UNIVERSITÀ DI PISA

DIPARTIMENTO DI INGEGNERIA DELL'ENERGIA DEI SISTEMI,

DEL TERRITORIO E DELLE COSTRUZIONI

RELAZIONE PER IL CONSEGUIMENTO DELLA

LAUREA MAGISTRALE IN INGEGNERIA GESTIONALE

Numerical Evaluation of Robustness in Manufacturing Systems

RELATORI

Prof. Ing. Gino Dini

Dipartimento di Ingegneria Civile e Industriale

Dr. Emanuele Pagone

Sustainable Manufacturing Systems Centre, Cranfield University

Dr. Konstantinos Salonitis

Sustainable Manufacturing Systems Centre, Cranfield University

IL CANDIDATO

Ludovico Barsotti

ludovicobarsotti@gmail.com

Sessione di Laurea del 02/10/2019
Anno Accademico 2018/2019
Consultazione non consentita

Sommario

ABSTRACT

Uncertainty affects significantly manufacturing systems both within the plant boundaries and externally. Therefore, many companies simulate their production processes to cope with disturbances and evaluate robustness. Collaborating with an aerospace manufacturing firm, the scope of this thesis is to devise a methodology to evaluate the robustness of a manufacturing system, starting from an already built discrete event simulation (DES) model in Tecnomatix Plant Simulation software. Different scenarios to test the simulation model were established and the confidence interval method was applied to assess key performance indicators (KPI) robustness against different disturbances. To analyse system variability two different Analyses of Variance (ANOVA) were conducted. The first one, between scenarios, evaluated the disturbances effects onto the system, while the latter, within each scenario, compared the dispatching rules. A design of experiment (DOE) analysis was performed to assess disturbances interaction and effect. Finally, a cost model was defined to perform an in-depth comparison between the policies. The analyses pointed out the minimum number of observations to get a robust system in the different operating conditions, the factor with the greatest impact on performances and the best policy to face disturbances allowing a fitted performances improvement.

1 Aim & introduction

The thesis aim is to analyse the robustness of an industrial assembly line with a discrete event simulation (DES) model and analytics tools by comparing the different dispatching rules that could be implemented in the shop-floor and assess the disturbances impact on the system.

Simulation is the imitation of a system which enables to describe its variability, interconnections and complexity (Robinson, 2004) in terms of entities, such as machines, parts and people, on behalf of classical analytical methods that look for an exact solution using variables, unlikely in real environments (Law, 2013). DES allows to test the effect of different scenarios on the key performance indicators (KPIs) to evaluate the system stability providing data to support fact-based decisions.

2 Research methodology

To achieve the thesis aim, the research methodology has been structured in five steps as shown in Figure 1. The starting point has to be defined in detail and knowledge about the topic and widespread approaches acquired. Then the preparation and experimentation phases are necessary to plan and deliver consistent results and data. Finally, the outcome has to be analysed to draw the conclusions.

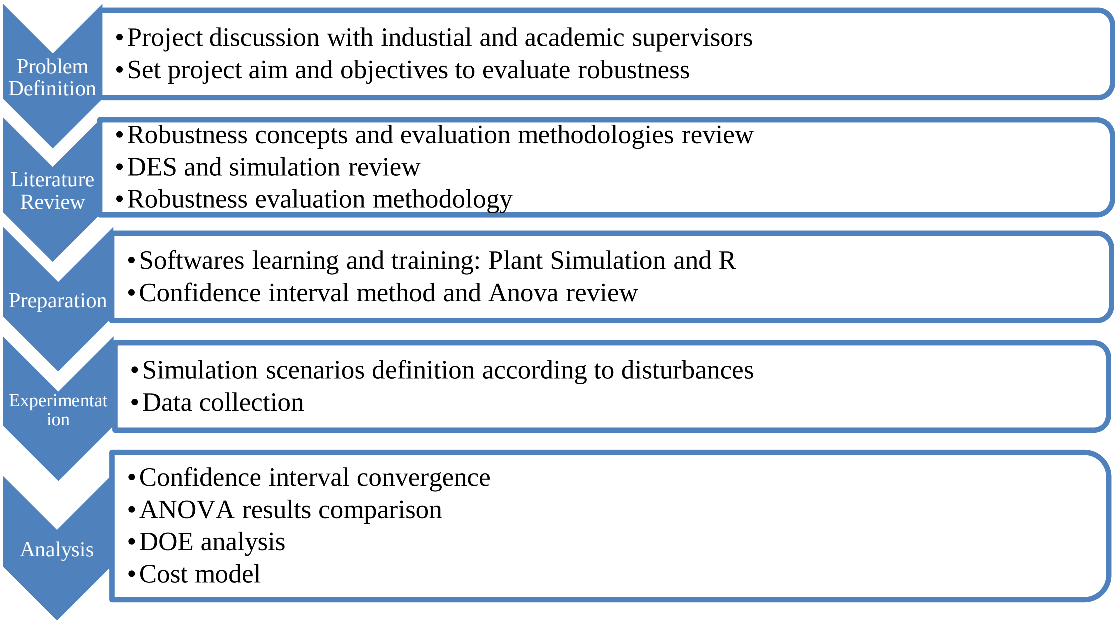

Figure 1 Research methodology step by step

3 Robustness definition and related concepts

Robustness is related to system stability and has to be characterized according to the operating environment and the company. (Alderson and Doyle, 2010) present the most comprehensive definition: “the system, properties, set of perturbations and invariance measure analysed must be set, then a property of a system is robust if it is invariant with respect to a set of perturbations”.

To assess stability, a target function is necessary, hence robustness is usually evaluated against the variation of one or more KPIs in order to have a complete representation of the advancement. (Meyer, Apostu and Windt, 2013) suggest calculating it by comparing the chosen KPI in disturbed conditions against the same in initial or stable conditions (Equation 1).

Equation 1 Robustness formula

$$Robustness = KPI_{dis}/KPI_{in}$$

Efthymiou et al. (2018) propose a stochastic evaluation, considering the different operating conditions *S* and establishing a limit *L* so that robustness is evaluated as the probability that a random variable satisfies Equation 2.

Equation 2 Robustness stochastic formula

$$f(S) \leq L$$

3.1.1 Disturbances

To go further in the dissertation, it is necessary to describe what are the factors that can perturbate the state of a system and classify them according to their origin and influence.

Stricker and Lanza (2014) define a disturbance as an element comprising a cause and an effect, resulting in a significant deviation from the expected result. It can be unforeseen or unintended and has a negative effect on cost, time or quality.

Disturbances can be both internal and external as explained by (Efthymiou et al., 2016) because of the increasing customisation and personalisation required that stresses the whole supply chain and productive system, leading to a lifecycle reduction and data collection increase.

- Internal: result of customers demanding more product variants, so system flexibility and complexity growth are necessary, affecting negatively machines breakdown rate.
- External: companies tend to specialise and supply chains results in intricate networks, furthermore customers' behaviour is always more unpredictable causing demand to be volatile.

4 Research gap and proposed methodology

The aim of this thesis is to analyse system robustness, devising a practical, easily applicable to industrial cases and up-to date with nowadays tools approach (Figure 2).

The real system is represented and tested via a DES model, using theoretical and mathematical ways to enable a concrete evaluation of the KPIs between the different scenarios and within them among the dispatching rules through statistical evidence. Then the robustness of the system has to be defined according to what explained in section 3

An exploration of the different factors that can affect system variability has to be carried out. The final disturbances selection should be done based on the findings and the scenarios experimental design has to follow. Starting from the experimental design, the DES model built in Plant Simulation is used to run multiple scenarios and observations.

First, an analysis of the confidence interval convergence is carried out to evaluate system variability and determine the number of observations to reach the set limit for an appropriate system stability. Then, two ANOVA studies are performed to determine how each disturbance affect the selected KPIs and how the different policies cope with them.

Then, a Design of Experiment analysis based on a full factorial design is performed to confirm the findings and study the disturbances interactions. Finally, a cost model is established to compare thoroughly the dispatching rules and determine the best one.

Manufacturing system definition

- Product routings
- Set up and process times
- Buffers capacity and location
- KPIs
- Discrete event simulation model to represent and test the system

Robustness definition

- Robustness definition: the system, properties, set of perturbations and invariance measure analysed must be set, then a property of a system is robust if it is invariant with respect to a set of perturbations.
- Robustness formula per KPI: $f(S) \leq L$, where *S are* operating conditions and *L* is the limit

Operating Conditions/Scenarios

- Different dispatching rules
- Due dates
- Control policies
- Batch sizes

Disturbances analysis

- Uncertainty types exploration
- Structured questions
- Final selection
- Scenarios selection

Scenarios planning and simulation

- Multiple replications per scenario and dispatching rule using DES software and sensitivity analisis
- KPI data collection and first evaluation
- Multiple replications per scenario and dispatching rule using DES (full factorial DOE)

Data analysis

- Probability estimation through confidence interval method to evaluate robustness
- Anova between and within scenarios to compare the effect of the disturbances onto the system and disptching rules advantages
- Full factorial design of experiment to confirm the results and analyse the disturbances interactions to conclude the process
- Cost model

Figure 2 Proposed methodology to evaluate robustness

5 Material and Methods

In this chapter the devised methodology is applied to an aerospace manufacturing flow line assembling six different part types and the methods constituting it are explained.

5.1 Disturbances analysis

The disturbances analysis is focused on looking for the factors that could alter the production plan. To determine manufacturing system variability, the different kinds of uncertainties that characterise its environment has to be explained in order to define the complexity and the analysis borders. (Graves, 2011), in the fifth chapter, defines the three main uncertainties that arise in a manufacturing system: demand forecast uncertainty, external supply process uncertainty and internal supply process uncertainty.

5.1.1 Scenarios selection

The scenario selection was performed to establish the operating conditions to test and assess the flow line, devising an experimental design. To change processing time variability, the coefficient of variance (Pagone et al., 2019) was selected as variability indicator because it allows to scale up its distribution by comparing the standard deviation with the respective mean (Equation 3). In conclusion, the coefficients of variance were multiplied for a factor (1.2) to scale the distributions (Equation 4).

Equation 3 Coefficient of variance formula

$$c_v = \sigma/\mu$$

Equation 4 Coefficient of variance scaling formula

$$c_{v'} = c_v * f_{ij}$$

5.2 Confidence interval analysis

The aim is to determine the minimum number of observations to reach a set width of the 95% normal confidence interval (CI) on KPIs of interest, mainly lead times and average tardiness. By setting the width of the CI, is possible to evaluate if its variability can be controlled and tends to a steady value, resulting robust among the different dispatching rules implemented over the initial set of 300 replications.

In Table 1 the KPIs recorded from the DES model for this and the following analyses are listed and described.

Table 1 KPIs table

<table>
<tr><th colspan="2">KPI</th><th>Description</th></tr>
<tr><td>LT1 weekly</td><td>LT1 annual</td><td rowspan="6">Mean of the weekly lead times across the year or annual lead times per part type 1,2,3,4,5 and 6.</td></tr>
<tr><td>LT2 weekly</td><td>LT2 annual</td></tr>
<tr><td>LT3 weekly</td><td>LT3 annual</td></tr>
<tr><td>LT4 weekly</td><td>LT4 annual</td></tr>
<tr><td>LT5 weekly</td><td>LT5 annual</td></tr>
<tr><td>LT6 weekly</td><td>LT6 annual</td></tr>
<tr><td>AvgLT</td><td></td><td>Mean of the lead times of all the parts that go through the model over the year.</td></tr>
<tr><td>Cumulative tardiness</td><td>Avgtardiness</td><td>Annual sum or average of part types tardiness.</td></tr>
</table>

5.3 ANOVA, full factorial DOE analyses and cost model

5.3.1 ANOVA analyses

To analyse the system variability and provide reliable statistics to improve robustness two different ANOVA have been conducted. The first one, between scenarios evaluates the disturbances effects onto the system, while the latter, within each scenario, aims at determining the best dispatching rule to cope with the disturbances themselves.

The number of observations per policy and scenario γ used was the minimum number from the confidence interval analysis as the system demonstrated to be robust with this number.

5.3.2 **DOE analysis**

A full factorial DOE analyses was carried out to compare the scenarios, confirm the disturbances main effects on the KPIs from the previous analyses and investigate possible interactions among the disturbances themselves to adapt the analysis based on the results.

The observations number per policy was set to γ from the confidence interval analysis to get a robust system, obtaining a total of *3*γ* observations per scenario encompassing the three dispatching rules: first in first out (FIFO), shortest processing time (SPT) and earliest due date (EDD). The coefficient of variance was used to distinguish between high and low level.

5.3.3 **Cost model**

The following cost model was devised to compare thoroughly EDD and FIFO policies and evaluate if a shift to the latter could be convenient. The most turbulent operating conditions were assumed as benchmark: scenario 1_1_1.2 where rework likelihood disturbance is set at maximum level using γ replications per policy. To compare the policies deeply all the part types were considered concerning tardiness and lead times apart from average indicators.

The model assumes the adoption of EDD, is comparative and is structured on five basic elements:
1. Manual work and electricity reduction costs;
2. Material holding costs reduction;
3. Penalty opportunity costs advantage;
4. Cost to implement the EDD option;
5. Throughput possible increase, hence capacity.

The procedure for the analyses is shown in Figure 3.

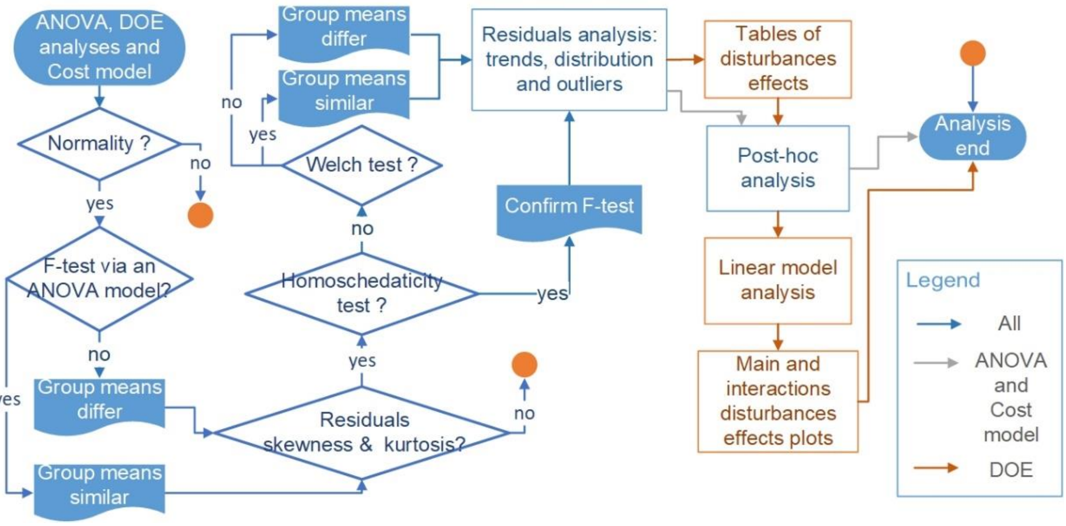

Figure 3 ANOVA, DOE analyses and cost model procedures

6 Results and discussion

The following nomenclature was used to refer to scenarios:

S.*i_j_k or scenario i_j_k* where "S." is the abbreviation for scenario and *i, j,* and *k* represent the disturbances levels of the scenario itself with the element "_" used to distinguish them.

6.1 Disturbances analysis results

The main disturbances affecting the system are internal and can be summarised in:

- Assembly time variability: variability of process times being the process manual intensive;
- Rework time variability: variability of process time to rework a product;
- Rework likelihood: variability of occurrence of a rework to happen.

6.1.1 Final experimental design

The coefficients of variance were then multiplied for a factor to scale the distributions and depict new possible scenarios according to Equation 4, devising a one time at factor design on two levels, the normal value of 1 and the scaled value of 1.2.

6.2 Confidence interval analysis

To be robust against the different set of disturbances the system has to be run for at least 280 (γ) observations with the set thresholds of 0.01 for the lead times KPIs and 0.02 for the tardiness ones (limits L for the KPIs).

The indicators that gathers more variability are the annual lead times as they demand more observations compared to the weekly ones across all the scenarios. Consequently, the KPIs reductions in the ANOVA analyses regarded the weekly lead times, focusing only on the annual ones for part types 1,2 and 3.

6.3 ANOVA between scenarios

It can be stated that assembly time variability does not have any effect onto the system, rework time variability a little one and rework likelihood the greatest as showed in Table 2, according to Equation 5:

Equation 5 Relative error formula

$$KPI\ relative\ error = {KPI\ scenarios\ means\ difference}\Big/_{KPI\ Base\ Scenario\ mean}$$

Table 2 Scenarios errors

Scenarios comparisons	LT1annual	LT2annual	LT3annual	AvgLT	Avgtardines
S.1.2_1_1-S.1_1_1	0.01%	0.40%	-0.27%	0.06%	0.85%
S.1_1_1.2-S.1_1_1	17.82%	19.84%	15.03%	18.01%	48.14%

S.1_1.2_1-S.1_1_1	2.14%	2.71%	1.81%	2.23%	6.34%

Scenario 1_1_1.2 is the one causing the system to vary the most, therefore rework likelihood is the factor to focus on to improve robustness, system efficiency and enable the line to meet due dates promptly.

6.4 ANOVA within each scenario

In the following section the dispatching rules are compared, reporting the relative errors per KPI and dispatching rule comparison with FIFO rule, the benchmark one currently used. The formula used for the error is reported in Equation 6. Only the results concerning the most turbulent condition, scenario 1_1_1.2 are reported.

Equation 6 Relative error policy formula

$$\text{Relative error} = \text{ Difference between selected policy and FIFO } / \text{KPI mean according to FIFO policy}$$

Table 3 Legend for Table 4

	Legend
(red)	indicates errors higher than the 5% threshold
(green)	Indicates negative errors

Table 4 Error table scenario 1_1_1.2

Policies comparison	LT1annual	LT2annual	LT3annual	AvgLT	Avgtardiness
SPT-FIFO	*5.26%*	*4.99%*	*7.96%*	*4.91%*	*2.44%*
EDD-FIFO	*-2.28%*	*-3.01%*	*1.60%*	*-0.62%*	*1.11%*

From Table 4 is noticeable that SPT performs worse than FIFO, going very close or exceeding the set 5% error threshold for all the KPIs except for Avgtardiness. On the other hand, EDD occurs to be better compared to FIFO for all the indicators but LT3annual returning good improvements for LT1annual and LT2annual respectively. Similar results concerning the policies comparison were obtained for the remaining scenarios.

SPT is not the policy to adopt as it returns worse results compared to FIFO, usually for all the KPIs. On the other hand, EDD results to be always the best policy for “LT1annual”, “LT2annual” and returns similar values in all the scenarios concerning “AvgLT” and “Avgtardiness” compared to FIFO.

6.5 Full factorial Design of Experiment analysis

Considering 280 replications per policy averaged every 7 samples (*k* set to 7), 120 points were obtained. The final dataset to perform the analysis per KPI was consequently composed of 960 data, considering the 8 scenarios and 3 disturbances factors, enabling the disturbances main effects and disturbances interactions effects on the single KPI assessment.

6.5.1 Effects estimation

The main effects results are reported in the first three rows of Table 5 according to Equation 7.

Equation 7 Disturbances percentage effect formula

$$Percentage\ effect = Total\ effect\ on\ KPI/KPI\ mean\ across\ all\ the\ scenarios$$

Assembly time variability doesn't have any effect on any KPI, most of its p-values are higher than the 0.05 threshold and the one that is lower has a negligible effect on "Avgtardiness". Rework time variability has always some effect on all the KPIs, but this are lower than 3% except for "Avgtardiness" for which it accounts for 5.72%. It is evident that rework likelihood has a huge impact on all the KPIs as its p-values are zero and effects range from 14% to almost 18% concerning lead times indicators and up to 38% for "Avgtardiness".

The interaction effects results are reported in Table 5 rows from the fourth till the last one. It can be stated that no relevant interactions are present between the disturbances.

Table 5 Main and interaction effect

Disturbance \ KPI		LT1annual	LT2annual	LT3annual	AvgLT	Avgtardiness
Assembly time variability	*P-value*	0.666	0.316	0.178	0.92	0.027
	Effect %	0.11%	0.27%	-0.34%	0.02%	0.67%
Rework time variability	*P-value*	2.00E-16	2.00E-16	3.14E-15	2.00E-16	2.00E-16
	Effect %	2.49%	2.51%	2.02%	2.39%	5.72%
Rework likelihood	*P-value*	2.00E-16	2.00E-16	2.00E-16	2.00E-16	2.00E-16
	Effect %	16.79%	17.75%	14.12%	16.68%	38.31%
Assembly time variability: Rework likelihood	*P-value*	0.737	0.747	0.742	0.866	0.949
	Effect %	0.09%	-0.09%	-0.08%	-0.04%	-0.02%
Assembly time variability: Rework time variability	*P-value*	0.98	0.953	0.952	0.998	0.975
	Effect %	0.01%	0.02%	-0.02%	0.00%	0.01%
Rework time variability: Rework likelihood	*P-value*	0.035	0.727	0.152	0.088	0.014
	Effect %	0.54%	0.09%	0.36%	0.36%	0.75%
Assembly time variability: Rework time variability: Rework likelihood	*P-value*	0.971	0.937	0.989	0.989	0.955
	Effect %	-0.01%	0.02%	0.00%	0.00%	-0.02%

Rework likelihood resulted to have the main effect on the KPIs, rework time variability a little one while assembly time variability a negligible one. The conclusions drawn from the ANOVA analysis have been confirmed regarding the factors with greater impact.

The DOE analysis was conducted as full factorial to investigate any possible interaction between the disturbances, finding out that no relationship stands and confirming that the focus of a possible strategy should be mainly on rework likelihood disturbance.

Being the line complex and parts lead times very high it is reasonable that every part reinserted into the system for rework stresses it, increasing variability. Out of the ordinary is the proportion between assembly time variability effect, being the line manual intensive, that is null and rework likelihood one, that is huge.

6.6 **Cost model**

The devised cost model enables a saving of 5456 hours, a reduction of parts late delivery of 50, a general decrease of 0.6% of productive lead time and assuming data from literature, for an amount of 40 engineering working hours a benefit of about 100 k£ (Table 6).

Considering Little's LAW: WIP= TH*LT, a capacity increase of the same percentage of average lead time decrease can enable the system to be more robust against disturbances or customer order variations.

Table 6 Cost model summary

EDD benefits over FIFO	**Hrs saved**	**Parts late difference**	**Software engineer hrs required for EDD**	**Average LT decrease**	**Total monetary benefit (£)**
Values	5456	50	40	0.6%	101486

7 Conclusions

A manufacturing system robustness evaluation methodology was devised and applied to the proposed case study. A robustness assessment was performed examining the system behaviour over replications under different operating conditions by mean of specific variability analyses, aimed at identifying the disturbances impact, interactions and the best dispatching rule to cope with them to find the suitable configuration to improve performances.

To conclude:

• Efthymiou et al. (2018) robustness definition proved to be useful, setting thresholds for the KPIs and performing a confidence interval analysis, determining 280 as minimum observations number for the system to be robust.

• ANOVA and DOE analyses proved to be suitable tools to compare different operating conditions and dispatching rules, understanding negligibility of assembly time variability and FIFO and EDD comparability while SPT demonstrated the worst policy;

• A standardised methodology to evaluate robustness was devised and applied to an industrial case study, determining rework likelihood as greatest disturbance, affecting lead times for a maximum of 17.75% and tardiness for 38.31%;

• A specific cost model was devised to prove economic and performance efficiency of policies, determining that EDD implementation could save almost 100 k£.

REFERENCES

Alderson, D.L., Doyle, J.C., 2010. Contrasting views of complexity and their implications for network-centric infrastructures. IEEE Trans. Syst. Man, Cybern. Part ASystems Humans 40, 839–852.

Efthymiou, K., Mourtzis, D., Pagoropoulos, A., Papakostas, N., Chryssolouris, G., 2016. Manufacturing systems complexity analysis methods review. Int. J. Comput. Integr. Manuf. 29, 1025–1044.

Efthymiou, K., Shelbourne, B., Greenhough, M., Turner, C., 2018. Evaluating manufacturing systems robustness: An aerospace case study. In: Procedia CIRP. Elsevier B.V., pp. 653–658.

Graves, S.C., 2011. Uncertainty and production planning. Int. Ser. Oper. Res. Manag. Sci. 151, 83–101.

Law, A.M., 2013. Simulation Modeling and Analysis, 5th edn. ed, Simulation Modeling and Analysis. McGraw-Hill Education, Tucson, Arizona, USA.

Meyer, M., Apostu, M.V., Windt, K., 2013. Analyzing the influence of capacity adjustments on performance robustness in dynamic job-shop environments. In: Procedia CIRP. Elsevier B.V., pp. 449–454.

Pagone, E., Efthymiou, K., Mahoney, B., Salonitis, K., 2019. The effect of operational policies on production systems robustness: an aerospace case study. In: Procedia CIRP. Elsevier B.V., pp. 1337–1341.

Robinson, S., 2004. Simulation: the practice of model development and use, 1st edn. ed. Wiley, Chichester, Eng. ; Hoboken, N.J.

Stricker, N., Lanza, G., 2014. The concept of robustness in production systems and its correlation to disturbances. In: Procedia CIRP. Elsevier B.V., pp. 87–92.