Journal of Manufacturing Systems 47 (2018) 1–11

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Technology portfolio adoption considering capacity planning under demand and technology uncertainty

Kung-Jeng Wang*, Phuc Hong Nguyen, Shaw-Yi Wu, Jin Xue

Department of Industrial Management, National Taiwan University of Science and Technology, Taipei City, 106, Taiwan, ROC

ARTICLE INFO

Article history:
Received 4 April 2017
Received in revised form
23 November 2017
Accepted 21 January 2018

Keywords:
Capacity planning
Differential evolution
Markov decision process
Technology portfolio

ABSTRACT

How to tackle technology adoption and capacity planning simultaneously under uncertainty is a challenging issue for industries to improve their competitiveness. In this research, a technology portfolio adoption model considering capacity planning under demand and technological uncertainties is proposed. The model optimizes technology portfolio and simultaneously addresses the capacity planning to maximize the profit of a firm over a planning horizon. The problem is modeled by Markov decision process (MDP), of which each action is presented as a desired length of time to retain the currently used technologies and the corresponding capacity plan. Each action is modeled by a stochastic mixed integer programming (SMIP) problem. For achieving an efficient solution, a sampling-based hybrid algorithm called PSO–DE, which integrates the particle swarm optimization (PSO) algorithm with the differential evolution (DE) algorithm, is employed to solve the SMIP problem. After that, an optimality backward recursive function is employed to solve the MDP problem. Further, a parallel computing technique is utilized to relax the computational burden of the MDP model. A sensitivity analysis is conducted to investigate effects of the algorithm parameters by using Taguchi method. A performance comparison among DE-PSO and other popular algorithms is conducted. Finally, we evaluate the impact of different levels of demand variance and risk of investment on the expected profit.

1. Introduction

In hi-tech manufacturing industries, resource investment is one of crucial decisions due to the involvement of intensive capital requirement and stochastic market demands [43]. For example, in the Thin Film Transistor-Liquid Crystal Display (TFT-LCD) and semiconductor industries, the cost of building a modern production facility is over several billion US dollars. Further, an excess or shortage of capacity will cause enormous loss of profit due to uncertain demands. For the above observations, strategic capacity investment is a complicated problem; and a minor improvement in decision quality might result in huge savings for a company.

In recent decades, strategic capacity planning becomes more complex due to the involvement of rapid changes in manufacturing technology. In semiconductor industries, one famous observation is the Moore's Law [42]. He extrapolated that a new technology/product would appear approximately every 18 months while the complexity and performance double. For 50 years, the Moore's Law has set the pace for innovation and development. The display industry is also facing rapid changes in display technologies, i.e. Organic light-emitting diode (OLED) (launched in 2007), Surface-conduction electron-emitter display (SED) and Field emission display (FED) (launched in 2010), and Quantum dot display (QD-LED) (launched in 2012). For the substrate generation sizes, the mother glass size has increased from Generation 1 (launched in 1990, approximately 300 mm × 400 mm) to Generation 10 (launched in 2009, 2880 × 3130 mm); and the mother glass size is projected to be increased.

Under such a fast-moving technology environment, a manufacturing equipment invested today might be obsolete in the near future. Therefore, to hedge risks involved in technology uncertainty and maintain the competitive advantages, the decision-makers have to keep in view the tradeoff among the costs involving in investing different processing technologies under technological changes. One possible action in this circumstance is to replace the currently used technology by the new one. However, this action might suffer risks involved in the payback burden and uncertain magnitude of technology changes. For example, a more advanced technology, compared with the currently launched, might be introduced shortly. This situation causes the currently adopted

* Corresponding author.
E-mail addresses: kjwang@mail.ntust.edu.tw (K.-J. Wang), nhphuc72@gmail.com (P.H. Nguyen), quae5353061@yahoo.com.tw (S.-Y. Wu), 15876517929@163.com (J. Xue).

https://doi.org/10.1016/j.jmsy.2018.01.009
0278-6125/

technology to be obsolete quickly. Furthermore, the presence of uncertain demands also makes the new technology adoption more challenging. Therefore, how to form the optimal technology portfolio considering those above mentioned uncertainties has become a key decision to maximize a firm's profit by finding the most profitable technology portfolio instead of completely replacing the current ones. To achieve this purpose, a formal modeling and solution approach is urgent, particularly in hi-tech manufacturing industries.

This research will tackle the following questions: (i) How long should the firm keep the currently used technology portfolio? (ii) What is the appropriate level/capacity of resources corresponding to such technology portfolio? And (iii) What is the optimal production quantity of these products to fulfill customers' demands to maximize the firm's profit?

The remainder of the paper is arranged as follows. Section 2 reviews related works to technology replacement modeling, capacity planning and resource allocation and solving approaches. Problem formulation and mathematical model are presented in Section 3. The solution method is expressed in Section 4. Section 5 illustrates the development of a DE-PSO algorithm. The experimental results will be shown in Section 6. Finally, the conclusion and future research will be discussed in Section 7.

2. Literature review

2.1. Approaches to technology adoption

Due to the rapid growth of technology evolution, invested technologies become obsolete faster, and they might be a payback burden for the company. A proper decision concerning technology adoption significantly affects the long-term profitability of a company [1,2]. An early equipment replacement model was proposed by Bellman [3]. He introduced a solution for an asset replacement problem by using dynamic programming. From each decision epoch there are two alternative actions, i.e. keep or replace decision. Wagner [44] developed an alternative equipment replacement model. For each decision epoch, alternative actions are of the number of time periods in the planning horizon that an asset is kept. The Wagner [44] is more efficient than the Bellman [3]. The complexity of the Wagner [44] grows slowly than the Bellman [3] because the Wagner [44] can eliminate inferior arcs before solving compared with the Bellman [3]. Furthermore, the Wagner [44] considers the economic life of the currently used asset while the Bellman [3] only considers one-period decision, i.e. keeping or replacing. Derman [4] studied a maintenance or replacement decision problem in which the asset conditions follow some transition probabilities. However, these studies only considered the physical erosion of assets.

The influence of technological innovations was considered in Hopp and Nair [1,2]. They studied the technology replacement problem under an assumption that technological innovations might be introduced into the market with unknown timing and magnitude. An optimal maintenance and replacement decisions under technological changes using MDP was modeled by Nguyen et al. [5], which considered spare parts inventories. Hitt and Schmidt [33] developed a model of analyzing the technology obsolescence impact on future costs. This study proposed a method for a method for assessing technology obsolescence, and tools to determine the impact of technology obsolescence on business management. These studies allowed only one type or generation of technology involved in decisions. However, it is well-known that manufacturing equipment in hi-tech manufacturing industries is capital intensive and rapidly obsolete. Therefore, completely replacing the currently used technology by a new one is risky due to the payback burden and technological obsolescence.

For resource portfolio planning problems, Rajagopalan [6] proposed a capacity expansion problem in which the evolution of technology was modeled by a semi-Markovian process. This model allows multiple technology types or generations involved in production. However, this study allowed only one new technology available for investment in each decision epoch. Other resource portfolio planning models ignored the presence of technological innovations. For instance, Wu and Chuang [7,8] study a capacity planning problem which only considers dedicated and flexible technologies. Wu and Huang [9] proposed an electricity portfolio model to find the effect of electrical technology portfolio with renewable energy on the environment. This study applied portfolio theory, learning curve theory and the capacity credit to consider characteristics of renewable energy.

Motivated by the above observations, our study aims to propose a more generalized model in which three important issues will be tackled simultaneously. The first issue is the optimal technology portfolio selection problem under technological changes. Second, the economic life of the selected technology portfolio will be considered to hedge risks derived from payback burden and technological obsolescence. Finally, a capacity planning and resource allocation problem is also considered to satisfy customers' demands and maximize expected profit under demand uncertainty.

2.2. Approaches to capacity planning and resource allocation

Without considering technology adoption, models concerning capacity planning and resource allocation have been investigated by many researchers. Some excellent reviews of the capacity planning problem under uncertainties can be found in Martínez-Costa et al. [10]. Most studies concerned demand uncertainties, of which demand scenarios were intensively considered. Demand scenarios were utilized in Wang et al. [11], Wang and Wang [45]. These studies addressed a capacity planning and resource allocation problems under stochastic demands and limited budget in the semiconductor testing industry. They assumed that the mean and variance of demands can be estimated from the market.

For solution efficiency, soft-computing approaches, supported by high-performance computers, have emerged rapidly in use due to large-scaled problem sizes in real industries. Genetic algorithm (GA) was widely used in solving capacity planning problems [12,13]. Bard et al. [14] solved a capacity expansion problem in the semiconductor manufacturing industry by simulated annealing algorithm. An ant algorithm was utilized to solve a capacity planning problem in a decentralized supply chain [15].

Differential evolution (DE) [16] is also a promising algorithm. Mohajery and Khoshalhan [17] employed DE algorithm to solve a single-item resource-constrained aggregate production planning problem. DE algorithm was utilized by Lieckens and Vandaele [18] to solve a lot size problem in a stochastic supply chain management system. Comparing with GA, Tušar and Filipič [19] showed that DE explores the decision space more efficiently.

PSO is a stochastic population-based optimization approach and is inspired by the social interaction of animals [20]. PSO has been successfully applied in many studies and application areas in the past several years [21]. PSO is efficient, has a reasonable ability to handle optimization problems with multiple local optima, and can be implemented in a simple manner [22]. However, PSO also has a few critical problems: it easily sticks in the local optimum when updating the personal and global best after determining the best position in the overall population [23].

Several studies hybridized DE and PSO in sequence. Hendtlass [24] used the DE perturbation approach to adapt to particle positions. Particle positions are updated only if their offspring has improved fitness. Ali et al. [25] proposed a similar procedure. It enters the PSO phase if the optimality criteria were not met by the