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Factory-level performance evaluation of buffered multi-state production systems

Abstract: This paper proposes a performance evaluation model for production systems considering: i) the need of a factory-level performance metric tracking system effectiveness and ii) the need of ex-ante performance evaluation models for buffered multi-state systems. Potentialities of Overall Equipment Effectiveness (OEE) calculation approach and reliability analysis methods are combined. Indeed, even if OEE is widely adopted in the industrial practice, including different inefficiency factors, its use for supporting asset-related decision-making has got two main pitfalls. Firstly, it is limited to equipment level without considering the typical complexity of production systems. Secondly, it is traditionally computed through ex-post analysis of data, being not sufficient for decision-making at the beginning of the asset lifecycle. Conversely, in the reliability theory, different modelling methods are proposed for multi-state systems performance evaluation. Nevertheless, they usually focus on reliability/availability computation, lacking specific consideration of buffers and not measuring the inefficiency factors that may affect a system, relevant for practitioners. The combination of the two approaches is proposed, with the purpose to develop a simulation-based performance evaluation model for buffered multi-state production systems and to compute the Overall Factory Effectiveness (OFE). The model is applied in a manufacturing company to support evaluating improvement scenarios of an existing plant.

Keywords: performance measurement; manufacturing systems; modelling; overall equipment effectiveness

1. Introduction

The evaluation of the performance of production assets is the basis of every improvement action supporting informed decision-making about the best corrective/preventive actions to be carried out along the asset lifecycle (from the Beginning of life, through the Middle of life, until its End of Life).

Looking at the industrial practice, the most popular approach that is used by companies for performance evaluation of production systems comes from Total Productive Maintenance (TPM) and is about the evaluation of the Overall Equipment Effectiveness (OEE) [1,2]. OEE was introduced by [3] as the reference Key Performance Indicator (KPI) used to attempt revealing production systems related hidden losses and controlling the effect of improvement actions [3,4]. The OEE calculation is computed using ex-post data collected from the real system and it 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 [5]. It is a three-part analysis tool for equipment performance based on its availability (A), performance (P), and quality rate (Q) of the output.

Even though the OEE has become increasingly popular and has been widely used as a quantitative tool essential for measurement of productivity, several limitations still exist and are identified in the literature [1,6]. In particular, the main acknowledged pitfalls of OEE are the following:

(1) OEE is only limited to productivity behavior of individual equipment [7–11].
(2) OEE is calculated as an aggregated information based on detailed information mostly created at the shop floor level [12].

Concerning the first disadvantage, [10] have pointed out that the gains in OEE, while important and ongoing, are insufficient because no machine is isolated. It is, therefore, necessary to focus one’s attention beyond the performance of individual equipment toward performance of the factory. The ultimate objective of any factory is to have a highly efficient integrated system and not brilliant individual equipment [4]. This insufficiency of OEE has led to modification and enlargement of the original OEE to fit a broader perspective as deemed important in the production systems. As reviewed by [1,13], several studies have tried to expand the application scope of OEE from individual equipment to the entire processes/factories, like: Overall Fab Effectiveness (OFE) by [4,10], Overall Throughput Effectiveness by [8], Overall equipment effectiveness of a manufacturing line by (OEELM) [14] and Overall line effectiveness (OLE) by [15]. Nevertheless, according to [1], 'the OFE metric are in the development stage'. The underpinning condition is that, to measure performance and to systematically perform diagnostics at the factory level, quantitative metrics consistent with a manufacturing system modelling technique capturing equipment interconnectivity information is essential [8].

Concerning the second disadvantage, two main consequences derive from it. On one side, it means that the results of improvement actions can only be observed directly on the real system but are not usually predicted in advance in the moment in which those actions are chosen. In fact, OEE typically supports ex-post analysis and is not used to support decision-making at all stages of the system lifecycle (like, for example, to support decision about system design). On the other side, being a cumulated function over a monitoring period, the OEE does not point out the variability of a manufacturing process. This is seen as a major limitation because variability is one of the main causes of waste [16,17]. To solve this issue, [16] proposed a stochastic OEE calculation deriving the probability density function of the OEE starting from the probability density function of the main determinants of waste. Nevertheless, this approach is still limited to individual equipment, linking back with the first enunciated drawback.

Concluding, despite the widely recognized relevance by practitioners of OEE calculation for considering the so-called hidden losses related to system inefficiency, several limitations for it to be used as an ex-ante computed performance metric to support lifecycle decision-making when dealing with complex production systems still exist. In fact, when evaluating the performance of a production system, it must be considered that production systems are a typical example of multi-state systems (MSSs) [18]. A multi-state system is composed by multi-state components, which can perform their tasks within a range of performance levels varying from perfect functioning to complete failure [19–21]. A good overview of the historical developments in the context of MSSs theory has been provided by [22]. MSS reliability evaluation methods are based on four different approaches [23]: extension of Boolean model [24], stochastic process approach [18], Monte Carlo simulation [25,26] and Universal Generating Function (UGF) method [27]. These approaches take into account the characteristics of multi-state systems, i.e. i) that the system structure may be very complex (with different abstraction levels; vast array of units, components, etc.); ii) that the components have a range of potential failure modes and follow various failure distributions; and iii) that the failure modelling may be complicated because based on various (functional, technical) dependencies between the components [28]. In general, such approaches are defined Operations research-based methods (OR-based methods), which are oriented to rigorous mathematical modelling leading to a deep understanding of the behaviour of the system [29]. Nevertheless, they usually focus on reliability/availability computation, lacking specific consideration of buffers (see for example, [25]) and not measuring the inefficiency factors that may affect a system, relevant for practitioners.

It is evident that there is a significant difference in how OR-based approaches address the performance evaluation process with respect to a metric-based approach like the OEE calculation. In fact, OR-based methods rely on a model of the system on which it is possible to perform experiments in order to predict how the system will reasonably respond to specific factors, while the metric-based approaches rely on a computation that is done using ex-post data coming from the components of the real system. On the other side, metric-based approaches allow tracking the overall effectiveness of a production equipment by addressing its specific cause in terms of inefficiency factors (A, P and Q). This is a relevant issue for practitioners in manufacturing domain and should be considered in performance evaluation models.

The objective of this work is to investigate the possibility to combine the theoretical background that lies behind these different methodologies. In fact, the founding idea is that the performance evaluation process should be approached using the modelling perspective, distinctive of Operations Research techniques, but, at the same time, taking into account the holistic orientation typical of the OEE metric, which aims to monitor and control all the main production losses that can negatively affect the valuable time of the equipment. At the same time, this research is based on three requirements to be fulfilled, established considering the manufacturing domain, that are: i) the necessity to push the performance evaluation towards a factory-level orientation; ii) the need for addressing performance evaluation of buffered multi-state production systems; iii) the need to propose a method to calculate the performance metric through an ex-ante modelling approach. The effort in merging those two approaches, together with the will to fulfil these requirements, have resulted into the creation of a simulation-based performance evaluation model that aims to compute the OFE (Overall Factory Effectiveness) and WIP (Work in progress) of a buffered multi-state production system. In particular, the simulation model has been created with a modular approach based on specific building blocks in order to facilitate the possibility to use it to evaluate a wide range of applications.

Section 2 provides an overview on the proposed model, describing its scope of application, the theoretical background and proposed development. Section 3 describes the performance evaluation model as the integration of two components: states generators and system model. Section 4 presents an application case where the model has been applied in a manufacturing company for analysing the performance of a section of its buffered multi-state production system, thus evaluating alternative scenarios of configuration and management. Section 5 concludes the paper.

2. Performance evaluation model proposition

2.1. Scope of application

The aim of the model presented in this work is to compute a factory-level performance metric such as OFE, under the modelling perspective typical of OR-based methods, such as stochastic process approach, Monte Carlo simulation or UGF method, as previously defined according to the literature background.

On the one hand, the holistic consideration of different kinds of inefficiency that can characterize the behaviour of an equipment are well expressed by a metric like the OEE. Besides, OEE is a widely used metric in industry and, for this reason, it is worthy proposing a method for its estimation by extending its scope of application, i.e. at factory-level and for buffered production systems. On the other hand, advantages of experiments based on mathematical models, i.e. OR-based methods, over real system-based experiments are many. In fact, they allow identifying precisely cause-effect relations (input-output links) that can lead to a deeper what-if analysis, and they enable a pro-active decision making process through the conduction of experiments on systems that might not even exist yet at the moment of analysis, or that would be too expensive if conducted on the real system. These advantages can be exploited in practice when estimating performances of a system at its Beginning of Life stage, with the purpose to support the decision-making process through estimations of future performance (OFE) along the whole asset lifecycle (e.g. as asset-related decision, this is needed when choosing among different design alternatives). In the literature it is in fact assessed that 'developing a methodology using a metric like OFE to perform what-if scenario analysis to facilitate new factory design, is one of the potential future research development in this area' [8]. The same is valid at the Middle of Life stage of a system for evaluating reconfiguration or management alternative solutions (e.g. as asset-related decision, this is needed when choosing the installation of a new equipment, or changing the maintenance plans, etc.).

Therefore, this paper proposes a simulation-based OFE metric evaluation model that enables calculating the performance metric through an ex-ante modelling approach. The final aim is to get to a model that can be used in practice to support the asset-related decision-making process through scenario analysis and the possibility of estimating the future value of the OFE of a production system through ex-ante analysis. The following Table 1 summarizes the main characteristics of the proposed solution with respect to the traditional OEE metric.

Table 1. Comparison between the traditional OEE computation and the proposed modelling solution

	Calculation at production system level	Estimation through ex-ante analysis based on modelling
Traditional OEE	No	No
Simulation-based OFE	Yes	Yes

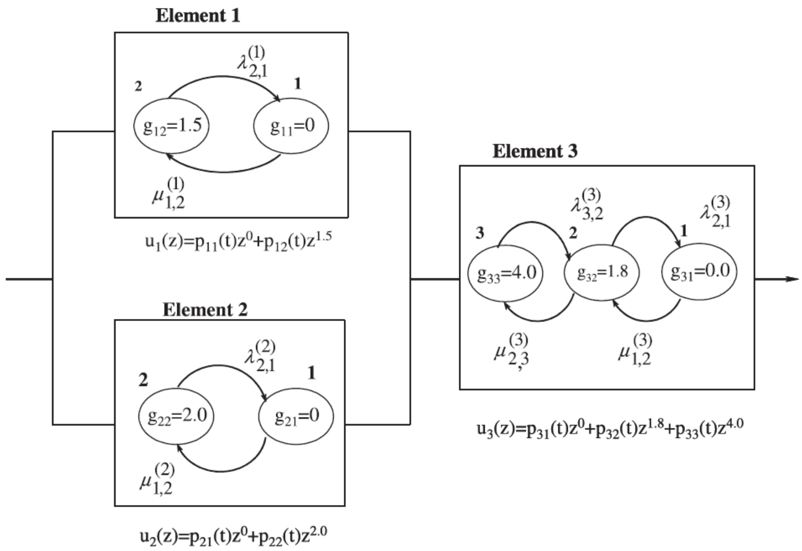
2.2.Theoretical background and proposed development

The developed performance evaluation model is based on the reliability theory approach based on Combined UGF and Stochastic Process [30]. This OR-based approach is originally proposed by the authors as a good solution for engineering applications. In particular, the three pillars of such approach are the following:

- the system structure is modelled using a Reliability Block Diagram (RBD) logic: each component of the system is a block of the diagram and can be connected using the usual RBD operators (series, parallel, stand-by);
- each component can have its own multi-state evolution and can be studied both with an individual Markov or Semi-Markov process;
- the derivation of the system function is based upon the UGF, which combines the behaviour of the components using an analytic approach.

An example of an UGF model of a Multi-state system (MSS) is the one in Figure 1. Element 1 and 2 are two states components, while Element 3 is a multi-state component; the three elements are modelled with their respective state-space diagram. Then, in the system structure modelled as RBD, the individual functions of Elements 1 and 2 are combined using the parallel operator and the result is combined with Element 3 using the series operator. The advantages of the proposed approach are: i) simplification of the MSS model building; instead of building a complex model for the entire MSS, one should build n separate, relatively simple models for system's elements; ii) simplification of the process for solving a system of equations; instead of solving one high-order system of differential (for Markov process) or integral (for semi-Markov process) equations, one must solve n low-order systems for each system's element [30].

Figure 1. Multi-state system structure and state-space diagrams for the system's elements by (Lisnianski 2007).



Nevertheless, two main limits still affect the opportunity to apply this formalism to a broader range of use:

- If the state of the component has a non-exponential sojourn time the resolution of the Markov-Chain needs to be based upon Semi-Markov process; in this last case the resolution of the individual chain gets more complex especially if the analyst is interested in the dynamic evolution of the performance rather than in its steady-state condition [19];

- the use of UGF cannot account for decoupling elements between the components of a system, that is instead a common characteristic of production systems – i.e. buffers stocking materials as decoupling elements between two machines in a production system – that plays a relevant role on the propagation of the effect of a failure along the entire system [31].

Thus, in this work the use of discrete event simulation is proposed in order to emulate the modelling framework of Combined UGF and Stochastic Process method, aiming to overcome the two issues introduced above (generic distributions for sojourn time and buffer presence). This approach allows modelling situations where transition rates are not constant and a buffer is placed between components.

Overall, the objective of the performance evaluation model is to compute the Overall Factory Effectiveness (OFE) and the work in process (WIP) of the production system. OFE has been defined starting from the definition given by [8] of the Overall Throughput Effectiveness (OTE) by extending the unit-based interpretation of the Nakajima's conventional OEE [3]. OTE is shown in Equation (1).

$$\text{OTE} = \frac{\text{good product output from factory [units]}}{\text{theoretical attainable product output from factory in total time [units]}} \quad (1)$$

Moving the metric into a simulation context, considering that the simulation model is built in order to compute the *actual product output* that the system is able to complete during the simulation horizon, the final definition of OFE is shown in Equation (2).

$$\text{OFE} = \text{D} \times \frac{\text{actual product output from factory during simulation time[units]}}{\text{TH}_{\text{system}}\text{[units/t.u.]} \cdot \text{simulation lenght [t.u.]}} \quad (2)$$

where:

- $\text{TH}_{\text{system}}$ is the theoretical throughput of the system based on the bottleneck equipment working in the state of the maximum throughput (ideal condition);

- D is a deterministic coefficient that accounts for the deterministic time losses that are given as an input for the OFE calculation, since we suppose they are known by the analyst at the time he/she wants to compute the system performance (example: scheduled maintenance time, R&D time, engineering time and set-up time); D can be computed analytically as the loading time divided by the calendar time;

- the *actual product output from factory* is an effect of the stochastic performance losses in the different equipment within the system; in particular, failure leading to fault states and downtimes, idling and minor stoppage, as well as working states at reduced speed, have been considered as the different types of stochastic losses to be quantified in the system. To this end, the observation period (hence the simulation time) does not include deterministic losses (already accounted by D).

3. Performance evaluation model

3.1. Model overview

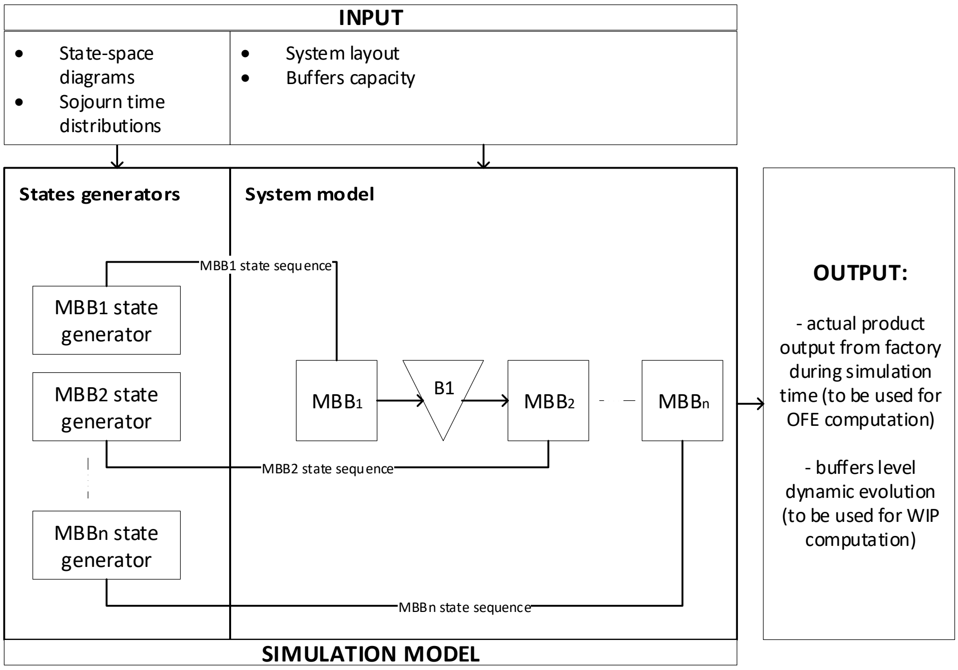
The idea of the proposed model is about implementing the theory based on UGF and Stochastic Process method, relying on the potentialities of numerical analysis given by simulation. The developed simulation-based performance evaluation model is made up by two main modelling elements:

- States generators, which aim to generate a sequence of states for each machine (i.e. equipment) of the system;

- System model, which aims to model the dynamic interaction between the elements component of the system, i.e. machines (i.e. equipment) and buffers.

Figure 2 provides a graphical visualization of the links between the two parts of the simulation model, and summarizes the input variables needed to run the simulation model and the output variables.

Figure 2. Proposed performance evaluation model logical scheme



The input variables for each states generator are the state-space diagram that drives the state evolution of each machine, and the time to failure / to repair (TTF, TTR) distributions of the machine. The input variables for the system model are the capacity of the buffers, and the system configuration in terms of logical interconnections among the machines, built in the layout to allow the system functionality of material flow processing. In particular, typical connections among components in a production system – i.e. series, redundancy (active/partially loaded/passive), and assembly/disassembly – can be modelled.

Thus, the objective of the performance evaluation model is to allow the calculation of the OFE and WIP of a generic production system. It results from modelling and simulation capabilities built in the model:

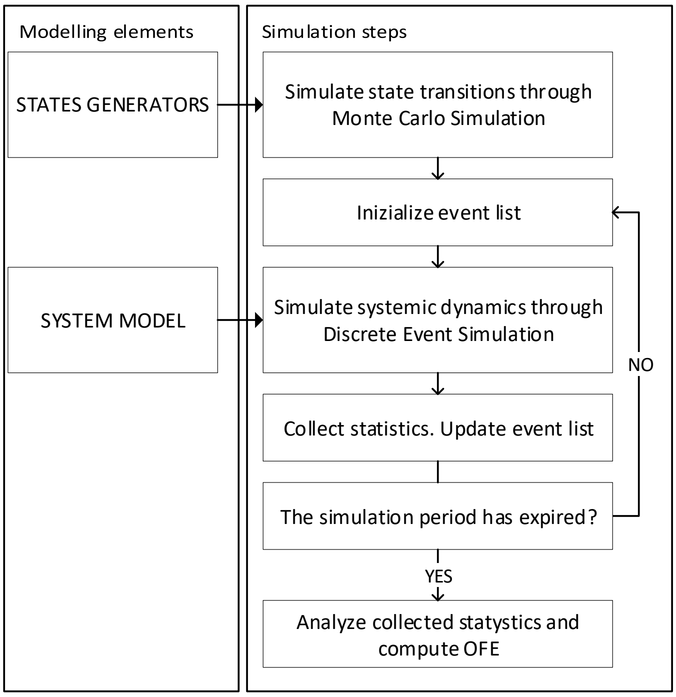
- the real production system is modelled in terms of a system model (created by combining “machine building blocks”, in the remainder MBBs) and n states generators (one for each MBBs);

- Monte Carlo simulation is used to simulate the states transition mechanism for each machine (each MBB) in the system, relying on the states generators modelling;

- the system model and states generators are implemented in a discrete event simulation model; the simulation model is run to compute the OFE and the buffers level (WIP).

Figure 3 focuses on the simulation process steps, remarking the role of system model and states generators as modelling elements informing them. This is illustrated more in detail in the following sections (section 3.2 and 3.3) before concentrating on simulation modelling and running (section 3.4).

Figure 3. Simulation process steps and modelling elements



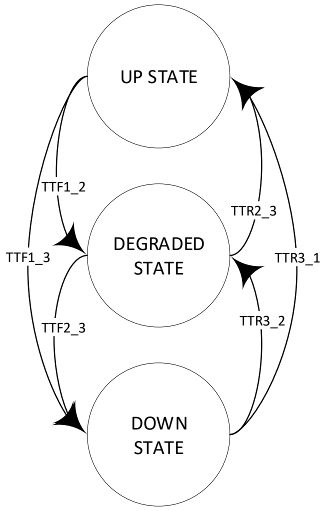
3.2. States generators

The objective behind the construction of the states generators is to simulate the dynamic evolution of each machine of the system in terms of state transitions. The idea is that the state of each system's component, starting from an initial one, evolves and changes over time due to specific events occurring. Each event coincides with a state transition.

State-space diagrams are defined for representing and modelling state transitions for multi-state system [19].

In the classical Markov chain approach, the transitions are viewed under a "rate-based" perspective; in our model, a "time-based" view was used in order to exploit the discrete event simulation framework to introduce the states generator behaviours as a "mirror" of the components (machines) in the real system, operated in the time domain. In fact, it would be easily understandable from a practical perspective, as it is well aligned with the monitoring practice of extant, real systems. While doing so, we aimed that the states generators also modelled sojourn times with non-exponential distribution, being flexible for the generic needs arising from real cases where the transition rates are not necessarily constant. Computationally speaking, in our model, as normally occurring within a discrete event simulation framework, a transition takes place when a certain time is expired (i.e. the time related to the next event scheduled, based on the Monte Carlo generation, in the simulation clock). Therefore, for example, assuming that a state-space diagram is built as the one shown in Figure 4, there are three possible states and every transition is enabled. All in all, this means that each machine within the system is modelled as a repairable multi-state component with minor and major failures and repairs.

Figure 4. Example of a state-space diagram according to the "time-based" view



In general, the number of states and the generic sojourn time distributions can be defined when modelling each component (machine) of the system by extending the state-space diagram as required. The state evolution's dynamic is modelled by Monte Carlo simulation mechanism based on the "time-to" distributions (Time To Failure (TTF) and Time To Repair (TTR) distributions) that drive the transitions. To this regard it is worth remarking that, as different states can be considered in the state-space diagram, we may have more TTF and TTR distributions to model the transitions from and to states, wherein only one down state is the fault state with no functionality at all provided by the component (machine), while other degraded states are also seen as fault states, but with some performance level still available – however degraded – for their functionality: overall, this allows to implement a range of performance levels, varying from perfect functioning to complete failure/fault state. Last but not least, it is also relevant to underline that the "time-to" distributions needed in input are conditional distribution because they depend, in term of distribution shape and parameters, on the current state of the machine.

3.3.System model

The creation of the system model is based on the combination of “machine building blocks” (MBBs), which represent the elementary parts of a system.

A MBB represents a machine (i.e. the equipment) and at the same time allows to control the dynamic of both upstream and downstream buffer of that machine, in case they exist. This means that the model of a *n* machines system will be made up by *n* MBBs. Different types of MBB are defined depending if: i) upstream buffer exists and ii) downstream buffer exists. In this concern, the modelling through proper MBBs allows controlling the dynamic of the inbound production flows in the buffer/outbound production flows from the buffer.

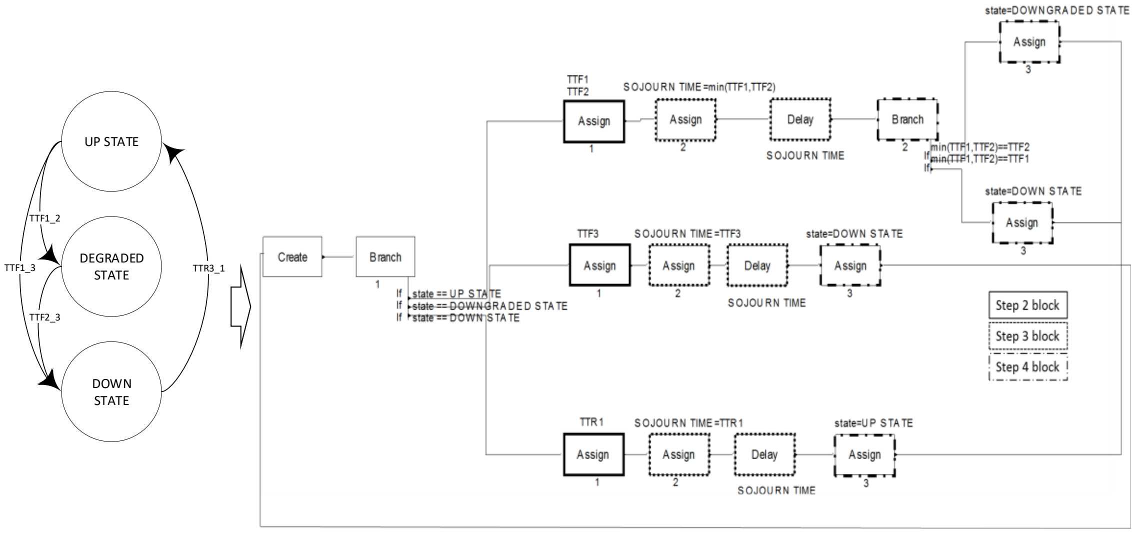
Moreover, the logical connections among MBBs allowing system functionality is modelled. In particular, a functional-logic system modelling approach expresses MBBs interrelationship based on the following possible connectors: series, redundancy (active/partially loaded/passive), and assembly/disassembly, all relevant for a production system. Thus, specific modelling archetypes have been defined to support setting the simulation model based on existing connections among the MBBs. For example, an archetype was defined for total redundancy connection of two MBBs, in which a “decide” block is to be introduced (with a “n-ways by chance” condition based on equal probabilities) when setting the system model up in order to govern the input flow splitting among the MBBs (in fact, total redundancy means that all components share the same load right from the start until one of them fails). In the specific case of passive redundancy connection archetype, based on an Operation Dependent Failures modelling approach [32], an algorithm for modification of the states generators of the MBBs involved was also defined. In fact, in this specific connection, downgrading state changes (i.e. failures as transitions towards downgraded states) of the equipment/machine in stand-by to the main one can happen only during the fault state of the latter, while upgrading state changes (i.e. repairs) can happen at any time (both when the standby machine is active or not). Thus, the random number extraction for failure in the states generator of that MBB can only take place during the main component/machine downtime, while random extraction for repairs can always occur.

3.4. Simulation modelling and running

Once the production system under analysis is represented through the modelling of the states generators (guiding the states transitions for each equipment/machine) and of the system model (controlling the interrelationships among the equipment/machines from a logical point of view), the simulation model can be finally built up in a software environment. In this work, Arena software (https://www.arenasimulation.com/) was chosen to implement the discrete event simulation model. Within this simulation environment, both the states generators and the system model have been translated according to the software language.

Concerning the states generators, an example of the model built in Arena is presented in the following Figure 5. The figure shows the representation of the states diagram in Arena and its related states generation algorithm. The "create" block generates the unique entity (dummy entity) to track the state evolution; "branch" blocks are introduced to control the state transitions; eventually, the "delay" blocks are used to implement the transitions accordingly with the "time-based" view of the model.

Figure 5 Example of implementation of states generator through Arena software



The final output of the states generator is a sequence of states over time of the specific related machine in the model.

Concerning the system model, an Arena solution for the model of each of the required MBBs has been defined, making them available as building blocks that can be combined according to the possible logical interrelationships (series, parallel, partial loaded redundancy etc.) that connect, depending on the specific layout/configuration, the different equipment/machines in a system.

Once the model is built in the simulation environment, usual steps to prepare the simulation experiments are to be done. The ramp up length, the simulation length and the number of replications have to be set before running the simulation (to achieve consistent results, in a non-terminating simulation [33]). The procedure proposed by [34] can be used for deciding the ramp up length; the statistical MSPE (mean squared pure error) procedure can be used for defining the simulation length and the sequential procedure proposed by [33] can be used for the determination of the number of replications.

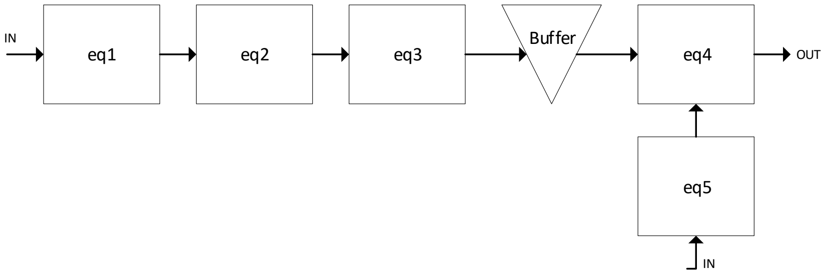
Once the simulation is run and validated, the OFE and buffer level (i.e. WIP level) are computed as the output of the analysis. Concerning the model validation, more details are provided within the context of the application case.

4. Application Case

4.1. Introduction

The proposed performance evaluation model has been implemented in the production system of a company in the mechanical sector. The system produces an assembly according to the production flow presented in Figure 6.

Figure 6. Reference section of the production system layout (application case)



Equipment1 (eq1) is a feeding robot used to automate the operation of metal sheets loading of the following equipment. Equipment2 and Equipment3 (eq2 and eq3) constitute an integrated sub-system that is able to punch, shear and bend the metal sheet automatically. A subsequent buffer decouples this part of the system from Equipment4 (eq4), which is an assembly robot that combines the processed metal sheets with the metal brackets fed by Equipment5 (eq5), which performs folding operation on the raw brackets entering the system.

In the current practice, the company has started collecting data from the shop floor, thus keeping the OEE of each of the equipment of the plant under control to guide improvement decisions. Nonetheless, the plant is a new installation, thus, a complete knowledge of the OEE of all equipment is not actually available. Furthermore, no performance metric at the factory-level is calculated. Last but not least, there is no performance evaluation model that accurately estimates the performance of the production equipment through an ex-ante approach in order to support configuration and management decisions. Configuration / reconfiguration and management are currently based on rough capacity models, lacking of a proper capability to compute the systemic effect of stochastic events such as failures and other inefficiencies due to minor stoppages or reduced speed.

The proposed model was applied in order to support decision-makers in the company to evaluate the performance of the system in terms of OFE and WIP at its current configuration, and to identify and evaluate alternative improvement scenarios. It is worth remarking that, in order to model the “as-is” scenario that represents a newly installed production system, reference data have been collected from similar equipment working in similar conditions and installed in already existing systems of the company, or from information provided by vendors. After modelling the “as-is” system – i.e. the new installation – and after computing the OEE of each single component and OFE, two alternative scenarios were identified. Each scenario was then evaluated by applying the model to the new solution and calculating the expected OFE that would result from the foreseen improvement actions. In particular, the two scenarios that were evaluated deal with:

- an improvement of the critical equipment through a performance monitoring plan (scenario 1);
- an increment of the buffer capacity (scenario 2).

The decisions in each scenario were achieved based on a bottleneck-orientation, a well-known concept in industrial engineering applications [17]. Therefore:

- the equipment that result to have the lowest actual OEEs are the bottlenecks, i.e. the critical equipment; as such, they are worth of an improved performance monitoring plan (scenario 1);
- the buffer capacity should be placed primarily to protect the bottlenecks from

the variabilities generated by other equipment along the system (scenario 2).

It is clear that scenario 1 can be achieved without changing the installation / configuration: it is a management decision. Scenario 2 is instead requiring a plant re-configuration, as the layout should be changed to increment the space provided to the buffer capacity: this re-configuration was considered feasible (at some cost) by the company.

4.2. Modelling and simulation set up

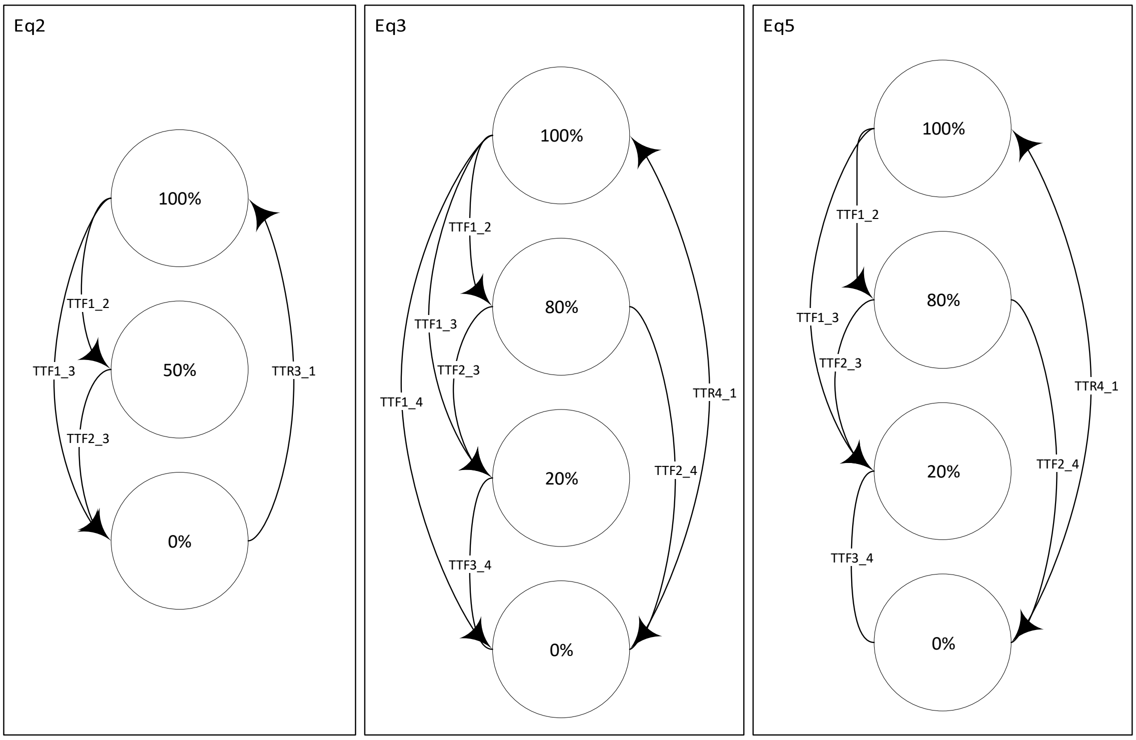
The first step is about the modelling phase of the as-is system. Five states generators (one for each equipment) and one system model (made up by eq1, eq2, eq3, a buffer, eq4 and eq5) have been defined. MBBs were used in order to create the overall model and one states generator for each equipment was created representing the behaviour based on the available data. In particular, three equipment, out of five, present a multi-state evolution, i.e. eq2, eq3 and eq5 (see Figure 7). Moreover, regarding the repair procedures, the state-space diagrams follow the following assumptions:

- repairs are not possible while the equipment is working at a downgraded speed; they can take place only during the downtime;

- repair brings the equipment to the good-as-new state (the maximum throughput state of the equipment).

Figure 7 represents the state-space diagrams for Equipment eq2, eq3 and eq5, indicating the number of states for each equipment corresponding to the performance levels they can provide (indicated as percentages), and each possible transition specifying the specific Time To Failure (TTF) and Time to Repair (TTR) from one specific state and the other.

Figure 7. States-space diagrams of Equipment eq2, eq3 and eq5 (application case)



As far as the simulation length regards (based on MSPE procedure), 6 pilot simulation runs, each one of 900 hours, have supported the procedure, resulting in a MSPE lower than 10% in case of a simulation length at least 800 hours. Concerning the ramp-up length (based on Welch procedure [34]), 150 hours appears appropriate. Last but not least, an iterative procedure was applied to determine – given the simulation and ramp-up length as fixed decisions – the right number of replications of the simulation experiments: fifty-five replications allowed to achieve the desirable relative percentage error γ=5%, with α=1% (calculated according to [33]).

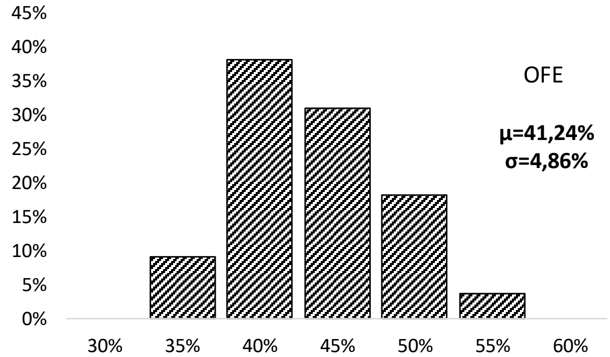
As far as regards the model validation, it was implemented majorly through comparison with experts' opinion. In particular, given that the model was tested in a newly installed plant, a complete knowledge of the OEE of all equipment was not considered available by the plant manager and the technical director. In fact, data currently collected by the company could not be considered enough to record all types of variations due to performance decays and failures for all machines, especially the equipment with high reliability. Hence, the comparison of the simulation model output data with the output data collected from the actual system was not feasible in a complete and systematic way. To overcome this issue, comparison with experts' opinion was done, as a pure quantitative validation was not possible [33]. Knowing similar equipment working in similar conditions as well as installed in already existing systems of the company, or information provided by vendors, was helpful as a reference for the experts' opinion. Moreover, the validation was backed up by means of the use of rough estimates built on simple analytical expressions as well as data available on nominal and average values, especially concerning the bottleneck equipment/machines, as currently monitored by the company. Thus, the technical director responsible of the company was interviewed and the results of the simulation analysis were shown to him. The output of the simulation was in line with its expectations, also compared with the results of simple analytical estimates, the benchmarks from similar equipment and the information from the vendor.

4.3. Scenarios comparison

4.3.1. As-is scenario

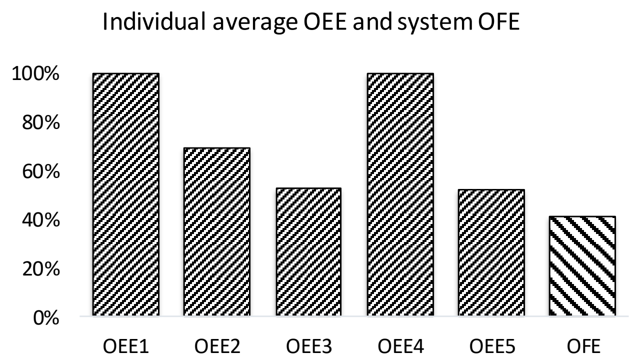
The output distribution of OFE, obtained by running the simulation model for the as-is scenario, is shown by the histogram in Figure 8; mean and standard deviation of OFE are shown as descriptive statistics.

Figure 8. As-is scenario: OFE distribution



The performance at the equipment level has been recorded in the form of single equipment OEE (see Figure 9). Each OEE is computed based on the data from the states generators, thus, it represents the performance "in isolation" of the single equipment. As it was expected by the company itself based on its previous knowledge of the equipment, the two robots (eq1 and eq4) have the better performance in term of OEE; moreover, their Performance indicator P is 100 % because they are not MSSs. Eq2, eq3 and eq5 have a significantly worst performance in terms of OEE compared to the robots: their performance in term of A is comparable to the one of the robots; nonetheless, their P is affected by the possibility to work at a lower speed than the ideal, as they are MSSs with downgraded states featuring a reduced throughput, this leads to the OEE decrease.

Figure 9. As-is scenario: average OEE of individual equipment and OFE

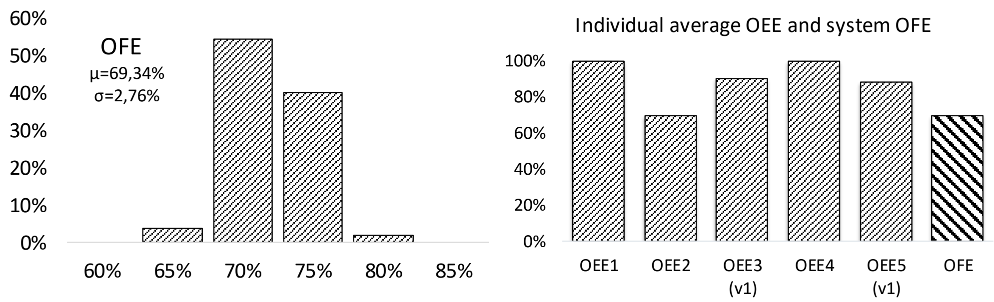


The OFE at the factory level is minor than the OEE of each single equipment: once the equipment is placed into the system, its performance is obviously affected by the performance of the other equipment belonging to the system. For example, eq1 – the alimentation robot – is highly affected by the blocking phenomenon: it could potentially process a higher quantity but the downstream machine, eq2, connected without a decoupling buffer, has a worse performance "in isolation" that limits the unloading activity of eq1, which has to wait for eq2 to be unloaded. Similar considerations apply to the assembly robot, i.e. eq4, now affected by material starvation: it has to wait for a sub-component fed by eq5, that has a poor performance “in isolation”. Overall, the good performance “in isolation” of eq1 and eq4 (the two robots) is negatively impacted by the poor performance “in isolation” of other equipment once the system is considered as integrated one. This results in a worst performance at the factory level.

4.3.2. Scenario 1: improving the critical equipment through a performance monitoring plan

Based on the analysis of the performance of the “as-is” scenario, the best candidates for scenario 1 are the equipment with the lowest OEE, i.e. eq3 and eq5 that represent two bottlenecks for the system. Hence, scenario 1 is about the evaluation of the effect of the introduction of a performance monitoring plan of eq3 and eq5, in order to plan a repair intervention before reaching an excessive performance decay. From a modelling point of view, modified state-space diagrams are introduced in the states generators for the two equipment in order to reflect the expected behaviour after the implementation of the monitoring plan (it is supposed that the two equipment do not transit through the 20% state anymore). The impact of this action can be quantified looking at changes in the system OFE which mean value increases substantially (Figure 10). Moreover, Figure 10 shows how the improvement action would affect the distribution of individual OEE and the distance between the average individual OEE and the average OFE.

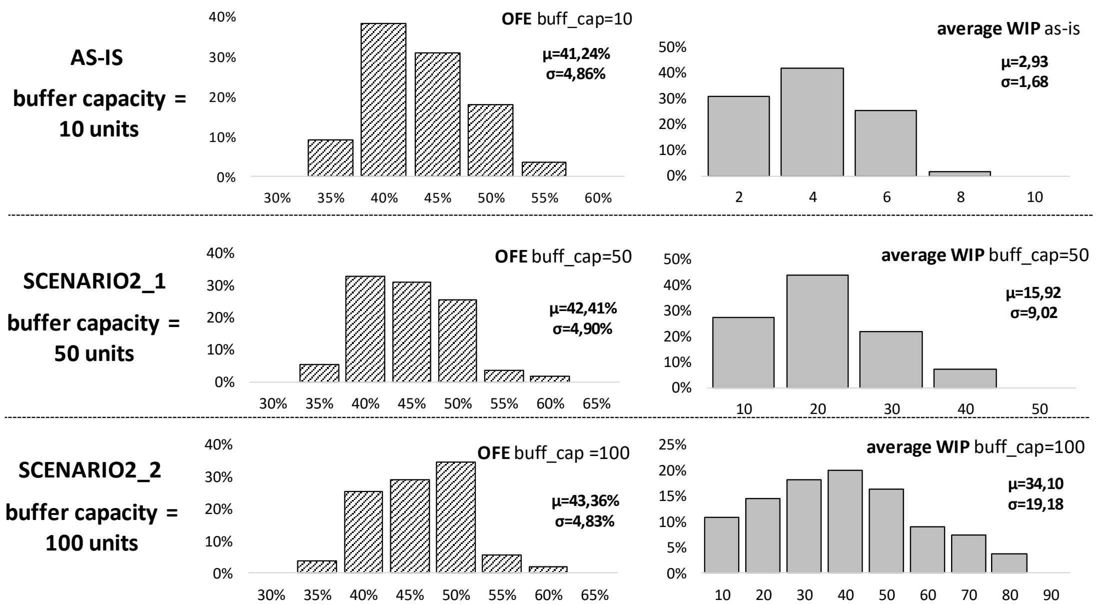
Figure 10. Scenario 1: OFE due to the introduction of performance monitoring plan for eq3 and eq5



4.3.3. Scenario 2: incrementing the buffer capacity

Scenario 2 analysis allowed evaluating the effect on OFE of the increment of the buffer capacity, which has got a capacity of 10 units maximum in the "as-is" case. The decision-maker identified such scenario since the buffer is placed after the eq3 (one of the two bottleneck of the system). Moreover, since the functioning of the assembly robot (eq4, placed after the buffer) is bounded from the subcomponent arriving from eq5 (the other bottleneck), a bigger decoupling power could also help to better isolate the two bottlenecks from each other. Two different increments of the buffer capacity are tested: to 50 and to 100 units. Figure 11 shows the obtained results from such experiment.

Figure 11. Scenario 2: OFE and WIP in the as-is scenario with respect to scenarios 2 where buffer capacity is increased to 50 units (scenario 2_1) or 100 units (scenario 2_2)



Increments in the buffer maximum capacity do not have a great impact on the OFE while the average WIP grows significantly. Besides, the simulation model confirms the typical relationship between throughput and buffer capacity: marginal throughput gains decreases when the buffer capacity (and the average WIP) grows. Overall, in this case, improvements are not effective as those achievable by a proper performance monitoring plan (i.e. scenario 1).

5. Discussion and conclusions

This paper proposes the computation of a factory-level performance metric, i.e. OFE, through a simulation-based performance evaluation model able to merge the two perspectives of Operations research-based techniques and Metric-based approaches. The research was carried out considering different stakeholders in diverse domain. The summary of main scientific outcomes can be correspondingly presented as concluding remarks.

- The performance evaluation model can be considered as an extension of the theory of UGF and stochastic process approach. It leads to an application of the theory in the manufacturing domain for buffered multi-state production systems. We believe that the application enriches the theory as it is considering a factory-level performance metric to measure inefficiencies in the frame of a well-known metric used in the manufacturing domain (i.e. OEE).

- The performance evaluation model extends the OEE theory, leading to the computation of the OFE considering the systemic effect of stochastic losses such as failures, minor stoppages, and reduced speeds. Under this perspective, it is a contribution in the manufacturing application field, with potential effect on practices of performance improvement.

Furthermore, we identified practical hints for further development and application, referring to two different targets: i) to implement the performance evaluation model in simulation environment. In this concern, we believe that we have provided a model that can inform future implementation in correspondent libraries of existing commercial simulation tools. In fact, the proposed modelling elements (system model and states generators) are aimed to inform the implementation of the simulation that can be run in different simulation environment solutions; ii) to improve production engineering theories with stochastic modelling of performances. In this last field, the calculation of the OFE can support the analyst to evaluate the effect of potential improvement actions through an ex-ante estimation based on simulation. The proposed approach allows modelling multi-state systems made up of many components that can be coupled using various logical connections, with particular emphasis on buffered production systems. At the same time, it enables to include in the analysis all the potential losses that are traditionally considered within the OEE metric. The application of the model in a real industrial case proved its usefulness and applicability. Future research is required to better detail how the proposed solution could be adapted for multi-stage, multi-product system such as a job shop setting, by addressing the complexity characterizing such systems.

Last but least, referring to the knowledge background, it is worth underlining that, within the scope of this research, UGF was selected as the methodology to be used to model system reliability, hence the simulation model was informed by UGF approach. Therefore, in terms of modelling method, it is worth to address future research on comparing this approach with the use of other approaches, such as Agent Based simulation, which appears to be suitable as well to solve the reliability modelling and simulation problem of large and complex systems [35].

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