CIRP Annals - Manufacturing Technology 73 (2024) 349–352

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: https://www.editorialmanager.com/CIRP/default.aspx

Performance evaluation of multi-stage manufacturing systems operating under feedback and feedforward quality control loops

Maria Chiara Magnanini*, Ozan Demir, Marcello Colledani (1), Tullio Tolio (1)

Department of Mechanical Engineering, Politecnico di Milano, via La Masa 1, 20143 Milano, Italy

ARTICLE INFO

Article history:
Available online 7 May 2024

Keywords:
Manufacturing system
Quality control
Decision model

ABSTRACT

In manufacturing, the essential product characteristics are often created through multiple stages. Coupling product data obtained through inspection and controllers based on decision models with prediction capabilities enables quality control loops, enhancing both feedback and feedforward mechanisms. This paper proposes a methodology to merge the formulation of feedback and feedforward quality control loops into a performance evaluation model for multi-stage manufacturing systems. This approach evaluates quality control loop impacts system-wide, aiding in configuring and reconfiguring quality gates. A case study illustrates how allocating inspection technologies and efficient decision models improves overall system performance through effective feedback and feedforward control loops.

1. Introduction

In manufacturing, the essential product characteristics, such as mechanical properties or geometrical accuracy, are often created through multiple stages. The rise of cyber-physical systems as well as quality prediction models based on process-level digital twins [1], and virtual metrology methodologies [2], are boosting the interest towards the understanding of the relationship between quality strategies and system dynamics. Quality control loops are a significant aspect of system operations. They are often based on complex decision models that link process variables to product measurements [3,4].

Feedback and feedforward control loops to improve quality and to control part deviations, have primarily been analysed at process level in multi-stage manufacturing systems, in multi-stage assembly systems [5,6], and in lithography threads [7], by identifying suitable control laws to adjust controllable variables. However, control strategies of this type interact with the dynamics of the manufacturing system, depending on the inspection policy or measurement technology used, as well as the complexity of the decision model [8]. The aim of this paper is to explore this less addressed research area, to allow further developments in the integration of product-process models and system-level performance evaluation, with a zero-defect manufacturing perspective.

Both feedback and feedforward quality control strategies are initiated by the observation of quality information. In feedback quality control loops, the information delay between the stage where the deviation is generated and the inspection stage where the deviation is observed is well known in production theory [9]. These loops aim to be implemented as close as possible to the process that caused the deviation. However, this is not always the case as accurate inspection may require long times hence quality gates may be put downstream in the process chain to identify several quality characteristics at once. In any case, feedback quality control loops always imply a delayed reaction to a shift in the process. In feedforward quality control loops, the control action takes place in processes that are downstream the machine that generated the deviation. If the control action is represented by the tuning of some parameters, the time needed to perform the control action is negligible as it is part of usual process time. In other cases, the feedforward control strategy may need time-consuming interventions, as in manual set-ups of fixtures, or a modification in the routing of the parts [10,11]. Moreover, both feedback and feedforward quality control loops imply the use of digital models used for simulation and prediction, which are characterized by specific elaboration time as well as accuracy. In this context, digital models for deviation identification and classification of defects according to product features are quite spread [12-14]. In the case of feedforward quality control loops, the prediction accuracy is essential for a positive effect on quality performance since it affects the way the downstream processes are tuned to counteract the original deviation.

Traditionally, system level and process control level have been treated separately. Consequently, the allocation of inspection points and quality gates along a line is done considering local quality aspects and does not consider the impact of feedback and feedforward control loops on system level performance. This work aims at addressing this gap, hence assessing the impact of inspection points allocation and quality loop management in the progress toward zero-defect manufacturing. Specifically, feedback and feedforward control strategies in multi-stage manufacturing systems are considered. The methodology firstly defines the feedback and feedforward quality control loops. It then considers their impact on system dynamics to derive the performance of the manufacturing system. Therefore, this methodology is meant to be used to configure and reconfigure complex manufacturing systems, taking into account not only the dynamics of the physical resources but also the dynamics of quality control loops at system level.

* Corresponding author.
E-mail address: mariachiara.magnanini@polimi.it (M.C. Magnanini).

https://doi.org/10.1016/j.cirp.2024.04.015

2. Methodology

Firstly, the feedback and feedforward quality control loops are defined, with respect to a generic multi-stage manufacturing system (MMS) (Fig. 1).

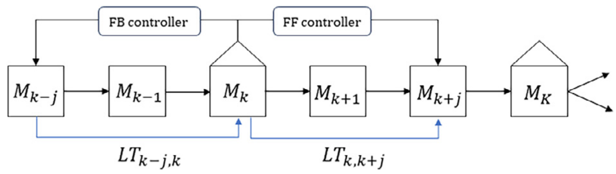

Fig. 1. Multistage manufacturing system with feedback and feedforward quality control loops.

In a MMS characterized by K stages, it is assumed that at least one process is critical with respect to the generation of deviated parts, according to its capability. The probability of generating deviated parts is defined as p_{dev}. Each inspection station in position k enables a set U_{FB} of feedback and a set U_{FF} of feedforward quality control loops, and it is characterized by an inspection time TI and a measurement uncertainty. The decision model used as controller in feedback and feedforward control loops is based on a classification mechanism that, according to the class of the identified deviation, defines the control action. According to the measurement uncertainty coupled with the decision model used as a controller, it is possible to define a function linking the type I error α and the type II error β, so that $\beta = f(\alpha)$.

When a feedback quality control loop is enabled in a given stage $k-j$, as soon as the inspection station triggers the quality control loop by identifying a potential deviation in the part, a certain time $T_{decFB,k}$ is required to elaborate the quality information in order to identify the suitable feedback action, then a certain time $T_{FB,k-j,k}$ is required to perform the corrective action on process $k-j$. According to the confusion matrix of the decision model, the feedback control action may have a positive or detrimental effect.

When a feedforward quality control loop is enabled in a given stage $k+j$, as soon as the inspection station triggers the quality control loop, a certain time $T_{decFF,k}$ is required to elaborate the quality information in order to identify the suitable feedforward action, and a certain time $T_{FF,k,k+j}$ is required to perform the proactive action on process $k+j$. Considering the implementation of prediction models to identify the correct feedforward control, the identification of the feedforward control action may be correct or not according to the confusion matrix of the prediction model that is used to take the decision.

According to the system dynamics, the following situations may occur:

- When the feedback quality control loop is activated, the information delay given by the inspection in k always enables the control actuation in $k-j$, at the cost of multiple deviated parts already produced in stage $k-j$. The amount of deviated parts depends on the lead time (LT) between stage $k-j$ and stage k, and it can be defined as:

$$W_{FB,k-j,k} = (LT_{k-j,k} + T_{decFB,k})CT_j \tag{1}$$

- When the feedforward quality control loop is activated, the control actuation is enabled if $T_{dec,k} < LT_{k,k+j}$ where $LT_{k,k+j}$ represents the lead time between stage k and stage $k+j$. If on the other hand $T_{dec,k} > LT_{k,k+j}$, parts are processed according to nominal parameter setting and no downstream adjustments are implemented, therefore they result in defective products.

At system level, we are interested in evaluating the effect of inspection allocation and quality control loops on the effective productivity th^{eff}, the system lead time LT, and the yield Y, according to the decision time, the accuracy of the decision model and the capability of critical processes.

2.1. Solution method

The solution method is based on approximate analytical methods [15], however this approach can be integrated in any performance evaluation model based on state-based representation, as in fluid Petri Nets [16]. The advantage of using the proposed approach is that analytical relationships between the parameters characterizing the quality control loops and the functions describing the system dynamics can be derived. The relationships defined in the following can then be used as synthetic evaluation kernels in more complex models and optimization algorithms.

The aim of the performance evaluation model is to obtain the steady-state performance measures of a system characterized by feedback and feedforward quality control loops, by defining separately the dynamics of the resources in the system and automatically deriving the system-level dynamics by means of analytical equations.

Each process stage k in the system is modelled by a set of states describing its dynamics and reliability, and it is characterized by cycle time equal to CT_k. Each inspection stage in the system is modelled by a set of identification states. The decision model used to identify the feedback control action is defined by a confusion matrix with precision $1-\alpha_{FB}$, and false omission rate β_{FB}.

From the state-space perspective, if a feedback quality control loop is to be evaluated, the event-graph in Fig. 2 describes the relationship between the controlled stage $k-j$ and the inspection stage k, where P represents the operational state of the $k-j$ stage when the $k-j$ process does not produce deviated parts, $\overline{P}$ represents the operational state where the $k-j$ process produces deviated parts, I represents the inspection state in stage k where a deviation is detected, $\bar{I}$ represents the inspection state where no deviation is detected, and U_{FB} represents the decision state of the feedback controller.

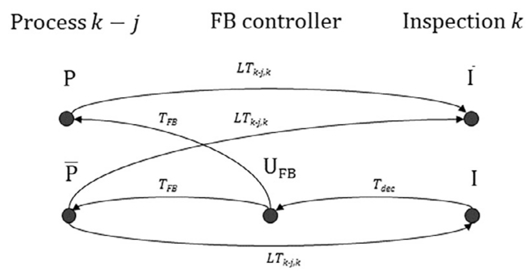

Fig. 2. Feedback quality control loop.

Similarly, if a feedforward quality control loop is to be evaluated, the decision model used to identify the feedforward control action according to a prediction model is defined by a confusion matrix with precision $1-\alpha_{FF}$, and false omission rate β_{FF}.

Then, the event-graph in Fig. 3 describes the relationship between the inspection stage k and the controlled stage $k+j$, if possible due to the time constraint and the accuracy of the decision model, where P represents the operational state, $\overline{P}$ represents the operational state where the $k-j$ process produces deviated parts, I represents the inspection state in stage k where a deviation is detected, $\bar{I}$ represents the inspection state where no deviation is detected, U_{FF} represents the decision state of the feedforward controller, and FF and $\overline{FF}$

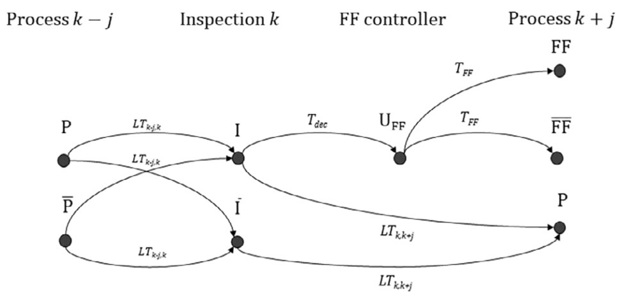

Fig. 3. Feedforward quality control loop.

represents the change of operational mode for the $k+j$ stage from nominal to feedforward, when the decision model correctly identifies the control action or not, respectively.

The solution method is based on the Markovian representation introduced in [15], here enhanced by the integration of feedback and feedforward quality control loops.

Let $(x,S)=(x_1,x_k,\ldots,x_{K-1},S_1,S_k,S_{k+1},\ldots,S_K)$ be the vector describing the state space of the system, where x_k describes the average amount of material between stage k and stage $k+1$, and S_k and S_{k+1} represent the state of stages k and stage $k+1$, respectively. Let $f(x_k,S_k,S_{k+1})$ be the probability density function in each two-stage line composing the long line.

Then, with respect to system dynamics, the following transition rates depending on the system dynamics describe the change of state in stage $k-j$ where the feedback quality control loops is actuated:

$$\boldsymbol{q_{\overline{P}\to P}} = \boldsymbol{u_{FB}}\cdot(1-\boldsymbol{\beta_{FB}})\cdot\frac{\boldsymbol{p_{dev}}}{\boldsymbol{LT_{k-j,k}}+\boldsymbol{TI_k}+\boldsymbol{T_{decFB,k}}+\boldsymbol{T_{FB,k-j}}} \tag{2}$$

Where $u_{FB}\in\{1,0\}$ indicates if the feedback quality control loop is actuated or not.

Similarly, the following equations describe the state transition rates for the actuation of feedforward quality control loops in stage $k+j$:

$$q_{P\to FF} = u_{FF}\cdot p_{dev}\cdot(1-z)\cdot(1-\alpha_{FF})\cdot(1-\beta_{FF})\cdot\frac{1}{CT_{k+j}} \tag{3}$$

$$q_{P\to\overline{FF}} = u_{FF}\cdot(1-p_{dev})\cdot(1-z)\cdot\alpha_{FF}\cdot\frac{1}{CT_{k+j}} \tag{4}$$

where $u_{FF}\in\{1,0\}$ indicates if the feedforward quality control loop is actuated or not, and where

$$z=\int_0^{T_{decFF}\cdot th} f(x_k,S_k,S_{k+1})dx \tag{5}$$

represents the fraction of parts for which the feedforward control decision cannot be actuated on time because $LT\leq T_{dec,FF}$.

For each of the stages $k+j$ where deviated parts may cause quality faults, the inter-arrival rate of deviated parts can be computed as:

$$q_{k+j}=p_{dev}\cdot z\cdot\frac{1}{CT_{k+j}} \tag{6}$$

Moreover, it is possible to define the inter-arrival rate of parts where the feedforward control had a detrimental effect:

$$q_{k+j}=(1-z)\cdot\beta_{FF}\cdot\frac{1}{CT_{k+j}} \tag{7}$$

Then, the steady-state performance are obtained by solving a linear system

$$\begin{cases}\dfrac{\delta}{\delta x}f(x,S)=Q^T\cdot f(x,S)\\ \sum_S\int_x f(x,S)dx=1\end{cases} \tag{8}$$

where Q represents the transition rate matrix of the underlying Markovian model in the state space (x,S).

The performance measures in terms of system throughput th, throughput of non-defective parts th^{eff}, and system yield Y can be computed as a function of the decision model accuracy in terms of α and β, and the decision time:

$$th=\frac{1}{CT_K}\cdot\int_x f(x,P_K,\cdot)dx \tag{9}$$

$$th^{eff}=[(1-p_{dev})\cdot(1-\alpha_{FF})+p_{dev}\cdot(1-z)\cdot(1-\beta_{FF})]\cdot th \tag{10}$$

$$Y=(1-p_{dev})\cdot(1-\alpha_{FF})+p_{dev}\cdot(1-z)\cdot(1-\beta_{FF}) \tag{11}$$

As it can be noticed, for $z\neq 1$, i.e. if the time to take the decision cannot allow to always implement the feedforward quality control loop, not only the effective throughput of good parts th^{eff} depends on the effectiveness of the control strategy, but also the yield Y.

3. Case study from automotive industry

The target product in this case study is an aluminium profile used as shock-absorber in bumpers for the automotive industry. This product is obtained starting from extremely long extruded aluminium profiles, that are cut into shorter bars and finally sawed before the final machining and assembly. Critical features include specific curved profiles, holes and pockets, all necessary for the assembly in the final bumper.

The multi-stage manufacturing system consists of an extrusion area, a completely automated machining and assembly line, and a quality control area. Looking more in details to Fig. 4, M_e and M_c represent the extrusion and the cooling stations, B_1 is the buffer storing extruded profiles before being cut in shorter profiles in M_{cut}. Then, the profiles are brought to the machining and assembly area, where they are loaded onto a multistage automated line. Here, the profiles are firstly sawed according to the product length in M_s and later machined in two parallel machining centres, $M_{m,1}$ and $M_{m,2}$, to manufacture final features. The machined parts are washed in M_w and finally are riveted and assembled in M_a with other minor components by a robotic arm. The robot places the part on pre-defined fixtures and assembles minor components before unloading the finished product into a buffer B_4, from where the products are sampled for the final quality check by means of a dedicated CMM, I_{CMM}, in a separate room.

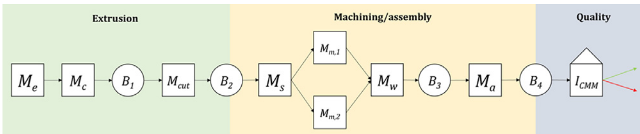

Fig. 4. Representation of multistage manufacturing system.

The extruded profiles are subject to critical geometrical deviations (e.g. twisting, bending) due to the difficult control of the extrusion process and the uncontrolled cooling. Although the deviations that exceed the tolerances are rejected, the ones that comply with specification limits and barely accepted in quality gates can generate downstream issues, especially during machining and assembling, which result in defective parts at the end of the line. In particular, if the accumulated deviations are severe, the automated assembly station can stop because of extreme misalignment in the part fixturing, hence calling for manual intervention to start over the production. At the end-of-line quality gates, where the manufacturing errors are identified, the root-cause is diagnosed and the control action is returned much after the deviation occurs therefore production continues for a long time out of control, resulting in many defective parts produced. Given that the improvement of the extrusion process is an expensive difficult and long-term action a possible reconfiguration of in-line inspection stations is analysed based on the proposed methodology.

3.1. Analysis of feedback and feedforward quality control loops

Since extrusion and machining/assembly areas are decoupled, only p_{dev} in extrusion propagates to the downstream stages. In order to apply feedforward adaptation of machining settings based on the incoming profile characteristics, a fringe projection system is expected to be installed prior to the machining. Fringe projection are a particular type of inspection technology, where the part is exposed to a high-resolution camera, capturing a point cloud of the part according to the focus. The advantage of using a fringe projection system is that a modular inspection is possible, as each part may require from ~20 s to 3–4 min of inspection depending on the complexity of part and on the number of features needed to be measured for classification of deviation. At the same time, since the part is made of aluminium, it is highly reflective, hence the fringe projection system has a high measurement uncertainty if the time of exposure for the projection is insufficient, or if the part is badly oriented with respect to the measured feature. Hence, type-I error (α) of fringe projection depends on the number of points measured during the inspection. Based on gathered measurements, a better definition of deviation classes can be derived. As per the type-II error (β) the function depending on the precision of the digital model preliminarily developed as controller is considered. The digital model used as controller identifies the correct part program, which had been adapted for the specific deviation class. For example, the position of the holes in the product may be adapted according to geometrical deviations. As a consequence, if the deviation class identified by the combination of measurement and trained decision model is not correct, and a non-suitable part program is implemented, an already good part can lead to a defect. In Fig. 5a the effective throughput calculated with the proposed model as a function of $1-\alpha_{FF}$ and β_{FF} of the feedforward control is presented, whereas Fig. 5b shows the effect on the effective throughput of reducing by 2 % the probability of generating deviated parts p_{dev} at the extrusion, by means of feedback control.

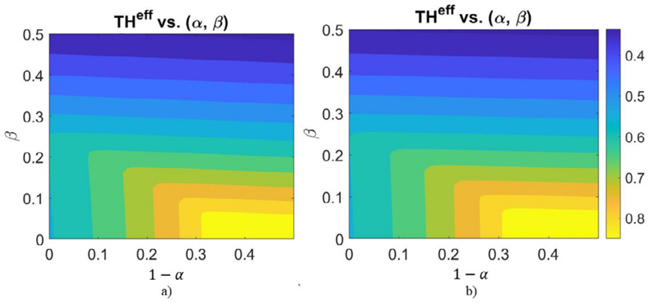

Fig. 5. (a) TH^{eff} vs(α_{FF}, β_{FF}) with feedforward and (b) with feedforward and p_{dev} improvement due to feedback.

It can be noticed that the effective throughput of the multistage manufacturing system is significantly affected by the quality inspection gate performance and the control strategies. The results show that the trade-off between α and β must be taken into account carefully in order to decide whether to invest more effort into decision models or inspection technologies since they both influence the system dynamics: in case no remarkable enhancement can be performed to reduce α, more emphasis can be placed on the decision model; on the other hand, for a given model accuracy, accepting a higher measurement uncertainty (in this case spending less time in gathering fringe projection measurements) to increase the throughput can be detrimental, resulting in higher scrap rates and therefore, lower effective throughput after a certain point. In this case it is possible to notice that measuring a number of features linked to have $1-\alpha_{FF}=0.4$ guarantees the highest effective throughput, only if β_{FF}, depending on the controller, is guaranteed lower than 0.15. These performance maps are going to be used to decide the target performance in terms of accuracy of the decision model used in the feedforward control loop, hence linking together the decisions related to the inspection allocation, used for data gathering, with the decisions related to the quality control loops, targeting the data use effectively.

4. Conclusion

The allocation of inspection stations in multi-stage manufacturing systems enables the gathering of product quality data, in terms of dimensions and geometry, as well as product functionalities. The increased use of digital models as kernel to choose control actions in feedback and feedforward quality control loops poses significant challenges when the system-level perspective is considered. Hence, a change of paradigm is needed in manufacturing systems configuration and reconfiguration, in order to allocate inspection stations with a control-driven perspective, i.e. by accounting for the efficacy of the quality control loops enabled by the use of digital models as controller. In this work, the feedback and feedforward quality control loops are formalized with respect to the controller's performance of the decision model in terms of precision and accuracy, then, linked to the system dynamics to evaluate the system steady-state performance. The case study demonstrates that using the proposed method enhances the awareness in allocating inspection stations, and poses concrete targets for the use of controllers based on quality predictions models. Limitations to the applicability regard the challenges in the accuracy characterization of the digital models, as well as in the causal identification of quality control loops based on available process and product information. Future developments relate to strengthen even more the relationship between process models and system dynamics, in order to ease the model-based control at system level. Possible applications could include the use of the proposed approach to define the training dataset for prediction models, in order to reach the target accuracy to maximize the production performance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Maria Chiara Magnanini: Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Ozan Demir:** Writing – review & editing, Visualization, Validation, Software, Investigation. **Marcello Colledani:** Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Tullio Tolio:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

References

[1] Franciosa P, Sokolov M, Sinha S, Sun T, Ceglarek D (2020) Deep Learning Enhanced Digital Twin For Closed-Loop In-Process Quality Improvement. *CIRP Annals* 69(1):369–372.
[2] Jin X, Shui H, Shpitalni M (2019) Virtual Sensing And Virtual Metrology For Spatial Error Monitoring Of Roll-To-Roll Manufacturing Systems. *CIRP Annals* 68(1):491–494.
[3] Colledani M, Tolio T, Fischer A, Iung B, Lanza G, Schmitt R, Váncza J (2014) Design And Management Of Manufacturing Systems For Production Quality. *CIRP Annals* 63(2):773–796.
[4] Wagner R, Haefner B, Biehler M, Lanza G (2020) Digital DNA In Quality Control Cycles Of High-Precision Products. *CIRP Annals* 69(1):373–376.
[5] Izquierdo L-E, Shi J, Hu S-J, Wampler C-W (2007) Feedforward Control Of Multistage Assembly Processes Using Programmable Tooling. *Transactions of NAMRI/SME* 35:295–302.
[6] Yue X, Shi J (2018) Surrogate Model–Based Optimal Feedforward Control For Dimensional-Variation Reduction In Composite Parts' Assembly Processes. *Journal of Quality Technology* 50(3):279–289.
[7] Djurdjanović D, Haq A-U, Magnanini M-C, Majstorović V (2019) Robust Model-Based Control Of Multistage Manufacturing Processes. *CIRP Annals* 68(1):479–482.
[8] Huang J, Zhang J, Chang Q, Gao R-X (2021) Integrated Process-System Modelling And Control Through Graph Neural Network And Reinforcement Learning. *CIRP Annals* 70(1):377–380.
[9] Colledani M, Tolio T (2006) Impact Of Quality Control On Production System Performance. *CIRP Annals* 55(1):453–456.
[10] Lanza G, Haefner B, Kraemer A (2015) Optimization Of Selective Assembly And Adaptive Manufacturing By Means Of Cyber-Physical System Based Matching. *CIRP Annals* 64(1):399–402.
[11] Demir O-E, Magnanini M-C, Colledani M, Hemyari D (2023) Reconfiguration of Quality Gates Based on Part Variation Modes in Multi-stage Manufacturing Systems. In: *Proceedings of the Changeable, Agile, Reconfigurable and Virtual Production Conference and the World Mass Customization & Personalization Conference*, Springer International Publishing, Cham, 247–254.
[12] Weimer D, Scholz-Reiter B, Shpitalni M (2016) Design Of Deep Convolutional Neural Network Architectures For Automated Feature Extraction In Industrial Inspection. *CIRP Annals* 65(1):417–420.
[13] Thiede S, Turetskyy A, Kwade A, Kara S, Herrmann C (2019) Data Mining In Battery Production Chains Towards Multi-Criterial Quality Prediction. *CIRP Annals* 68(1):463–466.
[14] Ferhat M, Ritou M, Leray P, Le Du N (2021) Incremental Discovery Of New Defects: Application To Screwing Process Monitoring. *CIRP Annals* 70(1):369–372.
[15] Magnanini M-C, Tolio T (2023) A Markovian Model Of Asynchronous Multi-Stage Manufacturing Lines Fabricating Discrete Parts. *Journal of Manufacturing Systems* 68:325–337.
[16] Vazquez C-R, Silva M (2015) Stochastic Hybrid Approximations Of Markovian Petri Nets. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 45(9):1231–1244.