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# IMPROVING THE EFFICIENCY OF MAINTENANCE PROCESS IN MANUFACTURING SYSTEMS USING INDUSTRY 4.0 TOOLS

**Abstract.** *In ever bigger quest to maximal efficiency, this article wants to show a route for Total Production Maintenance (TPM) at maximal efficiency. By bringing the digital twin into the real world, this essay wants to show how a digital twin can be used as a reliable basis for controlling the running line. But before the digital twin can be used at its maximal potential, a common ground must be defined not only in calculating Overall Equipment Effectiveness (OEE), but also in categorizing TPM tasks according to 3 factors of OEE. The paper outlines the foundations of a new concept that has not been applied in practice.*

**Keywords:** *TPM; predictive maintenance; executable Digital Twin; OEE.*

## 1. INTRODUCTION

Not only energy crisis due to the Russian Ukrainian war, but especially the vastly unfolding climate crisis, will force each and every company, independent of its profile and its activities to search for solutions to maximize efficiency and sustainability (1, 2). Maintenance will not be spared from this quest and maintenance teams will be forced to improve the use of their resources to maximal efficiency.

This paper presents a possible road for increasing maintenance efficiency for serial production lines, using industry 4.0 solutions. The chosen concept is however a concept that should be applicable not only to the latest and newest lines but should also find use in older production lines without the hassle of a full-scale renovation, needed to use most recent technologies and so-called smart sensors.

## 2. TO TPM OR NOT, SHOULD NOT BE THE QUESTION

The seeds of this concept can be found in short book from Mr. Arno Koch, OEE for the production team (4). In this book Mr. Koch mentioned TPM or the time needed for maintenance as a time loss. For him this interval can be defined as an interval where machines are available for production but are not used for the purpose of production. On the other hand, in numerous thesis, papers and works (9-11), as well as in personal experience, TPM can be seen as a way of making unplannable events or at least the loss due to unplannable events, more or almost fully plannable.

Out of the perspective of efficiency, these two ideas are fully contradictive. If one tries to minimize maintenance and reach maximum production efficiency, one risks unexpected losses. Even the idea of preventive maintenance, especially for serial production with low and very low cycle times, poses a potential risk, because although breakdown is prevented, the standstills can only be predicted on relative short notice.

The idea surveyed in this thesis, is to try and find a break even between on the one side the possibility of reducing maintenance activity and on the other side minimizing losses due to unplannable events by fixed maintenance activities.

## 3. STRUCTURE OF THE CONCEPT AND PREVIEW OF MAIN ARGUMENTS

The following figure presents the concept of this thesis. The main three pillars, discussed in this order are:

1. a general OEE-Calculator,
2. a graph mapping maintenance task against the 3 factors of OEE
3. an executable Digital Twin, for advice on maintenance tasks.

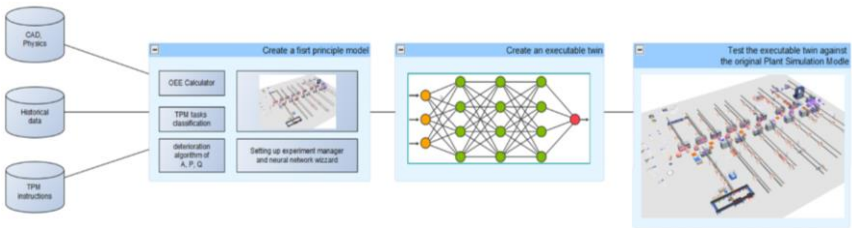


Figure 1 – Proposed solution

### 3.1. A GENERAL OEE-CALCULATOR

Definition of OEE by Nakajima, S. (1988, Introduction to total productive maintenance, Productivity Press, Inc.): Probability that the machine is producing without any loss (5). If we define the different losses of a production system or unit in the following way:

- $\overline{A_G}$: Planned Losses,
- $\overline{A_U}$: Unplanned Losses,
- $\bar{A}$: Availability Losses, where $\bar{A} = (\overline{A_G} \cup \overline{A_U})$,
- $\bar{P}$: Speed Losses,
- $\bar{Q}$: Quality Losses.

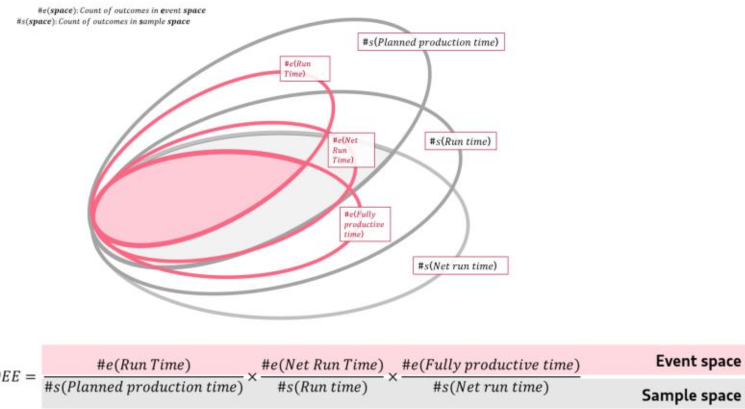


Figure 2 – Explanation on correlation and statistical independence of the 3 factors of OEE (own editing)

OEE can be written as:

$$OEE = 1 - P(\bar{A} \cup \bar{P} \cup \bar{Q})$$

or

$$OEE = P(A \cap P \cap Q)$$

Using the Bayes' theorem, under the condition that the 3 factors are statistical independent, this expression can be rewritten as the general formula for OEE:

$$OEE = P(A) \times P(P) \times P(Q)$$

Formula for OEE, as defined by its inventor (6):

$$OEE = \frac{\#e(Run\ time)}{\#s(Planned\ production\ time)} \times \frac{\#e(Net\ run\ time)}{\#s(Run\ time)} \times \frac{\#e(Fully\ productive\ time)}{\#s(Net\ run\ time)}$$

where:

$$\#e(space): Count\ of\ outcomes\ in\ the\ event\ space$$
$$\#s(space): Count\ of\ outcomes\ in\ the\ sample\ space$$

The decay of OEE and its three factors in time will be used to arrange TPM tasks in order of their importance. To make certain that the results of the simulation can be carried to the real system, a common way of calculating OEE must be defined. This general calculator should respect the following topics:

- the model as well as the real line, should use the same signals and structures to calculate OEE.
- the calculating algorithm should respect the correlation of the three factors as well as their statistical independence of each other.
- the algorithm should not use any predefined or “subjective” parameters, all parameters must be calculated based on the data available.

Plotting the change of throughput against the 3 factors of OEE, each factor has a very distinct signature. And it is this signature, that gives further direction in defining the OEE calculator. During production without loss and during the interval of quality loss, an arithmetic average can be used to describe central tendency, unfortunately this average is not capable of describing the loss during speed loss. In case of performance there is no loss if the production units produce at average throughput. But any deviation from this ideal throughput, will act as punishment and reduce performance and so OEE.

A better indicator would be the median. If we look at the bottleneck of the system, all predecessors and successors will clearly follow the bottleneck, the faster units before the bottleneck will be partly blocked, all faster successors will show an amount of waiting time. The changes in speed are induced on one side by the availability of the different units and here more specific the MTTR (Mean Time To Repair) of the units, on the other side by the buffers between the bottleneck and the faster machines. If we define performance by all cycle times between 0 and 2 times the median, the availability interval is then defined by the sum of the remaining cycle times over 2 times the median. The count of these cycle times is a good indicator for the number of failures and so a good indicator for MTBF (Mean Time Between Failures).

Last but not least remains Quality loss. In this case we have the following possibilities:

1. We have no detection after the unit. In this case we will assume that all parts are passed as iO-parts and the factor is neglected
2. We have post process measurements and parts out of specification will be taken from the system immediately. In this case the loss of this part can cause small performance loss at the successor units.
3. We have in process measurement and tooling is corrected during machining. In this case there is some performance loss at the unit itself as well as with the predecessor and successor units.

In the best case Quality loss can be neglected, in the worst case Quality loss will clutter the measurements and create some error on the observations.

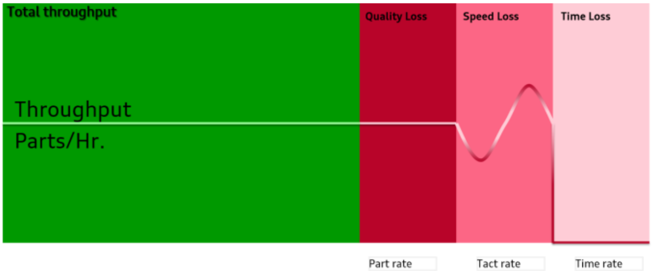


Figure 3 – OEE heartbeat visualizing the loss signatures (own editing)

## 3.2. MAPPING MAINTENANCE TASK AGAINST THE 3 FACTORS OF OEE

Before we can map each maintenance task against OEE, one first has to position the proposed strategy within existing maintenance strategies. TPM is a basically a form of preventive maintenance. In this type of strategy, the trend is to ensure safety and service maintenance by over-maintaining the asset, thus causing a high economic cost. (Digital Twin for Maintenance: a literature review, 2020)

Within the Industry 4.0 movement, one of the most investigated topics, is the topic of predictive maintenance. In predictive maintenance, we see two different approaches (8). A first approach is a data driven approach, where fast amounts of data are collected and analyzed. The hassle with this approach is not only developing the algorithm for analyzing the data, but also an immense deployment of appropriate sensors for collecting the data needed.

A second approach is a model-driven approach, where a model is developed that describes the asset in a mathematical way. Besides the need of specialized personal to operate the model, another big disadvantage of this approach is the very high cost computationally speaking. The idea of this assay is to use model-driven approach to minimize the economic cost of preventive maintenance, without the need for special trained personnel for operating the model. The executable digital twin will be used to anticipate and to advice on maintenance tasks, based on evidence of degradation and deviation from the normal behavior of the line modeled.

A first step in classifying maintenance tasks, can be found within the eight pillars of TPM. Each task can be classified as either autonomous maintenance or maintenance done by the operators or on the other hand as planned maintenance or maintenance done by the maintenance team. The main difference lays in interval length. Autonomous maintenance tasks are tasks that will return every hour, every shift, every day. The cycle is relatively short, and the loss of time is minimal and can be expressed in minutes. On the other hand, planned maintenance tasks have a relative long interval, every week, every month, every 6 months or year. Their duration or time loss is also more elaborated and may range from 15 minutes to half a day or even a full day.

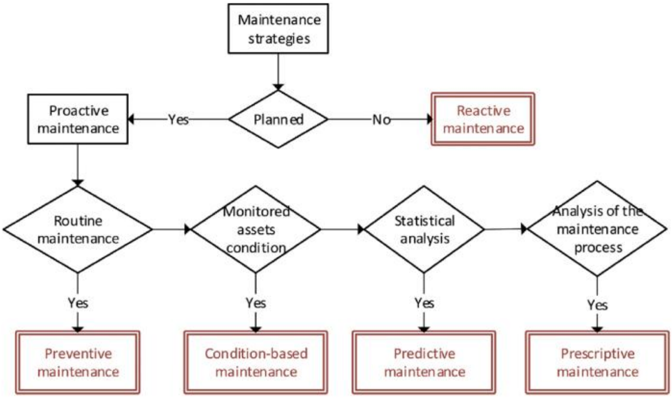


Figure 4 – Maintenance strategies diagram (7)

A second classification, also supported in literature, can be made on the their influence on MTTR and/or MTBF . Expected is that each task will influence MTTR (Mean Time To Repair) and MTBF (Mean Time Between Failure) at the same time. The idea is to combine interval length, duration, influence on MTTR and influence on MTBF by means of fuzzy logics techniques. Over the fuzzifier and the defuzzifier the four factors will be condensed into 1 factor which expresses the decay of OEE, Availability and/or Performance.

Although each maintenance task will probably get its own unique decay factor, it is not the idea to run the model for each unique factor several times. The values will be grouped in buckets and for each bucket several runs will be made to find a breakeven between loss of time and not doing certain group of activities. It is the historic data that these models will produce, which are of importance to the next phase.

### 3.3. THE EXECUTABLE DIGITAL TWIN, XDT

Although the previous steps do find support in literature, this last step makes the study unique. In this step we will harvest the full power of the digital twin, by integrating the digital representation of the production system with the operational environment in which it operates. In other words, we will use the digital twin as a tool of real-time monitoring, rather than just a simulation or planning tool (8). By extracting a dedicated encapsulation from the digital twin, which models the decay of OEE and the 3 factors, we can create an executable representation that can be integrated into the operational execution environment of the physical asset it represents.

An executable digital twin should comply with following expectations:

- The response time of the digital twin should be minimal, preferred within seconds, eventually minutes,
- The digital twin is restricted to one certain element of interest, in this case the decay of OEE,
- The digital twin should be easily accessible from any controller,

Within industry 4.0 tools, neural networks offer themselves as a good solution. Furthermore, the Plant Simulation framework offers besides the experiment manager also a neural network wizard, simplifying the work of building and training a neural network. By use of the available wizards, all efforts can be shifted onto positioning the neural network outside plant simulation. And also, here Siemens offers with Mendix and the Mendix ML Kit a good solution to implement the idea at high speed.

## 4. SUMMARY

In the essay, we have discussed the concept of improving the efficiency of maintenance processes in manufacturing systems using Industry 4.0 tools. Several important aspects of the concept were touched, including categorizing TPM tasks in availability, performance, and quality; creating a standard algorithm for calculating OEE; building a model to mimic the decay of OEE based on changes in TPM task frequency; using historic data to train a neural network to prioritize TPM tasks based on continuous OEE monitoring; and the differences between TPM and predictive maintenance.

The main object of this essay is to highlight the importance of TPM in promoting sustainability and improving the efficiency of maintenance processes in manufacturing systems. By using Industry 4.0 tools like neural networks and simulation models, companies can prioritize TPM tasks and reduce the amount of maintenance resources needed, ultimately leading to increased productivity and profitability.

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## ПІДВИЩЕННЯ ЕФЕКТИВНОСТІ ПРОЦЕСУ ТЕХНІЧНОГО ОБСЛУГОВУВАННЯ У ВИРОБНИЧИХ СИСТЕМАХ ЗА ДОПОМОГОЮ ІНСТРУМЕНТІВ ІНДУСТРІЇ 4.0

**Анотація.** *У цій статті представлено можливий шлях підвищення ефективності технічного обслуговування серійних виробничих ліній за допомогою рішень індустрії 4.0. Повне виробниче обслуговування (ПВО) або час, необхідний для обслуговування, як втрату часу можна визначити як інтервал, коли машини доступні для виробництва, але не використовуються для цілей виробництва. З іншого боку, ПВО можна розглядати як спосіб зробити неплановані події або, принаймні, втрати через неплановані події, більш або майже повністю. планований. З точки зору ефективності ці дві ідеї повністю суперечать один одному. Якщо хтось намагається мінімізувати технічне обслуговування та досягти максимальної ефективності виробництва, то ризикує отримати несподівані втрати. Навіть ідея профілактичного обслуговування, особливо для серійного виробництва з малим і дуже коротким часом циклу, становить потенційний ризик, тому що, хоча поломка запобігає, простої можна передбачити лише за відносно короткий термін. Ідея, розглянута в цій статті, полягає в тому, щоб спробувати знайти розбіжність між можливістю скорочення технічного обслуговування, з одного боку, і мінімізацією втрат через неплановані події, з іншого боку, завдяки постійній технічній діяльності. Були обговорені кілька важливих аспектів концепції, включаючи класифікацію завдань ПВО за доступністю, продуктивністю та якістю; створення стандартного алгоритму розрахунку загальної ефективності обладнання (ЗЕО); створення моделі для імітації розпаду ЗЕО на основі змін у частоті завдань ПВО; використання історичних даних для навчання нейронної мережі визначати пріоритетність завдань ПВО на основі постійного моніторингу ЗЕО; і відмінності між ПВО і прогнозним обслуговуванням. Використовуючи такі інструменти Industry 4.0, як нейронні мережі та симуляційні моделі, компанії можуть визначати пріоритетність завдань ПВО і зменшувати кількість необхідних ресурсів для обслуговування, що в кінцевому підсумку призводить до підвищення продуктивності та прибутковості.*

**Ключові слова:** *ПВО; прогнозне обслуговування; виконуваний Digital Twin; ЗЕО.*