Reverse Logistics Design with Neural Networks

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INTRODUCTION

In recent years, because natural resources are running out rapidly, environmental protection by recovering value from product returns has become a major concern. The management of product returns is in the scope of Reverse Logistics (RL) which is one of the most important trends in sustainable economies. RL is defined by The European Working Group on Reverse Logistics (REVLOG) as the following (De Brito & Dekker, 2004): "The process of planning, implementing and controlling backward flows of raw materials, in process inventory, packaging and finished goods, from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal".

The successful fulfillment of that process has a hard nature because there is high uncertainty in quantity, quality and time of product returns. This situation makes development of processes complicated. It becomes important to know how to define data, and reveal the linkages between them in order to get desirable forecasting results. An effective forecasting system could decrease uncertainty and give chance to decision makers have more realistic future directions by evaluating the results. With this study, it is aimed to contribute the RL literature by proposing a hybrid MILP optimization model that is integrated with a return forecasting system developed by using ANN. Consequently, a hybrid model is developed decreasing uncertainty on product return, with a multiechelon, multiproduct, capacity constrained, cost minimization model. This study differs from other RLND models in that it focuses on optimization of RL network integrating with product return amount forecasting by using ANN. In the view of these goals, the rest of paper is organized as follows: first, the methodology of the study which has two main phases: decision making approach and optimization model is described. Then, the application is conducted by using the data of a recycling firm. The study is concluded with sensitivity analysis and suggestions for future research.

BACKGROUND

To the best of our knowledge, the number of RL studies that has a comprehensive forecasting methodology on product return amount is low because of RL's complicated structure. Kelle and Silver (1989), Hess and Mayhew (1997), Gomez et al. (2002), Toktay et al. (2004), Hanafi et al. (2007), Klausner and Hendrickson (2000), Guide and Van Wassenhove (2001) analyse product return processes. The drawback of these studies is that they are mostly taking a few factors into consideration at forecasting process. In a successful forecasting method, an extended factor set should be taken into consideration. The factors that are compiled from European Union legal regulation on e-wastes (WEEE Directive), different studies in the RL literature and negotiations with managers could be classified into two main categories: macro and micro factors (as seen in Table 1).

On the other side, a quick look at RLND literature reveals that the main topics range from

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Table 1. Main factors affecting return amount

Micro Factors	**Firm Based**	-Firm strategy (Mukhopadhyay & Setoputro, 2004; Klausner & Hendrickson, 2000) -Advertisements (Klausner & Hendrickson, 2000) -Giving information to customers (Hess & Mayhew, 1997) -Ability of firms to repair products (Thierry et al., 1999) -Warranty period (Thierry et al., 1999) -Take-back price (Klausner & Hendrickson, 2000; Guide & Van Wassenhove, 2001)
	Product Based	-Product category and type (Hess & Mayhew, 1997; Rogers & Tibben-Lembke, 1999) -Life cycle point of product (Tibben-Lembke, 2002) -Complexity of product modularity (Östlin et al., 2009) -Seasonality of product (Tibben-Lembke, 2002) -Easiness of product returns (Klausner & Hendrickson, 2000) -Product price (Hess & Mayhew, 1997) -Economic life of product (Östlin et al., 2009) -Sales amount (Gomez et al., 2002; Tibben-Lembke, 2002) -Rate of defects (Gomez et al., 2002) -E-waste quantity (Managers)
Macro Factors	**Governmental**	-Legal enforcement (Koster et al., 2002) -Investment on environment (Managers)
	Socioeconomic	-Customer segment (De Brito, 2004) -Education level (WEEE Directive) -Population density (WEEE Directive; Hanafi et al., 2007) -Income (WEEE Directive)

strategic decisions to operational decisions. As Dekker et al. (2004) state, RLND is one of important topics in RL research area. One of the main issues in RL is to define the best locations for WEEE recycling centers (Queiruga et al., 2008). There are many operations research models generated by researchers for obtaining optimal solution under specific objectives and constraints (Spengler et al., 1997; Krikke et al., 1999; Fandel & Stammen, 2004; Listeş, 2007; Sasikumar et al., 2010; etc.). The researchers mostly assume that all inputs and all relationships of the model are known with certainty. In the literature, uncertainty is commonly considered by scenario analysis in the mixed integer network design (Dekker et al., 2004) or by some stochastic programming models but there is lack of hybrid studies regarding forecasting system development.

MAIN FOCUS

The proposed hybrid model includes facility location selection problem and comprises of two main phases: “decision making approach” to develop a forecasting system belongs to historical data and “optimization model” to propose a mathematical model that decides on opening the collection and recycling centers by aiming the minimization of the total cost. The proposed approach can be used as an analytical decision making tool that helps to increase business performance of the actors in RL such as infacility location problem as a strategic planning decision.

Decision Making Approach Phase

Because studies using neural network systems outperform traditional statistical methods in

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