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Multidimensional SME Performance Evaluation: Upgrading to Data Warehousing & Data Mining Techniques

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Abstract

We present a fully implemented expert diagnostic system which evaluates the performance of SMEs on a benchmarking basis. The system has been in use for several years and has gone through a constant and quite challenging evolution in order to meet both the needs of research and the production of benchmarking reports. We discuss why we decided to upgrade our system with data warehousing and data mining techniques. At the time of writing, we are about to activate the new data warehouse and start our experimentations with data mining techniques—newest results will be available when the conference will be held. We think data warehousing and data mining will allow us to significantly extend our knowledge on SMEs, and further improve our performance evaluation model.

Keywords: *Benchmarking, Data Warehousing, Data Mining, Diagnosis, Expert Systems, Performance, SME.*

1. Introduction

In this paper, we first briefly describe an expert diagnosis system we have developed for SMEs [18] which can be considered as a decision support system [15, 19]. Based on a benchmarking approach [3, 21], our system performs a multidimensional evaluation of a SME's production and management activities, and assesses the results of these activities in terms of productivity, profitability, vulnerability and efficiency. This system is fully implemented and operational, and has been put to use on data from actual SMEs for the last couple of years. Then, in the second part of the paper, we move on to the main topic: explaining why traditional database techniques used by our system must be upgraded with the integration of data warehousing and data mining techniques to boost

its data intelligence capabilities. This portion of the paper describes ongoing and future work.

Our work takes place within the context of a research institute for SMEs—the Institute's core mission is to support fundamental and applied research to foster the advancement of knowledge on SMEs to contribute to their development. The specific lab in which we have conducted the research reported here is mainly concerned with the development of scientific expertise on the study and modeling of SMEs' performance and risk, including a variety of interrelated subjects such as finance, management, information systems, production, technology, etc. Research projects carried out at our lab involve both theoretical and practical aspects, often necessitating in-field studies with SMEs. As a result, our research projects always attempt to provide practical solutions to real problems confronting SMEs.

2. The SME Performance Evaluation Software

2.1 An Overview of the PDG System

The PDG ("Performance, Development and Growth) software system, which runs on computers located in our lab, evaluates a SME from an external perspective and on a comparative basis in order to produce a diagnosis of its performance and potential, complemented with relevant recommendations. Although we usually refer to our system as a diagnostic system, it is in fact a hybrid diagnostic-recommendation system as it not only identifies the evaluated SME's weaknesses but it also makes suggestions on how to address these weaknesses in order to improve the SME's performance. An extensive (18-page) questionnaire is used to collect relevant information items on the SME to be evaluated. This questionnaire, once filled

by the SME, is sent to our lab along with the financial statements of the last five years.

Data extracted from the questionnaire and the financial statements is computerized and fed into the system. The latter performs a multidimensional evaluation in approximately 3 minutes by contrasting the particular SME with an appropriate group of SMEs for which we have already collected relevant data—this is the crux of the benchmarking process. The output is a detailed report in which 28 management practices (concerning human resources management, production systems and organization, market development activities, accounting, finance and control tools), 20 results indicators and 22 general information items are evaluated, leading to 14 recommendations on short term actions the evaluated SME could undertake to improve its overall performance.

Our expert diagnosis system is connected to an Oracle database that collects all the relevant data for benchmarking purposes—the system also uses the SAS statistics package, plus Microsoft Excel for various calculations and the generation of the final output report. The output reports are constantly monitored by a team of multidisciplinary human experts in order to ensure that recommendations are valuable for the entrepreneurs. This validation phase, which always takes place before the report is sent to the SME, is an occasion to make further improvements to our system, whenever appropriate. It is also a valuable means for the human experts to update their own expertise on SMEs. An intermediary partner is part of the process in order to guarantee confidentiality: nobody in our lab knows to what companies the data are associated.

The current version of our system has been in production for 2 years. So far, we have produced more than 600 reports and accumulated in the database the evaluation results of approximately 450 different manufacturing SMEs. A recent study was made of 307 Canadian manufacturing SMEs that have used the evaluation report, including 49 that have done so more than once. Our results show that the expert benchmarking evaluation allows these organisations to improve their operational performance, confirming the usefulness of benchmarking but also, the value of the recommendations included in the output report concerning short-term actions to improve management practices.

As far as we know, our system is unique. A somewhat similar system is presented in [4]. However, their system was especially developed for SMEs that produce goods in relatively small volumes and in batch. It is based on a specific benchmark focusing on manufacturing and assembly processes. Moreover, the system they describe is mostly semi-automatic (if not mostly manual), whereas ours is entirely automatic, let alone a final revision of the final wording of the main recommendations which usually takes between five to ten minutes.

2.2 Knowledge Engineering Aspects

The system's expertise is located in two main components: the in-depth questionnaire and the benchmarking results interpretation module. The first version of the questionnaire was developed by a multidisciplinary team of researchers in the following domains, thus contributing to the multidimensional nature of the evaluation: business strategy, human resources, information systems, industrial engineering, logistics, marketing, economics, and finance. The questionnaire development team was faced with two important challenges that quickly became crucial goals: i) find a common language (a shared ontology) that would allow researchers to understand each other and, at the same time, would be accessible to entrepreneurs when answering the questionnaire, and ii) identify long-term performance indicators for SMEs, as well as problem indicators, while keeping contents to a minimum since in-depth evaluation was not adequate.

The team was able to meet these two goals by the assignment of a “knowledge integrator” role to the project leader. During the 15-month period of its development, the questionnaire was tested with entrepreneurs in order to ensure that it was easy to understand both in terms of contents and question formulation, and report layout and information visualization. Texts were written with a clear pedagogical emphasis since the subject matter was not all that trivial and the intended lectureship was quite varied and heterogeneous. Several prototypes were presented to entrepreneurs and they showed a marked interest for graphics and colours.

The researchers' expertise was precious in the identification of vital information that would allow the system to rapidly produce a general diagnosis of any manufacturing SME. The diagnosis also needed to be reliable and complete, while being comprehensible by typical entrepreneurs as we pointed out before. This was pioneering research work that the whole team was conducting. Indeed, other SME diagnosis systems are generally financial and based on valid quantitative data—see [9, 11, 20] for examples of expert systems in finance. The knowledge integrator mentioned above played an important part in this information engineering and integration process. Each expert had to identify practices, systems, or tools that had to be implemented in a manufacturing SME to ensure a certain level of performance. Then, performance indicators had to be defined in order to measure to what extent these individual practices, systems, or tools were correctly implemented and allowed the enterprise to meet specific goals—the relationship between practices and results is a distinguishing characteristic of our system. Next, every selected performance indicator was assigned a relative weight by the expert and the knowledge integrator. This weight is used to position the enterprise being diagnosed with regard to its reference group, thus allowing the

production of relevant comments and recommendations. The weight is also used to produce a global evaluation that will be displayed in a synoptic table. Contrary to many performance diagnostic tools in which the enterprise's information is compared to norms and standards (e.g. [9]), the system evaluates an enterprise relative to a reference group selected by the entrepreneur—or recommended by our lab if the entrepreneur let us decide. Research conducted at our institute seriously questions this use of norms and standards: it appears to be dubious for SMEs as they simply are too heterogeneous to support the definition of reliable norms and standards.

Performance indicators are implemented as variables in the system—more precisely in its database, and in the benchmarking results interpretation module (within the report production module). These variables are defined in terms of three categories: i) binary variables, which are associated with yes/no questions; ii) scale variables, which are associated with the relative ranking of the enterprise along a 1 to 4 or a 1 to 5 scale, depending on the question; and iii) continuous (numerical) variables, which are associated with numerical figures such as the export rate or the training budget.

Since variables come in different types, they must also be processed differently at the statistical level, notably when computing the reference group used for benchmarking purposes. In order to characterize the reference group with a single value, a central tendency measure that is representative of the reference group's set of observations is used. Depending on the variable category and its statistical distribution, means, medians, or percentages are used in the benchmarking computations. The evaluated enterprise's results are ranked and associated with codes that will next be used to produce the various graphics in the benchmarking report. The resulting codes indicate the evaluated enterprise's benchmarking result for every performance indicator. They are then used by the report generation module to produce the benchmarking output report, which contains many coloured graphical representations, as well as comments and recommendations.

A good deal of multi-domain expertise and informal knowledge engineering was invested into the design of the expert diagnosis system. In fact, at the early stage of the project, it was even hoped that a “traditional” expert-system approach would apply naturally to the task we were facing. Using an expert system shell, a prototype was in fact developed for a subset of the full system dealing only with human resources. However, reality turned out to be much more difficult than anticipated. In particular, the knowledge acquisition, knowledge modelling, and knowledge validation/verification phases ([13, 9, 16, 14]) were too demanding in the context of our resources constraints especially in the context of a multidisciplinary domain such as that of SME for which little formalized knowledge exists. Indeed, many people were involved, all of them in various specialization fields, as mentioned in

Section 2.2, and with various backgrounds (researchers, graduate students, research professionals and, of course, entrepreneurs). The development of a truly multidimensional performance evaluation scheme especially tailored to SMEs was, and still is, a quite demanding and challenging endeavour.

The current version of the system, although not implemented with “traditional” AI techniques, e.g. knowledge base of rules and facts, inference engine, etc., qualifies as a “black-box” expert diagnosis system. This unique system is based on knowledge, information and algorithms that allow it to produce outputs that only a human expert, or in fact several human experts in different domains, would be able to produce in terms of diagnosis and recommendation quality. The output report contains mostly coloured diagrams and simple explanations that are formulated in plain English (or French) so that SMEs entrepreneurs can easily understand it. The system also uses some relatively old AI techniques. For instance, the comments produced in the output report are generated via a template-based approach, an early technique used in natural language processing.

3. The Need for Greater Data Intelligence Capabilities

Our system is now at a stage where we can now reconsider the introduction of AI techniques in new developments. We have started to develop new modules that will increase even more the intelligence features of the system:

a) Development of data warehouses and data mining algorithms to facilitate statistical processing of data and extend knowledge extraction capabilities—see, e.g., [6]. Such extracted knowledge will be useful to improve the systems' meta-knowledge level, which could be used in the systems' explanations for instance, and also to broaden human experts' domain knowledge. This phase is already in progress and is the main focus of our current work: see Section 4.

b) The huge number of database attributes and statistical variables manipulated by the system is overwhelming. A conceptual taxonomy, coupled with an elaborated data dictionary, has now become a necessary addition. For instance, the researcher should be able to find out quickly to what concepts a particular attribute (or variable) is associated, to what computations or results it is related, and so on. This phase has recently begun.

c) Development of an expert system to eliminate the need for any human intervention in the system. Currently, a human expert must revise all automatically-produced reports before they are sent to the SME. Most of the time, only minor adjustments are required. The knowledge used to perform this final revision takes into consideration individual results produced in various parts of the benchmarking report and analyze potential consequences of interrelationships between them in order to ensure that

conclusions and recommendations of the evaluated SME are both valid and coherent. This is part of our future work.

d) Augment the PDG system with case-based reasoning and related machine learning algorithms—see, e.g., [10]. In several aspects of the system, evaluation of the problem at hand could be facilitated if it were possible to establish relationships with similar problems (cases) already solved before—see [17]. Determining the problems' salient features to support this approach would also offer good potential to lessen the users' burden during the initial data collection phase. This phase is part of our future work.

e) Study the potential of agent technology to reengineer some elements of the system, especially from a decision support system perspective ([2]). This could be especially interesting for the modelling and implementation of distributed sources of expertise that contribute to decision processing. For example, in the system, each source of expertise in the performance evaluation of a SME could be associated with a distinct agent controlling and managing its own knowledge base—see [1]. Interaction and coordination between these agents would be crucial aspects of a new system based on a community of cooperative problem-solving agents.

4. Data Warehousing and Data Mining

4.1 Motivations

Our system has led to the creation of a large database on many different SME-related themes. This database is constantly updated with numerical, qualitative, and financial historical (yearly) data from evaluated SMEs. The database was designed to support the production of the benchmarking report, but also to support scientific research on SMEs conducted here by researchers and graduate students. These two realities, sometimes associated with conflicting goals, have caused structural problems in the database itself, more specifically in the database uploading (“feeding”) mechanism and in the applications that use the data. The design process was incremental over many years and we must say that, when the project started six years ago, we never envisaged that it would grow to such a scale. For that reason, there is no unique, coherent philosophy behind the current database structure. There are many tables and many software tools to load and extract data from the database. As a consequence, maintenance of the system is tricky, mainly because of the system's internal complexity and the numerous kinds of use we do have to support. Despite these difficulties, our system and its database constitute a very rich source of information on SMEs.

Until recently, only one professional user had sufficient working knowledge about the database to properly extract and prepare data for research-related needs. This person was always solicited for the entire lab's data needs. Several researchers use the database. There are also research professionals and graduate students that need all kinds of

data sets—data sets are data extractions from the database that are especially prepared to study a SME-related hypothesis or problem. So far, all these people had to ask the same person for a data set tailored to their needs, and preparing a single data set could take as much as a week. As these users come from different backgrounds, they tend to have different views of the data. Although the initial creators and developers of the system had defined a common ontology, many of them have left since. All new users have to be trained before being able to adequately use the smallest portion of the system or the database, and this training is a very demanding task.

Continuing our tradition of incremental improvement, we recently adopted a data warehousing (DW) and data mining (DM) approach in order to better exploit the rich information contained in the database, to better meet the need for integration of various data sources, to better meet the need for a metadata repository, and for the general usefulness of the various tools that are already available in a DW supported with a database environment such as Oracle. The presence of several systems, each contributing its own data to the database, makes it more difficult to exploit the data without an adequate approach. Integration of all needed sources of data must be made for every new project. With a lot of work, it is possible to keep current applications working and to create new projects. But with DW, all applications will benefit from the associated extract, transform and load (ETL) procedures. The presence of integrated data reduces the time and number of data manipulations. The number of errors due to manipulations is also reduced because the integration is done in one central place for ease of understanding and data reusability.

Another problem that we face for every new project is the absence of a unified source of documentation. Our solution is to create a repository for metadata in the DW. This will allow users to access metadata about “variables” (attributes and calculated fields), questionnaires and special information (for example, how to change the currency in financial data). Most of this documentation already exists, but the users have to painfully search through many documents to find what they need. This is why all these documents are being consolidated and organized in the metadata repository.

Finally, many methods are now available to efficiently exploit data in a DW, such as DM tools. Since the database is very large, researchers usually make data sets from a relatively small subset of the database (financial statements, human resource, innovation, business collaborations, etc.). DM applications can potentially use all available data and identify links between many themes. For example, here are few typical questions that DM techniques will allow us to address quite naturally: Is there a link between innovation in a SME and its financial situation? Is it important to have business partnerships to increase sales figure? What influences sales figures? What influences partnerships? Why do these SMEs innovate

more than these other ones? All the data in the DW will be used with DM applications to answer these questions, and others, and possibly uncover previously unknown patterns, rules, facts, etc., allowing researchers to acquire new knowledge on SMEs and, eventually, to produce an even better benchmarking evaluation of SMEs. This illustrates very well the research-application cycle in which our work takes place.

A major problem that we face when evaluating these techniques was the fact that the uploading systems were created to facilitate the insertion of data in the database and to generate reports. The structure of the database was not very well suited to the use of DM tools and AI applications. This structure had to be changed. For that reason, we designed an ETL phase to create an intermediary database more directly adapted to the needs of the lab's users and researchers. Furthermore, this method allows much more easily the integration of different sources of information (metadata, data from other projects, commercial databases, etc.), a definite plus in our research environment.

4.2 Setting Up the Foundations

To set up the DW, we must first harmonize all data through an integration phase: the ETL (extract, transform and load) procedures—see a depiction of our DW infrastructure in Figure 1 below. Longitudinal studies were complicated with the original database. For instance, no information was kept as to when or why certain data elements were changed. In the DW, timestamps are added to the data at loading time and historical information is associated with the data (e.g. a period of validity).

Most of the data in the system comes from questionnaires that are sent to our lab where answers are typed in. Sometimes, an error (i.e. typo) is introduced at entry time. This is why a process of manual verification was created several years ago. This process uses flags to signal to the system when new data can be considered reliable, once manual verification has been completed. These flags need to be processed by the ETL procedures so that no “unreliable” data is used in the DW—as in all DW endeavours, data has to be “clean” as much as possible. This initial phase is also appropriate to update and complete the metadata documentation. The structure of the tables is studied and modified to allow an easier access for all foreseeable uses of the data. A security process also ensures that users are granted adequate access to the DW.

The benchmarking report will soon be redesigned to benefit from the new possibilities offered by the DW. An immediate advantage will be a substantial reduction of the time required to produce the report. Currently, it takes about 3 minutes to automatically create a benchmarking report. This relatively long time is explained in part by the need to transform all data in the same currency (we have data in US dollars, Canadian dollars, and Euros). The complexity of the tables in the database makes it very difficult to perform these transformations, and the creation of a materialized view with a fast refresh was not possible.

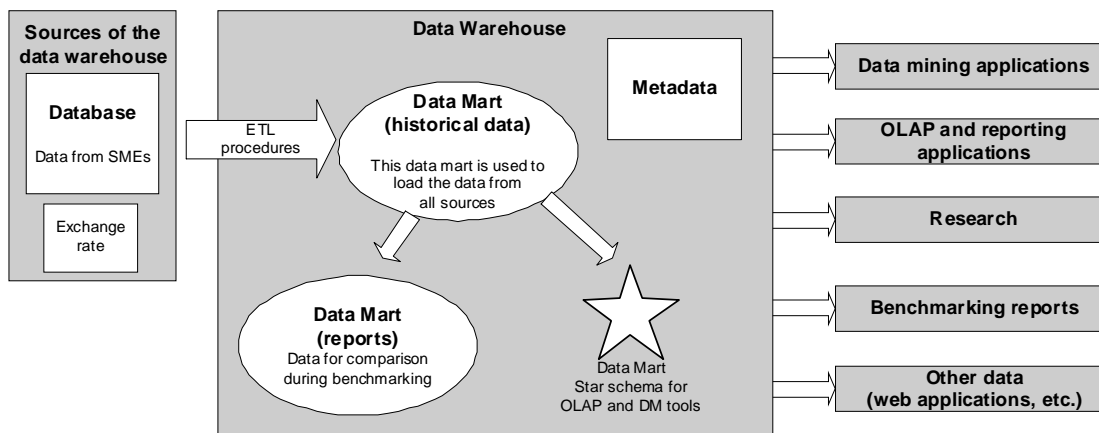


Figure 1. A representation of our data warehouse (DW) infrastructure.

There are other transformations that are also needed. One of them is due to the fact that data about a specific SME can be disseminated in different questionnaires (corresponding to different years). The data has to be reconciled. This has to be done every time a report is requested. The particularities of the database (and the fact that it was built incrementally) lead to several compromises in performance. However, in the DW, all of these considerations are taken care of by the ETL procedures. The data is saved in a correct and much more usable form amenable to report production, and data mining for research purposes. Once the DW is completed, we expect a creation time of about 30 seconds for benchmarking reports. Furthermore, several new tools, some of which will be AI-based, will be made available to increase the value of the report. These are some of the many benefits that DW brings to our system.

The DW supports a variety of tools that allow users (researchers, professionals, assistants, students) an immediate access to the data without the help of a database specialist. We have also developed a custom-made, user-friendly Web-based tool that allows users to create data sets from the DW. Metadata also allow users to correctly interpret data in the warehouse. One of the metadata tools is a dictionary of “variables” (questionnaire fields). This is an invaluable tool for users since there are hundreds of variables, and many variables have custom formats (e.g. 0=no, 1=yes, -97=maybe, etc.). Also, as mentioned before, many changes have occurred over time in the questionnaire and in the database. Even today, our system continues to evolve and new questionnaires are created. This is why it is so important to know what a variable represents exactly, because even this definition can change over time—see slowly changing dimensions in DW [8]. For example, a question with three possible answers (A, B and C) in a previous questionnaire can now have five answers (A, B, C, D and E). The literature on DW deals with many of these questions, including methodological aspects [5].

There are different views as to how the core of the DW should be designed. Some practitioners say that using a multidimensional database is the best way to increase performance [12], while others say that using such a design can be the cause of great torment when changes have to be made [7]. Still, we chose to implement a multidimensional data mart based on a star schema. It will be used for OLAP (On-Line Analytic Processing) and DM tools. It is from this data mart that we will be able to explore the system’s data from a new perspective.

Our database is large, but not huge. Our current resources are sufficient to handle the volume of data, and we even have a bit of extra capacity if need be. The benchmarking reports could still be produced from the original relational database. But the multidimensional data mart is of great value to the work in progress on DW and DM. Not all DM tools necessarily need a multidimensional database to operate however. We are nevertheless very confident that this DW and DM approach we have taken

recently will pave the way to a new, thorough comprehension of many important facets of SMEs as they are (implicitly) modeled in our database. As mentioned earlier, the researchers usually use only a subset of all the available data in their data set. They test their hypotheses on these samples using their expertise to find new facts. But by using DM tools, they can now quickly test their hypotheses against the entire DW. Not only will access to data be much faster, compared to the several days needed before to simply create a data set, but the amount of data used will be increased as well. With the availability of DM tools for classification, estimation, prediction, clustering, etc., extra data intelligence capabilities will be available by comparison to classical statistics. We can expect users to be interested in queries that are currently unnecessarily complicated to compute with the initial database, such as: Since their last evaluation, what changed in the SMEs that used our report? What kind of SME decides to get an international accreditation or standard? These are but a few examples of the many queries that will be easy to process with DM techniques applied to our DW.

In the system, there is also a need for various information reports about the data in the DW. The applications currently used to generate these reports are not easy to create and update for non-programmers as they are implemented in PL/SQL. Often, such information reports have a very short period of life. For example, a report shows the geographical distribution of the SMEs we have in the database. Other reports show the sector in which the SMEs operate, while others show the date at which the questionnaires were received at our lab. Sometimes, there may be a need to know exactly how many benchmarking reports were sent per month in the United States only. This kind of information is easy to obtain with an OLAP application. OLAP applications will use the multidimensional data mart, but will also have access to all other data in the DW.

Some experimentation has already been done with the database and specialized algorithms such as automatic cluster detection. The preparation of data sets was difficult at best, and the data could not be updated easily. With the DW, these tools (decision trees, neural networks, K-means, etc.) will be much easier to use and will allow researchers to find entirely new ways to analyze and understand SMEs and, ultimately, carry out SME performance evaluation and benchmarking. Other AI-related tools, as mentioned in Section 3, are also being considered.

5. Conclusion

We have briefly presented a fully implemented expert diagnostic system which evaluates the performance of SMEs on a benchmarking basis. The system has been in use for several years and has gone through a constant and quite challenging evolution in order to meet both the needs of SME-oriented research (numerous research projects have used the system so far) and the production of

benchmarking reports for SMEs (approximately 500 so far).

We have come to a point where data warehousing and data mining techniques had to be introduced, considering the benefits they offer to support our work, notably our research on SMEs and, consequently, the performance evaluation carried out by our system. At the time of writing, we are about to activate the new data warehouse and start our first experimentations with data mining techniques. We will be able to report on our newest progress at the time the conference will be held.

Data warehousing has many practical uses in our SME-oriented context and it will, along with data mining techniques, positively affect the way researchers use the rich data we have collected and continue to collect on SMEs. We hope to significantly extend our knowledge on SMEs, and further improve our evaluation model of SME performance.

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