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Application of neuro-fuzzy networks to forecast innovation performance – The example of Taiwanese manufacturing industry

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ABSTRACT

In this paper, we elaborate a neural network model to predict innovation performance with fuzzy rules, as well as implement an adaptive neuro-fuzzy inference systems (ANFIS) to measure the innovation performance through technical information resource and innovation objective. Building on the findings from fuzzy neural network approach, using Sugeno ANFIS, we also compared the artificial neural network with statistical techniques. We found strong support for ANFIS method has better results than the neural network and statistical techniques with regards to forecast performance. Finally, on the basis of our analysis, our results hold an important lesson for decision makers who may clearly picture the rules and adjust the resource allocation to meet their innovation objectives.

1. Introduction

Over the past decade, technology is considered to be highly important for corporation's to sustain competitiveness in the dynamic landscape (Prahalad & Hamel, 1990). Specifically in the manufacturing industry, enterprises are confronted by the challenges of global competition, technological capability, infrastructure, and innovative process and product setup. Despite the large number of researchers has intensively discussed a new business model, derived from so-called innovative activities, the decision maker who determines new business strategies or shares information resource with alliances to stimulate business growth are based on continuing innovative activity through technology in a rapidly changing market. Consequently, innovation performance, which complies with suitable innovation objectives and information resources, is an intense interest to decision makers. The outcomes of this process are based on the resource allocation and the accuracy of prediction. The forecasting techniques themselves are categorized by qualitative and quantitative approaches (Vanston, 1995). Together, the choice of which technique using is dependent on the research goals and the research scope of the enterprises.

On the academic front, a rich body of research on technological forecasting activities has focused on competitive technological intelligence, technology foresight, and technology road mapping (Zhu & Porter, 2002). Those activities aimed to provide timely insight into prospects for significant technological change. In other words, such activities could help managers to make better decisions with regard to strategic objectives, information resources, R&D management, product development as well as new production investment. Similarly, Watts and Porter (1997) emphasized that innovation forecasting is the degree of orderliness in the innovation process. They contended a successful innovation relies on several variables, including the technology's characteristics, the fit between the innovation objectives and technology information resources, familiarity of the firm with the market and associated infrastructure, market forces, and other socioeconomic factors (Porter, 1985; Souder, 1987; Twiss, 1992). Together, the accuracy of innovation forecasting is based on the synergy of the information of technology life cycle status, innovation context receptivity, product value chain, and market prospects. Following these processes, it may provide a good means to combine technological trends, roadmaps of technological interdependencies, and competitive intelligence to produce a good forecast.

Most previous forecasting studies have focused on social, political, business, and institutional drivers, but these studies seldom take innovation performance and the versatile indicators of long-term technology investment into consideration. In other words, some of the fitness between innovation objectives and information resources for innovation performance in specific industries has been neglected in previous research. Although Wang and Chien (2006) elaborated an innovation performance forecasting model wing an adaptive neural network (ANN), it still existed some problems, such as choosing the influence indicators, solving the linguistic character of sources, explaining the training procedure of outcome, describing how to simulate the rules for prediction, and finding robust forecasting techniques.

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With regards to influence indicators, a rich body of research has examined the interrelationships between innovation performance and other influential factors (Hamel & Prahalad, 1989; Kwaku, 1996; Manu & Sriram, 1996; Subramanian & Nilakanta, 1996). Mostly, the relationships among innovation performance, organizational culture, marketing strategy and changeable environment have been examined (Choi & Valikangas, 2001; Gopalakrishnan, 2000; Hall & Sharmistha, 2002; Irwin, Hoffman, & Lamont, 1998; Kwaku, 1996; Meeus & Oerlemans, 2000). Since the variable dimension is drawn more attention by several researchers to discuss a single dimension of variables, such as, timing of market entry (Ansoff & Stewart, 1967), R&D expenditures (Freeman, 1974), and the rate of product and market change (Miles & Snow, 2003). Manu and Sriram (1996) argued the prior studies excluded the link effect of each factor. Particularly, how R&D expenditure, market timing, and the rate of both product and market change will simultaneously affect innovation strategy and performance. Admittedly, developing a business model based on multiple dimensions of innovation and examining their marketing strategies, environment, and performance are vital to the study of the innovation process.

A number of researchers have emphasized the importance of information resource and strategies/objective in the innovation process. Likely, Hamel and Prahalad (1989) assert that there is a relationship between a corporation's goals and its allocation of resource. In general, goals are originated from corporate strategy, which refers to how an organization plans to adapt to and/or change aspects of its environment to calibrate the relationship between goal and resource allocation. The generation of strategy has been described variously as strategic choice, strategic trust, strategic fit, and strategic predisposition (Chaffee, 1985). Consequentially, the information resources include internal sources (within the firm and business group), external market sources, educational and research institutions, and generally available sources (Uzun, 2001). Similarly, Padmore, Schuetze, and Gibson (1998) classified the information sources proposed by OECD into five categories – in-house, supplier, peers, customers, and the public sector. These findings were tempered by the conclusions of Quadros, Furtado, Roberto, and Franco (2001), which stated that the information resources and innovation objectives in industrialized countries were different from those in Brazilian industry. Accordingly, how to obtain the information resources and cultivate the objectives suitable for maximizing the innovation performance are the priorities for organizations.

From the methodology viewpoint, the work of Lin and Lee (1992) is the earliest study to combine fuzzy theory with neural networks. They proposed a hybrid model which combines the idea of a fuzzy logic controller, neural network structure and learning abilities into an integrated neural-network-based fuzzy logic control and decision system. Subsequently, some researchers have investigated the application of this combined approach and developed several methods (Arifovic & Ramazan, 2001; Chang & Hsieh, 2003; Chang & Lai, 2005; Chang, Wang, & Tsai, 2005; Chang, Wang, & Liu, 2007; Elalfi, Haque, & Elalami, 2004; Kim & Han, 2000; Kuo & Chen, 2004; Liang, 1999; Montana & Davis, 1989; Sexton & Gupta, 2000; Srinivasan, 1998; Yao, 1999). Further, Chang et al., 2007 summarize those methods into five categories, Fuzzy Adaptive Learning Control Systems (FALCON), Fuzzy Back-Propagation Network (FBPN), adaptive neuro-fuzzy inference systems (ANFIS), Fuzzy Hyper Rectangular Composite Neural Networks (FHRCNNs), and fuzzy neural network (FuNN), respectively. Briefly, to build a neuro-fuzzy inference system, the applications of fuzzy neural networks in forecasting utilizes the results of trained neural networks to extract the crisp or fuzzy rules in order to build a neuro-fuzzy inference system. Apparently, soft computing forecasting tools such as fuzzy neural networks can solve certain problems with a better degree of accuracy and shorter computational times (2007).

In this article, we conducted the ANFIS model proposed by Jang, Sun, and Mizutani (1997) to predict the innovation performance through innovation objectives and technical information resources. ANFIS is not only embedded in MATLAB software but is a convenient way to simulate the forecasting process. Basically, the rules of the fuzzy system are derived from experts' opinions or the training rules; the former usually lack sufficient linguistic fuzzy rules, leading to an incomplete ANFIS. Conversely, the latter can often support a rule bases through the complete training data. Further, the accuracy of ANFIS depends on the complete rule bases and input/output membership functions. Those characteristics are suitable to solve the problems addressed in this paper. Consequently, we present a forecasting model, as illustration in Fig. 1 to predict innovation performance, with special attention given to information resource and innovation objective.

In term of the Taiwanese manufacturing industry, although its share of gross domestic product (GDP) has gradually decreased (to about 30% of GDP in 2006), similarly, this has also occurred in other developed countries. Nevertheless, the country's economic growth still depends on manufactured goods, and manufacturing industries play a more important economic role than the service industry. Wang (1999) indicated that the effects of innovation on economic growth can be achieved only through a strong national information infrastructure that supports technology applications and utilization. In this respect, we argue both information & communication technology (ICT) and innovation are the key drivers for national economic growth. Building on the recent World Economic Forum (WEF) "*The Global Information Technology Report 2005–2006*" (World Economic Forum, 2006), the Networked Readiness Index (NRI), with record coverage of 115 economies worldwide, noted that Taiwan has progressed steadily in the areas of innovation and ICT. Accordingly, the contribution of our study on innovation performance with technical information resource and innovation objective is a meaningful issue for the Taiwanese manufacturing industry.

In the first section of this article, we discuss the construction of an ANFIS. Next, we provide supporting the data analysis of our study. Finally, we present our conclusions and suggestions for future research.

2. The construction of an ANFIS

In this section, we define the structure of the adaptive neuro-fuzzy inference systems and the input/output indicators.

2.1. Adaptive neuro-fuzzy inference systems

A forecasting mechanism for innovation performance has been constructed by adaptive network-based fuzzy inference systems (ANFIS). Basically, ANFIS encodes the fuzzy if-then rules into a neural network-like structure and then uses the appropriate learning algorithms to minimize the output error based on the training/validation data sets. According to the past studies, there are a number of methods to develop adaptive neuro-fuzzy networks (Horikawa, Furahashi, & Tokumaru, 1992; Jang, 1993; Lin & Lee, 1992; Masouka, Watanabe, & Kawamura, 1990; Wang & Mendel, 1992; Yager, 1994). Mostly, the decision is made to use the ANFIS and its optimization process for the consideration of its accuracy (Chiu, 1994).

The ANFIS approach adopts Gaussian functions (or other membership functions) for fuzzy sets, linear functions for the rule outputs, and Sugeno's inference mechanism (Takagi & Sugeno, 1985). The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters) and