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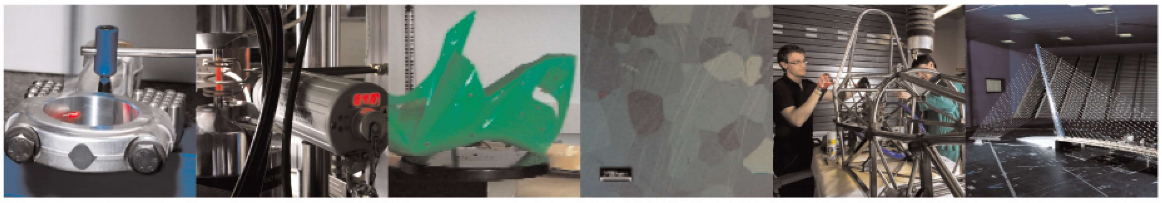

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A model-based Digital Twin to support responsive manufacturing systems

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Manufacturing systems are subject to continuous changing conditions, which are due both to external reasons (e.g. changing demand) and to the natural system evolution, (e.g. machine degradation, operators' upskilling). At tactical level, production engineers are challenged to continuously improve the system performance. At strategical level, the manufacturing company must monitor the system status and proactively identify reconfiguration actions to ensure system fitness to the evolving competitive scenario. A novel Digital Twin based on an analytical model for performance evaluation of manufacturing system embedding evaluation of joint parameter variations is introduced. In particular this work concentrates on how tactical decision makers can benefit from an integrated system model. The method is proved in a real industrial case in the railway sector.

Manufacturing systems; Digital Twin; Evolution planning.

1. Introduction

Manufacturing systems are continuously changing objects which resemble living entities [1]. Their overall performance depend on the combined effects of the system design and operation. The system configuration, which includes the choice of resources (machines, buffers, workforce, etc.), represents a strategic decision for manufacturing companies. The system operation includes tactical and operational decisions, as the workforce allocation, the machines availability, the production planning strategy [2].

Changing the system configuration is less frequent, while tactical decisions belonging to different production areas are continuously taken and optimized according to evolving operating conditions [2]. For instance, maintenance operators may gain experience in the job after some time, and therefore the repair time decreases. This results in higher system availability, which should be properly exploited by the production planning strategy. In other cases, a machine may degrade, i.e. stoppages occur more frequently, which requires either to change process parameters such as the production speed (if possible), or to increase the system availability by reducing non-productive times as set-ups, in order to keep the same system productivity, or even increase it [3]. The joint effect of decisions belonging to various production areas which are traditionally considered in isolation, as logistics, maintenance and quality, is difficult to predict. More in general, manufacturing companies are continuously facing the challenge of operating their manufacturing processes and systems in order to deliver the required production rates of high quality products, while minimizing the use of resources [4] and keeping it sustainable [5].

When tactical decisions are not sufficient to cope with the situation in an effective way, strategical decisions should be considered, e.g. new machines should replace the obsolete ones, or buffer capacities should be acquired, or new operators should be hired and trained. Tactical and strategical decisions depend also on the corporate culture [6], as well as on the context of the market sector the manufacturing company operates in, which is hard to capture in models for decision support [7]. Tactical and strategical decisions also depend on the ability and expertise of decision-makers, as production managers, manufacturing system engineers, continuous improvement managers, which makes the decisional structure more hierarchical than those decisional structures which can be encountered at operational level [8].

At operational level, Digital Twins (DT) have been proven to be useful in supporting the evaluation and control of manufacturing entities. According to [9], 'a DT is the digital representation of a unique asset [...] that compromises its properties, condition and behaviour by means of models, information and data'. DT can be used to digitally represent products [10], single-stage machines or processes [11], or, less often, multi-stage manufacturing systems [12]. When DT are used to model single or multi-stage systems, the design elements of DT [13] is fundamental and includes the definition of suitable data architectures capable of following the DT during its life-cycle [14]. This is particularly relevant when DT is integrated into in-process control loops, as presented in [16] for process quality improvement. Using DT for decision support, together with predictive engineering [15], leads to the capability of proactively address changes by exploring possible future scenarios and choosing the best available option that optimizes target objectives.

This work explores the use of a novel model-based DT in a decision support framework to address tactical decisions for the responsiveness and continuous improvement of manufacturing systems throughout the system life-cycle. At the same time the model supports the identification of situations in which the strategic decisions become necessary. Indeed the advantage of having a unique and comprehensive model for the performance evaluation and joint parameter variation of the manufacturing system, based on data gathered from the real operating system, is shown in particular when tactical, but also strategical decisions are to be considered.

The paper is organised as follows: the proposed methodology is presented in Section 2; in Section 3 a real case is introduced and discussed with respect to the problem formulation; conclusion and future research are discussed in Section 4.

2. Methods

2.1. Outline of the methods

The proposed method is depicted in Figure 1 and can be applied to any manufacturing system where the System Digital Twin (SysDT) is based on the Markovian representation of the system resources and their interactions. The resulting parametric analytical model is based on continuous updated information from the shop-floor, i.e. log of alarms and repairs coming from different sensors of the machines to update the estimate of failure times (*f*) and repair rates (*r*), as well as product tracking time-stamps to estimate the processing rates (*m*) of the various resources. In this way, the digital counterpart SysDT is continuously aligned with the real system.

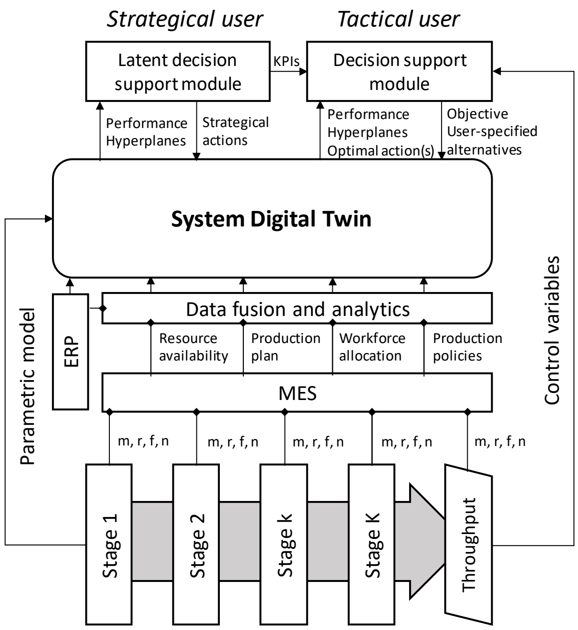

Figure 1. Outline of the method

From MES and ERP systems additional information about the operation and management of the line are gathered, as illustrated in the software architecture presented in [17]. On the basis of the data and on the basis of the analytical formulation, the SysDT can predict not only the performance of the current configuration, but embeds an extremely fast comprehensive evaluation of the change of performance deriving by any modification affecting the operating conditions of the system. This evaluation is obtained by means of a map of performance hyperplanes obtained from the first-order analytical derivatives of the performance, which guide the optimization method in promising search areas. In these areas, new hyperplanes are then calculated to refine the performance estimate and lead to a precise selection of the new optimal conditions:

- At tactical level, the user, e.g. the production engineer who manages the continuous improvement, can evaluate the effect of improvement actions on the current system performance, by exploiting the SysDT. Optimization problems based on linear programming can be solved within the framework thanks to the performance hyperplanes which are added as constraints to the problems. Also the DSS signals to the manager when a system reconfiguration would be more cost effective than insisting on local improvements.
- At strategical level, the SysDT thanks to the updated map of hyperplanes spanning the whole combined parameter domain, allows to evaluate the effect of specific system reconfigurations and therefore to identify focused and effective reconfiguration actions not changing the overall system architecture (if the system architecture is changed, however, a new parametric model must be created).

This work focuses in particular on the tactical level. Indeed, the tactical user must cope with the day-by-day system operations, and take decisions to keep the system running in the most efficient way, by dynamically adjusting the actions to the changing system conditions and by reacting to disruptive events.

2.2. The novel SysDT for the performance evaluation and analysis

Notation	
k	Production stage k=1,…,K
th	System throughput
n_k	Capacity of buffer k
m_k	Processing rate of stage k, m=1/CT
r_k	Repair rate of stage k, r=1/MTTR where MTTR = Mean Time to Repair
f_k	Mean Time to Failure of stage k
$\delta th/\delta n_k$	Partial derivative of throughput with respect to capacity of buffer *k*
$\delta th/\delta m_k$	Partial derivative of throughput with respect to production rate of stage *k*
$\delta th/\delta r_k$	Partial derivative of throughput with respect to repair rate of stage *k*
$\delta th/\delta f_k$	Partial derivative of throughput with respect to Mean Time to Failure of stage *k*

The parametric model of the SysDT is based on a stochastic analytical model for performance evaluation of manufacturing systems, where for each buffer *k* of the system a representation of the whole system centred on that buffer is given. In each representation, the buffer level is represented by the continuous variable x_k and the possible combinations of system states, as seen by the considered buffer *k*, are represented by the vector S_k. The transition rates among the various states are contained in the matrix Q_k. On the basis of this information, the method described in [18] allows to calculate the vector of probability density functions $f(x_k,S_k)$, which can be expressed as

$$f(x_k, S_k) = A_k \cdot diag(C_k) \cdot e^{\Gamma_k \cdot x_k} \qquad (1)$$

Where:

- A_k and Γ_k are the eigenvectors and eigenvalues of the matrix Q_k;
- C_k is a vector of constants depending on the system dynamics.

Basing on the various functions $f(x_k,S_k)$ it is possible to evaluate the steady-state probabilities of the whole system, and to derive the performance measures as the throughput *th* and the average buffer levels. The advantage of using an analytical model is that the explicit relation between input parameters and output performance can be obtained. Equation (1) can be differentiated with respect to the generic system parameter *d*

$$\frac{\delta f(x_k, S_k)}{\delta d} = \frac{\delta A_k}{\delta d} \cdot diag(C_k) \cdot e^{\Gamma_k \cdot x_k} + A_k \cdot diag\left(\frac{\delta \Gamma_k}{\delta d} \cdot x_k \cdot e^{\Gamma_k \cdot x_k}\right) \cdot C_k + A_k \cdot diag\left(e^{\Gamma_k \cdot x_k}\right) \cdot \frac{\delta C_k}{\delta d} \qquad (2)$$

From Equation (2), the vector of partial derivatives of the throughput with respect to the set of parameters can be obtained

$$Der = \left\{\frac{\delta th}{\delta m_k}, \frac{\delta th}{\delta r_k}, \frac{\delta th}{\delta f_k}, \frac{\delta th}{\delta n_k}\ \forall k = 1, \dots, K\right\} \qquad (3)$$

The partial derivatives are then used to write the first-order approximation of the throughput (hyperplane) with respect to the combined set of system parameters. The advantage of using the analytical derivatives is that each hyperplane is obtained with a single evaluation. In this way, it is possible to avoid the calculation of the derivatives by means of finite differences; indeed, this normally results in a reduction of computational time of more than one order of magnitude, especially when the number of parameters is very high as in real systems.

Since performance measures such as system throughput do not depend linearly on the system parameters, linear approximations must be calculated in different points. The envelop of these different first order approximations represent a piecewise linear approximation of the performance.

To exemplify, the piecewise linear approximation of the throughput of a manufacturing line with respect to the capacity n of one of its buffers, is shown in Figure 2.

Indeed, once the first order derivative of the throughput with respect to the buffer capacity is known in a certain point (th_0,n_0), the tangent line in that point can be written as:

$$th_{lin} = \frac{\partial th}{\partial n_0}(n - n_0) + th_0 \tag{4}$$

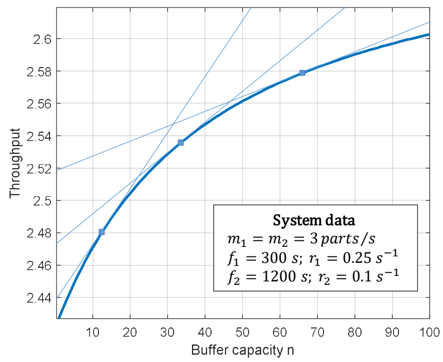

Figure 2. Throughput as a function of buffer capacity with first-order linearization.

As it can be seen, even few lines are able to capture very well the shape of the curve which in turn represents many system configurations. Since the analytical model allows to mathematically obtain the partial derivatives of the throughput with respect to all the parameters characterizing the system, it is possible to write the first-order approximation of the throughput with respect to all the system parameters and calculate the tangent hyperplanes in the n-dimensional space of system parameters:

$$\begin{aligned} th_{lin} = {} & \sum_{k=1}^{K} \frac{\delta th}{\delta n_k}(n_k - n_{k,0}) + \sum_{k=1}^{K} \frac{\delta th}{\delta m_k}(m_k - m_{k,0}) + \\ & + \sum_{k=1}^{K} \frac{\delta th}{\delta r_k}(r_k - r_{k,0}) + \sum_{k=1}^{K} \frac{\delta th}{\delta f_k}(f_k - f_{k,0}) + th_0 \end{aligned} \tag{5}$$

The key features of the resulting piecewise linear approximation of the performance are

- it captures the performance of an extremely large set of alternative systems
- it can be used in linear optimization models [19].

Therefore, each time the MES and IIoT systems identify new system conditions, e.g. degraded machine, improved cycle time, change in the product flow, the DT adds the corresponding tangent hyperplane to the collection of hyperplanes already calculated. The set of hyperplanes are used by DSS tools at tactical level for the optimal selection of responsive actions and at strategical level for the proactive identification of improvement directions.

3. Real case study: a railway company

3.1. Description of the multi-stage manufacturing system

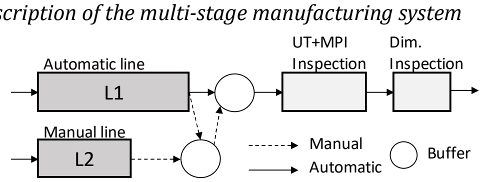

Figure 3. Multi-stage machining department.

The proposed method has been applied to a manufacturing company producing axles for the railway sector. The axles are produced from carbon steel and low alloyed steel. The overall production is carried out in different departments [20]. In this work the focus is on the machining department, which is graphically represented in Figure 3. Numerical parameters are omitted and numerical results have been scaled for privacy.

- The operations performed in the machining department are rough turning, finish turning and stone grinding. There are two parallel lines, which are called line 1 (L1) and line 2 (L2). L1 is a new automatic production line with limited buffers between stations, in which the handling is performed by an automated gantry system, transferring the axles from one station to the next one and finally to the inspection station which is fully integrated in the line. L2 is older, but functionally it performs almost the same operations, while the loading and unloading are carried out by hoist cranes with manual intervention. Large buffers are allowed between stations in L2, with parts stored on the floor. Inspection operations, i.e. 100% ultrasonic testing (UT) and magnetic particle inspection (MPI) are carried out on the axles coming from L1, L2. Given the space in the automated buffer between L1 and inspection (buffer capacity = 2), lines may occur in blocking. In the future the size of the automatic buffer will be increased but for the moment the policy is that operators create extra buffer space by unloading parts to avoid blocking of the lines and reloading them when the lines stop due to failures or setups.
- A part tracking system, together with Industrial Internet of Things (IIoT) distributed sensor network allow the data gathering from multiple sources, i.e. machines cycle time, failures occurrence, repair times, as well as buffer levels and axles current location.
- Operators with different skills and roles are allocated to the lines. Those supervising L1 are in charge of minor maintenance activities on the line, the set-up of the stations for product changes, and the manual unloading and reloading of the final buffer to manage the flow of parts. Operators in L2 are in charge of the machining operations, minor maintenance, and axles handling to the inspection station.
- The machining department follows the production plans decided by the planning department. Production lots are assigned weekly to the two lines. The number of axles in each lot is quite variable, and the availability of the lines depends on the number of required set-ups.

3.2. Challenges for the production manager

The production manager of the machining department is responsible for the operations and continuous improvement of the lines. In the short-term, i.e. in the day-by-day routine, he has the goal of attaining the throughput required by the production plan. The operational flexibility which the production engineering manager can use includes a wide set of alternatives as the prioritization of axles from the two lines at the inspection station; the re-allocation of the operators to the tasks and to the lines, according to their skills; the prioritization decision among maintenance, set-ups, and unloading operations in L1; the decisions on rework or scrapping operations of axles which do not pass the inspections, the dynamic definition of the extra buffer space used to download the parts from the line. In the medium- and long-term, the production engineering manager should ensure the implementation of actions for the improvement of the system efficiency and productivity. These include the activation of training courses for the upskilling of operators, focused work-shops for the reduction of repair time, improvement of set-up operations, as well as technological actions to avoid machine degradation over time. The impact of both tactical and strategic actions on the overall system performance is not known *a priori*. Similarly the impact of continuously changing exogenous parameters is hard to predict The manager has to continuously take decisions to cope with the evolving situation and the proposed approach provides an important support.

3.3. Exemplary results

To exemplify the proposed approach, one of the many decisions to be taken by the manager is considered. As seen before, in reality, different potential decisions have to be considered together, but for the sake of simplicity, only one decision will be analysed in this example.

Production plans vary from week to week, in terms of total planned production and lot sizes. When small lots are planned, setups reduce the availability of the machines and keep the operators busy, which results, on average, in longer reaction times to disruptive events like stoppages. Despite these weekly variations, the manager has to reach the target throughput required by the plan. He is free to take different actions as described before. One of the actions is to download parts from the final buffer of L1 to artificially increase its capacity to feed inspection which is the bottleneck machine. Figure 5a presents one of the results provided by the approach to support the production manager. The map shows the piecewise linear evaluation obtained by taking a specific section of the hyperplanes defined within the proposed SysDT. It shows the impact of the buffer capacity (starting from the physical buffer=2 to larger values obtained by unloading and reloading axles) on the throughput of the line for various production plans decided by the production planning department. These are approximate values to lead further analysis in specific areas.

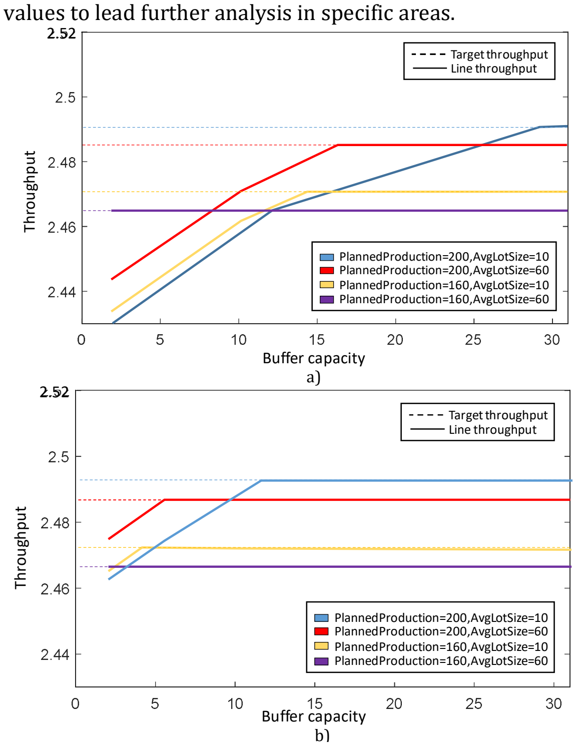

Figure 4. Control-point policies and target throughput for the current system condition (a) and for future system condition (b).

When the planned production is high and lots are small (blue case in Figure 4), a quite large buffer capacity is needed to satisfy the target throughput (n=29). When lot sizes are larger, the minimum buffer capacity reduces to n=15. Indeed, the buffer absorbs the variability caused by disruptions, which is smaller when operators are less busy with setups. At the same time the proposed method can be used by the manager to assess medium term decisions. For instance the impact of a 25% reduction of the repair time of the inspection station (which may require extra training and augmented reality tools) would change the day by day situation leading to the map of Figure 4b. In particular, small buffer capacities would be needed, because the reduction of repair times at the inspection station would have the double effect of increasing its availability and reducing its variability. This action seems to be a quite good step also in view of potential strategical decision of reconfiguration of the line in which the capacity of the automates buffer might be structurally increased to avoid the manual download and reload of axles.

4. Conclusions and future work

This paper presents a novel model-based methodology for tactical and strategical decisions in manufacturing systems. It is shown how complex decisions can be addressed by exploiting a unique Digital Twin, which provides both performance evaluation and analysis with respect to changing parameters. The proposed methodology opens new relevant research questions, as the relation among tactical and strategical decisions in evolving manufacturing systems, the hierarchical data architecture to incorporate advanced models for the single-process evaluation and analysis, as well as the integrated optimization of production engineering decisions usually treated independently, as maintenance, quality and logistics.

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