Proceedings of the 2007 Industrial Engineering Research Conference
G. Bayraksan, W. Lin, Y. Son, and R. Wysk, eds.

A New Model for Closed-loop Product Lifecycle Systems

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Abstract

Closed-loop supply chain systems are increasingly attracting attention because of cost competition, resource constraints and environmental issues. Electronic products are of particular concern due to short lifecycles and hazardous material used in production. We formulate the closed-loop product lifecycle system with stochastic dynamic programming methodology. By applying the reverse logistics concepts, we are able to provide guidelines for product strategic decision making throughout the closed-loop product lifecycle.

Keywords: Closed-loop Product Lifecycle, Stochastic Dynamic Programming, Reverse Logistics, Sequential Decision Making

1. Introduction

The landscape of the world economy has changed significantly over the last twenty five years. The inter-connectedness of national economies and the rapid ascent of the BRIC countries (Brazil, Russia, India, China) in the global engineering environment have forced organizations to become more competitive with little room for error in product lifecycle decisions [1]. Product full lifecycle analysis has drawn increasing attention in the recent years because of production cost, environmental cost, total cost of ownership and total cost of society. However, product lifecycle decision making systems involve almost every facet of the whole society: manufacturing industry, distribution network, service providers, customers and the governments. Therefore, making the right decision at the right time is critical for manufacturing companies.

Product lifecycle theory has been a key organizing principle in studies of technical innovation and has been promoted by leading management theorists as a tool for strategic decision making [2]. The majority of existing literature on decision making in product lifecycle management focuses on the new product development phase before it enters the market, and the methodology used in decision making is mainly from conceptual rather than quantitative perspective. Ali, Krapfel and Labahn [3] define product lifecycle time to be the elapsed time from the beginning of idea to the end of product launch and do not consider the decision making after the products are released into the competitive market. Both Olson et. al. [4] and Srinivasan, Lovejoy and Beach [5] discuss methodologies that incorporate the product marketing information into new product development. Day [6] discusses the factors that determine the progress of the product through the stages of the lifecycle and the role of the product lifecycle concept in the formulation of competitive strategy.

Companies make decisions that have both immediate and long-term consequences. Decisions must not be made in isolation; today's decisions impact tomorrow's choices. In this paper, we take a stochastic dynamic programming approach to develop a quantitative model for this sequential decision making throughout the closed-loop product lifecycle evolution process. This product lifecycle decision model is developed at a strategic level with the objective to maximize the long term total discounted net profit of the entire company. Stochastic dynamic programming, i.e. Markov decision process (MDP) is an effective technique in modeling sequential decision making, especially under uncertainty [7]. At a specified point in time, the decision maker chooses an action. This choice produces an immediate reward or cost. As a result of the action/choice, the system evolves to a new state. At the next point in time, based on a probability distribution, the decision maker will again face a similar situation. The system might now be in a different state with a different set of available actions to choose from. The goal of this decision making model is to choose the sequence of actions that allows the system to perform optimally with respect to predetermined performance criteria.

The major contribution of this paper is considering the sequential decision making involved in product lifecycle management from a quantitative perspective. It is demonstrated that the Markov decision process is a suitable methodology for this problem since it takes into account both the outcome of current decisions and future decision making opportunities. The remainder of this paper is organized as follows: the motivation and detailed problem description is introduced in section 2. The closed-loop product lifecycle decision model is discussed in section 3, including model assumptions, model parameters and solution techniques in section 3.1, 3.2 and 3.3 respectively. Finally, the paper concludes with a summary and guidelines for corporate decision makers in Section 4.

2. Problem Description

Sustainable closed-loop product lifecycle systems are popular topics in both academia and industry due to the growing concern about energy and environmental issues as well as cost effectiveness. There have also been many regulations enacted recently. Examples include the Waste from Electrical and Electronic Equipment (WEEE) Directive, the Restriction of Certain Substances Hazardous to Health (ROS) Directive, Electrical & Electronic Equipment (EEE) Directive and Home Appliance Recycling Law (HARL)[8].

A typical logistical system follows the following path in Figure 1 which is open-loop.

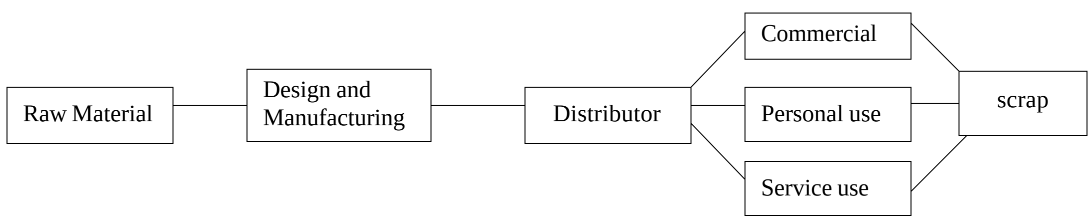

Figure1: Open-loop logistics system

Nowadays, “3R: reduce, reuse, and recycle” is accepted gradually. And more and more manufacturing companies start to adopt the closed-loop logistics system displayed in Figure 2.

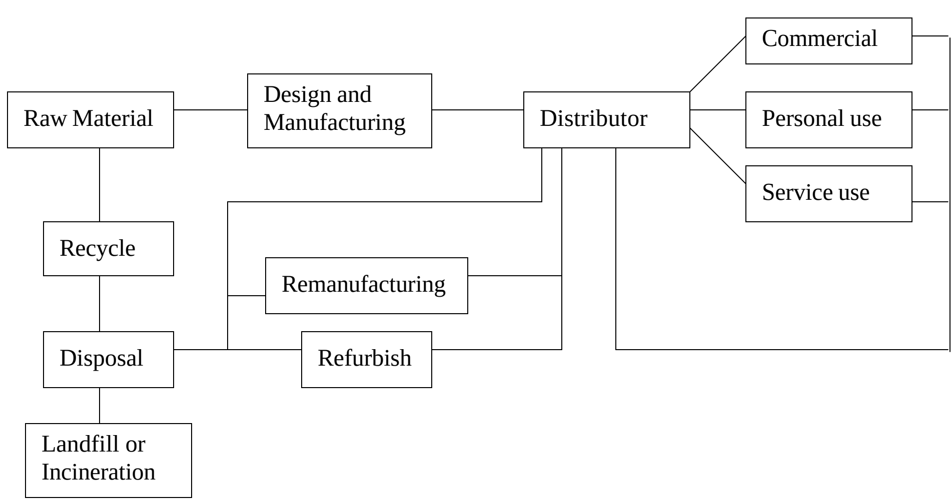

Figure 2: Closed-loop logistics system

This paper focuses on identifying the optimal strategy in order to maximize the overall net profit for manufacturing companies. The concept of "total cost of ownership" is adopted to calculate the overall revenue and cost, considering the reuse, recycle and environmental issues. Consumer electronic products are especially of interest for this research because of short product lifecycles, hazardous material contained in products, and small profit margins. Landfills and incinerators are the usual destination of electronic waste and these negatively impact the environment.

Here is the scenario we are considering in this paper: A company manages *M* products. Each may be in different phases of their lifecycles: introduction, growth, maturity, decline, and end-of-life. Products evolve through the entire lifecycle based on manufacturing, marketing, and competitive constraints. The selling prices and profitability of these products are assumed to be known from R&D departments, and market demand follows seasonal fluctuations. Ideally, a company would like to keep all of its products in their mature phase as long as possible since it has the highest profitability.

At each stage of the product lifecycle, the decision maker is faced with the decision of whether or not to invest in an existing product by upgrading it, for example, initiating a new marketing campaign, investing in repackaging it, and so on. This process is analogous to the stage gate process that has been validated at many diverse organizations over the last decade [9]. After a product has reached its end-of-life phase, the company has to decide whether to recycle, reuse or simply discard the product. And there are costs and benefits associated with each decision at each stage.

The company's objective is to maximize its long term total expected profit. The core issue here is to make effective and optimal sequential investment decisions before the product reaches the end-of-life stage and to dispose the end-of-life product optimally when it is no longer on the market.

3. Model Formulation

3.1 Model Assumptions

The major model formulation assumptions are as follows:

1. Traditionally, the life of a product is divided into multiple lifecycle phases or stages. Variations of this sequence have been described in product development literature and have been found to be valid across a diverse range of products and environments [10],[11],[12]. In this paper, we establish five product lifecycle phases as shown in Figure 3.

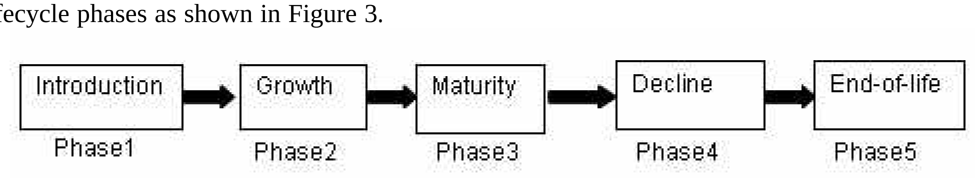

Figure 3: Product Lifecycle Phases

2. Each of the *M* products is independent of other products from the perspective of profit making and decision making.
3. The more a company invests in a product, the faster it matures and the slower it declines in the product lifecycle.
4. Seasonal demand fluctuations and market competition changes are incorporated into the MDP model state so that the system obtains the Markovian property.
5. The probability transition matrix is time-independent, i.e. the transition probability is only based on the state and action.

3.2 Model Parameters

We formulate a discrete-time, infinite horizon, discounted Markov decision process model of this problem. The key ingredients of this sequential decision model are:

1. A set of decision epochs: $T = \{t_1, t_2, ...\}$. We assume that the products' lifecycle phases, market demand and competition are observed, and decisions are made on a periodic basis (e.g. monthly).
2. A set of system states: $S = \{s_1, s_2, ..., s_L\}$. A system state consists of three elements: the phases of the *M* products, the market competition, and the monthly demand.

   Product phases: each product can be in one of the five lifecycle phases.
   Seasonal demand: the market seasonal demand is assumed to be known by market research.
   Market competition: two levels of market competition scenarios are considered.

   To quantify the partition of the market demand, we assign a *Phase_Competition_Index* to each of the *M* products from the company, and also assign a *Market_Index* to the other products in the market. The demand of a given product is then established product in proportion to its *Phase_Competition_Index*.

   For example, if the total market demand for the product at a certain decision epoch t is *D*, the *Phase_Competition_Indexes* of the *M* products are $PCI_1, PCI_2, \ldots, PCI_M$, and the *Market_Index* of the rest of the market is MI_{Market}, then the market demand share for product *i* is

   $$D \cdot PCI_i \Bigg/ \left(\sum_{j=1}^{M} PCI_j + MI_{Market} \right)$$

   A product's competition index is a variable. It increases as the product evolves towards its maturity lifecycle phase, and then decreases as the product declines towards its end-of-life phase. Similarly, MI_{Market} also has some uncertainty. In the low competition scenario, the market index of competing products MI_{Market} is smaller than the index in the high competition scenario.
3. A set of available actions can be taken corresponding to each state *s*: $A_s, \forall s \in S$. These actions, which may or may not be the same for different products, including the investment levels of all *M* products at the current month. When the product reaches its end-of-life stage, the action set becomes *A*={ *reuse*, *recycle*, *discard*}.
4. A set of state and action dependent immediate reward: $r_t(s,a)$ where $a \in A_s$. This reward is calculated as the sale revenue subtracting investment, i.e. the net profit, of the current month.
5. A set of state and action dependent transition probabilities: $P(j \mid s,a,t)$ where $t \in T$. This is the probability that the system transfers to state *j* the next month given the current state *s* and the action *a* taken this month.

   We assume the probability matrix is time-independent, so $P(j \mid s,a,t)$ becomes $P(j \mid s,a)$. Suppose there are a finite number of actions: $a_1, a_2, ..., a_n$, the transition probability matrices corresponding with action a_i is $P(a_i)$:

   $$P(a_i) = [p_{ij}]_{|s|\times|s|}$$

   where p_{ij} is the transition probability from state *i* to *j*, and $|S|$ is the cardinality of *S*. Then $\sum_j P_{ij} = 1$ is true for every row *i*, where p_{ij} can be determined by statistical estimate for the product.

   In the next decision epoch (at time t+1), a product can stay in its current stage or can also evolve to the next stage. An end-of-life product is an extinguished product, and its transition to introduction represents the introduction of a new product.

   Values of these transitions from phase to phase depend on the lifecycle phases of the products and the investment levels of a company into those products. It is also assumed that the transitions of different products are independent of each other.

The product lifecycle phase transition diagram is shown in Figure 4:

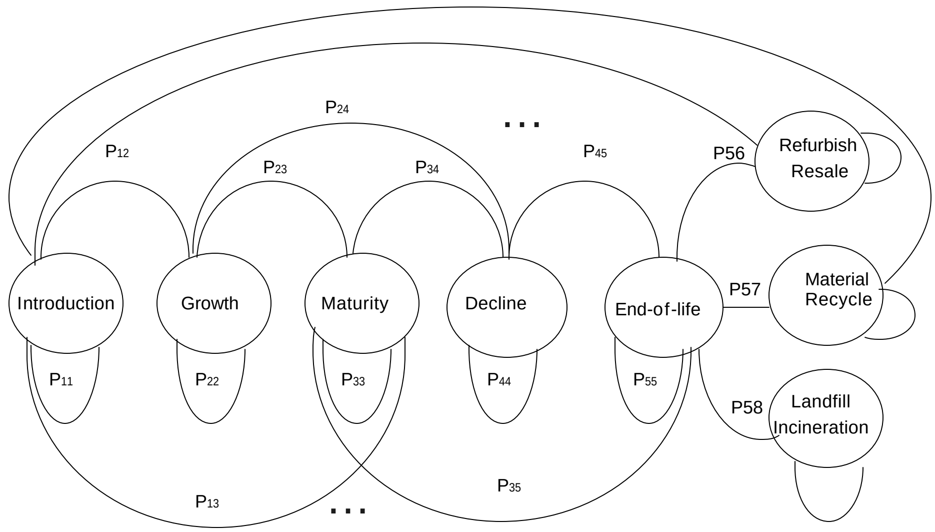

Figure 4: Product Lifecycle Phase Transition Diagram

Market competition: It is assumed that market competition is a Markov chain, as shown in Figure 5.

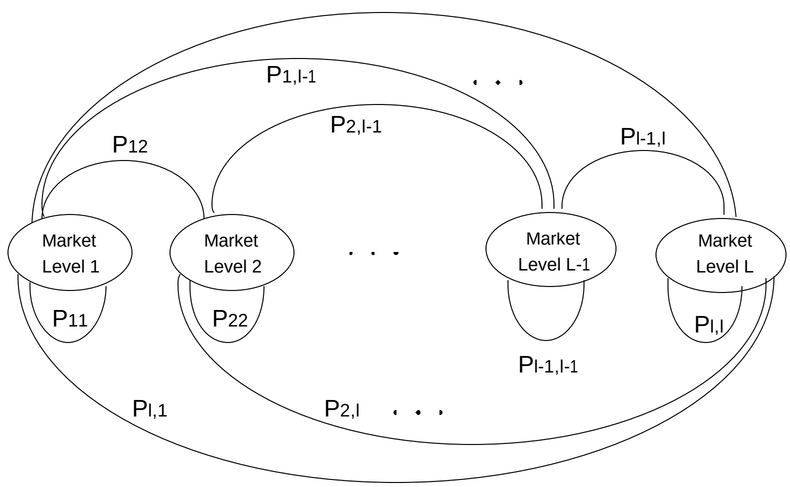

Figure 5: Market Competition Transition Diagram

Seasonal demand: In order to maintain the Markovian property, seasonal demand fluctuations are incorporated into the system state. Thus the transition of demand follows the chronological sequence with certainty.

6. Reward function $r_t(s,a)$ is defined to be the net profit gained after taking action a at decision epoch t when the company is in state s. And $r_t(s,a)$ can be estimated by economic survey and analysis for a specific industry or company.

7. Objective: to maximize the expected discounted total profit from all products over the rest of the time horizon. The long-term discounted profit for the product at state s is denoted as $V(s)$. The optimal solution to this problem can be obtained by solving the following set of recursive equations [7]:

$$V(s) = \max_{a \in A_s} \{ r_t(s,a) + \lambda \sum_{j \in s} P(j \mid s,a) V(j) \}, \; s \in S$$

It can be shown that there exists a stationary optimal policy for this discounted, discrete-time Markov decision process.

3.3 Solution Techniques

Policy iteration algorithm [7] can be used to solve this MDP problem, and the basic steps are as follows:

1. Set n=0, and select an arbitrary decision rule $d_0 \in D$.
2. (Policy evaluation) Obtain the policy value v^n by solving

$$(I - \lambda P_{d_n})v = r_{d_n}$$

3. (Policy improvement) choose d_{n+1} to satisfy

$$d_{n+1} \in \arg\max_{d \in D} \{ r_d + \lambda P_d v^n \}$$

setting $d_{n+1} = d_n$ if possible.

4. If $d_{n+1} = d_n$, stop and set $d^* = d_n$, otherwise increment n by 1 and return to step 2.

Finally, d^* is the optimal policy for this MDP problem.

4. Conclusions

In this paper, a Markov decision process is used to model sequential decision making throughout product lifecycle management. Simple numerical examples validate our model, and with this model we are able to provide guidelines for the company decision maker. It is a general model that can be adapted for a multitude of other industries and products. Future research includes the collection of application real data from manufacturing organizations and improving the existing model.

Acknowledgements

This paper is supported in part by a grant from the Air Force Research Laboratories and the Doyle Center for Manufacturing Technology.

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