Multilinear Decomposition Application into Students' Evaluation of Teaching Effectiveness

F. Herbert L. Vasconcelos, Thomaz. E. V. da Silva,
André L. F. de Almeida, João. C. M. Mota
Dept. of Teleinformatics Engineering
Federal University of Ceará - UFC
Ceará, Brazil
{herbert, thomazveloso}@virtual.ufc.br,
{andre, mota}@gtel.ufc.br

Wagner B. Andriola
Dept. of Fundamental Education
Federal University of Ceará - UFC
Ceará, Brazil
w_andriola@ufc.br

***Abstract*—This paper presents a comparative analysis between a bilinear decomposition (Principal Component Analysis - PCA) and a multilinear decomposition (Parallel Factor - PARAFAC) on the data obtained by the students' evaluation of teaching effectiveness in an engineering course. It is known that the teaching and learning relationship is a nonlinear process related to many fundamental subjects, which are highlighted into students' evaluation of the teaching effectiveness methodology. The comparison was made in order to know which additional knowledge is obtained when the analysis takes into account the multilinear process model of this. The results shown the importance of the latent characteristics in a students' professional formation in accordance with the results presented in the application of PARAFAC decomposition, that has been reveled as a powerful tool for data analysis in the assessment area.**

Keywords-component; engineering education; multilinearity, PCA; PARAFAC; data analysis.

I. INTRODUCTION

THE constant evolution of resources and computer technology in contemporary society is a reflection of several research studies in engineering and technological innovation that emerged in recent years in the areas of computing, telecommunications and information technology (CTIT). In this scenario, increasingly industry, research centers and several companies all over the world demand for professionals and researchers in CTIT engineering and this has led to a growing number of people to search this career [1]-[3].

However, there is a considerable number of engineering courses in the world that suffer high withdrawal and failure rates of students in their early years, especially in fundamental discipline areas like mathematics and science [1]-[3]. Moreover, during the formation of a basic engineering course, in general, it is necessary that the student in the first year obtains knowledge and skills in core content basic scientific areas like Physics, Calculus, Algebra, Chemistry and, sometimes, also in introductory technological areas. Bayond that, the number of engineering graduates is increasing as a problem, since high school enrollments in mathematics and physics are currently significantly higher [1].

In particular, the Federal University of Ceará (UFC) by the Department of Teleinformatics Engineering (DTIE) of Technology Center, located in northeastern Brazil, offers the Teleinformatics Engineering (TIE) undergraduate course. This course was created in 2003 under the direct responsibility of DTIE and put together two important research areas, Informatics and Telecommunications, with the perspective to have students with vocation to both areas in an integrated, and then forming a professional with skills and competencies with a great impact to current society. Telecommunications is largely responsible for the agility and integrability of the flow of information, thus constituting a key element in ensuring reliable and affordable communication among people, leading to widespread development [1]-[3]. The telecommunications and computing technological development as well as the industry that integrates teleinformatics, in the last decade has reached an extremely high level of complexity, pointing to new forms of relationships that strongly indicate a better quality of life for people in general. Globally, the effects of this new era are felt in different ways, both in social and professional experience. Job opportunities in these sectors are increasing, giving rise to even repressed demands, where the labor market is eager for a highly qualified workforce, and reflecting the global reality.

In order to detect possible indicators in the quality of education as well as explaining the factors such as evasion, failure rates and to promote possible suggestions for restructuring the TIE course curriculum, a study was conducted to assess the effectiveness of teaching students (Student Evaluation of Teaching Effectiveness - SETE) [4]-[7] in the basic disciplines of the TIE first year course.

The research indicates that the student can provide valid information and opinions about many aspects of teaching. This assessment can often be taken into account for the success in the process of leveling up teaching staff, that can be to used to approve or even to promote the reformulations in a course curricular structure [1].

Universities and education programs around the world regularly use the student for the evaluation of teaching effectiveness to determine the quality of their courses (SETE), although some faculty members question the usefulness and validity of student ratings [4]-[7]. Although some disagreements have occurred, the SETE is an important tool for measuring the quality of education courses, especially in the context of higher education [9].

This research has been partially supported by CNPq, CAPES and BNB.

In general, learning refers to student perceptions of personal growth and progression and development in different areas of the development of professional knowledge [10].

The SETE was applied to TIE students who had attended all the basic disciplines of the first year engineering course in which students are interviewed to assess the performance of their teachers and the quality of education taking into consideration various aspects of the disciplines and students themselves in terms of quality through a survey that used the Likert scale.

Although SETE is used as an important tool for evaluating teaching effectiveness, it is noticed in several studies [2, 5], [10] that the data analysis is often limited to the use of basic statistical descriptive analysis or factor analysis in order to validate the instrument for data collection and to form a cluster on scales of issues presented in the evaluation form applied to students. However, descriptive statistics does not reveal the correlation between the factors analyzed.

The utilization of the mathematical methods to analyze data obtained through educational interventions is called Educametrics [1, 8]. A preliminary study presents the application of multivariate analysis in this context [1], however this problem is essentially nonlinear with many variables and this aspect has not been taken into account in the application of the bilinear decomposition method. In this case, this research aims to apply the multilinear method called Parallel Factor (PARAFAC) analysis and compares it with the bilinear method Principal Component Analysis (PCA) applied previously [1]. With the goal of to expand the studies obtained in [1], this research aims to detect with a high degree of accuracy the following evaluation indicators: 1. the relation obtained among the SETE factors and indicators that can be related to the course's evasion; 2. the relationship among the disciplines studied by engineering students within their curriculum structure; and 3. the degree of homogeneity in the students' responses to fill the SEEQ instrument used to collect research data

In this context the application of the PARAFAC decomposition method seems to be promising, since the nonlinear aspect that was modeled as a multilinear, model of the dataset, was taken into consideration, and thus a broader interpretation of the relationships obtained, can be made by the variables analyzed. In other words, the students' point of view that was fundamental for the multilinear analysis would differ from the bilinear analysis.

This paper is structured as follows. Section II presents a review of the relevant SETE literature. Section III describes the mathematical tools used in this research. Section IV shows the course context and the methodological approach of the proposal. The main findings of the paper are presented in Section V. Finally, Section VI discusses some concluding remarks.

II. STUDENTS' EVALUATION OF TEACHING EFFECTIVENESS

The Students' Evaluation of Teaching Effectiveness (SETE) methodology that was created by Herbert M. Marsh [6, 7] is widely used around the world. The main purposes of SETE are [4]: (a) diagnostic feedback to teachers about the effectiveness of their teaching that will be useful to the improvement of teaching; (b) measuring teaching effectiveness to be used in personal decisions; (c) information for students to use in the selection of courses and teachers; and (d) an outcome or a process description to research on teaching. Certain student rating forms provide important feedback that can be used to improve teaching performance [4]-[13].

Researchers [4]-[13] agree that teaching is a complex activity consisting of multiple dimensions and that formative diagnostic evaluation of teachers should reflect this multidimensionality. This contention is supported by common sense and a considerable amount of empirical research [4].

Marsh [4] concludes that SETE is: (a) multidimensional; (b) Reliable and stable; (c) primarily a function of the instructor who teaches a course rather than the course that is taught; (d) valid in relation to a variety of indicators of effective teaching; (e) relatively unaffected by a variety of variables hypothesized as potential biases; and (f) considered to be useful to students to use in course selection, to administrators to use in decisions about staff and to teachers as feedback on teaching. An instrument was created in order to obtain the students feedback. This instrument is called Students' Evaluation of Educational Quality (SEEQ) that appears to measure the most broadly representative set of scales and has the strongest factor of analytic support of these instruments [4].

The strongest support for the multidimensionality of SETE is based on the nine-factor (Learning/Value, Instructor Enthusiasm, Organization/Clarity, Group Interaction, Individual Rapport, Breadth of Coverage, Examinations/Grading, Assignments/ Readings, and Workload/Difficulty) SEEQ instrument [9]-[13]. These factors are based on various sources (e.g., reviews of current instruments, interviews with students and teachers) and psychometric analysis, and were supported by Marsh and Dunkin's evaluation in relation to theories of teaching and learning.

In this research, we consider these factors from the measured statistical data that comes from the application of the SEEQ instrument applied to students in the first year of the TIE course, under the organizational and operational approach of linear and multilinear algebra, which allows the decomposition of the statistical representations in dimensions associated with the factors extracted from the dataset.

III. PCA AND PARAFAC DECOMPOSITION METHODS

PCA and PARAFAC are bi- and multi-linear decomposition methods that decompose the array into sets of scores and loadings that describe the data in a more condensed form than the original data array [15]-[22]. They assume the existence of a latent structure in each mode of the data sets, which allows one to compact related descriptors and describe the variance within each mode by a reduced number of factors, which facilitates the interpretation of relevant information.

A. PCA Decomposition Methods

Known as Hotteling transform that derives from the Spectral Decomposition Theorem [17], the PCA is a multivariate statistical method, which aims to identify the relationship among features extracted from the data regarding its reduction, elimination of overlap and the choice of the most relevant linear data combinations from the original variables [17]-[22].

A data matrix $\mathbf{X} = \{x_{ij}\}$ can be approximated by PCA as a linear transformation $\mathbf{X} = \mathbf{AB^t} + \mathbf{E}$, where $\mathbf{A} = \{a_{ir}\}$ ($I \times R$) contains mutually orthogonal columns with successively maximum sums-of-squares, and $\mathbf{B} = \{b_{jr}\}$ ($J \times R$) is columnwise orthonormal. Columns of $\mathbf{A}$ and $\mathbf{B}$, we shall call as components, indicates the relative weights of the rows and columns of $\mathbf{X}$ for the corresponding R-components selected (where $R \leq \min(I, J)$), and $\mathbf{E} = \{e_{ij}\}$ ($I \times J$) is the information in $\mathbf{X}$ that cannot be explained by the R-components, it is import to observe that the new generated data is a full-rank matrix. The PCA model can be alternatively written for an arbitrary entry x_{ij} as $x_{ij} = \sum_{r=1}^{R} a_{ir} b_{ir} + e_{ir}$.

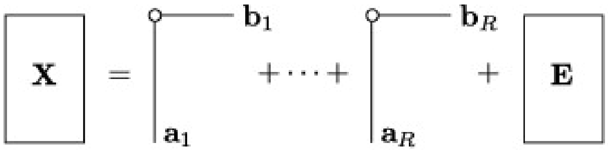

Figure 1. Pictorial representation of PCA decomposition [14].

In PCA, a two-way array is decomposed into a sum of vector products (see Fig. 1). The vectors in the object direction are scores and the ones in the variable direction are loadings for convenience.

B. PARAFAC Decomposition Methods

The Parafac model can be considered a straightforward extension of the PCA model. In the PARAFAC method [14]-[16], a trilinear model is found to minimize the sum of squares of the residues, e_{ijk}, according to $x_{ijk} = \sum_{r=1}^{R} a_{ir} b_{jr} c_{kr} + e_{ijk}$, where R is the number of components used in the PARAFAC and a_{ir}, b_{ir} and c_{ir} indicate weights of the r-th component and e_{ijk} denotes the entry's unexplained information.

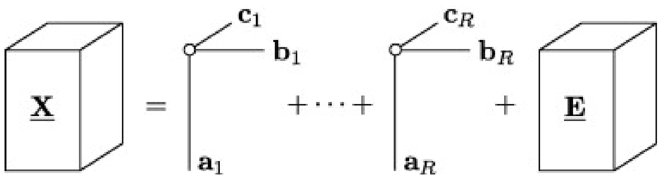

Figure 2. Pictorial representation of PARAFAC decomposition [14].

Connections between PCA and PARAFAC can be further visualized via tensor product notation: PCA approximates $\mathbf{X}$ as a sum of R rank-1 second-order tensors (i.e., outer-products) (Fig. 1), and PARAFAC approximates $\underline{\mathbf{X}}$ as a sum of R rank-1 third-order tensors (Fig. 2). In PARAFAC, a three-way array $\underline{\mathbf{X}}$ is decomposed into a sum of triple products of vectors.

An important step in using the PARAFAC method consists of estimating the number of components or latent variables (R) in the dataset. Several criteria can be used to determine this parameter, such as the explained variance and core consistency diagnostic (CORCONDIA) that was used in this work [4]. The PARAFAC algorithm used in this work was implemented in MATLAB® code.

IV. Methodology

A. Subjects and Course

1) Department of TIE: The TIE course that was created in 2003, belongs to the Department of TIE (DTIE), which is a sub-unit of the Technology Center of UFC. The DTIE was created in March 2001 and it was the pioneer in Brazil in relation to the provision of undergraduate, master's and Ph.D. in TIE, as well as outreach activities, which focus mainly on processing information in the context of integrated telecommunications and computing.

The performance of the DTIE in undergraduate teaching is done on TIE undergraduate courses (www.cgeti.deti.ufc.br). Every year 110 students enter it, and the post-graduate studies of the DTIE contains master's and doctoral. The post-graduate program in TIE (www.ppgeti.ufc.br) consists of two areas of concentration: Signals and Systems and Applied Electromagnetics.

Regarding the extension, DTIE acts with their laboratories in partnership with companies of productive society, performing the training of engineers and researchers, as well as the scientific and technological research focused on cutting-edge intellectual and industrial development in various sectors such as systems and mobile phone networks, computer architecture, robotics, optical systems and devices, among others.

2) TIE Course: The world is experiencing a transformation at a pace never before experienced. The world population is growing increasingly demanding for goods and services in an ascending scale, set in a finite ecosystem. Society is demanding a greater degree of rationalization of its resources for the benefit of a better redistribution of wealth, and more fairly.

However, areas of knowledge regarded as independent, are now not only touching, but are transposing their borders and are leading to the emergence of new areas of human knowledge. More than a mix, we are witnessing a convergence of technologies.

In this context, based on the hypothesis that the vocation promotes an integration of Telecommunications and Informatics areas the objective of the TIE course is to train engineers in the Teleinformatics area with a solid and consistent technical and scientific training which will enable them to absorb and develop new technologies, encouraging their critical and creative role in identifying and solving related problems, considering its political, socioeconomic, environmental and cultural, ethical and humanistic vision in meeting the needs of society.

Among the specific objectives of the course, we can emphasize:

- Provide multidisciplinary knowledge of current technologies used in telecommunications systems and computer systems, including aspects of processing, transmitting and receiving information.

- Provide training in TIE with emphasis on telecommunications engineering and computer engineering, consistent with emerging markets, still in need of skilled labor.
- Enable the professional engineer to carry out assignments in the following technical areas: signal transmission, antenna and switching, transmission systems, data, video and voice by cable, optic fiber, microwave links, satellites, television and radio systems; systems and mobile phone networks, optical communications systems, high-speed networks, Internet and mobile computing.

We emphasize that the TIE course is designed to have a strong appeal to technological formation in all years of formation, since the course's first year. This was a paradigm shift in the traditional engineering education, which reserves, in general, their first two years of the course to form a strong scientific background, and then balances the professional formation content with the engineering sciences, as technologies for engineering. Finally, the course present daytime and evening classes and the average duration of the completion of the regular TIE course is 5 years for the daytime class and 6 years for the evening class.

3) Characteristics of the Sampling: The research on which this study is based was administered with students in the 3th and 4th years of the TIE course. The SEEQ instrument was performed in 4 classes of students who were enrolled in the disciplines of Signals and Systems (SS) and Digital Signal Processing (DSP). Students of both disciplines were invited to participate voluntarily in this research, ensuring them, as well as teachers, anonymity. Students were selected from these two disciplines, because all of these students had already attended the basic disciplines of the TIE first year and also had a prior authorization of the teachers of the four classes for the data collection instrument that was used on students during the classes. During the implementation of SETE some characteristics of the instrument were clarified to the participants, and also a process of awareness to the participants was done, highlighting the importance and necessity of the questionnaires to be answered in the truest and faithful way to the reality of events during classes taught in the disciplines investigated in the first year.

All data was collected between the last fortnight of April 2012 and the first fortnight of May 2012.

B. *Sampling*

The research was conducted with students in the 3rd and 4th year of the TIE course. From the total of 120 students who enrolled in four classes, 100 students completed the questionnaire, yielding a participation rate of 83.3%. The disciplines that have been analyzed were: Fundamental Physics (FP), Experimental Physics (EP), General Chemistry (GQ), Engineering Design (ED), Fundamental Calculus (FC), Linear Algebra (LA), Programming Techniques (PT) and Digital Logic Project (DLP).

C. *Measurement Instrument*

The instrument used in this research was the Students' Evaluation of Educational Quality (SEEQ) proposed by Marsh and Bailey [4]. For lack of space reasons, the questionnaire used is not given here, but is available upon request. Following the scales that are evaluated using the SEEQ.

The Learning (Lrn) subscale reflects what students learned in the classroom. Four items examine the student's interest, knowledge and skill in the discipline area. The Enthusiasm (Enth) is a subscale made up of four questions about the motivation, dynamism and enthusiasm conveyed by the teacher during class. The third factor is the Organization (Orgn), which also assesses claims by four transmission qualities and clarity of content by the teacher, as if the objectives were achieved and the lessons taught eased the assimilation of the content from reading the classes notes. The next item was the Interaction Group (Grp), which investigates the stimulus that the teacher causes to intervene in the classroom during class and if the students are encouraged to participate with their own ideas or to answer questions posed by the teacher. The fifth subscale deals with the relationship between teacher and students and is called the Individual Rapport (Ind). This item explores the relationship between teacher and students in extracurricular activities and their availability to serve them. Another important subscale is Breadth (Brd) that investigates the opinions of students towards teacher's skills and concepts and ideas he develops in class, presenting their views and presenting research results in the content of that particular area.

The Examinations (Exam) subscale, assesses the availability of the teacher in correcting the assessments and judging if their methods are appropriated. The next subscale is the Assignments (Asgn) that assesses whether the workload of the activities as well as the readings and available texts contribute to learning. The ninth and tenth subscales have the same goal, namely Overall, the first of which refers to the overall discipline (O_Disc) in relation to other disciplines, while the second evaluates the teacher (O_Inst) in relation to other teachers that students have been students at, in the institution. Finally, the last evaluated indicator with four items is the Student and Discipline Characteristics (C_Carac) respects to the difficulty of the course in relation to the another one, as well as the classes rate and the time required for commitment of the pupil.

D. *Multivariate Data Collected*

Fig. 3 shows the data obtained from this research. In this regard, the application of chemometric methods is an elegant way of exploring data of this nature [16]. First, a two-dimensional array is explored by PCA through an average configuration matrix (Fig. 3a), where the average information about the students is considered. In the second, a three dimensional array is evaluated by PARAFAC and individual students' information is taken into consideration (Fig. 3b).

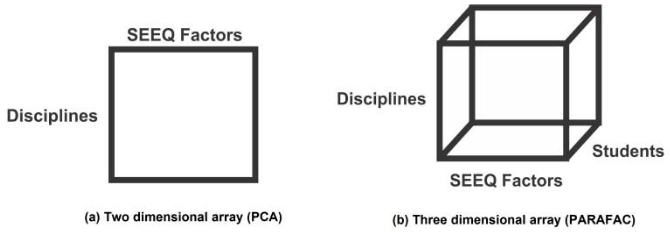

Figure 3. Structure of the dataset collected.

V. RESULTS AND DISCUSSION

Next is a description of the main findings obtained by the PCA and PARAFAC decomposition application. First, we present the PCA results that were applied previously [1]. Then, the analysis of the PARAFAC, that takes into account the students' responses as a three-way modeling, is compared with the PCA application.

A. Reliability of the Dataset

In this study, Cronbach's α was calculated to estimate the reliability of the SEEQ scales, and the results revealed high internal consistency (0.9536) [23].

B. PCA Modeling

PCA was applied to the matrix **X** with dimensions *8 x 11* (Fig. 3a), obtained by calculating the average of the students' responses that were described in section IV-D.

Due to I < J, by the spectral decomposition theorem we find only 8 distinct eigenvalues witch are associated to 8 linear independent eigenvectors [17].

Each discipline, which has been represented in the 8 dimensional spaces defined by SEEQ factors according to the spectral decomposition theorem, has now to be represented by the *R* principal components related to the latent structure. According to the variance explained and cumulative variance for each of the 8 major components, the first two major components are corresponding to 91,011% (*R=2*) of the variance explained. Fig. 4 shows the scores for the first two principal components relating to the disciplines.

Analyzing Fig. 4, we see a consistency in the arrangement of the points. We highlight that Component 1 has a strong relationship between the main areas that are related to the disciplines. The disciplines PT and DLP form Cluster 1 related to the technological cycle of the TIE course, while Cluster 2 formed by the disciplines FC, LA, GQ, FP, EP and ED are related to the basic science cycle.

These high load values in Component 1 can be explained because the analysis has been made in different disciplines with different contents and methodologies. Regarding the component 1, the two regions have the same variability. The PCA allows us to give names to these two components and not just clustering the points. Thus we can identify the components 1 and 2. The component 1 can be interpreted as the intrinsic relationship among the disciplines that belongs to the sciences and mathematical areas involving logical thinking. Already the variability of the component 2 may indicate the dispersion of the evaluation of each discipline in SEEQ, then in the disciplines of the basic science cycle there are a wide variation, while in technological cycle is low and may indicate a proximity indicator and consistency / factors.

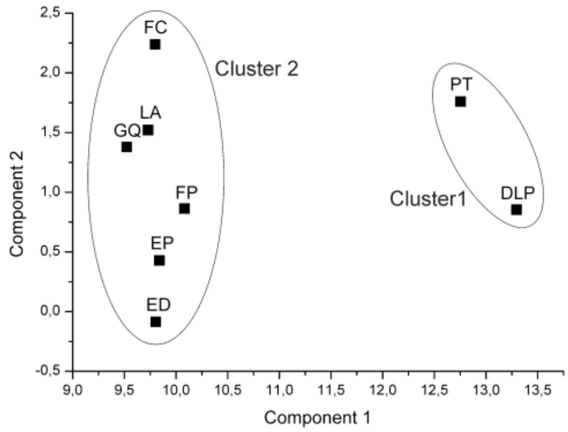

Figure 4. Score plot by PCA.

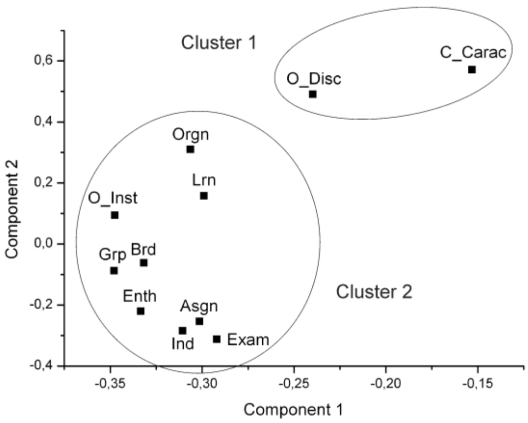

Figure 5. Loading plot by PCA.

Fig. 5 shows the loadings for the first two principal components representing the relationship between the 11 SEEQ factors, so we can infer an interpretation for the main components. It is interesting to note that the arrangement of the variables along Component 1 modeling contains 71.449 % of the variance of the original data matrix. We can see high loading values for the attributes that are related to the characteristics of the disciplines and their difficulty with the others. This behavior can be seen in both Component 1 and Component 2. Characteristics related to the teacher are clustered in one area of Fig. 5, forming a clustering only related to behaviors of the teacher in the disciplines.

C. PARAFAC Modeling

The data has been organized in a three-way array $\underline{\mathbf{X}}$ (Fig. 3b). Analyzing the performance of the calculated PARAFAC model, we can affirm that the model with 2 components is adequate, since the values for CORCONDIA (99.98%) and the explained variance (93.83%) confirm the model's validity [14]-[16].

In Fig. 6, we highlight three groups of disciplines, the first covers the disciplines DLP and PT (Cluster 1), the second includes FC, LA and GC (Cluster 2) and the last one is related to FP, EP and ED (Cluster 3).

Comparing Fig. 4 and Fig.6, it is observed that Cluster 1 in Fig. 4 is decomposed forming two new clusters in Fig. 6, Cluster 2 and Cluster 3.

This result becomes more plausible, compared to PCA application, considering the disciplines belonging to Cluster 2 and Cluster 3 require different degrees of abstraction, knowledge materialization and cognitive learning. Therefore, these clusters should be classified in different ways.

Although the change of the points' arrangement in relation to Fig. 7, we can see that the PARAFAC modeling has generated the same clusters as the PCA modeling in Fig. 5. We can observe a cluster linking most factors, however the factors C_Carac and O_Disc, as in Fig. 5, stand out from the others. These indicators should suggest changes in the disciplines and in the posture of teachers or even the course programs, as these contributions are typical of educational assessment. Further study of these indicators needs to be conducted in order to return a feedback to teachers about the disciplines they are teaching.

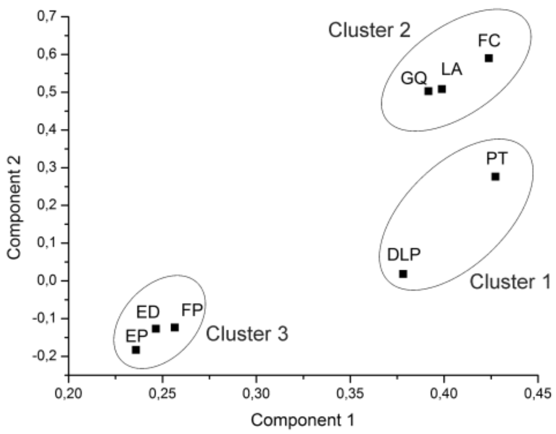

Figure 6. Score plot Mode 1 by PARAFAC.

Fig. 8 shows the loadings plot for the two first factors of the third mode, the students' response. Here one can infer that students were more homogeneous in evaluating the factors of the first component (compare the axes' scale) and highly heterogeneous in evaluating, principally, the Exam, Ind, Orgn and Enth factors of the second component. This information diverges from the scores attributed by some students reflected in the different modes of evaluating the disciplines.

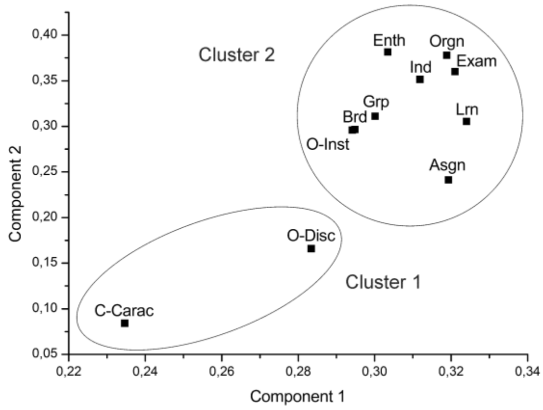

Figure 7. Loading plot Mode 2 by PARAFAC.

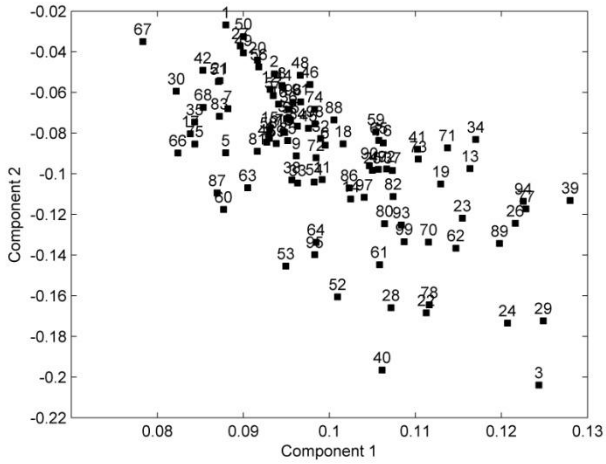

Figure 8. Loading plot Mode 3 by PARAFAC.

VI. CONCLUSIONS

The PARAFAC method has demonstrated a potential model for modeling data related to the evaluation of the teaching effectiveness in student perspective revel latent characteristics. This study provided intrinsic information that use of students' perception about the disciplines and factors analyzed, and assesses the degree of consistency of the students' response including the abstraction degree of the disciplines.

We can observe that taking into account the students' responses in the mathematical modeling provides more information about the features analyzed as we can see in two different perspectives (two and three way modeling) in the relationship between the disciplines in Fig. 4 and Fig. 6. However, the PCA provides only two clusters, while the PARAFAC has three. We can see that the latent structure formed by the multilinear model is more complex and rich than the bilinear model.

In general, students' ratings can make instructors focus too much on improving rather than reflecting upon and improving the teaching itself. However, in this study, we use the students' rating to know the relationship among the disciplines that have been analyzed, and in this case we can see that the curriculum structure of the TIE course using a mathematical model. The PCA model validates the curriculum design of the TIE course first-year [1], but the PARAFAC reveals that the disciplines require different degrees of abstraction, knowledge materialization and cognitive learning and this must be taken into account in the curriculum formalization.

Considering the complexity of the dataset analyzed and the intrinsic factors assessed in the evaluation, our results are useful and deserve consideration by the educational assessment area, especially to the curriculum design development.

In future works can be investigated other tensor decomposition methods such as TUCKER [14], PARAFAC2 [14] and CONFAC [24], and use new metrics to validate the clusters obtained by PCA and PARAFAC modeling.

ACKNOWLEDGMENT

The authors would like to thank Walner Mendonça dos Santos, for his important contribution into the implementation of the Matlab® codes and in the conception of this research.

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