Modeling Sustainable Product Lifecycle Decision Support Systems

Guiping Hu, Bopaya Bidanda
Industrial Engineering, University of Pittsburgh, Pittsburgh, PA 15261

Abstract: Sustainable product lifecycle systems are attracting increasing attention because of cost competition, resource constraints and environmental issues. Short lifecycle products, such as consumer and defense electronics, are of particular concern. We formulate a closed-loop supply chain with Stochastic Dynamic Programming method. By applying the concept of a sustainable product lifecycle, guidelines for product strategic decision making throughout the closed-loop lifecycle are provided.

Keywords: Sustainable Product Lifecycle, Closed-loop Supply Chain, Environmental Regulation, Stochastic Dynamic Programming.

1 INTRODUCTION

Product lifecycle theory has been a key principle in studies of technical innovation and has been promoted by leading management theorists as a tool for strategic decision making [1]. Making the 'right' decisions at each stage of a product's lifecycle is important to the healthy, sustainable development of manufacturing industry. With the growing concern about the global warming and environmental issues, sustainable manufacturing and efficient resource utilization are gaining popularity with significant potential in theoretical study as well as industrial applications.

Sustainable development means passing on to future generations a stock of 'capital' that is at least as big as the one that our own generation inherited [2]. Here, 'capital' encompasses the world's assets, including money, buildings and intangible assets such as intelligence, skills and social systems, as well as natural resources. Today, 6 billion people reside on Earth; without a cure for AIDS (which has caused more deaths than any other pandemic in history) or a solution to rapid population growth, there will be 8 billion people living on this planet by 2020 [3]. Therefore, researchers from various disciplines emphasize the sustainable utilization of the limited amount of available resources. The traditional methods in sustainable product lifecycle management are often conceptual. In this study, principles of industrial engineering are utilized to develop rational decision making mechanisms when there are conflicts and trade-offs between various stakeholders.

This study concentrates on developing and validating mathematical models within the framework of the sustainable product decision support systems. There are mainly four interrelated parts of this research: waste management in manufacturing, green product manufacturing strategy, product upgrade strategy and reverse logistics. The linkage between these segments loosely follows the evolution of the product through its lifecycle as shown in Figure 1.

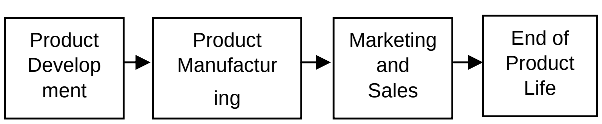

Figure 1. Product Lifecycle Evolution

In this paper, we focus on the last part in the lifecycle evolution process where decision making mechanisms for end-of-life products are developed. The major contribution of this paper is to consider the sequential decision making involved in product lifecycle management systems from a quantitative perspective. It is demonstrated that the Markov decision process (MDP) 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: a brief literature review is included in section 2; the motivation and detailed problem description is introduced in section 3; the closed-loop product lifecycle decision model is discussed in section 4, including model assumptions, model parameters and solution techniques in section 4.1, 4.2 and 4.3 respectively. A numerical example for model validation is presented in section 5. Finally, the paper concludes with summaries and guidelines for effective decision making in section 6.

2 LITERATURE REVIEW

Closed-loop supply chain as an effective and efficient method to deal with end-of-life product disposal issues has become a popular topic in both academia and industry. The importance of integrating the economical and environmental impacts of manufacturing industry is now increasingly recognized in policy level worldwide. Pioneers include the United Nations' World Commission on Environment & Development in 1987 and United Nations Conference on the Environment & Development in 1992 [4]. Wu and Low [5,6] conducted a study on legislation and regulations in the European countries. They discuss possible environmentally responsible logistics systems and potential impacts to the whole society.

Both Fleischmann [7] and Guide [8] offer, in their survey papers, comprehensive reviews of remanufacturing related research. Guide and Wassenhove [9], who focus on the business aspects of developing and managing profitable closed-loop supply chains, identify the common processes in a closed-loop supply chain: product acquisition, reverse logistics, inspection, remanufacturing, and distribution. Majumder and Groenevelt [10] present a game-theoretic model of competition in manufacturing sector. Their research suggests that incentives should be given to the Original Equipped Manufacturers (OEMs) to increase the fraction of remanufacturable products or to decrease the costs of remanufacturing. However, there is a gap in how to deploy the regulations in manufacturing companies and where the incentives lie for the company executives to make the decisions to invest on remanufacturing sectors.

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 perspective. Ali, Krapfel and Labahn [11] 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. [12] and Srinivasan, Lovejoy and Beach [13] discuss methodologies that incorporate the product marketing information into new product development. Day [14] 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. These are all qualitatively focused.

In this paper, we take a stochastic dynamic programming approach to develop a quantitative product lifecycle model for sequential decision making. The product lifecycle model that is presented here is developed at a strategic level with the objective to maximize the long term total discounted profit of the entire company. 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. Markov decision process is an effective technique in modeling sequential decision making, especially under uncertainty [15]. At a specified point in time, a decision maker must choose 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 makes the system to perform optimally with respect to predetermined performance criteria.

3 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)[16].

A typical logistical system follows the following path in Figure 2 which is open-loop.

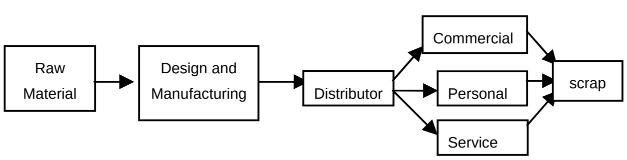

Figure 2. Open-loop logistics system

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 3.

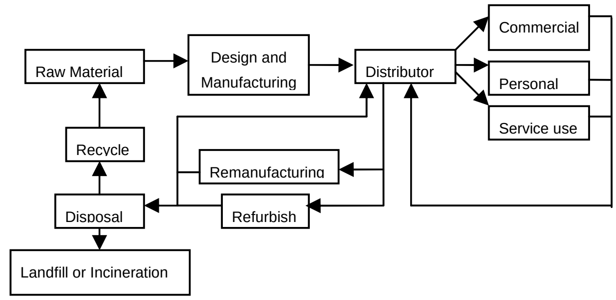

Figure 3. Closed-loop logistics system

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.

We consider the following scenario: 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 further R&D, and so on. This process is analogous to the stage-gate process that has been validated at many diverse organizations over the last decade [17]. 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.

4 MODEL FORMULATION

4.1 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 [18],[19],[20]. In

this paper, we establish five product lifecycle phases as shown in Figure 4.

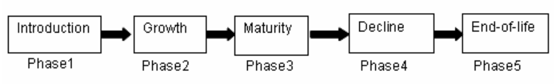

Figure 4. Product Lifecycle Phases

2. Each of the *M* products is independent of other products from the perspective of profitability and decision making.

3. The more the company invests in a product, the faster it matures and the slower it declines from the maturity phase 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.

4.2 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 lifecycle phases of the *M* products, the market competition, and the monthly demand.

   Product lifecycle 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, …, 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, therefore, $P(j \mid s,a,t)$ becomes $P(j \mid s,a)$. Suppose there is 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 5:

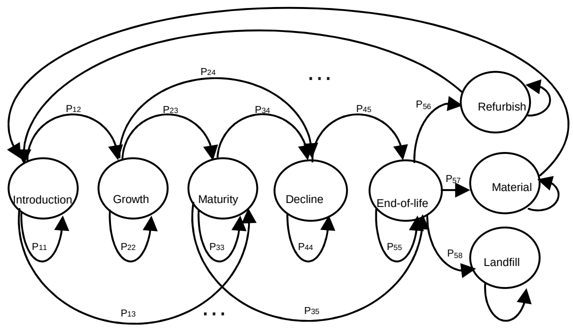

Figure 5. Product Lifecycle Phase Transition Diagram

Market competition: It is assumed that market competition is a Markov chain, as shown in Figure 6.

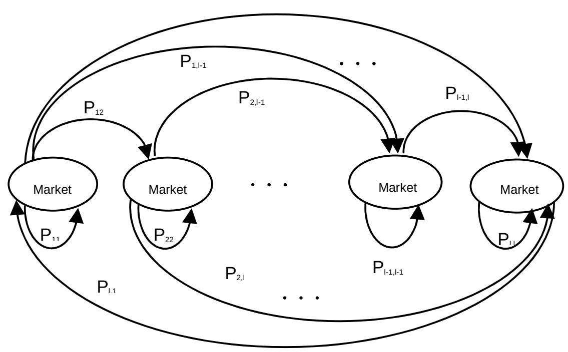

Figure 6. Market Competition Transition Diagram

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 [15]:

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

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

4.3 Solution Techniques

Policy iteration algorithm [15] 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.

5 NUMERICAL EXAMPLE

Industries ranging from the defense to engineered products to consumer electronics introduce style changes or new products on a periodic basis. This is also followed to a greater degree in the consumer electronics industry that is characterized by a high degree of competition and an especially short lifecycle. In this section, we provide a numerical example and analysis in the digital camera market.

5.1 Further Assumptions

We introduce some further assumptions in the case to be presented. However, it should be noted that most of them can be released by minor adjustments to the model parameters.

1. Assume there is no backward transition except at the end-of-life stage. This implies that a new product has been developed and released to the market replaces an existing end-of-life product.

2. The lifecycle of each product is sequential with no leapfrogging between phases. This can easily be extended by adjusting the transition probability matrices.
   The simplified product lifecycle phase transition diagram is shown in figure 7.

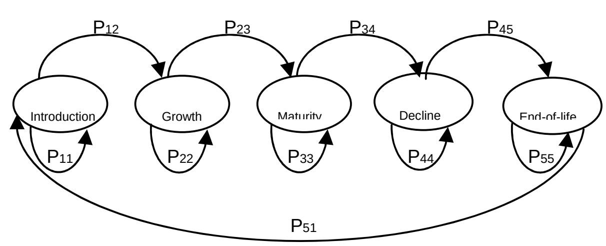

Figure 7. Simplified Product Lifecycle Phase Transition Diagram

3. We assume that the consumer electronics company that produces and markets these digital cameras (hereafter referred to as Company DC) can keep at most three types of cameras

simultaneously in the market. These three types of cameras can be at any of the five lifecycle phases: introduction, growth, maturity, decline and end-of-life.

4. The total market demand varies from month to month, and peaks occur in May (Mother's day), June (Father's day), November (Thanksgiving) and December (Christmas).

5. To simplify the model, we combine the competitive factors from inside and outside the company together. In this numerical example, we consider two competitive levels, which can easily be generalized to the L level case.
   It is assumed that market competition is a Markov chain as follows.

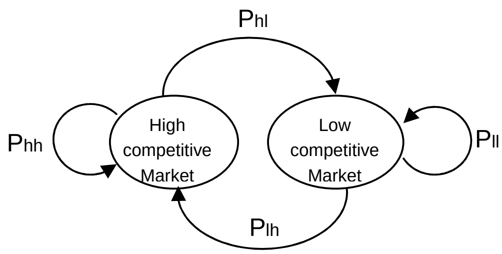

Figure 8. Market Competition Transition Diagram

6. In this numerical example session, there are three levels of support or investment that the company can make: $A_s = \{a_1, a_2, a_3\}$. This can be extended to other types of actions.

5.2 Result Analysis

In the computation experiments, we implement three scenarios: normal case, higher demand case and higher competition case. In the higher demand case, the total market demand is increased by 10% in May, June, November and December. In the higher competition case, the market competition index is increased by 20%.

We investigate the monthly decision throughout the year. Figure 9 shows the total market demand, company's investment on product combination and the corresponding expected discounted total profit. The left half is the scenario with market competition level L (MI_{Market} = 20) and the right half of the figure is the scenario with market competition level H (MI_{Market} = 30).

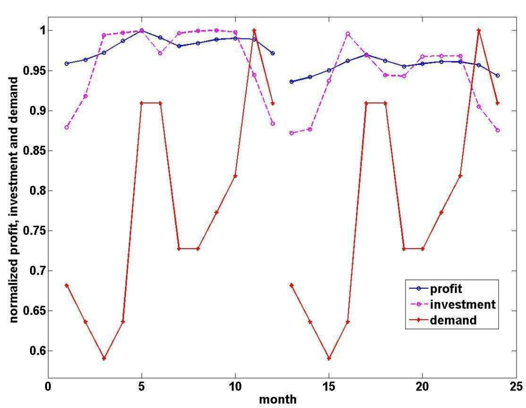

Figure 9. Profits, Investment and Demand

As we can see from the Figure 9, optimal decisions are usually far-sighted. The market demand is at its peak in May, June, November and December. Based on the model output, the big investment action should be taken in April and October in order to get the company ready for the coming high demand. If the company forecasts the high demand in June and provides high investment in June, the products typically do not have enough time to grow to maturity in order to meet the high demand.

In the numerical example, we find that when a product is at its decline phase, the company should consider providing low or no investment support. The company should just let the product evolve through its product lifecycle, since it may not be worthwhile to invest large amount of efforts for a declining product. Because of the capacity constraint of keeping *M* types of products in market, the company can make more profit out of products that are in their maturity phase.

When a product is at its end-of-life stage, the company should consider making a significant investment. The explanation is that since the company has the ability to maintain a certain amount (*M*) of products, it should utilize the capacity to the maximum in order to make more profits.

We also observe from the output that when a product is at its introduction phase, high support level is recommended. A company wants to keep products as close to maturity as possible, which means more profit can be made by the product. And when a product is at its maturity phase, the company may want to invest most as well. In this way, this product can remain in its maturity phase for a longer period of time.

6 CONCLUSIONS

In this paper, a Markov decision process is used to model sequential decision making throughout product lifecycle management.

Preliminary 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. In addition, research focus will be shifted to the end-of-life phase and effects of environmental regulations will be incoporated into the model formuation.

7 ACKNOWLEDGEMENTS

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