MULTIVARIATE MONITORING OF QUALITY OF A SPARKLING WINE

GIOVANNI DI RUZZA (*) - PATRIZIA PAPETTI (**)

Abstract

The purpose of this work was to establish statistical control of an italian "sparkling wine" (prosecco doc) production process. At the same time we aimed to monitor the process stability over time and effectiveness to achieve a consistently high quality product as well, while starting from the inherent high variability of raw materials.

Moreover we tried to find out an effective statistical methodology for the initial quality control and conseguent monitoring and then for the investigation of the main problems pointed out.

Given the multi-dimensional nature of the quality of the sparkling wine, multivariate techniques were extensively used. With that view, multivariate quality control charts were developed starting from the "Hotelling" T" statistic, first for the control of the process, thereof to allow the monitoring and maintenance of the quality achieved.

The investigation of irregularities detected during the quality monitoring of the process, was based upon the principal component analysis methodology. The study outcomes, substantially confirm the effectiveness of the examined process to achieve a finished product of constant quality over the time, despite of the high variability of wines and musts used as raw materials.

(*) DNV Lead Auditor, Bologna unit e-mail: giovanni.drz@alice.it.
(**) Dipartimento "Impresa Ambiente Management" University of Cassino - via S.Angelo - Campus Folcara - 03043 Cassino papetti@eco.unicas.it.

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Riassunto

Lo scopo del presente lavoro è di stabilire controllo statistico del processo di produzione di uno spumante “prosecco doc” e di monitorarne la stabilità nel tempo e l’efficacia ad ottenere un prodotto di qualità costante pur partendo dall’intrinseca elevata variabilità delle materie prime. Allo stesso tempo ci si propone di individuare un’efficace metodologia statistica per il controllo e monitoraggio della qualità e analisi delle anomalie rilevate.

Considerata la natura multidimensionale della qualità del vino spumante, sono state estensivamente utilizzate procedure multivariate. A tal proposito, sulla statistica T” di Hotelling sono state sviluppate carte multivariate dapprima per il controllo del processo ed in seguito per consentire il monitoraggio ed il mantenimento della qualità.

L’investigazione delle anomalie rilevate in fase di monitoraggio della qualità si è basata sulla metodologia dell’analisi delle componenti principali.

I risultati della ricerca confermano sostanzialmente l’efficacia del processo di spumantizzazione esaminato a conseguire un prodotto finito di caratteristiche qualitative costanti nel tempo, non risentendo della elevata variabilità dei vini e mosti base utilizzati come materia prima.

Keywords: Sparkling wine, Process analysis, Multivariate statistical methodologies.

Introduction

The initial purpose of research, was to monitor the performance of a "sparkling wine" production of multivariate nature, relying on statistical methods which were unable to capitalise existing relationships between the several variables, while monitoring these.

The ultimate goal of our statistical control process 'SPC' was to analyse the performance of the production process as to obtain a finished product with a constant and under control quality level, while starting from raw materials of considerable variability. This has indirectly achieved through the multivariate quality control of the qualitative variables of the finished and semi-finished product, in order to detect any "unusual" event which can occur through the running of the production process (1).

The production method of the examined sparkling wine, was the so called "Charmat", an industrial quick method for sparkling wine production, which allows the foam to develop into the basis wine by means of addition of sugar in capable and sealed tanks and afterwards just fill the

bottles with the obtained sparkling wine. This technology, allows to process the wines quickly and with continuous production.

The first phase of processing is specifically addressed to the preparation of wine through wine-making in autoclaves and then keep there the base-wine chilled and at a constant temperature.

The second phase is designed to the taking of foam; it is to submit the base-wine to a second fermentation that has the effect the production of CO_2, obtained through the addition of a solution of sweet syrup and active yeasts, measured in relation to the desired final pressure accorded with the pre-arranged sugar residual.

Later, when the re-fermentation will come to term, then you keep on transferring and contemporary dividing of sparkling wine from the lees that accompanied it through the process. You still will need to proceed to the stabilisation of the product that gets through the cycle of refrigeration in the same autoclaves, then it will be bottled and packaged (2).

The legislation requires that “d.o.c.” wines as in the case of the Prosecco of Valdobbiadene, are to be analysed before being started marketing. The industry legislation, technical specification and technological considerations require for “d.o.c.” wines as in the case of the “Prosecco of Valdobbiadene” several laboratory analysis during the wine process and before marketing phase.

The chemical analysis is then supported by the sensorial analysis which focuses on the assessment of the organoleptic characteristics of wine. On the basis of these considerations, the quality of the sparkling wine, in this study has been monitored both at semi-processed level (at the end of the "preparing" phase of the batch) and at finished product level (sparkling wine already bottled).

The study, analyzed the scores of relevant quality characteristics of wine, have been extracted from the chemical analysis of the factory oenological laboratory.

These quality characteristics, at the end of an appropriate exploratory phase of historical data, which is preparatory to the effective application of the proposed multivariate statistical methodologies, were eventually in the number of 11 as shown in Table 1. Of these only 5 were observed on the semi-processed wine and 11 on the finished product (3-4).

TABLE 1

VARIABLES ANALYSED

Variable	Acronimo	Unit of measurement
Actual Alcohol	V1	% vol.
Total Alcol	V2	% vol.
Total Acidity(in tartaric acid)	V3	g/L
pH (or real acidity)	V4	Acidity scale
Free SO^2 (total sulphurous anhydride)	V5	mg/L
Pressure (indirect measure of CO)	V7	atmosphere
Volatile Acidity in acetic acid	V8	g/L
Total SO^2	V9	mg/L
Ashes	V10	g/L
Dried Extract (total extract)	V11	g/L
Sweet Residual	V12	g/L

The statistical methodology

The methodology used is based on the use of multivariate control charts Q_i and Q_f developed on Hotelling T^2 statistics (5).

Applying these statistics, first on a sufficiently large sample of p-variate observations concerning the semi-processed and finished product batches, eventually you figure out a stable process situation and all information about this desired condition are summarised in an average vector $\bar{x}_m$ and in a covariance matrix S_m.

Then, vectors of observations concerning the lots at present time, are monitored by comparison with parameters estimated previously from stable process, i.e. in "statistical control". Each change in the statistical structure of the measures of quality of semi processed / finished wine in relation to the representative values of the stable process, highlights abnormal conditions that must be analysed.

The T^2 statistic of Hotelling is the similar multivariate of the Student's t distribution that widespread for p variables becomes

$$T^2 = n(\bar{x}-\mu_0)'\Sigma^{-1}(\bar{x}-\mu_0),$$

when μ and Σ are known, then we get

$$\chi_0^2 = n(\bar{x}-\mu_0)'\Sigma^{-1}(\bar{x}-\mu_0)$$

Or, estimating them from the "in-control" process, as in our case, we get

$$T^2 = n(\bar{x}-\bar{\bar{x}})'S^{-1}(\bar{x}-\bar{\bar{x}})$$

Our sample is characterised by p-dimensional individual observations $x' = (x_1, x_2, ..., x_p)$ and the T^2 minimizes down to the case of *m* vectors of individual observations $n = 1$ i.e.

$$T^2 = (x-\bar{x})'S^{-1}(x-\bar{x}).$$

The T^2 is a measure of statistical distance and expresses itself in a one-dimensional value, this practical relevance to build a control chart

$$Q_\iota = (x_i-\bar{x}_m)'S_m^{-1}(x_i-\bar{x}_m)$$

with $N_p(\mu, \Sigma)$ and i =1,2,…,m , plotting on a chart, against control limits, the individual values of the T^2 meanwhile keeping the information hold in all the *p* variables.

A T^2 value of a vector of observations x_i, plotted on the Q_ι chart, measures how far the observation is from the centre of the process x_m, relatively to sample covariance matrix:

$$S_m = \frac{1}{m-1}\sum_{i=1}^{m}(x_i-\bar{x})x(x_i-\bar{x})'.$$

On the X axis of the control chart Q_i are shown the *m* observations, where on the Y axis the T^2 values related to each p-variate observation are stated.

The T^2 values that exceed the Upper Control Limit "UCL" are considered not complied with the purpose of the definition of the reference model. The Q_i chart presents only the upper control limit UCL since the plotted T^2 values, measure a distance. The exact calculation of the UCL is essential for the purposes of the accuracy of the reference model and requires knowledge of the statistical distribution of the T^2 that for

individual observations is not widely known, so that until 1992 it was approximated in turn to χ^2 a or an *F* statistical distribution (6-7) using previous studies (8), indicate the solution in two different UCL based on a *Beta* distribution, the first in the control phase and the second in the monitoring phase: deployment in the stages of monitoring and control.

We will then have the

$$UCL\ (1.1) = \frac{(m-1)^2}{m} B_{\alpha\ [p/2,(m-p-1)/2]_{d.f.}} \quad \text{and}$$

$$UCL\ (1.2) = \frac{(m-a-1)^2}{m-a} B_{\alpha\ [p/2,(m-a-p-1)/2]_{d.f.}}$$

respectively in stage 1 and 2 of the control phase, and

$$UCL = \frac{p(m-1)(m+1)}{m(m-p)} F_{\alpha\ (p,m-p)_{d.f.}}$$

in the monitoring phase.

The use of control charts based on the T^2 for the statistical quality monitoring , applying the same terminology of Alt (9-10) and Mason *et al*., (11), requires two separate macro-phases:

• **Phase I** *(Control)* using Q_i chart : in turn is divided in :

- Stage 1 *(retrospective)*: we first estimate the parameters of the chart i.e. the vector of means $\bar{x}_m$ and the covariance matrix S_m, hence we plot on the Q_i chart so characterized, the *m* scalar numbers with the view of uncovering the "outliers" observations whose values T^2 exceed the UCL(1.1).
- Stage 2 *(perspective)*: through an iterative process, the "*a*" values that do not conform against the time to time amended UCL(1.2) are identified, and the parameters of the control chart are recalculated.

  The chart at this stage takes the following form

$$Q_i = (x_i - \bar{x}_{m-a})' S^{-1}_{m-a} (x_i - \bar{x}_{m-a}).$$

The output is the process model of the stable and statistically under control production.

• **Phase II** *(Monitoring)*: use of parameters estimated in Phase I, for monitoring the future k observations x_f; f=1,2…,k, plotting the T^2_f values on the chart

$$Q_f = (x_f - \bar{x}_m)' S_m^{-1} (x_f - \bar{x}_m).$$

Phase I was preceded by a preliminary phase to the end of which, from initial data we come to the definition of the *preliminary data set* "PDS". Historical data, collected by the chemical-physical laboratory analysis of the observed variables, are indeed not directly statistically usable, but they need to be properly filtered and modelled in order to meet the basic assumptions (essentially multi-normality and independence) for the application of proposed multivariate statistical methods.

We turned the marginal distributions of the p=11 analysed variables with logarithmic base function log(x), having all positive and >0 values; we processed the data series of the variables affected by autocorrelation, with appropriate auto regressive models AR of first and second order, in order to obtain a series of normally and independently distributed residuals, with average 0 and constant variance $e_f \sim N(0,\sigma^2)$.

All variables are then standardised before being analysed by means of the control charts in phase I.

As regards the choice of level of the type I error "α", the values of T_i^2 i=1,2,...,m of historical observations x_i are all at once subject to control through the chart Q_i, in practice is as if had m tests simultaneously, this way the overall probability of "false alarm" increases considerably.

Hence, without corrections, "α" is to be used only to compute the UCL in Phase II, when the process is already in "statistical control" and must be corrected in Phase I, according to the "Bonferroni-limits" approach suggested by Alt (9-10).

Analysis

Phase I: Control on semi-processed and finished product (Stage 1 e 2). At this stage the data examined are related to the observed qualitative variables in the lots of

- **Semi-processed wine**

associated with the base-wine batches, charged with yeast and before adding sugar for fermentation and sparkling in autoclave.

- Finished product (sparkling wine)
associated with the sparkling wine, after sparkling, stabilization, corrective treatments and already bottled and put away for about 2 weeks. Obtained values are given in Table 2.

TABLE 2

SUMMARY DATA OBTAINED IN STAGE 1

	Control of *Semi-processed wine*	Control of *Finished product*
Historical observation	$m = 64$	$m = 63$
Sub-group size	$n = 1$	$n = 1$
Type1 error	"α"= 0.002	"α"= 0.002
Estimator	$m\mathbf{S}$ = pooled	$m\mathbf{S}$ = pooled
Observed variables	$p^* = 5$	$^{**}p=11$

Form the analysis of these data in Stage I, (Fig.1 and 2) we noticed the need to analyze in stage 2 only the semi-processed wine; indeed, the control chart of the finished product does not highlight any abnormal observation-vector and therefore does not require of the progressive removing of "outliers". The situation presented by the chart concerning finished sparkling wine already bottled, after the Stage I, is already the desirable stable process "in statistical control".

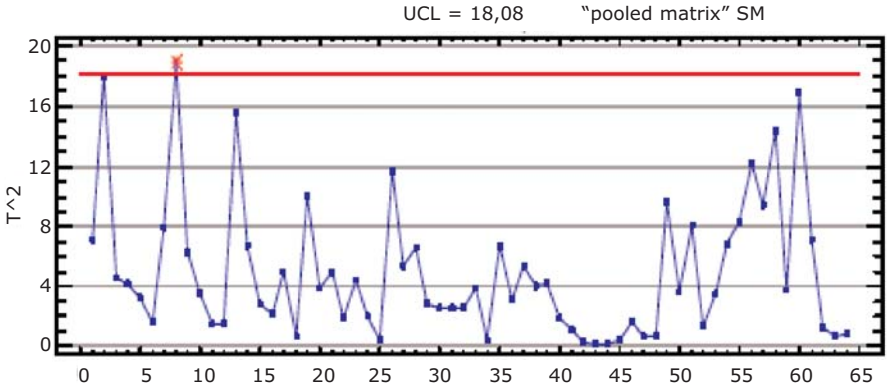


Fig. 1 – Phase I - Stage 1: retrospective- multivariate Control Chart Q_i for *Semi-processed wine.*

* The observed variables for semi-processed wine were: actual Alcohol, total Alcohol, total Acidity, pH, total SO_2
** The observed variables for finished sparkling wine were: effective Alcohol, total Alcohol, total Acidity, pH, total SO_2, pressure, volatile Acidity, free SO_2, Ashes, net dried extract (or Total extract), sweet Residual.

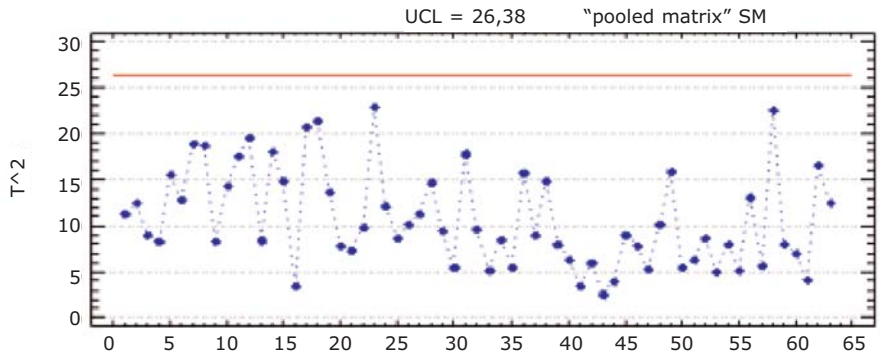


Fig. 2 - Phase I - Stage 1: retrospective- multivariate Control Chart Q_i for *Finished sparkling wine.*

In "Stage 2", just for the semi-processed product, we preceded in the progressive removal of phasing of "outliers" observations until reaching a stable process situation or better "in statistical control", where the Q_i chart does not point out any abnormal observation. The final result was eventually obtained after four reiterations and led to the exclusion of $a=4$ outlier observations corresponding to batches n. 2, 8, 13, 60 from the final parameters calculation and consequent time to time recalculation of the T_i^2 values to plot on the Q_i chart (12-13).

The (m-a) observations in "statistical control" remained at the end of Phase 1 and from whose we extracted the definitive parameters for using in the next phase of process monitoring, were in number of 60 for the semi-processed wine and all the original 63 for the finished sparkling wine. These observations are the *Historical Data Set "HDS"* of the stable production from which we got the estimators to use later with the monitoring chart.

Phase II : Monitoring on semi-processed wine and on finished sparkling

Having defined through the historical data, the situation of a stable process in "statistical control", we moved to monitoring the quality of the lots of current production again as semi-processed and finished product.

Individual T_f^2 values plotted on the Q_f monitoring chart are, this time, each one individually the object of analysis and are distributed as an F of Snedecor-Fisher and not more as a *Beta* distribution. Indeed the vectors of the K future observations, are now independent from the previously estimated mean vector $\boldsymbol{x}_m$ and covariance matrix $\mathbf{S}_m$.

The main target of this phase is to point out every deviation of the current production from the “in control” conditions of the stable process, with the final goal to detect process anomalies. Current production, was monitored on k = 23 and k = 22 batches respectively of semi-processed and finished sparkling wine, corresponding to *p*-variate observations on the same *p* variables of the previous control phase.

In the monitoring phase, through the monitoring chart Q_f, we pointed out signals of anomalies, i.e. "outlier" vectors that indicate us, how the quality level of the corresponding monitored lots differs from the stable production reference model which in turn was defined applying the Q_i control chart control on the historical production lots. These signals of anomalies can originate from:

- Crack of the stable relations between the "*p*" correlated variables (represented by the covariance matrix $\mathbf{S}_m$) ;
- Deviation by one or more of the “p” variables from the mean stable value $\bar{x}_m$

In the process monitoring phase eventually we pointed out :

- 3 anomalous obervation-vectors (lots) of *Semi-processed wine*;
- 1 anomalous obervation-vector (lot) of *Finished sparkling wine.*

It is well to remember, that the T^2 statistic does not directly provides the operator the cause of the anomaly and it is therefore necessary to define solutions so that we can have control of the process.

Analysis of anomalies

We analysed the identified anomalies by applying the methods of “principal components” and " decomposition of T^2 signal”.

For simplicity and brevity of description, we outlined the whole procedure as below, only for the anomalous vector identified while monitoring the quality of the current production of finished sparkling wine (observation n ° 4 corresponding to lot 40-05) (Fig. 3 and 4).

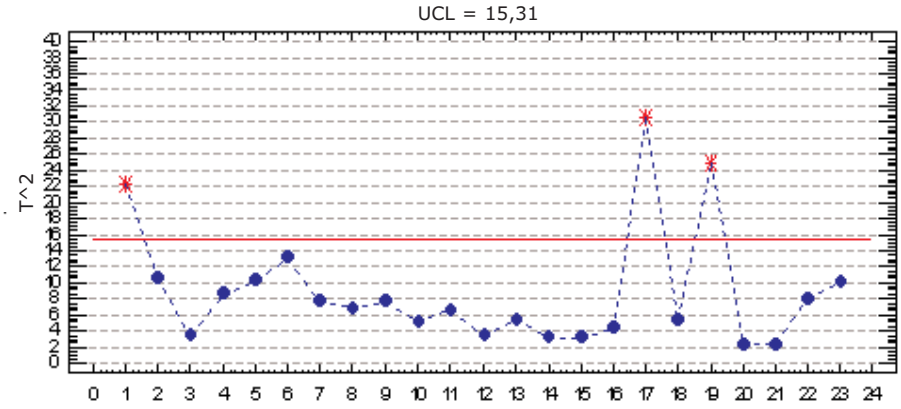


Fig. 3 – Phase II, monitoring - Multivariate monitoring chart Q_f: semi-processed wine.

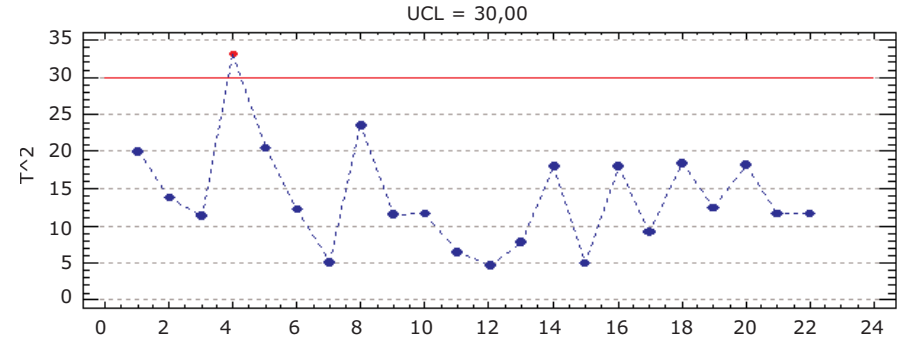


Fig. 4 – Phase II, monitoring - Multivariate monitoring chart Q_f: Finished sparkling wine.

Analysis through the method of "Principal component"

The method, proposed by Jackson (14) and Kourty *et al*. (15), provides for an unusual use of the principal component technique.

The assumption is the invariance of the T^2 statistic computed in the original space and in the principal components space; the condition is that all of the principal components must be considered, that is the same number of P.C. as that of the observed variables; hence we get a = 11 P.C. for the finished product.

The method provides for the projection of the matrix of the *m* observation-vectors "in control" (Fig. 5), that in turn represent the stable reference model derived from the Q_i chart, on the orthogonal space of the P.C..

Then the normalized "scores" (Fig. 6) of future observations (i.e. current production) are calculated and those one with the highest absolute values are investigated through the technique of "*contribution plot*" (16-17). The contribution plots are like charts illustrating the contribution of each original variable to the value of the individual score. The contribution of the "j*th*" variable to the normalized anomalous individual score for the to "a *th*" P.C. is given by:

$$cont_{a,j} = \frac{t_a}{\lambda_a} p_{a,j} (z_j - \mu_j)$$

$Z = \sum_{a=1}^{p} t_a p_a + E$; $t_a = 1$, a=1,…p are the orthogonal P.C. and $\mathbf{p}_a$ are the eigenvectors, ordered so that the first $\mathbf{t}_a\mathbf{p}_a$ will capture most of the variation in the data, etc... where **E** represents the amount of variation not captured by the model.

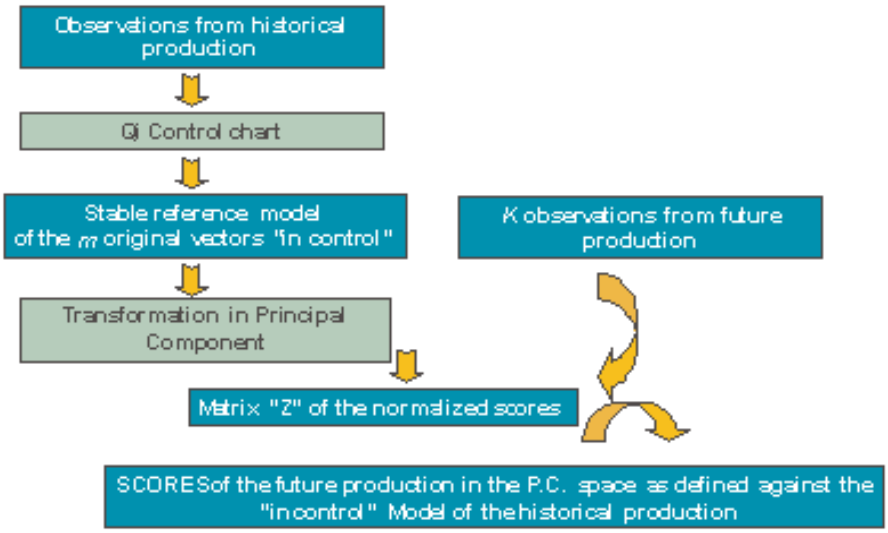


Fig. 5 - Matrix of Z scores.

We need to consider the Variables with the highest contribution and the same sign as the value of the "score" of the P.C. (18) because it is this squared value which contribute to the value of the T^2 statistic.

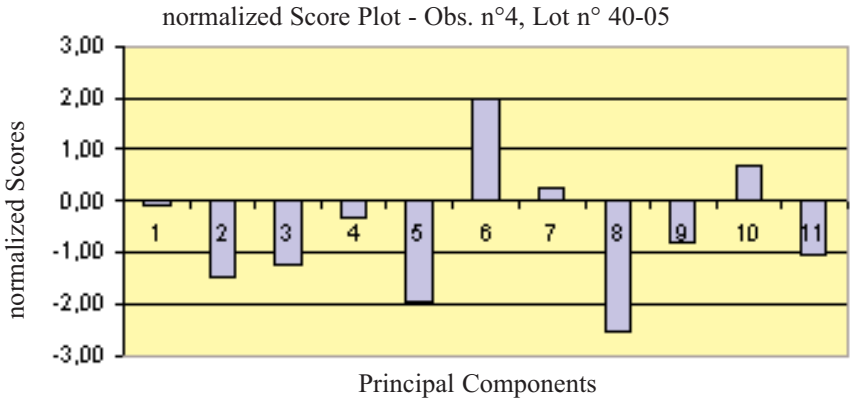


Fig. 6 - Normalized Score Plot – Observation n. 4 – Finished sparkling wine.

To deepen further and confirm this major statement, we built a chart that shows the quadratic series of the scores for the P.C. n. 8, and a 3D diagram in the dimensions of the concerned P.C.s, the scores relating to the observation n ° 4 (Lot n. 40) pointed out from Qf monitoring chart.

For the finished product (sparkling wine) we obtained the contribution plots in which the actual values of variables are represented rather than the absolute values, precisely with a view to identifying variables with high value but only these with the same sign as the score of the P.C. was at anomalous observation.

The analysis of charts, shows us (Fig. 7, 8 and 9) "Dried extract" and "Ashes" being the variables that contribute more than others to the anomaly in the process of the finished product, as shown in Table 3.

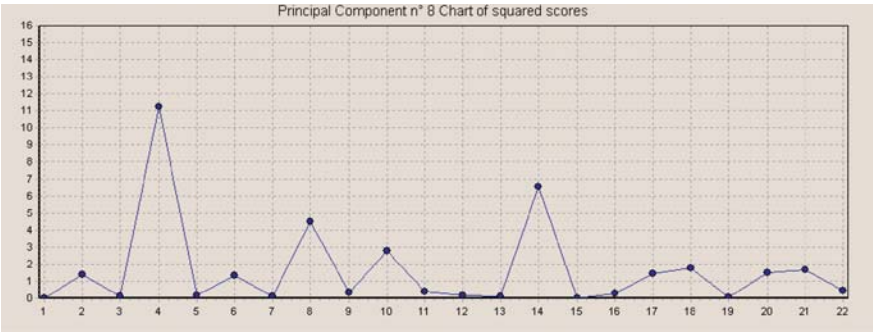


Fig. 7 - Squared Scores C.P.n°8 – Finished sparkling wine.

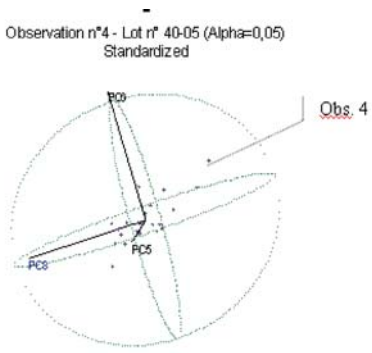


Fig. 8 - 3D diagram of P.C. n°8, 6, 5 – Finished sparkling wine.

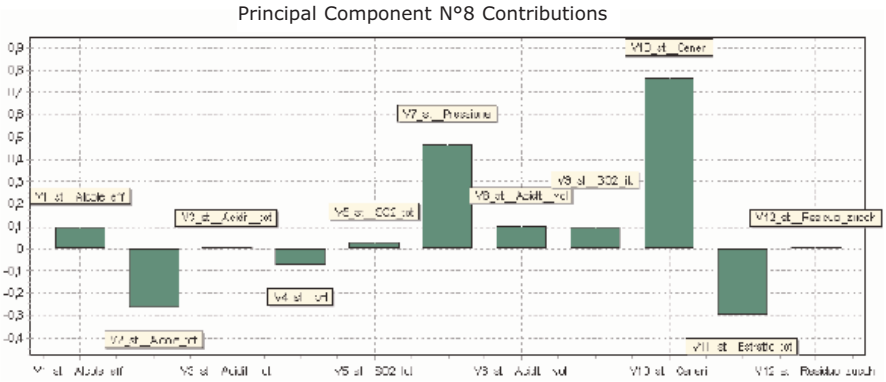


Fig. 9 - Contribution Plots for P.C. n. 8 – Finished sparkling wine.

TABLE 3

FINISHED SPARKLING WINE – CONTRIBUTION OF THE VARIABLES TO ANOMALY N. 4

Obs. n°	*Lotto n°*	*C.P.*	*Score*	*Primary variable*	*Secondary Variable*	*Third variable*
4	40-05	n. 8 n. 6 n. 5	−2.55 2.02 −1.97	**Total extract (dried)** Volatile Acidity Total Acidity	Total Alcohol Free SO_2 **Ashes**	pH **Ashes** **Total extract (dried)**

Analysis through the method of "decomposition of T² signal"

Proposed by Mason *et al.* (19) and known as "MYT" Decomposition , the method is based on the decomposition of the T² value into *p* independent orthogonal components. *p* ! different partitions are possible, but each one of those, returns the same T² value; a form of the MYT is given by:

$$T^2 = T_1^2 + T_{2.1}^2 + ... + T_{p.1,2,...,p-1}^2 ;$$

where T_1^2 is an unconditional term, independent from the other variables, and $T_{p.1,2,...,p-1}^2$ is a conditional term.

The procedure applies only in the instance where the sub-sample is of size n=1 as indeed is in our study. Also, each term of the partition is distributed (under the null-hypothesis) as an *F* distribution multiplied by a constant term.

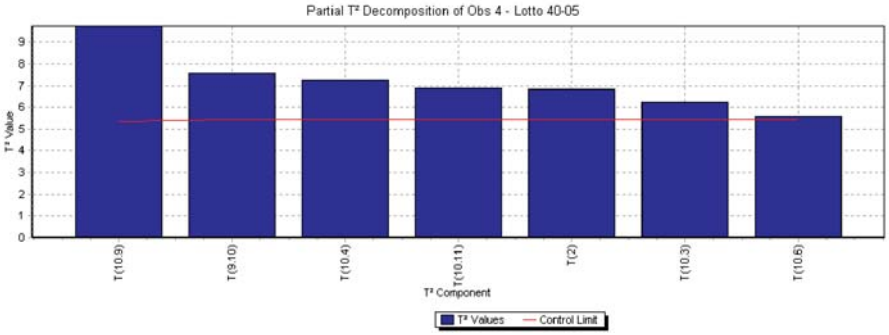
$$T^2_{j+1.1,\ ...,\ j} \sim \frac{m+1}{m} F_{(1,\ m-1)\ d.f.}$$

where *m* is the number of the "in control" observations constituting the reference model. This in turn allows us to use a Control Limit (*Critical Value*) (Table 4). The breakdown of anomalous T² value (Fig. 10), easily identify the most responsible variable of the indications of anomaly.

TABLE 4

TERMS OF THE PARTION THAT EXCEED THE CRITICAL VALUE/CONTROL LIMIT

Termo f the MYT partition	T^2 value	Critical Value	T^2 overall
T (Total Alcohol)	6.8329	5.333	33.0899
T **(Ashes Dried (or total) Extract)**	**7.5587**	5.333	33.0899
T (Dried Extract. Total Acidity)	6.2435	5.333	33.0899
T (**Dried Extract.** pH)	**7.2773**	5.333	33.0899
T (Dried Extract. Pressure)	5.6083	5.333	33.0899
T (Dried Extract. **Ashes**)	**9.7521**	5.333	33.0899
T (Dried Extract. Sweet Residual)	6.8684	5.333	33.0899



1=V1 Alcohol, 2=V2 Total Alcohol, 3= V3 Total Acidity, 4= V4 pH, 5= Total SO_2, 6= V7 Pressure, 7= V8 Total Acidity, 8= V9 SO_2 free, 9= V10 Ashes, 9= V11 Dried Extract, 10 = V11 Sweet Residual

Fig. 10 - MYT Partial decomposition – Obs 4.

The variables that contribute more than others to the anomaly in the finished product are clearly: Dried extract and Ashes (Fig.11).

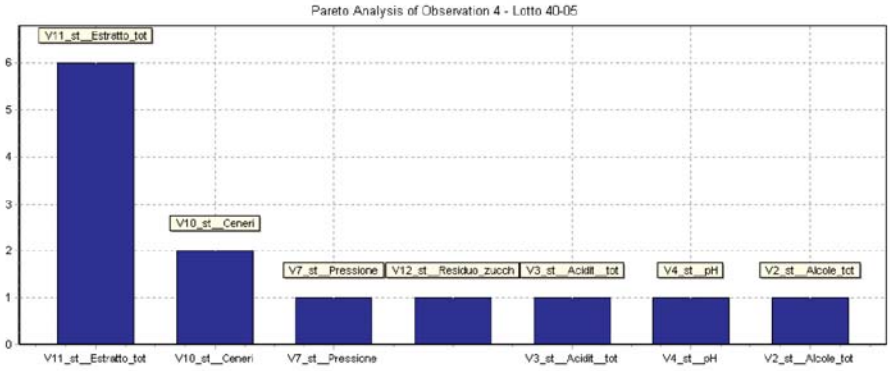


Fig. 11 - Pareto chart of the variables with greater contribution to the anomaly.

Remarks about the results of the analysis of anomalies

Both methods lead to find out the same variables as responsible for anomalies, but the "principal components" approach, provides information less clear then "MYT decomposition" when the contribution to the anomalous signal lies in a deviation in the relationships among

variables, summarized in the covariance matrix $\mathbf{S}_m$ of the reference model. Indeed is important to highlight how for the variable "dried extract", the total contribution to the anomalous T^2 signal, lies in the conditional terms rather then in the unconditional (independent) terms, i.e. in the relationship of the variable “dried extract” with the other variables.

The information of the conditional or absolute contribute of the variables to anomalies, in turn, is particularly useful because it allows us to focus not on the single variable but on the relationship between "dried extract" and other qualitative variables considered for the finished sparkling wine (Table 5).

For the variable "dried extract", it is clear how the alteration in its relationship with the variables: pressure, total acidity, pH and sweet residual, as compared with the "in control" reference model, is the main cause of the anomalous T^2 value for the observation value n ° 4 from current production.

Actually we can see how the values for the observation n° 4, go in the opposite direction than the correlations shown under the in control model. The chart below (Fig. 12) illustrates these considerations.

TABLE 5

CORRELATIONS VALUES FOR THE VARIABLE “DRIED EXTRACT” UNDER THE “IN CONTROL” REFERENCE MODEL

	Ashes	*Total Alcohol*	*Total Acidity*	*pH*	*Sweet Residual*	*Pressure*
Dried Extract	0.376038	0.605633	0.18014	0.245148	0.232106	0.0635485

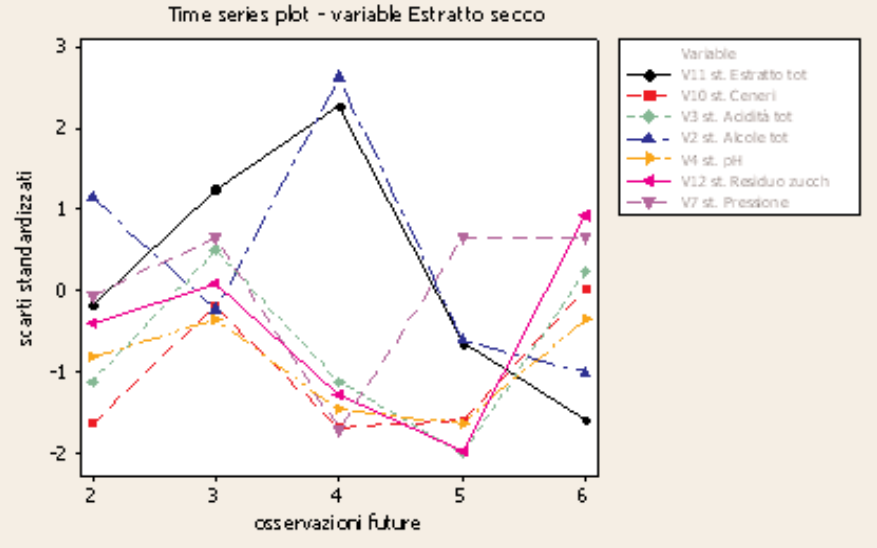


Fig. 12 - Changed relationships among variables - Example. Dried (total) Extract - Obs.4.

Eventually, we computed the indices of process capability C_p, C_{pk}, C_{pL}, C_{pU}, that is the ability of the production process, to meet over time the specific technological tolerances defined for the product.

We computed the indices for the variables of the finished sparkling wine, for which regulating or technological specifications are defined and for all the analysed lots.

Values were satisfactory for all the variables, with the consideration that values of the indices ≥ 1,33 are usually regarded as being good by the industrial experience.

We show for instance the capability indices computed for the "dried extract" (Fig. 13).

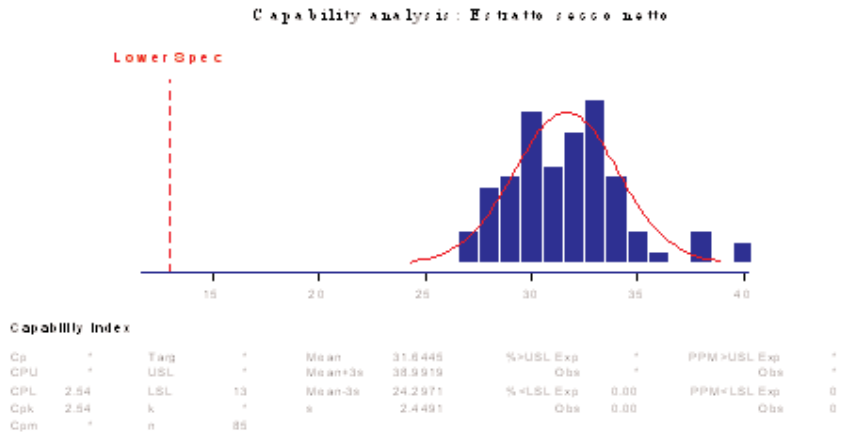


Fig. 13 - Potential capability indices - Dried (total) extract.

It is important to well distinguish a process in "statistical control" process from a process which respects the technological specifications stated for the product. The condition of stable process and in "statistical control" status not necessarily implies that the resulting product complies with the specifications. The statistical control limits, cannot and should not be directly compared to the technical specification limits. It can happen actually, that some processes that are not in "statistical control", comply with specifications and vice versa. In practice is desirable that processes meet specifications as well as stay in "statistical control" but the two conditions are not uniquely linked.

Conclusions

Process analysis

The process of sparkling wine production, resulted effective and robust to eliminate basic variability present in raw materials. Lots recorded as "abnormal" at the stage of semi-processed product, are indeed "in control" on the finished product. The quality level of finished sparkling wine is very steady over time (only 1 lot anomalous). Variables identified as major contributors of detected anomalies and where is necessary to focus attention were: actual alcohol at semi-processed level and dried extract at the finished product level. The main cause is pointed out in the momentary breaking of the relationships among variables.

Statistical Methodology

We can stress as the control "Q_i" and monitoring "Q_f" charts used in this study, built on variations of the T^2 Hotelling statistic, has been effective to detect both deviations from average quality level of the product and especially changes in the relationships among the correlated variables that all together only contribute to the final product quality. This last proved property already underlined by Mason *et al.* (20) was particularly appreciated because the statistic charts based on the T^2 are almost known more as multivariate charts for averages.

Anyway it is essential well distinguish between the 2 stages of: "control" (Q_i chart) and "monitoring" (Q_f chart) of the process and also eliminate the autocorrelation , if present, in historical data, which otherwise may dramatically distort the results of the Q_i control chart.

With regard to the analysis of anomalies, the two proposed methods were equally effective leading to the same results although the principal components method, even if easier, requires several steps and is less accurate, where the so called "MYT" decomposition procedure is more precise in identifying the cause variables of the anomalies but requires complex calculations.

The results of this work are certainly susceptible of refinements and constitute a starting point for further investigations, in particular, it is appropriate to refine the methodology of analysis of causes through principal components, in a way to better quantify in numerical terms against control limits, the total contributions of variables to the anomalies. We underline that statistical process control and monitoring, must have a substantially different purpose than that of control of compliance to specifications. The purpose of the statistical process control is to get the control of process indirectly, through the monitoring of the resulting product. The control of technical specifications is an activity which does not consider the statistical inference and has the main task to establish whether the product out of the process is compliant to the technical requirements. This task for the wine is what normally is operated through laboratory analysis. The two activities are instrumental to each anther and should not be confused instead they must be a single tool for the continuous quality improvement.

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