Proceedings of the 10th International Conference on Computational and Mathematical Methods in Science and Engineering, CMMSE 2010
27–30 June 2010.

Integrating Manufacturing Execution and Business Management systems with soft computing

Alba Berzosa[1], Javier Sedano[1], José R. Villar[2], Emilio S. Corchado[3] and Enrique de la Cal[2]

[1] *Department of Artificial Intelligence and Applied Electronics, Castilla y León Technological Institute*

[2] *Department of Computer Science, University of Oviedo*

[3] *Department of Computer Science and Automatica, University of Salamanca*

emails: `alba.berzosa@itcl.es`, `javier.sedano@itcl.es`, `villarjose@uniovi.es`, `escorchado@usal.es`, `delacal@uniovi.es`

Abstract

A Manufacturing Execution System (MES) is a highly complex, large, multi-task application that is used to manage production in companies and factories. It monitors and tracks every aspect of all factory-based manufacturing processes. One of the challenges of a MES is to find ways of integrating it with other information techology (IT) systems; i.e., business process management (BPM) systems, so that compatible information may be shared between both systems. This work studies the integration of a local company MES into a BMP to assist with budgeting, in which a data set is gathered from the MES and a soft computing model helps the expert with cost-level estimation. Various modelling methods are used, such as fuzzy rule based ones, in order to determine whether white box or black box models are suitable for the task. The results of the study show how information may be integrated between manufacturing and business management software.

Key words: Manufacturing Execution Systems, Fuzzy Rule Based Systems, Applied Soft Computing

1 Introduction

Over recent years, the presence of IT applications in industry has increased considerably. IT has been applied to different tasks such as assisting with production or on-line process management and manufacturing, which includes what are nowadays known as Enterprise Requirements Planning (ERP) and Manufacturing Resources Planning (MRP) [11, 19]. Manufacturing Execution Systems (MES) are information systems that are used to manage the way in which manufacturing resources -equipment, employees and inventories- are planned [2, 18].

The objective of a MES depends on whether it is implemented in the context of a production control system or for manufacturing monitoring and supervision. In the former case, the objective is to provide the company with a research laboratory for products and processes, while in the latter, the MES is considered a computer-aided system that assists with decision-making processes related to manufacturing.

However, designing and deploying a user-friendly MES, which has to fulfil the above-mentioned objectives, represents a significant challenge, owing in great part to the complexity of the different production systems, plants and products in use. In this study, several soft-computing techniques are applied, in order to assist with budgeting for a plastic products factory. The main objective of this study, however, is to develop a computer-based assistant to detect faults and loss of competitiveness in the production system. The problem is defined in the following section, while in section 3 the chosen models are described and the results are discussed. Finally, the conclusions and future lines of work are outlined.

2 The case of a plastic products factory

In this study, the system will be applied to a plastic products factory in Spain. It manufactures different products, such as tubes, sheets, bags, polypropylene sheets, garbage bags and others. Its production process is divided into a storage area, an extrusion area, and a printing and clothing area.

The schema of the local plastic bags factory is depicted in Figure 1, where the production system is totally supervised and monitored. Each machine includes its own control system based on Programmable Logic Controllers (PLC). There are up to 75 machines, each producing a range of different products. There are also several Human Machine Interfaces (HMIs) all connected to an ethernet network; a Data Acquisition System (DAQ) which collects various process signals, among which pressures and temperatures. The operators can control and operate the machines that are programmed to manufacture the product. Finally, the monitoring and supervising computers are connected to this network to request information from the PLCs and DAQs. This is known as the Manufacturing Control System (MCS). The company has recently started to store all available data in a data-base management system to broaden the capacity of its staff to plan production processes in the factory, as the amount of available data was rather small.

This is the scenario into which the MES has to be integrated. Production dynamics characteristics should firstly be determined. For this purpose, manufacturing conditions in the current operational stage have to be defined, in the form of data that may be gathered from the MCS network. Once the manufacturing dynamics data have been gathered, then a model of the present production operation may be obtained [4]. In other words, the relevant variables for measurement and storage need to be determined.

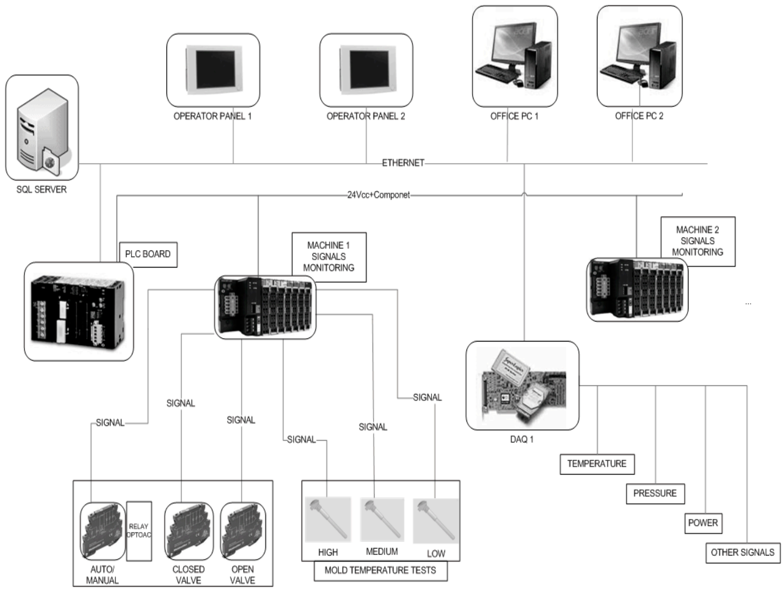

Figure 1: Schematic diagram of the MES installed in the plastic products factory. The PLCs controlling each machine and the DAQs and HMIs connected through the field network constitute the MCS.

2.1 The expected objectives

The final objective of this study is to develop a computer-based assistant to detect faults and loss of competitiveness in the production system. Consequently, the available data from the MCS should be examined in order to design the final data base; rather than storing all the signals, it was only intended to store those signals that were sufficiently informative of the process evolution in the MCS. As this represents a virtually costless task, the factory representative and the research group agreed to present a prototype for a simpler task; the factory would invest in such a system according to the obtained results.

The simpler task involved assisting the staff in budgeting a manufactured product. The working method was as follows: a client requests a product, following which a staff member assigns the job to a certain machine chain and a cost is estimated. This is not automated yet, so before assigning a machine chain, the employee must analyse several plots and reports. So, the challenge was to develop a model to automatically assist the staff in establishing the cost level for a tuple <product, client, machine>. They collected a data set of 1471 examples, including the available historical records of 22 input variables such as client identification, product identification, the machine, the operator, units produced and length of operation, among others. The output of the data set was a variable indicating whether the cost was high, medium or low.

3 Generating the models for computer-aided decision making

Several tasks were carried out once the data set was defined. Firstly, the data set had to be analysed and pre-processed, in order to determine whether there were any dependent variables. It was also analysed to decide whether it was necessary to normalise and partition the data. KEEL software was used [1] in all the experimental and modelling stages.

3.1 Soft Computing tools and algorithms used

KEEL stands for Knowledge Extraction based on Evolutionary Learning. KEEL software is a research and educational tool for modelling data mining problems which implements more than one hundred algorithms, including classification, regression, clustering, etc. Moreover, it includes data pre-processing and post-processing algorithms, statistical tests and reporting facilities. Finally, it has a module for data set analysing and formatting, which was used for the first task in this experiment.

As the model would be used as a IT support tool, it was considered desirable to obtain a white box model, such as Fuzzy Rule Based Systems or Decision Trees. Several different techniques provided the ability to manage the type of available data. Different techniques compared the results and the viability of the models. The statistical methods included Quadratic Discriminant Analysis (QDA) [12], the Multinomial Logistic regression model with a ridge estimator (LOG) [3], the Kernel Classifier (KC with 0.01 and 0.05 sigma values) [12], and the K-nearest neighbour (KNN with 1 and 3 K values) [7]. The fuzzy rule-based methods included the Fuzzy Adaboost rule learning method (ADA) [10], the Fuzzy GA-P algorithm (FGAP) [15] and the Ishibuchi Hybrid Fuzzy GBML (HFG) [9]. Finally, the decision tree and decision tree rule-based methods were the well-known C4.5 [13] and C4.5 rule-based methods. (C45R) [14].

In the QDA algorithm, the cost of classifying an example X with class k is calculated through Eq. 1, where π_k is the unconditional prior class k probability estimated from the weighted sample, and μ_k and Σ_k are the population mean vector and covariance matrix for the k class. Hence, an example X is assigned with the minimum cost class as stated in Eq. 2.

$$d_k(X) = (X - \mu_k)^T \Sigma_k^{-1} (X - \mu_k) + \ln |\Sigma_k| - 2 \ln \pi_k \quad (1)$$

$$d_{\hat{k}}(X) = min_{1 \leq k \leq K} d_k(X) \quad (2)$$

The LOG algorithm is based on the standard logistic regression. The probability that the class k correctly classifies the example $X = \{X_1, ..., X_p\}$ is calculated following Eq. 3,where the parameter $\beta = \{\beta_1, \ldots, \beta_p\}$ is estimated, i.e., with the maximum likelihood estimation obtained by maximising Eq. 4. It is classified in the class with the higher probability, as in the example.

$$p(k|X) = \frac{\exp(\sum_{j=1}^{p} \beta_j X_j)}{1 + \exp(\sum_{j=1}^{K} \beta_j X_j)} \tag{3}$$

$$l(\beta) = \sum_{k} [k \log p(k|X) + \neg k \log\{1 - p(k|X)\}] \tag{4}$$

The Kernel method is a classifier that uses the Bayes rule using a "non-parametric estimation of the density functions through a Gaussian kernel function" as stated in [8]. In the KEEL software, covariance matrix tuning is carried out by means of an ad-hoc method. On the other hand, the K-nearest neighbour method classifies the example X with the majority class in the K examples of the data set with a shorter distance to X. Note that the use of the KNN implies that a metric is defined in the space to measure the distance between examples.

The Fuzzy Adaboost method is based on boosting N weak fuzzy classifiers (that is, N unreliable fuzzy classifiers are weighted according to their reliability) so that the whole outperforms each of the individual classifiers. Moreover, each example in the training data set is also weighted and tuned in relation to the evolution of the whole classifier.

The GAP is a Fuzzy Rule-Based Classifier learned using the Genetic Programming principles but using the Simulated Annealing algorithm to mutate and to evolve both the structure of the classifier and the parameters. At each iteration, the whole Fuzzy Rule set will evolve.

The Ishibushi Hybrid Fuzzy Genetic Based Machine Learning method represents a Pittsburgh style genetic learning process which is hybridised with the Michigan style evolution schema: after generating the $(N_{pop} - 1)$ new Fuzzy Rule sets, a Michigan style evolutionary scheme is applied to each of the rules for all the individuals. Recall that each individual is a complete Fuzzy Rule set.

The Ishibushi Hybrid Fuzzy Genetic Based Machine Learning method represents a Pittsburgh-style genetic learning process which is hybridised with the Michigan style evolution schema: after generating the $(N_{pop} - 1)$ new Fuzzy Rule sets, a Michigan style evolutionary scheme is applied to each of the rules for all the individuals. Recall that each individual is a complete Fuzzy Rule set.

Finally, the C4.5 algorithm is a well-known decision-tree method based on information entropy and information gain. A node in the decision tree is supposed to discriminate between examples of a certain class based on a feature value. At each node, the feature that produces the higher normalised information gain is then chosen. In the case of C4.5R, the decision tree is presented as rules, where each node in the path from the root to a leaf is considered an antecedent of the rule. These rules are then filtered to eliminate redundant or equivalent rules.

3.2 The experimentation and results

After analysing the original data set it was found that most of the examples corresponded to the tuning of the plant, which could therefore be discarded. In addition,

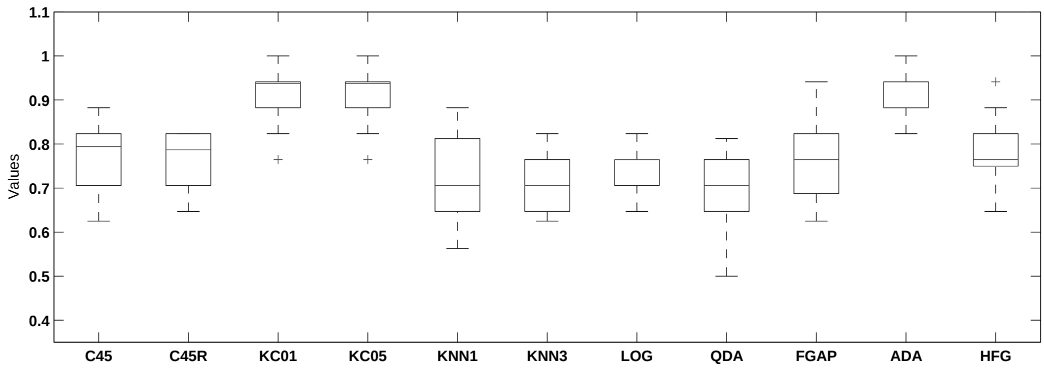

Figure 2: Boxplot of the classifiers results for the {Low, ¬ Low} experiments.

there was also a large quantity of totally erroneous samples, which were also discarded. Finally, the data set included 168 examples corresponding to 9 machines.

Several relationships were found, such as the one between the number of faulty units and the weight of discarded material. In the end, the data set included information on the product, the machine, client identification and the number of units to produce. The output variable was the class of the cost level, which could be Low, Medium or High.

The second task consisted of the modelling step, in which the modelling algorithm had to be chosen and the statistical tests carried out. The 9 methods described in the previous Sub-Section were used to obtain a classifier.

Two series of experiments were designed. The first experiment generated two classifiers. On the one hand, one discriminated between Low and ¬Low classes, on the other hand, the second classifier, which was run when a ¬Low example was found, discriminated between Medium and High classes. As a result of the first experiment, two different data sets were generated: one contained the examples characterised with class Low or ¬Low, and another one contained only the ¬Low examples characterised by the corresponding class Medium or High. The second experiment made use of all 150 examples in the data set to generate a 3-class classifier. Finally, in both cases, since the number of examples was so small, the 10-fold cross-validation schema was selected and performed in a KEEL environment.

The results from the first experiment are presented in Table 1, Figure 2 and Figure 3. As it can be seen, the kernel methods and Fuzzy AdaBoost, although not interpretable, were found to be the best models. On the other hand, in view of the results and considering the standard deviation of the FGAP and the HFG algorithms, it could be said that these two methods may improve their performance by means of a better definition of their parameters (population and sub-population sizes, number of islands, etc.) and a larger number of generations. It is worth remarking on the ease with which the problem of discriminating between Medium and High may be solved, provided no Low class classifications are involved.

	{Low, ¬Low}			{Medium, High}		
	GCE	SGCE	CC	GCE	SGCE	CC
C4.5	0.2276	0.0748	0.7724	0.1018	0.1220	0.8982
C4.5R	0.2324	0.0620	0.7676	0.1018	0.1230	0.8982
KC01	0.0949	0.0651	0.9051	0.0949	0.0651	0.9051
KC05	0.1143	0.0879	0.8857	0.1018	0.0758	0.8982
KNN1	0.2860	0.1002	0.7140	0.2464	0.1746	0.7536
KNN3	0.2857	0.0695	0.7143	0.3107	0.2295	0.6893
LOG	0.2504	0.0530	0.7496	0.0750	0.0829	0.9250
QDA	0.3040	0.0858	0.6960	0.0911	0.0820	0.9089
FGAP	0.2335	0.0973	0.7665	0.0893	0.0810	0.9107
ADA	0.0945	0.0598	0.9055	0.0500	0.0829	0.9500
HFG	0.2206	0.0800	0.7794	0.0750	0.0829	0.9250

Table 1: Mean results of the classifiers for the {Low, ¬Low} {Medium, High} experiments. GCE, SGCE and CC stand for Global Classification Error, standard deviation of the GCE and the percentage of correctly classified examples.

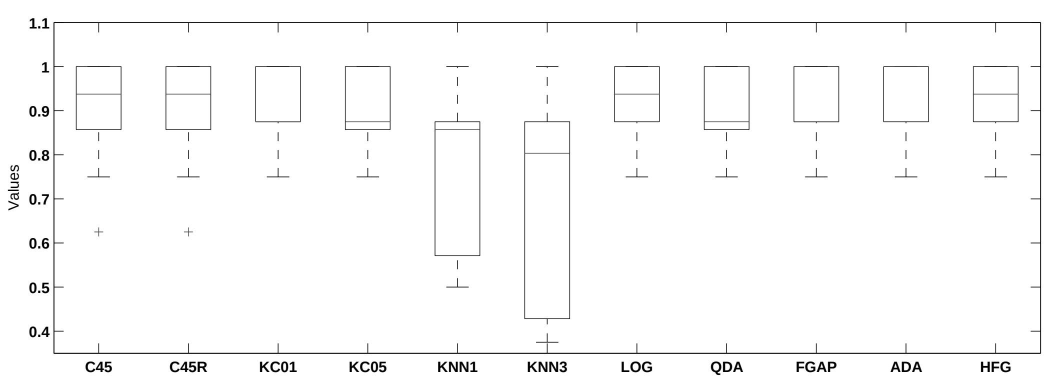

Figure 3: Boxplot of the classifiers results for the {Medium, High} experiments.

	GCE	SGCE	CC
C4.5	0.2974	0.0441	0.7026
C4.5R	0.3103	0.0967	0.6897
KC01	0.1077	0.0648	0.8922
KC05	0.1077	0.0531	0.8923
KNN1	0.3445	0.0796	0.6555
KNN3	0.3684	0.1120	0.6316
LOG	0.2434	0.0840	0.7566
QDA	0.3338	0.0857	0.6662
FGAP	0.4118	0.0975	0.0975
ADA	0.1783	0.0785	0.8217
HFG	0.3857	0.0799	0.6143

Table 2: Mean results for the {Low, Medium, High} classifier experiment. GCE, SGCE and CC stand for Global Classification Error, standard deviation of the GCE and the percentage of correctly classified examples.

The results of the first experiment did not prepare us for the results of the second experiment. A much poorer performance of the methods was observed, despite method C4.5, which is unable to manage a three-class problem. Only the kernel methods keep track of the problem. The reason for these results is related to the kind of features involved in the modelling; several of them being integer valued features with an unknown upper limit. As an example, the number of units to be produced is quite dependent on the machine, as each machine has a maximum production rate. But this data was not given for the experimentation, so it was not possible to normalize those variables which, in turn, make the classifier worse.

A main conclusion may be drawn from this experimentation: the data set should be more informative and representative of the problem, if better models are to be generated. The company should rely on an in-depth analysis of available data and measurements, but it is also necessary for it to study the relationships between the variables under study, i.e. using Cooperative Maximum Likelihood Hebbian Learning (CMLHL) [6] as shown in [17, 16]. The results illustrate the way in which the research team may help the company to design their MES.

4 Conclusions and future work

A MES development to improve its capacity and link up with other business management applications has been tested in this work. A computer assisted-budgeting problem has been solved through the application of different computing techniques. Nevertheless, it was shown that the data gathered from a MCS must be carefully chosen and the amount of data should be representative and informative of the real process. A clear list of the objectives to be accomplished by the MES should be prepared prior to the collection and analysis of relevant data.

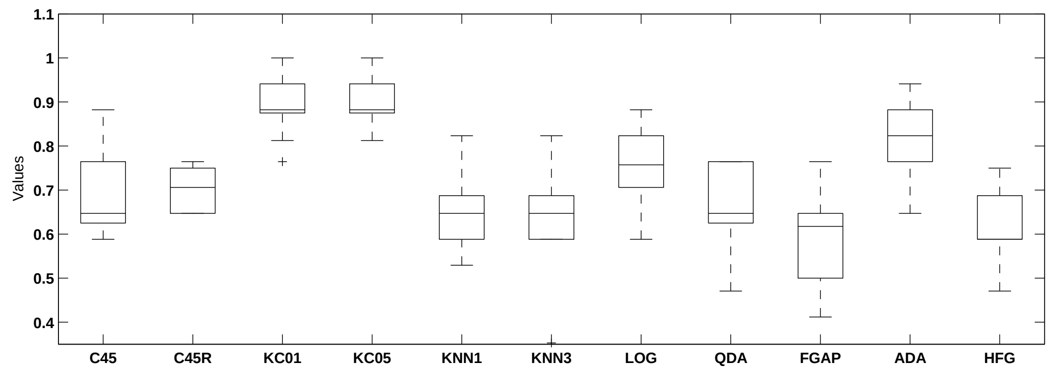

Figure 4: Boxplot of the classifiers results for the {Low,Medium, High} experiments.

Future work will include modelling the relationships between operators, machines, products and the overall performance of the plant, so that resource planning may be introduced. More knowledge and data should be gathered from the plant, such as machine operating limits. Finally, a complete analysis of the data through the use of well-known techniques (such as CMLHL) would contribute to reliable MES design and engineering.

Acknowledgements

This research work has been funded by the Spanish Ministry of Science and Innovation, under grant TIN2008-06681-C06-04 and the Spanish Ministry of Science and Innovation through project PID 560300-2009-11

References

[1] J. Alcalá-Fdez, L. Sánchez, S. García, M.J. del Jesus, S. Ventura, J.M. Garrell, J. Otero, C. Romero, J. Bacardit, V.M. Rivas, J.C. Fernández, F. Herrera, *KEEL: A Software Tool to Assess Evolutionary Algorithms to Data Mining Problems*, Soft Computing **13:3** (2009) 307–318.

[2] Apriso Corporation, *Manufacturing Execution Systems Strategy Update: Trends and Tips for 2010*, http://www.bitpipe.com/detail/RES/1268690867_382.html.

[3] S. le Cessie and J.C. van Houwelingen, *Ridge Estimators in Logistic Regression*, Applied Statistics **41:1** (1992) 191-201.

[4] R. S. Chen and Y. S. Tsai and C. C. Chang, *Design and implementation of an intelligent manufacturing execution system for semiconductor manufacturing*

industry, Proceedings of the 2006 IEEE International Symposium on Industrial Electronics (2006) 2948–2953.

[5] B. K. Choi and B. H. Kim, *MES (manufacturing execution system) architecture for FMS compatible to ERP (enterprise planning system)*, International Journal of Computer Integrated Manufacturing **15:3** (2002) 274–284.

[6] E. Corchado and C.Fyfe, *Connectionist techniques for the identification and suppression of interfering underlying factors*, International Journal of Pattern Recognition and Artificial Intelligence **17:8** (2003) 1447-1466.

[7] T.M. Cover and P.E. Hart, *Nearest Neighbor Pattern Classification*, IEEE Transactions on Information Theory **13** (1967) 21-27.

[8] Salvador García and Francisco Herrera, *An Extension on "Statistical Comparisons of Classifiers over Multiple Data Sets" for all Pairwise Comparisons*, Journal of Machine Learning Research **9** (2008) 2677-2694.

[9] H. Ishibuchi and T. Yamamoto and T. Nakashima, *Hybridization of Fuzzy GBML Approaches for Pattern Classification Problems*, IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics **35:2** (2005) 359-365.

[10] M.J. del Jesus and F. Hoffmann and L. Junco and L. Sánchez, *Induction of Fuzzy-Rule-Based Classifiers With Evolutionary Boosting Algorithms*, IEEE Transactions on Fuzzy Systems **12:3** (2004) 296-308.

[11] M. McClellan, *Introduction to Manufactoring Execution Systems*, Proceedings of MES Conference and Exposition, USA 2001.

[12] G.J. McLachlan, *Discriminant Analysis and Statistical Pattern Recognition*, John Wiley and Sons, 2004.

[13] J.R. Quinlan, *C4.5: Programs for Machine Learning*, Morgan Kauffman, 1993.

[14] J.R. Quinlan, *MDL and Categorical Theories (Continued)*. Machine Learning: Proceedings of the Twelfth International Conference. Lake Tahoe California (United States of America, 1995) 464-470.

[15] L. Sánchez and I. Couso and J.A. Corrales, *Combining GP Operators With SA Search To Evolve Fuzzy Rule Based Classifiers*, Information Sciences **136:1-4** (2001) 175-192.

[16] J. Sedano and J. R. Villar and E. S. Corchado and L. Curiel and P. M. Bravo, *Modelling a Pneumatic Drill Process by a two-steps AI Model*, International Journal of Computer Mathematics **86:10-11** (2009) 1769-1777.

[17] J. Sedano and L. Curiel and E. Corchado and E. de la Cal and J. R. Villar,*A soft computing method for detecting lifetime building thermal insulation failures*,Integrated Computer-Aided Engineering **10:2** (2010) 103-115.

[18] B. S. de Ugarte and A. Artiba and R. Pellerin, *Manufacturing execution system - a literature review*, Production planning and control **20:6** (2009) 525–539.

[19] L. Van Dyk, *Manufacturing execution systems, MEng dissertation*, University of Pretoria, Pretoria, http://upetd.up.ac.za/thesis/available/etd-11092006-125332/, (1999).