Multi-objective optimization of OEE (Overall Equipment Effectiveness) regarding production speed and energy consumption

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ABSTRACT

Using condition monitoring to track machine health and trigger maintenance actions is a proven best practice. By monitoring machinery health, costly failures are avoided and downtime due to outages is reduced. This results in an improved OEE (Overall Equipment Effectiveness). Many papers discuss the implementation of condition monitoring to prevent failures and optimize maintenance interventions. However, much less attention is paid to the use of condition monitoring information in order to optimize production capacity of a machine or a plant. This optimization is often translated in production plants by maximizing the production capacity (speed) and minimizing machine's downtime. As energy consumption is becoming more and more an important decision criterion in modern manufacturing plants, the former optimization needs to take this parameter into account. As such a trade-off has to be made between the gain in capacity and the cost of the additional energy consumed. Therefore, in this paper we will develop a multi-objective optimization of OEE to allow multiple-criteria decision making. More precisely, the goal of this paper is to establish the link between condition monitoring information and production capacity optimization by continuously adjusting production parameters (i.e. production speed) taking into account the machine's condition and the energy consumption.

1. INTRODUCTION

Condition-based maintenance (CBM) and predictive maintenance (PdM) approaches have been extensively developed these last two decades (Mobley, 1990; Sholom, et al. 1998). The technical approach consists on monitoring the condition of an asset through a condition monitoring system and triggers a maintenance action when the condition monitoring signal crosses a critical value in case of CBM policy or uses this condition monitoring signal together with a prognostics model to predict when a maintenance action is needed in case of PdM policy (Blair, et al 2001; Goh, et al 2006, Bey-Temsamani, at al. 2009). Maintenance optimization based on these policies often consists of finding the optimal threshold, associated to the condition of the monitored asset, where maintenance should be triggered. In our previous works, this concept was successfully validated on packing machines (Van Horenbeek, et al. 2011) and extended with an optimal threshold determination taking into account the product quality. In this respect the end-user may decide to tolerate more degradation of the monitored asset if he judges the product quality is still acceptable. In some other industrial applications, the end-user prefers to control the degradation of the monitored assets by fixing a threshold on the condition monitoring signal (e.g. by implementing a thermal protection). In this case, if no optimization is implemented, a risk of 'too often' production stops could rise. In our previous work (Bey-Temsamani, et al. 2013), maximization of steel production capacity using temperature monitoring of production assets proved a production gain up to 21%. The technical approach followed in that work consists of optimizing the production (machine) speed taking into account the remaining time to trigger the thermal protection and the needed time to finish the product. If the first time is lower than the second, the machine speed should be adjusted accordingly. Although this approach would results on a high productivity gain, this does not mean a high profit could be obtained. Higher speed means directly higher energy consumption. The evolution of the energy price these last years is monotonically increasing. Therefore taking the energy consumption in the

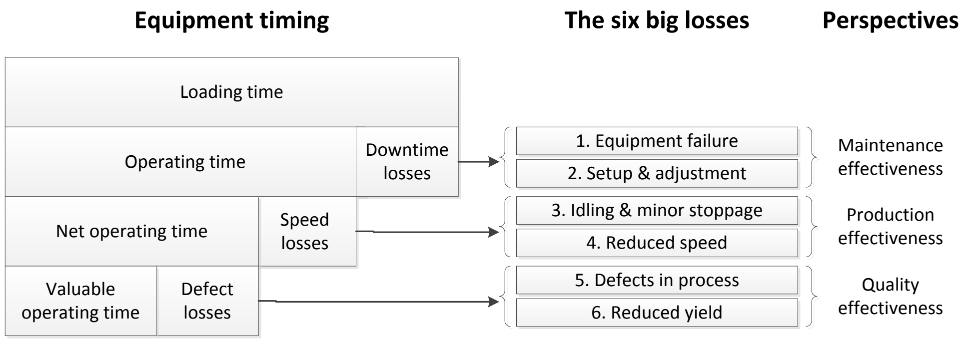

Figure 1. OEE concept and the six big production losses.

optimization scheme seems logical. In this paper we will extend our previous work by developing a multi-objective optimization taking into account production speed and energy optimization. This paper is structured as following. In Section 2, the OEE approach is explained. In Section 3, Run by Run (RbR) production concept is described. Single-objective and multi-objective OEE optimizations applied to RbR production are explained in Section 5. Results of validation on a steel cord production machine are given in Section 6. Finally, conclusions are summarized in Section 7.

2. OVERALL EQUIPMENT EFFECTIVENESS (OEE)

Different measures of productivity exist in the available literature. The overall equipment effectiveness (OEE) concept has been widely used as a quantitative tool essential for measurement of productivity (Muchiri and Pintelon 2008). The OEE measurement tool evolved from the total productive maintenance (TPM) concept introduced by Nakajima (1988) and is defined as a measure of total equipment performance, that is, the degree to which the equipment is doing what it is supposed to do. It is a three part analysis tool in order to determine equipment performance based on its availability, performance and quality rate of the output. It is used to identify the related equipment losses for the purpose of improving and optimizing the total productivity and performance of the considered system. Six major categories of losses are identified within the OEE concept; these are depicted in Figure 1, and can be summarized as follows:

- Breakdown losses categorized as time losses and quantity losses caused by equipment failure or breakdown.
- Set-up losses occur when production is changing over from one item to another.
- Idling and minor stoppage losses occur when production is interrupted by temporary malfunction or when a machine is idling.
- Reduced speed losses refer to the difference between equipment design speed and actual operating speed.
- Quality defects and rework are losses in quality caused by malfunctioning production equipment.
- Reduced yield during start-up are yield losses due to machine start-up

Based on the definition of the six big losses, OEE can be defined as follows:

$$OEE = A \times P \times Q \tag{1}$$

Where:

$$Availability\ rate\ (A) = \frac{Operating\ time\ (h)}{Loading\ time\ (h)} \times 100 \tag{2}$$

$$Performance\ (P) = \frac{Theoretical\ cycle\ time\ (h) \times Actualoutput\ (units)}{Operating\ time\ (h)} \times 100 \tag{3}$$

$$Quality\ rate\ (Q) = \frac{Total\ production\ (units) - Defect\ amount\ (units)}{Total\ production\ (units)} \times 100 \tag{4}$$

By considering the six major losses defined in OEE an optimal performance of the process can be achieved by monitoring the availability, performance and quality rates. This can be done by defining an efficient maintenance schedule (Availability), a qualitative product output (Quality) and an optimal production speed (Performance). In order to optimize OEE in this paper, we target to reduce two specific losses (i.e. breakdown losses and reduced speed losses) defined within the OEE concept by considering condition monitoring information. This extension shows a direct added value when applied to the Run by Run (RbR) production concept (see Section 3). At every production run, the production speed can be optimized using the condition monitoring signal (avoid to reach risk zone for the monitored asset). This will result in minimal downtime losses due to failures and minimal speed losses. In order to be able to optimize OEE with regard to speed and

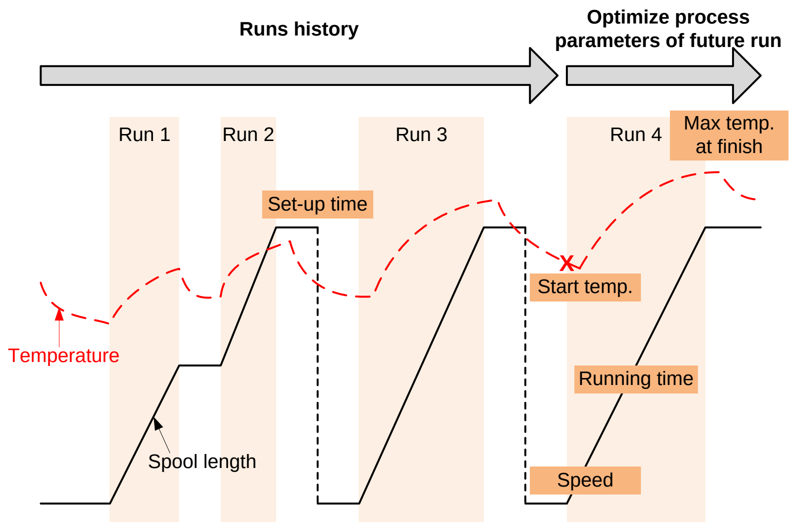

Figure 2. Run by Run (RbR) production concept

breakdown losses several important parameters have to be monitored, these are:

- Production versus time in each run
- Production speed versus time in each run
- Condition monitoring information on the degradation of the machine
- Degradation threshold beyond which normal operation of the machine is impossible

3. RUN BY RUN (RBR) PRODUCTION CONCEPT

The Run by Run (RbR) production concept is schematically shown in Figure 2. For every run, the production output (e.g. produced wire length measured as spool length at a given speed) and the condition monitoring signal (e.g. temperature of the bearing) are monitored. Based on these collected information from previous production runs, modeling the temperature using only its value at the start of the run and the production speed become possible. In our previous work (Bey-Temsamani et al., 2013), modeling the monitored temperature at a given run based on historical data was perfectly possible with a coefficient of determination (R^2=0.9815) between modeled and measured temperature. This way it becomes possible to predict the temperature at the end of the run already at the start of the run. On the other side, production output (e.g. produced wire length) is possible to predict at the beginning of the run if the production set-point and the current production speed set-point are known. Once these two models are defined, the remaining time to reach condition monitoring signal threshold and remaining time to finish the production in a run are determined.

4. OEE OPTIMIZATION OF RBR PRODUCTION

4.1. Single-objective optimization of OEE

As explained in Section 3, The production speed optimization consists of proposing a production speed for the current and future cycles that maximizes machine's capacity without the risk of crossing the condition monitoring signal threshold. This threshold was determined by off-line analysis to avoid bearings overheating. Based on the condition at the start of the run and the production length, the condition during and at the end of the run can be determined, for a given speed, by a predictive model. This is a physics-based parametric model whose parameters were estimated using Restricted Maximum Likelihood Estimator (RMLE). The determination of the optimal production speed v^*, while avoiding the crossing of the condition monitoring signal threshold, can be formulated as a constrained maximization problem as follows and is also illustrated in Figure 2 and 3.

$$v^* = \{\max\{v|[t_r(v,l_p) < t_{th}(v,l_p,d_i)] \wedge (v \geq 0) \wedge (l_p \geq 0)\} \quad (5)$$

Where v is the production speed for the next production run, l_p is the production set point for the next production run and d_i is the initial degradation at the start of the production run. t_r is defined as the time to finish the production run and is function of v and l_p. t_{th} is defined as the time to reach the degradation threshold and is function of v, l_p and d_i.

This single-objective optimization of OEE based on condition monitoring information for run-by-run production systems is thoroughly described in (Bey-Temsamani, et al. 2013).

This single-optimization problem is also described in Figure 3 which illustrates the different times to finish production and to reach the critical threshold of the condition monitoring signal. The same information is depicted in Figure 4 where variations versus production time are depicted. In Figure 4, t_r, t_{th}, denote, respectively, the time to finish production and the time to reach the critical threshold (defined here as a failure) of the condition monitoring signal versus the production speed v and the production time t. This graph also indicates the optimal speed v^* where t_r, t_{th} need to be compared. The goal would be to set the optimal machine speed v^* such as the time to reach the temperature threshold t_{th} would be just lower than the time to finish the production spool t_r.

4.2. Multi-objective optimization of OEE

The major drawback of the OEE concept is that the increase in OEE is never linked to the necessary investment or cost in order to achieve this increase. In other words maximizing OEE (i.e. Section 4.1) in a single-objective problem structure could lead to major cost increases to reach the necessary increase in OEE. Hence, a trade-off should be made between the increase in OEE and corresponding costs of achieving these improvements. Therefore, extension of the approach described in Section 4.1 is needed. This extension consists of constructing a multi-objective optimization problem where two objective functions are minimized, these are energy consumption cost and lost capacity cost (i.e. OEE as described in Section 4.1), which can generally be combined into a single objective of profit maximization (i.e. if the cost of energy and lost capacity are known). Both functions depend on the production speed in the sense that when the production speed increases, the energy consumption increases and the lost capacity decreases. The multi-objective optimization problem can be formulated as follows:

$$\begin{aligned} & min\big(f_1(v), -f_2(v)\big) \\ & s.t.\ t_r(v, l_p) < (t_{th}(v, l_p, d_i) \\ & v \geq 0 \\ & l_p \geq 0 \end{aligned} \tag{6}$$

Where $f_1(v)$ is the function that describes the energy consumption in relation to the production speed and $f_2(v)$ is the production capacity in relation to the production speed.

In the case study covered in this paper, $f_1(v)$ is derived from collected energy-speed data as depicted in Figure 6.

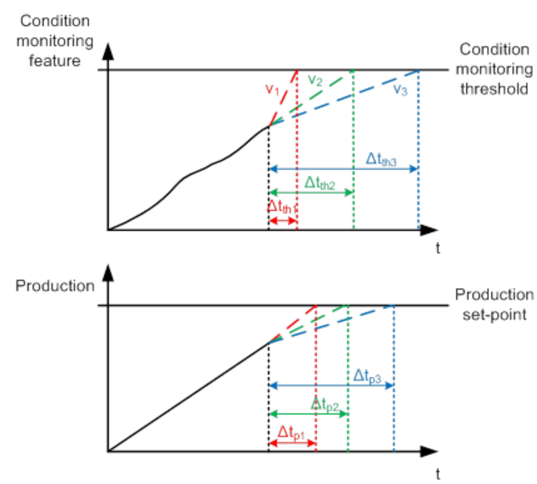

Figure 3 : Optimization problem formulation

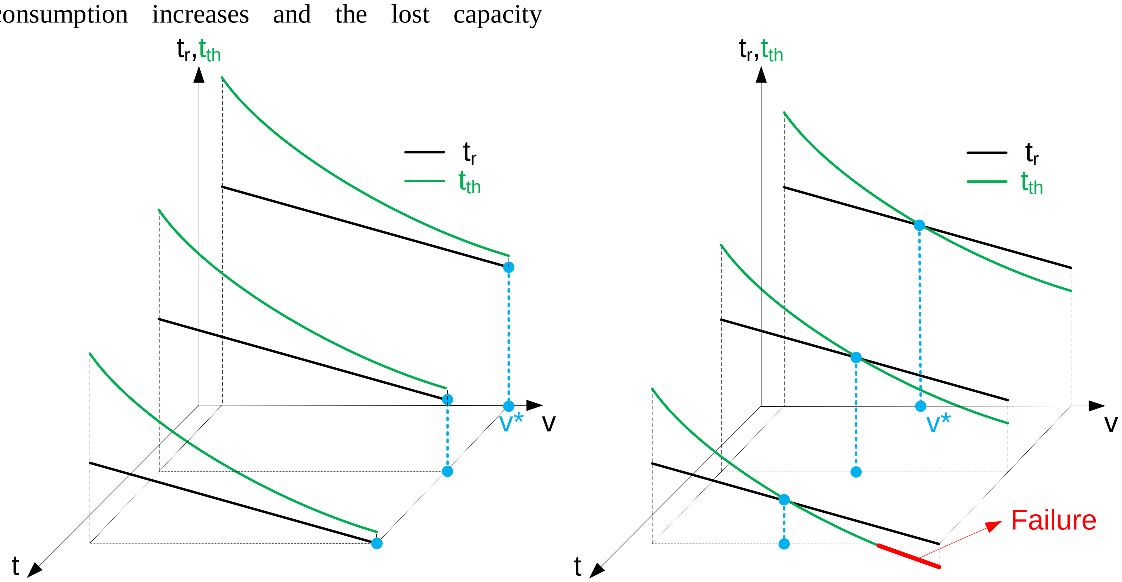

Figure 4. Production speed maximization problem

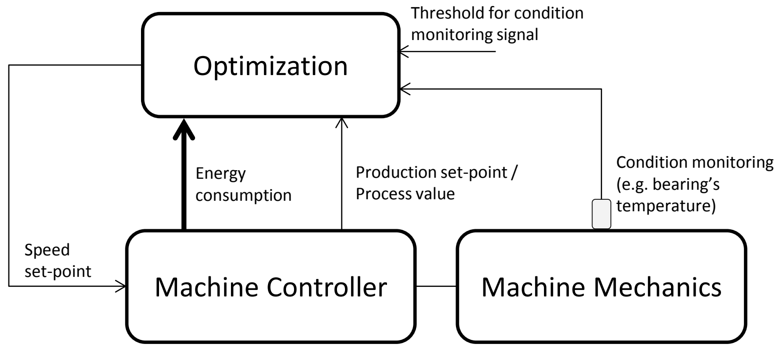

Figure 5. Machine / production set-up

5. VALIDATION ON STEEL PRODUCTION MACHINE

In this section the results of validating the multi-objective OEE optimization approach on RbR production are given.

The ultimate goal would be to set the production (machine) speed such that the productivity is maximized AND the energy consumption is minimized (maximizing the profit function described in Section 4.2. An illustration of the set-up is given in Figure 5. The optimization algorithm could run in parallel to the machine's controller or be integrated in the machine's controller. In this work, the machine was emulated using data recorded in the production plant. The inputs to the optimization algorithm are the condition monitoring signals and its associated threshold, the production process values, and the energy consumption. In this work as energy was not recorded directly in production plant, it was calculated using some expert-knowledge from the production plant. This is shown in Figure 6 where R^2 denotes the coefficient of determination. The output of the optimization block is the optimal machine's speed set-point.

The production profit is defined as:

$$PROFIT = PR \times PU - ER \times CU$$

Where:

- *PR*: production rate (m/min)
- *PU*: profit unit (€/m)
- *ER*: energy consumption (kW/min)
- *CU*: cost energy (€/kW)

The optimization has been validated on more than 6500 hours production data records. In Figure 7 the estimated production profits without optimization, with single-objective optimization and with multi-objective optimization are respectively shown.

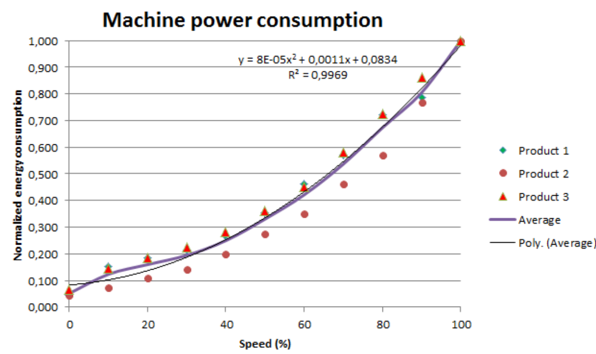

Figure 6. Energy consumption versus machine speed

The results of both the single-objective (Section 4.1) as multi-objective (Section 4.2) optimization approach are compared to a reference scenario. The reference scenario is based on real measured production data. The results in terms of production per time unit (i.e. production capacity) and profit per time unit are shown in Figure 7 and Table 1. First of all, it is clear that the optimized solutions always outperform the reference scenario. This clearly illustrates the added value of using condition monitoring information to optimize the production speed of the machine. In terms of production capacity the single-objective approach is the optimal one (+28.18% compared to reference). This is the case because within the concept of OEE the better solution is always the one with the highest speed without considering costs. However, when considering the cost of energy consumption into the optimization problem it is clear that the multi-objective optimization outperforms the single-objective optimization in terms of profit per time unit (+4.89% compared to reference for multi-objective optimization versus +1.67% for single-objective optimization compared to reference), although the production capacity is lower. Hence, an additional increase in profit per time unit of 3.17% can be gained by considering multi-objective optimization rather than single-objective optimization with limited focus on OEE (i.e. production capacity) maximization without considering relevant costs. As such a trade-off is made between the gain in capacity and the cost of the additional energy consumed

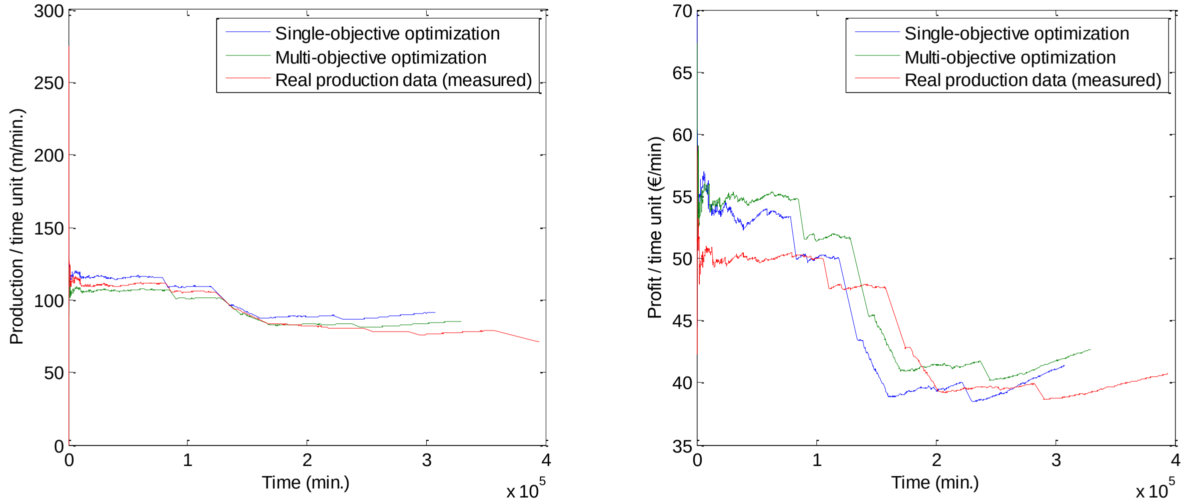

Figure 7. Production/time unit and profit/time unit versus time for three different scenarios.

Capacity (m/min.)			**Profit**		
Reference	Single-objective	Multi-objective	Reference	Single-objective	Multi-objective
71,43	91,56	85,47	40,70	41,38	42,69
	+28.18%	+19.66%		+1.67%	+4.89%

Table 1: Production capacity (m/min.) and profit (€/min.) for the three different scenarios.

in the multi-objective optimization approach. Therefore, it is of major importance to consider costs associated to a possible increase in OEE to make a well thought and optimal decision.

6. Conclusions

Industrial productivity profit maximization was discussed in this paper using single-objective and multi-objective optimization concepts by considering condition monitoring information. These concepts were validated on a concrete industrial example where production speed and energy consumption were used in the optimization constraints while at the same time avoiding catastrophic failures. As such the usefulness of condition monitoring information is extended from purely avoiding breakdowns to process and production optimization. Hence, a multi-objective optimization model of OEE (Overall Equipment Effectiveness) regarding production speed and energy consumption is proposed in this paper. The results clearly illustrate the importance to consider the trade-off between the gain in capacity and the cost of the additional energy consumed by increasing the production speed. The results indicate a significant gain in profit by applying the developed model to the case study of a production machine. This paper establishes the link between condition monitoring information and production capacity optimization by continuously adjusting production parameters (i.e. production speed) taking into account the machine's condition and the energy consumption.

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Nomenclature

CBM	Condition-Based Maintenance
OEE	Overall Equipment Effectiveness
PdM	Predictive Maintenance
POM	Prognostics for Optimal Maintenance
RbR	Run by Run
TPM	Total Productive Maintenance

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BIOGRAPHIES

Adriaan Van Horenbeek received his M.Sc. in mechanical engineering from GroepT University College in 2008, and masters in industrial management in 2009. He received a PhD in mechanical engineering at KU Leuven for the dissertation entitled ‘Information-based maintenance optimization with focus on predictive maintenance’. He published more than 10 high impact journal papers and 15 international conference papers. His research interests are in maintenance management, inventory management, prognostic maintenance, and maintenance decision making.

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