Integrated mathematical model for scheduling and rebalancing configuring the production systems

Deliverable 5.4

MUWO

MULTI-METHOD WORKSPACE FOR HIGHLY SCALABLE PRODUCTION LINES

Project identifier	MUWO
Project title	Multi-method workspace for highly scalable production lines
Document version	1.0
Planned delivery date	M36 (December 2023)
Actual delivery date	M30 (July 2023)
Document title	Integrated mathematical model for scheduling and rebalancing configuring the production systems
Work Package	WP 5
Abstract	This document outlines the development of the algorithms designed to optimize production, predict product quality, and enhance efficiency with industry applications.
Keywords	Enhanced Production Scheduling Algorithm, Manufacturing Optimization, Predictive Quality, Textile Industry, Real-time Production, Predictive Maintenance, Energy Efficiency, Profitability, Flexibility, Use Case Analysis

Function	Name	Entity
Author	Ricardo Martins	SISTRADE
Editors	Irene Torrego	Accuro
Contributors	Fábio Coelho	SISTRADE
	Filipe Correia	
	Ricardo Martins	
	Bruno Mota	ISEP
	Pedro Faria	
	Carlos Ramos	
	Irene Torrego	Accuro
	Iván Hernández	
Reviewer		

Executive summary

This document outlines de integration of mathematical models for scheduling, predictive quality, and predictive maintenance. The algorithms aim to leverage increase production and equipment flexibility, optimizing production across different lifecycles phases and distributed facilities while enhancing delivery time, equipment balance, energy efficiency, and profitability.

Partner contributions record

#	Entity	Contributor on Phase 1	Date of Contribution1	Contributor on Phase 2	Date of Contribution2
1	Accuro	X	23/06/2023		
2	ACD	X			
3	Alpata	X			
4	Evosoft				
5	Hefona				
6	Inovasyon	X			
7	ISEP	X	21/06/2023		
8	Progim				
9	SisTrade	X	15/05/2023		

Changes record

Version	Date	Entity	Description of Changes
V0.1	22/11/2022	Sistrade	Creation of document template, initial contributions
V0.2	15/05/2023	Sistrade	Added predictive quality analysis
V0.3	21/06/2023	ISEP	ISEP contributions to mathematical models for production line optimization and production scheduling reconfiguration
V0.4	23/06/2023	ACCURO	New information about the mathematical model used for production planning in Albero.
V1.0	31/07/2023	ACCURO	Final editing and formatting.

Contents

List of Figures

List of Tables

1. Introduction

1.1. Document objectives and scope

This document aims to provide information regarding the several stages involved in the development of the Enhanced Production Scheduling Algorithm capable of reacting in near real-time to production demand changes. Briefly, this algorithm must be capable of exploiting the improved production equipment flexibility provided by Muwo, optimizing production of a complex product mix within different lifecycle phases in one or several distributed production facilities, and optimizing delivery time, equipment and line balance, energy efficiency, and profitability.

1.2. Document structure

This document is organized into six distinct sections, the first one is the Introduction, and the last one is a summary of the Conclusions regarding the work developed in ***Task T5.4 Enhanced production scheduling algorithm***. Similarly to previous reports, the four intermediate sections respect the work conducted by the partners in each Use Case individually, on the scope of the development of scheduling and rebalancing configuring the production systems model. In the following paragraphs, a brief overview of each Use Case Section is presented.

Section 2 respects the work of UC1 regarding the development and implementation of a Smart Manufacturing for Planning (SMP) in IDEPA, a textile manufacturing industry based in Portugal. Briefly, this section is organized into three main subsections including: 1) Predictive Quality; 2) Predictive Maintenance; and 3) Scheduling Optimization.

Section 3 is focused on UC2 (Turkey) which main purpose of this use case is to operate GTF Rotor cell, that produces 45 different parts with 4 Cnc machines with minimal loss. This section is subdivided into: Simulated Annealing, Genetic algorithm and Models for Master Production Scheduling.

Section 4 is focused on ALBERO's Use Case (UC3, Spain), in this UC a trained Deep Q-Learning agent will be used to assign priorities based on the criteria selected by the Spanish SME. This section is subdivided into: Reinforcement learning and Q-Learning agents.

2. UC1 – IDEPA Use Case (Portugal)

The PT Use Case respects the development and implementation of a Smart Manufacturing for Planning (SMP) in a textile manufacturing industry based in Portugal. In the scope of this demonstrator, it was necessary to combine the requirements of the textile industry with the already established processes of the third party involved in this pilot (IDEPA company).

From a general perspective, the developments of the IDEPA Use Case rely upon 4 main topics: i) Predictive Quality, ii) Predictive Maintenance, iii) Scheduling Optimization, and iv) Sensor Forecasting, which details are presented in the following subsections.

2.1. Predictive Quality

The predictive quality module consists of anticipating and forecasting product quality outcomes based on existing historical data. For IDEPA Use Case, the predictive quality section was divided into three main subsections, including: 1) subsection contextualization; 2) Quality historical analysis, 3) prediction Quality Modelling. For each one of these subsections, short specific assumptions and use case assumptions used to conduct statistical, and analysis and modeling are presented.

The statistical analysis was conducted using JASP (Version 0.16.4), [Computer software], JASP Team (2022), and the statistical significance was established for $\alpha = 0.05$.

2.1.1. Sub-section Contextualization

2.1.1.1. Definition of Quality

The quality of a product is directly related to the degree to which a product meets the established requirements, specifications, or standards that satisfy both the manufacturer and the customer. For IDEPA, it is a fundamental concept and a key factor for its success in the competitiveness of the textile market. In the context of predictive quality, the definition of quality pertains specifically to the characteristics and attributes of products being produced or manufactured. These characteristics can be both tangible and intangible, encompassing physical features, performance, reliability, durability, and customer satisfaction.

For the IDEPA use case, the analysis of products' quality involves anticipating and forecasting quality outcomes based on historical data. The quality assessment process involves various statistical and analytical techniques to identify patterns, trends, and associations between production processes and product quality. This information is then used to make data-driven decisions, optimize production processes, and ensure that products consistently meet or exceed the desired quality standards.

2.1.1.2. Conformity and Non-conformity Products

To ensure IDEPA maintains its quality brand, IDEPA has a very strict policy to identify nonconformities in its products. When the product fails to meet one or more of the required specifications, standards, or expectations, they are considered defective or substandard and do not meet the intended purpose or use (see Figure 1 for examples of non-conformities). This defective product is inserted in the ERP, in kilograms, and either is returned to the client, or it is disposed of as garbage. When the product meets all the specified requirements, standards, and expectations, it is deemed as conform and it is inserted in the ERP, in kilograms.

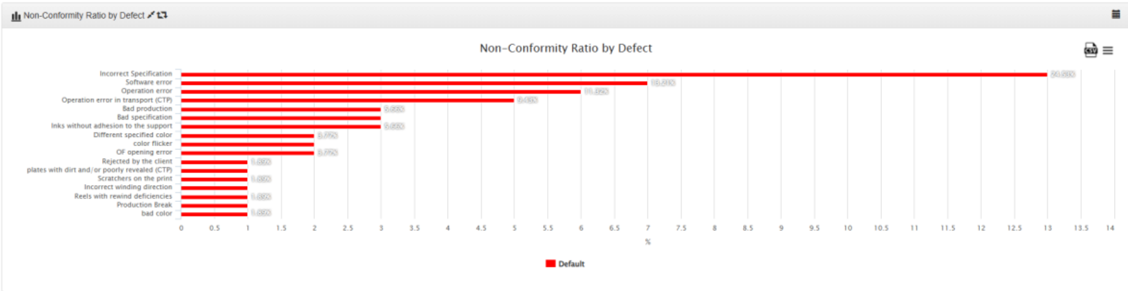


Figure 1 - Non-conformity ratio by defect

2.1.1.3. A Cycle of Quality Evaluation: Use Case Assumptions

IDEPA utilizes a combination of human expertise and artificial intelligence to ensure the highest standards of quality in its textile manufacturing operations. The computer vision algorithms integrated into the looms are designed to identify any deviations or defects in the produced textiles or the weaving patterns. After all quality checks during production, a human final quality control allows us to decide on sending the product to the client or re-manufacturing the product order if any requirement or specification are not met.

During the COVID-19 outbreak, IDEPA took advantage of the reduced production activity to update its facilities by replacing some of its looms with more modern equipment. This was precisely the case with the instrumented looms used in the MUWO project (i.e., loom 9, loom 10, loom 11, and loom 12). Therefore, to understand the past production patterns and unravel the new trends, it was decided to analyze the quality of the production processes at two different moments:

- M1, covering the period between 01-01-2019 and 31-05-2022 (production with older looms);
- And M2, from 01-01-2023 to 31-05-2023, in which the production processes were already carried out with the new looms instrumented in the context of the MUWO project.

2.1.2. Quality Historical Analysis

The quality historical analysis was made considering the data available at SISTRADE ERP. The data retrieved included the ***production order***, ***resources used***, ***quantity to be produced***, ***the quantity of conform and non-conform products,*** **and** ***articles*** to be produced. Notably, the analysis was conducted considering the production orders associated with the 4 instrumented looms of the MUWO project, as well as the previous looms replaced by those. As a way of associating product quality with individual loom's production, it was only considered product orders in which the main production has occurred exclusively in one of MUWO looms, with a minimum of 2 entries. Therefore, thin the following subsections, it was considered the following historical data:

Table 1 - IDEPA Use case product orders in M1 and M2.

ERP Code	Product ERP Name (IDEPA)	Product Description	N_{M1}	N_{M2}
1111	ETIQUETA TECIDA OURELA CORTADA	Woven Edge Cut Label	982	131
1112	ETIQUETA TUBULAR	Tubular Label	70	17
1121	GALÃO OURELA CORTADA	Woven Edge Cut Stripe	73	2
1122	GALÃO TUBULAR	Tubular Stripe	5	5
1140	EMBLEMA	Emblem	473	7

2.1.2.1. Product Quality Analysis: M1 – Historical Data

The general descriptive statistics of production in M1 are presented in Table 2.

Table 2 - Descriptive statistics general product quality M1

	Produced qty.	Rejected qty.	Conformity ratio
Valid	1603	1603	1603
Missing	0	0	0
Mean	101.650	90.778	0.680
Std. Deviation	665.934	655.167	0.333
Minimum	0.220	0.000	0.003
Maximum	11000.000	10931.610	1.000
25th percentile	1.500	0.000	0.427
50th percentile	5.400	0.500	0.776
75th percentile	13.000	1.910	1.000
Sum	162944.165	145517.440	

As shown in the previous table, there were 1603 entries or production orders, registered between 01-01-2019 and 31-05-2022. As it's possible to observe, there is high heterogeneity in produced quantities (per production order) with minimum values ranging from 0.220 kilograms to more than 11.000 kilograms. A better picture of quantities distribution is provided by the percentiles distribution which registered respectively 1.5, 5.4, and 13 kilograms. When looking at the rejected quantities it is also possible to observe an extremely high maximum value (10931.61 kg). Notably, this maximum value seems to be a production order that possibly fails to meet one of its initial client specifications, and, thus, results in a massive nonconformity rate.

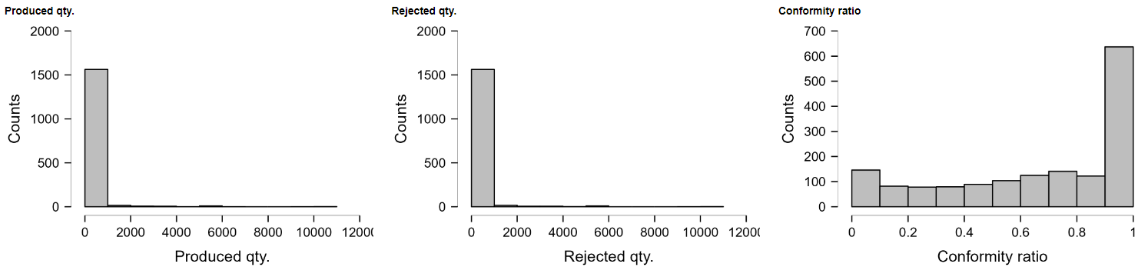


Figure 2 - General distribution by production order: (left) – quantity produced; (middle) - quantity rejected; (right) – conformity ratio

When looking at the distribution plots present in **¡Error! No se encuentra el origen de la referencia.** (*left*), it's possible to observe that most production orders are focused on quantities below 1000 kg. Similarly, and as expected, the same pattern is observed when considering the rejected quantities (*middle*). Finally, (*on the right*) it's possible to observe the distribution of the conformity ratio. Herein it's possible to observe that more than 600 production orders had a conformity ratio between 90% and 100%, but there were also several entries in which the conformity ratios were above 50%.

Considering the previous results, an additional analysis by type of product manufactured was conducted to understand if there is any pattern associated with lower conformity ratios. The descriptive statistics for the produced quantity and conformity ratio are presented in the following tables:

Table 3 - Descriptive statistics of quantity produced per product type (M1).

	Produced qty.				
	1111 Woven Edge Cut Label	1112 Tubular Label	1121 Woven Edge Cut Stripe	1122 Tubular Stripe	1140 Emblem
Valid	982	70	73	5	473
Missing	0	0	0	0	0
Mean	16.986	5.105	1983.562	5.800	2.279
Std. Deviation	31.308	10.736	2467.895	1.095	3.385
Minimum	0.500	0.220	5.000	5.000	0.700
Maximum	650.000	55.000	11000.000	7.000	53.000
25th percentile	3.800	0.700	330.000	5.000	1.350
50th percentile	7.350	1.300	1050.000	5.000	1.350
75th percentile	20.000	3.900	2600.000	7.000	2.350
Sum	16680.010	357.380	144800.000	29.000	1077.775

Table 4 - Descriptive statistics of conformity ratio per product type (M1).

	Conformity Ratio				
	1111 Woven Edge Cut Label	**1112** Tubular Label	**1121** Woven Edge Cut Stripe	**1122** Tubular Stripe	**1140** Emblem
Valid	982	70	73	5	473
Missing	0	0	0	0	0
Mean	0.737	0.626	0.065	0.350	0.668
Std. Deviation	0.299	0.331	0.179	0.381	0.318
Minimum	0.003	0.013	0.006	0.026	0.007
Maximum	1.000	1.000	1.000	1.000	1.000
25th percentile	0.536	0.368	0.018	0.154	0.400
50th percentile	0.834	0.701	0.021	0.236	0.777
75th percentile	1.000	0.981	0.033	0.333	0.978

As depicted in Table 4, there are two products with mean conformity ratios below 40%, whereas the other 3 products demonstrate conformity ratios superior to 60%. As a way of confirming that these differences are statistically significant, as well as to unravel other possible insights, it was decided to conduct an ANOVA analysis. Before the ANOVA, the equality of variances was tested by Levene's test. Levene's test showed that the variances for conformity ratio were not equal, F (4,1598) = 27.544, p < .001; thus, the homogeneity correction was made considering Welch's test. Besides this, the Q-Q plot of residuals was also analyzed, verifying that the normality assumption is met. The results of the analysis of variance are presented in the table below:

Table 5 - ANOVA for conformity ratio considering product type factor (M1).

ANOVA - Conformity ratio

Homogeneity Correction	Cases	Sum of Squares	df	Mean Square	F	p	η²
Welch	Product Type	31.657	4.000	7.914	202.836	< .001	0.178
	Residuals	145.839	29.130	5.007			

Note. Type III Sum of Squares

Results show that there were statistically significant differences between group means of conformity ratio as determined by one-way ANOVA [F (4,29.130) = 202.836, p < .001)]. Notably, the effect size (η^2) demonstrates that around 18% of conformity ratio variability is explained by the type of textile product manufactured.

As a way of unraveling which groups these difference residuals Games-Howell Post Hoc analysis was also conducted.

Table 6 - Games-Howell Post Hoc Comparisons on conformity ratios (M1)

Games-Howell Post Hoc Comparisons - Product Type

		95% CI for Mean Difference					
Comparison	Mean Difference	Lower	Upper	SE	t	df	p_{tukey}
1111 - 1112	0.111	−0.002	0.225	0.041	2.735	77.238	0.058
1111 - 1121	0.672	0.609	0.736	0.023	29.272	104.793	< .001***
1111 - 1122	0.388	−0.368	1.143	0.170	2.274	4.025	0.311
1111 - 1140	0.070	0.022	0.117	0.017	3.989	881.718	< .001***
1112 - 1121	0.561	0.437	0.685	0.045	12.542	105.042	< .001***
1112 - 1122	0.276	−0.461	1.014	0.175	1.582	4.443	0.567
1112 - 1140	−0.042	−0.159	0.076	0.042	−0.987	88.930	0.861
1121 - 1122	−0.285	−1.035	0.466	0.171	−1.660	4.121	0.535
1121 - 1140	−0.603	−0.673	−0.532	0.026	−23.626	154.263	< .001***
1122 - 1140	−0.318	−1.072	0.436	0.171	−1.862	4.059	0.451

*** $p < .001$

Note. Results based on uncorrected means.

As shown in **¡Error! No se encuentra el origen de la referencia.**, there were found significant statistical differences among groups (see *p*-values above .05). Indeed, Post Hoc testing revealed significant differences with Woven Edge Cut Stripe (1121) [*M* = 0.065, *SD* = 0.179] having lower conformity ratios than Woven Edge Cut Label (1111) [*M* = 0.737, *SD* = 0.299], Tubular Label (1112) [*M* = 0.626, *SD* = 0.331], and Emblem (1140) [*M* = 0.668, *SD* = 0.318]. Notably, no conclusions can be retrieved from comparisons with Tubular Stripe (1122) [*M* = 0.350, *SD* = 0.179] due to the high variability in data. Finally, although there is a significant difference between the Woven Edge Cut Label (1111) [*M* = 0.737, *SD* = 0.299] and Tubular Label (1112) [*M* = 0.626, *SD* = 0.331], this is justified by the high number of observations as well as by the heterogeneity of data in each group, with the small the mean difference observed (i.e., 0.070) does justify further data exploration. For easy interpretation of results, a graphical representation of the previous conclusion is also presented in the distribution mean plot of Figure 3.

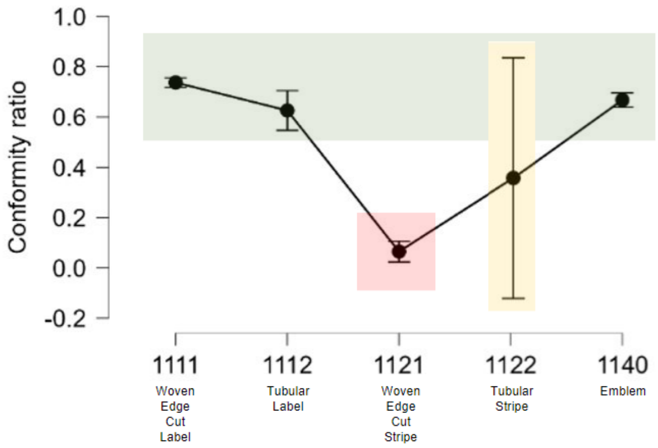


Figure 3 - Conformity ratio means distribution by textile product manufactured (M1)

2.1.2.2. Product Quality Analysis: M2 – Current Data

As described in the introductory section, IDEPA looms were replaced during covid-19 outbreak. Therefore, this section embraces the same analysis conducted in the previous subsection but considers the new equipment installed.

Firstly, the general descriptive statistics regarding production quality analysis were conducted. Then, an analysis of variance regarding product type was computed, and final post hoc analyses were considered to unravel further conclusions.

Table 7 - Descriptive statistics general product quality M2

Descriptive Statistics

	Produced qty.	Rejected qty.	Conformity ratio
Valid	162	162	162
Missing	0	0	0
Mean	47.338	39.612	0.697
Std. Deviation	247.114	241.356	0.306
Minimum	0.500	0.000	0.017
Maximum	2750.000	2678.470	1.000
25th percentile	3.000	0.000	0.501
50th percentile	7.000	0.700	0.754
75th percentile	11.000	3.125	1.000
Sum	7668.800	6417.170	

As presented in Table 7, there were 162 production orders registered between 01-01-2023 and 31-05-2023. Notably, it was also observed high heterogeneity in quantities produced and rejected, maintaining the similar pattern observed in M1.

When looking at the distribution plots of Figure 4, similar patterns are observed compared to M1, but it is denoted that most of the production orders comprise now orders below 500 kg, which is in line with the previously stated change in customer behaviors (and consequently client orders).

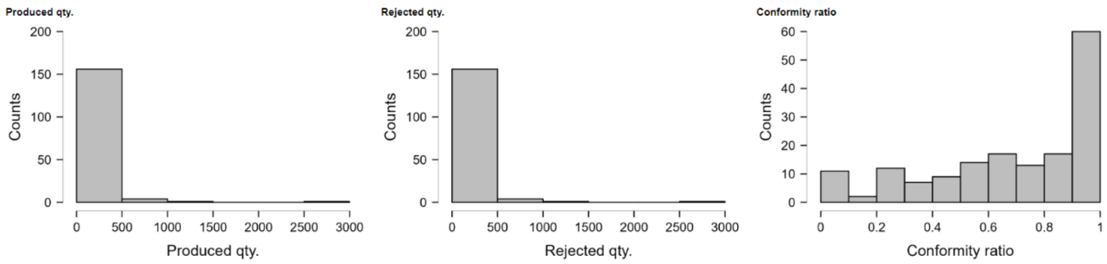


Figure 4 - General distribution by production order (M2): (left) – quantity produced; (middle) - quantity rejected; (right) – conformity ratio

When conducting the descriptive statistics for the produced quantity and conformity ratio, Table 8 and Table 9 were obtained:

Table 8 - Descriptive statistics of quantity produced per product type (M2).

	Produced qty.				
	1111 Woven Edge Cut Label	1112 Tubular Label	1121 Woven Edge Cut Stripe	1122 Tubular Stripe	1140 Emblem
Valid	131	17	2	5	7
Missing	0	0	0	0	0
Mean	9.698	2.947	1925.000	491.000	6.186
Std. Deviation	10.842	5.102	1166.726	216.864	3.313
Minimum	1.000	0.500	1100.000	105.000	1.300
Maximum	82.000	19.000	2750.000	600.000	11.000
25th percentile	3.000	0.600	1512.500	550.000	4.500
50th percentile	7.000	0.600	1925.000	600.000	6.000
75th percentile	11.000	2.100	2337.500	600.000	8.000
Sum	1270.400	50.100	3850.000	2455.000	43.300

Table 9 - Descriptive statistics of conformity ratio per product type (M2).

	Conformity Ratio				
	1111 Woven Edge Cut Label	1112 Tubular Label	1121 Woven Edge Cut Stripe	1122 Tubular Stripe	1140 Emblem
Valid	131	17	2	5	7
Missing	0	0	0	0	0
Mean	0.741	0.595	0.030	0.024	0.789
Std. Deviation	0.271	0.321	0.006	0.004	0.208
Minimum	0.036	0.017	0.026	0.018	0.535
Maximum	1.000	1.000	0.034	0.028	1.000
25th percentile	0.530	0.333	0.028	0.025	0.629
50th percentile	0.837	0.638	0.030	0.026	0.727
75th percentile	1.000	0.833	0.032	0.026	1.000

Herein, and again, it was observed the existence of production orders of products with conformity ratios superior (or rounding) 60%, and production orders of products with conformity ratios almost equal to 0. Considering the differences observed, an ANOVA analysis was also conducted to infer if the variability observed can be explained by the type of product manufactured. Foregoing, the equality of variances was tested and the Levene's test showed that the variances for conformity ratio were not equal, F (4,157) = 4.787, p = .001; thus, the homogeneity correction was made considering Welch's test. The Q-Q plot of residuals was also analyzed, verifying that the normality assumption is met. The results of the analysis of variance are presented in the table Table 10:

Table 10 - ANOVA for conformity ratio considering product type factor (M2).

ANOVA - Conformity ratio

Homogeneity Correction	Cases	Sum of Squares	df	Mean Square	F	p	η²
Welch	Product Type	3.636	4.000	0.909	212.363	< .001	0.241
	Residuals	11.425	8.074	1.415			

Note. Type III Sum of Squares

Once again, the ANOVA demonstrates that there are statistically significant differences between group means of conformity ratio as determined [F (4,8.074) = 212.363, p < .001].

Notably, herein the effect size (η2) demonstrates that more than 24% of conformity ratio variability is explained by the type of the textile product.

Figure 5 and Table 11, respectively represent the distribution of conformity ratios and the Games-Howell Post Hoc analysis for M2.

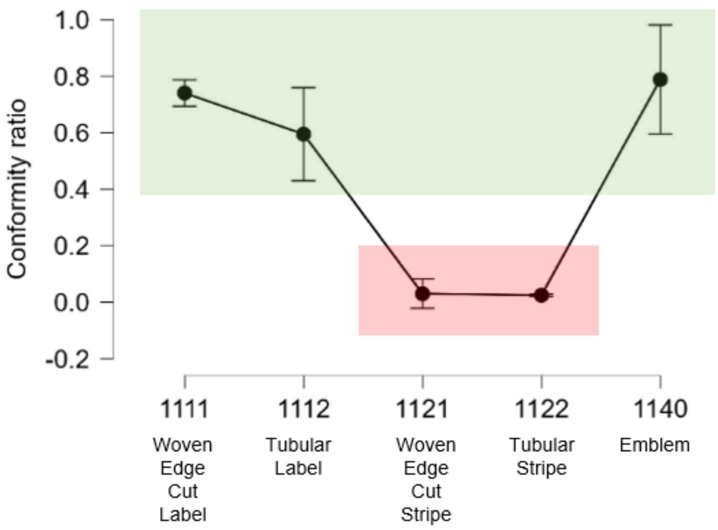


Figure 5 - Conformity ratio means distribution by textile product manufactured (M2)

Table 11 - Games-Howell Post Hoc Comparisons on conformity ratios (M2)

Games-Howell Post Hoc Comparisons - Product Type

		95% CI for Mean Difference					
Comparison	Mean Difference	Lower	Upper	SE	t	df	p_{tukey}
1111 - 1112	0.146	−0.099	0.390	0.081	1.791	19.068	0.407
1111 - 1121	0.711	0.644	0.777	0.024	29.622	123.716	< .001***
1111 - 1122	0.716	0.651	0.782	0.024	30.224	131.113	< .001***
1111 - 1140	−0.048	−0.341	0.245	0.082	−0.584	7.126	0.973
1112 - 1121	0.565	0.326	0.803	0.078	7.248	16.086	< .001***
1112 - 1122	0.570	0.332	0.809	0.078	7.328	16.014	< .001***
1112 - 1140	−0.194	−0.530	0.143	0.111	−1.749	17.260	0.432
1121 - 1122	0.006	NaN	NaN	0.004	1.276	1.328	NaN
1121 - 1140	−0.759	−1.054	−0.463	0.079	−9.615	6.032	< .001***
1122 - 1140	−0.764	−1.060	−0.469	0.079	−9.696	6.005	< .001***

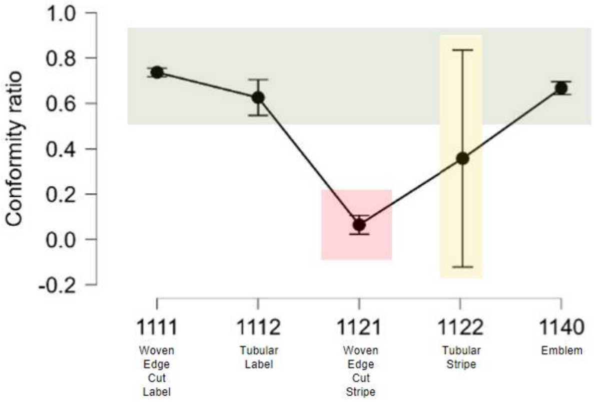
* p < .05, ** p < .01, *** p < .001
Note. Results based on uncorrected means.

Similarly, to the pattern observed in M1, the conformity ratios of M2 also present two different main groups. Firstly, with higher conformity ratios, the Woven Edge Cut Label (1111) [*M* = 0.741, *SD* = 0.271], Tubular Label (1112) [*M* = 0.595, *SD* = 0.321], and Emblem (1140) [*M* = 0.789, *SD* = 0.208], that not differing among them, are statistically significantly different of the second group, which is composed by the Woven Edge Cut Stripe (1121) [*M* = 0.030, *SD* = 0.006] and the Tubular Stripe (1122) [*M* = 0.024, *SD* = 0.004] (with those also not differing among each other).

2.1.3. Predictive Quality Modelling

2.1.3.1. Longitudinal analysis: definition of predictors and sampling data

As previously demonstrated, it was unraveled that conformity ratios are highly dependent on product type. Indeed, whereas the production of Woven Edge Cut Label (1111), Tubular Label (1112), and Emblem (1140), present similar conformity ratios, the manufacturing of Woven Edge Cut Stripe (1121) and Tubular Stripe (1122), failed consistently in meeting IDEPA conformity requirements, not being suitable to be manufactured at the monitored looms. When evaluating the number of entries registered for these products, it is verified a small number of entries, particularly for M2 (respectively 2 and 5), which can be associated with the fact the instrumented looms are not optimized for that kind of production, or that these production orders rely upon sample tests.



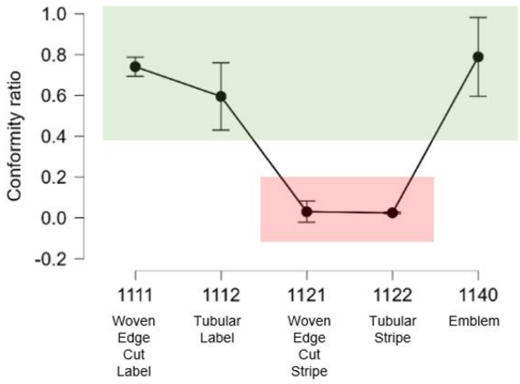


Figure 6 - Comparison of the distribution of conformity ratios in M1 and M2 per product type.

Considering the above, as well as the changes verified at IDEPA facilities, it was decided to conduct a longitudinal analysis of product quality considering the moment and product type factors. Due to differences in the number of entries per level and data availability, the verified dependence of conformity on product type, the violation of the assumption to conduct a two-way ANOVA, and independent samples Welch's tests were conducted to evaluate the variability in conformity ratios due to equipment change in Looms 11 and 12 for the production of Woven Edge Cut Label (1111), the product which has registered more entries in both time frames. Herein, no significant results were found as shown follows:

- A Welch's t-test was used to compare the means of conformity ratios on factor moment (levels: M1 and M2) for the production of Woven Edge Cut Label (1111) in Loom 11. Results show that there are no significant differences between the conformity ratio of M1(M = 0.751, SD = 0.287) and the M2 (M = 0.742, SD = 0.295) [(t(97.644) = 1.276, p =.205].
- A Welch's t-test was used to compare the means of conformity ratios on factor moment (levels: M1 and M2) for the production of Woven Edge Cut Label (1111) in Loom 12. As results show that there are no significant differences between the conformity ratio of

M1(*M* = 0.705, *SD* = 0.260) and the M2 (*M* = 0.739, *SD* = 0.242) [(*t*(95.791) = -0.985, *p* =.327], this variable was excluded for the construction of the predictive model.

2.1.3.2. Prediction of product quality

As previously shown, conformity ratios are highly dependent on the Product to be manufactured, which indicates that this variable must be considered as a predictor of quality. Contrary to this, no effect was verified regarding IDEPA facilities update, which enables the usage of both time frames in the analysis. Therefore, considering the insights of the previous sections, it was decided to model the predictive quality of IDEPA production processes exploring the product type and loom variables as predictive factors, and the conformity ratio as the dependent variable. In the following paragraphs, details regarding the predictive model obtained are presented.

The model computed was a generalized linear model considering both product type and loom as predictor variables. Results show that the model is significant ($p < .001$) with the model achieving an adjusted R squared of 0.391 (see Table 12 and Table 13 for more details). When looking at Table 14 it is possible to observe that not all product types are significant, which is also true for the loom used in the production. Indeed, as we are modeling the conformity ratio based on distinct product types and looms, the use of dummy variables was required to define the regressive model. Considering this, the model created considers the production of product ID 1111 in loom 9 as a reference, with the dummy variables codifying the patterns observed in the production of other product types or different machines. For instance, if an unstandardized value of a coefficient is negative (e.g., Product type ID 1112), this means that the expected conformity ratio for this type of product will be lower than the reference one. Similarly, if we are considering the production in loom 12, as the unstandardized value of this coefficient is positive, it is expected and higher conformity ratio than the conformity observed in the reference loom 9.

Table 12 - Predictive Model 1 Summary

Model Summary - Produced qty.

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	639.188
H_1	0.627	0.393	0.391	498.924

Table 13 - Predictive Model 1 details

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	$2.833\times10^{+8}$	7	$4.048\times10^{+7}$	162.608	< .001
	Residual	$4.374\times10^{+8}$	1757	248925.037		
	Total	$7.207\times10^{+8}$	1764			

Note. The intercept model is omitted, as no meaningful information can be shown.

Table 14 - Predictive Model 1 coefficient

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	96.665	15.214		6.353	< .001
H_1	(Intercept)	−72.429	29.003		−2.497	0.013
	Product Type (1112)	−76.640	59.627		−1.285	0.199
	Product Type (1121)	1977.548	59.715		33.117	< .001
	Product Type (1122)	167.076	159.958		1.044	0.296
	Product Type (1140)	27.827	30.049		0.926	0.355
	Loom (10)	53.067	35.452		1.497	0.135
	Loom (11)	96.801	35.203		2.750	0.006
	Loom (12)	153.753	37.858		4.061	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

In summary, the model predicted approximately 39% of the conformity ratio observed in production, $R^2_{adj} = 0.391$, $F(7,1757) = 162{,}608$, $p < .001$.

2.2. Integrated Mathematical Models for Scheduling of Production Lines

Following ISEP's mathematic models for the Genetic Algorithm (GA) scheduling system described in Deliverable 5.3, the selection phase of the GA has been updated to include product quality during its multi-objective function optimization process.

The selection phase begins with the union of the new and the old populations, that is, the crossed and mutated population with the initial population of the previous generation. Additionally, repetitions of individuals are eliminated.

Afterward, each individual is evaluated according to their fitness score, which follows a multi-objective function that minimizes the overall total costs, maximizes profit from selling energy, minimizes machine occupancy deviation, and maximizes product quality mean from all product requests.

The first two objectives (i.e., minimize costs and maximize profit) can be joined into a single function which is divided into four fundamental equations: period energy consumption, period energy to pay, period maintenance to pay, and total cost.

The Period Energy Consumption (PEC), represented by $PEC_{Demand(p)}$, gives the total energy consumed by the tasks in a given period p, it can be described by eq. (1).

$$PEC_{Demand(p)} = \sum_{m=1}^{M} E_{Demand(p,m)} \times P_{Machine(p,m)} \qquad (1)$$

The variable p portrays a specific period, m describes a machine index, and M the total number of available machines for production. Variables p and m can be compared to the x (i.e., column) and y (i.e., row) cartesian coordinates, respectively, in order to navigate in the individual matrix. The energy consumption of a machine m in period p is described by

$E_{Demand(p,m)}$. Furthermore, if a machine priority constraint is applied, variable $P_{Machine(p,m)}$ represents the priority of machine m in period p. For $P_{Machine}$ values above 1, the priority is decreased, while below 1 it is increased, as a result, neutral priority (i.e., no priority associated) is represented by the value 1.

Regarding the Period Energy to Pay (PEP), portrayed as $PEP_{Demand(p)}$, it represents the energy to pay (i.e., energy cost) in a given period p, it is represented by eq. (2).

$$PEP_{Demand(p)} = \begin{cases} PEP_{Demand(p)} = 0, \quad if\ E_{Generation(p)} = PEC_{Demand(p)} \\ PEP_{Demand(p)} = \left(E_{Generation(p)} - PEC_{Demand(p)}\right) \times E_{Selling\ Price(p)}, \\ \quad if\ E_{Generation(p)} > PEC_{Demand(p)} \\ PEP_{Demand(p)} = \left(PEC_{Demand(p)} - E_{Generation(p)}\right) \times E_{Buying\ Price(p)} \end{cases} \tag{2}$$

Variable $E_{Generation(p)}$ portrays available locally generated energy that is free of charge (e.g., PV generation) in period p, $E_{Selling\ Price(p)}$ describes the price for selling energy in period p, and $E_{Buying\ Price(p)}$ represents the price for buying energy in period p. In case PEP_{Demand} results in a positive value (i.e., above zero), it indicates that there are energy costs to be paid, while negative values (i.e., below zero) indicate that profit was made by selling generated energy in excess (i.e., all the PEC_{Demand} was covered by $E_{Generation}$ and the rest sold to energy buyers). Subsequently, zero indicates that there are no energy costs to be paid and no profit was obtained from generated energy in excess.

To calculate the maintenance costs, it is used the Period Maintenance to Pay (PMP), represented by $PMP_{Maintenance(p)}$ it portrays the maintenance costs to pay in a given period p, it is represented by eq. (3).

$$PMP_{Maintenance(p)} = \begin{cases} PMP_{Maintenance(p)} = 0, \quad if\ there\ is\ no\ maintenace\ scheduled \\ PMP_{Maintenance(p)} = M_{In\ Hours\ Price(p)}, \\ \quad if\ there\ is\ a\ maintenace\ scheduled\ in\ maintenance\ hours \\ PMP_{Maintenance(p)} = M_{Out\ Hours\ Price(p)} \end{cases} \tag{3}$$

Maintenances can be scheduled either in maintenance hours (i.e., the interval of periods in which the maintenance must/can be done) or out of maintenance hours (i.e., not in the stipuled interval of periods, normally has a monetary penalty). Accordingly, variable $M_{In\ Hours\ Price(p)}$ describes the price of a maintenance activity done in maintenance hours in period p, while $M_{Out\ Hours\ Price(p)}$ represents the maintenance price of a maintenance activity done out of maintenance hours in period p.

Finally, the Total Cost (TC) of an individual can be obtained through eq. (4).

$$TC = \sum_{p=1}^{P} PEP_{Demand(p)} + \left(\sum_{m=1}^{M} PMP_{Maintenance(p)}\right) \tag{4}$$

The total number of available periods in the time window of the schedule is represented by the variable P. Also, eq. (4) can be seen as the sum of the energy cost of each individual, determined as a result of the energy balance ($consumption - generation$) multiplied by the respective energy price, and the maintenances cost according to their respective maintenance hours price.

It is noteworthy that, variable $PEP_{Demand(p)}$ already includes the energy costs from all the machines in a given period p. However, variable $PMP_{Maintenance(p)}$ does not include all the maintenance costs from period p, thus the need to incorporate, in eq. (4), the sum of all maintenance costs from all the machines in period p.

To minimize machine occupancy deviation (i.e., machine occupation rates standard deviation), and thus maximize machine longevity by reducing overload and usage of single machines, it is employed a function that can be divided into the following three equations: machine degradation classifier, machine occupation rate, and occupation standard deviation.

To calculate the machine occupancy deviation, only tasks and setups are considered to influence the degradation of a machine, since they require the machine to be working. Therefore, the classification of factors that contribute to the degradation of a machine is done using the Machine Degradation Classifier (MDC), represented in eq. (5) as $MDC_{Factor(p,m)}$, which classifies a factor contributing to the degradation of a machine m in period p with the value 1, otherwise, it classifies it with 0.

$$MDC_{Factor(p,m)} = \begin{cases} MDC_{Factor(p,m)} = 1, & if\ there\ is\ a\ task\ or\ setup\ scheduled \\ & MDC_{Factor(p,m)} = 0 \end{cases} \tag{5}$$

The Machine Occupation Rate (MOR), portrayed by $MOR_{Factors(m)}$, gives the occupation rate of factors that contribute to the degradation in a given machine m, it can be described by eq. (6).

$$MOR_{Factors(m)} = \frac{\sum_{p=1}^{P} MDC_{Factor(p,m)}}{P} \tag{6}$$

Lastly, the Occupation Standard Deviation (OSD) of an individual can be determined by calculating the population standard deviation (i.e., not the sample standard deviation), as represented in eq. (7).

$$OSD = \sqrt{\frac{\sum_{m=1}^{M}\left(MOR_{Factors(m)} - \left(\frac{\sum_{m=1}^{M} MOR_{Factors(m)}}{M}\right)^{2}\right)}{M}} \tag{7}$$

To maximize product quality mean, and thus maximize overall product quality, it is used a mathematical function composed of two equations: product quality request and product quality mean.

The Product Quality Request (PQR), represented by $PQR_{Assessment(r)}$, gives the product quality value assessment of a given specific unit of product requested if applied with the planned schedule by the GA, it can be described by eq. (8).

$$PQR_{Assessment(r)} = \prod_{t=1}^{T} (1 - D_{Machine(r,t)}) \tag{8}$$

A specific product request is represented by r, variable t describes a task index from a product request r, and T portrays the total number of tasks needed to accomplish a product request r. Variable $D_{Machine(r,t)}$ describes the machine degradation of the machine scheduled to process task t from request r.

The Product Quality Mean (PQM), represented by PQM, gives the product quality mean for all requested products scheduled, it is portrayed by eq. (9).

$$PQM = \frac{\sum_{r=1}^{R} PQR_{Assessment(r)}}{R} \tag{9}$$

The total number of product requests to be scheduled by the GA is represented by the variable R.

After obtaining both the TC, OSD, and PQM for each individual a Min-Max normalization approach is taken, using the results obtained from the individuals in the population, to normalize the TC, OSD, and PQM values of each individual in the population. Then, each individual is evaluated according to the Fitness Score (FS), described by eq. (10).

$$FS = TC_{Norm} \times W_{TC} + OSD_{Norm} \times W_{OSD} + \frac{1}{PQM_{Norm}} \times W_{PQM} \tag{10}$$

Variables TC_{Norm}, OSD_{Norm}, and PQM_{Norm} describe the normalized TC, OSD, and PQM values, respectively, of an individual. The optimization weights, defined by the user in the input data, for the overall costs (i.e., TC), machine occupancy deviation (i.e., OSD), and product quality mean (i.e., PQM) are represented by variables W_{TC}, W_{OSD}, and W_{PQM}, respectively. The sum of variables W_{TC}, W_{OSD}, and W_{PQM} must always be 1, and they must assume a value from 0 to 1, inclusive. It is worth noting that, the objective function minimizes the FS, hence, while no inverse is needed for TC_{Norm} and OSD_{Norm}, because they are minimizations, the inverse had to be applied to the PQM_{Norm} in order to consider the maximization of product quality mean from all product requests.

The selection of the n best individuals is made according to the input parameter of the algorithm, chosen by the user. The remaining individuals (i.e., population size less n) are obtained from non-elite tournaments. Each tournament consists of two individuals randomly chosen, where they compete based on their fitness scores (i.e., FS). The algorithm calculates the chance of individual 1 winning the tournament using eq. (11).

$$Individual^{1}_{chance} = 1 - \frac{fit1}{fit1 + fit2} \quad (11)$$

where $fit1$ and $fit2$ represent the fitness of individual 1 and individual 2, respectively. Then, a random decimal number between 0 and 1 is generated. If the generated decimal is lower than the chance of individual 1 winning, eq. (11), then individual 1 is declared the winner. Otherwise, individual 2 leaves victorious. Therefore, the individual with the lowest fitness, which in turn has the lowest combination of overall cost and machine occupancy deviation, as well as highest product quality mean, is the one most likely to be chosen.

2.3. Rebalancing Scheduling Models for Production Reconfiguration

ISEP's proposed scheduling algorithm focuses on added flexibility and reliability in manufacturing environments when handling unexpected Machine Breakdowns (MB)s by completely removing a machine from production until it is repaired. To achieve this, it is used the same GA described in Deliverable 5.3 for production line optimization to minimize total cost and maximize machine longevity (currently also considering the maximization product quality), and a new Rescheduling Processing Data (RPD) module, as shown in Figure 7, which is vaguely described in Deliverable 4.3 for demand response participation and MB events. It is worth mentioning that, at present, the proposed ISEP rescheduling process only works with schedules obtained from ISEP's GA, as it requires a specific input data format. Nevertheless, the functions that constitute the RPD could be easily adapted to be applied to other schedules' input. Furthermore, for rescheduling, it is needed the initial GA input and the corresponding output.

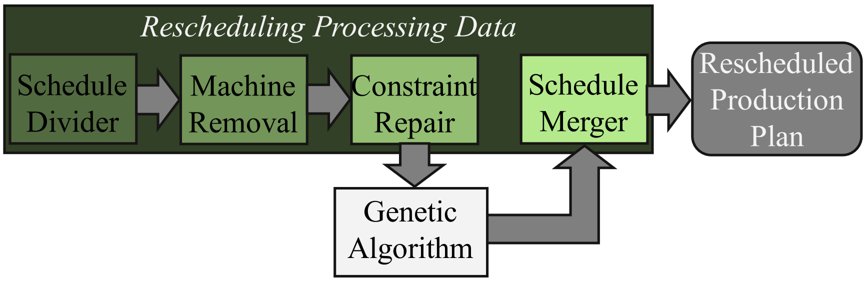


Figure 7 - Flowchart of ISEP's production plan rescheduling process for machine breakdown events.

For rescheduling a production plan, in order to respond to an unexpected MB, it is essential to define from which period in the production plan the rescheduling starts. The starting rescheduling period cannot be defined in a schedule transition where there are tasks still being executed, hence it is essential to define time leap constraints (i.e., non-schedulable periods in a production plan, can represent time transitions) along the schedule for possible future reschedulings. In the RPD schedule divider function, the production plan is divided into two segments according to the starting rescheduling period: the first segment contains all the tasks that have already been executed (i.e., production plan before the starting rescheduling period), and the second segment which has all the tasks yet to be executed (i.e., production plan after the starting rescheduling period). Accordingly, it is in the second production plan segment that the rescheduling will be applied.

Using the initial GA input data and the second segment (i.e., output to be rescheduled), the machine removal function applies a machine operability constraint (i.e., removes or adds machines from the production plan) in the input GA data in order to not include the broken-down machine. In addition, tasks that are impossible to shift to other machines, due to task incompatibilities, are removed from the second segment, and notified to the user.

To maintain constraint integrity, a constraint repair function is applied to account for constraints that were already complied with. For example, an order constraint complied with by a task in the first segment and another in the second, does not need the second segment task, which is going to be rescheduled, to comply with the order constraint again.

After the rescheduling data is generated from the RPD module which, only includes the segment of the schedule to reschedule, does not include the machine that broke down, and all constraints are properly maintained, the GA is executed to find a new production plan to substitute the second segment.

Finally, with the second segment rescheduled, in the RPD a schedule merger function is used to combine both the first segment and the newly rescheduled second segment.

It is worth noting that, if the removed broken-down machine is repaired, the rescheduled plan can be once again, rescheduled but with the machine restored, by changing the machine operability constraint to add the repaired machine.

The described steps could also be applied to Demand Response participation by using an energy limit constraint instead of the machine operability constraint for MBs. Nevertheless, the Demand Response participation process is much simpler and is already described in Deliverable 4.3.

2.4. Sensor Forecasting

In order to predict the next set of values for each sensor installed at the machine, an AI-based approach was employed.

Figure 8 represents a plotted set of 100 values from a sample sensor, retrieved from a test dataset data.

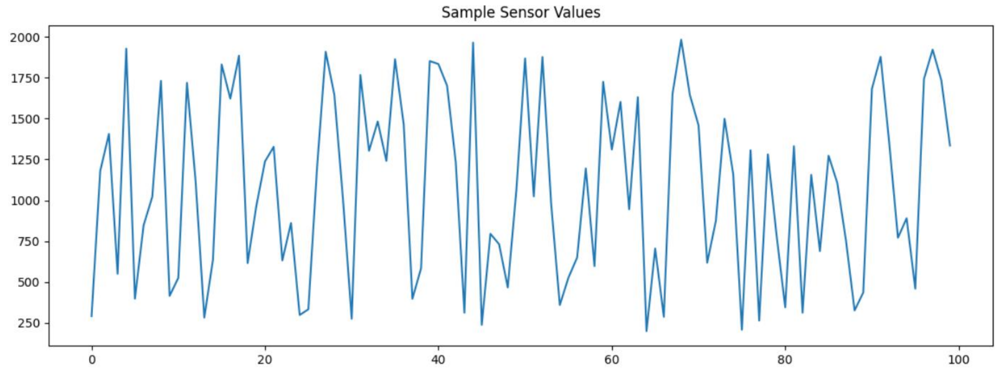


Figure 8 - Original Sensor Values Plot

The simplest way to predict the next values would be to use a regression algorithm. However, the data, as it can be seen from the plot, cannot be represented by a linear equation, since it is highly dispersed in the y-axis. Figure 9 represents a linear and a polynomial regression applied to the data, respectively.

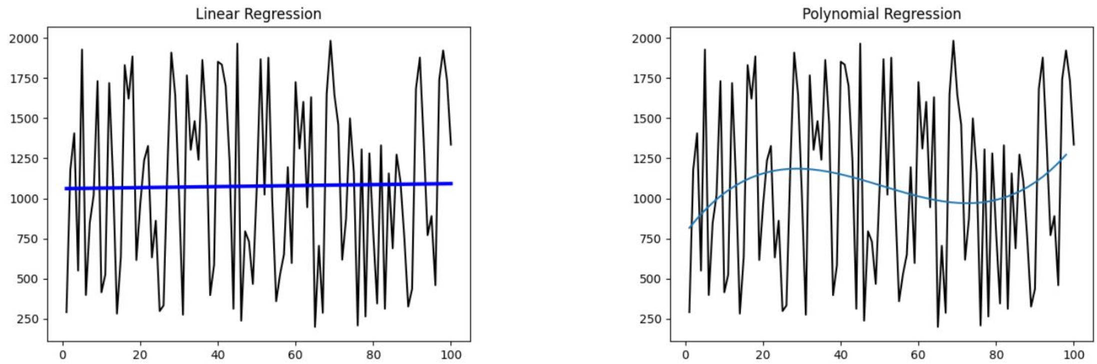


Figure 9 - Linear Regression vs Polynomial Regression

Nonetheless, the Polynomial approach is slightly better, it is still far from being an adequate model to use, even with a higher degree applied. Additionally, this data consists of time series: a sequence of data points recorded at specific times, where temporal continuity is the predominant factor to consider [3]. To overcome this, a different approach was used, called ARIMA Model - AutoRegressive Integrated Moving Average. Autoregressive means that "it predicts future values based on past values", meaning that represents time-variable processes with stochastic features. Integrated means that the data values have been replaced with the difference between their values and the previous ones. As for Moving Average, it means that the model uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

Each of these components is explicitly specified in the model as a parameter, with the standard notation of ARIMA(p,d,q):

- p: The number of lag observations included in the model
- d: The number of times that the raw observations are differenced
- q: The size of the moving average window

While it is possible to try each combination of parameters, it would be an exhausting and time-consuming task. For this, an *auto_arima* approach was used, which returns the best set of parameters for the algorithm in a specified range by testing each possible combination.

It is possible to observe that this approach better captures the trend (upward/downward) from the spikes pretty well, which is one of the most important factors to have in mind when using these types of approaches. The generated, and selected, ARIMA model is represented in Figure 10.

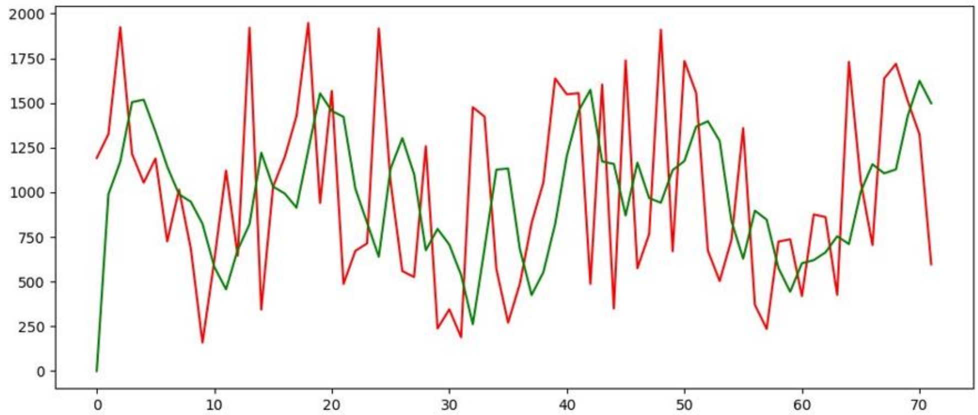


Figure 10 - Generated ARIMA Model

2.5. UC1 general conclusions overview

The IDEPA use case exemplifies the algorithm's practical implementation within a textile manufacturing context. The predictive quality analysis demonstrated that is possible to anticipate and forecast product quality outcomes by leveraging historical data together with production details. The predictive model developed for IDEPA showcased significance ($p<.001$) with around 40% of the variability in conformity ratios of textile manufacturing being explained by the product type and loom used in the production. Therefore, by using the constructed predictive model to run simulations on production quality, it becomes feasible to optimize production scheduling and resources. By doing so, i.e., by carefully choosing the appropriate loom for the manufacturing of specific products taking into consideration the distinct predictors, IDEPA will be able to save resources, be more efficient, and be more sustainable. In a scenario where all resources are fully engaged, having an accurate forecast of the conforming ratio is essential not only to save resources (e.g., raw material) but also to precise order completion, and, in some cases, to answer to client timing needs. For instance, if it is expected a high non-conforming ratio, and, in advance, is anticipated that 10kg of additional product will be required to complete a customer order, the extra operating time required to complete the order will be considered at IDEPA scheduling. As (sometimes) this industry works with very restricted time frames, computing the real operating time of a specific resource or loom, considering the non-conformity ratios and possible defects, is a valuable tool for negotiate orders delivery and evaluate production capabilities. Similarly, non-expected adjustments can impact the commencement of subsequent orders, emphasizing the intricate interplay between resource allocation and order scheduling.

3. UC2 - GTF Rotor Cell Operation (Turkey)

Scheduling is a decision-making process that seeks to optimize one or more objectives that deal with the allocation of available resources on a time basis to actions that need to be fulfilled. Examples of resources are the machines in a workshop, the actions that need to be performed and the work that needs to be done in the production process. In other words, scheduling is determining when and in what order the workpieces that make up a product will be processed on the machines at hand. With scheduling, problems such as using production facilities in the most effective way, responding to customer demands as quickly as possible, completing works without delay in delivery dates, shortening the production process, preventing bottlenecks in production, and reducing overtime work are solved. They are two different methods.

3.1. Simulated Annealing

Within the scope of the task, it first reads the tasks, the operations of the task, the machine information, the machines suitable for the operations and the processing times of the operations on the machines from the excel format and reads the algorithm related coefficients. Algorithm phases are:

- Initial Solution Creation: The initial solution is randomly generated. Generates a random value for each operation. By sorting these values, it also sorts the operations. Operations are assigned to machines randomly. Thus, it becomes an input to metaheuristic algorithms. The initial solution is ready.
- Searching Neighborhood: The objective function is calculated by considering the initial solution. This value is assigned as a starting point for the current solution and the best solution. As better solutions are obtained in each iteration, the best solution will be updated and improved. Neighborhoods are generated as much as the number of neighbors that need to be looked at from the solution at hand. Randomly 2 operations selected and returns their index. The locations of these operations are interchanged. All operations are then assigned to randomly selected alternative machines. In this way, a new neighborhood is created. Operation sequences and machine operation sequences are corrected. The objective function of this neighborhood is calculated.
- Assess Neighborhood Solutions: If the value of the neighboring solution is better or equal to the current solution (It will be greater or less than the objective function, this will be expressed as better) it is accepted as the current solution and the current solution is updated. If this value is better than the best solution, the best solution is also updated.

If the value of the neighboring solution is worse than the current solution, the acceptance probability is calculated. It is accepted or rejected according to the probability of acceptance. The temperature value is used to calculate the acceptance probability. If the probability of acceptance is greater than the random number produced, the solution is accepted and the opportunity for bad solutions is given. Other iterations continue over the accepted neighborhood. If this neighborhood is rejected, the iteration continues by calculating new neighborhoods over the previously accepted neighborhood. After the determined number of neighborhoods are calculated, the temperature value is updated again at the rate of the cooling coefficient before starting a new iteration. When the specified number of iterations are completed, the algorithm stops. The best solution is the result. This solution prints the solution as a table and as a Gantt chart.

3.2. Genetic Algorithm

The component first reads the tasks, the operations of the task, the machine information, the machines suitable for the operations and the processing times of the operations on the machines from the excel format, and reads parameter related to algorithm. Algorithm phases are:

- Initial Solution Creation: The initial solution is randomly generated. This generates a random value for each operation. By sorting these values, it also sorts the operations. Operations are assigned to machines randomly. All elements of the population are created in this way. Thus, it becomes an input to metaheuristic algorithms. The initial population is ready. After the population is formed, the objective functions of all the elements are calculated and the best solution is assigned to the current solution and the best solution as a starting point. As better solutions are obtained in each it eration, the best solution will be updated and improved. The following operations are performed for the number of iterations specified at the beginning.
- Selection process: Selection is done by roulette method. In this method, the cumulative probability is calculated. The ratio of the objective function value of each element in the population to the total objective function value becomes the probability of being selected. The cumulative probability of the first element is assumed to be 0 and the cumulative probability of that element is calculated when we add the probability of choosing each element with the probability of choosing the previous element. A random number is derived for each element in the population. Elements of random numbers falling into cumulative probability intervals are selected. In this way, the population is rebuilt.
- Xover Process: The crossover ratio is calculated by multiplying the population number by the crossover probability. Random 2-matched children are selected from the population at the rate of crossover. The crossover points of each 2 children to be crossed are selected. Pairs are crossed at the crossover points. That is, the genes

of the first child up to the crossover point are put into the genes of the second child after the crossover point. The genes of the second child after the crossover point are put into the genes of the second child up to the crossover point. The New Population consists of the offspring of the cross. If the number of populations cannot reach the required value due to the crossover ratio, the population number is kept constant by adding the children with the best value according to the objective function to the population. After the crossover, the locations of the repetitive genes and the missing genes are determined in children. Excess genes are replaced by missing genes. Then, the operation order is corrected, and the objective function values are calculated.

- Mutation Process: Mutations are made in each iteration. The mutation rate is calculated by multiplying the mutation rate by the population number and the number of genes. Operations in these genes are assigned to randomly selected alternative machines. After the mutation, the objective function is recalculated.
- Evaluating: The current solution is updated with the best objective function value in the population. If a better solution than the best available solution is reached, the best solution is also updated. As the population is here, the iteration is continued. The algorithm stops when the specified number of iterations is reached. The best solution is the result. This solution prints the solution as a table and as a Gantt chart.

3.3. Models for Master Production Scheduling

Master production schedule (MPS) is a plan for individual commodities to be produced in each time period such as production, staffing, inventory, etc. It is usually linked to manufacturing where the plan indicates when and how much of each product will be demanded. This plan quantifies significant processes, parts, and other resources in order to optimize production, to identify bottlenecks, and to anticipate needs and completed goods. Since a MPS drives much factory activity, its accuracy and viability dramatically affect profitability. Typical MPSs are created by software with user tweaking.

Set

- The set of lines $H = \{1,2,n\}$, line index = h;
- The set of weeks $W = \{1,2,\dots,r\}$, the week index = w ;
- The set of finished products $M = \{1,2,\dots,s\}$, the finished product index = m;
- öüp: preliminary production parameter $(0,..,z)$
- b: blocking week $(B = 1,..,c)$

Parameters:

- **h**. your line is W. let the $weekly\ working\ hour\ capacity = t\_hw$ for the week. w. h per week. the matrix containing the total working hours of the line will be marked with T: $T = (t\_hw)$;

- **m**. the unit quantity of the finished product is h. even the matrix containing the amounts of hours required for it to be labeled will be marked with A: $A = (a\_mh)$, m when calculating this number. the unit quantity of the finished product is h. even the number of workers (man) – hours required to be labeled can be used;
- **m. W_m** of the finished product. the matrix containing the quantities (requests) that needed to be delivered by the end of the week would be marked with $D = (d\_(mW\_m))$;
- **i_r**: the amount of i content based on the r prescription
- **l**: time limit for blocking
- **〖ym〗_(i_r mw)=w**. The amount of semi-finished products based on the content for the m product at the beginning of the week
- **〖sf〗_(mwi_r)=w**. The $order + forecast$ amount based on the i content of the m product at the beginning of the week

Decision variables

- $S\_bm = \begin{cases} if\ blocking\ is\ to\ be\ done\ for\ 1\ m\ product \\ 0\ o\ /\ w \end{cases}$
- $d_{\text{öüpm}} = \begin{cases} If\ there\ is\ a\ preliminary\ production\ parameter\ for\ 1\ m\ product \\ 0\ o\ /\ w \end{cases}$
- $v_{mwi} = \begin{cases} 1, \sum_{i_r} sf_{mwi_r} - ym_{i_r mw} \leq |0 \\ 0,\ o\ /\ w \end{cases}$
  - the amount of semi-finished products based on the content for the m product at the beginning of the week, w. if the i content of the m product at the beginning of the week is greater than the $order + forecast$ amount, it will receive a value of 1.
- $f = \begin{cases} 1, \sum_h a_{mh} x_{mhw} < l \\ 0\ o/w \end{cases}$
  - If the total production time of the m product per week is less than the blocking limit, f = 1.
- $j = \begin{cases} 1, fs_{bm} = 1 \\ 0,\ fs_{bm} = 0\ o/w \end{cases}$
  - product is made and the justification for that week production time the product is smaller than L, if 1 takes the appropriate value $x_{mhw}=m$. of the product $w.h$ per week. even the amount produced. $y_{mw}=1$, if m. manufactured w. if it will be produced per week, = 0 if it will not be produced.

Model

$$min\, z = \sum_{h,w} (t_{hw} - \sum_{m} a_{mh} x_{mhw}) \tag{12}$$

$$(1-j) \sum_h \sum_{\text{öüp}} x_{mh(w-\text{öüp})} + j \sum_h \sum_b x_{mh(w+b)} \leq (1-j)\mathrm{d}_{\mathrm{mW_m}} + \sum_b j\mathrm{d}_{\mathrm{mW_{m+b}}} \quad \text{(h=1,..,n)} \tag{13}$$

$$\sum_m a_{mh} x_{mhw} \leq t_{hw}, \ \forall\, h, \ \forall\, w \tag{14}$$

$$v_{mwi} \leq \sum_h x_{mhw} \leq (1 - v_{mwi}) \max\,(sf_{mwi_r} - ym_{i_r mw})\mathrm{d}_{\mathrm{mW_m}} + v_{mwi}\mathrm{d}_{\mathrm{mW_m}}, \quad \forall\, m, \quad \forall\, w, \forall\, i \tag{15}$$

$$y_{mw} \leq x_{mhw} \leq M y_{mw} \tag{16}$$

$$x_{mhw} \geq 0 \tag{17}$$

(1) The objective function expresses the remaining free time by subtracting the total duration of the products produced on that line from the total weekly production time on a line. Then, by summing this function from the line and week basis, it is aimed to find all the free time. By minimizing the objective function, the objective is to minimize the total free time.

(2) The purpose of the restriction is to produce a product by ignoring the preliminary production parameter if a product can be blocked and the weekly production time of the product is less than the maximum time required for the blocking Decommissioning. Otherwise, if necessary, production will be carried out by considering the preliminary production parameter.

(3) It prevents the total duration of the products to be produced on the weekly line from exceeding the weekly line-based production time.

(4) W. The m product produced per week will be produced as much as the order + forecast if the semi-finished product is sufficient, and if it is insufficient, the number of semi-finished products that can be produced will be produced.

(5) w of the product m. In order for the production to be made per week, the relevant product is defined that week

4. UC3 - ALBERO's Use Case (Spain)

In the ALBERO use case (UC3 - Spain) a trained Deep Q-Learning agent will be used to assign priorities to the machines according to the criteria selected by Albero. These criteria will be used by the scheduler to create the weekly work plan.

The Q-learning algorithm, which is a model-free, online, policy-free reinforcement learning method, will be used to train the agent.

4.1. Reinforcement learning

The goal of reinforcement learning is to train an agent to complete a task in an uncertain environment. At each time interval, the agent receives observations, rewards and actions from the environment. The reward is a measure of the success of the previous action (taken from the previous state) with respect to achieving the task goal. Therefore, the agent contains two components: a policy and a learning algorithm.

The policy is a correspondence between the observation of the current environment and a probability distribution of actions to be performed. Within an agent, the policy is implemented by a function approximator with adjustable parameters and a specific approximation model, such as a deep neural network. The learning algorithm continuously updates the policy parameters based on actions, observations and rewards. The goal of the learning algorithm is to find an optimal policy that maximizes the expected long-term cumulative reward received during the task.

Depending on the learning algorithm, an agent maintains one or more parameterized function approximators to train the policy. The approximators can be used in two ways:

- Critic - For a given observation and action, a critic returns the expected discounted value of the cumulative long-term reward.
- Actor - For a given observation, an actor returns as output the action that (often) maximizes the cumulative discounted long-run reward.

Agents that only use critical approximators to select their actions are based on an indirect representation of policy. These agents are also called value-based, and use an approximator to represent a value function (value as a function of observation) or a Q-value function (value as a function of observation and action). In general, these agents work best with discrete action spaces, but can be computationally expensive for continuous action spaces.

Agents that use both an actor and a critic are called actor-critic agents. In these agents, during training, the actor learns the best action it can perform using feedback from the critic (rather than using the reward directly). At the same time, the critic learns the value function from the rewards

in order to be able to properly criticize the actor. In general, these agents can handle both discrete and continuous action spaces.

4.2. Q-Learning agents

The Q-learning algorithm is a model-free, online, policy-free reinforcement learning method. A Q- learning agent is a value-based reinforcement learning agent that trains a critical approximator to estimate future performance or rewards. For a given observation, the agent selects and performs the action for which the estimated performance is highest. Q-learning agents can be trained in environments with observation and action spaces, where observation can be continuous or discrete while action must be discrete.

During training, the agent explores the action space using epsilon-greedy exploration. During each control interval, the agent selects a random action with probability ε; otherwise, it selects the action for which the value function is larger with probability $1 - \varepsilon$.

To estimate the value function, a learning agent Q maintains a critic $Q(S, A; \phi)$, which is a function approximator with parameters φ. The critic takes the observation S and the action A as inputs and returns the corresponding expectation of the long-run reward.

For critical approximations, table-based value functions are used, the parameters in ϕ are the actual values of $Q(S, A)$ in the table.

During training, the agent refines the parameter values in ϕ. After training, the parameters remain at their tuned value and the trained value function approximator is stored in the critical approximator $Q(S, A)$.

A deep neural network is used to approximate the Q-value function within the critique. This network must have two inputs: one for observation and one for action. The observation input must accept a four-element vector. The action input must accept a two-element vector. The network output must be a scalar, representing the expected cumulative long-run reward when the agent starts from the given observation and performs the given action.

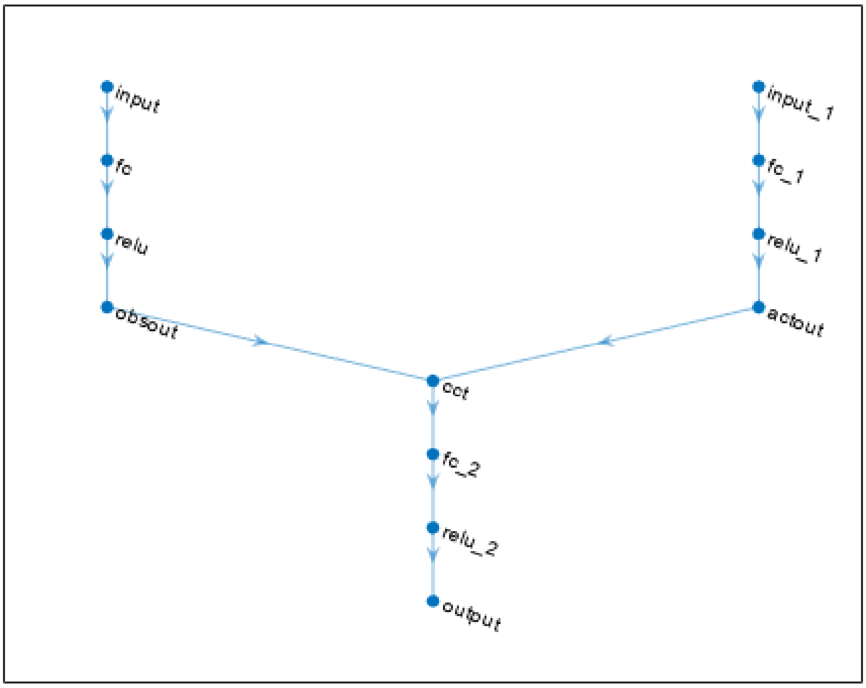


Figure 11 - Neural network architecture for the parameter net

Q-learning agents use the following training algorithm.

First, the critical approximator $Q(S, A; \phi)$ is initialised with random parameter values in ϕ. For each training episode, the following process is performed:

1. The initial observation S is obtained from the environment.
2. The following is repeated for each step of the episode until S is a terminal state.
   a) For the current observation S, a random action A with probability ε is selected. Otherwise, the action for which the critical value function is larger is selected.

$$A = \arg\max_{A} Q(S, A; \phi) \tag{18}$$

   To specify ε and its decay rate, the Epsilon Greedy Exploration is used.

   b) Action A is executed, observing the reward R and the following observation S'.
   c) If S' is a terminal state, set the objective of the y-value function to R. Otherwise, set it to:

$$y = \mathrm{R} + \gamma \max_{A} Q(S', A; \phi) \tag{19}$$

   d) The difference ΔQ between the objective of the value function and the current value of $Q(S, A; \phi)$ is calculated.

$$\Delta Q = y - Q(S, A; \phi) \tag{20}$$

   e) Update the critical approximator using the learning rate α. Specifying the learning rate when creating the critic by setting the LearnRate within the agent options object. For table-based critics, the corresponding $Q(S, A)$ value is updated in the table.

$$Q(S, A) = Q(S, A; \phi) + \alpha \cdot \Delta Q \tag{21}$$

   For all other types of critics, the gradients $\Delta\phi$ of the loss function with respect to the parameters ϕ are calculated. Then, you update the parameters based on the calculated gradients. In this case, the loss function is the square of ΔQ.

   f) Finally, the observation S is set to S'.

5. Conclusions

This document has outlined the comprehensive development of scheduling algorithms and predictive quality, aimed at meeting the dynamic demands of modern manufacturing environments. The algorithm's core objectives include exploiting the enhanced production equipment flexibility offered by MUWO, optimizing production across different lifecycles phases and distributed facilities, and maximizing delivery efficiency, equipment balance, energy utilization, and overall profitability.

In a rapidly evolving manufacturing landscape, characterized by ever-changing demands and technological advancements, enabling near real-time reactions to production demand changes and optimizing various production parameters, it empowers industries to enhance their efficiency, quality, and competitiveness.

6. References

There are no sources in the current document.