Industrial Product Deletion Decision: An Application of Artificial Neural Networks in Marketing

工業品的淘汰策略：人工類神經網路
在行銷管理上的應用

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Abstract

Phasing out weak products can bring firms a number of significant benefits, which include reduction of inventory levels, improved sales, increased profits, freeing up of resources and better use of management time. Recently, marketers and practitioners have shifted their attentions from keeping full product lines to the benefits of product elimination. However, the existing normative models and computer systems still suffer some problems (e.g., sophisticated procedures, time-consuming, subjective and inconclusive). These problems have made product deletion decisions a tough task for company CEOs and marketing executives. Thus, the purpose of this paper is to build an artificial neural network that systematically identifies weak products and selects elimination strategies. This paper first reviewed some models that were proposed previously and factors that were suggested to have impacts on the product elimination decisions. The reasons for using an artificial neural network and its advantages were discussed. Plans for data collection and training method were also presented. Results indicated that artificial neural systems satisfactorily performed in identifying weak products and choosing the optimal product elimination decisions. Industrial manufacturers and marketers would find significant values brought out by this paper, which also set out a practical, economic, and effective model for the decision making of product elimination.

Keywords: industrial marketing management; artificial neural network; product deletion decision

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摘要

淘汰弱勢或不具競爭力之工業產品可以為公司帶來一連串顯著的利益，這些包括降低庫存量、改善銷售量、增加利潤、解放公司資源、以及使得公司決策者更有效率地運用其寶貴之時間等利益。事實上，近年來行銷專家和業者已經將他們的注意力，由過去完整的產品線，轉移到淘汰弱勢產品所帶來之經濟利益。然而目前所存在的理論和電腦應用系統，仍然遭遇很多困難；這些困難包括繁複的作業程序、費時費力、主觀判斷、和尚未獲致結論等。這些問題造成公司總裁和行銷主管很多的困擾，也使得產品淘汰決策成為一個艱鉅而且龐大的任務。因此，本研究的目的乃在於建立一個人工類神經網路模型，系統化的確認弱勢產品和選取淘汰的策略。本文首先回顧學者過去所建議之理論，和一些被認為影響產品淘汰決策的因子，接著闡述為何應用人工類神經網路作為確認弱勢產品的原因，以及人工類神經網路優於傳統統計工具之處，其後介紹資料收集和訓練之方法。研究結果顯示，人工類神經網路能夠正確地辨認弱勢產品，並且建議最適的淘汰策略。作者相信，本研究一定對工業製造商和行銷專家提供一個很好的參考解決方案，並且為艱鉅的產品淘汰策略，展現一個絕佳的典範。

關鍵字：工業行銷管理；人工類神經網路；產品淘汰策略

1. INTRODUCTION

Due to the rapidly changing technology and competitive environment, firms must regularly and consistently audit their product lines to combat these changes if they try to retain in a viable condition (Avlonitis, 1989; Milmo, 1996; Purohit, 1994). Phasing out weak products can bring firms a number of significant benefits that include increased profits, improved sales, reduction of inventory levels, freeing up of resources, and better use of management time (Hise, et. al., 1984). Thus, marketers and practitioners have shifted their attentions from keeping full product lines to the benefits of product elimination (Bell, 1979; Saunders & Jobber, 1994; Wind, 1982).

Some descriptive models (Hise and McGinnis, 1975; Vyas, 1992; Wind and Claycamp, 1976) and system (e.g., Hamelman and Mazze's PRESS, 1972) have been developed. However, descriptive models require sophisticated procedures, interdisciplinary coordination and are very time-consuming and subjective. In addition, the existing computer-aid product elimination programs exclude external factors that might have significant impacts on product deletion decisions. This may be due to, at least partly, the limitation of computer programming and computing ability.

The purpose of this paper is to develop a training paradigm of artificial neural networks by which product deletion decisions and elimination strategies are made. It began with a review of marketing literature on product elimination. It then identified the factors that have been considered important by previous studies (Avlonitis, 1984, 1989; Hamelman & Mazze, 1972; Saunders & Jobber, 1994; Wind & Claycamp, 1976). Methodology was then presented and emphasized on 1)data collection plan, 2)measures, and 3)data training method.

2. SOME PROPOSED MODELS

Kotler (1965) introduced a six-step control system for phasing out weak products.

This system requires a computer program and an interdisciplinary executive team. The team member comes from different departments: marketing, manufacturing, purchasing, controlling (accounting and finance), personnel, and research and development. Those executives provide information and discuss problems confronted in their departments for each product. The information basically contains industry sales, company sales, physical volume, unit total cost, unit variable cost, price, cyclical adjustment factor, and overhead burden. A list of dubious products are then determined by a computer program based on the data provided by the team. The team members then fill out rating forms for those dubious products. Based on the rating, a retention index for each dubious product is generated by a computer Program. The team reviews those indexes and decides products to be dropped. Finally, policies and plans for phasing out "dropped" products are created.

Although Kotler's model provides a valuable concept for determining weak products, it takes a long process and requires excess management time. Thus, Hamelman and Mazze (1972) developed a computer-aid program (called PRESS) to simplify the review process and to minimize the management judgement time. The Primary differences between their system and previous models are 1) that it considers the whole product line instead of a single product, and 2) that it uses standard accounting data as inputs and provides ratios and other relevant information to each product. The PRESS consists four integrated parts. Based on standard accounting data, Press I generates a Selection Index Number (SIN) indicating the profitability of the product. The higher the SIN is, the more profitability the product represents. Press II examines the demand curve of each product to determining whether current prices should be modified. If the price changed, the original input data will be adjusted accordingly and PRESS I analysis will be reiterated. PRESS III projects the sales for each product based on the historical sales data by using exponentially weighted moving average method. PRESS IV adjusts the original SIN value for each product based on that product's complementarity and substitutability. The new value is called RESIN. Finally, PRESS offers cutoff points for deletion decisions by a systematic method.

Wind and Claycamp (1976) propose a matrix approach to develop a strategic plan for the existing product line. This approach uses the product's actual and anticipated performance characteristics in terms of sales, profits, and market share as inputs to the design of a strategic marketing plan for the firm's existing product line. It contains two definitional phases followed by five analytical stages. The definitional phases relate to the determination of the products under consideration and the relevant measurement instruments. The analytical phases include: 1) determination of product trend in terms of industry and company sales, market share, and profit; 2) integration of these four scales into a product evaluation matrix; 3) projection of future performance; 4) providing guidelines for marketing strategies; 5) incorporation of possible competitive actions and changes in environmental conditions into projection analysis.

Avlonitis (1984) proposes 19 evaluation factors which management in manufacturing industry generally considers. His finding tend to suggest that the nature and intensity of the weak product evaluation process and the evaluation factors considered by management in making the retention/elimination decision will always be determined by the environment within which the company operates and the role played by the product within the environment. Those 19 evaluation factors basically can be grouped into four major categories: financial consideration, resources released and external pressures considerations, marketing considerations, and managerial considerations.

More recently, Avlonitis (1989) reexamines the relationship between product elimination, PLC concept, and the deletion strategies. He finds that products may be eliminated irrespective of their position on the PLC. "New product failures" represent product elimination decisions in the early stages of the PLC. In addition, he suggests that the product elimination process varies significantly with the stage of the PLC. At the introduction stage, the most frequently used elimination strategy in these cases is the "phase-out immediately" strategy. "Competitive activities" and "decline in market potential" are most likely to initiate the elimination process of mature products. Finally, at the decline stage, management usually decides to either "milk" these products, or to phase them out immediately.

3. DETERMINANTS OF WEAK PRODUCTS

Previous literature has identified a number of factors which might have impacts on the product deletion decisions. Most of the studies on product elimination concentrate on the internal factors, while some other researchers find some companies depend on external forces to initiate the product deletion (Avlonitis, 1982; Avlonitis and Hart, 1988; Avlonitis and James, 1982; Hart, 1987). Thus, two major groups are identified: internal and external factors.

Internal factors include standard cost accounting data (standard cost, price, volume data and performance ratios) (Hamelman and Mazze, 1972), company sales (Calantone and Cooper, 1979; Wind and Claycamp, 1976), product elimination effect (PEE) on company sales (Avlonitis, 1984,1989; Hamelman and Mazze, 1972), PEE on company image (Avlonitis, 1984,1989), product share of total company sales, market share (Wind and Claycamp, 1976), gross margin, and change in marketing strategy (Hart, 1987; Wind and Claycamp, 1976). The external forces contain factors such as industry sales (Calantone and Cooper, 1979; Wind and Claycamp, 1976), market potential (Avlonitis, 1984, 1989; Calantone and Cooper, 1979; Gauthier, 1985;

Hart, 1987; Vyas, 1992), product life cycle (Avlonitis and James 1982; Wasson 1978), technology (Vyas, 1992), market competition (Hart, 1987; Vyas, 1992; Wind and Claycamp, 1976), raw material/parts problem, and government policies and regulation (Hart, 1987). Consequently, eight internal and seven external factors are identified. However, due to the difficulty in identifying which stage a product is in, the determinant of PLC will not be considered in the current study.

4. PRODUCT ELIMINATION STRATEGIES

According to Avlonitis (1989), there are five different strategies used to implement product elimination decisions. These strategies include drop immediately, phase-out immediately, phase-out slowly, sell-out, and special orders. Each strategy suggests a different implementation method of deleting weak products. The followings are the definitions of various strategies.

1. Drop Immediately: It means no further production. The company sells inventory and redirects investment.
2. Phase-out Immediately: The company satisfies orders received up to the decision day or a previously specified day, and ceases production thereafter.
3. Phase-out Slowly: The company minimizes production and marketing expenses to maximize profit.
4. Sell-out: The company sells or licenses the product to another manufacturer.
5. Special Order: The company drops the product from the standard range. If a customer still demands the product, the company manufactures and sells it as a special, charging a premium price.

5. ARTIFICIAL NEURAL NETWORKS

This study applies an artificial neural network to build a paradigm, by which weak products and elimination strategies are determined. Simply saying, an artificial neural network (ANN) is a highly simplified model of human nervous system that exhibits abilities of learning, generalization, and abstraction (Hammerstrom, 1993). An ANN is different from other conventional computer applications since it is not "programmed" in traditional sense. Rather, an ANN "learns" by the repetition interaction (e.g., training) with a data set (Hawley, et. al., 1990).

The reason for choosing an ANN is that it has several advantages over traditional regression techniques and other artificial intelligent devices (Bode, 1998; Lee, Cheng, and Balakrishnan, 1998; Lu, et. al., 1996; Sohl and Venkatachalam, 1995; Zhang and Huang, 1995). Hecht-Nielsen (1990, p. 120-121) address that "a primary advantage of mapping (neural) networks over classical statistical regression analysis is that neural networks have more general functional forms than the well developed statistical methods can effectively deal with." Generally, neural network has three primary advantages over the traditional statistical techniques.

First, the ANN applicators do not need to specify the "a prior" assumptions of the function underlying the data set (Sohl and Venkatachalam, 1995; Zhang and Huang, 1995). The only thing an executive needs to do is to select proper inputs and outputs to the system (Caporaletti, forthcoming). Whenever a researcher assumes a function or a model to analyze a problem, it always limits the nature of that problem. For example, marketers always apply linear regression to solve their research problems. This indicates that we assume the model/function is linear first (not because it is really linear), then we conduct some tests to justify its linearity. An ANN is superior to regression in nature. In addition, the simplicity and generalizability of application obviously make ANNs more appealing.

Second, ANNs can tolerates missing observations, outliers, or inaccurate data. It is no doubt that the survey data used in research always contain many incomplete responses. Besides, the nature of the response to survey questions brings in the question of the accuracy of each survey response. Regression cannot tolerate missing observations and handles poorly with inaccurate data because all relationship knowledge is stored in a single beta coefficient. However, a neural network is generally robust to missing or inaccurate data since the knowledge of relationships between variables is distributed across numerous network connections.

Third, ANNs do not suffer from the multicollinerity problem faced by regression analysis. Myers (1986, p. 80) states that "the reader will understand that an ordinary least squares analysis of a highly collinear data set may hide relevant information not uncover it." Based on its nature, a neural network can appropriately handle such problems as nonstandard conditions, violations of assumptions, high influence points, and transformations.

Based on the previous review, variables are determined and used to construct a paradigm of artificial neural networks. The independent variables include unit material cost (MC), unit labor cost (LC), unit variable overhead (VOH), unit sales price (SP), unit quantity sold, total unit variable cost, MC/SP, LC/SP, VOH/SP, contribution margin, company sales, percentage of contribution, industry sales, market share, market potential in dollars, product share of total company sales, change in marketing strategy, PEE on company image, technological change, market competition, raw material/parts problem, and government policies and regulations. The dependent variables are product elimination decisions (0,1) and strategies applied (1 to 5). For product elimination decisions, we define 0 as deleting the product and 1 as retaining the product. For strategies applied to implementing the elimination decisions, we define 1, 2 , 3, 4, and 5 as "drop immediately", "phase-out immediately", "phase-out slowly", "sell-out", and "special order", respectively. Thus, the model is presented in Figure 1.

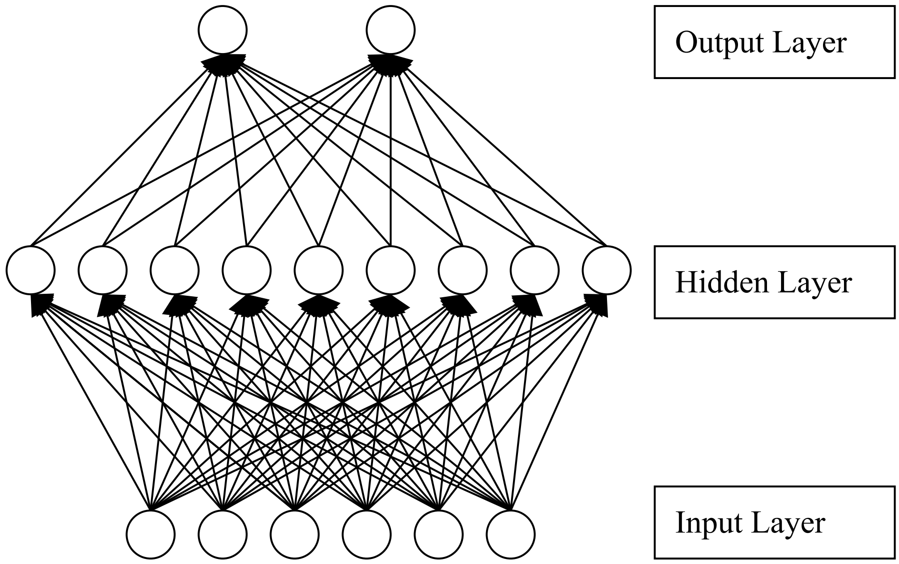

Figure 1: An Artificial Neural Network for Product Deletion Decision

6. METHODOLOGY

6.1 Sample

An invitation letter was sent to the top 1000 manufacturing companies in Taiwan. The invitation letter addressed only the purpose of the study, the importance and potential contribution of the program, the invitation of participation, the reward for responding, and a self-stamped response postcard. The reward for participation was a copy of the abridged version of the study, which would be found considerably valuable. Twenty postcards were returned two weeks after the invitation letter was mailed. However, only one single firm provided all the data we needed along the way. Thus, due to the scarcity of the data that we had, the artificial neural network was trained and tested on this data set.

6.2 Measures

According to the previous research, a number of factors have been identified. In addition to the independent variables, the dependent variable, product elimination strategies (Avlonitis, 1989) were also measured.

A. A comprehensive data sheet for each product was first required. This sheet contained the year of the product first introduced and the year deleted. It followed a table asking data such as unit material cost, unit labor cost, unit variable overhead, unit sales price, unit quantity sold, total sales, company sales, industry sales, estimated industry sales for the following year, and company sales change due to the elimination. Based on these data, other factors (standard performance ratios, PEE on company sales, product share of total company sales, gross margin, market potential) could be easily calculated.

B. PEE on Company Image

A single-item eleven-point Likert-type scale ranges from -5 to +5 to measure the product elimination effect on company image. -5 means the elimination of this product will cause a very bad company image while +5 implies the deletion will improve company image significantly. 0 stands for no effect at all.

C. Change in Marketing Strategy

This measures how much effect of the change in marketing strategies on the product deletion. A single-item seven-point Likert scale ranges from 0 to six was developed. 0 means no effect while six implies a significant effect.

D. Technological Change

This measures the rapidity of technological change resulting in new products in their respective industries. The ratings was on an anchored scale where 1 represents as "no new products marketed in the past decade" and 5 as "major market changes result in many new products."

E. Market Competition

The market competition was measured in terms of the intensity and importance of price, product, and delivery. The ratings for the intensity and importance of early type of competition were multiplied. The resulted scores were aggregated to obtain a weighted measure of the level of the overall competitive pressures on the company.

F. Raw Material/Parts Problem

This measures the problem confronted (if any) by the company in terms of raw material or parts. A single-item five-point Likert type scale was used where 1 represents "no problem at all" and 5 as "severe shortage".

G. Government Policies and Regulation

This measures the impact or limitation of government policies and regulation on the product elimination decision. A single-item five-point scale was used where 1 represents "no impact at all" and 5 as "severe impact."

H. Product Elimination Strategy

This measures how a company implements the product elimination decision. The instrument was a multiple choice form where 1 represents "drop immediately" and 2, 3, 4, 5 as "phase-out immediately", "phase-out slowly", "sell-out", and "special order only", respectively. The definition of each strategy was given after each strategy name.

6.3 Data Training Method

This data set was trained on a Pentium III machine with software NeuralSolutions 3.0. Backpropagation and gradient search techniques was applied to determine the weight matrix. Backpropagation, a supervised training methodology, was yielded by the independent works of LeCun (1986), Parker (1985), Rumelhart et al. (1986), and Werbos (1974). The purpose of training data was to discover patterns representing input and output vectors. Prior to training, a priori assumptions and "true" functions were not required. An executive only had to define proper inputs and outputs and the system took care rest of them. The simplicity, generalizability, and powerfulness of applications have made backpropagation the most commonly used algorithm to set up the appropriate weights for neural networks.

Basically, backpropagation obtained the appropriate weights by iterating the following steps.

Step 1: Initialize the weight matrix and threshold to small random values.

Step 2: Get the initial input and target output training pair.

Step 3: Generate a trial output vector through a certain function.

Step 4: Compare the trial output vector and target output vector.

Step 5: Determine the error.

Step 6: Adjust the weight matrix in proportion to the error.

Step 7: Iterate Step 3 until convergence.

Step 8: Repeat the whole process from step 2 with another training pair.

In this study, 22 independent variables and two dependent variables were identified. The network randomly selected 90% of the data for training and used the remaining (holdout sample) for testing. The network "learns" in the training process by adjusting the weights between nodes of the network. The input data must be presented to the network many times. The exact number of times the data should be presented was unknown and determined by the network. The stopping rule was the sum of square error (SSE). In other words, the network stop training when it reached a global minimum of SSE; otherwise, it kept training.

7. RESULTS

This data set was trained on a Pentium III IBM compatible PC. The purpose of training was to obtain an optimal solution for the network, which normally is a global solution. The training results were shown in Table 1. In general, this network had a good performance. In most cases, this network was able to correctly predict the product deletion decisions and the deletion strategies. As shown in Table 2, the hit

Table 1: The Training Results

Product Number	Predicted Values		Actual Values	
	Deletion	Strategy	Deletion	Strategy
1	1*	5**	1*	4**
2	1	2	1	1
3	0	4	1	4
4	1	3	1	3
5	0	0	0	0
…	…	…	…	…
71	1	3	1	2
72	1	3	1	5

Note: * 1 denoted deletion decision was made while 0 represented retention.

** 1=drop immediately 2 = phase-out immediately

3 = phase-out slowly 4 = sell-out

5 = special order only 0 = no action

Table 2: The Hit Ratio Using Training Sample

Iteration	Deletion Decision	Deletion Strategy
1	85%	64%
2	84%	58%
3	90%	73%
4	95%	60%
5	82%	55%
6	90%	78%
7	91%	63%
8	88%	48%
9	83%	68%
10	75%	51%
Average	86%	62%

ratio of the product deletion decisions were very high, ranging from 75% to 95% with an average of 86%. In other words, on the average 86 out of 100 cases were correctly determined. This percentage, according to many industrial marketing professionals, was favorably higher than other frequently used statistical techniques. Compared to the results of product deletion decisions, those of deletion strategies had a much lower hit ratios, which ranged from 48% to 78% with an average of 62%. This low ratio was expectable since there were more choices for strategy selection than for deletion decisions.

In order to test the robustness of this network, the holdout sample was used for this purpose. As shown in Table 3, 7 and 5 out of 8 cases were correctly predicted for product deletion decisions, respectively. Both tests yielded satisfactory results. Similarly, the ratio using testing sample (see Table 4) was very close to those of training sample. For deletion decision, it generated a good ratio, ranging from 69% to

Table 3: The Testing Results

Product Number	Predicted Values		Actual Values	
	Deletion	Strategy	Deletion	Strategy
73	0*	0**	0*	0**
74	1	5	1	5
75	0	0	0	0
76	1	2	0	0
77	1	4	1	5
78	1	3	1	3
79	1	2	1	1
80	1	2	1	2

Note: * 1 denoted deletion decision was made while 0 represented retention.
** 1 = drop immediately 2 = phase-out immediately
3 = phase-out slowly 4 = sell-out
5 = special order only 0 = no action

91% with an average of 80%. For deletion strategy, it yielded a hit ratio, ranging from 38% to 88% with an average of 64%. Although the average hit ratio using testing sample for deletion strategy is 2% higher than that of using training sample, the former has a larger variation than the latter.

Table 4: The Hit Ratio Using Testing Sample

Iteration	Deletion Decision	Deletion Strategy
1	88%	63%
2	90%	50%
3	75%	75%
4	83%	88%
5	91%	63%
6	77%	75%
7	79%	38%
8	65%	63%
9	87%	75%
10	69%	50%
Average	80%	64%

8. CONCLUSION

Although the benefits of product elimination have obtained marketers' attention, the existing normative models and computer systems still suffered some problems. These problems included sophisticated procedures, time-consuming, subjective and inconclusive. In addition, the existing computer-aid product elimination programs excluded external factors that might have significant impacts on product deletion decisions. Thus, a simple, reliable, and powerful computing paradigm seemed required. This study reviewed and identified a number of factors having impacts on product elimination decisions. Plans for data collection and training method were also discussed. Results showed that artificial neural networks did outperform than the average industry records. The author believed that the completion of this study has made significant contribution to industrial manufacturers and marketers as well.

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