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Maximizing Recyclability and Reuse of Tertiary Packaging in Production and Distribution network

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Abstract

Tertiary packaging is necessary for transportation in any production and distribution network because of the benefits in enhancing the logistics efficiency. However, in the meantime, it produces a lot of packaging waste every day. In fact, some tertiary packaging after transportation may still be in good condition and can be collected back for reuse. However, this has not been widely studied in the existing literature. The purpose of this research is to fulfill this research gap. Accordingly, the contribution of this paper is to propose a new optimization methodology, named modified Genetic Algorithm with Crossing Date heuristic, to maximize the collection of used tertiary packaging for reuse, meanwhile minimize the total operating cost by taking the advantages of simultaneous optimization of a multi-day planning. From the numerical experiments, it is found that the optimization ability of proposed new optimization methodology outperform the traditional genetic algorithm by a maximum of about 10%. In addition, the total operating cost is found can be reduced by using the proposed multi-day planning approach.

Keywords:

Recycle and Reuse, Tertiary Packaging, Production and Distribution, Genetic Algorithm, Logistics Network

1. Introduction

Recycling of packaging waste can directly reduce the consumption of raw materials. Meanwhile it can minimize the demand on landfill and land pollutions. Earlier before the issue of the Directive 94/62/EC on Packaging and Packaging Waste (PPW) in 1994, many research studies have already working on the minimization of packaging usage and more importantly, is the maximization of recycling of packaging. By that time, the focus was mainly on taxation approach (Pearce and Turner, 1992; Rousso and Shah, 1994). Nowadays, the research focus is shifting from the legislation point of view onto the economic and financial benefits that can be obtained (Cruz et al., 2012).

In general, a packaging system consists of three main parts knowns as primary, secondary, and tertiary packaging (Palsson and Hellström, 2016). Primary packaging is regarded as the first envelop to protect directly the product. Secondary packaging is used to protect the primary packaging. Lastly, tertiary packaging is used for bulk handling in warehousing, and transportation. Tertiary packaging will affect the logistics efficiency in supply chains and induce different requirements on the handling equipment, vehicles, etc. (Jahre and Hatteland, 2004). In a typical production and distribution network, products will usually be sent from the source points with large batch size into different transit points, known as Distribution Centers (DC), for further dispatching in smaller sizes to the demand points. Accordingly, products will usually be packed with different tertiary packaging, such as plastic films, polystyrene foam, carton box, net, rope, etc. in order to reduce damages and tight different products together for the ease of handling.

In reality, DCs are usually designed with different configurations and equipped with different handling equipment to serve and handle different product types (Baker and Canessa, 2009). As a result, different products to be handled may induce different handling cost, handling lead time, and efficiency (Gaiardelli et al., 2007). Although in literature, the factor of different DCs possessing different recyclability in handling different product types has been considered (Chung et al., 2013), the optimization methodology is usually designed to maximize the return on each individual planning day alone, and lack of the consideration of the interrelationship between the demands on different planning days. However, in practice, planning horizon is usually in multiple planning days, which is in fact given sufficient data to determine a better global solution. However, the difficulty is the much higher problem complexity it induced. For this reason, a more powerful optimization methodology is required. Accordingly, the research question here is how to allocate the orders from different source points to different DCs with the aim of minimizing the total operating cost and maximizing the reuse of tertiary packages in a long run.

In this connection, the main academic contribution of this paper is to propose a new optimization methodology, named modified Genetic Algorithm with Crossing Date heuristic, in this research area to solve this complicated problem. In addition, the proposed methodology bring some practical contributions to environment and logistic companies by maximizing the reuse of tertiary packaging during the transportation, meanwhile minimizing the total operating cost. This paper is divided into the following sections. Section 2.0 gives a literature review of the recent works in the field. Section 3.0 describes the problem to be studied. Section 4.0 presents the proposed optimization approach named modified genetic algorithm with crossing date approach. Section 5.0 discusses the resulting and findings, and lastly will be concluded by a conclusion.

2. Literature Review

In general, optimization of the recycling and reuse of items in production and distribution network will usually involve the simultaneous planning of both the forward and reverse flow of the items. In which, many of them focus on designing an optimal transportation route, facility location and allocation, etc. (Ozceylan and Paksoy, 2013). Recently, Agrawal et al. (2015) gave a very detail literature review on reverse logistics.

Practical applications of production and distribution network in recycling and reuse of products can be easily found in many literatures. For example, Krikke et al. (2003) studied the recyclability and the design of the logistics network structure for electronic home appliances products (refrigerators). Jayaraman (2006) studied a remanufacturing model of mobile phone. They considered the recycling and remanufacturing of several core components, and proposed a Remanufacturing Aggregate Production Planning approach to minimize various costs including inventory, dissembles, and remanufacturing. Olugu and Wong (2012) proposed a fuzzy rule based system to measure the green supply chain management performance of automotive industry.

Other than recycling and reuse of products or components, there are many papers specially focusing on the recycling of plastic related items. For example, Kartalis et al. (2000) studied the recycling of post-used polyethylene packaging film and their possibility of being reuse. Gomes et al. (2008) also studied the recycling of plastic waste initiated by the huge consumption of plastic in Brazil with an estimation of 1150 thousand tons per year. Lee and Lee (2012) studied to determine the optimal delivery route for the reuse of plastic bottle for distilling water. They proposed a multi-criteria decision support system to support recycling decisions. Bing et al., (2015) carried out a feasibility study of redesigning a reverse supply chain for household waste, which distributed from Europe to China under the emission trading scheme. However, there are not many papers studying in the recycling and reuse of territory packaging.

Optimization methodologies applied in solving the production and distribution network problems in recycling and reuse can generally be classified into two main approaches, i) Linear Programming, and ii) Meta-heuristic. Regarding linear programming, earlier in 1996, BloemhofRuwaard et al., (1996) applied linear programming to test the benefits of different the recycling strategies that may be obtained in pulp and paper sector. Krikke et al., (1999) applied Mixed Integer Linear Programming approach to minimize the total operating cost for recycling and discard of products for Original Equipment Manufacturers under the producer responsibility. Shih (2001) also applied Mixed Integer Programming to optimize the infrastructure design and the reverse network flow of a recycling network. Pati et al., (2008) applied Mixed Integer Goal Programming to optimize the paper recycling network in India. Demirel and Gokcen (2008) proposed a Mixed Integer Programming to optimize the production and transportation quantities of manufactured and remanufactured products for reuse. Ozceylan and Paksoy (2013) applied Mixed Integer Programming to optimize the transportation flow, location of factories, and retailers of a recycling and reuse network with multi-products multi-periods. Recently, Demirel et al., (2016) proposed a Mixed Integer Programming to determine the reverse flow for end-of-life vehicles in Turkey.

It is obvious that many papers have applied Linear Programming to deal with their problem. However, because of the problem complexity, applications of Linear Programming in some cases may become more difficult or sometimes even impossible (Banaszewski et al., 2013). Accordingly, there are many papers proposing different heuristic / meta-heuristics / approximation approaches. For example, Chouinard et al., (2008) applied Monte Carlo sampling methods to deal with a randomness rising from the quantities of recovery items, processing, and demand. Schweiger and Sahamie (2013) proposed a hybrid Tabu search approach to design the recycling network, which consists of external procurement, and in-house recycling of paper. Kannan et al., (2009) applied Particle Swarm Optimization approach and Genetic Algorithm (GA) to solve the recycling network with forward and reverse flow. Later on, Kannan et al., (2010) constructed a Mixed Integer Linear Programming modeling for a battery recycling network, however, due to the problem complexity, they proposed Genetic Algorithms to solve the model. In fact, Genetic Algorithms (GA) has been widely used in solving this kind of problem, and is recognized to be a very promising approach. Wang and Hsu (2010) also constructed an Integer Linear Programming model to model the recycling, reuse, and recovery of a green supply chain, but proposed a revised spanning-tree based GA to deal with the problem. Tuzkaya et al., (2011) proposed a GA with ANP-fuzzy

TOPSIS methodology to design the recycling and reuse network for the white goods industry in Turkey. Accordingly, in this paper, the proposed optimization methodology will also be developed based on GA.

3. Model Description

Set

S set of source points

D set of demand points

$\emptyset$ set of DCs

I set of Items

φ set of Days

Index

s no. of source points, *s* = 1, 2, …, **S**

i no. of Item types, *i* = 1, 2, …, **I**

j no. of demand points, *j* = 1, 2, …, **D**

k no. of DCs, *k* = 1, 2, …, $\emptyset$

d no of days, *d* = 1, 2, …, φ

Parameter

q_{ijd} demand quantity of item *i* at demand point *j* on day *d*.

c_k maximum handling capacity of DC *k*.

p_s maximum production capacity of source point *s*.

r_{ik} recycle rate of item type *i* at DC *k*.

$c_{sk}^{S\emptyset}$ travelling cost between source point *s* to DC *k*.

c_{ik}^{H} handling cost of item type *i* at DC *k*.

c_s^{I} storage unit cost of collected packaging at source point *s*.

$c_{kj}^{\emptyset D}$ travelling cost between DC *k* to demand point *j*.

Variable

σ_{isd} quantity of collected packaging of item *i* to be sent back to source point *s* on day *d*.

y_{isd} quantity of unused packaging for item *i* to be stored at source point *s* on day *d*.

Decision Variable

x_{iskjd} =1, if the item type *i* is supplied by source point *s* transited through DC *k* to demand point *j* on day *d*, otherwise = 0.

The distribution network studied is shown as in Fig. 1. It consists of source points (**S**), distribution centers (∅), and demand points (**D**). The demand of each item type *i* at each demand point *j* is supplied by only one source point through only one distribution center. The demand quantity (q_{ijd}) for different types of item *i* at each demand point *j* is different along the planning horizon *d*. For the reason of batch delivery, items will usually be further packaged by using various simply packaging, such as carton box, plastic wrap, foam box, etc. for the ease of transport and protection in practice. Each source point *s* and each DC *k* has its maximum production (p_s) and handling capacity (c_k). Moreover, the skills of labor in each DC *k* on handling different types of items are varied. Therefore, the handling cost (c_{ik}^H) and the rate of collecting the packaging back for reuse (r_{ik}) is varied. In this model, the collected packaging for the items will be sent back to the source point during the return of the trip. Therefore, no extra transportation will be considered. However, if the collected packaging will not be reused on the next day, storage cost (c_s^I) will be induced. In addition, demand splitting is not being considered.

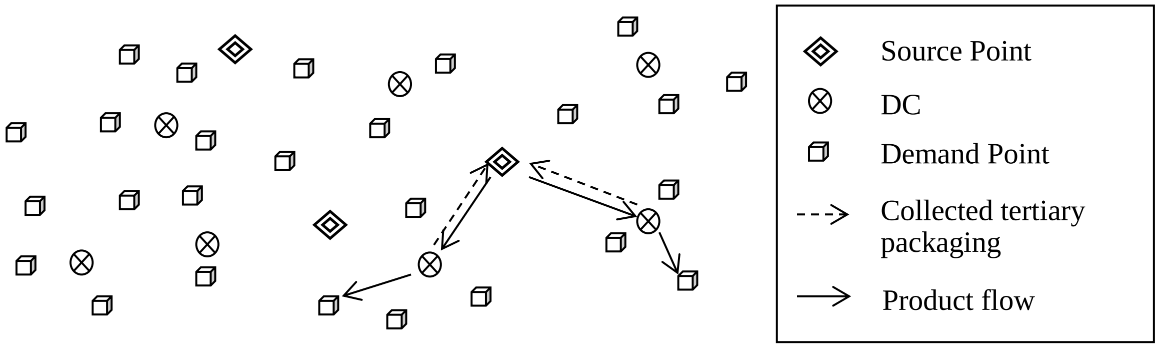

Fig 1. Outline of the distribution network model

The objective of the system is to minimize the total operating cost and maximize the total quantity of packaging being collected at DCs for reuse as shown in Equation (1). Among which, Z_1 is the total operating cost consisting of the total traveling cost from source points to DCs, total handling cost at DCs, total traveling cost from DCs to demand points, and total storage cost for collected packaging as shown in Equation (2). Z_2 is total quantity of packaging being collected at DCs for reuse as shown in Equation (3). Z_1' and Z_2' are used to normalize the total operating cost and total quantity of reused items. They can be the best known (or optimal) solution obtained by the optimization of only Z_1 and Z_2 as objective function respectively.

$$\textbf{Min } Z = \alpha(Z_1/Z_1') + (1-\alpha)(Z_2'/Z_2) \tag{1}$$

$$Z_1 = \sum_{i\in I}\sum_{s\in S}\sum_{k\in\emptyset}\sum_{j\in J}\sum_{d\in\varphi} x_{iskjd}\left(c_{sk}^{S\emptyset} + c_{ik}^{H} + c_{kj}^{\emptyset D}\right) + \sum_{i\in I}\sum_{s\in S}\sum_{d\in\varphi} y_{isd}(c_s^I) \tag{2}$$

$$Z_2 = \sum_{i\in I}\sum_{s\in S}\sum_{d\in\varphi} \sigma_{isd} \tag{3}$$

, where $y_{isd} = \max\left\{\left[\sum_{k\in\emptyset}\sum_{j\in J}(x_{iskjd}q_{ijd}) - \sigma_{is(d-1)} - y_{is(d-1)}\right],0\right\}$

,where $\sigma_{isd} = \sum_{k\in\emptyset}\sum_{j\in J} x_{iskjd}q_{ijd}r_{ik}$.

s.t.

Network flow constraints:

$$\sum_{s\in S}\sum_{k\in\emptyset}\sum_{j\in J} x_{iskjd} = 1 \qquad \forall i \in I,\ \forall d \in \varphi \tag{4}$$

Constraints (4) ensure each demand will be supplied by exactly one source point and transit through only one single DC.

Capacity constraints:

$$\sum_{i\in I}\sum_{k\in\emptyset}\sum_{j\in J}(x_{iskjd}q_{ijd}) - p_s \le 0 \qquad \forall s \in S,\ \forall d \in \varphi \tag{5}$$

$$\sum_{i\in I}\sum_{s\in S}\sum_{j\in J}\left(x_{iskjd}q_{ijd}\right) - c_k \le 0 \qquad \forall k \in \emptyset,\ \forall d \in \varphi \tag{6}$$

Constraints (5) ensure the items supplied by source point *s* will not exceed the maximum production capacity of the source point. Constraints (6) ensure the items passing through the DC will not over the handling capacity of the DC.

4. Modified Genetic Algorithm with Crossing Day Effect Heuristic Approach

The decision in this problem is to determine the flow of the supply of items to demand points by passing through which DC. In addition, this paper aims to maximize the collection of packaging for reuse meanwhile minimizing the storage cost of the reused packaging induced due to not being used. As the demands of items at demand points along the planning days are different. Therefore, this characteristic is modeled in the encoding of the chromosome. Accordingly, a new encoding of chromosome is designed as follows.

Encoding and Decoding of Chromosome

The chromosome consists of $D \times J \times I$ number of genes as shown in Fig. 1. Each gene consists of two values, representing i) the source point with value (1 to S), and ii) the DC (1 to $\emptyset$). Accordingly, the first gene with value of (4,2) in the chromosome value row represents that the Item 1 at Demand Point 1 will be supplied by Source Point 4 via DC 2. If there is no demand for a particular item at the demand point, a "-" will be given, such as Item 1 at Demand Point 2 on Day 1.

Chromosome *n*

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**4,2**	**3,1**	…	**3,3**	**-**	**-**	…	**2,3**	…	**4,4**	**1,2**	…	**-**
…	…												
…	…												
…	…												
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,2**	**-**	…	**3,4**	**5,2**	**2,1**	…	**1,3**	…	**3,5**	**4,2**	…	**-**

Fig 2. A sample of chromosome encoding

Traditional Uniform Crossover Operation

Two types of crossover mechanism are applied. The first type is traditional uniform crossover, in which a predefined number of chromosomes are randomly selected for crossover from the same Day *d*, which is also randomly selected. The reason of not selecting genes from different days is to avoid too random search. Fig. 3 shows an example of crossover mechanism, in which two values are being selected from Parents A and B at the same position for crossover. After crossover, validation will be carried out to avoid invalid chromosome, which will be explained in later part.

Proposed Crossing Date Crossover Operation

The second type of crossover mechanism is a newly proposed Crossing Date Crossover heuristic approach. The idea is to increase the genetic searching ability by retaining the crossover structure and characteristic of the chromosome related to a particular demand point and item type along the planning days. This can avoid random search. First of all, a day is randomly being selected as the starting date. Accordingly, the starting date does not necessary to be the first day. Then, a demand point and an item type are being selected to define the section for crossover. For example in Fig. 4, assuming Day 1, Demand Point 1, and Item I are randomly being selected.

Parent *A*

Day	1												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	4,2	3,1	…	3,3	-	-	…	2,3	…	4,4	1,2	…	-
…	…												
Day	D												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	2,2	-	…	3,4	5,2	2,1	…	1,3	…	3,5	4,2	…	-

Parent *B*

Day	1												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	2,1	4,2	…	2,4	-	-	…	1,3	…	2,2	3,1	…	-
…	…												
Day	D												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	1,1	-	…	1,3	2,1	3,2	…	3,2	…	2,4	2,3	…	-

Offspring *A*

Day	1												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	4,2	3,1	…	2,4	-	-	…	2,3	…	4,4	3,1	…	-
…	…												
Day	D												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	2,2	-	…	3,4	5,2	2,1	…	1,3	…	3,5	4,2	…	-

Offspring *B*

Day	1												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	2,1	4,2	…	3,3	-	-	…	1,3	…	2,2	1,2	…	-
…	…												
Day	D												
Demand Points	1				2				…	J			
Item	1	2	…	I	1	2	…	I	…	1	2	…	I
Chromosome value	1,1	-	…	1,3	2,1	3,2	…	3,2	…	2,4	2,3	…	-

Fig. 3. Sample crossover of uniform crossover operation

Parent *A*

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**4,2**	**3,1**	…	**3,3**	**-**	**-**	…	**2,3**	…	**4,4**	**1,2**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,2**	**-**	…	**3,4**	**5,2**	**2,1**	…	**1,3**	…	**3,5**	**4,2**	…	**-**

Parent *B*

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,1**	**4,2**	…	**2,4**	**-**	**-**	…	**1,3**	…	**2,2**	**3,1**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**1,1**	**-**	…	**1,3**	**2,1**	**3,2**	…	**3,2**	…	**2,4**	**2,3**	…	**-**

Offspring *A*

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**4,2**	**3,1**	…	**2,4**	**-**	**-**	…	**2,3**	…	**4,4**	**3,1**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,2**	**-**	…	**1,3**	**5,2**	**2,1**	…	**1,3**	…	**3,5**	**4,2**	…	**-**

Offspring *B*

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,1**	**4,2**	…	**3,3**	**-**	**-**	…	**1,3**	…	**2,2**	**1,2**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**1,1**	**-**	…	**3,4**	**2,1**	**3,2**	…	**3,2**	…	**2,4**	**2,3**	…	**-**

Fig 4. Sample crossover of Crossing Date Crossover Heuristic Approach

Traditional Uniform Mutation Operation

Two types of mutation will be applied. The first type is traditional uniform mutation operation. Similarly reason as in tradition uniform crossover, all the selected genes for mutation will be selected among the same day. Accordingly, a day will be randomly selected first. Then a predefined number of genes will be selected according to the mutation rate. The purpose is to prevent solution prematurity and increase solution diversity. In here, any selected gene will undergo mutation either in the value of source point or DC. For example as in Fig. 5, the gene with value (3,3) and (2,3) being selected are undergo mutation into (4,3) and (2,2) in the value of source point and DC respectively.

Parent A

Day	1														
Demand Points	1				2				…	**J**					
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**		
Chromosome value	**4,2**	**3,1**	…	**3,3**	**-**	**-**	…	**2,3**	…	**4,4**	**1,2**	…	**-**		
…	…														
Day	**D**														
Demand Points	1				2				…	**J**					
M Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**		
Chromosome value	**2,2**	**-**	…	**3,4**	**5,2**	**2,1**	…	**1,3**	…	**3,5**	**4,2**	…	**-**		

Offspring A

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**4,2**	**3,1**	…	**4,3**	**-**	**-**	…	**2,2**	…	**4,4**	**1,2**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,2**	**-**	…	**3,4**	**5,2**	**2,1**	…	**1,3**	…	**3,5**	**4,2**	…	**-**

Fig. 5. Sample mutation of uniform mutation operation

Proposed Crossing Date Mutation Operation

The second type of mutation operation is a newly proposed Crossing Date Mutation heuristic approach. The idea is to increase the chance of getting a better solution by reducing the storage cost of unused reuse packaging due to no demand being assigned for the item on the next few days. For this reason, this mutation is designed to reassign the randomly selected item to be supplied by the same source point for the rest of the planning days. Accordingly, first of all, a day will be randomly selected as the starting day. Similarly, the starting date then does not necessary to be the first day because demand pattern may vary along the planning horizon. Then a demand point and an item type will be randomly selected. Lastly, all items in the rest of the days will be reassigned into the same source point as in the one in the first randomly selected day. For example in Fig. 6, the gene with value (4,4) on Day 1 is assumed to be randomly selected. Since the selected gene is at Demand Point *j* and for Item 1, the rest of the Item 1 at Demand Point *j* will reassigned to Source Point 4.

Parent A

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**4,2**	**3,1**	…	**3,3**	**-**	**-**	…	**2,3**	…	**4,4**	**1,2**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
M Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,2**	**-**	…	**3,4**	**5,2**	**2,1**	…	**1,3**	…	**3,5**	**4,2**	…	**-**

Offspring A

Day	1												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**4,2**	**3,1**	…	**4,3**	**-**	**-**	…	**2,2**	…	**4,4**	**1,2**	…	**-**
…	…												
Day	**D**												
Demand Points	1				2				…	**J**			
Item	1	2	…	**I**	1	2	…	**I**	…	1	2	…	**I**
Chromosome value	**2,2**	**-**	…	**3,4**	**5,2**	**2,1**	…	**1,3**	…	**4,5**	**4,2**	…	**-**

Fig. 6. Sample mutation of Crossing Date Mutation Heuristic Approach

Validation Process

Validation will be checked after every crossover and mutation operation. In general, a chromosome will become invalid only because of the overloading capacity in the either the source point or DC. Accordingly, the validation process will simply be done by randomly reassigning the overloaded capacity to the other source point or DC.

Elitist Strategy

Similar to traditional GA approach, elitist strategy will be applied by inserting back the best found chromosome into the mating pool in order to avoid the loss of the best chromosome.

5. Numerical Experiments

Three experiments are carried out. The first experiment is to test the optimality of the proposed modified genetic algorithm with crossing date heuristic approach over the traditional genetic algorithm. The second experiment is to test the importance of simultaneously considering all the days in the planning horizon, and the last experiment is to test the performance of the system by adjusting the α value.

Numerical Experiment 1: Testing of proposed algorithm

First of all, the optimality of the proposed crossing date heuristic approach will be tested. It will be compared with the traditional genetic algorithm approach, which is the one without the use of the proposed Crossing Date Crossover Operation and proposed Crossing Date Mutation Operation as mentioned in Section 4. Some hypothetical testing cases are randomly generated with different problem scale: small, normal, and large case as shown in Table 1. The α is 0.5.

Table 1. Testing problem parameters

Problem Scale	No. of Source Points	No. of DCs	No. of Demands Points (per day)	No. of Item Types	No. of Days
Small	5	5	10	3	5
Medium	10	10	30	3	15
Large	20	20	50	5	30

The genetic parameters used for the traditional genetic algorithm and the proposed genetic algorithm with crossing date heuristic approach are:

Solution pool size : 4
Crossover rate : 0.1
Mutation rate : 0.1
No. of evolutions : Small – 1000, Medium – 5000, Large – 10000

The two algorithms will run individually for each problem scale for 10 times and the average results obtained are summarized and plotted as in Fig.s 7a, 7b, and 7c. The computational time required by the traditional GA and the proposed modified GA are similar because of the same number of evolutions used. For small, medium, and large problems are <1s, 2s, and 5s.

In small scale problem as shown in Fig. 7a, the result shows that both algorithms can reach the steady solution stage, and the best value obtained by both algorithms is the same. However, one can see that the proposed algorithm can reach the steady stage faster from 650 number of evolutions required by the traditional approach down to about 350 number of evolutions by the proposed algorithm. This demonstrates that the proposed algorithm is more efficient. Moreover, as the problem scale increased to the medium scale as shown in Fig. 7b, the best solutions obtained by the Traditional GA and the proposed algorithm becomes obvious with a total of about 7%. Similar as in small scale problem, the solution reaches a steady stage earlier. The improvement obtained in large scale problem is even more significant. The solution obtained by the proposed algorithm outperforms the traditional GA approach by about 20%. As a summary, this experiment demonstrates that the proposed Crossing Date Crossover Operation and proposed Crossing Date Mutation Operation can reduce the computational time required by using less number of evolutions, meanwhile improving the solution quality significantly.

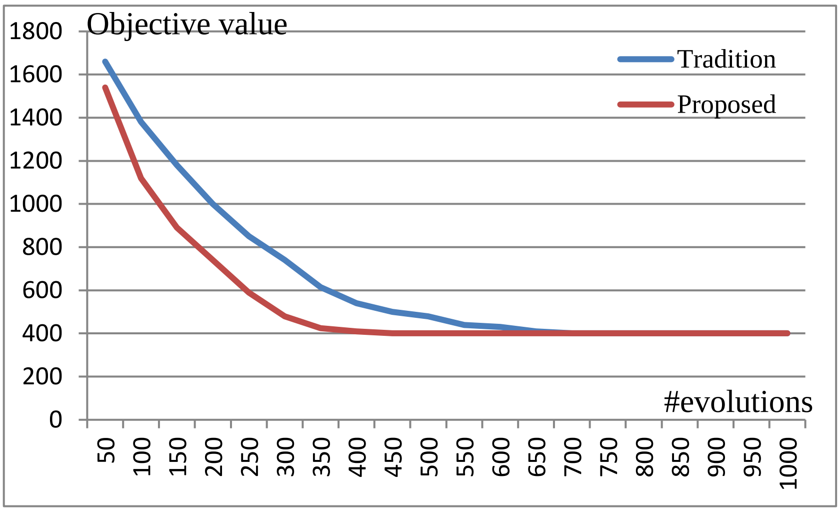

Fig. 7a. Small scale problem

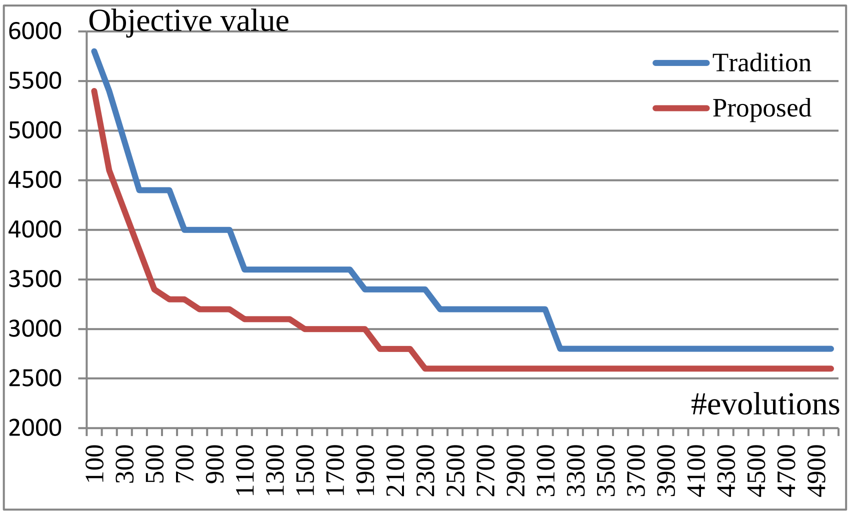

Fig. 7b. Medium scale problem

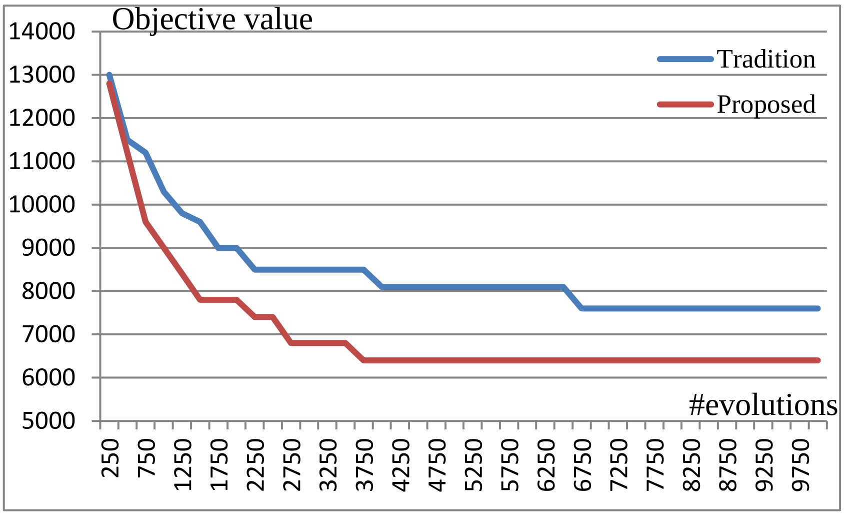

Fig. 7c. Large scale problem

Fig. 7. Result of comparison of the two algorithms

Numerical Experiment 2: Testing of the significance of simultaneously multi-day optimization

In this experiment, the aim is to test and demonstrate the significance of simultaneously optimizing a multi-day plan. As Numerical Experiment 1 has already demonstrated the reliability of the proposed algorithm, only the proposed algorithm will be used for optimization in the rest of the experiments. In here, the result obtained by simultaneously optimizing a multi-day plan will be compared with the one that obtained by individually optimizing on each day. Table 2 summarized the results obtained.

Reduced Cost

$$= -\left(\frac{\text{Total cost obtained by Multiday plan} - \text{Total cost obtained by Single day plan}}{\text{Total cost obtained by Single day plan}}\right)$$

Reduced Returns

$$= -\left(\frac{\text{Total packaging collected by Multiday plan} - \text{Total packaging collected by Single day plan}}{\text{Total packaging collected by Single day plan}}\right)$$

The results in Table 2 show the percentage of improvement obtained by using simultaneously approach. In general, cost reduction is obtained in all the cases with α equals 1 to 0.1 in small, medium, and large scale problems. First of all, this result demonstrates that multi-day planning approach is better than single planning one. In addition, by looking at the individual α value, along each row from small to large scale problem, one can see that the percentage of reduction is increased along the number of days increased. This is because more storage cost can be reduced. This demonstrates that simultaneously optimizing multi-day plan is significant. It is also noted that when comparing the number of packaging collected, the percentage of improvement is varied in a very small percentage when α is smaller than 0.4 in the three cases. When α is smaller than 0.4, there is no different between the two approaches. This demonstrates that although the total operating cost can be reduced, the number of tertiary package returns has not been reduced. This demonstrates the advantages of the proposed multi-day planning approach.

Table 2. Summary of the results for comparing with multi-day plan approach

	Small		**Medium**		**Large**	
α	**Reduced Cost**	**Reduced Returns**	**Reduced Cost**	**Reduced Returns**	**Reduced Cost**	**Reduced Returns**
1	5.1	0.1	7.9	-0.2	10.7	-0.2
0.9	4.8	0.2	7.7	0.1	10.2	0.2
0.8	4.5	-0.2	7.6	0.3	10.1	0.1
0.7	4.1	0.1	7.1	0.2	8.7	-0.1
0.6	3.6	-0.3	6.8	-0.1	8.1	0.3
0.5	3.2	0.2	6.4	0.1	7.6	0.2
0.4	2.9	0.1	5.9	-0.1	7.1	0.1
0.3	2.6	0.0	5.1	0.0	6.9	0.0
0.2	2.3	0.0	4.6	0.0	6.8	0.0
0.1	1.8	0.0	4.3	0.0	6.5	0.0

Numerical Experiment 3: Testing the cost and reuse weighting

In the last experiment, our main focus is to study the changes in terms of cost and the corresponding number of packaging(s) collected by reduction of the α value by using the same multi-day planning approach. The results are summarized in Table 3, in which, one can see that the total costs generally increased along with the reduction of the α value in small, medium, and large scale problems. This can be expected because the cost weighting is being reduced. Accordingly, on the other hand, the number of return packaging(s) collected is then increased. This can be seen in the all problem scales.

Increased Cost for each α

$$= \frac{\text{Total cost obtained by using } \alpha - \text{Total cost obtained by using } \alpha{=}1}{\text{Total cost obtained by using } \alpha{=}1}$$

Increased Returns for each α

$$= \frac{\text{Total packaging collected by using } \alpha - \text{Total packaging collected by using } \alpha{=}1}{\text{Total packaging collected by using } \alpha{=}1}$$

Table 3. Summary of the results for adjusting cost and reuse weighting

	Small		**Medium**		**Large**	
α	**Increased Cost**	**Increased Returns**	**Increased Cost**	**Increased Returns**	**Increased Cost**	**Increased Returns**
1	0.0	0.0	0.0	0.0	0.0	0.0
0.9	0.7	1.1	1.3	2.2	1.6	3.1
0.8	0.8	1.3	2.1	3.1	2.6	4.7
0.7	0.8	1.3	2.7	3.6	3.4	6.3
0.6	1.1	2.3	3.1	4.9	4.6	8.2
0.5	1.4	2.5	3.4	5.2	5.8	8.6
0.4	1.5	2.8	3.9	6.1	6.5	9.7
0.3	1.8	2.9	4.3	6.8	7.1	10.5
0.2	2.1	3.0	4.4	7.0	7.2	10.6
0.1	2.2	3.1	4.6	7.1	7.4	10.8

Conclusion and Future work

Although many papers have been studied on recycling and reuse problem, recycling and reuse of tertiary packaging is not being studied thoroughly. In logistics operation, tertiary packaging helps in bulk transportation. However, this packaging will induce packaging waste and increase the demand on landfill and induce land pollution. For this reason, this paper proposed a new multi-day planning approach to determine the product flow for production and distribution network. The new approach took in the consideration of the variety in the handling ability and recyclability of DCs, and the interrelationship of demands between different planning days. The objective was to maximize the reuse of packaging and minimize the total operating cost.

Through the numerical experiments, it is found that the proposed modified Genetic Algorithm with Crossing Date heuristic achieves better optimization ability than the traditional GA in the Numerical Experiment 1. The newly proposed crossover and mutation operations enhanced the solution quality with a maximum of 20%. In addition, the proposed algorithm can reach the steady solution stage much faster in small, medium, and large scale problems. This demonstrates that the proposed new crossing date crossover operation and mutation operation contribute in improving the genetic searching ability of the GA. In Numerical Experiment 2, it is found that by the consideration of the interrelationship of demands between different planning days, the total operating cost in general is lower than planning for every individual day with a maximum reduction of about 10%. This demonstrates the significance of the proposed multi-day planning approach. Lastly, in the sensitivity analysis carried out in Numerical Experiment 3, the results demonstrated that the proposed algorithm can obtain the pareto solution according to the weighing defined. As a conclusion, this paper can contribute in this research area by providing a better optimization algorithm, which also contributes to the logistic industry by reducing the total operating cost and to the environment by maximizing the result of tertiary packaging.

Regarding the limitations in the current work, this paper is modeled under a deterministic environment, in which the reuse rate and quality of returns are assumed to be constant. However, in reality, they may vary along the planning days. Accordingly, it is suggested that more effort can be devoted into stochastic modelling approach so that this system stability can be further improved.

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References:

Baker, P., Canessa, M., 2009. Warehouse design: A structured approach. European Journal of Operational Research 193, 425–436.

Agrawal, S., Singh, R.K., Murtaza Q., 2015. A literature review and perspectives in reverse logistics, Resouces, Conservation and Recycling 97, 76-92.

Banaszewski, R. F., Arruda, L. V., Simao, J. M., Tacla, C. A., Barbosa-Povoa, A. P., Relvas, S., 2013. An application of a multi-agent auction-based protocol to the tactical planning of oil product transport in the Brazilian multimodal network. Computers & Chemical Engineering 59, 17-32.

Bing X., Bloemhof-Ruwarrd, J., Chaabane, A., Vorst, J., 2015. Global reverse supply chain redesign for household plastic waste under the emission trading scheme. Journal of Cleaner Production 103, 28-39.

BloemhofRuwaard, J. M., VanWassenhove, L. N., Gabel, H. L., Weaver, P. M., 1996. Environmental life cycle optimization model for the European pulp and paper industry. Omega-International Journal of Management Science 24(6), 615-629.

Chouinard, M., D'Amours, S., Ait-Kadi, D., 2008. A stochastic programming approach for designing supply loops. International Journal of Production Economics 113(2), 657-677.

Chung, S.H., Chan, H.K., Chan, F.T.S., 2013. A modified genetic algorithm for maximizing handling reliability and recyclability of distribution centers. Expert Systems with Applications 40, 7588-7595.

Cruz, N.F., Simões, P., Marques, R.C., 2012. Economic cost recovery in the recycling of packaging waste: the case of Portugal. Journal of Cleaner Production 37, 8-18.

Demirel, N. O., Gökcen, H., 2008. A mixed integer programming model for remanufacturing in reverse logistics environment. International Journal of Advanced Manufacturing Technology 39, 1197-1206.

Demirel, E., Demirel N., Gökcen, H., 2016. A mixed integer linear programming model to optimize reverse logistics activities of end-of-life vehicles in Turkey, Journal of Cleaner Production 112, 2101-2113.

Gaiardelli, P., Saccani, N., Songini, L., 2007. Performance measurement of the after-sales service network – Evidence from the automotive industry. Computers in Industry 58, 698–708.

Gomes, C. F. S., Nunes, K. R. A., Helena Xavier, L., Cardoso, R., Valle, R., 2008. Multicriteria decision making applied to waste recycling in Brazil. Omega 36(3), 395-404.

Jahre, M., C.J. Hatteland., 2004. Packages and Physical Distribution: Implications for Integration and Standardisation. International Journal of Physical Distribution and Logistics Management 34(2), 123–139.

Jayaraman, V., 2006. Production planning for closed-loop supply chains with product recovery and reuse: an analytical approach. International Journal of Production Research 44(5), 981-998.

Kannan, G, Haqaan, D.M., 2009. Analysis of closed loop supply chain using genetic algorithm and particle swarm optimisation. International Journal of Production Research 47(5), 1175-1200.

Kannan, G., Sasikumar, P., Devika, K., 2010. A genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling. Applied Mathematical Modelling 34(3), 655-670.

Kartalis, C.N., Papaspyrides, C.D., Pfaendner, R., 2000. Recycling of post-used PE packaging film using the restabilization technique. Polymer Degradation and Stability 70, 189-197.

Krikke, H. R., Van Harten, A., Schuur, P. C., 1999. Business case Océ: Reverse logistic network re-design for copiers. OR Spektrum 21(3), 381-409.

Krikke, H., Bloemhof-Ruwaard, J., Van Wassenhove, L. N., 2003. Concurrent product and closed-loop supply chain design with an application to refrigerators. International Journal of Production Research 41(16), 3689-3719.

Lee, J. E., Lee, K. D., 2012. Integrated Forward and Reverse Logistics Model: A Case Study in Distilling and Sale Company in Korea. International Journal of Innovative Computing Information and Control *8*(7A), 4483-4495.

Olugu, E. U., Wong, K. Y. 2012. An expert fuzzy rule-based system for closed-loop supply chain performance assessment in the automotive industry. Expert Systems with Applications 39(1), 375-384.

Ozceylan, E., Paksoy, T., 2013. A mixed integer programming model for a closed-loop supply-chain network. International Journal of Production Research 51(3), 718-734.

Ozceylan, E., Paksoy, T., 2014. Interactive fuzzy programming approaches to the strategic and tactical planning of a closed-loop supply chain under uncertainty. International Journal of Production Research 52(8), 2363-2387.

Palsson, H., Hellström, D., 2016. Packaging logistics in supply chain practice – current state, trade-offs and improvement potential. International Journal of Logistics: Research and Applications http://dx.doi.org/10.1080/13675567.2015.1115472.

Pati, R. K., Vrat, P., Kumar, P., 2008. A goal programming model for paper recycling system. Omega 36(3), 405-417.

Pearce D., Turner, R.K., 1992. Packaging Waste and the polluter pays principle: a taxation solution. Journal of Environmental Planning and Management 35(1), 5-15.

Rousso, A.S., Shah, S.P., 1994. Packaging Taxes and Recycling Incentives: The

German Green Dot Program. National Tax Journal 47(3), 689-701.

Schweiger, K., Sahamie, R., 2013. A hybrid Tabu Search approach for the design of a paper recycling network. Transportation Research Part E: Logistics and Transportation Review 50, 98-119.

Shih, L. H., 2001. Reverse logistics system planning for recycling electrical appliances and computers in Taiwan. Resources, Conservation and Recycling, 32(1), 55-72.

Tuzkaya, G., Gulsun, B., Onsel, S., 2011. A methodology for the strategic design of reverse logistics networks and its application in the Turkish white goods industry. International Journal of Production Research 49(15), 4543-4571.

Wang, H. F., Hsu, H. W., 2010. A closed-loop logistic model with a spanning-tree based genetic algorithm. Computers & Operations Research 37(2), 376-389.