Improve Supply Chain Management Using Neural Networks and Regressive KPI Relationship Metamodels

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Abstract
The economic development of the emerging countries has been regarded in the recent time as a serious opportunity for cost reduction from western manufacturer, results obtained from this vision were the increase of the delocalization of the production process and the increase of the management complexity. In order to answer to the new market demand industry turn to software vendors looking for specific ERP systems (Davenport 1998) and starting specific projects for supporting Business Process Redesign (BPR). As seen in several industrial contexts few projects ended with success while the majority of them running very quickly out of budget and in serious delay.
In this sector authors identified a lack of anticipatory models able to drive the ERP implementation process to the right and they propose in this paper a meta modeling approach able to bridge this gap.
Proposed methodology integrates Data Analysis, Regression Meta-Modeling and Artificial Neural Networks processing in order to identify hidden relationships among KPI and guide the BPR decision makers. The paper outline the proposed methodology as well as a practical application to a real life industrial case.
Keywords: KPI, Supply Chain Management, Regression, Metamodel, Artificial Neural Networks

1 Introduction

Since the Nineties we have managed to integrate enterprises ERP systems. Modern ERP systems have integrated the main management aspects (Human Resources Management, Sales, Marketing, Distribution/Logistics, Manufacturing & Accounting) and they have become the point of reference for business process (Kamath et al. 2003). From an evolution point of view, ERP systems have shifted their focus either on terms of functionality or on a technological level. That has led to direct consequences on the ERP specific market. Recent success of Information and Communication Technology clearly shows the information value is a more and more important aspect of the industrial product value. As a matter of fact, not only the production methods, but also time and availability do help in the quality of it. Therefore ERP systems shift their objective on those applications enabled to manage data in order to transpose them in information useful for the decision-making process. In fact, the chief ERP Vendors are working at an evolution of the species which is leading to an integration of additional modules such as CRM, Advanced Planning System, SCM, Business on Demand, BPR, BI, PDM. Analysts, like Gartner Group, believe that such an evolution will lead to a new ERP model, called ERP II (Zrimsek 2002) or VCRP (Value Chain Resource Planning), which should substitute the current ERP systems from the year 2005 onward. However, looking back to recent past, except for few and rare successful cases, companies have met great difficulties to carry out their plans with consequent exceeding budgets in costs and time. The main difficulty of the companies is still their business process formalization, analysis and rationalization. The problem is still to adapt the ERP system to the company context, or to make it a chance to modify radically their own business process. We would like to put in evidence that the ERP model is not a software application but a method of organization and management to rationalize and optimize a complex system. In general, can we be sure that nowadays companies are able to install and implement an ERP system being sure of its result in terms of cost and performance? And in particular, are really systems controlling and measuring the companies performances, the so called CPM (Corporate Performance Management), able to have the company capitalize the carried out investment? An article published by Gartner Group in June 2003 relates expressly a new management area called Business Performance Management (BPM). In particular it relates that it is able to set an integration of planned, elaborated and collected performances through an advanced setting of data analysis and summary based on ERP system. Moreover, encouraging results about a few management areas are published with a related hypothetical improvement in several other fields, as well, such as banking, financial, medical, pharmaceutical, governmental and in particular manufacturing ones. Actually BMP represents an evolution of Business Intelligence (BI) based on the idea of Business Activity Monitoring (BAM). The aim of the integration of BAM solutions overtakes the physical boundaries of an deployment or of a department, and the idea of real time (time required for one or more data processing) is not necessarily expressed in nanoseconds but it is rather determined by the business process bill. Therefore, BMP is in general an amount of services and implements offering an explicit management process in analyzing, planning, programming, executive and monitoring areas. The ideal setting of it, inside the manufacturing industry, is in collaborative contexts with evolved transactional systems (ERP II) and with supply Chain (Bruzzone and Revetria 2003) Management systems. On the other side BMP refers to Corporate Performance Management systems (CPM), assigned to coordinate formalization of clue enterprise methodologies, metrics and processes with a view to improve the company performances. Both BMP and CPM are based on parameters permitting to determine the efficiency of an aspect of the company activity objectively; these parameters have been defined Key Performance Indicators (KPI) (Drucker et al. 1998). Actually they provide the base for strategic decisions. CPM appears transversal to different applications systems such as ERP, CRM, SCM, and legacy systems; in other words it appears transversal to an ERP II system. Either technologies or applications in this area are already consolidated, even if not completely widespread, above all on our nation. About

86% of the companies is expecting a competitive benefit reducing the time wasted to collecting and answering to information, while a good 74% of the companies has executive managers demanding IT manager to restrain the clue operation data receiving time. Nevertheless, today only 35% of the companies is able to exploit the benefits received from real time information. What makes the difference between the value expected from applications and the applicability of them in order to goal the planned results? As far as the more recent international literature is regarded, the following steps are not explained:

Lack of a theory for the quantitative evaluation of the proposed business schemes in order to identify:

- Better processes
- Better KPI
- Lack of a support for the distribution of the transactional systems modeling; in fact, ERP are often composed by connected parts on geographical nets of even wide dimensions.
- Lack of specific semantics for Process Redesign, not based on General Purpose approaches.
- Extensive gap between the clue productive point of view (physical processes) and the clue commercial one (processes linked to demand and to financial fluxes).

Quoting a recent article from a technical revue: "To be effective, process design, control and improvement demand the use of modeling methods with scalable and dynamic properties providing seamless links between business and technical process issues" (Kamath et al 2004). The paper proposes an innovative and holistic approach of modeling enabled to provide a quantitative evaluation of companies Business Processes by identifying the relationships among the various KPI by using RSM and neural networks meta-modeling (Merkuryeva 2000).

2 Proposed Methodology: from Massive Simulation to Meta Modeling

In distributed manufacturing Supply Chain Management (SCM) play a central role by identifying the correct value stream and the complex relationship existing among SCM actors (Mosca et al. 2002). The comprehension of the underlying process that drive a complex production and distribution systems is generally affected by several blocking factors such as: the complexity level required to build a credible model, time consumed by specific stream projects and data unavailability.

This last point is one of the more critical and less evident of the entire problem. Modern ERP, in fact, produces huge amount of information that made Data Warehousing a difficult task, more a lack of the comprehension of the KPI structure demonstrates that some time set points are just guessed rather than designed on a specific purpose. Control matrix available on highest direction levels presents static view of the business while managers needs dynamic interpretation of the emerging forces present in a complex

system. Data are collected without finalization and poorly interrelated, reports, very often, are meaningless.
In the proposed methodology KPI are assumed as measures of an underlying process only partially known where the true hidden relationship has to be identified, main activity emerging from the application of the proposed methodology can be summarized in the following tasks:

- Comprehension of relationships occurring between KPI;
- Review of common used KPI;
- Addition of new KPI, if necessary to better control specific process' areas.

In the proposed application of the methodology a real life case study specific SCM KPI have been considered resultion in the following control tree (figure 1).
On the top level general SCM performances are measured with referenced to the following 3 high level KPI: ATP, DTP and DOS.

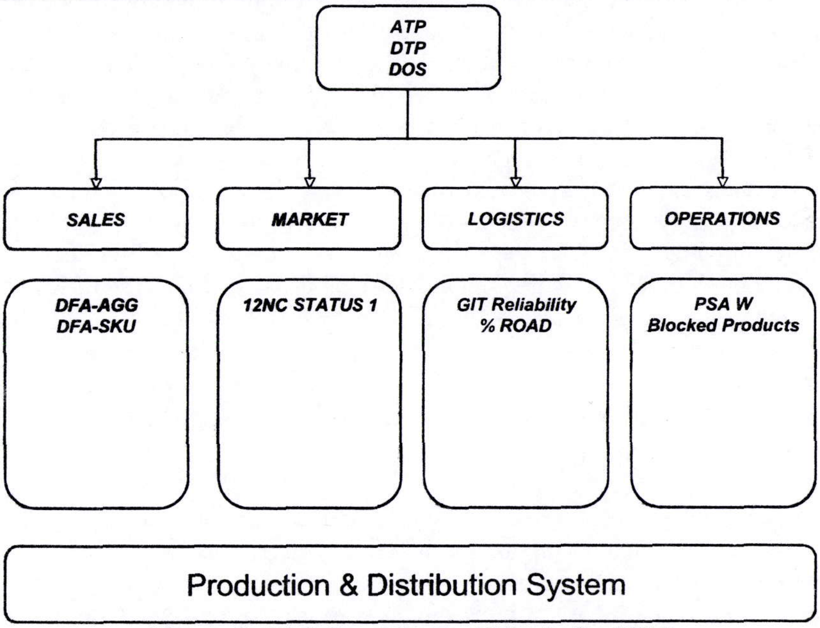


Figure 1: High Level Control Matrix for SCM

ATP measures the level of customer satisfaction regarding his products request on his first request, while DTP measures the level of customer satisfaction on the last delivery date promised, DOS is a measure of the total product inventory available in the reference period. Below this high level view 4 streams specify their KPIs according to common used Balanced Score Cards. On Sales stream 2 KPI measure the Demand Forecast Accuracy (DFA) both at SKU level and aggregation level. Market stream's KPI identify the offering range of products in term of #items available, while Logistic stream is focused on the delivery reliability (GIT Reliability) and transportation choices (% ROAD). Operations stream is driven by two separate KPIs, the first measure the

actual production execution performances versus the planned ones (PSA W) and the second measure the level of production flow failures (Blocked Products). In such schema hierarchical relationship among KPI is clear but the interdependences among KPI are unknown. Managers can now measure their position respect their competitors and can evaluate the differences between actual values an set points but cannot know which stream they have to improve to maximize the effect on the high level KPI.
Perfect diagnosis, unknown therapy is the typical condition of the complex systems management where the lack of a Computer Anticipatory Systems turns every action on the system into a crystal ball guess.
Considering the target to achieve and the analysis done so far, the proposed methodology is able to link primary performance indicators with objective indicators based on decreasing hierarchical level (top-down) by analyze the existing connection between KPIs as well as the relation between one KPI and the others and identify, at the same time, the relevant coefficients using Multivariate Analysis of Variance Tests (Kaplan and Norton 2004). Effective models codified into specific algorithms enables, by imposing one ore more independent KPIs, to know the dependent KPI behavior in the form of an iso-level chart. The neural model, particularly, is used for those relationships, whose regressive performance won't be considered satisfactory (Sarle 1994). This model, even if more powerful by the regressive side, is more difficult to use due to it's lack of an effective statistic test when doing hypotesis on performances achieved. As the system realized is strongly "data driven" by itself, the tool allows, through it's modular structure, the maintenance and laying out of models related to a precise data evolution. In order to track data reliability, a series of statistics signals are used on regressive model, and a series of performance warnings are calculated neural algorithms (Tan 1999).

3 Regression Metamodels and Artificial Neural Networks for Supporting BPR

A simulation meta-model or a response surface in the simplest case is an approximation of the input/output function implied by the underlying simulation model. It's behavior could be represented as a black-box or a function $y = (x_1, x_2, \dots, x_n)$, with n model input parameters. The objective of a meta-model is to accurately reproduce the simulation over wide ranges of interest, and to help in simulation analysis due to its higher transparency and easier handling than the original simulation model. Computer simulation could be used to define interconnections between independent and dependent KPI, in similar way such relationship could be built by applying Design of Experiment (i.e. Central Composite Design in order to fit a 2^{nd} order response surface) to the simulation output. For specific opportunity reasons the use of a complete simulation model some time is not applicable due to its high cost level, in this case raw data coming up from KPI records could be used directly to identify the hidden relationship by applying regressive multivariate analysis in the form of Linear Regression (Steppan et al. 1998).

Linear Regression simply means that the functional relationship between KPI_{dep} and the regressors can ($KPI_{indep,k}$) be expressed by a linear equation or, in other words, a sum of terms including the error (1).

$$KPI_{DEP} = b_0 + \sum_{i=1}^{k} b_i KPI_{INDEP,i} + \sum_{i=1}^{k}\sum_{j=i}^{k} b_{ij} KPI_{INDEP,i} KPI_{INDEP,j} + err \qquad (1)$$

The method used to find the coefficients b_j and b_{ij} of model equation (1) is called least squares estimation. This means that the error term used in the model equations is defined as the difference between observed response variable {KPI_{DEP}} and estimated KPI_{DEP} for a given setting of the $KPI_{IDEP,k}$ at each data point. The total error must somehow be defined by summations over all data points or "cases". Since is assumed a random distribution of the individual errors with a mean of zero, a simple summation would ideally lead to zero. At least it leads to negative and positive differences canceling each other out. This can be avoided by squaring the errors for each data point and sum these squares. The desired optimum regression model then has to give a minimum for this sum of squared errors. Suffice it to say that the starting point of the calculations is the matrix notation (2) for the system of sample equations, where *k* are the total KPI_{INDEP} and *n* is the total number of data set available

$$KPI_{DEP} = \begin{bmatrix} 1 & KPI_{INDEP,1,1} & \cdots & KPI_{INDEP,k,1} \cdot KPI_{INDEP,k,1} \\ 1 & KPI_{INDEP,1,2} & \cdots & \cdots \\ \cdots & \cdots & \cdots & KPI_{INDEP,k,n-1} \cdot KPI_{INDEP,k,n-1} \\ 1 & \cdots & \cdots & KPI_{INDEP,k,n} \cdot KPI_{INDEP,k,n} \end{bmatrix} \times \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_{k-1,k} \\ b_{k,k} \end{bmatrix} + \begin{bmatrix} err \\ err \\ \vdots \\ err \\ err \end{bmatrix} \qquad (2)$$

By using a quick notation is possible to rewrite the (2) in the compact form of (3) and present some interesting calculation on it (bold small letters or words denote vectors, bold capital letters symbolize matrices):

$$\mathbf{y} = \mathbf{Xb} + \mathbf{err} \qquad (3)$$

Finally, the vector of the estimated coefficients **b** is given by (4) where **X'** denotes the matrix transpose and $\mathbf{X}^{-1}$ denote the inverse of matrix **X**:

$$\mathbf{b} = (\mathbf{X'X})^{-1}\,\mathbf{X'y} \qquad (4)$$

Second Order regression meta-models sometimes suffer from lack of performances when used with data affected from high order relationship, in this way a different approach should be used.

For the particular purpose of the application a special feature of the Artificial Neural Networks (ANN) may be used in order to approximate the unknown relationship between dependent KPI and independent ones. ANN differ from conventional techniques in that is not required to specify the nature of the relationships involved.

Starting from simple identification of the inputs and the outputs the MLP's main strength lies in its ability to model problems of different levels of complexity, ranging from a simple parametric model to a highly flexible, nonparametric model. For example, an MLP that is used to fit a nonlinear regression curve, using one input, one linear output, and one hidden layer with a logistic transfer function, can function like a polynomial regression or least squares spline. It has some advantages over the competing methods. Polynomial regression is linear in parameters and thus is fast to fit but suffers from numerical accuracy problems if there are too many wiggles. Smoothing splines are also linear in parameters and do not suffer from numerical accuracy problems but pose the problem of deciding where to locate the knots. MLP with nonlinear transfer function, on the other hand, are genuinely nonlinear in the parameters and thus require longer computational processing time. They are more numerically stable than high-order polynomials and do not require knot location specification like splines. However, they may encounter local minima problems in the optimization process.

4 The Implemented Application

The implemented methodology as been set in a software solution made of a light web application built on top of an Apache-Tomcat servlet container using a mix of JSP Tag library and applet modules. This choice is due to guarantee the interoperability of the implemented application in a LAN where users can actively interact based on a set of predefined roles.

The application can be logically split in several layers according to the responsibility of the single component designed as a building block. The JSP application part is representing the "glue" of the entire application connecting a Relational Database (RDBMS) hosting the raw data coming from the EDI systems in general and the ERP system in particular.

The access is based on a predefined set of profile in which is possible to recognize: Administrators, Users, Viewers; while the first has the complete control of the application the second can operate with full rights except the possibility of grant privileges to users. Viewer Role has a limited capability of accessing elaborated data and can operate drill down analysis on the results.

An applet is designed for supporting data import from the Excel files generated by the ERP providing the minimum instruments to support data manipulation, a backup procedure is fired periodically on the collected data. Two applet module have been implemented in order to model the relationships among the KPI and to perform goodness-of-fit tests on the various models. A set of "traffic lights" is used to present criticalities in the implemented model re trained with the actual data; the first applet is based on mathematical models (multivariate statistical analysis & regression) while a second one is designed around a Neural Network model.

A simple yet powerful reporting module is made of JSP Tag in order to provide a way to compare results and to help decision makers to better understand the relationships among the KPI. Statistical tests is used to monitor model confidence in order to identify

the significance of the implemented model and to provide extra training and deeper analysis.
The architecture is based on a MS Windows server, connected to the company's LAN; on this server is installed and configured the Apache webserver, integrated to the servlet container Tomcat, and the DBMS MySQL; both tools are worldwide recognised and widespread.
The application interface is realized using HTML/JSP pages; it will call up and execute, locally on the client, Java applets realized following the J2SE 1.4.x. specifics.

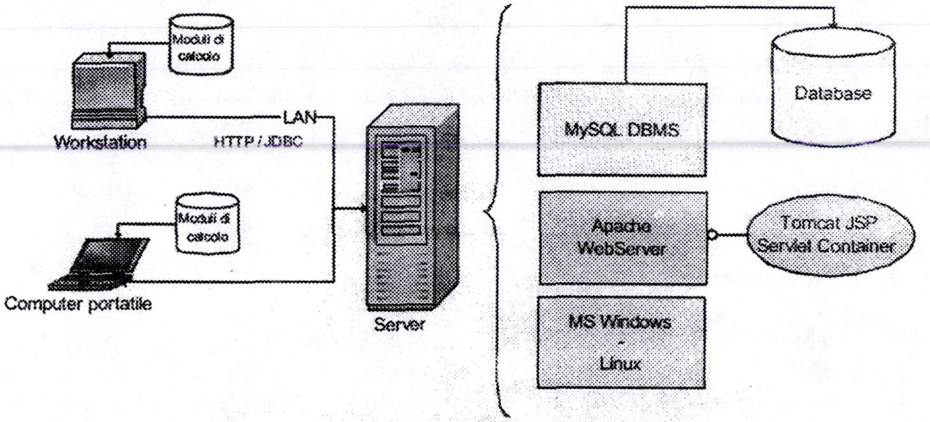


Figure 2: Implemented Tool Architecture

When executed, the features opens a direct connection via JDBC on the MySQL database, in order to transfer and store data. The loading and maintenance main application (applet java), is composed by 4 procedures, which acquire data from company ERP and perform consistence checks.
The calculation core of the proposed tool is implemented as a separate applet performing two separate tasks:

- Training and Testing Artificial Neural Neworks to be used as intelligent regressor;
- Perform Statistic and Multivariate Analysis building 2^{nd} order Regression Metamodel..

The computational module performs also a set of statistical and testing check in order to ensure proper generalization to the implemented models. For the Regressive Metamodels the test was performed by extracting 5% of the data randomly from the dataset, using the remaining part for model building and investigate the difference between output of predicted value and this 5% real life data. For Neural meta-models, no F-tests were possible so the authors decided to extend the testing phase by increase the percentage from 5% to 8%, no further test were possible since the limitation of the training case (#45 data rows).

Data feeding and system management were centralized, leaving computation execution to independent clients. This approach can cut application management costs, maintaining at the same time optimum conditions of "team working".

5 Verification and Validation of the Proposed Implementation

In order to validate the proposed methodology a set of tests was performed, practically data coming from designed relationships were randomly extracted and used to build input datasets for the proposed methodology. Based on such data both regressive module and neural module were able to construct an approximating relationship that was compared with the real response surface. After successfully implement such test a new set of investigation was posed by adding, to a newly randomly extracted data, a white noise signal on top. Again the two modules were able to recognize the underline model linking the input variables with the output. Dataset were collected in the same magnitude and in the same size of the real data. In the following tables the 5 experimental tests are presented and discussed.

- **5.1 First Validation Experiment**

First model was a 2^{nd} order as the basic regression metamodel used, as is possible to see regressive metamodel was closed to perfect fitting. Neural network approximation was also close to the real model itself. Similar results were obtained from noisy data. Max amplitude of the imputs was 10.0 and max amplitude of the noise was 2.0.

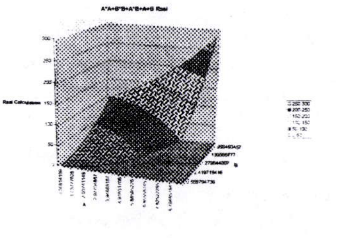


Figure 3: 2^{nd} Order Model

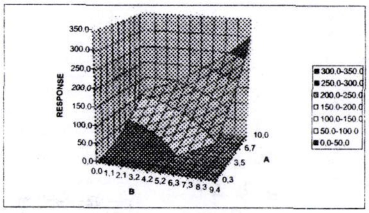


Figure 4: Regressive Metamodel

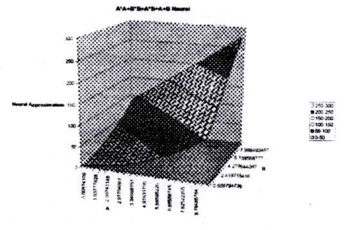
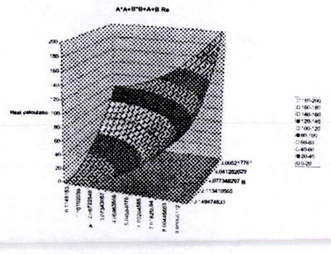


Figure 5: Neural Metamodel

5.2 Second Validation Experiment

Real life model was built as quadratic linear relationship showing higher curvature respect the precedent one. Again both the module were able to correct reconstruct the right behavior also in presence of noise.



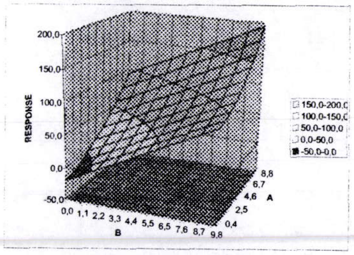


Figure 6: Quadratic Model **Figure 7:** Regression MM

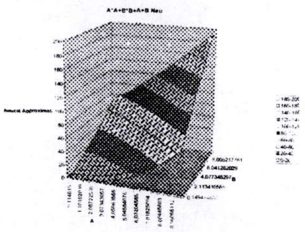
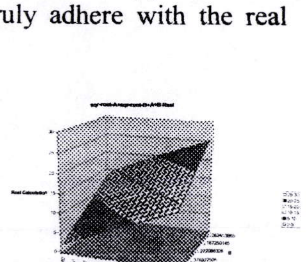


Figure 8: Neural MM

5.3 Third Validation Experiment

This experiment presents some interesting behavior since the real life model was based on a linear composition of the squared roots of the inputs. According to the expected regressive metamodel approximate the surface with a 1st order surface while the neural networks truly adhere with the real data, similar results were obtained with noisy datasets.



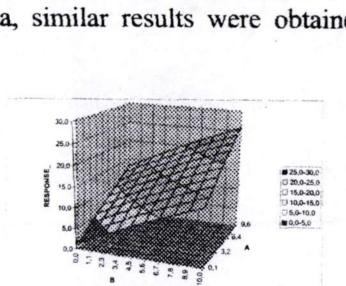


Figure 9: Squared Root Model **Figure 10:** Regression Metamodel

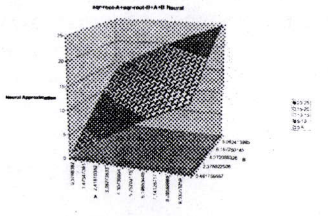


Figure 11: Neural Metamodel

o 5.4 Fourth Validation Experiment

The implemented model was based on 3rd order linear composition of the inputs resulting for the regressive metamodel a bit hard to cope, neural approximation was much closer to the real model. The general approximation theorem demonstrates here, with noisy datasets, its powerfulness adapting very sparse data with the right model.

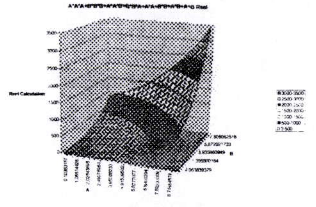


Figure 12: 3rd Order Model

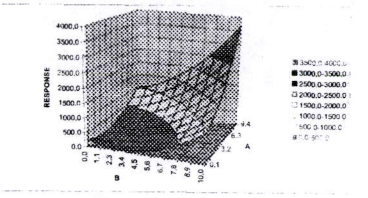


Figure 13: Regression Metamodel

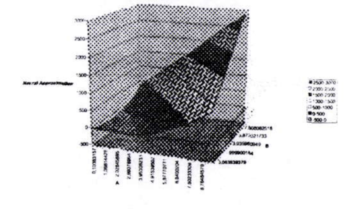


Figure 14: Neural Metamodel

o 5.5 Fifth Validation Experiment

Last experiment was used to test the capability of the model to operate with sparse dataset, model was based on a 2nd order linear composition of the inputs with mixed sign coefficients. Regression metamodel was able only to perform well on the central part of the function while the neural approximation fits the right underlying function.

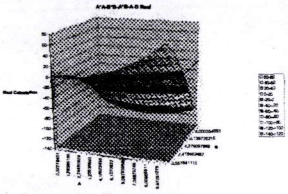


Figure 15: Mixed Model

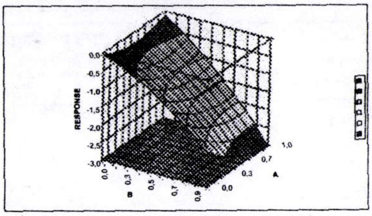


Figure 16: Regression Metamodel

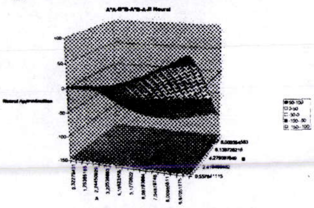


Figure 17: Neural Metamodel

6 Quantitative Results

Proposed methodology has been used on a real data in order to identify relationship among KPI for a manufacturing industry. Production was split across several plants along Europe, KPI were calculated for each plant and for each country aggregation.
The data obtained directly from ERP procedures were integrated in a ad hoc database in order to validate them and to identify inconsistency and reporting error.
Former presentation of the KPI report was known as "control matrix" so the investigation was extended in the previous 45 reporting weeks where data were available. In effect, data were considerably more than 45 weeks but the rapid change of the Supply Chain structure introduce a loose of significance of the data proportional to the elapsed time (Simchi-Levi et al. 2000). First studied relationship was obtained with a regression meta-model and was designed to understand the dependence of the DOS KPI from other low level KPI, the 2nd order regressive model was tested significant by Fisher and obtained a adjusted R^2 value of 0.72. As is possible to see from the figure 18, the behavior of the DOS KPI, and lastly the inventory, can be predicted by looking at the independent KPI through the regressive identified relation. In particular a reduction in the market offer (12NC STATUS 1) can be considered one of the best hypothesis to cut inventory costs. From the other hand, a significant increase of the forecast quality (DFA-AGG) is some time related to an increase of the DOS. This last issue rose from the data analysis in a surprising manner, managers usually expected that an increase in the sale forecasts capability will determine a reduction in the DOS but here is just the opposite. From an analytical point of view this phenomena can be seen as an effect of the raising DOS on the DFA-AGG capability rather that an effect of the DFA-AGG on the DOS. In this way the proposed methodology was clearly able to identify a criticality in the system previously not seen in the "control matrix".

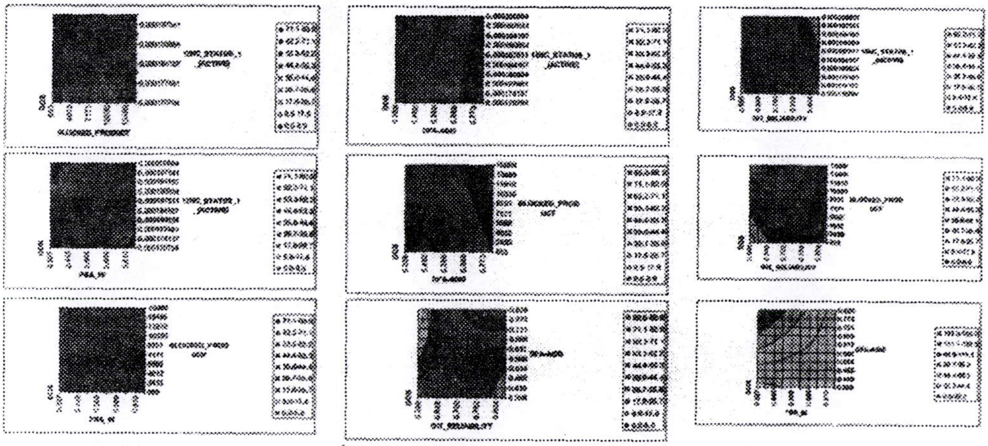


Figure 18: DOS Regressive Meta – Model

Another example taken from the investigated relationship is the ATP behavior as calculated from the neural model, the auto-fitted model was built as back-propagation feed forward full connected neural network built by 4 input neurons, 2 hidden layer neurons with a sigmoidal transfer function and a single neuron with a linear transfer function on the output layer.

Since the lack of statistical tests available for estimating the generalization error, authors used a small subset (8%) of the available data as a testing set. On a total base of 44 weeks of published data 2 weeks were kept separated from the training set and used to verify the generalization skill of the implemented meta-model.

Based on such assumption ATP data from week 200445 was estimate within an error of 1.65% and week 200510 within an error of 5.11%, as is possible to see error in the evaluation of the performances for unknown data were below 10%.

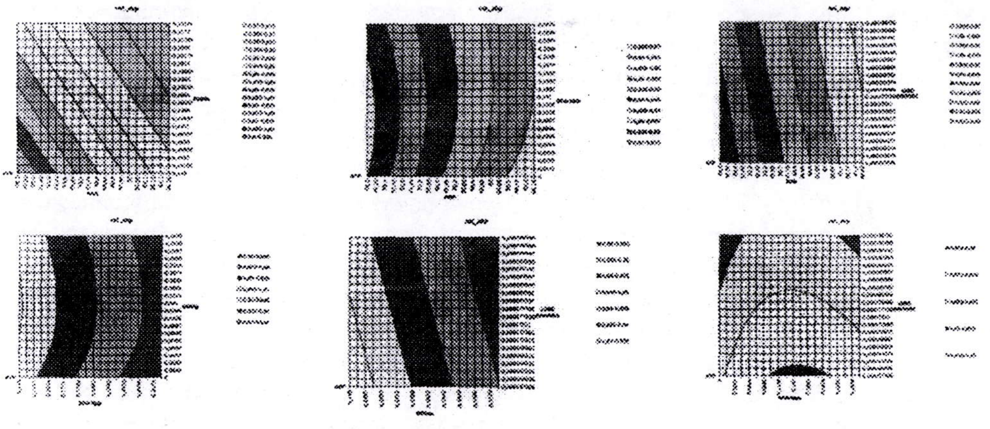


Figure 20: ATP Neural Meta – Model

Neural meta-model was able to clearly identify a priority in the Supply Chain intervention action lists, it was clear, in fact, that the increasing of the demand forecast accuracy was less important than the reduction of the blocked products. In the logistics GIT Reliability was able to play a decisive role only in conjunction of a high inventory level (DOS) and this last aspect was related to an increase in the percentage of good shipped by truck.

Proposed methodology was able, under several points of view, to correctly identify known relationship starting from poorly collected data as well as investigate unknown relationships among KPI later confirmed by ad hoc investigation and analysis.

7 Conclusions

The use of regressive and neural meta-modeling have been demonstrated to be very effective for supporting unknown KPI relationship approximation by identifying underlying behavior among indipendent KPI.

The use of the proposed methodology applied to a real industrial case served as base case to demonstrate the high potential of such meda-modeling technique.

The use of a black box technique such as neural network have been enhanced via the complete mapping of the response surface explicating the relationship among the independent KPi and the dependent one via the slicing technique.

Future improvement will adopt a combined neural-fuzzy logic model able to express the training pattern in term of enumerable relationships.

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