

Multivariate Profile Monitoring Method

An Application in Product Portfolio Management

Rafael Herzer¹, André Luis Korzenowski^{1,2*}, Cristiano Richter¹, Janine Fleith de Medeiros³, Lucas Schmidt Goecks¹, Taciana Mareth²

¹ Polytechnic School, Faculty of Production and Systems Engineering, University of Vale do Rio dos Sinos, 950 Cristo Rei Av., 93022-750 São Leopoldo, Brazil

² Management and Business School, Faculty of Accounting, University of Vale do Rio dos Sinos, 1600 Nilo Peçanha Av., 90470-280 Porto Alegre, Brazil

³ Department of Agricultural Sciences, Innovation and Business, Faculty of Business, University of Passo Fundo, BR 285 Passo Fundo, São José, P.O.B. 611, Brazil

* Corresponding author, e-mail: akorzenowski@unisinis.br

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Abstract

Several authors refer to product portfolio management as an essential process because it may be used as a corporate management tool. However, the product portfolio management methods which are often adopted have limitations that prevent its use in practice, mainly due to the high dimensionality of selecting an optimal portfolio. Moreover, the large amount of available data is a relevant issue for practical applications. Thus, the contribution of this article is to propose a method for the product life cycle to monitor time-series behaviour patterns. The goal is to identify changes that may indicate that the product portfolio needs to be revised. The proposed method uses a multivariate regression model to relate financial variables associated with the products portfolio, the performance of products against competition, and even macroeconomic data. The objective is, through profile monitoring, to identify the specific time for the product portfolio review decision-making. We adopted three tools to develop a method – principal component analysis, multivariate regression model, and profile monitoring with Hotelling T^2 Control chart. A Monte Carlo simulation validated the approach. The results showed false alarm rate and average time to signal to be similar to previous studies. Finally, the application of the model is illustrated in a real case, using data provided by a company's portfolio of agricultural equipment.

Keywords

product portfolio management, multivariate regression model, profile monitoring

1 Introduction

In recent years, portfolio management has received increasing attention, given that companies are introducing several projects simultaneously (Mohammed, 2021). However, products that have been made available by the organisations in the market are highly vulnerable to the changing needs and preferences of buyers, new technologies, and increased domestic and foreign competition (Kock et al., 2015). Therefore, the practice of innovation, combined with appropriate management of the existing portfolio, must be repeated in companies that want financial sustainability (Kang and Montoya, 2014; Slack et al., 2009; Tadeu de Oliveira Lacerda et al., 2011).

Indeed, product portfolio management has been a fundamental organising principle in studies of innovation

over the last 40 years and is an essential tool for strategic decision making (Aitken et al., 2003; Cooper et al., 2001; McNally et al., 2013; Shahmarichatghieh et al., 2015; Windrum and Birchenhall, 1998). Once it promotes the competitive advantage for each of the different brands, analysis of all the products that compose the portfolio has become essential for the market success of organisations (Barksdale and Harris, 1982; Chang, 2003; Rink, 1976; Seifert et al., 2016). Thus, managing the product portfolio is a dynamic process, extremely important to the performance and the achievement of business objectives (Aitken et al., 2003; Archer and Ghasemzadeh, 1999; Kavadias and Chao, 2008; Kester et al., 2011; Lapersonne, 2013; Mohammed, 2021).

Operationally, managing the products' life cycles composing the portfolio demands analyses, planning, and constant review (Hannila et al., 2019; Lahtinen et al., 2021; Shahmarichatghieh et al., 2015). Studies from Coulon et al. (2009), Jugend et al. (2016), Killen et al. (2008), Kahn et al. (2006), McNally et al. (2009) have found that companies that adopt formal and systematic mechanisms for conducting such activity achieve better portfolio performance. However, in practice, this process is considered a complex aspect for business management because the portfolio management methods usually adopted have limitations that prevent its use (Jacobs and Swink, 2011; McNally et al., 2013; Shahmarichatghieh et al., 2015). For example, there is a requirement to input a large amount of data, inadequate treatment of risk and uncertainty, the disregard of interdependencies between the design and external factors of the organisation, as well as the impossibility of portfolio management being used as an organised process (Donaldson, 1985; Shahmarichatghieh et al., 2015; de Villiers et al., 2017). Consequently, according to Hannila et al. (2022), how this data will be refined and processed becomes a challenge.

A proper understanding of portfolio management and its characteristics can nonetheless help develop the decision-making method (Danesh et al., 2017). As each project is unique, there are always changes, such as environment, resources, and destinations. This makes portfolio management a complex task, with many processes and steps inevitably linked with decision-making problems (Hannila et al., 2022).

While it is complex and dynamic, product portfolio management can be subdivided into three decision areas:

1. development and introduction of new products,
2. the maintenance of the portfolio of current products, and
3. decisions to decline products (Chang, 2003; Guoqing and Zhongliang, 2011; Rink, 1976; Rink and Swan, 1979).

Nevertheless, even though all areas are interconnected, only the consequences and implications of the product portfolio size and composition are connected (de Villiers et al., 2017). Hence, the dynamic interaction of product development, maintenance of the portfolio, and methodologies to decline products require academic attention (Kester et al., 2011; Seifert et al., 2016; Shahmarichatghieh et al., 2015).

Still, considering the constant changes in the market from a large volume of data and the introduction of Industry 4.0 technologies for process monitoring, decision making becomes a challenge (Goecks et al., 2020).

According to Hannila et al. (2019), the development of data-oriented practical studies is essential in portfolio management. In this sense, efficiency indicators become essential (Hannila et al., 2022) and data management for product life cycle analysis and effective decision-making regarding portfolio management (Neacşa et al., 2014).

Thus, a method of monitoring the product lifecycle to evaluate behaviour patterns to identify changes that may indicate that the portfolio needs to be revised is the contribution of this article. The proposed method relates financial information associated with a product portfolio to economic performance, product performance against the competition, and even macroeconomic data. The objective is to immediately identify the right time for the product portfolio decision review through a profile monitoring scheme.

The proposed model was evaluated using data generated by Monte Carlo simulation. A total of 5000 runs were developed, and the results showed that false alarm rate and average time to signal have the expected behaviour. The results are also comparable with those found by Villalobos et al. (2005), showing a better result in the ATS detection. Finally, the model's applicability is illustrated in a real case, using data provided by a company's portfolio of agricultural equipment.

2 Portfolio management methods

Business managers consider the decision-making process related to the product portfolio management aspect complex. Therefore, their decisions are associated with their political and corporate values (Kester et al., 2011; Weissenberger-Eibl and Teufel, 2011), which may affect the optimisation of the choices related to portfolio and better performance (Heising, 2012; Koen et al., 2002; McNally et al., 2009). Because of this strategic and complex character, there are several studies on product portfolio management that recommend the application of formal and systematised mechanisms to manage it (Archer and Ghasemzadeh, 1999; Cooper et al., 1992; Cooper et al., 2001; Killen et al., 2008; Mathews, 2010; Mikkola, 2001; Oh et al., 2012). Among the methods, we can highlight the financial, market research, checklist, scoring and ranking methods, charts, graphs, and diagrams, as described below:

- *Financial methods*: these have the objective of maximising portfolio value (Kavadias and Chao, 2008; Oliveira and Rozenfeld, 2010). The following financial evaluation mechanisms are often cited as appropriate: net present value, expected commercial value, break-even point, payback, and return on investment (Cooper et al., 2001; Kavadias and Chao,

2008; Oliveira and Rozenfeld, 2010). According to Cooper et al. (1992) and Killen et al. (2008), financial methods are the most used by companies for portfolio assessment, but only using financial criteria in portfolio management may be risky. This is because economic evaluation often cannot make accurate demand forecasts and either measure correctly the impact of a given product of technological innovation, particularly those for the long term (Blau et al., 2004; Kavadias and Chao, 2008; Killen et al., 2008)

- *Scoring and ranking methods*: Scoring models suggest that product designs are ranked and scored according to the expected average performance and, according to their degree of alignment with business strategy (Cooper et al., 2001; Oliveira and Rozenfeld, 2010). Scoring models require the prior establishment of criteria to be judged. Afterward, scores are attributed to each of these criteria. It is recommended that a cross-functional team or a committee develop such criteria to assess product projects. Significantly, the scoring model carries the subjectivity of the scores awarded (Kester et al., 2011).
- *Maps, chdiagramsnd diagram*: Some studies, such as Phaal et al. (2008) and Oliveira and Rozenfeld (2010), are getting attention to applying product maps to balance goals and strategic alignment. These maps can be made using the technology roadmap method, as suggested by Phaal et al. (2003). The adoption of graphs and charts, such as blisters and BCG matrix, are also recommended as applicable mechanisms to simultaneously analyse the relationship between product portfolio, the company's strategy, and the correct balance between both (Kavadias and Chao, 2008; Killen, 2013; Mikkola, 2001).

Kavadias and Chao (2008) and Kester et al. (2011) recommend that portfolio management decisions be taken in strategic planning times or in shorter periods denominated as portfolio review process, using the methods presented. In the research conducted by Dutra et al. (2014), a summary table can be found with the main methods used in portfolio management and the references of the studies about this subject.

Weissenberger-Eibl and Teufel (2011), and Jonas (2010) point out that a significant cause of failure in portfolio management occurs due to the presence of mismanagement in the process of planning the product portfolio. Argouslidis and Baltas (2007) and Oghojafor et al. (2012) also found that many researchers and professionals are only engaged

in the product life cycle's development or the initial stages. However, the current product management process has not received the same attention, precisely the final stage of project life (Engwall and Jerbrant, 2003; Kester et al., 2011).

The literature in the field presents several methods that can be used to help select and prioritise projects. These procedures range from simple screening strategies to sophisticated mathematical procedures. However, there is no consensus on the most effective methods. Furthermore, there is little evidence in the literature regarding the practical use of these methods, considering that most do not recognise the interdependence between projects. The authors also highlight that only a few appear to have been effectively tested in companies using real data (Archer and Ghasemzadeh, 2004; Cooper et al., 1992; Dutra et al., 2014; Ghasemzadeh and Archer, 2000; Henriksen and Traynor, 1999; Lawson et al., 2006; Meredith and Mantel Jr., 2011; Verbano and Nosella, 2010).

For Rajegopal et al. (2007), the correct selection criteria are characterised by a few numbers, without overlapping, and being understandable, clearly measurable, applicable, directly connected to the strategy, and appropriate to the purpose of the portfolio. Thus, developing a simple and easy method to interpret, with the possibility of performing ongoing product portfolio management, has a fundamental role in spreading portfolio management practices.

3 A new approach to product portfolio management

The method for product portfolio management consists of multivariate monitoring residuals, provided by an economic data monitoring profile reduced through principal component analysis (PCA). The regression left-hand side (LHS) comprises indicators due to product performance. On the other hand, the regression right-hand side (RHS) contains macroeconomic indicators such as commodities prices, exchange rate, inflation, etc. The system for pattern monitoring and change detection consists of a Hotelling T^2 control chart applied in the residuals of the regression model. The signal produced by the control chart indicates the specific time for a review in one or more indicators. It represents that the performance of the product portfolio or changes in the economic scenario must be treated in the company's strategic business plan. The complete method is illustrated in Fig. 1.

The proposed method is divided into four steps. Step I is composed of the identification and selection of the variables. In Step II, the application of the PCA technique is used to resize the monitoring database creating

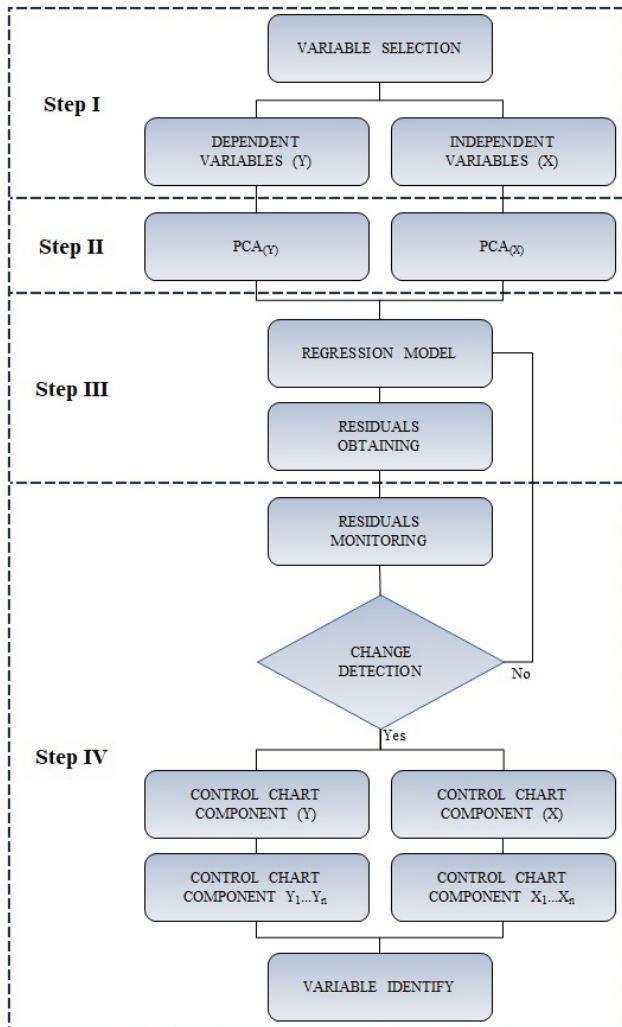


Fig. 1 Method for decision-making on product portfolio management

quantitative indicators. A multivariate regression model is adjusted to obtain the residuals (Step III) for control chart monitoring, to be held in Step IV.

The proposed model does not consider specific criteria for certain types of projects and/or companies, considering that the method seeks to ensure the model's generality. Thus, it offers an open platform, facilitating the exclusion or addition of new specific criteria. An overview of the techniques used in the proposed method follows in Section 3.

3.1 Principal components analysis

According to Jolliffe (2002), some may be redundant when many variables make some elimination useful. Some only increase the evaluation work and do not have additional information. PCA is one of the techniques used to reduce dimensionality. The statistical technique aims to retain most information into the first components, resulting in a smaller amount of data to be analysed (Hair et al., 2006).

PCA is a multivariate method of transforming a group of p original variables X_1, X_2, \dots, X_p , belonging to n subjects, in a set of variables, Y_1, Y_2, \dots, Y_p with equivalent dimensions. The components Y_i obtained are linear combinations of the original variables, supposedly uncorrelated, and ordered variances. Based on the principle that the score or variance of the principal components decreases from first to last, it means that the last components explain a tiny fraction of the total variance and, therefore, could be neglected. A detailed explanation of the entire PCA may be found in Lachenbruch (1981), Rencher and Christensen (2003), or Hair et al. (2006).

In the proposed method, variables are divided between dependent (Y) and independent ones (X). Y variables are the product ones, and X variables are the macroeconomic data of the business. There is no maximum limit of selected variables. However, to make the model easier, PCA is used to reduce the model's complexity significantly. We propose to apply PCA in the dependent and independent variables to obtain the model residuals. The Y vector in the LHS is the Y components and, in the RHS, the X vector of X components. The eigenvalues define the number of retained components. The components that will be included are those with eigenvalues greater than 1.

3.2 Multivariate linear regression model

Multivariate linear regression is a technique whose primary purpose is to obtain a mathematical relationship between dependent variables and a set of variables describing the system (independent or explanatory variables). A regression model in matrix form is shown in Eq. (1):

$$Y = X\bar{\beta} + e, \tag{1}$$

where $\bar{\beta}$ is the regression coefficient matrix, e is the fitting error matrix that is normally distributed, independent, with zero mean and constant variability, Y is the dependent variables matrix, and X is the independent variables matrix. Solving $\bar{\beta}$ we have the estimates of ordinary least squares for the regression parameters, according to Eq. (2):

$$\hat{\bar{\beta}} = (X'X)^{-1}(X'Y), \tag{2}$$

where X' is the transpose of X . For calculating the inverse of $(X'X)$, it is necessary that the independent variables do not have high relativity, because in this situation the $(X'X)$ matrix cannot become the inverse and we will have more error. To solve this problem, we should remove the multicollinearity between independent variables with PCA

methods. More information about multivariate regression can be found in Rencher and Christensen (2003), as well as a practical application in Noori et al. (2010).

After obtaining the components, a cause-effect model is built using this model. So, the residuals obtained will be used to monitor the product portfolio in a multivariate control chart. This technique is already applied in several studies, such as Hosseinifard et al. (2011), Jeong et al. (2013), and Woodall and Montgomery (2014).

3.3 Hotelling Control Chart

To control the quality of a product, Montgomery (2007) highlights that identifying and measuring the variations in the process through control charts is required. Control Charts are valuable tools for assessing the state of statistical process control. These charts determine if variations occur due to assignable causes or random reasons. The effectiveness of a control chart is measured by the speed with which this device detects changes in the process and by its false alarm rate (Korzenowski et al., 2020).

Multivariate control charts can control multiple process factors and combine various product features into a single chart (Rodrigues et al., 2021). The best-known control chart is the T^2 , initially proposed by Hotelling (1947) and applied in data bombs in World War II. The purpose of the T^2 chart is to evaluate whether the variables are simultaneously under control. In this type of chart, the statistics of two or more related measurement variables. A multivariate chart shows how several variables together may influence a result or a process (Montgomery, 2007).

The statistic for monitoring T^2 control charts is presented in Eq. (3), while the control limits in Phase 2 are given in Eqs. (4) and (5). More details about T^2 control chart, inclusive UCL for Phase I, can be found in Montgomery (2007):

$$T^2 = (\mathbf{X} - \bar{\mathbf{X}})' \mathbf{S}^{-1} (\mathbf{X} - \bar{\mathbf{X}}), \quad (3)$$

$$LSC = \frac{p(m+1)(m-1)}{m^2 - mp} F_{\alpha, p, m-p}, \quad (4)$$

$$LIC = 0, \quad (5)$$

where \mathbf{X} is the variable matrix, Σ is the covariance matrix of \mathbf{X} , p is the number of variables, m is the sample size and F is the α quantile of the Snedecor distribution with p and $m - p$ degrees of freedom.

4 Simulation procedures and results

To evaluate the performance of the proposed procedure, a total of 5000 runs were generated from a multivariate normal distribution by Monte Carlo simulation. The warm-up of the simulation process where the running data until the first signal, being the size of the first run, was disregarded in the analysis. The data used in the simulations were generated using population parameters estimated from the company's historical data. The objective is to model good operating behaviour only and test for any future deviations from this model (MacGregor and Kourti, 1995).

The UCL for the T^2 chart was set up in $UCL = 14.00$ by the simulation to obtain an average run length (ARL) of approximately 200, when the process was in-control, to compare the results with those obtained by (Villalobos et al., 2005). The same simulation process to get an (ARL) was performed by Villalobos et al. (2005), who used $UCL = 12.85$ and obtained an ($ARL = 201.0598$). This ARL means an alpha error (significance level) of $\alpha = 0.005$.

The ARL was obtained through Eq. (6):

$$ARL = \frac{\sum_{i=1}^N \left(\sum_{j=1}^k I_j \{T^2, T^2(UCL | \mu = \mu_0)\} \right)}{N}, \quad (6)$$

where N is the number of simulated runs, k is the point in time where the chart shows a signal, T^2 is the monitoring statistic, UCL is the upper control limit, according Eq. (4), I_j is an indicator variable that shows when the point is out-of-control and $j = 1, 2, \dots, k$.

A δ size shift was inserted in the process going to an out-of-control state ($\mu = \mu_0 + \delta$) to evaluate the average time to signal (ATS). Since the variables \mathbf{X} are dependent, a mean shift was simulated in the set of independent variables $\mathbf{Y} = f(\mathbf{X})$ by simply adding a vector of constants to \mathbf{Y} , as previously performed by González and Sanchez (2008). Villalobos et al. (2005) have inserted a shift in just one variable. Our simulation includes a shift in just one variable and later in the entire set of \mathbf{Y} variables to test the procedure. ATS was obtained by Eq. (7).

$$ATS = \frac{\sum_{i=1}^N \left(\sum_{k=1}^l I_k \{T^2, T^2(UCL | \mu = \mu_0 + \delta)\} \right)}{N}, \quad (7)$$

where N is the number of runs simulated, T^2 is the monitoring statistic, UCL is the upper control limit, I_k is an indicator variable that shows when the point is under control, $k = t, t + 1, t + 2, \dots, l$, t is the time when the shift was introduced, and l is the time when the signal occurs. The

Table 1 Simulated *ARL* and *ATS* for the Hotelling Control Chart

| Measurements | Villalobos et al. (2005) | One <i>Y</i> variable out-of-control | All <i>Y</i> variables out-of-control |
|-----------------------------|--------------------------|--------------------------------------|---------------------------------------|
| <i>UCL</i> | 12.85 | 14.00 | 14.00 |
| <i>ARL/ATS</i> (δ) | 201.0598 | 209.5086 | 210.5782 |
| 0.5 | 132.5168 | 86.9826 | 51.5891 |
| 1.0 | 52.7745 | 19.3600 | 7.3604 |
| 1.5 | 20.3010 | 5.2402 | 2.1452 |
| 2.0 | 9.0323 | 2.2240 | 1.2488 |
| 3.0 | 2.5807 | 1.1392 | 1.0082 |

results obtained by Villalobos et al. (2005), as well as the simulated results obtained by the method proposed are presented in Table 1.

The proposed control procedure found one false alarm every 209/210 months on average. This difference is due to the simulation process. These results are comparable with Villalobos et al. (2005). When a shift was inserted in one of the main components, the *ATS* quickly declined, and a constant change was inserted in all the components, as expected. Notwithstanding, these results decrease faster in comparison to those presented by Villalobos et al. (2005). For example, using our approach, after a shift, $\delta = 2\sigma$, the procedure takes only two months on average to detect, according to Table 1.

5 Application of the method in the evaluation of product portfolio in an agricultural machinery company

The proposed approach was applied in a multinational agricultural equipment machinery company. The model was adjusted in a limited scenario restricted to a one products family. According to Argouslidis and Baltas (2007), it is important to consider market conditions in which the proposed product or service is located, costs, and indicators. Based on this information, with the assistance of industry experts, 17 indicators were selected in 60 months.

Table 2 Selected variables

| Independent variables (<i>X</i>) | Dependent variables (<i>Y</i>) |
|------------------------------------|----------------------------------|
| GDP | Product Cost 1 |
| Soybean Price | Product Cost 2 |
| Corn Price | Product Gross Profit 1 |
| Exchange Rate (US\$) | Product Gross Profit 2 |
| Inflation Indicator (IPCA-Food) | Volume of Product 1 |
| Interest Rates | Volume of Product 2 |
| Rainfall rates (Dourados City) | Warranty of Product 1 |
| Industry Volume of Product 1 | Warranty of Product 2 |
| Industry Volume of Product 2 | |

The indicators of the economic environment/agriculture are classified as independent variables and the business indicators as dependent variables, according to Table 2.

Industry experts interviewed have been investigated for at least five years in the company's branch. The specialists were selected in critical areas, marketing, engineering, finance, market intelligence, to obtain the most significant possible number of variables to be used in the proposed method.

The chosen independent variables were *GDP*, *Exchange Rate*, *Inflation Indicator (IPCA-Food)*¹, and Interest Rates were obtained from the Brazilian Institute of Applied Economic Research website (IPEA-Brazil)¹. IPEA is Brazil's official economic and financial data department in a series of annual, monthly, and daily rates. The values of the indicators were converted into their current values to remove inflation effects.

The variables related to agricultural commodities - *Soybean*, *corn prices*, and *Rainfall rates* - were obtained from the National Supply Company site (CONAB). CONAB is a Brazilian state-owned enterprise under the Ministry of Agriculture, Livestock and Supply, responsible for the agricultural index. The industry volume was obtained through the Brazilian Association of Machinery and Equipment (ABIMAQ) website.

The data of the dependent variable were collected in a multinational agricultural company. The total of the historical data and the variables available were used in this study (a total of 8 variables collected within 60 months), thus completing Step I. Obtained the variables; step II is started, where two PCA were performed, one on each side of the equation and three components were retained according to predefined criteria in the proposed model. Table 3 shows the eigenvalues obtained for the independent and dependent variables and the variance of each component after applying the PCA method. Eigenvalues more significant than 1 were selected, representing 68.15% of the total variance explained between the independent variables and 69.39% between the dependent variables.

In step III, multivariate regression was used to make future forecasts and estimate the residuals of the data set obtained by PCA carried out in step II. Residuals of the adjusted model were obtained to be used in the monitoring process by the Hotelling T^2 control chart.

A Hotelling T^2 control chart controls the residuals obtained from the multivariate regression model. This monitoring aims to detect changes in the model standards, to show the

¹ See in the website of Instituto de Pesquisa Econômica Aplicada (<https://www.ipea.gov.br/>)

Table 3 Eigenvalues and explained variance obtained by principal component analysis

| Independent variables (X) | | | Dependent variables (Y) | | |
|---------------------------|--------|--------|-------------------------|--------|--------|
| [1]* | [2]** | [3]*** | [1]* | [2]** | [3]*** |
| 2.845 | 31.61% | 31.61% | 2.396 | 29.95% | 29.95% |
| 1.928 | 21.42% | 53.03% | 1.785 | 22.32% | 52.27% |
| 1.361 | 15.12% | 68.15% | 1.370 | 17.12% | 69.39% |
| 0.996 | 11.59% | 79.74% | 0.998 | 12.64% | 82.03% |
| 0.847 | 9.41% | 89.15% | 0.482 | 6.03% | 88.06% |
| 0.449 | 4.99% | 94.14% | 0.471 | 5.89% | 93.95% |
| 0.252 | 2.80% | 96.94% | 0.304 | 3.79% | 97.74% |
| 0.173 | 1.92% | 98.86% | 0.180 | 2.25% | 100% |
| 0.102 | 1.14% | 100% | | | |

* Eigenvalues;
 ** Explained variance;
 *** Accumulated variance.

exact time to review the current product portfolio, possibly requiring the change/removal of one or more portfolio products. The results of the prospective analysis can be verified in Fig. 2, after the vertical dashed line. The vertical line divides Phase I of Phase II in the residual control chart. Although not necessary, considering that no out-of-control data point was found, a monitoring chart for X and Y components was generated to illustrate the applications of the method. The control chart for X and Y components is shown in Fig. 3(a) and (b).

It is essential to generate the control chart for each component (X and Y) when an out-of-control data point is identified in the residual control chart, Fig. 2. Doing so can determine which variable is responsible for changing the regression model pattern. If the change is derived from the X component, the macroeconomic scenario in which the company operates has changed, requiring a review of the strategical business plan. However, if the change is derived

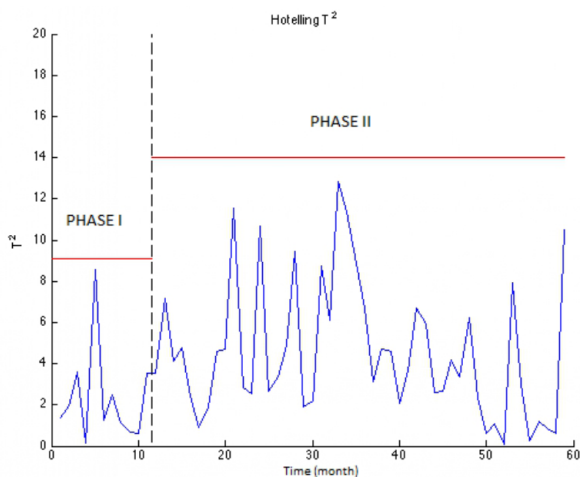
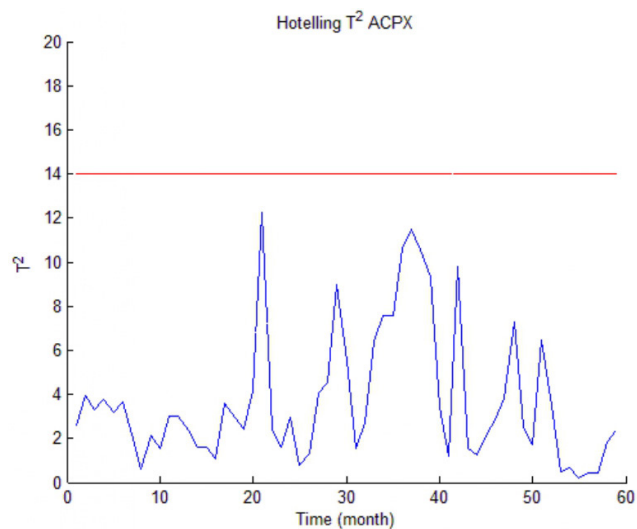
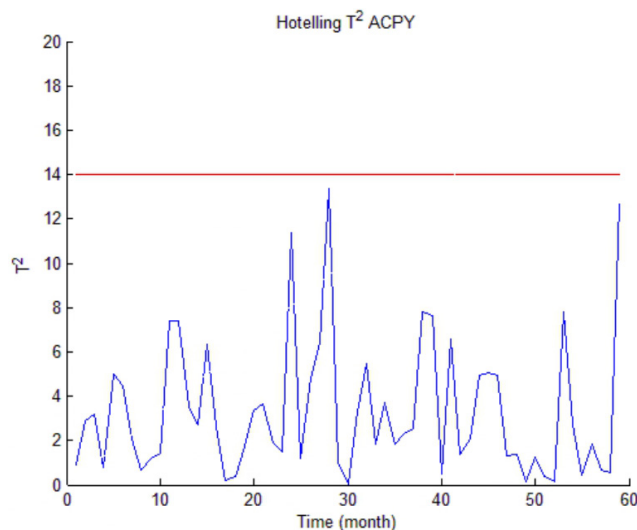


Fig. 2 Hotelling T^2 Chart applied to real data



(a)



(b)

Fig. 3 T^2 control chart for each component; (a) Hotelling T^2 PCA X; (b) Hotelling T^2 PCA Y

from the Y component, an intervention in the company's product portfolio is required. Among the possible actions, it can be cited: increased investment in advertising for certain products, implementation of a cost reduction program to increase the profit margin, development of quality improvement projects, improvement of the relationships with the dealers through finance and promotions strategy, and even the discontinuation of a product and its replacement in the company's portfolio.

Thus, this study presents the market share strategy as a way to define the product portfolio. This is demonstrated in the company's real data, whose mechanism developed in this article allows the maintenance of strategic products, even if they are not profitable for the company. That

is, differing from questions related to profit or profitability, according to the gap identified in the research by Hannila et al. (2019; 2022).

Goecks et al. (2020) reinforce the findings found by this research, that is, the high number of available data raises the challenges in the decision-making process. However, digital systems (from Industry 4.0 technologies) facilitate this process. In this sense, the control systems elaborated in this study indicate changes in the product portfolio in dynamic systems, contributing to current demands, which, in practice, are constantly changing.

Still, an out-of-control data point was found during retrospective analysis, and it was deleted. During the online monitoring process, no out-of-control data point was found. These results were expected since the economy was stable in the period selected, and there were no changes in the family of products analysed.

6 Conclusions

Portfolio management is an essential tool to increase market competitiveness. Generally, portfolio management methods have limitations that avoid real applications or require a lot of interference from managers. In addition, managers must figure out when is the right time to review the product portfolio. The contribution of this paper is to provide a method to identify the right time to perform a portfolio review. The approach uses residual monitoring from a profile between business and economic variables,

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putting together as many factors that can impact the decisions and results of the organisation in a single method.

The simulation study shows that the chosen approach performs better than a usual multivariate monitoring procedure based on PCA. It means that the proposed method identifies and indicates changes in the patterns of the model faster than a usual multivariate monitoring procedure. The faster the model is, the faster the information for decision-making is obtained. Contributing to more agile and effective decision-making, as indicated by Neaça et al. (2014).

The application of real data from a company's agriculture machinery portfolio illustrates the proposed method. The results obtained using the method were similar to the real data, confirming the gap presented by Hannila et al. (2019; 2022). Significant results emphasise the real applicability of the proposed method.

For faster detection of small shifts, MEWMA charts could be used to monitor the residuals. A self-start procedure to evaluate the beginning of the portfolio lifecycle is also an interesting topic to be discussed in the future, even though dimensionality reduction could be seen as a challenge. Also, it suggests applying the method in different industry segments to verify the model's adaptability to other variables.

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