Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 54-3 (2021) 164–169

An Automatic System for Modeling and Controlling Color Quality of Dyed Leathers in Tanneries

Riccardo Bacci di Capaci [*,****] Gabriele Pannocchia [*] Colm Kenny [**] Giacomo Pacchi [***] Roberto Lupi [***] Claudio Scali [*]

[*] *Department of Civil and Industrial Engineering, University of Pisa, Italy*
[**] *Kentec s.r.l., Peccioli (PI), Italy*
[***] *BCN Concerie S.p.A., S.Croce Sull'Arno (PI), Italy*
[****] *Corresponding author: riccardo.bacci@unipi.it*

Abstract: This paper presents an automatic system for modeling and controlling color quality of dyed leathers of an Italian tannery. The proposed software is implemented within the IT company system, and is fully integrated with the machineries of the finishing line, that is, a spraying cabin with a robotic carousel, and an electronic tintometer system. Suitable experimental tests according to the Design of Experiments (DoE) are firstly defined, executed and analyzed for a series of color tones of interest. In order to derive and validate a set of colorimetric models able to evaluate and predict the color rendering of painted leathers, a set of recipes of basic dye pigments and data of light reflection measured by a multispectral camera are used. Principal Component Analysis is applied for dimensionality reduction, and linear least squares regression is employed to identify these data-driven models, which are then used for color control purpose. A color correction feedback strategy is indeed developed in order to converge towards the various target formulations. The control algorithm aims at reaching the multispectral reading values of the reference, that is, the first sample of unknown color recipe starting from the most similar archive base and appropriately updating the recipe of pigments, by using the measurement of leather samples prepared from time to time by the finishing line machineries. A set of company data are used to successfully validate the identified colorimetric models and the proposed color correction strategy.

Keywords: Process modeling; process control; quality management; colorimetry; industry 4.0

1. INTRODUCTION

Controlling color quality is a crucial issue in many industrial sectors, as textile, automotive, paint, plastic, ink, paper, cosmetics, among others. Many examples of automatic systems for color analysis and control are indeed available on the market (Gerelettronica, 2020; HunterLab, 2020; Datacolor, 2020). Color quality analysis is usually performed by employing three key elements: a spectrophotometer, that is, a color measurement instrument; a quality control software to analyze, track and communicate the color; a calibrated light booth for a precise color quality inspection (Mouw, 2016).

However, a reliable color control may be a very hard task to achieve, as sources of performance degradation are quite common and difficult to rebut. For example, color quality control ensures high consistency in leather production, but obtaining a suitable dye color on leather substrate is easier said than done due to many reasons. Among others, structural differences such as the grain, whorls, and folds actually prevent an even dispersion of dye (Ramanathan, 2017).

In particular, the process of leather finishing is a crucial phase in the tannery industry, since final appearance and aesthetic characteristics are here given to the product. One of the main problems is tuning the “finishing recipes”, that is, setting up suitable procedural operations and appropriate formulations of basic dye pigments. Usually, identifying correct dye recipes implies a series of manual spraying tests necessary to obtain the specific color tone required by every customer. Once desired test results are obtained, a small pilot production is then run, aimed in turn at identifying appropriate industrial settings. Finally, the actual industrial commissioning is carried out, which however requires a further testing phase of dye formulations and operating conditions. It is clear that such step-by-step approach tends to propagate uncertainties introduced by the human factor. For example, manual mixing and spraying procedures may led to unexpected results, which then requires heavy corrective actions. Moreover, leather finishing is very critical and time-consuming also because is drastically dependent on the operators experience and their subjective color quality control ability, as well intrinsic leather characteristics which may vary within the same raw material batch.

Therefore, in order to overcome all these difficulties and reduce, possibly eliminate, human errors, an automated system performing the finishing leather process is highly desirable. The system proposed in this work thus consists in a fully automated system composed by three main elements: i) a robotic finishing cabin to perform the color spray phase by means of a rotary carousel; ii) an automatic tintometer, that is, an electronic mixing system of dye pigments and additives, and iii) a process quality management software interfaced with a spectrophotometer, i.e., a multispectral camera, to measure and then control color of dyed leathers.

In particular, the main objective addressed in this paper is to develop the third element, that is, the color quality management and control software. The proposed system is able to identify a set of colorimetric models based on multispectral data in

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2021.08.236

order to provide a reliable evaluation of chromatic effect of the dyed leathers and then identify the unknown recipes of dye pigments to obtain the various desired colors. A target recipe is reached through iterative corrections given by a feedback control strategy and guided by the multispectral analysis of new formulated leather samples. Once the final recipe is obtained, full production can be started with remarkable savings in terms of time, resources and chemicals. To the best of authors' knowledge, this paper has original features for the literature of process control, as there is no similar work devoted to color control quality applied to the tannery field.

The paper is thus organized as follows: the system definition is reported in Section 2; while the main aspects of the proposed methodology are illustrated in Section 3. The identified models and the proposed control strategy are then validated over company data in Section 4. Results and discussions are here reported. Finally, in Section 5 conclusions are drawn.

2. SYSTEM DEFINITION

This section illustrates the main features of the system under study. As a matter of fact, this work is part of a larger project addressed to improve the technology level of an Italian tannery company (BCN Concerie S.p.A) under the initiatives of Industry 4.0 by developing a fully automated finishing line.

2.1 Variables and Parameters Definition

Previously to the software development, an extensive experimental activity was carried out. Tests were oriented according to the technique of Design of Experiments (DoE). This methodology, through careful planning of the experiments, allows one to obtain an accurate model of the system under study (Oehlert, 2010). In particular, it was possible to analyze which factors are most significant and how they influence the output variable, i.e. the chromatic effect of the dye paint on leather samples.

In our case, the adopted factors U, that is, the manipulable input variables, are the mass fractions of the N basic dye pigments to be mixed. The response X, the output variable to be modeled, is the color rendering of the final mixture on the leather. Note that by examining the mass fractions, it is sufficient to consider only the first $N-1$ components, being the fraction of the last component - the one in minor quantity - linearly dependent on the others, that is, its mass fraction is complementary to 1 with respect to the sum of the others. For example, for the MAHOGANY production color, three basic pigments are required: Red, Blue and Yellow; the factors are thus $3-1=2$, having excluded the fraction of Yellow, the least present component.

As color preparation procedure, mixing in small commercial drums with production mixers on a basis of 10 kg of formulation is firstly considered. The mixture of dye pigments is then combined with a standard compound, a completely colorless resin that allows paint to perfectly stick to the substrate. The obtained final mixture is thus applied on leather samples of the size of an A4 sheet. As color application procedure, a manual mode with 6 passes of spray gun is firstly adopted; then the automatic mode by means of the robotic spray carousel is considered. The color rendering of the final mixture is analyzed through a multispectral camera (KEYENCE, 2020). To obtain robust results, the color measurement of each leather is evaluated in the sample central point and replicated more times.

To limit operation variability, the following parameters of the color application automatic system in the finishing cabin are set: the rotation speed of the spraying carousel; the sliding speed of the carpet; the position of the leather sample and the relative angle between the edge of the sample and the direction of the carpet, as well as temperature, pressure and flow rate of the color sprays. It is to be noted that these parameters are taken as insignificant factors in the definition of the experimental design, since they do not represent manipulable variables for our color quality control system.

2.2 Architecture Definition

The proposed color quality management and control software is fully integrated with the company management system (AS/400) within the Local Area Network of the industrial site, as shown in Figure 1. The core algorithm is developed in *Python*^{TM} and installed on a dedicated industrial PC. The system communicates in input and output with another industrial PC, which implements a specific management software for communication with AS/400 and the tintometer, the fully automated mixing system of basic dye pigments and additives.

The communication takes place through a continuous exchange of text files into a shared folder on a NAS server. The software also communicates via TCP/IP protocol in output with the multispectral camera and in input with an FTP server, where the camera reading data are stored from time to time.

Note that the developed quality software consists of two distinct main sections: CIANO and OCRA. In particular, with CIANO (Collect Identify ANd Organize), it is possible to:

- collect the input and output data to build a colorimetric model, that is, the color recipes of leather samples in terms of mass fraction of basic dye pigments, and the readings of the multispectral camera, respectively;
- identify the colorimetric model;
- populate the database with the model parameters;
- generate a new model from an existing dataset of recipes and readings, with the subroutine EXTRA MODEL.

With OCRA (Optimal Color Research Algorithm), one can:

- analyze a new leather sample of unknown color recipe;
- associate the sample with the best color model, choosing from those already available in the database;
- activate the color correction algorithm to determine the unknown recipe.

3. PROPOSED METHODOLOGY

The various features of the method developed for modeling and controlling the color quality of dyed leathers are here presented.

3.1 Experiments Design

In order to define a first set of models of the chromatic effect of the various formulations, a series of DoE is performed. It is to be recalled that a standard DoE provides a multivariate analysis, i.e., simultaneous variations of all factors, increasing or decreasing, starting from a basic configuration, called the central point. The tests are here carried out according to a standard program, that is, a simple design, called Full-Factorial (FF), in which, for N factors, with 2 levels (high/low), 1 replica,

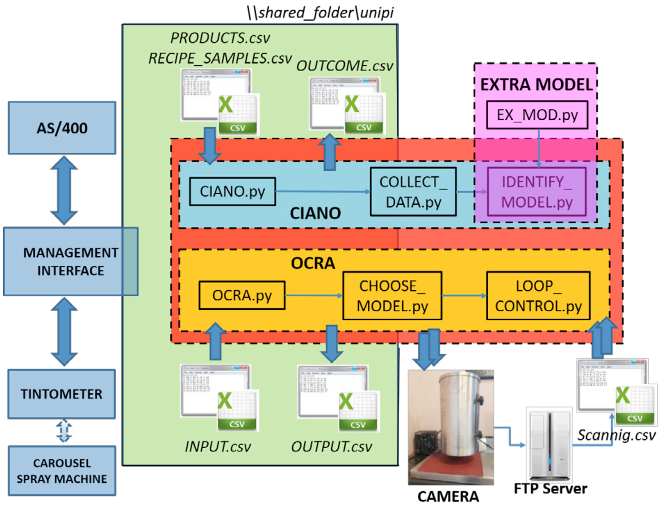

Fig. 1. Architecture of the color quality management and control system.

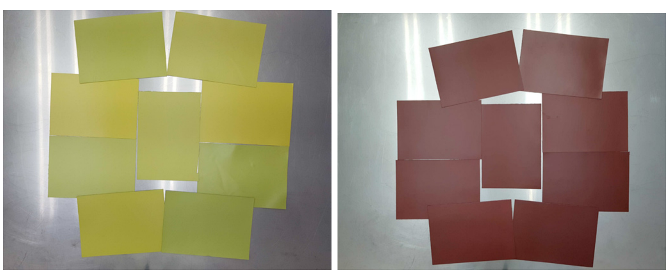

Fig. 2. Experimental set for LIGHT GREEN and MAHOGANY; basic formulation is the sample at the center.

without repetitions of the central point, a total of 2^N distinct tests are run. Therefore, for 3 factors, i.e. a cube-shaped design space, 8 (2^3) variants are performed to evaluate the model at the 8 vertices. In the case of 4 factors, in a 4-dimensional space, 16 (2^4) tests at the corners of the hypercube are executed.

As an example, Table 1 shows the experimental program for two central points, MAHOGANY and LIGHT GREEN, that is, two typical color tones of the company production. Corresponding factors, i.e. mass fraction of basic dye pigments, and low/high levels are reported. Note that regular spaces are considered, with symmetrical levels in two directions, but different variations of $N = 2$ factors with respect to the central point are applied (i.e. ± 1, ± 1.5, $\pm 2.0\%$). Table 2 shows the details of the randomized experimental design for the LIGHT GREEN. An analogous plan was performed for MAHOGANY. Two Full-Factorial designs (FF1, FF2) are organized for a total of 9 distinct leather samples, basic formulation as central point and 8 variants around. The 9 samples for the two color tones are shown in Figure 2.

The experimental designs here defined are then used to derive a first set of models of the chromatic effect of painted leathers.

3.2 Dimensionality Reduction

The multispectral camera interfaced with the proposed system returns 8 different values of light reflection, one for each characteristic wavelength, corresponding to the following spectrum channels: 1) UltraViolet - UV; 2) Blue; 3) Green; 4) Amber; 5) Red; 6) FarRed; 7) InfraRed; 8) White. It was decided to use all the 8 raw channels, possibly discarding one or more outputs (typically, the InfraRed), and then project them onto a lower dimensional space through the Principal Component Analysis (PCA). Therefore, a smaller number of Principal Components (PC), that is, c equivalent pseudo-channels of light reflection, are obtained specifically for each color tone of interest, i.e., for each central point of an experimental design previously organized, thus forming the vector of the projected response $Y \in \mathbb{R}^{c \times t}$, where t is total number of tests.

In particular, the suitable number of PCs is obtained in such a way that Y represents at least 95% of the explained variance of the multispectral raw data $X \in \mathbb{R}^{8 \times t}$. The dimension c of matrix Y is therefore not known a-priori, but it depends on the intrinsic characteristics of the raw data. Note that X and Y are linked by a linear transformation $Y = WX$, where $W \in \mathbb{R}^{c \times 8}$ is the projection matrix, evaluated in a preliminary stage to the identification of the colorimetric model.

3.3 Model Design

The response Y of each color tone is then described by a relatively simple model, function of the corresponding $N-1$ factors U. It was decided to consider at most linear single effects, quadratic single effects, and linear interaction effects, that is, of order two, in pairs of factors. In particular, the projected response of a dyed leather sample, in deviation from the lecture of the central point, that is, the basic formulation ($\Delta Y = Y - Y_b$), is expressed for each PC as follows:

$$\Delta Y = \sum_{i=1}^{N-1} K_i \Delta U_i + \sum_{i=1}^{N-1} K_{ii} \Delta U_i^2 + \sum_{i=1, i \neq j}^{\frac{1}{2}(N-1)(N-2)} K_{ij} \Delta U_i \Delta U_j + \Delta Y_0 \quad (1)$$

For each principal component, one can identify the m parameters of the corresponding model, i.e. coefficients K_i and K_{ii} associated with single linear and quadratic factors, linear interaction coefficients K_{ij} associated with pairs of factors and a constant term of bias ΔY_0. Note that also inputs, the mass fractions of basic dye pigments, are defined in deviation with respect to the basic recipe, corresponding to the central point ($\Delta U = U - U_b$). The model output is thus expressed by the following relation in compact form:

$$\Delta Y = K \Delta U_a \quad (2)$$

In particular, the gain matrix $K \in \mathbb{R}^{c \times m}$:

$$K = [K_1, \ldots, K_{N-1}, K_{11}, \ldots, K_{N-1N-1}, K_{12}, \ldots, K_{N-1N-2}, Y_0] \quad (3)$$

relates the matrix of output deviation ΔY with the matrix of augmented input deviation $\Delta U_a \in \mathbb{R}^{m \times t}$:

$$\Delta U_a = [\Delta U_1, \ldots, \Delta U_{N-1}, \Delta U_1^2, \ldots, \Delta U_{N-1}^2, \Delta U_1 \Delta U_2, \ldots, \Delta U_{N-1} \Delta U_{N-2}, 1]^T \quad (4)$$

The gain matrix K is here identified in a least squares sense:

$$\bar{K} = \Delta Y \Delta U_a^+ \quad (5)$$

where ΔU_a^+ is the pseudo-inverse matrix of ΔU_a. Once a colorimetric model is identified, is then stored in the software database.

3.4 Controller Design

A recursive strategy for color quality control can be activated by evaluating the output of the most appropriate archive model.

Table 1. Features of the adopted experimental designs for two color tones of interest.

Color Tone	Dye Pigment	Central Point Recipe	FF1		FF2	
			Low Level	High Level	Low Level	High Level
MAHOGANY			[-0.015/-0.01]	[+0.015/ +0.01]	[-0.01/-0.015]	[+0.01/+0.015]
	Red	0.6451	0.6301	0.6601	0.6351	0.6551
	Blue	0.3226	0.3126	0.3326	0.3076	0.3376
	Yellow	0.0323	0.0073	0.0573	0.0073	0.0573
LIGHT GREEN			[-0.02/-0.01]	[+0.02/ +0.01]	[-0.01/-0.02]	[+0.01/+0.02]
	White	0.6097	0.5897	0.6297	0.6197	0.5997
	Yellow	0.3049	0.2949	0.3149	0.2849	0.3249
	Blue	0.0854	0.0554	0.1154	0.0554	0.1154

Table 2. Details of the experimental design for LIGHT GREEN color.

	Test	Deviations	White	Yellow	Blue
Basic Recipe	B0	00	0.6097	0.3049	0.0854
Variants FF1	V1	+ +	0.6297	0.3149	0.0554
	V2	+ -	0.6297	0.2949	0.0754
	V3	- -	0.5897	0.2949	0.1154
	V4	- +	0.5897	0.3149	0.0954
Variants FF2	V5	+ +	0.6197	0.3249	0.0554
	V6	+ -	0.6197	0.2849	0.0954
	V7	- -	0.5997	0.2849	0.1154
	V8	- +	0.5997	0.3249	0.0754

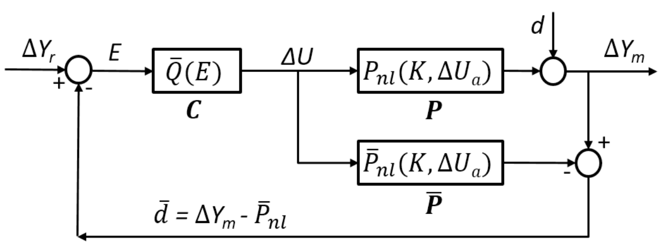

Fig. 3. Scheme of the control system for the color correction.

The proposed algorithm implements a feedback control loop based on a previously identified colorimetric model, in a fashion similar to the classic Internal Model Control (IMC) approach (Garcia and Morari, 1982). Figure 3 shows the control system scheme adopted for the color quality correction.

At the first run cycle ($k = 1$), the camera reading of the leather sample is set equal to the reference value (ΔY_r) of the control loop; the reading of the archive basic formulation ($\Delta Y_b = 0$) is set equal to the measured value (ΔY_m); while the color recipe of the basic formulation ($\Delta U_b = 0$) is assumed as the initial correction computed by the algorithm. In subsequent cycles ($k > 1$), the reading of the current dyed leather sample is actually the measured value (ΔY_m), while the recipe is updated according to the deviation from the reference. In fact, the control algorithm is required to reach the reference reading, that is, the first sample of unknown recipe (U_r), starting from the most similar archive base and appropriately updating the color recipe, by using the measurement of leather samples prepared from time to time by the finishing line machineries.

In particular, the control error E is evaluated as follows:

$$E = \Delta Y_r - \Delta Y_m + \bar{P}_{nl}(K, \Delta U_a) \tag{6}$$

where $\bar{P}_{nl}(K, \Delta U_a)$ is the output of the non-linear model as a function of the gain matrix K and augmented input deviation ΔU_a. The output of controller C is evaluated as solution of the following constrained optimization problem:

$$\min_{\delta} \|\bar{P}_{nl}(K, \Delta U_a) - E\|_2 \tag{7a}$$

subject to:

$$\sum_{i}^{N-1} U_i + \delta_i \leq 1 \tag{7b}$$

$$U_i + \delta_i \geq 0 \quad \forall\, i = 1, \ldots, N-1 \tag{7c}$$

The optimal vector of color correction (δ) is thus researched, that is, the variation of mass fraction of $N-1$ basic dye pigments, which minimizes the difference in norm between the output of the non-linear model and the control error, in respect of a set of simple constraints: i) the recipe is limited to 1 and ii) each mass fraction is positive. In order to ensure a robust convergence, the controller output is then filtered as:

$$\Delta U_k = \lambda \delta_k + (1 - \lambda) \Delta U_{k-1} \tag{8}$$

where δ_k is the solution of the optimization problem, U_{k-1} is the correction computed at the previous cycle (k–1), and $\lambda \in (0, 1]$ is the filter constant, set as parameter by the user. This approach, with the choice of a low value of λ, in particular, allows one to impose soft corrections and to avoid possible instabilities.

The algorithm also checks two stopping criteria based on two tolerances settable by the user. In details, an arrest occurs if:

- the difference in norm between the leather sample reading ΔY_m and the reference reading ΔY_r with respect to the norm of the reference itself is less than the camera tolerance T_C:

$$E_{\Delta Y} = \frac{\|\Delta Y_r - \Delta Y_m\|_2}{\max(1, \|\Delta Y_r\|_2)} < T_C \tag{9}$$

- the difference between the current correction ΔU_k and the previous one ΔU_{k-1} is less than the recipe tolerance T_R:

$$DU_k = \|\Delta U_k - \Delta U_{k-1}\|_2 < T_R \tag{10}$$

In fact, the first stopping criterion checks the relative error on the multispectral camera reading, i.e., on the chromatic effect between the reference sample and the current sample; the second criterion monitors the instantaneous variation in the recipe correction indicated by the algorithm. When either criterion is respected, the color recipe is not updated and a stop procedure is activated.

4. APPLICATION TO COMPANY DATA

In this section, examples of application of the proposed software to real data are presented.

4.1 Model Validation

By using the experimental campaigns organized according to the DoE methodology, a first set of colorimetric models has

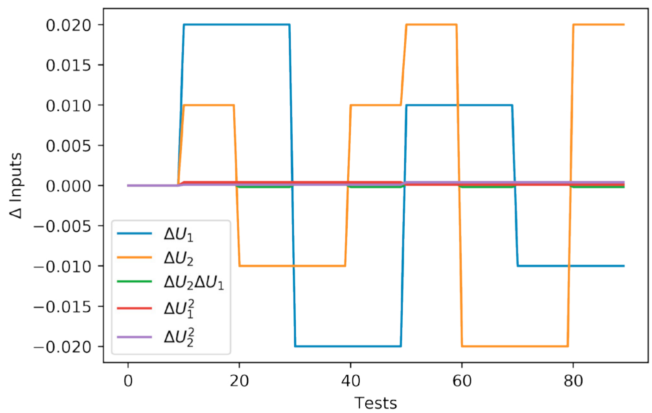

Fig. 4. Augmented inputs for the colorimetric tests of LIGHT GREEN.

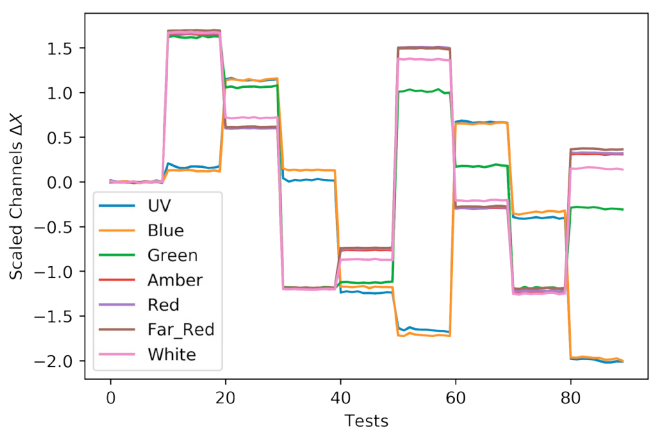

Fig. 5. Raw channels for the colorimetric tests of LIGHT GREEN.

been successfully developed and validated. In particular, detailed results are illustrated below for LIGHT GREEN color. The model is identified on the basis of the following settings:

- $n = 9$ leather samples; i.e., the basic formulation as center point and 8 variants, according to the DoE of Table 2.
- $f = 10$ flashes; for each dyed leather, 10 readings of the multispectral camera are acquired, for a total of $t = n \times f = 90$ tests.
- 5 augmented inputs; that is, two linear terms (ΔU_1, ΔU_2), two quadratic terms (ΔU_1^2, ΔU_2^2), one linear interaction term ($\Delta U_1 \Delta U_2$).
- scaled data; e.g., base-centered and normalized data, that is, data with (substantially) zero mean and unit variance.
- excluded channels: #7; that is, channel #7 of the camera (InfraRed) is excluded, thus, a matrix ΔX of 7 raw channels in deviation from the base is considered.
- projection: yes; the output data is projected by using PCA; in particular, matrix W is computed and matrix ΔY of c PCs is obtained from ΔX.
- $m = 5$ terms in K; for each PC, 5 coefficients are evaluated, for a total $c \times m$ terms (that is, bias ΔY_0 is not computed).

The major results are illustrated here below. Figure 4 shows the trend along the 90 tests of the augmented input matrix:

$$\Delta U_a = [\Delta U_1, \Delta U_2, \Delta U_1^2, \Delta U_2^2, \Delta U_1 \Delta U_2]$$

Figure 5 shows the trend of raw data of light reflection channels ΔX in deviation from the basic formulation.

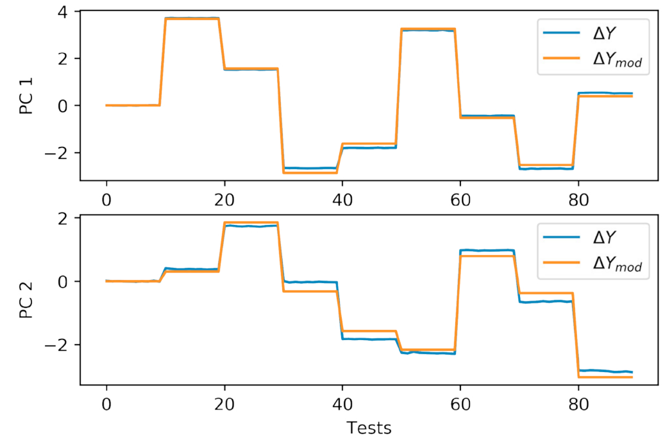

Fig. 6. Principal Components: real data and model outputs for LIGHT GREEN tests.

The main features of the identified model are listed below:

- 2 Principal Components ($c = 2$); from raw channels ΔX, projected outputs ΔY, which describe at least 95% of the variance of the original data, are obtained;
- Relative Projection Error: 4.09%; the dimensionality reduction with PCA is thus to be considered sufficiently reliable (since optimal value is 0%).
- Condition Number of K matrix: 2.91; the identified model is to be considered sufficiently balanced and stable (optimal value is 1).
- Average Explained Variance: 99.0%; the identified model is very accurate in describing the original data variance (optimal value is 100%).

Figure 6 shows the trend of the two principal components: real data (ΔY) and corresponding model outputs (ΔY_{mod}). It can be observed that the model is able to fit properly these time trends.

Similar results have been obtained for the color MAHOGANY. Briefly, with the same parameter settings adopted for LIGHT GREEN, the following results occur: 2 PC; Relative Projection Error: 8.93%; Condition Number of K: 4.29; Average Explained Variance: 83.1%. Also this model is to be thus considered sufficiently accurate in original data description. Note that colorimetric models for the other colors of interest for the company production were analogously identified and validated.

4.2 Software Validation

The whole color quality management and control software has been successfully tested on the basis of a first set of colorimetric models and some color correction cycles. In particular, validation tests were carried out to verify the complete and effective communication of the algorithm with the company management software, on the one hand, and with the multispectral camera and the FTP server, on the other. The software was also tested from a performance point of view: that is, check whether the color correction strategy provides good results in terms of convergence towards the target sample of unknown recipe. Detailed results for LIGHT GREEN color are here illustrated. The correction cycle was executed with the following parameters:

- 20 flashes; 20 readings of the multispectral camera are acquired for each new leather sample;

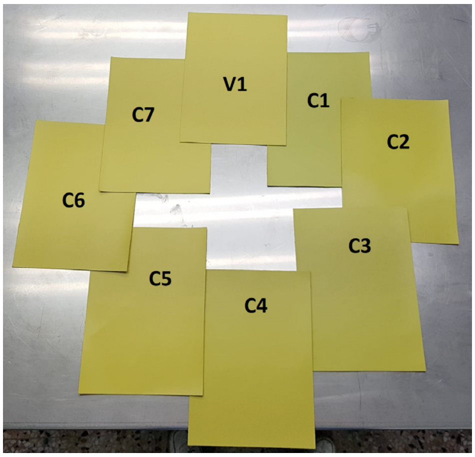

Fig. 7. Samples for the color correction cycle for LIGHT GREEN.

Table 3. Details of the color correction cycle for LIGHT GREEN.

Sample	White	Yellow	Blue	$E_{\Delta Y}$	DU_k
V_1	0.6297	0.3149	0.0554	1.0	0.0125
C_1	0.6206	0.3109	0.0685	0.5097	0.0089
C_2	0.6286	0.3070	0.0644	0.4808	0.0061
C_3	0.6327	0.3114	0.0559	0.2480	0.0032
C_4	0.6346	0.3140	0.0514	0.1706	0.0024
C_5	0.6355	0.3162	0.0483	0.2560	0.0044
C_6	0.6315	0.3181	0.0504	0.1313	0.0026
C_7	0.6323	0.3156	0.0521	0.0412	0.0005
C_8	0.6319	0.3154	0.0524	-	-

- $T_C = 0.05$: the tolerance on the relative error in the multispectral camera readings;
- $T_R = 0.001$: the tolerance on the absolute variation in the recipe correction of dye pigments;
- $\lambda = 0.5$: the filter constant of the algorithm.

Figure 7 shows the samples of painted leather obtained for the correction cycle of color LIGHT GREEN by using the machineries of the finishing line, that is, the robotic spray carousel and the automatic tintometer. The variant V1, previously used for the model identification, was here assumed as the reference sample, that is, as the target formulation of unknown recipe, to be reached starting from the corresponding archive base. The first seven correction samples were produced on the basis of the indications provided by the control algorithm illustrated in Section 3.4. Table 3 shows the details of the color correction cycle: for the reference formulation and the first seven corrections, the color recipe and the two algorithm performance indices are reported, that is, the mass fractions of basic dye pigments, the relative error on camera readings $E_{\Delta Y}$ and the correction variation in the recipe between two successive cycles DU_k.

A good convergence can be observed: the corrections tend to the variant V1, the target recipe of the cycle; the relative error on the camera reading and the update of recipe variation decrease significantly. In particular, the algorithm automatically stops at cycle #8, since a relative error in the multispectral reading ($E_{\Delta Y} = 0.0412$) lower than the set tolerance ($T_C = 0.05$) is obtained and, at the same time, a total variation in the color recipe ($DU_k = 0.0005$) lower than the tolerance ($T_R = 0.001$) is indicated. This means that sample #7 has a chromatic effect very similar to the target formulation, and the new color recipe (#8) would be very close to the previous one. In fact, the recipe #7 has a visual effect on the leather almost equal to the sample V1; in particular, the company finishing technician has observed a similarity of the color tone higher than 90% with naked eye in the color booth. Finally, it should be noted that, recipe correction cycles were successfully tested also for other production colors, but they are not reported for sake of brevity.

5. CONCLUSIONS

In this paper, an automated system for modeling and controlling color quality of dyed leathers has been designed and tested within an Italian tannery company. The proposed software is fully integrated with the machineries of the finishing line, that is, a robotic spray carousel and an automated tintometer system. Suitable experimental tests according to the DoE methodology are firstly defined, executed and analyzed for the various color tones of company interest. The recipes of dye pigments and light reflection data measured by a multispectral camera are subsequently used to derive and validate a set of colorimetric models, in order to evaluate and predict the color rendering of painted leathers. The identified models proved suitable in describing the variance of the original data, especially once PCA is employed for dimensionality reduction. These models also proved to be particularly reliable, since the proposed color correction strategy, inspired by classical IMC approach, has provided satisfying results in terms of convergence towards the target formulations of unknown recipe. Future developments may involve some minor aspects for the software: as examples, colorimetric models of enhanced structure, refined research algorithms of the most appropriate basic formulation stored in the database to be used as first guess recipe, and improved strategies for color correction update will be investigated.

ACKNOWLEDGMENT

This work has been supported by Sviluppo Regione Toscana through the POR FESR 2014 - 2020 funding program (Tintometro Robotizzato per Conceria - TRUE COLORS).

REFERENCES

Datacolor (2020). Datacolor TOOLS: Smart color analysis and visualization for quality control. https://www.datacolor.com/business-solutions/product-overview/datacolor-tools.

Garcia, C.E. and Morari, M. (1982). Internal Model Control. 1. A Unifying Review and Some New Results. *Ind. Eng. Chem. Process Des. Dev.*, 21, 308–323.

Gerelettronica (2020). IRIS – in line system for color quality control. https://www.gerelettronica.com/products/iris/.

HunterLab (2020). EasyMatch QC: Color quality control software. https://www.hunterlab.com/solutions/color-measurement/easymatch-qc/.

KEYENCE (2020). Intuitive vision system: CV-X series. https://www.keyence.co.uk/products/vision/vision-sys/cv-x100/.

Mouw, T. (2016). 8 Reasons Controlling Color Quality is Hard. https://www.qualitymag.com/articles/93646-reasons-controlling-color-quality-is-hard. *Quality Magazine*.

Oehlert, G.W. (2010). *A First Course in Design and Analysis of Experiments*. W. H. Freeman & Co.

Ramanathan, G. (2017). Color quality control ensures consistency in leather furniture production. https://blog.hunterlab.com/blog/color-in-textiles/color-quality-control-ensures-consistency-leather-furniture-production/. *HunterLab Blog*.