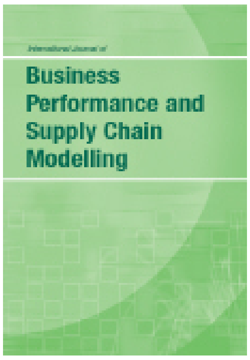

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Scenario-based multi-objective optimisation model based on supervised machine learning to configure a plastic closed-loop supply chain network

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Abstract: Plastic recycling has received a lot of attention around the world. In this regard, a multi-objective optimisation model for plastic closed loop supply chain (CLSC) configuration is developed. Specifically, this paper simultaneously investigates the impact of adding washing machines to plastic recovery centres and corporations' role in consumer awareness on plastic recycling on plastic CLSC network configuration cost and carbon dioxide (i.e., CO_2) emissions. Our numerical results indicate that the combination of adding washing machines to recovery centres, and increased return of plastic products due of increased corporate responsibility in consumer awareness have the potential to contribute to both economic and environmental pillars of sustainability by decreasing the design cost, i.e., by 3.93%, and CO_2 emissions, i.e., by 14.24%. Furthermore, sensitivity analysis is conducted to consider the effects of unpredictable changes in demand and return. The implications of our study concerning social sustainability, policymakers, and municipalities are discussed.

Keywords: multi-objective optimisation; machine learning technique; logistic regression; corporate responsibility; closed loop supply chain; CLSC; plastic.

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1 Introduction

Supply chain management is about managing the flow of products, services, funds, and information between different stages that are involved in a supply chain network including suppliers or vendors, manufacturing plants, warehouses, destruction centres, wholesalers, retailers, and customers (Chopra and Meindl, 2016; Shekarian et al., 2020). Supply chains are classified into forward supply chains and reverse supply chains. Forward supply chain management (Klose and Drexl, 2005; Melo et al., 2009) involves procuring and processing raw materials, manufacturing products based on demand, and fulfilment of orders (Abdallah et al., 2012; Cooper et al., 1997). Decisions in forward supply chain planning include determining the optimum number and location of facilities to open, optimal product flow between different stages in a distribution network in a such a way that the total fixed and variable costs are minimised while the network demand is satisfied (Geoffrion and Graves, 1974; Dearing, 1985; Owen and Daskin, 1998; Ashtab et al., 2015). On the other hand, reverse supply chains involve managing the logistics of collecting used products and recovering the value in materials via application of R-principles such as recycling (Jawahir and Bradley, 2016), and remarket the products. Closed loop supply chains (CLSCs) consist of forward and reverse supply chains.

Several studies have investigated different aspects of plastic recycling and recovery (Al-Maaded et al., 2012; Eriksen et al., 2018; Gradus et al., 2016; Gu et al., 2017). Different types of Plastics are used in a variety of products; however, only a small fraction of the plastic waste is recycled. For example, the recycling rate in Europe for plastics in 2016 was approximately 14% (PlasticsEurope, 2017). Another example is the findings of the published report entitled 'Economic study of the Canadian plastic industry, market and waste' which indicates that approximately 4,667 kilotonnes of plastics enter the domestic market in Canada on an annual basis (Environment and Climate Change Canada, 2019). This amount consists of 3,068 kilotonnes of durable plastic products with average lifetime of more than a year, and 1,599 kilotonnes of non-durable plastic products. Given the durability of some plastic products, they do not turn into waste the same year they were produced. This leaves Canada with approximately 3,268 kilotonnes of plastic in discarded products from which 86% is landfilled representing a lost opportunity of CA$7.8 billion for Canada in 2016, and only 9% being recycled.

In a smaller scale, provinces are also concerned with plastic recycling. For example, there is a great amount of plastic circulating in the province of Nova Scotia, Canada. According to Waste Audit Report published by Divert NS for the Province of Nova scotia for year 2017 (Waste Audit Report, 2018), approximately 59.260 kilotonnes of the material that ended up in the landfills of the Province of Nova Scotia were different types of plastics, which comprised 21% of the total waste amount, including rigid plastics and plastic film.

The ban enforced by foreign countries on importing different types of waste material, including plastics, impacted some countries including Canada, US and Britain who used to export a great amount of their recyclables (Freytas-tamura, 2018). For instance, while 300 tons of plastic bags and wrapping were buried in a landfill in the province of Nova Scotia in Canada with a special permission (Valley Waste Resource Management, 2018), 5 kilotonnes of plastics and mixed paper were stored in warehouses and shipping containers in the province of Calgary, Canada (Freytas-tamura, 2018). These statistics on the low rates of plastic recycling in different countries, high amounts of landfilled plastics in some areas, and the ban on importing recyclables materials including plastics signify the importance of establishing CLSCs for plastics in different regions.

In an attempt to provide insights from the real world, we conducted some interviews in the Canadian province of Nova Scotia in a recycling facility as well as a waste management facility to find out about their operations, and learn whether there are any established and operating closed supply chain networks inside the province for different product categories. We also investigated what really happens to the recyclable materials after they are collected. A CBC report, broadcasted in 2019, on 'Where does your recycling really end up?' indicates that, in some cases, Canada's plastic is ending up in countries overseas with health implications for the people living in those areas (https://www.cbc.ca/marketplace/episodes/2017-2018/tracking-your-trash-where-does-your-recycling-really-end-up). This matter concerns the social pillar of sustainability, e.g., well-beings of communities. These circumstances add to the vitality of establishing CLSCs in different regions more than before. To this aim, the optimal configuration of plastic CLSC network provides benefits to the companies involved in reverse flow (e.g., optimising the resource utilisation), and contributes to both environmental sustainability (e.g., preserving natural resources) and social sustainability (e.g., well-beings of communities). Furthermore, there are different applications for used plastics; examples are fence posts, building panels, park benches, curb stops, and composite structures (Ashtab and Whyte, 2019). Another example is the initiative of turning plastic bottle caps into building materials (Connors, 2020). In this process, bottle caps are heated after they are shredded and then pushed through an extruder to make plastic lumber. There is interest from public to take their bottle caps voluntarily to this company. In this regard, mathematical models can be developed to design and optimise CLSCs.

2 Literature review

Several papers have studied CLSCs and reverse logistics in the literature (Chari et al., 2016; Pishvaee et al., 2009; Francas and Minner, 2009; Amin and Zhang, 2013; Fleischmann et al., 1997; Govindan and Soleimani, 2017; Guide and Van Wassenhove,

2009) for different products such as tyre (Amin et al., 2017; Kannan et al., 2009; Sasikumar et al.; 2010; Subulan et al, 2015), battery (Tosarkani and Amin, 2018b; Gaur et al., 2017; Kannan et al., 2010), electronic (Tosarkani and Amin, 2018a; Tosarkani et al., 2020), plastic pallets (Amin et al., 2018), and citrus fruits' crates (Liao et al., 2020). Different methods such as multi-objective models are used for configuring CLSCs (Pishvaee et al., 2010; Pati et al., 2008). The models in the literature for CLSCs consider multiple products and multiple periods, as well as multiple facilities such as collection facilities, disposal centres, distribution centres. Our paper is no exception; however, this is a first study of its kind in which combination of a machine learning technique, i.e., logistic regression model, and qualitative approach, i.e., conducting interviews in a recycling facility as well as a waste management facility, is utilised to provide insights from the real world to inform the quantitative analysis of plastic CLSC optimisation model, and explore its impact on design cost and carbon dioxide (i.e., CO_2) emissions which concern the economic and environmental pillars of sustainability with implications for social sustainability, e.g., well-being of communities. By deploying multi-objective approach, we simultaneously consider the total plastic CLSC design cost and CO_2 emissions. Furthermore, we conduct sensitivity analysis on the parameters associated with demand for plastics as well as quantity of retuned products at plastic recovery centres. Specifically, this paper simultaneously investigates the impact of adding washing machines to plastic recovery centres, which we found out about in our interviews, and corporations' role in consumer awareness on plastic recycling on plastic CLSC network configuration cost and CO_2 emissions.

Consumer awareness contributes to plastic recycling (Khan et al., 2019). Ashtab and Whyte (2019) investigated whether companies inform consumers on the plastic type and/or provide recommendations on proper disposal of plastic. Having information on plastic type, i.e., resin code, is also important because used plastics are utilised in different applications based on their characteristics which depend on their type, i.e., resin code. These two research studies establish that educating consumers on proper plastic recycling and providing information on plastic type will contribute to more recovery of products with plastic in them. In this regard, we collected a real sample of products with plastic in them and applied a logistic regression model to investigate whether a correlation between corporations educating consumers and/or providing information on plastic type, and their status, e.g., being a known brand, exists. This exploration not only will inform the multi-objective optimisation model on the impact of increased amount of returned plastics, to which consumer awareness contributes, on the design cost and CO_2 emissions but also provide insights for policy makers on extending EPR. Our contributions to the literature are summarised below.

1 By deploying a qualitative approach, we interview a recycling facility as well as a waste management facility in the Canadian province of Nova Scotia, to bring insights from the real world to inform the multi-objective optimisation model for configuration of plastic CLSC. In this regard, we investigate the impact of adding washing machines to plastic recovery centres on design cost and CO_2 emissions. This scenario is studied in Subsection 7.1.

2 This is a first study which utilises a machine learning technique to inform the multi-objective plastic CLSC optimisation model. In this regard, we apply a logistics regression model to a real sample of plastic products to investigate corporations' role in consumer awareness on plastic recycling. The outcome of the logistic regression

model informs the plastic CLSC optimisation model. Our numerical results indicate that increased amount of returned plastic products, to which consumer awareness contributes, has a considerable positive impact on reducing design cost and CO_2 emissions, and therefore, contributes to both economic and environmental pillars of sustainability. The implications of this finding for policy makers is extending EPR for manufacturers to educate consumers regarding post-consumption phase and proper disposal of products with plastic in them. This scenario is studied in Subsection 7.2.

3 Our numerical results indicate that the combination of adding washing machines to plastic recovery centres and increased return of plastic products have the potential to further reduce CLSC design cost and CO_2 emissions simultaneously. The implication of this finding is contribution to the social sustainability, e.g., well-being of communities.

3 Problem statement

Figure 1 shows a multi-echelon, multi-period, multi-product plastic CLSC. In the reverse flow, plastics flow from residential areas to the regional collection depot(s), and to the recovery centre(s). Used plastics undergo the recovery process in plastic recovery centres. Washing machines are embedded in recovery centres to clean up the dirt of mixed plastics. The quality of plastics arriving at plastic recovery centres can be inconsistent and that impacts the disposal rate for recyclable items. By investing in installation of washing machines in plastic recovery centres, the disposal rate can be decreased resulting in more recyclable precious materials returning to the manufacturing cycle. The fixed costs and CO_2 emissions associated with a washing machine are incorporated to the fixed cost of building and operating a plastic recovery centre, and generated CO_2 emissions, respectively.

The recoverable portion of returned plastic is shipped to the remanufacturing plants, and the unrecoverable portions are transferred to the disposal centre. In the forward flow, plastic manufacturers are responsible to supply retailers with required quantities of plastic to fulfill market demand. In this regard, the plastic manufacturers will have to send orders to supplier(s) if they encounter shortage of raw materials due to low recovery rates and output from plastic recovery centres. In this study, we intend to configure an optimal plastic recovery network for the purpose of minimising the total cost and CO_2 emissions. The solution of the optimisation model will determine the location of supplier(s), remanufacturing/ plastic producers, regional collection depot(s), and plastic recovery centre(s) as well as the product flow between different echelons in the supply chain network and the amount of raw materials which must be purchased from the supplier(s) by plastic manufacturers (based on the recovery rate of the plastic recovery centre(s)) to fulfill the market demand.

We also investigate the impact of corporations' role in educating consumers on plastic CLSC design cost and CO_2 emissions given that enhanced consumers' awareness contributes to plastic recycling.

Figure 1 The plastic CLSC (see online version for colours)

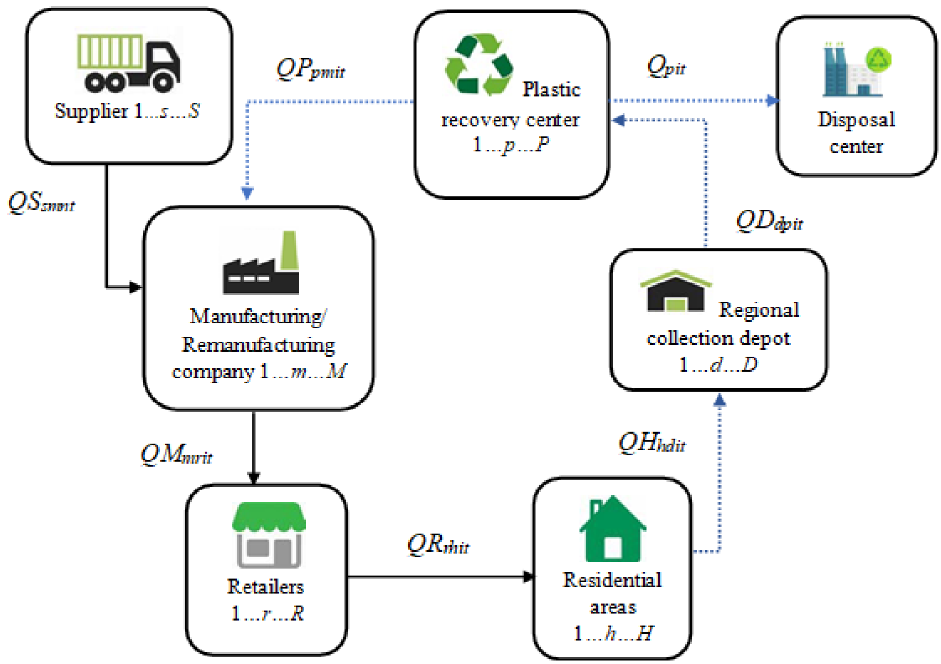


Table 1 All the sets of the proposed model

I	set of returned products (1 … *i* … *I*)
N	set of components (1 … *n* … *N*)
P	set of plastic recovery centres (1 … *p* … *P*)
D	set of regional collection depots (1 … *d* … *D*)
M	set of manufacturing/remanufacturing company (1 … *m* … *M*)
S	set of suppliers (1 … *s* … *S*)
R	set of retailers (1 … *r* … *R*)
H	set of residential areas (1 … *h* … *H*)
T	set of periods (1 … *t* … *T*)

4 Optimisation model

Nowadays, developing and enforcing new policies and practices for environmental sustainability in different businesses across different industry sectors is a common practice for countries. In this regard, we first consider minimising the total cost of establishing plastic CLSC network.

Then the impact of minimising the CO_2 emissions on designing the plastic CLSC network is considered. Therefore, the following sets, parameters, and decision variables are deployed in developing a mixed-integer linear programming model.

Table 2 The parameters of the proposed model

A_p	fixed cost of building and operating plastic recovery centre at location *p*
B_m	fixed cost of agreement with manufacturing/remanufacturing company *m*
E_s	fixed cost of agreement with supplier *s*
F_d	fixed cost of agreement with regional depot *d*
G_r	fixed cost of agreement with retailer *r*
Y_n	purchasing cost of component n from suppliers*s*
C_i	unit cost of recovery associated with product *i*
V_{sm}	distance between locations *s* and *m*
V_p	distance between plastic recovery centre *p* and disposal centre
U_i	unit cost of transportation per Km associated with returned product *i*
L_n	unit cost of transportation per Km associated with component n
K_i	disposal cost of returned product *i*
W_{hit}	demand of area *h* for returned product *i* in period t
e_{pi}	disposal rate of returned product i at plastic recovery centre *p*
X_{hit}	return of returned product *i* related to area *h* in period *t*
J_{in}	quantity of component *n* in product *i*
f_{pi}	maximum capacity of plastic recovery centre *p* for returned product *i*
k_{mi}	maximum capacity of manufacturing/remanufacturing company *m* for component *n*
p_{sn}	maximum capacity of supplier *s* for providing component *n*
b_{ri}	maximum capacity of retailer *r* for product *i*
l_{di}	maximum capacity of regional depot *d* for returned product *i*
g	truck capacity
u	truck CO_2 emissions per km
u_d	CO_2 emissions due to operation of regional collection depot(s)
u_p	CO_2 emissions due to operation of plastic recovery centre(s)
u_m	CO_2 emissions due to operation of manufacturing/remanufacturing company(s)
u_s	CO_2 emissions due to operation of supplier(s)
u_r	CO_2 emissions due to operation of retailer(s)

Table 3 The decision variables of the proposed model

QS_{smnt}	quantity of component *n* shipped to manufacturing/remanufacturing company *m* by supplier *s* in period *t*
QP_{pmit}	quantity of returned product *i* recovered by plastic recovery centre *p* for manufacturing/remanufacturing company *m* in period *t*
QM_{mrit}	quantity of returned product *i* sent by manufacturing/remanufacturing company *m* to retailer *r* in period *t*
QR_{rhit}	quantity of product *i* selling by retailer *r* to area *h* in period *t*
QH_{hdit}	quantity of product *i* returned from area *h* to regional depot *d* in period *t*
QD_{dpit}	quantity of returned product *i* shipped to plastic recovery centre *p* from regional depot *d* associated with period *t*

Table 3 The decision variables of the proposed model (continued)

Q_{pit}	quantity of unrecoverable returned product *i* shipped to disposal centre from plastic recovery centre *p* in period *t*
w_m	1, if the manufacturing/remanufacturing company is located and set up at potential site *m*, 0, otherwise
x_p	1, if the plastic recovery centre is built and set up at potential site *p*, 0, otherwise
$y_d = 1$	if the regional collection depot at potential site d is selected, 0, otherwise
$q_s = 1$	if the supplier *s* is selected, 0, otherwise
$v_r = 1$	if the retailer *r* is selected, 0, otherwise

$$
\begin{aligned}
Minz_1 = & \sum_p \sum_m \sum_i \sum_t (C_i + U_i V_{pm}) QP_{pmit} + \sum_s \sum_m \sum_n \sum_t (Y_n + L_n V_{sm}) QS_{smnt} \\
& + \sum_m \sum_r \sum_i \sum_t (U_i V_{mr}) QM_{mrit} + \sum_r \sum_h \sum_i \sum_t (U_i V_{rh}) QR_{rhit} \\
& + \sum_h \sum_d \sum_i \sum_t (U_i V_{hd}) QH_{hdit} + \sum_d \sum_p \sum_i \sum_t (O_i + U_i V_{dp}) QD_{dpit} \\
& + \sum_p \sum_i \sum_t (K_i + U_i V_p) Q_{pit} + \sum_s E_s q_s + \sum_m B_m w_m + \sum_r G_r v_r + \sum_d F_d y_d \\
& \sum_p A_p x_p
\end{aligned}
$$

$$
\begin{aligned}
Minz_2 = & \left(\sum_p \sum_m \sum_i \sum_t \left(\frac{QP_{pmit}}{g} \right) V_{pm} + \sum_s \sum_m \sum_n \sum_t \left(\frac{QS_{smnt}}{g} \right) V_{sm} \right. \\
& + \sum_m \sum_r \sum_i \sum_t \left(\frac{QM_{mrit}}{g} \right) V_{mr} + \sum_r \sum_h \sum_i \sum_t \left(\frac{QR_{rhit}}{g} \right) V_{rh} \\
& + \sum_h \sum_d \sum_i \sum_t \left(\frac{QH_{hdit}}{g} \right) V_{hd} + \sum_d \sum_p \sum_i \sum_t \left(\frac{QD_{dpit}}{g} \right) V_{dp} \\
& \left. + \sum_p \sum_i \sum_t \left(\frac{Q_{pit}}{g} V_p \right) \right) + \sum_s u_s q_s + \sum_m u_m w_m + \sum_r u_r v_r + \sum_d u_d y_d \\
& + \sum_p \sum_z u_p x_p
\end{aligned}
$$

$$\sum_r \sum_i (QM_{mrit}) J_{in} = \sum_p \sum_i (QP_{pmit}) J_{in} + \sum_s QS_{smnt} \qquad \forall m, n, t \tag{1}$$

$$\sum_m QM_{mrit} = \sum_h QR_{rhit} \qquad \forall r, i, t \tag{2}$$

$$\sum_r QR_{rhit} \geq W_{hit} \qquad \forall h, i, t \tag{3}$$

$$\sum_d QH_{hdit} = X_{hit} \qquad \forall h, i, t \tag{4}$$

$$\sum_h QH_{hdit} = \sum_p QD_{dpit} \qquad \forall d,i,t \tag{5}$$

$$\sum_d QD_{dpit} = \sum_p QP_{pmit} + Q_{pit} \qquad \forall p,i,t \tag{6}$$

$$e_{pi} \sum_d QD_{dpit} \leq Q_{pit} \qquad \forall p,i,t \tag{7}$$

$$\sum_m \sum_n QS_{smnt} \leq q_s \sum_n p_{sn} \qquad \forall s,t \tag{8}$$

$$\sum_r \sum_i QM_{mrit} \leq w_m \sum_i k_{mi} \qquad \forall m,t \tag{9}$$

$$\sum_h \sum_i QR_{rhit} \leq v_r \sum_i b_{ri} \qquad \forall r,t \tag{10}$$

$$\sum_p \sum_i QD_{dpit} \leq y_d \sum_i l_{di} \qquad \forall d,t \tag{11}$$

$$\sum_m \sum_i QP_{pmit} + \sum_i Q_{pit} \leq x_p \sum_i f_{pi} \quad \forall d,t \tag{12}$$

$$w_m, x_p, y_d, q_s, v_r \in \qquad \forall m,p,d,s,r \tag{13}$$

$$QS_{smnt}, QP_{pmit}, QM_{mrit}, QR_{rhit}, QI_{rit}, QH_{hdit}, QD_{dpit}, Q_{pit} \text{ integer} \quad \forall s,m,n,p,r,h,s,i,t \tag{14}$$

The first objective function (z_1) is to minimise the total design cost of the plastic CLSC network. In this regard, fixed costs of building and operating plastic recovery centre(s), and agreement with supplier(s), manufacturing/remanufacturing company(s) and regional collection depot(s), along with variable costs (i.e., transportation, costs of recovery, purchasing new products, and disposal) are considered. The second objective function is introduced to minimise the CO_2 emissions of operations in different facilities as well as transportation in the CLSC network. First set of constraints is required to balance the outbound shipments from plastic manufacturers/remanufacturers to retailers with the inbound shipments to manufacturers/remanufacturers from suppliers of raw materials and plastic recovery centre(s).

Second and third sets of constraints are to ensure that demand at different market zones (i.e., retailers), and residential areas are fulfilled, respectively. Fourth set of constraints indicates the number of returned products while the fifth set of constraint ensures that the inbound shipments to the regional collection depots are equal to the outbound shipments from regional collection depots to the plastic recovery centres. Sixth set of constraints is to ensure that the summation of recoverable products at plastic recovery centres flowing to manufacturers/remanufacturers and unrecoverable flowing to the disposal centre is equal to the number of products arriving at plastic recovery centres. The seventh set of constraints shows the disposal rate of returned products.

Equations sets (8)–(12) are associated with the capacities of supplier(s), manufacturers/remanufacturers, retailer(s), regional collection depot(s), and plastic recovery centre(s), respectively. Equations sets (13) and (14) represent the binary and non-negative integer decision variables, respectively.

5 Distance method

To obtain the non-dominated solutions neighbouring to ideal values, the distance method can be utilised for multi-objective problems (Branke et al., 2008). As illustrated by equation (15), z_1^* and w_i denote the ideal values and distance metrics, respectively. Each objective function is solved to optimality individually with respect to the defined constraints to find z_1^* (Mirzapour Al-E-Hashem et al., 2011). In our study, there are two objective functions including the total cost of plastic CLSC (i.e., z_1), and CO_2 emissions (i.e., z_2) associated with transportation in CLSC. The objective function for the proposed bi-objective CLSC network can be written as equation (16).

$$z = \left(\sum_i w_i^t \left(\frac{zi - z_i^*}{z_i^*} \right)^\tau \right)^{\frac{1}{\tau}} \qquad \forall_i = 1, 2 \ldots, \infty \tag{15}$$

$$Min\ z = \left(w_1^\tau \left(\frac{z_1 - z_1^*}{z_1^*} \right)^\tau + w_2^\tau \left(\frac{z_2 - z_2^*}{z_2^*} \right)^\tau \right)^{\frac{1}{\tau}} \tag{16}$$

Equations (1)–(14)

6 Parameters' value and solutions

The optimisation model is solved to optimality for the plastic CLSC network. In this study, it is assumed that there are seven locations for the remanufacturing plant, three suppliers, six locations for the recovery centres, 22 markets, five locations for regional collection centres, and one location for the disposal centre. The values of the other parameters applied in the optimisation model are presented in Table 4. In the real life, the demand associated with specific product varies in different seasons or months depending on the product type. Therefore, configuring a multi-period model is necessary for effective decision-making process in real life. In this application, two periods have been considered that represent two seasons.

To solve the proposed model, IBM ILOG CPLEX 12.10.0 is applied on a LENOVO ThinkPad P71 laptop with 32.0 GB of RAM and two 3.10 GHz Intel(R) Xeon(R) CPU E3-1535M v6 on a 64-bit operating system. As illustrated in Table 5, each objective function was solved separately to optimality with respect to the defined equations (1)–(14) to determine z_1^* (where $i = 1, 2$). Then, distance technique is deployed to obtain the non-dominated solutions between the two defined objectives. The non-dominated solutions for the proposed plastic CLSC with equal weight factors ($w_1 = w_2 = 0.5$) as well as computational times are presented in Table 6. For example, the final optimisation problem (including 560 constraints, 3,111 decision variables, 31 binary variables, and 17,483 non-zero coefficients) with equal weight factors ($w_1 = w_2 = 0.5$)

was solved in 0.93 seconds. The non-dominated objective function values are illustrated in Figure 2.

Table 4 Parameters' values applied to solve the proposed model

$I = 3$	$A_p = 90{,}000$	$n = 5$	$L_n = 0.097$
$D = 5$	$B_m = 100{,}000$	$e_{pi} = 0.1$	$K_i = 11.8$
$P = 6$	$E_s = 110{,}000$	$U_i = 0.097$,	
$M = 7$	$F_d = 140{,}000$	$f_{pi} = 2{,}000$	
$H = 22$	$G_r = 150{,}000$	$k_{mi} = 70{,}000$	
$R = 10$	$Y_n = 10$	$p_{sn} = 70{,}000$	
$S = 3$	$O_i = 8$	$b_{ri} = 70{,}000$	
$T = 2$	$C_i = 12$	$l_{di} = 70{,}000$	

Table 5 Ideal values of z_1^* and z_2^*

Objective functions	*Ideal values*	*Computational times (Sec)*
Total cost (i.e., z_1^*)	19,434,719.09	0.84
CO2 emissions (i.e., z_2^*)	8,960,673.96	0.98

Table 6 Non-dominated solutions for the proposed plastic CLSC for different weight factors

Objective value		*Network configuration*	*Computational times*	w_i
Z_1	20,361,000	$(y_1, y_2, y_3, y_5), (x_2, x_3, x_4, x_5), (q_1, q_2, q_3)$	0.64	0.05
Z_2	8,961,900	$(v_1, v_3, v_4, v_7), (w_2, w_3, w_4, w_5)$		0.95
Z_1	20,222,000	$(y_1, y_3, y_5), (x_2, x_3, x_4, x_5), (q_1, q_2, q_3)$	1.08	0.2
Z_2	8,962,700	$(v_1, v_3, v_4, v_{10}), (w_2, w_3, w_4, w_5)$		0.8
Z_1	20,074,000	$(y_1, y_3, y_5), (x_2, x_3, x_4, x_5), (q_1, q_2, q_3)$	0.93	0.5
Z_2	8,984,600	$(v_1, v_3, v_4, v_{10}), (w_2, w_3, w_4, w_5)$		0.5
Z_1	19,585,000	$(y_3), (x_2, x_3, x_4, x_5), (q_1, q_2, q_3)$	1.09	0.8
Z_2	9,405,400	$(v_1, v_{10}), (w_2, w_3, w_4)$		0.2
Z_1	19,492,000	$(y_5), (x_2, x_3, x_5, x_6), (q_1, q_2, q_3)$	1.16	0.95
Z_2	9,988,200	$(v_7), (w_2, w_3, w_4)$		0.05

As indicated by Figure 2, different non-dominated solutions are obtained for different wi values. The trade-off surfaces of plastic CLSC network indicate that the CO_2 emissions' value cannot be decreased, unless the total CLSC network cost is increased.

Sensitivity analysis is conducted to consider the effects of unpredictable changes in demand and return. The ideal and non-dominated values of total network cost and CO_2 emissions associated with eight scenarios of unpredictable changes in demand and return are presented in Table 7. The non-dominated values presented in Table 7 are compared with original solutions (with equal weights) provided in Table 6. It can be observed that solutions of plastic CLSC are very sensitive to such changes.

Figure 2 Non-dominated solutions for the bi-objective model (see online version for colours)

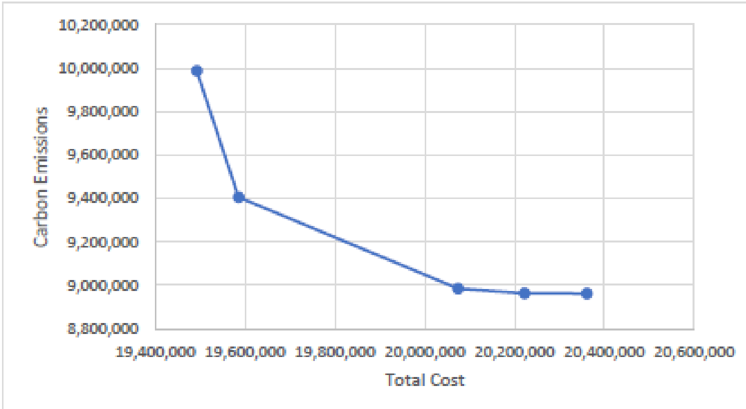


Table 7 Sensitivity analysis for equal weight factors

Scenarios		*Ideal values*		*Non-dominated values*		*Change (%)*	
1	15% increase in demand and return	Z_1	22,393,411.89	Z_1	22,819,000	Z_1	13.67
		Z_2	11,930,806.61	Z_2	12,064,000	Z_2	34.27
2	15% increase in demand and 15% decrease in return	Z_1	22,615,496.97	Z_1	22,943,000	Z_1	14.29
		Z_2	12,352,615.15	Z_2	12,485,000	Z_2	38.96
3	15% decrease in demand and 15% increase in return	Z_1	16,089,180.00	Z_1	16,706,000	Z_1	–16.78
		Z_2	5,868,002.97	Z_2	5,903,600	Z_2	–34.29
4	15% decrease in demand and return	Z_1	16,387,796.85	Z_1	17,014,000	Z_1	–15.24
		Z_2	6,039,577.60	Z_2	6,060,900	Z_2	–32.54
5	15% increase in demand, while return is not changed	Z_1	22,550,717.39	Z_1	23,106,000	Z_1	15.10
		Z_2	12,138,922.20	Z_2	12,169,000	Z_2	35.44
6	15% decrease in demand, while return is not changed	Z_1	16,225,939.64	Z_1	16,847,000	Z_1	–16.07
		Z_2	5,937,004.25	Z_2	5,955,400	Z_2	–33.72
7	15% increase in return, while demand is not changed	Z_1	19,277,413.59	Z_1	19,919,000	Z_1	–0.77
		Z_2	8,753,574.39	Z_2	8,794,400	Z_2	–2.12
8	15% decrease in return, while demand is not changed	Z_1	19,503,795.15	Z_1	20,006,000	Z_1	–0.34
		Z_2	9,173,282.98	Z_2	9,244,400	Z_2	2.89

In scenarios, 1, 2 and 5, demand is increased by 15%. This has led to approximately 13 to 15% increase in total design cost, and 34 to 39% increase in CO_2 emissions, respectively.

The scenario that has led to the largest increase in CO_2 emissions is where demand is increased by 15% while return is decreased by 15%. This is likely due to increased procurement and transportation of raw materials through the supply chain network starting from the suppliers.

Increasing demand by 15% when return is not changed causes the largest increase in the total design cost, i.e., 15.10%. Increasing return by 15% when demand is increased reduced both design cost and CO_2 emissions. That is, when demand is increased by 15%, while the total design cost and CO_2 emissions are both increased regardless of changes in return, increased reverse logistics activities, i.e., return, contribute to less increase in both design cost and CO_2 emissions compared to scenarios where return is not changed or is decreased.

In scenarios 3, 4 and 6, demand is decreased by 15%. This has led to approximately 15 to 17% decrease in total design cost, and 32 to 34% decrease in CO_2 emissions, respectively. The least costly design and lowest CO_2 emissions occur when demand is decreased by 15% and return is increased by 15%. Increase in reverse logistics activities contributes positively to design costs and CO_2 emissions like the scenarios where demand is increased by 15%.

7 Model extensions

7.1 Addition of washing machines

We analyse the impact of adding washing machines to potential plastic recovery centres on non- dominated solutions for total network cost and CO_2 emissions. Washing process consumes both energy and water and has sustainability implications (Fletcher, 2014). Subsequently, adding washing machines will increase the fixed cost of operating plastic recovery centres, i.e., A_p, as well as CO_2 emissions in these facilities, i.e., u_p, and decrease disposal rate of returned product, i.e., e_{pi} = 0.01. We assume 5% increase in fixed costs and CO_2 emissions of plastic recovery centres, i.e., A_p = 94,500, u_p = 945. The ideal values as well as non-dominated solutions are presented in Tables 8 and 9, respectively.

Table 8 Ideal values of z_1^* and z_2^*

Objective functions	*Ideal values*	*Computational times (Sec)*
Total cost (i.e., z_1^*)	19,265,835.57	0.71
CO_2 emissions (i.e., z_2^*)	8,757,479.44	0.63

According to the numerical results reported in Table 9, adding washing machines to plastic CLSC can decrease both total cost and CO_2 emissions by 0.82% and 2.26%, respectively.

Table 9 Non-dominated solutions for the proposed plastic CLSC for different weight factors

Objective value		*Network configuration*	*Computational times*	*Change (%)*
Z1	19,909,000	(y_1, y_3, y_5), (x_2, x_3, x_4, x_5), (q_1, q_2, q_3),	0.73	–0.82
Z2	8,781,500	(v_1, v_3, v_7), (w_2, w_3, w_4, w_5)		–2.26

7.2 Corporate responsibility in consumer awareness

According to Khan et al. (2019), consumer awareness is one of the contributing factors to plastic recycling. Specifically, Ashtab and Whyte (2019) investigated whether companies inform consumers on the plastic type and/or provide recommendations on proper disposal of plastic.

Furthermore, in the context of sustainable development, Stal and Jansson (2017) suggest that the current research which primarily focus on consumer behaviour and sustainable consumption can be extended to include firms' role on aspects of use and disposal. It is important to identify the type of plastic, e.g., plastic film, in the recycling process because different plastic products are made up of different resin codes, e.g., low density polyethylene (LDPE) with resin code of #4, high density polyethylene (HDPE) with resin code of #2 and, consequently, provide different characteristics and, subsequently, are utilised in different applications. The information regarding the plastic type can be provided on the packaging. Ashtab and Whyte (2019) concluded that, at 5% significance level, there was not enough evidence to reject the hypothesis that less than 50% of products with plastic in them provided information regarding the type of plastic or recommendation for disposal. To investigate if there is a correlation between a characteristic of a manufacturer, i.e., being a known brand, and information on plastic type and/or proper plastic recycling found on the product, we collect a sample of 69 plastic products in the Canadian province of Nova Scotia (See Appendix A). The distribution of manufacturers based on their status, i.e., a known brand or not, is nearly even. In total 33 manufactures are in the brand category (47.82%), and 36 products are in the non-brand category (52.18%). In the brand category, 26 out of 33 manufacturers provided information on the type of plastic and/or educating consumers on the importance of plastic recycling. In the non-brand category, only 3 out of 36 manufacturers provided information on the type of plastic and/or educating consumers on the importance of plastic recycling.

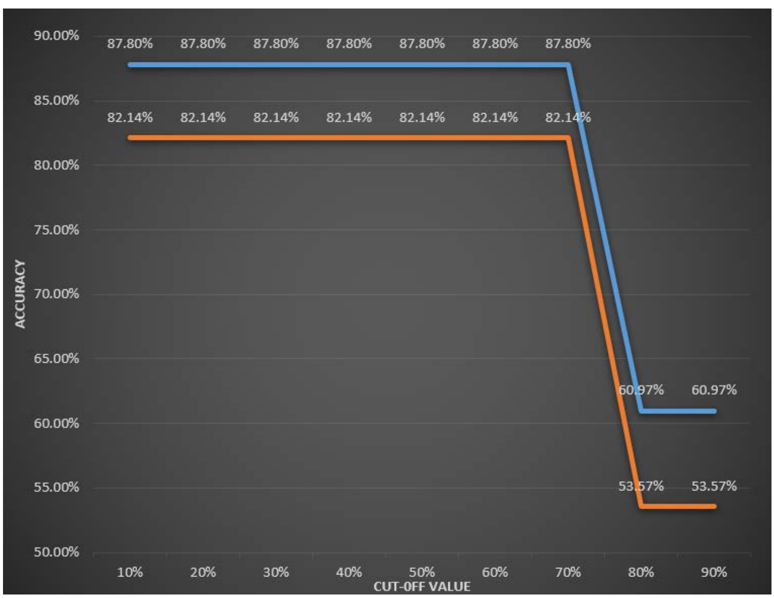
A legitimate research hypothesis posed to data is the likelihood of a known-brand manufacturer providing information on the product or its packaging regarding the plastic type and/or importance of recycling. To test the research hypothesis, one-predictor logistic regression model is fitted to data. Logistics regression model is a suitable machine learning technique to model the relationship between a categorial dependent variable and a categorial independent variable (Peng et al., 2002). While our sample size is small, it does not take away from the insights this technique provides, and the sample can easily be expanded. We choose Brand (value of 1 is assigned when a product is a brand, and 0 otherwise) as independent variable. Whether the manufacturers provide information about the plastic type and/or educate consumers on the importance of plastic recycling is the dependent variable. Value of 1 is assigned to a manufacturer if the manufacturer provides information on the product about the plastic type and/or educate consumers on the importance of plastic recycling, and 0 otherwise. Table 10 provides information on coefficients of the independent variable, 95% confidence intervals (CI) for the estimated values, standard error (SE), and P-value. The low P-value, i.e., 0.000185366, is statistically significant and model coefficients are reliable. The intercept for the logistic regression model is -3.044519503.

The data is partitioned to 60% training and 40% validation sets. The accuracy of prediction is 87.80% and 82.14% in the training set and validation set, respectively. Success probability cut off or threshold probability is set at 50%. That is, a manufacturer will be classified as 1 if the probability of providing information on plastic type and/or educating consumers on the importance of plastic recycling for that manufacturer is higher than 50%. The performance of training set and validation set with different cut-off values is presented in Figure 3. The accuracy of prediction in the training and validation sets is calculated based on the values of true positives (TPs), true negatives (TNs), false negatives (FNs), and false positives (FPs) in the confusion matrixes (See Appendix B). As the cut-off values increases, the number of TPs and FPs decrease while the number of FNs and TNs increase. In our example, after the cut-off value passes the 70% mark, 15 TPs and 4 FPs become FNs and TNs, respectively, in the training set. In the validation set, 11 TPs and 3 FPs become FNs and TNs, respectively, when the cut-off value passes the 70% mark. These changes translate to decreased accuracy in prediction in the training set from 87.80% to 60.97%, and from 82.14% to 53.57% in the validation set.

Table 10 Information on independent variables in model fitting

Variable	*Estimate*	*CI: Lower*	*CI: Higher*	*SE*	*P-value*
Brand	4.366275343	2.076987975	6.65556271	1.168025222	0.000185366

Figure 3 Accuracy of training set (blue) and validation set (orange) with different cut-off values (see online version for colours)



The results from Table 10 indicate that known-brand manufacturers are more likely to fall in the category of manufacturers which provide information about the plastic type and/or educate consumers on the importance of plastic recycling. In fact, the probability of success, i.e., $p(y = 1)$, is 78.94% when Brand variable is equal to one (see Appendix C). Indeed, as our regression model has one dependent and one independent variables, the desired parameter can be estimated by taking 26 divided by 33. In different cases and contexts, the number of variables in the regression model can easily be extended to inform the application of the multi-objective optimisation model. The probability of success translates to, for one unit of increase in the Brand variable, the likelihood of having information on the product about the plastic type or importance of recycling increases by 78.94%. Given that consumer awareness contributes to plastic recycling Khan et al. (2019), we interpret this as 78.94% increase in return for plastic products and use it to inform the multi-objective model. According to the results provided in Table 7, the non-dominated solutions are very sensitive to change in demand and return. We solve the multi-objective optimisation problem with equal weights and increased return of 78.94% to obtain the non-dominated solution for this scenario.

Table 11 Ideal values of z_1^* and z_2^*

Objective functions	*Ideal values*	*Computational times (Sec)*
Total cost (i.e., z_1^*)	18,790,893.823	0.70
CO2 emissions (i.e., z_2^*)	8,037,810.111	0.77

Table 12 Non-dominated solutions for the proposed plastic CLSC for different weight factors

Objective value		*Network configuration*	*Computational times*	*Change (%)*
Z1	19,586,000	(y_1, y_3, y_4, y_5), $(x_1, x_2, x_3, x_4, x_5, x_6)$	0.67	–2.43
Z2	8,059,700	(q_1, q_2, q_3), (v_1, v_3, v_7), (w_2, w_3, w_4, w_5)		–10.29

Results from Table 12 indicate that, increased return of 78.94% has a considerable impact on reducing the CO_2 emissions, i.e., by 10.29%, and the design cost, i.e., by 2.43%. Compared to the results for the scenario with equal weights presented in Table 6, there are more regional depots and recovery centres built. Compared to results provided in Table 9, we see that increased return by 78.94% have more impact on reducing CO_2 emissions and design cost rather than adding a washing machine; however, both scenarios reduce the CO_2 emissions and the design cost when considered separately. The implications of the findings presented in Table 12 for policy makers is to extend the extended producer responsibility (EPR) in terms of involving manufacturers in different aspects of use and disposal of products, and establish and promote specific policies, to be executed by the manufacturers, on educating consumers on the importance of recycling.

Last, we apply both scenarios simultaneously. That is, we investigate the impact of increased return of 78.94% and adding washing machines to the recovery centres on both CO_2 emissions and design cost. Results are provided in Tables 13 and 14.

Table 13 Ideal values of z_1^* and z_2^*

Objective functions	*Ideal values*	*Computational times (Sec)*
Total cost (i.e., z_1^*)	18,484,717.44	1.39
CO_2 emissions (i.e., z_2^*)	7,682,414.111	0.85

Results from Table 14 indicate that the combination of adding washing machines to recovery centres and increased return due of increased corporate responsibility in providing information on plastic type and educate consumers on the importance of recycling have the potential to contribute to both economic and environmental pillars of sustainability by decreasing both the design cost, i.e., by 3.93%, and CO_2 emissions, i.e., by 14.24%.

Table 14 Non-dominated solutions for the proposed plastic CLSC for different weight factors

Objective value		*Network configuration*	*Computational times*	*Change (%)*
Z1	19,286,000	(y_1, y_3, y_4, y_5), $(x_1, x_2, x_3, x_4, x_5, x_6)$,	0.66	–3.93
Z2	7,704,700	(q_1, q_2, q_3), (v_1, v_3, v_{10}), (w_2, w_3, w_4, w_5)		–14.24

8 Discussion and conclusions

The statistics on the low rates of plastic recycling in different countries, high amounts of landfilled plastics in some areas, and the ban on importing recyclables materials including plastics signify the importance of establishing CLSCs for plastics in different regions. The ban enforced by foreign countries on importing different types of waste material including plastics impacted some countries including Canada, the US. and Britain who used to export a great amount of their recyclables. According to a study funded by environment and climate change Canada, there is a great amount of plastic circulating in Canada from which 86% is being landfilled. The plastic recycling rate in Europe and Canada were both less than 15% with Europe having a slightly better plastic recycling rate than Canada.

Reportedly, some recyclable items including plastics are still being exported, and in some cases, getting burnt in some areas causing an unhealthy living environment for the residents in those neighbourhoods. In this regard, establishing plastic CLSCs in different regions can improve both environmental sustainability, e.g., decreased demand for raw material, and social sustainability, e.g., wellbeing of communities.

Several papers have studied CLSC in the literature for different product types. It is a common practice to consider multiple objectives, multiple products and multiple periods, as well as multiple facilities such as collection facilities, disposal centres, and distribution centres in the optimisation model to configure a CLSC. Our paper is no exception; however, this is a first study of its kind in which combination of a machine learning technique, i.e., logistic regression model, and qualitative approach, i.e., conducting interviews in a recycling facility as well as a waste management facility in the Canadian province of Nova Scotia, is utilised to provide insights from the real world to inform the quantitative analysis of plastic CLSC optimisation model, and explore its impact on design cost and CO_2 emissions with implications for social sustainability, e.g., well-being of communities.

Our numerical results indicate that adding washing machines to plastic CLSC can decrease both total design cost and CO_2 emissions by 0.82% and 2.26%, respectively. On the other hand, increased return of 78.94%, to which consumer awareness contributes, has a considerable impact on reducing the CO_2 emissions, i.e., by 10.29%, and the design cost, i.e., by 2.43%. That is, increased return by 78.94% have more impact on reducing CO_2 emissions and design cost rather than adding a washing machine; however, both scenarios reduce the CO_2 emissions and the design cost when considered separately. Furthermore, the combination of adding washing machines to recovery centres and increased return of plastic products due of increased corporate responsibility in providing information on plastic type and educating consumers on the importance of plastic recycling have the potential to decrease both the design cost, i.e., by 3.93%, and CO_2 emissions, i.e., by 14.24%. The implication of this finding is contribution to the social sustainability, e.g., well-being of communities.

These findings also provide insights to policy makers and guidelines for municipalities. Specifically, our findings from applying a logistic regression model to a real sample of products with plastic in them indicate that, for one unit of increase in the Brand variable, the likelihood of a manufacturer educating consumers on the importance of plastic recycling and/or plastic type increases. The implication of this finding for policy makers is to extend the EPR in terms of involving manufacturers, specifically non-brand manufacturers according to our findings, in the post-consumption phase and proper disposal of products with plastic in them, and establish and promote specific policies on educating consumers on the importance of plastic recycling and providing information on plastic type. Furthermore, municipalities can consider the option of investing in adding washing machines to plastic recovery centres.

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Appendix A

This sample of products with plastic in them is based on the observations we have made, and by no means provides a basis for making a judgment about any brand or a manufacturer.

Table A1 List of plastic products

#	*Information on plastic type and/or importance of recycling is available (yes = 1)*	*Known-brand manufacturer (yes = 1)*
1	1	1
2	1	1
3	1	1
4	1	1
5	1	1
6	1	1
7	1	1
8	1	1
9	1	1
10	1	1
11	1	1
12	1	1
13	1	1
14	1	1
15	1	1
16	1	1
17	1	1
18	1	1
19	1	1
20	1	1
21	1	1
22	1	1
23	1	1
24	1	1
25	1	1
26	1	1
27	0	1
28	0	1
29	0	1
30	0	1
31	0	1
32	0	1
33	0	1

Table A1 List of plastic products (continued)

#	*Information on plastic type and/or importance of recycling is available (yes = 1)*	*Known-brand manufacturer (yes = 1)*
34	1	0
35	1	0
36	1	0
37	0	0
38	0	0
39	0	0
40	0	0
41	0	0
42	0	0
43	0	0
44	0	0
45	0	0
46	0	0
47	0	0
48	0	0
49	0	0
50	0	0
51	0	0
52	0	0
53	0	0
54	0	0
55	0	0
56	0	0
57	0	0
58	0	0
59	0	0
60	0	0
61	0	0
62	0	0
63	0	0
64	0	0
65	0	0
66	0	0
67	0	0
68	0	0
69	0	0

Appendix B

Part 1 Below the confusion matrix is provided for cut off values of 70%, 60%, 50%, 40%, 30%, 20%, 10%

Table B1 Confusion matrix for the training set with 10% to 70% cut-off values

Confusion matrix for the training set			*Accuracy*
Actual\Predicted	0	1	$\frac{\mathbf{15+21}}{\mathbf{21+4+1+15}} = \mathbf{87.805}$
0	21	4	
1	1	15	

Table B2 Confusion matrix for the validation set with 10% to 70% cut-off values

Confusion matrix for the validation set			*Accuracy*
Actual\Predicted	10	1	$\frac{\mathbf{11+12}}{\mathbf{11+12+2+3}} = \mathbf{82.14\%}$
0	12	3	
1	2	11	

Part 2 Below the confusion matrix is provided for cut off values of 90% and 80%

Table B3 Confusion matrix for the training set with 80% and 90% cut-off values

Confusion matrix for the training set			*Accuracy*
Actual\Predicted	0	1	$\frac{\mathbf{25}}{\mathbf{25+16}} = \mathbf{60.97\%}$
0	25	0	
1	16	0	

Table B4 Confusion matrix for the validation set with 80% and 90% cut-off values

Confusion matrix for the validation set			*Accuracy*
Actual\Predicted	0	1	$\frac{\mathbf{15}}{\mathbf{15+13}} = \mathbf{53.57\%}$
0	15	0	
1	13	0	

Appendix C

We can construct the log of odds according to the information from Table 10. For more information see (Peng et al., 2002).

$$Log\left(\frac{p(y=1)}{1-p(y=1)}\right) = \alpha + \beta x = [-3.044519503 + 4.366275343 * Brand] \tag{C.1}$$

The following formula can be extracted. We set brand to be equal to 1in the following formulation.

$$p(y=1)\frac{1}{1+e^{-(\alpha+\beta x)}} = \frac{1}{1+e-1.32175584} = 0.7894 \tag{C.2}$$