engineering proceedings

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Proceeding Paper

Defining the Technical Availability of a Production System with Respect to Its Complexity †

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† Presented at the 1st International Electronic Conference on Machines and Applications, 15–30 September 2022; Available online: https://iecma2021.sciforum.net.

Abstract: Production systems are becoming increasingly complex, which means that the main task of industrial maintenance, ensuring the technical availability of a production system, is also becoming increasingly difficult. The previous focus of maintenance efforts on individual machines must give way to a holistic view encompassing the whole production system. Against this background, the technical availability of a production system must be redefined. The aim of this publication is to present different definition approaches of production systems' availability and to demonstrate the effects of random machine failures on the key figures considering the complexity of the production system using a discrete event simulation.

Keywords: production system; maintenance; availability; complexity; definition

Citation: Sielaff, L.; Lucke, D.; Sauer, A. Defining the Technical Availability of a Production System with Respect to Its Complexity. *Eng. Proc.* **2022**, *24*, 20. https://doi.org/10.3390/IECMA2022-12892

Academic Editor: Antonio J. Marques Cardoso

Published: 15 September 2022

1. Introduction

Production systems are becoming increasingly complex. Digital solutions, increased levels of automation, smaller batch sizes, special customer requirements, and new forms of organization make interactions between individual machines and systems increasingly important [1]. An important factor in mastering the complexity and contributing to the efficiency of a production system is maintenance. The goal of maintenance is to ensure the production system's operational readiness by maximizing the equipment's availability while reducing costs and limiting the necessary maintenance interventions during productive times [2]. To maximize the production system's availability, it is not sufficient to determine the technical availability of individual machines. The interactions between machines and the production system systems must be included. Averaging the individual downtimes of the machines may give an overview of the availability but neglects the effects of downtimes on the production system. A shutdown of an insignificant or redundant machine is not as important as a bottleneck machine failure. To be as efficient as possible, these impacts must be considered to enable maintenance to use its limited resources where they are most needed in a production system [3]. To achieve this, the focus has to change from key figures looking at the availability of individual machines to key figures with a holistic approach [4]. The aim of this publication is to provide transparency and present the difference between key figures focusing on the availability of machines and on the availability of the production system.

In order to achieve this transparency, first, a literature overview on the availability evaluation of machines and production systems is presented. Based on this overview, two main definitions are presented to be compared within a simulated production system varying in complexity. The results of the simulations are presented, evaluated, and discussed. In the conclusion, the results are summarized and compared to an availability measurement in a real-life production environment. Based on that, it is recommended which key figure should be used depending on the situation and which areas should be further investigated.

2. Materials and Methods

2.1. Literature Review

When looking for indicators to evaluate production performance or the availability of production systems, the overall equipment efficiency, or OEE, indicator is well known, which was introduced by Nakajima in the context of the total productive maintenance framework [5]. This indicator is composed of an availability, a performance, and a quality indicator, thus providing an overview of the efficiency. For the calculation of availability, it refers only to planned production time and thus excludes planned maintenance measures from the evaluation [6]. Nevertheless, the OEE metric has gained acceptance, is widely used and recognized [7], and includes a description of availability, which is partly adopted to evaluate maintenance. There is no generally accepted definition for the key figure availability. Even current publications that refer to Nakajiama's original source vary. In their 2022 study on predictive capabilities of OEE, Dobra and Jósvai consider the impact of all losses on the availability [8]. For their OEE case study in a spinning unit, Murgugesan et al. use a definition of availability consisting only of equipment failures, setup, and adjustment time [9]. A recent comparative study of OEE measurement systems contrasts several types of OEE and thus availability measurement and calculation options [7].

Even in publications that focus not on OEE but solely on availability, there is no consensus. In some cases, only times for machine malfunctions and inspection times are included in the availability calculations [10], and other papers are not clear on which calculation method they use for availability. In a case study within the bag production industry, only machine failures are included [11], but the description points out that according to [12], availability is composed of delays due to maintenance and material supply.

In addition to the different ways availability is calculated for a single machine, there are also different opinions on how availability should be calculated for a production system. Nachiappan and Anantharaman have summarized the different viewpoints in their publication: either the average of the individual machine availabilities is used without looking at their interactions, or the environment of the production system is included [4]. Multiple approaches to predicting or measuring the availability, including the interactions of machines, are presented in the thesis by Sun [13], well summarized by Bourouni in his availability analysis of an osmosis plant [14]. In Bourouni's analysis, the two most commonly used approaches are compared, and the reliability block diagram seems to be best suited to analyzing the availability of (complex) systems. Instead of just averaging or multiplying the individual availabilities of the machines, the type of linkage specifies how the availability of the machine is to be included in the calculation. Comprising buffers and combinations of intermediate products in the calculation, the throughput analysis for which Li et al. published an overview [15] is another possibility. Here, the amount of products manufactured by the system is monitored, including deviations. However, the availability of the individual machines is normally included as a variable in this analysis.

To summarize the evaluation of calculation methods for the availability of production systems, it can be stated that there is no uniform method and that the most common key figures differ. It is not clear which variables are included in the availability of an individual machine or how they are combined into an overall availability measurement, even though there are promising approaches.

2.2. Definitions and Assumptions

The availability of a production system is determined by different methods in practice. The first method is to calculate the individual machine availabilities of a production system as the percentage of actual uptime compared to the scheduled time. In a second step, the availability of the production system is calculated as the average of the individual machines' availabilities. In this paper, this definition is called machine-based availability. The second method to determine the availability of a production system is based on counting the output of products within a reference time. This key figure is called output-based availability and is defined as the percentage of the possible output within the machine uptime and the theoretical maximal possible scheduled output. For this definition, the possible output is only reduced by the products not produced due to maintenance-related machine downtime.

To examine how the two definitions of availability perform for different complex production systems, the definition of complexity needs to be addressed. Alkan et al. published a literature review in 2018 on the topic of complexity in production systems in which they summarize the different types of complexity [16]. The symptoms of complexity presented by Alkan et al. were compared with ways to measure complexity and published in another literature review by Vidal et al. in 2022 [17]. Filtering through a maintenance perspective, both cite system configuration and material flow patterns as important factors of complexity, with Vidal et al. going further and identifying them as main causes.

For this reason, the complexity of these two factors is varied for this study using simulation. For system configuration, machine redundancies and combinations of intermediate products are used. In order to make different systems comparable, a production line without branches was defined to have a complexity level of 0. For each linkage by redundancy, one complexity level is subtracted; for each linkage by combination, one level is added. The principle is shown in Figure 1.

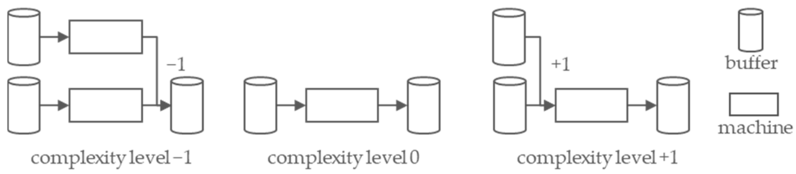

Figure 1. Complexity level definition for production systems used for the simulation.

2.3. Structure of the Simulation

In order to compare the definitions, different production variants were simulated using SimPy, a discrete-event simulation framework based on Python [18]. All parameters were kept constant, and only the buffer size and the system structure were changed. Continuous production (24/7) was simulated in one-minute increments for an operating year. The production system contains 24 machines, each of which is scheduled to fail an average of eight times per year with a uniformly distributed random failure duration between 10 and 30 h. For the machine failures, the Python random module is used to check whether the machine is functional or currently down due to a failure before a product is processed. In order to be able to produce a product, the buffers in front of the machine must hold at least one intermediate product, and the buffer behind the machine cannot be full. Initially, all buffers are at half (rounded down) of their maximum capacity. The production time for each production step in the simulation is 12 min, and for redundant machines a multiple of 12, to reach the same production speed as non-redundant steps.

System structures were simulated with a complexity level of −15 to 15 and buffer sizes of 1 to 1280 each, with increasing intervals between buffer sizes. A buffer size of one is equivalent to a direct connection between two machines. The maximum buffer size of 1280 was chosen to simulate a buffer covering the maximum expected downtime. In the results, the relative buffer size is used to relate the buffer size to the average downtime. The relative buffer size is defined as the actual buffer size divided by the expected product loss for an average downtime. The simulation was repeated 30 times for each combination in order to dampen possible outliers with the help of average values.

3. Results

The simulation results for the two key figures, machine-based availability (blue) and output-based availability (green), are shown in Figure 2. Figure 2a,c shows the two availability values for different relative buffer sizes of a production system with a complexity level of 0. The distribution and variance of the 30 simulation runs for each combination are indicated by the filled-in area. The machine-based availability initially drops from 98.6% to 98.1% as the relative buffer size increases and stays more or less constant from two to the maximum. Output-based availability, on the other hand, rises sharply from an initial 70% until it reaches about 98.1% availability at about a relative buffer size of six and one-half. For larger buffer sizes, it behaves like machine-based availability and continues at a constant level.

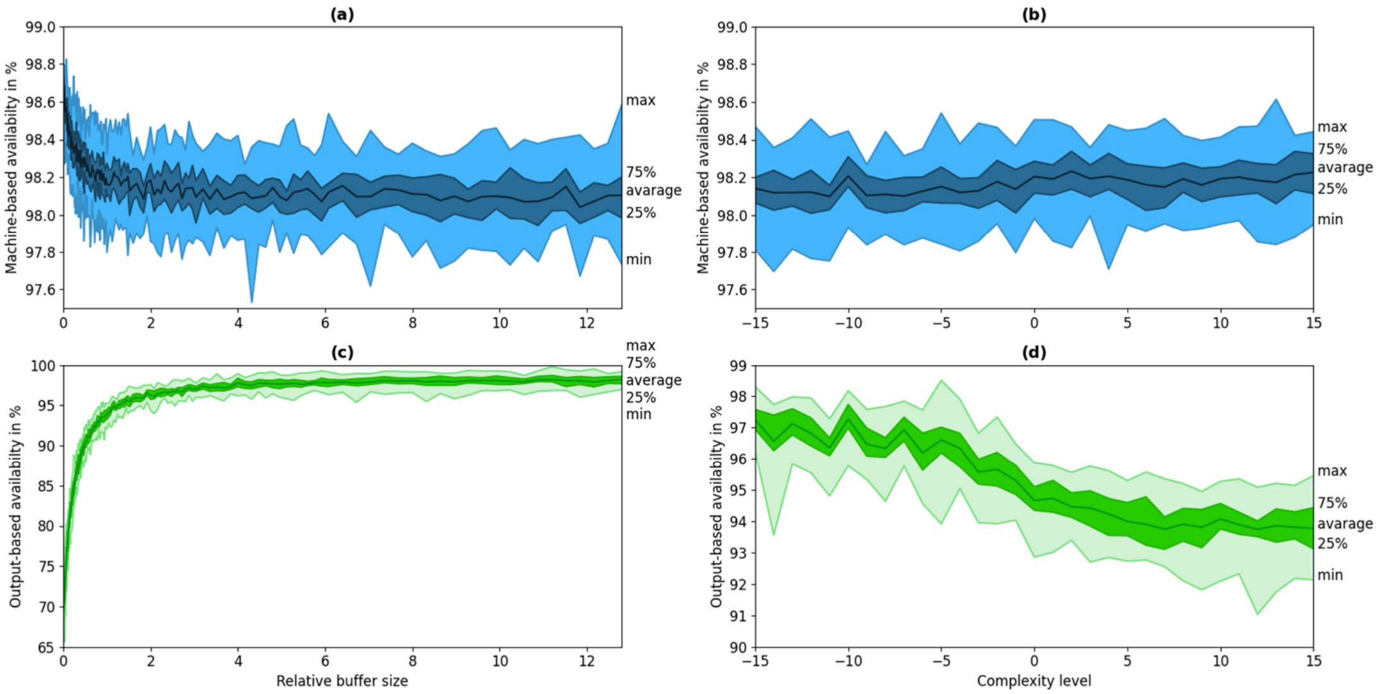

Figure 2. (**a**) Machine-based availability and (**c**) output-based availability over relative buffer size for complexity level 0; (**b**) Machine-based availability and (**d**) output-based availability over complexity for relative buffer size 1.

Figure 2b,d presents the two availability values for the relative buffer size of one for the different complexity levels of the production system. The machine-based availability increases very slightly from 98.15% to 98.25% as the complexity level increases. The output-based availability behaves the opposite way and decreases from about 97% to just below 94% with an increasing complexity level.

Figure 3 shows the averages for each simulated combination of buffer size and complexity level. The z-axes for machine-based availability on the left (Figure 2a) and output-based availability on the right (Figure 2b) are at different scales. The machine-based availability ranges between 98.0% and 98.7%, whereas the output-based availability ranges between 65% and 99%. The trends described are also evident in the overall presentation of the results. With small buffer sizes and high complexity, the two key figures run in opposite directions. The machine-based availability increases, and the output-based availability decreases. This trend stops at a complexity level of 0 (linear production without redundancies), where both availabilities do not change significantly due to further increases in the complexity level.

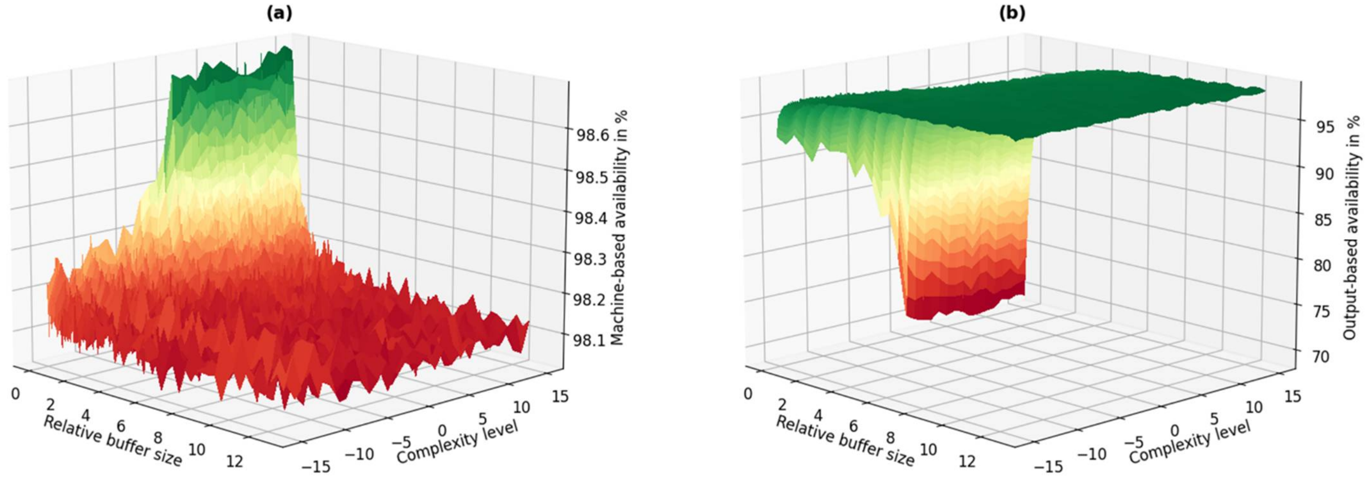

Figure 3. (**a**) Machine-based availability and (**b**) output-based availability over relative buffer size and complexity level.

4. Discussion

At first glance, the results for machine-based availability are unexpected. Because each machine was scheduled to have the same failure time for each simulation run, one might expect the machine-based availability to be independent of the buffer size and complexity level. The results show a clear trend towards a positive effect of more complex systems and smaller buffer sizes on the machine-based availability. This can be explained by the simulation setup. A machine can only fail when it is producing. If a machine is idle because no intermediate products are available or the next buffer is full, the machine cannot fail. Therefore, it does not reach its expected eight downtimes, leading to a higher machine-based availability indicator. The trends seen in the results for the output-based availability are to be expected. Machine failures in more complex systems and smaller buffer sizes lead to fewer products being produced. It is noteworthy that from complexity level 0 (production line without redundancy), further complexity does not have such a strong impact.

It becomes clear that the machine-based availability and the output-based availability only assume similar values for production systems with very large buffers. For all other systems, the key figures differ by up to 28%. Even if the buffers are large enough to cushion an average disruption completely, the key figures still differ by up to four percent depending on the complexity level.

Calculating the two availabilities for a real manufacturing facility with nine production stations, most with redundant machines and relative buffer sizes between stations of about 1/20, similar differences in the metrics were found, confirming the trend of the results. The machine-based availability was several percentage points higher compared to the output-based availability. During the measurements, it was hard for the employees to calculate the output-based availability because for each missed product, the cause needed to be investigated to determine whether it was maintenance-related or not. Even though this method may lead to more detailed results, it is much more difficult to use it in a real production environment.

5. Conclusions

This paper first highlights how important the availability of production systems is as a key figure for maintenance. Different options for calculating availabilities are discussed, and, using an event-based simulation, the two most relevant ones are examined and compared. Differences of up to 28% can be found between the availability definitions for the same system, depending on the buffer sizes and the production system's complexity level. When measured in a real production environment, similar deviations between the machine-based and output-based availability were found.

If the availability of the production system is used to assess maintenance, it must be clear to those involved what variables are included in this metric. If the frequently applied key figure of machine-based availability is used, the production systems presented here would have an availability of over 98%, which suggests little need for action. Using output-based availability as a key figure would highlight the need for maintenance action but would also require significantly more measuring effort. Therefore, the more accurate output-based availability as a key figure is more suitable for planning and optimization and, without further research, less suitable for use in production environments.

Author Contributions: The idea, concept, simulation, and first draft were mainly produced by L.S.; D.L. and A.S. were guiding, reviewing, and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by a grant from the German Federal Ministry of Education and Research within the project "DigiBattPro4.0", grant number: 03XP0374C.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Conflicts of Interest: The authors declare no conflict of interest.

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