulted in the understanding that speed loss was a large and easily addressed contributor to a low OEE score. Once this was understood, an optimized numerically controlled program was developed, which on the first iteration drastically reduced the need to adjust the speed. The final solution slowed down the overall programmed speed but returned a faster production time with fewer errors.

5.9 Discussion

The transition to using OAME and its losses as a way to manage this work center was not quick or easy. From implementation to the study's end, two years of focused and dedicated support from the team were required to achieve a processing time reduction of over 40 percent and an OAME score improvement of over 300 percent. The need for collective support from all organizations coincides with how the OAME calculations employ interconnected manufacturing measurements to create a single component score. While OEE is "a reactive measurement," it is its ability to provide an understanding "of the proactive maintenance done to the equipment" (Andersson & Bellgran, 2015) that makes it such a strong resource for deployment in manufacturing at large, and especially in additive manufacturing as OAME.

CHAPTER VI

CONCLUSION

"The OEE [calculation] becomes today not only simultaneously a short-term diagnosis tool but also a mid-term and long-term improvement tool" (Foulloy et al., 2019). This speaks well to the history of OEE to inspire change in the manufacturing environment. It is on this foundation that Overall Additive Manufacturing Effectiveness has been developed by moving the quality component from stand-alone to an integral part of the performance. This integration of quality into the performance equation was accomplished to provide the same benefits traditional manufacturing enjoys to the growing additive manufacturing industry.

This type of improvement system is in greater demand as additive manufacturing expands in industry. As pointed out by Diggs-McGee et al., (2019), and Matilainen et al., (2014), much work is needed to improve the additive system. OAME is poised to fill that need and provide an established method for improvement. Coupled with the many other manufacturing advantages of additive processing, OAME provides the leverage to push additive manufacturing further into the future of industry.

REFERENCES

Ahmed, M. H. (2013). OEE can be your key. *Industrial Engineer*, *45*(8), 43–48.

Andersson, C., & Bellgran, M. (2015). On the complexity of using performance measures: Enhancing sustained production improvement capability by combining OEE and productivity. *Journal of Manufacturing Systems*, *35*, 144–154. https://doi.org/10.1016/j.jmsy.2014.12.003

Chand, G., & Shirvani, B. (2000). Implementation of TPM in cellular manufacture, *103*, 149–154.

Chergui, A., Hadj-Hamou, K., & Vignat, F. (2018). Production scheduling and nesting in additive manufacturing. *Computers and Industrial Engineering*, *126*(September), 292–301. https://doi.org/10.1016/j.cie.2018.09.048

Diggs-McGee, B. N., Kreiger, E. L., Kreiger, M. A., & Case, M. P. (2019). Print time vs. elapsed time: A temporal analysis of a continuous printing operation for additive constructed concrete. *Additive Manufacturing*, *28*(October 2018), 205–214. https://doi.org/10.1016/j.addma.2019.04.008

Djatna, T., & Alitu, I. M. (2015). An Application of Association Rule Mining in Total Productive Maintenance Strategy: An Analysis and Modelling in Wooden Door Manufacturing Industry. *Procedia Manufacturing*, *4*(Iess), 336–343. https://doi.org/10.1016/j.promfg.2015.11.049

Djatna, T., & Munichputranto, F. (2015). An analysis and design of mobile business intelligence system for productivity measurement and evaluation in tire curing production line. *Procedia Manufacturing*, *4*(Iess), 438–444. https://doi.org/10.1016/j.promfg.2015.11.060

Esmaeel, R. I., Zakuan, N., Jamal, N. M., & Taherdoost, H. (2018). Understanding of business performance from the perspective of manufacturing strategies: Fit manufacturing and overall equipment effectiveness. In *Procedia Manufacturing* (Vol. 22, pp. 998–1006). https://doi.org/10.1016/j.promfg.2018.03.142

Eyers, D. R., & Potter, A. T. (2017). Industrial Additive Manufacturing: A manufacturing systems perspective. *Computers in Industry*, *92–93*, 208–218. https://doi.org/10.1016/j.compind.2017.08.002

Foulloy, L., Clivillé, V., & Berrah, L. (2019). A fuzzy temporal approach to the Overall Equipment Effectiveness measurement. *Computers and Industrial Engineering*, *127*(November 2018), 103–115. https://doi.org/10.1016/j.cie.2018.11.043

Gusarov, A. V, Grigoriev, S. N., Volosova, M. A., Melnik, Y. A., Laskin, A., Kotoban, D. V, & Okunkova, A. A. (2018). On productivity of laser additive manufacturing. *Journal of Materials Processing Technology*, *261*(September 2017), 213–232. https://doi.org/10.1016/j.jmatprotec.2018.05.033

Hartman, E. (1992). *Successfully Installing TPM in a Non-Japanese Plant*. Charlotte: TPM Press.

Hedman, R., Subramaniyan, M., & Almström, P. (2016). Analysis of critical factors for automatic measurement of OEE. *Procedia CIRP*, *57*, 128–133. https://doi.org/10.1016/j.procir.2016.11.023

Heng, Z., Aiping, L., Liyun, X., & Moroni, G. (2019). Automatic Estimate of OEE Considering Uncertainty. *Procedia CIRP*, *81*, 630–635. https://doi.org/10.1016/j.procir.2019.03.167

Iranzadeh, S., & Bagherzadeh, M. (2019). Journal of Loss Prevention in the Process Industries Investigating the relationship between RPN parameters in fuzzy PFMEA and OEE in a sugar factory. *Journal of Loss Prevention in the Process Industries*, *60*(May), 221–232. https://doi.org/10.1016/j.jlp.2019.05.003

Jauregui Becker, J. M., Borst, J., & Van Der Veen, A. (2015). Improving the overall equipment effectiveness in high-mix-low-volume manufacturing environments. *CIRP Annals - Manufacturing Technology*, *64*(1), 419–422. https://doi.org/10.1016/j.cirp.2015.04.126

Kumar, S. V., Mani, V. G. S., & Devraj, N. (2014). Production Planning and Process Improvement in an Impeller Manufacturing Using Scheduling and OEE Techniques. *Procedia Materials Science*, *5*, 1710–1715. https://doi.org/10.1016/j.mspro.2014.07.360

Mainea, Marin; Duta, Luminita; Patic, Paul C.; Caciula, I. (2010). A Method to Optimize the Overall Equipment Effectiveness. In *IFAC Proceedings Volumes (IFAC-PapersOnline)* (pp. 237–241). https://doi.org/10.3182/20100908-3-PT-3007.00046

Matilainen, V., Piili, H., Salminen, A., Syvänen, T., & Nyrhilä, O. (2014). Characterization of process efficiency improvement in laser additive manufacturing. In *Physics Procedia* (Vol. 56, pp. 317–326). Elsevier B.V. https://doi.org/10.1016/j.phpro.2014.08.177

Moreira, A., Silva, F. J. G., Correia, A. I., Pereira, T., Ferreira, L. P., & De Almeida, F. (2018). Cost reduction and quality improvements in the printing industry. In *Procedia Manufacturing* (Vol. 17, pp. 623–630). Elsevier B.V. https://doi.org/10.1016/j.promfg.2018.10.107

Muchiri, P., & Pintelon, L. (2008). Performance measurement using overall equipment effectiveness (OEE): Literature review and practical application discussion. *International Journal of Production Research*, *46*(13), 3517–3535. https://doi.org/10.1080/00207540601142645

Muñoz-Villamizar, A., Santos, J., Montoya-Torres, J. R., & Jaca, C. (2018). Using OEE to evaluate the effectiveness of urban freight transportation systems: A case study. *International Journal of Production Economics*, *197*(January), 232–242. https://doi.org/10.1016/j.ijpe.2018.01.011

Mwanza, B. G., & Mbohwa, C. (2015). Design of a Total Productive Maintenance Model for Effective Implementation: Case Study of a Chemical Manufacturing Company. *Procedia Manufacturing*, *4*(Iess), 461–470. https://doi.org/10.1016/j.promfg.2015.11.063

Nakajima, S. (1988). *Introduction to TPM: Total Productive Maintenance*. Cambridge, MA: Productivity Press.

Niaki, M. K., Torabi, S. A., & Nonino, F. (2019). Why manufacturers adopt additive manufacturing technologies: The role of sustainability. *Journal of Cleaner Production*, *222*, 381–392. https://doi.org/10.1016/j.jclepro.2019.03.019

Puvanasvaran, A. P., Mei, C. Z., & Alagendran, V. A. (2013). Overall equipment efficiency improvement using time study in an aerospace industry. In *Procedia Engineering* (Vol. 68, pp. 271–277). Elsevier B.V. https://doi.org/10.1016/j.proeng.2013.12.179

Relkar, A. S., & Nandurkar, K. N. (2012). Optimizing & analysing overall equipment effectiveness (OEE) through design of experiments (DOE). In *Procedia Engineering* (Vol. 38, pp. 2973–2980). https://doi.org/10.1016/j.proeng.2012.06.347

Roschli, A., Gaul, K. T., Boulger, A. M., Post, B. K., Chesser, P. C., Love, L. J., … Borish, M. (2019). Designing for Big Area Additive Manufacturing. *Additive Manufacturing*, *25*(September 2018), 275–285. https://doi.org/10.1016/j.addma.2018.11.006

Singh, R., Shah, D. B., Gohil, A. M., & Shah, M. H. (2013). Overall equipment effectiveness (OEE) calculation - Automation through hardware & software development. In *Procedia Engineering* (Vol. 51, pp. 579–584). https://doi.org/10.1016/j.proeng.2013.01.082

Sivakumar, R., & Manivel, R. (2019). Analysis on overall equipment effectiveness of a PEMAMEK panel processing machine. *Materials Today: Proceedings*, (xxxx). https://doi.org/10.1016/j.matpr.2019.06.132

Sonmez, V., Testik, M. C., & Testik, O. M. (2018). Overall equipment effectiveness when production speeds and stoppage durations are uncertain. *International Journal of Advanced Manufacturing Technology*, *95*(1–4), 121–130. https://doi.org/10.1007/s00170-017-1170-8

Waqas, M., Tariq, S. M., Shahzad, M., Ali, Z., & Saqib, S. (2015). Performance Measurement of Surface Mining Equipment By Using Overall Equipment Effectiveness. *Pakistan Journal of Science*, *67*(2), 212–216.

Zhang, B., Liu, S., & Shin, Y. C. (2019). In-Process monitoring of porosity during laser additive manufacturing process. *Additive Manufacturing*, *28*(March), 497–505. https://doi.org/10.1016/j.addma.2019.05.030

APPENDIX A

EXAMPLE CALCULATIONS

A.1 OEE Calculation

Table A.1 Sample Set

Term	Example Data
Calendar Time (T_C)	1 week – 168 hours (7 days)
Products Produced	6 units
Running Time (T_R)	12 hours for each unit
Not Scheduled (L_{NS})	Sunday (24 hrs) and off shifts on Saturday (16 hrs) – 40 hours
Planned Downtime (L_{PD})	Saturday for 1 shift – 8 hours
Unplanned Downtime (L_{UD})	Setup/breakdowns – 28 hours
Minor Stops (L_{MS})	15 hours
Idle (L_E)	2 hours
Speed Loss (L_S)	3 hours
Quality Loss (L_Q)	10 hours

A.1.1 Availability

$$\mathrm{T_{PP}} = \mathrm{T_C} - \mathrm{L_{NS}} - \mathrm{L_{PD}}$$

$$\mathrm{T_{PP}} = 168 - 40 - 8$$

$$\mathrm{T_{PP}} = 120 \qquad \text{(Eq.A1)}$$

$$T_A = T_{PP} - L_{UD}$$

$$T_A = 120 - 28$$

$$T_A = 92 \qquad \text{(Eq.A2)}$$

$$Availability = \frac{Available\ to\ Run\ (T_A)}{Planned\ Production\ Time\ (T_{PP})}$$

$$Availability = \frac{92}{120}$$

$$Availability = \ 0.766\ or\ 76.6\% \qquad \text{(Eq.A3)}$$

A.1.2 Performance

$$T_R = T_A - L_S - L_E - L_{MS}$$

$$T_R = 92 - 3 - 2 - 15$$

$$T_R = 72 \qquad \text{(Eq.A4)}$$

$$Performance = \frac{Running\ Time\ (T_R)}{Availabile\ to\ Run\ (T_A)}$$

$$Performance = \frac{72}{92}$$

$$Performance = \ 0.782\ or\ 78.2\% \qquad \text{(Eq.A5)}$$

A.1.3 Quality

$$T_{VA} = T_R - L_Q$$

$$T_{VA} = 72 - 10$$

$$T_{VA} = 62 \qquad \text{(Eq.A6)}$$

$$Quality = \frac{Value\ Added\ Time\ (T_{VA})}{Running\ Time\ (T_R)}$$

$$Quality = \frac{62}{72}$$

$$Quality = 0.861\ or\ 86.1\% \qquad \text{(Eq.A7)}$$

A.1.4 Summary

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

$$OEE = 0.766 \times 0.782 \times 0.861$$

$$OEE = 0.515\ or\ 51.5\% \qquad \text{(Eq.A8)}$$

A.2 OAME Calculation

See Table A.1 for sample calculation data

A.2.1 Availability

$$\mathrm{T_{PP}} = \mathrm{T_C} - \mathrm{L_{NS}} - \mathrm{L_{PD}}$$

$$\mathrm{T_{PP}} = 168 - 40 - 8$$

$$\mathrm{T_{PP}} = 120$$

$$T_A = T_{PP} - L_{UD}$$

$$T_A = 120 - 28$$

$$T_A = 92$$

$$Availability = \frac{Available\ to\ Run\ (T_A)}{Planned\ Production\ Time\ (T_{PP})}$$

$$Availability = \frac{92}{120}$$

$$Availability = 0.766\ or\ 76.6\%$$

A.2.2 Performance

$$T_R = T_A - L_S - L_E - L_{MS} - L_Q$$

$$T_R = 92 - 3 - 2 - 15 - 10$$

$$T_R = 62 \tag{Eq.A9}$$

$$Performance = \frac{Running\ Time\ (T_R)}{Availabile\ to\ Run\ (T_A)}$$

$$Performance = \frac{62}{92}$$

$$Performance = 0.673\ or\ 67.3\%$$

A.2.3 Summary

$$OEE = Availability \times Performance$$

$$OEE = 0.766 \times 0.673$$

$$OEE = 0.515\ or\ 51.5\% \tag{Eq.A10}$$

APPENDIX B

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