A QUANTITATIVE ANALYSIS OF THE IMPLEMENTATION OF THE LAST PLANNER SYSTEM IN BRAZIL

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ABSTRACT

In Brazil, the Last Planner system has been implemented since 1996 in a large number of construction sites. However, most research studies developed so far have emphasized the analysis of qualitative data, based on single or on a small number of case studies. Therefore, it seems that a good opportunity exists to learn more from the implementation of the Last Planner System by analysing data that are available from large samples of projects.

A database was built including data from 115 projects, which have been investigated in previous research projects at the Building Innovation Research Unit (NORIE) of the Federal University of Rio Grande do Sul (UFRGS). This sample of projects was divided into three market sectors (residential and commercial building, industrial building and low-income housing). The PPC (percentage of plans completed) indicator was analyzed for all those projects. In 51 of them the causes for the non-completion of work packages was also investigated. Moreover, a checklist of production planning and control good practices has been proposed to assess the application of some core ideas of the Last Planner system. Data mining tools, like decision trees and neural networks were also evaluated in searching for interesting patterns in the sample of 51 projects.

Preliminary results on the causes for non-completion of work packages indicate that most projects still have limited success in the implementation of look-ahead planning. The paper also presents future steps in this research project.

KEY WORDS

Last Planner, Performance measurement, Data mining.

INTRODUCTION

The Last Planner system has been implemented in a large number of projects across several countries since 1992 (Ballard and Howell 2003). In Brazil, the first case studies on the application of Last Planner were carried out in 1996, and since then several research studies have investigated its implementation (Oliveira 1999, Bernardes and Formoso 2002, Marchesan and Formoso 2001, Alves 2000, Soares et al. 2002). However, most research studies developed so far have emphasized the analysis of qualitative data, based on single or on a small number of case studies. Therefore, it seems that a good opportunity exists to learn more from the implementation of the Last Planner System by analysing data that are available from large samples of projects, and also using data collected in companies that have adopted this control tool for several years.

International studies highlighted the importance of quantitative analysis in order to evaluate the Last Planner. Ballard (2000) pointed out that it is necessary to quantify and understand the benefits of greater plan reliability for safety, quality, time and cost.

The main data produced through the implementation of the Last Planner System is the Percent-

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age of Plan Completed (PPC) and the causes for non-completion of work packages. Both of them can be considered as leading indicators, because they provide pro-active information and people can be used to predict the future performance of the activity being measured (Beatham et al. 2004, Alarcón 2001). Besides those two measures, there is also a wide range of qualitative and quantitative data for each case study.

It is likely that this large amount of data may hide important information, and it is necessary turn such data into useful information and knowledge. Data Mining is one of the approaches, which have been used in different applications such as business management, production control, market analysis and engineering design aiming to discover interesting patterns (Han and Kamber 2001).

Therefore, this paper presents the preliminary results of an exploratory study about data mining concerning the implementation of the Last Planner System by analysing data from a sample of different projects. The aim is to assess the feasibility of identifying interesting patterns in the evolution of Last Planner system in three different market sectors (residential and commercial building, industrial building and low-income housing). The sample of projects was initially described by using basic statistical analysis. After that, some data mining tools were also used to search interesting patterns about PPC and causes for non-completion of work packages. The data used in this investigation come from a database of 115 projects carried out by companies involved in different research projects developed at the Building Innovation Research Unit (NORIE) of the Federal University of Rio Grande do Sul (UFRGS).

This study is part of the SISIND-NET Project, which has been developed by NORIE/UFRGS with the partnership of the Association of Contractors of the state of Rio Grande do Sul (SINDUSCON/RS), and the support of the National Council for Scientific and Technological Development. This project involves the design and implementation of a performance measurement system for benchmarking for construction companies. One of the aims is devise a web site for collecting and disseminating data, including a web based tutorial that can be used for training. At the moment, there are eighteen companies involved in this initiative (Costa et al. 2004).

DATA MINING

Data mining refers to extracting or "mining" knowledge from large amounts of data (Han and Kamber 2001). Many people treat this as a synonym for Knowledge Discovery in Databases (KDD); however, data mining became more popular than KDD (Han and Kamber 2001). For this reason, in this paper data mining refers to the whole process that includes the following steps: data cleaning, data integration, data selection, data transformation, data mining, pattern evaluation and knowledge presentation (Han and Kamber 2001).

Data mining involves an integration of techniques from multiples disciplines such as machine learning, artificial intelligence, pattern recognition, statistics, databases and visualization to automatically extract concepts, interrelationships and patterns of interest from large databases (Soibelman and Kim 2002). By performing data mining, interesting knowledge, regularities or high-level information can be extracted from database and viewed or browsed from different angles (Han and Kamber 2001).

Databases are also rich with hidden information that could be used for business decisions. Classification and prediction are kinds of data analysis used to describe important data classes or to predict future data trends (Han and Kamber 2001).

A simple and useful learning algorithm for classification and prediction is the decision tree. This tool takes as input an object or situation described by a set of properties and the output is a yes/no decision. Besides that, it is possible to use a large range of outputs for the classification and prediction (Russell and Norvig 2003). This is a powerful tool for establishing relationships among attributes.

For Han and Kamber (2001), the attributes that do not appear in the tree are supposed to be irrelevant. The data analysis that aims to remove irrelevant or redundant attributes in the learning process is known as **feature selection**. For example, it is possible to remove attributes that have not been included in the decision tree from a neural network in order to reduce the error rate.

Besides the decision trees technique, another Data Mining tool used in this paper was neural networks. A neural network is a set of connected input/output units where each connection has a weight associated with it. In the learning phase, the weights are adjusted to predict the correct class label of the input samples. The advantages of neural networks are the high tolerance to noisy data and the ability to classify patterns that have not been trained to (Han and Kamber 2001). Neural networks are good in domains where data cannot be represented symbolically, such as voice recognition and interpreting signal data from scientific instruments (Watson 1997).

These structures are criticized by the difficult interpretability, because it is very hard to understand the meaning of the resulting weights. For this reason, much research has been done on how to extract the knowledge in the neural networks to represent them symbolically. It is possible, for instance, to extract rules and do sensitivity analysis (Han and Kamber 2001). A neural network system functions as a "black box", because no explanation or justification comes from this system. It limits applications in some circumstances. In Europe, for instance, it is illegal for a bank refuse a costumer credit without explanations about the decision, and this tool cannot explain how this decision was reached (Watson 1997).

Decision tree is one of the simplest and most successful forms of learning algorithm (Russell and Norvig 2003). For this reason, this technique was used in this exploratory study. Neural networks were also selected to allow the comparison of results in test sets between these tools.

RESEARCH METHOD

The database of 124 projects was built using data from different sources. Some of the projects were investigated in previous M.Sc. dissertations and Ph.D. theses, developed at NORIE/UFRGS. In addition, some data were also obtained from companies that had been using the Last Planner system for several years in Porto Alegre. These projects were carried out between 1996 and 2004.

The sample of projects was divided into groups. They were initially divided into three market sectors (residential and commercial building, industrial building, and low-income housing). The initial sample had 124 cases. However, 9 projects were excluded from the database, because there were data for a period shorter than four weeks, or the average PPC was 100%. In the remaining sample, the number of weeks was between 4 and 55. The PPC (percentage of plans completed) indicator was analysed for all 115 projects. In 51 of them, the causes for non-completion of work packages were also investigated. Such causes were classified into eight main groups: (1) work force, (2) materials, (3) equipments, (4) design, (5) planning, (6) clients, (7) weather conditions and (8) suppliers. They were also classified into internal (work force, materials, equipments, design and planning) or external problems (clients, weather conditions and suppliers).

In the beginning, descriptive statistic characterized the sample. It was used to characterize the sample about central tendency and data dispersion (Han and Kamber, 2001). For central tendency, "…the median best represents the real situation of the industry sub sector and has the effect of filtering out out-of-range data, which are included in calculation of the mean" (Ramírez, 2004). Regarding data dispersion, the following measures more used are: quartiles, outliers and variance. The kth percentile of a set of data in numerical order is "the value x having the property that k percent of the data entries lie at or below x" (Han and Kamber, 2001). The median (M) corresponds to the 50th percentile while the first quartile (Q1) is the 25th percentile and the third quartile (Q3) is the 75th percentile. Therefore, the distribution was represented by the following measures: minimum, Q1, M, Q3 and maximum. Besides, the standard deviation and the coefficient of variation were also used as measures of dispersion.

Some data mining tools were used to search for interesting patterns in the average PPC and causes for non completion of work packages. In this case, PPC was classified in three groups (PPC<70%, 70%<=PPC<80% and PPC>=80%). There were 6 occurrences in the first group, 23 in the second and 22 in the third one. If the median of PPC were used instead of project average PPC, the groups would have been the same. For this reason, the average PPC were used, because it is more widely disseminated.

Preliminary results using decision trees or neural networks highlighted high error rates. For this reason, two forms of entering data related to causes for non completion of work packages were investigated: (1) the rate between the number of problems and the total number of weeks during the evaluation (problems average, which appear in table 3) and (2) the percentage of problems during the evaluation (also in table 3).

Two samples were necessary in decision tree or neural network (training and test set). In the training set, 36 projects were used, including the extreme values, avoiding discrepancies in the test. The test set has 11 occurrences, selected to reflect the distributions of the different groups in the training data. These groups were the same in the decision tree and in neural network, allowing the comparison in results. The Weka[4] software was used, since it allows the construction of a decision tree and a neural network, enabling the comparison of both error rate in test data in these two techniques. In the beginning, the error rate in the neural network was very high, because all attributes available were used. Then, a decision tree was built aiming to select the most relevant attributes. After that, a new neural network was constructed with the chosen attributes, and as a result, the error rate was much lower than the initial neural network.

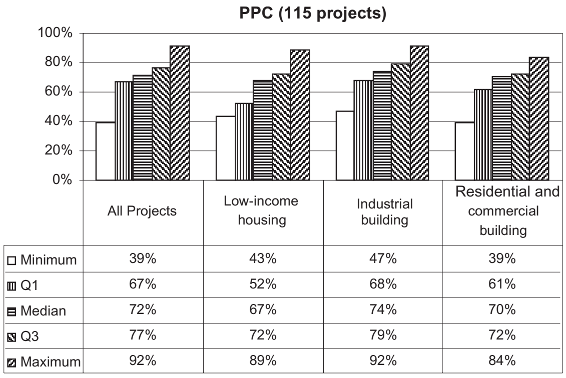
4 Weka is open source software: http://www.cs.waikato.ac.nz/~ml/weka/

Table 1: Other statistical analysis in the sample of 115 projects

	All Projects	Low-income housing	Industrial building	Residential and commercial building
Average	70.04%	64.47%	73.89%	66.03%
Standard deviation	11.42%	13.36%	8.93%	11.85%
Variation coefficient	16.31%	20.72%	12.09%	17.95%
Sample	115	22	63	30

PRELIMINARY RESULTS

This section presents some preliminary results of this research project. Figure 1 presents data on PPC, including minimum, Q1, M, Q3 and maximum, while Table 1 presents the average, standard deviation, variation coefficient and the number of occurrences for each group of projects. Figures 2, 3, 4 and 5 contain histograms comparing the PPC with their frequencies.



	All Projects	Low-income housing	Industrial building	Residential and commercial building
Minimum	39%	43%	47%	39%
Q1	67%	52%	68%	61%
Median	72%	67%	74%	70%
Q3	77%	72%	79%	72%
Maximum	92%	89%	92%	84%

Figure 1: Data dispersion in the sample of 115 projects

According to figure 1, values of Q1 and Q3 are near to median. This result can be better visualized in the histograms (figures 2, 4 and 5); concerning that there is a great distribution around the median. The exception is in the sample of low-income housing (figure 3). In this sample, significant values of the average PPC are around two values (50% and 75%). This data dispersion is corroborated by the highest standard deviation and variation coefficient in this sample (table 1). The main reason for this relatively low PPC was the fact that look-ahead planning and constraints analysis was not properly implemented in those projects.

In 51 projects, the causes of non-completion of work packages were also investigated. Data dispersion in this sample is described in Figure 6. The percentage of causes for non-completion of work packages is presented in Figure 7. In Table 2 there is a description of each problem for each market segment.

In the sample of 51 projects the dispersion was similar to the whole sample (figure 6). In figure 7, the most important problems were related to the work force and planning failures. These problems were also observed in all three markets segment (table 2). However, work force and planning could be very wide categories, avoiding a good classification. For this reason, more investigation is necessary in order to understand the real causes.

Regarding the high score of these problems observed, it is fundamental the improving of the look-ahead planning, aiming to identify constrains related to the work force and planning, which prevents the completion of work package. In the future, for instance, the relationship between PPC and the rate of constraints removed on time could be investigated.

Often, when there is no systematic production control, external causes such as weather conditions are pointed out as major sources of delays. However, adding the three groups of problems concerning the external causes (clients, weather

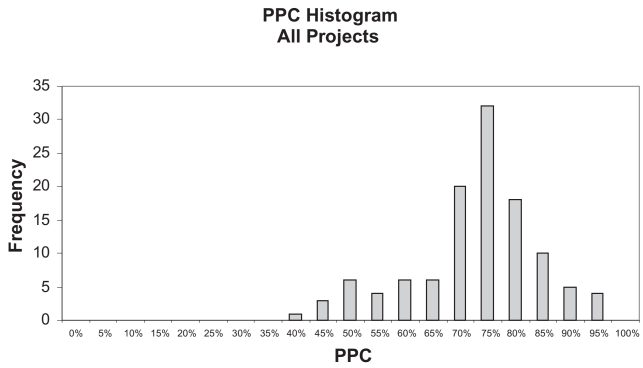


Figure 2: PPC histogram of the whole sample

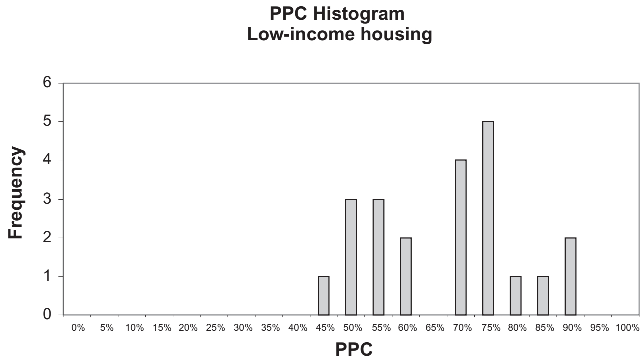


Figure 3:PPC histogram for low-income housing market sector

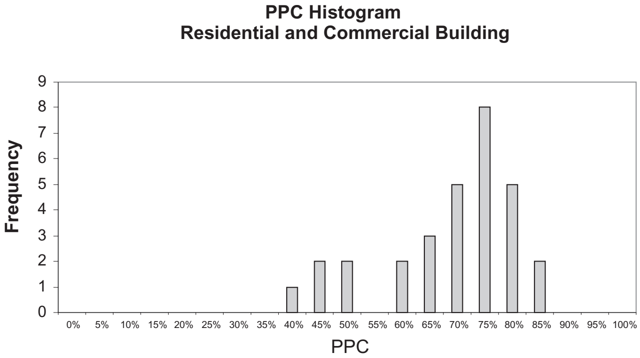


Figure 4: PPC histogram for residential and commercial building market sector

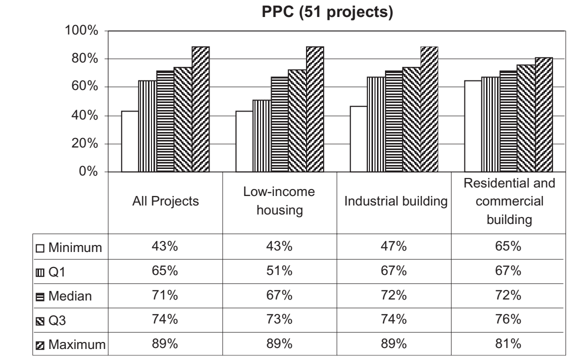


Figure 6: Data dispersion in the sample of 51 projects

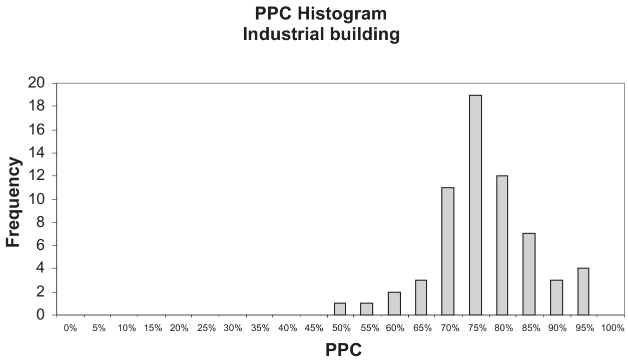


Figure 5: PPC histogram for industrial building market sector

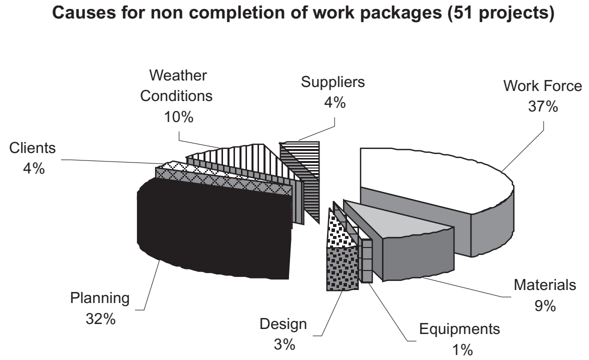


Figure 7: Causes for non-completion of work packages in 51 projects

conditions and suppliers) identified in the sample, the occurrence is less than 20% of the overall problems (17.5% in the whole sample, 18.0% in low-income housing, 19.7% in the industrial building and 12.4% in residential and commercial buildings).

Besides the basic statistic, data mining tools were used to search for interesting patterns concerning the average PPC and causes for non-completion of work packages. Error rates in test samples were so high, and for this reason, it was evaluated the change of the format in entering the data, trying to increase the liability of this application. In the database there is information of the PPC during the weeks of the project and the number of total occurrences of causes for non-completion of work packages. For this reason, two formats in entering data were evaluated. The column *Problems Average* indicates that the total number of occurrences of each group of problems was divided by the number of the weeks during the project. The column *Problems Percentage* is the percentage of each group of problems in the project. The main results concerning the error rates using decision tree and neural network are presented in table 3.

Between these decision trees highlighted in table 3, the most interesting is showed in figure 8.

Table 2: Causes for non-completion of work packages in 51 projects considering the market sector

	All Projects	Low-income housing	Industrial building	Residential and commercial building
Work Force	37.12%	48.52%	30.61%	41.31%
Materials	8.63%	7.93%	8.18%	10.16%
Equipments	1.30%	0.71%	1.31%	1.76%
Design	3.19%	0.12%	3.97%	4.10%
Planning	32.28%	24.73%	36.21%	30.27%
Clients	3.52%	0.00%	6.50%	0.20%
Weather Conditions	9.80%	14.20%	8.79%	8.30%
Suppliers	4.17%	3.79%	4.44%	3.91%

It seems to be the most interesting because the format in entering the data follows the pattern previously used in descriptive statistics (problems percentage instead of problems average). In this application, relations are searched between the percentage of problems identified and the groups of average PPC in the projects during the study. Related to the format in entering the data, in the decision tree it was not critical in order to reduce the error rate (table 3).

Table 3: error rates in a test sample of decision tree and neural network with two formats in entering data

Data Mining Tools	Format in entering data	
	Problems Average	Problems Percentage
Decision Tree	33.33%	33.33%
Neural Network	53.33%	46.67%
Neural Network with attributes selected from decision tree	33.33%	44.44%

Concerning the figure 8, the results of the decision tree shows that among the attributes considered in this classification the most relevant one (design) was chosen as the root node. A decision tree grows from the root node, growing upside down. The result is many nodes connected by branches. Each internal node in the tree corresponds to a test of the value of one of the properties, and the branches from the node are labelled with the possible values of the test. Nodes at the end of branches are called leaf nodes, with a special role if the tree is used for prediction (Russell and Norvig 2003, Soibelman and Kim 2002).

The advantage of using tools as decision trees is to make explicit some unknown patterns among attributes. In the decision tree described in figure 8, design was selected as a major root cause. Naturally, it is known that the design is an important factor that influences a better result in the planning commitment. However it represents just 3% of the problems in the descriptive statistic analysis.

For the present sample there are no clear relations among causes for non-completion of work packages and the PPC groups. The high values of error rates as a prediction tool can be attributed to the small and heterogeneous sample (different projects, in market sectors with very different features, construction sites in different phases and in different locations). Besides this, it was not possible to evaluate the quality and the standardization of the information provided for all projects because the implementation process and the way of data were collected in each project was different. For instance, in some of the projects the Last Planner system was implemented with the support of researchers, but not in others.

According to table 3, error rates in neural networks using decision tree as feature selection are lower. In the best result, the reduction of error rate is about 38%. This high error rate indicates that this application is not liable for predicting patterns. For this reason, further researches are necessary, looking for other features that are better related to the PPC.

Regarding the size of the database, it is clear that a small size is not enough to find interesting and consistent patterns, mainly due to the fact that the sample is very heterogeneous. This is why it is also necessary to search for patterns in a large amount of data in future researches.

Another important issue is the collection of PPC and causes of non-completion through a structure database and standard criteria. It could be achieved through data provided for companies, which are participating of the Benchmarking Club of Sisind-Net Project as well as using an information system of Last Planner as the Power Project Control (http://www.gepuc.cl/fdi), which has been developed by GEPUC (Program for Excellence in Production Management of the Pontificia Universidad Católica de Chile).

FUTHER STUDIES

Relationships among performance measures could be analysed using data collected from many projects, related to the impact of the Last Planner system in the project performance. For instance, the PPC measure could be compared to some leading indicators related to time deviation and cost.

These data also could be supported by qualitative information, such as a kind of checklist used by Bernardes and Formoso (2002), which aims to evaluate good practices observed during the implementation of Last Planner. It is also possible characterise the different projects related to complexity, uncertainty and costumer satisfaction. In each group identified, it is possible to detect improvement levels.

Another possibility is the search for interesting patterns in the PPC evolution. Previous results pointed out that external causes for non-completion of work packages might increase along the project (Ballard and Howell 1997).

Until now, data were collected in previous researches or with companies that have adopted the Last Planner control tool for several years. However, additional information is necessary, specially related to the characterisation of the projects, measures about the complexity and uncertainty of these constructions and overall customer

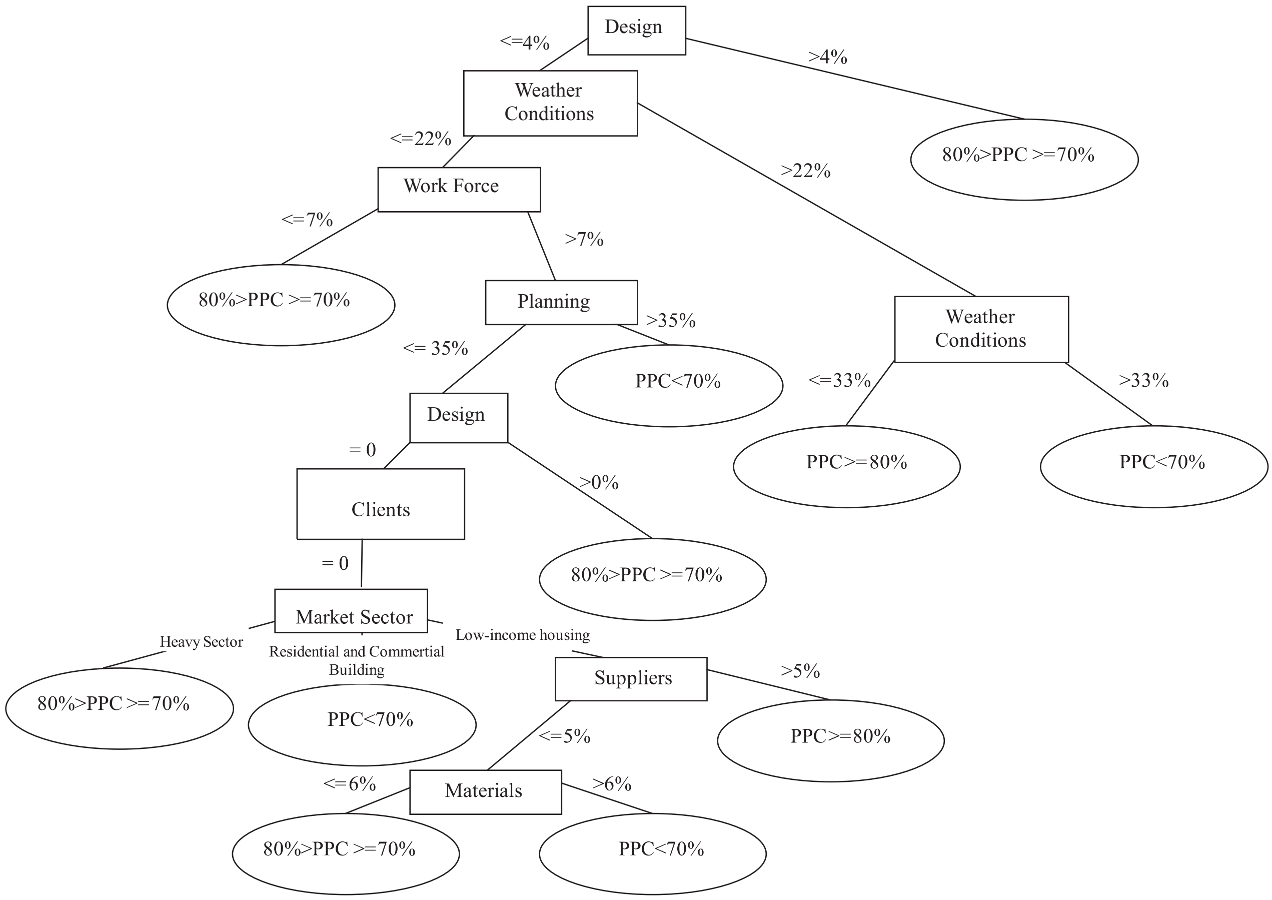


Figure 8: Decision tree considering as attributes the percentage of non-completion of work packages and classifying according to the average PPC

satisfaction. For this reason, now it is necessary to carry out questionnaires and interviews to data collected aiming to a deeper analysis of these projects. The last part of this research project is the validation in case studies of previous statements to increase the quality of data collected.

FINAL COMMENTS

Until the present moment, studies about Last Planner have focused their analysis in descriptive statistic methods. Due to this, the causes of non-completion of work packages identified were immediately indicated as the main responsible for the lower performance. However, this kind of analysis does not provide information about relationship among different attributes. It could be exploited using tools aiming to discover knowledge through databases that are easily understood by human, like the data mining tools (decision tree) used in the present paper.

However, in this paper the decision tree and neural network did not present final conclusions due to the high error rates, the small and heterogeneous sample. These results indicated that it is necessary to have a larger database as well as to investigate ways of improve the data collection process (more structured and standardized, with relevant features), aiming to obtain reliability and quality in the information.

It is also important to identify other data mining tools that are more appropriate to the types of variables analysed in the Last Planner implementation process, which is characterized by high variability and heterogeneity of the projects. For further applications it is suggested the use of the case based reasoning.

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