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Identification of Potential Recovery Facilities for Designing a Reverse Supply Chain Network Using Physical Programming

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ABSTRACT

Although there are many quantitative models in the literature to design a reverse supply chain, every model assumes that all the recovery facilities that are engaged in the supply chain have enough potential to efficiently re-process the incoming used products. Motivated by the risk of re-processing used products in facilities of insufficient potentiality, this paper proposes a method to identify potential facilities in a set of candidate recovery facilities operating in a region where a reverse supply chain is to be established. In this paper, the problem is solved using a newly developed method called physical programming. The most significant advantage of using physical programming is that it allows a decision maker to express his preferences for values of criteria (for comparing the alternatives), not in the traditional form of weights but in terms of ranges of different degrees of desirability, such as ideal range, desirable range, highly desirable range, undesirable range, and unacceptable range. A numerical example is considered to illustrate the proposed method.

Keywords: Potential Recovery Facilities, Physical Programming, Reverse Logistics, Uncertainty, Decision-Making.

1. INTRODUCTION

A reverse supply chain can be defined as a series of activities required to retrieve a used product from a consumer and either recover its left-over market value or dispose it of (Figure 1). Besides environmental regulations and asset recovery, an important driver for companies to engage in a reverse supply chain is that many used products represent a resource for recoverable value [3], [4]. Though direct reuse is sometime practiced, remanufacturing and recycling are the major recovery options applied in the reverse supply chain. While this process is prevalent in European companies, it is still in its infancy in American companies. In the USA, cities and towns are responsible for retrieval of used electronic products, and properly disposing of the potentially environmentally dangerous and/or waste components (also called e-waste). Recently, there was a report [1] that in the State of Massachusetts (USA), support is building for a re-filed bill that would require manufacturers of electronic goods to pay for retrieval and recycling of their equipment. If passed, the statewide take-back program would be the first of its kind in the nation and would relieve cities and towns, which are bracing for local aid cuts, from the costs associated with retrieving and disposing of the e-waste. The bill's supporters say that cities and towns in the USA spend between \$6 million and \$21 million a year on such endeavors.

Implementation of any reverse supply chain network requires at least three parties: collection centers where consumers return used products, recovery facilities where re-processing (remanufacturing or recycling) is performed, and demand centers where customers buy re-processed products, *viz.*, outgoing products from recovery facilities.

There are many quantitative models in the literature to design a reverse supply chain (see [3] for a good review). However, every model assumes that all the recovery facilities that are engaged in the supply chain have enough potential to efficiently re-process the incoming used products. Motivated by the risk of re-processing used products in facilities of sufficient potentiality, the authors of this paper, in their previous works (see [6], [7]), proposed approaches that employ

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Analytic Hierarchy Process (AHP) [8] and Charnes-Cooper-Rhodes (CCR) model [2], to identify potential facilities in a set of candidate recovery facilities operating in a region where a reverse supply chain is planned to be established. In this paper, an attempt is made to solve the problem using a newly developed method called physical programming [5]. The most significant advantage of using physical programming is that it allows a decision maker to express his preferences for values of criteria (for comparing the alternatives), not in the traditional form of weights but in terms of ranges of different degrees of desirability.



Figure 1. A Generic Reverse Supply Chain Network

For the convenience of reader, we first introduce the physical programming method in the next section. In Section 3, we present the criteria that we consider in our physical programming approach, to identify potential recovery facilities. Section 4 presents a numerical example to demonstrate the approach and Section 5 gives some conclusions.

2. PHYSICAL PROGRAMMING

In the physical programming (PP) method, four distinct classes (1S, 2S, 3S, and 4S) are used to allow the decision maker to expresses his preferences for the value of each criterion in a more detailed, quantitative, and qualitative way than when using a weight-based method like Analytic Hierarchy Process [8]. These classes are defined as follows: smaller-isbetter (1S), larger-is-better (2S), value-is-better (3S), and range-is-better (4S) [5]. Figure 2 depicts these different classes. The value of the *p*-th criterion, g_p , for evaluating the alternative of interest, is categorized according to the preference ranges shown on the horizontal axis. Consider, for example, the case of Class 1S. The preference ranges are:

Ideal range	$g_p \leq t_{p1}^+$
Desirable range	$t_{p1}^+ \le g_p \le t_{p2}^+$
Tolerable range	$t_{p2}^+ \le g_p \le t_{p3}^+$
Undesirable range	$t_{p3}^+ \le g_p \le t_{p4}^+$
Highly Undesirable range	$t_{p4}^+ \le g_p \le t_{p5}^+$
Unacceptable range	$g_p \ge t_{p5}^+$

The quantities t_{p1}^+ through t_{p5}^+ represent the physically meaningful values that quantify the preference associated with the *p*-th generic criterion. Consider, for example, the cost criterion for Class 1S. The decision-maker could specify a preference vector by identifying t_{p1}^+ through t_{p5}^+ in dollars as (10 20 30 40 50). Thus, an alternative having a cost of \$15 would lie in the Desirable range, an alternative with a cost of \$45 would lie in the Highly Undesirable range, and so on. We can accomplish this for a non-numerical criterion too, such as color, by: (i) specifying a numerical preference structure and (ii) quantitatively assigning each alternative a specific criterion value from within a preference range (e.g., Desirable, Tolerable). The class function, Z_p , on the vertical axis in Figure 2, is used to map the criterion value, g_p , into a real, positive, and dimensionless parameter (Z_p is, in fact, a piecewise linear function of g_p). Such a mapping ensures that different criteria values, with different physical meanings, are mapped to a common scale. Consider Class 1S again. If the value of a criterion, g_p , is in the Ideal range, then the value of the class function is small (in fact, zero), while if the value of the criterion is greater than t_{p5}^+ , that is, in the Unacceptable range, then the value of the class function is very high. Class functions have several important properties such as: (i) they are non-negative, continuous, piecewise linear, and convex, and (ii) the value of the class function, Z_p , at a given range intersection (say, *Desirable-Tolerable*) is the same for all class types.



Figure 2. Class Functions for Physical Programming

Basically, ranking the alternatives is performed in four steps, as follows:

Step 1 - Identify criteria for evaluating each of the alternatives (In the next section, we present some important criteria that we consider in our physical programming approach to evaluate the candidate recovery facilities).

Step 2 - Specify preferences for each criterion, based on one of the four classes (see Figure 2).

Step 3 - Calculate incremental weights: Based on the preference structures for the different criteria, the PP weight algorithm (see [5]) determines incremental weights, Δw_{pr}^+ and Δw_{pr}^- (used in Step 4) that represent the incremental slopes of the class functions, Z_p . Here, *r* denotes the range intersection.

Step 4 - Calculate total score for each alternative: The formula for the total score, J, of the alternative of interest is constructed as a weighted sum of deviations over all ranges (r = 2 to 5) and criteria (p = 1 to P), as follows:

$$J = \sum_{p=1}^{P} \sum_{r=2}^{5} \left(\Delta w_{pr}^{-} d_{pr}^{-} + \Delta w_{pr}^{+} d_{pr}^{+} \right)$$
(1)

where J represents the total score of the alternative of interest, P represents the number of criteria governing the evaluation, Δw_{pr}^+ and Δw_{pr}^- are the incremental weights for the p-th criterion, and d_{pr}^+ and d_{pr}^- represent the deviations of the p-th criterion value of the alternative of interest from the corresponding target values. An alternative with a lower total score is more desirable than one with a higher total score.

The most significant advantage of using PP is that no weights need to be specified. The decision maker only needs to specify a preference structure for each criterion, which has more physical meaning than a physically meaningless weight that is arbitrarily assigned to the criterion.

3. IMPORTANT CRITERIA FOR EVALUATION OF RECOVERY FACILITIES

In this section, we present only some important criteria that we consider in our physical programming approach, to evaluate the candidate recovery facilities.

3.1. Nomenclature

- C_v inventory (space) cost at recovery facility *v*;
- CS_v customer service rating of recovery facility v;
- DT_{v} average disassembly time of products supplied to recovery facility v;
- *p_i i*-th criterion for evaluation of candidate recovery facilities
- F_v fixed cost of recovery facility *v*;
- IT_{uv} transit time between collection center *u* and recovery facility *v*;
- *K* transportation cost per unit time;
- L_v labor cost at location of recovery facility v;
- OT_{vw} transit time between recovery facility v and demand center w;
- QI_v average quality of products supplied to recovery facility *v*;
- QO_v average quality of outgoing products from recovery facility *v*;
- SU_v supply to recovery facility *v*;
- TP_v throughput of recovery facility *v*;
- *u* collection center;
- v recovery facility;
- w demand center.

3.2. Criteria for evaluation of recovery facilities

Class 1S criteria (smaller-is-better)

We consider the cost of transportation of goods (used as well as re-processed), the cost of labor, the inventory cost, and the fixed cost, to calculate the total cost incurred by a recovery facility. Thus,

$$p_1 = \text{cost incurred by the recovery facility } v = \sum_u (IT_{uv})(K) + \sum_w (OT_{vw})(K) + L_v + C_v + F_v;$$
(2)

Class 2S criteria (larger-is-better)

Unlike in the production of new products, components of incoming end-of-life products of even the same type in the reprocessing function are likely to be of varied quality (worn-out, low performing, etc). Though the average quality of reprocessed goods (QO) is a criterion that can evaluate a recovery facility, it is not justified to use QO as an independent criterion for evaluation because QO depends on average quality of incoming products (QI). However, QI must not be taken as an independent criterion too because it cannot evaluate the recovery facilities. So, the idea is to take the difference between QO and QI as a criterion for evaluation. Thus,

$$p_2 =$$
 Increment in quality of products at recovery facility $v = (QO_v - QI_v);$ (3)

The only driver to produce new products is their demand. Thus, if there is a low demand for them, the production is low. However, this is not the case in re-processing where even if there is a low supply (and/or a low demand) of end-of-life products (SU), reverse flow must be administered due to environmental regulations. In supply-driven cases like these, it is unfair to judge a recovery facility without considering SU. Though throughput of re-processed products (TP) is a criterion that can evaluate a recovery facility, it is not justified to use TP as an independent criterion because TP depends on SU. However, SU must not be taken as an independent criterion too because it cannot evaluate the recovery facility. Furthermore, a low SU might lead to a low TP and a high SU might lead to a high TP. So, the idea is to take (TP)/(SU) as a criterion for evaluation. Thus, we compensate for the effect of a low TP by dividing TP with a possibly low SU, in order not to underestimate the recovery facility under consideration. Similarly, we dampen the effect of a high TP by dividing TP with a possibly high SU, in order not to overestimate the recovery facility under consideration. Thus,

$$p_3 = (TP_\nu / SU_\nu); \tag{4}$$

Disassembly time (DT) is not exactly the inverse of TP because TP takes into account the whole re-processing (disassembly plus recovery) time. Unlike in the production of new products, components of incoming end-of-life products in the re-processing facility are likely to be deformed and/or broken and/or different in number even for the same type of products. Hence, products of the same type might have different re-processing times, unlike in the production of new products where manufacturing time and assembly time are pre-determined and equal for products of the same type. Since TP of a recovery facility depends upon DT, it is unfair to not consider DT for the evaluation. However, DT must not be taken as an independent criterion because it cannot evaluate the recovery facilities. Furthermore, a high DT might lead to a low TP and a low DT might lead to a high TP. So, the idea is to take (TP)(DT) as a criterion for evaluation. Thus, we compensate for the effect of a low TP by multiplying TP with a possibly high DT, in order not to overestimate the recovery facility under consideration. Similarly, we dampen the effect of a high TP by multiplying TP with a possibly low DT, in order not to overestimate the recovery facility under consideration. Thus,

$$p_4 = (TP_v)(DT_v);$$

CS basically gives an idea about how well a recovery facility is:

- Giving incentives to the collection centers supplying end-of-life products.
- Giving incentives to the customers buying re-processed goods.
- Utilizing incentives provided by the government.
- Meeting environmental regulations laid by the government.

(5)

Note that the term 'customer service' is used here because, in our opinion, any beneficiary is a customer, be it the government or the collection center or the actual customer buying re-processed goods.

(6)

 p_5 = Customer service rating of recovery facility $v = CS_v$;

4. NUMERICAL EXAMPLE

In our example, we evaluate three candidate recovery facilities (A, B and C) using the PP method, and rank them to identify the potential ones.

Table 1 shows the target values for each criterion detailed in Section 3. Table 2 shows the criteria values for each recovery facility. Table 3 shows the incremental weights obtained by using the PP weight algorithm (see [5]). Tables 4, 5 and 6 show the deviations of criteria values from the target values, for facilities A, B and C respectively. Table 7 shows the total scores and ranks of the recovery facilities, obtained using the PP method. It is obvious from Table 7 that C is the most desirable facility and A is the least desirable facility. If the decision maker has a cut-off limit of say, 90, he will identify facilities C and B as potential ones.

Criterion	$t_{p1}+$	$t_{p2}+$	$t_{p3}+$	t_{p4} +	$t_{p5}+$
p_1	10	15	25	30	45
	<i>t</i> _{p1} -	<i>t</i> _{p2} -	<i>t</i> _{p3} -	<i>t</i> _{p4} -	<i>t</i> _{<i>p</i>5} -
p ₂	0.6	0.4	0.3	0.2	0
<i>p</i> ₃	1.1	0.9	0.7	0.6	0.4
<i>p</i> ₄	250	200	140	120	100
<i>p</i> ₅	10	7	6	4	3

Table 1. Preference table

Table 2. Criteria values for each recovery facility

Criterion	Facility A	Facility B	Facility C
p_1	22	30	15
<i>p</i> ₂	0.4	0.3	0.1
<i>p</i> ₃	0.5	0.8	0.5
<i>p</i> ₄	200	220	145
<i>p</i> ₅	8	6	4

Table 3. Output of the PP Weight Algorithm (see [5])

Criterion	$w_{p2}+$	$w_{p3} +$	$w_{p4}+$	$w_{p5}+$	W_{p2} -	<i>W</i> _{p3} -	<i>w</i> _{p4} -	<i>W</i> _{<i>p</i>5} -
p_1	0.02	0.044	0.484	0.568	-	-	-	-
p_2	-	-	-	-	0.5	4.4	19.36	42.59
<i>p</i> ₃	-	-	-	-	0.5	2.2	19.36	42.59
<i>p</i> ₄	-	-	-	-	0.002	0.007	0.097	0.4259
p 5	-	-	-	-	0.033	0.44	0.968	8.518

Criterion	<i>r</i> =2	r=3	<i>r</i> =4	r=5
<i>p</i> ₁	$d_{12} + = 12$	$d_{13} + = 7$	$d_{14} + = 3$	$d_{15} + = 8$
<i>p</i> ₂	$d_{22} = 0.2$	$d_{23} = 0$	$d_{24} = 0.1$	$d_{25} = 0.2$
<i>p</i> ₃	$d_{32} = 0.6$	d_{33} -= 0.4	$d_{34} = 0.2$	$d_{35} = 0.1$
<i>p</i> ₄	$d_{42} = 50$	$d_{43} - = 0$	$d_{44} = 60$	$d_{45} = 80$
p 5	$d_{52} = 2$	$d_{53} = 1$	$d_{54} = 2$	$d_{55} = 4$

Table 4. Deviations of criteria values of recovery facility-A from target values

Table 5	5. Deviations	of criteria	values of	recoverv	facility-B	from targe	t values

Criterion	r=2	r=3	<i>r</i> =4	<i>r</i> =5
<i>p</i> ₁	$d_{12} + = 20$	$d_{13} + = 15$	$d_{14} + = 5$	$d_{15} + = 0$
<i>p</i> ₂	$d_{22} = 0.3$	d_{23} -= 0.1	$d_{24} = 0$	$d_{25} = 0.1$
<i>p</i> ₃	$d_{32} = 0.3$	d_{33} -= 0.1	$d_{34} = 0.1$	$d_{35} = 0.2$
<i>p</i> ₄	$d_{42} = 30$	d_{43} -= 20	d_{44} - = 80	$d_{45} = 100$
<i>p</i> ₅	$d_{52} = 4$	$d_{53} = 1$	$d_{54} = 0$	$d_{55} = 2$

Table 6. Deviations of criteria values of recovery facility-C from target values

Criterion	<i>r</i> =2	<i>r</i> =3	<i>r</i> =4	<i>r</i> =5
<i>p</i> ₁	$d_{12} + = 5$	$d_{13} + = 0$	$d_{14} + = 10$	$d_{15} + = 15$
p_2	$d_{22} = 0.5$	$d_{23} = 0.3$	$d_{24} = 0.2$	$d_{25} = 0.1$
<i>p</i> ₃	$d_{32} = 0.6$	d_{33} -= 0.4	$d_{34} = 0.2$	$d_{35} = 0.1$
<i>p</i> ₄	d_{42} - = 105	d_{43} - = 55	$d_{44} = 5$	$d_{45} = 25$
<i>p</i> ₅	$d_{52} = 6$	$d_{53} = 3$	$d_{54} = 2$	$d_{55} = 0$

Table 7. Total scores and ranks of recovery facilities

Recovery facility	Total score	Rank
Α	102.92	III
В	87.31	II
С	47.65	Ι

5. CONCLUSIONS

Every model in the literature, which designs a reverse supply chain, assumes that all the recovery facilities that are engaged in the supply chain have enough potential to efficiently re-process the incoming used products. Motivated by the obvious risk, in this paper, we proposed a physical programming approach to identify potential recovery facilities in a region where a reverse supply chain is to be established. The most significant advantage of using physical programming is that it allows a decision maker to express his preferences for values of criteria (for comparing the

alternatives), not in the traditional form of weights but in terms of ranges of different degrees of desirability. A numerical example demonstrated the feasibility of the approach.

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