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Modeling and Optimization of High-technology Manufacturing Productivity Based on Support Vector Machines and Chaos

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Abstract: In recent years, computing High-technology Manufacturing (HTM) productivity level and growth rate have gained a renewed interest in both growth economists and trade economists. Measuring productivity performance has become an area of concern for companies and policy makers. A novel way about nonlinear regression modeling of High-technology Manufacturing (HTM) productivity with the Support Vector Machines (SVM) is presented in this study Optimization of Labor Productivity (LP) is also presented in this study which is based on chaos and uses the SVM regression model as the objective function.

Key words: High-technology Manufacturing (HTM), Labor Productivity (LP), Support Vector Machines (SVM), chaos

INTRODUCTION

HTM productivity is perceived as being at the core of observed divergences among countries in the areas of long-run growth and increase in standard of living. In the empirical literature on HTM productivity determinants, an alternative approach to physical output is to use value-added (Nehru and Dhareshwar, 1994; Zinnes *et al*., 2001). Openness to trade, human capital and technology innovation activity are found to have very strong and robust impacts on HTM labor productivity, along with other factors as financial development, infrastructure development and quality (Ahmadou, 2002; Jones, 2001). For the evaluation of productivity performance, traditional regression models are being widely used as plural linear model, Cobb-Douglas functional model and gray models (Clerides *et al*,. 1998; Pilat, 1995). These models can illustrate the regression relationship between the explaining variables and the explained variables, but they would not help in finding the optimal results.

The SVM is grounded in the framework of statistical learning theory, which has been developed by Vapnik, (1995, 1999). It is a new and promising technique for pattern classification and regression. The theory of SVM is based on the idea of Structural Risk Minimization (SRM). Compared with the Artificial Neural Networks (ANN), it provides high generalization ability and overcomes the overfitting problem. Chaos optimization algorithm is a novel stochastic search algorithm (Wang *et al*., 2002, Liu and Hou, 2002). It differs from any of the existing evolutionary algorithms. Chaos is a universal phenomenon and a self-moving form of non-linear dynamics system that occurs in many systems in all areas of science and engineering. The stochastic property shown by chaos is the intrinsic one of the systems. The movement of chaos possesses ergodic property and within a certain scope, can experience any state according to its own regularity.

This study focuses on the reality of the HTM in China and collects data in a period as long as 15 years. A nonlinear SVM regression model of the HTM LP is also presented and it provides the objective function for optimization algorithm online. The present study also describes how chaos is successfully applied for the optimization of the structure parameter of the HTM LP, in order to improve the output performance. Then, results of the orthogonal optimum and the chaotic search algorithm optimum are found. According to the RAND Corporation report of Overholt (2005) for China, the optimal results are very consistent with China's development of HTM. Therefore, it has significance to believe that this approach can not be ignored.

HTM PRODUCTIVITY

HTMLP: An alternative approach to physical output is to use value-added. Value-added measures how much additional value is created in the market-place. Value

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added per unit of labor is a commonly used measure of productivity at the aggregate level (Van Ark and Pilat, 1993). Labor productivity is given by the following ratio:

$$LP = VA/L \qquad (1)$$

Where, LP refers to labor productivity for HTM, VA refers to value added for HTM, L is the quantity of HTM labor.

Factors affecting HTM LP growth: In the empirical literature on HTM productivity determinants, openness to trade, human capital and technology innovation activity are found to have very strong and robust impacts on HTM labor productivity, along with other factors such as financial development and infrastructure development and quality.

With the development of the globalization of the world economy, the export volume of HTM in every country is increasing year by year. The channels through which openness to trade affects HTM productivity are numerous and are indeed quite well documented. Some studies based on endogenous growth theory focus on the importance of knowledge spillovers due to trade and find that they positively affect income convergence and economic growth during transition period and in the long run. The availability of technology associated with imported inputs increases the return to innovation and hence the steady state growth rates. Moreover, export growth can mitigate foreign exchange constraints, which many developing countries are confronted with in an environment of declining foreign aid. Exporting firms are likely to benefit from lowered costs due to increasing returns to scale when operating at the international level. Furthermore, the exposure to foreign competition can lead domestic firms to adopt more efficient technologies. According to the situation of China, in this study it uses the variable of export per capita and the export of new products to illustrate the degree of trade openness in HTM and test their influences on HTM labor productivity through the model.

Human capital: The importance of human capital on output and productivity growth has been the main focus of HTM productivity growth accounting regressions. In addition, the new growth theories indeed set the ground for knowledge accumulation and education as giving an impetus to growth. However, recent literature in this area finds little evidence of education affecting growth. To explain these somewhat iconoclast findings, Pritchett (1996) emphasizes three possible factors: schooling not creating human capital, the marginal returns to education falling rapidly with a stagnant demand for educated labor and the existence of an institutional environment deflecting accumulated human capital from productive activities to growth-reducing ones. Using panel data on 12 Asian countries for the 1970-1994 period, Lopez *et al.* (1998) find that the more egalitarian the distribution of education, the greater its impact on growth. Cohen and Soto (2001) find that human capital exerts a great influence on HTM productivity growth in a study using 'new data set' on OECD members and non-members. According to the situation of China, in this study it uses the average number of employees, the number of people in engineering and technological activities and the full-time equivalent of R and D activities etc. to describe the human capital in HTM, test their influences on HTM productivity and then optimize them.

Technology innovation activity: Since HTM technology innovation decides the long-term increase of economy and the potential in productivity increase, it was considered by the world Economy Forum to be as important as banking factors and the internationalization. Disaggregated data will be used to build technology innovation activity variables at HTM. Patent is a very important index that reflects the technology innovation activity of HTM and many countries regard the output of patents as measurement of the technology innovation activity of HTM. In this study patent is taken into consideration. According to the situation of China, in this investigation, the following variables are used to explain the technology innovation activity of HTM, that is, the internal expense of R&D funds, the accumulation of funds for scientific and technological activities, the three expenses (the total amount of the expense of technological reformation funds, the expense of technological introduction and the expense of digestion and absorption), the number of patent applied, the number of patents owned, profit and sales income.

SVM AND SVM REGRESSION

Support Vector Machines (SVM) and Kernel Methods (KM) have become, in the last few years, one of the most popular approaches to learning from examples with many potential applications in science and engineering. As a learning method, it is often used to train and design Radial Basis Function (RBF) networks. Given a set of examples $\{(x_i, y_i), x \in R^n, y \in R, i = 1, ..., N\}$ the SVM learning method in its basic form creates an approximation function $f(x) = b + \sum_{j=1}^{m} y_j.\alpha_j.K(x_j, x)$ with $y \approx f(x)$ for regression. For that purpose, a subset of support vectors $\{x_j, j = 1, ..., m\} \subset \{x_i, i = 1, ..., N\}$ is determined, the kernel function K is chosen and the parameters b, α_j, j = 1, …, m are estimated.

KM is method that use kernels of the form $K(x_1, x_2) = \phi(x_1).\phi(x_2)$, is an inner product and ϕ is in general a nonlinear mapping from input space X onto feature space Z. The symmetry of the inner product determines the symmetric of the kernel. The necessary and sufficient conditions for a symmetric function to be a kernel is to be positive definite, thus statistically seen, kernels are covariance. In practice, the kernel function K is directly defined. ϕ and the feature space Z are implicitly derived from its definition. Kernel substitution of the inner product can be applied for generating SVM for classification based on margin maximization.

In the ϵ-SVM regression (Hao and Jung-Hsien, 2003; Kwok and Tin-Yau, 1998), the goal is to find a function f(x) that has at most ϵ deviation from the actually obtained targets y_i for all the training data and at the same time, is as flat as possible. The ϵ-insensitive loss function reads as follows:

$$e(f(x)-y)=\begin{cases} 0, |f(x)-y|\le\varepsilon \\ |f(x)-y|-\varepsilon, \text{ otherwise}\end{cases} \quad (2)$$

To make the SVM regression nonlinear, this could be achieved by simply mapping the training patterns by ϕ: $R^n \rightarrow F$ into some high dimensional feature space F. Suppose f(x) takes the following form:

$$f(x) = w.x + b \quad (3)$$

A best fitting function:

$$f(x) = (w'.\phi(x) + b) \quad (4)$$

is estimated in feature space F, where "." denotes the dot product in the feature space F. Flatness in the case of (4) means that one can seek small w'. Formally this problem can be written as a convex optimization problem by requiring the follows:

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ &\text{subject to} \quad y_i - (w'\phi(x_i)+b) \le \varepsilon - \xi_i \\ &\qquad (w'\phi(x_i)+b) - y_i \le \varepsilon - \xi_i^* \\ &\qquad \xi_i, \xi_i^* \ge 0, i = 1,\ldots l \\ &\qquad C > 0 \end{aligned} \quad (5)$$

Where, ξ_i and ξ_i^* are slack variables, the constant C determines the trade-off between the flatness of the f(x) and the amount up to which deviations large than ϵ are tolerated.

By constructing the Lagrangian function, the dual problem can be given as follows:

$$\begin{aligned} &\text{maximize} \quad -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(x_i \cdot x_j) \\ &\qquad + \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) \\ &\text{subject to} \quad \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ &\qquad 0 \le \alpha_i, \alpha_i^* \le C \end{aligned} \quad (6)$$

Where, α_i and α_i^* are the Lagrange multiplier coefficients for the ith training example of regression and obtained by solving the dual optimization problem in support vector learning (Vapnik, 1999). The non-negative coefficients α and α^* are bounded by a user-specified constant C. The training example for which $\alpha \neq \alpha^*$ is corresponded to the support vectors.

At the optimal solution from (6), the regression function takes the following form:

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_i \cdot x_j) + b \quad (7)$$

Where, K (., .) is a kernel function, where b is found by the Karush-Kuhn-Tucker conditions at optimality.

According to Vapnik (1999), any symmetric and positive semi-definite function, which satisfies Mercer's conditions, can be used as a kernel function in the SVM context. Mercer's conditions can be written as follows:

$$\begin{aligned} &\iint K(x,z)g(x)g(z)dxdz > 0, \int g^2(x)dx < \infty \\ &\text{where} \quad K(x,z) = \sum_{i=1}^{\infty}\alpha_i\psi(x)\psi(z) \\ &\qquad \alpha_i \ge 0 \end{aligned} \quad (8)$$

In this study the Gaussian kernel function used in the SVM regression method is as follows:

$$K(x,z) = \exp\left(\frac{-\|x-z\|^2}{\sigma^2}\right) \quad (9)$$

The SVM regression can be expressed by the following chat (Fig. 1). Where, x_i (1 = i, ..., n) is the input vectors, $K(x_j, s)$ (j = 1, ..., s) is the kernel function corresponding to support vectors (amount to s entries). y is the output.

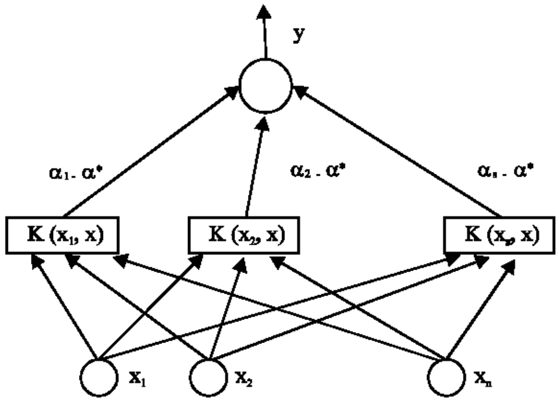

Fig. 1: The SVM regression chat

APPLICATION TO HTM MODELING

To study the determinants of productivity growth in china, this study should estimate the following equations:

$$LP = f(x_i),\ i = 1, 2, ..., 12 \quad (10)$$

A number of crucial parameters, which mainly determine the LP, are considered. Where:

LP is labor HTM productivity and unit of it is 100 million Chinese Yuan per person;

x_1 is the variable of export per capita and unit of it is 100 million Chinese Yuan per capita;

x_2 is the export of new products and unit of it is ten thousand Chinese Yuan;

x_3 is the average number of employees and unit of it is one person;

x_4 is the number of people in engineering and technological activities and unit of it is one person;

x_5 is the full-time equivalent of R&D activities and unit of it is one person per year;

x_6 is the internal expense of R and D funds and unit of it is ten thousand Chinese Yuan;

x_7 is the accumulation of funds for scientific and technological activities and unit of it is ten thousand Chinese Yuan;

x_8 is the three expenses and unit of it is ten thousand Chinese Yuan;

x_9 is the number of patent applied and unit of it is item;

x_{10} is the number of patents owned and unit of it is item;

x_{11} is the profit and unit of it is 100 million Chinese Yuan;

x_{12} is the sales income and unit of it is 100 million Chinese Yuan.

x_1 and x_2 indicate the influence of openness to trade on LP; x_3, x_4 and x_5 indicate the influence of human capital on LP; x_6, x_7, x_8, x_9, x_{10}, x_{11} and x_{12} indicate the influence of technology innovation activity on LP.

OPTIMIZATION WITH CHAOS

The optimum problem is a high nonlinear, multi-parameter, multi-extreme and non-differentiable one. Some optimization algorithm can be used here, such as Genetic Algorithm (GA), chaos and so on. But the GA optimum results are a solution set and a set of appropriate parameters must be selected artificially. In order to reduce the limitation of the artificially selection of GA and get the objective global solution, chaotic search algorithm to optimize is presented. The flow chat of the chaos operation is shown in (Fig. 2).

Chaos variables are usually generated by the well known Logistic map (Liu and Hou, 2002) The Logistic map is a one-dimensional quadratic map defined by the follows:

$$f(x) = ux(1 - x) \quad (11)$$

Where, u is a control parameter and $x \in [0, 1]$.

The logistic equation is parabolic like the quadratic mapping with $f(0) = f(1) = 0$.Varying the parameter changes the height of the parabola but leaves the width unchanged. The behavior of the system is determined by following the orbit of the initial seed value. The behavior of the logistic equation is more complex than that of the simple harmonic oscillator. The type of orbit depends on the parameter of the growth rate, but in a manner that does not lend itself to “less than”, “greater than”, “equal to” statements. The best way to visualize the behavior of the orbits as a function of the growth rate is with a bifurcation diagram. Pick a convenient seed value, generate a large number of iterations, discard the first few and plot the rest as a function of the growth factor. For parameter values where the orbit is fixed, the bifurcation diagram will reduce to a single line; for periodic values, a series of lines; and for chaotic values, a gray wash of dots.

Generally speaking, the mathematical formulation of the optimization problem can be formulated as follows:

$$\text{minimize} \quad f(x)$$
$$\text{subject to } x_{min} < x < x_{max} \quad (12)$$

Where, f(x) is the objective function; x_i is the pending optimal variable; x_{min} and x_{max} are the boundary. Chaos variable is mapped into the variance ranges of optimization variables by the following equation:

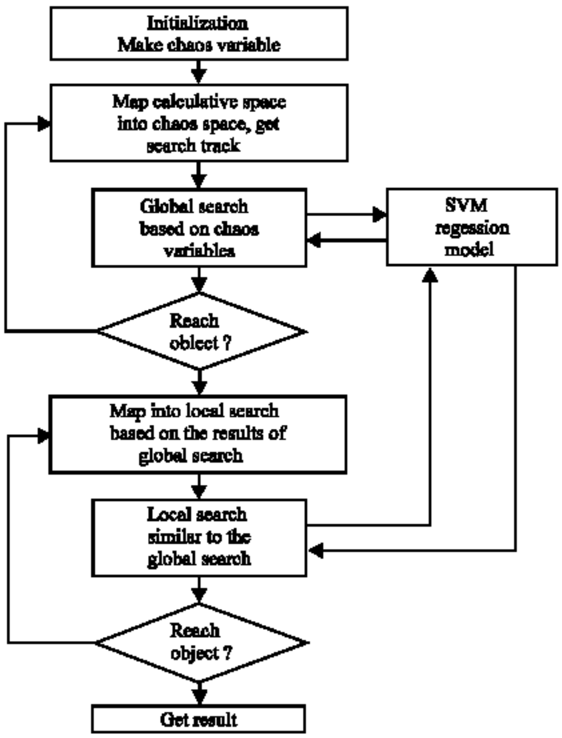

Fig. 2: Flow chat of optimization with chaos

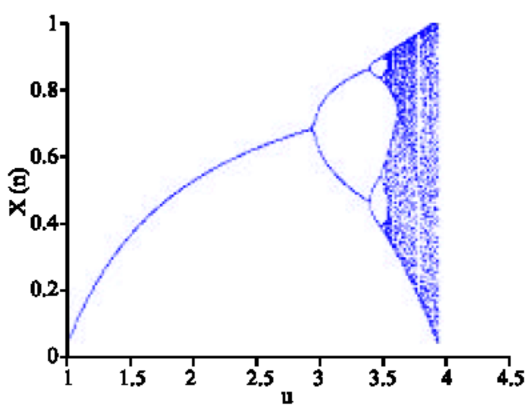

Fig. 3: The bifurcation diagram of the Logistic equation

$$z(n) = x_{min} + (x_{max} - x_{min}).x(n) \quad (13)$$

The solution of the equation exhibits a rich variety of behavior. Figure 3 is the bifurcation diagram of the Logistic equation. For u>3.75, system (13) generates chaotic evolutions.

The objective function offered on-line by SVM model during the optimal calculation. By the global search and the local search, the optimum parameter collection is gained.

Table 1: Compared results

parameters	Bad samples	Good samples	Optimal results
x_1	0.000106	0.000543	0.000557
x_2	2945052	25649389	27658653
x_3	70774100	48838300	47695601
x_4	2087839	2378297	2379238
x_5	227359	430179	430026.8
x_6	781424	6784183	6875265
x_7	3878636	14816338	14823567
x_8	13787756	21430408	15658793
x_9	3343	29810	29821
x_{10}	2189	14654	14623
x_{11}	1225	6165	6063.57
x_{12}	46207	124035	124165.3
LP	0.000173	0.000697	0.000712

RESULTS AND DISCUSSION

There is a hybrid non-linear relation between LP and x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, which are almost indescribable using traditional models like linear regression model, Cobb-Douglas functional model and gray models. In this study, SVM is used to modeling and chaos is used to optimize. The optimized LP and reasonable x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12} are found, which are shown in Table 1.

Before running the algorithm, several issues are needed to consider, in the SVM regression application some parameters are needed to determine. These parameters are needed to determine. These parmeters are ϵ, C, and the Gaussian kernal with σ. They are determined empirically as 0.1, 1000.0 and 4.7, respectively. The originality samples come from statistical yearbooks of china and statistical yearbooks on science and technology of china since 1990 to 2004.

According to the RAND Corporation report of Overholt (2005) for China, the optimal results are very consistent with Chinese development of HTM, especially the HTM technology innovation activity (x_6, x_7, x_8, x_9, x_{10}, x_{11} and x_{12}) and the optimal results are better than good samples. It shows that the proposed method is effective and feasible.

In the future, how to find the optimized LP with dynamic change of parameters ϵ, C and the Gaussian kernel width σ is further work. On the other side, in the SVM and chaos modeling, all available indicators can be used as the inputs, but irrelevant or correlated features could deteriorate the generalization performance of model due to the "curse of dimensionality" problem. Thus, it is very necessary to find out the main factors of affecting HTM LP growth by feature selection.

CONCLUSIONS

This study focuses on the reality of the HTM in China and collects data in a period as long as 15 years. In this study, the support vector machine for nonlinear regression is presented. It is shown that the optimization approach based on chaos is effective and feasible. Results of the optimization algorithm are found for China.

Also, the SVM and chaos are integrated together to analysis the HTM productivity, which provides a novel way for the optimum design of the other engineering.

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