Integrated Low-Carbon Location-Routing Method for the Demand Side of a Product Distribution Supply Chain: A DoE-Guided MOPSO Optimiser-based Solution Approach

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Abstract: This article contributes to location-routing literature on three inter-linked aspects viz., formulation of a novel integrated low-carbon/green location-routing model for the demand side of a Supply Chain (SC) with a single product and multiple consumers, i.e., Drop-off Points (DoPs), a novel and robust solution approach through a Design of Experiment (DoE)-guided Multiple-Objective Particle Swarm Optimisation (MOPSO) optimiser and exhaustive analysis of the location-routing solutions (i.e., prioritisation, ranking and scenario analysis). The total costs, CO_2 emission and the traversed distances of the vehicles during transportation are optimised. The optimisation model for the strategic decision-making is formulated by effectively integrating the 0-1 mixed-integer programming with a green constraint based on Analytic Hierarchy Process (AHP). Due to the computationally NP-hard characteristic of the model a systematic and technically robust DoE-guided solution approach is designed using a commercial solver – modeFRONTIER® . DoE guides the solution through the MOPSO optimiser in order to eliminate the un-realistic set of feasible and optimal solution sets. A popular multi-attribute decision-making approach, TOPSIS, evaluates the solutions found from the Pareto optimal solution space of the solver. Finally decision-makers' preferences are analysed for monitoring the changes in the controlling parameters with respect to the changes in the decisions. A scenario analysis of the location-routing events by considering alternative possible outcomes is also conducted. It is found that the implemented methodology successfully routes the vehicles with optimal costs and low-carbon emission thus contributing to greening the environment on the demand side of a SC network.

Keywords: Low-carbon; Multi-objective location-routing; Two-layer supply chain network; Single product; Transportation; Particle swarm optimisation.

1. Introduction

This article focuses on an integrated multi-objective low-carbon location-routing method on the demand side of a product distribution supply chain, its unique solution approach and analysis procedure. Location-routing problems focus on the demand side of Supply Chain (SC) networks in which deliveries are made along multiple stop routes (Berger et al. 2007). Demand side supply chain research descends from the focal firm toward product markets and consumers, i.e., drop-off points (Holmström et al. 2010; Priem and Swink 2012). In a supply chain, consumers are regarded as the purchasers of the chain's end product. This side of the SC has consumer centric strategies for value creation (Adner and Snow 2010; Ye et al. 2012). Product flow in a food value-chain plays a crucial role on its performance for the management and control of the demand side of the SC (Taylor 2006). Studies (Srivastava 2007; Vachon 2007; Seuring and Müller 2008) reveal that there is a growing need for sustainable preferences in supply chain research and practices. The low-carbon aspect of green SC management is an emerging environmental practice for manufacturers in order to gain economic profit through sustainable development (Zhu and Sarkis 2007). It has been reported that low-carbon operation of SCs is an efficient approach that aims at the overall optimisation of flow of materials, information and funds along a value chain (Benjaafar et al. 2013; Kumar et al. 2012). However, reported low-carbon location-routing research is relatively scant in the literature.

Effective logistics is one of the critical success factors for the demand side of a SC network (Tarantilis et al. 2005). A conventional logistics approach does not serve the purpose effectively as it does not consider the environmental impact of the distribution system. Therefore, the logistical operations on the demand side of a SC network should operate on optimal routes and reduced carbon emission with low operating costs of both the facilities and drop-off points (DoPs). A typical demand side of a SC with two facilities and multiple DoPs is illustrated in Fig. 1. This is known as two-layer representation of the location-routing problem. Both the flow of materials and information are indicated in Fig. 1. The green-coloured routes connecting the facilities and DoPs are the concerns of this article.

<**INSERT Fig. 1 ABOUT HERE**>

A traditional location-routing model is found in Berger (1997). Later, Daskin et al. (2005) improved the second constraint of the Berger's (1997) model . This article considers the models proposed by Berger (1997) and Daskin et al. (2005). In this article the low-carbon location-routing problem on the demand side of the SC is addressed by formulating an integrated multi-objective mathematical programming approach. The mathematical programming effectively integrates 0-1 mixed-integer programming with Analytic Hierarchy Process (AHP) (Saaty 1977). AHP is integrated in order to include the Decision-Makers' (DM) preferences in the low-carbon decision-making process on the demand side of the SC.

The solution of this integrated mathematical programming is complex as the proposed model is computationally NP-hard in nature. One of the known characteristics of NP-hard models is that traditional techniques do not yield an optimal set of solutions. It is an established fact that the application of meta-heuristic approach generates an optimal and feasible solution space in a better manner from such NP-hard formulations. Further, DoE aids in appropriate selection from the designs created during numerical experimentations. Hence, a DoE-guided Multiple-Objective Particle Swarm Optimisation (MOPSO) optimiser using the commercial modeFRONTIER® solver (Esteco 2012) is employed. This novel approach to solving this provides a large number of non-dominated optimal solutions distributed along the Pareto front. In order to further analyse the outcome of the DoE-guided MOPSO approach, the optimal solutions are prioritised and ranked using a well-established multi-attribute decision-making technique known as "Technique for Order Preference by Similarity to Ideal Solution" (TOPSIS) (Hwang and Yoon 1981). TOPSIS in this case trades off between the total costs and CO_2 emissions using different weights obtained from the consensus opinions of the DMs and locates the best set of realistic solutions. A scenario analysis of the realistic vehicle routes is provided by considering alternative possible outcomes for further guidance to DMs. The realistic low-carbon optimal solutions are then geographically mapped.

This article contributes to the literature in the field of low-carbon capacitated two-layer supply chain location-routing. Three independent but inter-linked aspects of the location-routing research are addressed in this article, viz.:
(i) a novel low-carbon (i.e., green) integrated multi-objective mathematical programming model integrating effectively AHP with 0-1 mixed integer programming is proposed;
(ii) a DoE-guided meta-heuristic-based (MOPSO) robust solution approach under the modeFRONTIER® commercial solver is provided and compared; and
(iii) the DMs' prioritisation and ranking of the realistic solution sets are performed using TOPSIS and various scenarios of the solved low-carbon location-routing are featured.

The research focus on the above three aspects contribute to the following elements on the demand side of the supply chain in the following ways:
(i) a novel low-carbon multi-objective location-routing optimisation model on the demand side of a manufacturing SC is formulated;
(ii) the model allocates drop-off points to the facilities, i.e., manufacturing plants;
(iii) the model optimally routes the vehicles to serve the demand-side of the supply chain,
(iv) total carbon emissions and total costs of transporting the products are optimised. These criteria are conflicting-in nature having incommensurable units of measurements;
(v) an effective integration of 0-1 mixed-integer programming with a green constraint based on AHP is presented. This model is found to be computationally NP-hard;
(vi) the computationally NP-hard methodology is implemented using DoE-guided meta-heuristic optimiser–MOPSO–under the modeFRONTIER® commercial solver platform (Esteco 2012);
(vii) the realistic set of solutions are then prioritised and ranked by the DMs. TOPSIS aids in evaluating the realistic set of solutions. An analysis reflecting DMs' preferences is performed to monitor the changes in the controlling parameters with respect to the changes in the decision-weights of TOPSIS;

(viii) a subsequent scenario analysis of the location-routing events is conducted by determining alternative possible outcomes. This validates the robustness of the realistic solution sets; and
(ix) the realistic set of low-carbon vehicle routes are geographically mapped.

The remainder of this paper is organised as follows. Section 2 focuses on the literature research relevant to location-routing on the demand side of supply chain. Section 3 proposes a novel low-carbon multi-objective integrated mathematical programming for the demand-side of the supply chain. The mathematical programming is implemented using the MOPSO optimiser as illustrated in Section 4. The results are illustrated and a critical discussion of the results is included in Section 5. The last section, i.e., Section 6, concludes the paper with an implication of the proposed approach on the low-carbon location-routing on the demand side of the SC.

2. Literature Review

Over the last couple of decades research has been conducted on the location-routing problems (LRPs) (Lee et al. 2010). Location-routing is a significant ingredient for logistics. Logistics is known as a customer service and product-support utility (Brimer 1995). Appropriate location-routing decisions have a positive impact on the profit of a company, the cost incurred to and ultimate satisfaction of its customers thereby contributing to the organisational efficiency (Brimer 1995). LRPs are essentially strategic decisions (Balakrishnan et al. 1987). Transportation plays one of the crucial roles in logistics formulation of strategic decisions especially when they account for a significant percentage of total distribution costs for food multiple retailers (Institute of Grocery Distribution 2009). LRPs are concerned with the optimal movement of products and vehicles on the demand side of a supply chain facilitating delivery of products from primary to secondary facilities and from secondary facilities to the customers (Eiselt and Laporte 1989; Srivastava 1993). It is reported that the research related to logistics is essential for evaluating their effects on the delivery performance and environment (Aronsson and Brodin 2006). The logistics when interfaced with the environmental aspects of a supply chain provides the value adding functions of a firm (Wu and Dunn 1995).

Location-routing literature is rich both in terms of methodologies and applications. Some prominent literature reviews are reported in (Madsen 1983; Balakrishnan et al. 1987; Laporte 1988; Laporte and Osman 1995; Min et al. 1998; Kenyon and Morton 2001; Nagy and Salhi 2007). Table 1 illustrates some reported LRPs and associated methodologies. Application of meta-heuristics in location and vehicle-routing is abundant (Golden and Skiscim 1986; Tuzun and Burke 1999; Prins et al. 2007; Bräysy et al. 2009; Prins et al. 2009). It has been reported that Tabu Search and Simulated Annealing are appropriate meta-heuristics for solving NP-hard combinatorial optimisation problems (Breedam 2001) of location-routing. However plenty of scope is still there to judge the efficacy of other meta-heuristics in solving location-routing problems. Scant evidences are available on the application of particle swarm optimisation (PSO) in LRP. Yang and Zi-Xia (2009) report the first research on location-routing using PSO. They propose a two-phase method for LRP based on PSO. PSO is an evolutionary algorithm that follows a collaborative population-based search approach which has the optimal solution in a multi-dimensional search space (Yang and Zi-Xia 2009). It is reported that PSO has many advantages over other heuristic methods as it has the capability of escaping local optima (Kennedy and Eberhart 1995; Yang and Zi-Xia 2009). Liu et al. (2012) report a multi-objective location-routing optimisation in reverse logistics using PSO. Marinakis and Marinaki (2008) report that PSO can be used in hybrid synthesis with other meta-heuristics for the solution of LRPs. Motivated with the solution aspect of LRP using a meta-heuristic optimiser this paper concerns itself with the use of MOPSO in solving a two-layer location-routing problem.

<INSERT TABLE 1 ABOUT HERE>

The aforementioned critical analysis of the literature facilitates an understanding the state-of-the-art on location-routing thereby designing research agenda. The critical study of the literature leads the research on low-carbon (i.e., green) location-routing on the demand side of dairy manufacturing supply chain in having the following advantages over the prior art:

- identification of the open and closed DoPs at a particular point of decision-making;
- determination of the vehicle routes for the delivery of the product to a compatible drop-off point;
- determination of the quantities of the CO_2 emission and optimised cost of the routing; and
- determination of the cost incurred and emission quantities for the closed routes if those are forced to open under certain situations.

3. Integrated Low-Carbon Location-Routing Model

Nomenclature

Parameters		*Decision variables*	
f_j	Sum of fixed costs of plant $\forall j \in J$	X_j	Plants
c_{jk}	Cost of serving the path $k \in P_j$	V_{jk}	Decision variable (=1 if path $k \in P_j$ is operated out of plant $j \in J$, = 0 if not)
v_j	Sum of variable cost for serving consumers at each plant $\forall j \in J$	T_n	Vehicles/trucks of different specifications, $n \in (1, 2, 3)$
r_i	Demand at DoP $\forall i \in I$	*Sets and indices*	
w_{mn}	Weight matrix for each vehicle/truck	I	Set of DoPs indexed by i
p_{ji}	CO_2 emission caused from transportation	J	Set of plants indexed by j
a_j	Variable cost of transporting the products to DoPs, per unit $\forall j \in J$	P_j	Set of feasible paths for plants $\forall j \in J$
z	Speed on different roads in *km*	K	Set of candidate vehicles indexed by k
B_m	Right hand side matrix for green constraint	M	Number of attributes in AHP decision matrix indexed by m
		N	Number of alternative vehicles/trucks indexed by n

The low-carbon model is formulated integrating AHP with 0-1 programming approach. This method can be extended to any two-layer supply chain. Realistically the proposed model can be extended to any number of plants and DoPs. However, for illustrative purpose, the implementation of the model is confined within the demand-side of an Irish dairy market SC.

Milk is considered as a staple of the Irish diet that provides a valuable source of nutrients. The Irish Co-operative Organisation Society (ICOS) report that Ireland has the second-highest per capita consumption of fresh milk in the world after Estonia (ICOS 2012). In Ireland average production volume of milk is 5.4 billion litres per annum from about 18,000 milk producers. The processed milk is bottled in plants and supplied to the demand side of the supply chain of the dairy market. Two plants are located in Drogheda and Ballitore in the east of Ireland (Fig. 1). The consumers are located in twenty-two DoPs. DoPs are located in the cities/towns of Ireland. Several feasible routes are available that connect DoPs to the two plants. As depicted in Fig. 1 the product distribution system is on the downstream side of the supply chain (i.e., outbound logistics) having two inter-connected layers. The processing plants are located in the first layer while the drop-off points are in the second layer. The integrated low-carbon model is implemented considering these two layers. However, the approach can be extended to a three-layer product distribution system.

The integrated method is formulated considering a set of realistic assumptions. It is assumed that the two milk processing plants always remain open. Locations of the plants and consumers are known. Twenty-two DoPs and single dairy product are considered on the demand side of the supply chain. The total demand on each distribution route is less than or equal to the capacity of each plant. Further, a portion of the variable costs is dependent on the demand at DoPs. Dissimilar vehicle capacities are considered and at least one vehicle is involved in each vehicle distribution route. The vehicles are operated using Diesel fuel and all the vehicles are refrigerated. The fuel consumption of the vehicles is dependent on the total mass of the vehicles. Therefore, transportation of the products between plants and DoPs results in CO_2 emission.

The proposed method (modelling phase of Fig. 2) considers integration of AHP and a mixed-integer programming approach. As shown in the modelling phase of Fig. 2, the formulated green objective function minimises the CO_2 emission from the transportation of the products to DoPs. The green objective function (objective function-I) is:

$$\text{Min} \sum_{j \in J} \sum_{i \in I} \sum_{k \in P_j} p_{ji} V_{jk} \qquad \dots (1)$$

The other objective function (objective function-II) for the low-carbon LRP model minimises the total costs associated with the transportation of the products. This objective function involves the fixed costs for operating the facilities, the variable costs for serving DoPs and the costs for vehicle-routing. Therefore, the second objective function is:

$$\text{Min }(\sum_{j\in J} f_j X_j + \sum_{j\in J}\sum_{k\in P_j} v_j V_{jk} + \sum_{j\in J}\sum_{k\in P_j} c_{jk} V_{jk}) \quad \ldots (2)$$

One of the operational constraints (Constraint-1) of these two objective functions is associated with the demand node on each route of the supply chain (equation 3):

$$\sum_{j\in J}\sum_{k\in P_j} V_{jk} = 1 \quad \ldots (3)$$

<INSERT Fig. 2 ABOUT HERE>

Besides the green objective function, a green constraint is involved in the model. This green constraint (Constraint-2) brings flexibility in the selection decision of the vehicles and aids in deciding the type of the vehicle used for the transportation of the products. This is illustrated in equation (4).

$$\sum_{k\in P_j} w_{mn} T_n \le B_m \quad \ldots (4)$$

where, $X_j = 1$, $V_{jk} \in (0,1)$ and $T_n \in (0,1)$.

The decision variables of the integrated model are:

$$V_{jk} = \begin{cases} 1, & \text{if path } k \in P_j \text{ is operated out of plant } j \in J \\ 0, & \text{otherwise} \end{cases} \quad \ldots (5)$$

$$T_n = \begin{cases} 1, & \text{if vehicle type } n \in T_n \text{ is selected to transport the products} \\ 0, & \text{otherwise} \end{cases} \quad \ldots (6)$$

Variable costs for serving the routes from the plants to DoPs are considered in the green methodology:

$$v_j = (a_j \,.\, r_i) \,.\, V_{jk} \quad \ldots (7)$$

4. Implementation of the Integrated Model

Among other objectives, the principal objectives of this low-carbon/green two-layer product distribution model are: (i) minimisation of the total CO_2 emission and (ii) minimisation of the total costs of transportation. The optimisation model is implemented considering some preliminary data sets. Fixed and variable costs for operating the plants, product demand, speed limits of the vehicles on all the feasible paths, distance between the plants and DoPs, CO_2 emissions from the vehicles during transportation, costs associated for serving the feasible paths and green constraint data are computed beforehand. These sets of information are used in the modeFRONTIER® solver when implementing the integrated model. The next two sections illustrate the information abstraction process prior to implementation of the integrated optimisation model.

4.1 Preliminary data sets

The following sets and indices of the methodology are considered:

$i = 1, 2, \ldots, 22,\ \ j = I, II,\ \ k = I1, I2, \ldots, I22, II1, II2, II22,\ \ m = 2$ and $n = 3$.

This follows the following set of decision variables:

$V_{jk}: V_{I1}, V_{I2}, ..., V_{I22}, V_{II1}, V_{II2}, ..., V_{II22}$ and $T_n: T_1, T_2, T_3$.

A relationship between the litres of Diesel burnt in each route and fuel efficiency is generated and shown in equation (8):

Litres of diesel burnt in each path = fuel efficiency (in *l*/*km*) × Distance (in *km*) … (8)

Equation (9) computes the total CO_2 emission from the vehicles which has been constructed from the guidelines to DEFRA's (2008) greenhouse gas conversion factors:

CO_2 emission from a Diesel vehicle (in *kg*) = Litres of Diesel burnt × 2.64 … (9)

The cost of serving each of the twenty-two transportation routes is the sum of fuel costs and driver's wage:

$$\text{Cost of serving a route} = (\text{Litres of Diesel burnt per } km \times €1.53) + (€11.5 \times \frac{\text{Distance } (km)}{z} \quad \ldots (10)$$

<INSERT TABLE 2 ABOUT HERE>

The costs associated with the plants are shown in Table 2. These costs refer to the total fixed costs of operating each plant in a cycle time of 2-3 days. The variable costs are the costs required to serve each DoP from each plant. These costs are related to the demand at each DoP per unit. Equation (7) computes these costs considering the information represented in Table 2. In both the tables one 'unit' refers to a two-litre carton of milk. An average demand at each DoP is assumed. This is considered to be equal to 2/3 of the population of the twenty-two DoPs located in sixteen counties as illustrated in Table 3.

<INSERT TABLE 3 ABOUT HERE>

The 'Road Traffic Act 2004' in Ireland stipulates speed limits on the roads for refrigerated heavy duty vehicles and heavy goods vehicles. Considering this speed limit average working speeds for the vehicles are considered and illustrated in Table A1.

The volume of burnt Diesel in each path is calculated using equation (8). The average price of Diesel in Ireland at the time of this study is €1.53/land the average wage of the driver of a vehicle is €11.50/hr. This wage is estimated from information available on irishjobs.ie. The speed of the vehicles contributes to the cost of serving each route. Further, each route includes a combination of different types of roads, viz., motorways, national routes, regional and local roads. Table A2 shows the connecting paths considered as routes between the plants and DoPs and the traversed distance between each.

Using equation (9) and the information of Table A2 the CO_2 emission from a Diesel vehicle (in *kg*) is calculated. Table 4 illustrates the CO_2 emission from the burnt Diesel and the corresponding cost of serving each route during transportation of the products to the DoPs from the two plants using the designated routes.

<INSERT TABLE 4 ABOUT HERE>

4.2 Green constraint data

The green constraint, Constraint-2, has been constructed based on the concepts of AHP (Saaty 1977). AHP is a multi-criteria decision-making approach that adds flexibility to the constraint of the mixed-integer programming model. The DMs opinions are captured by this constraint during the selection of the type of vehicles to be used. The two criteria used for the selection of vehicle types are CO_2 emissions and costs. The DMs' preferences are considered using the parameters B_m and w_{mn} of Constraint-2 through AHP. The DMs can consider three different types of vehicles for the transportation activities with alternative levels of CO_2 emission and costs (Table 5). The DMs are asked to provide their preferences using Saaty's nine-point scale (Saaty 1977). A pair-wise comparison matrix is generated using the preferences of the DMs in Table 5 and is illustrated in Table 6. The w_{mn} matrix is computed using the steps of AHP and this matrix is illustrated in Table 7. The right hand side matrix of Constraint-2, i.e., B_m is found considering the average rounded up values from Table 4. This matrix is illustrated in Table 8.

<**INSERT TABLE 5 ABOUT HERE**>
<**INSERT TABLE 6 ABOUT HERE**>
<**INSERT TABLE 7 ABOUT HERE**>
<**INSERT TABLE 8 ABOUT HERE**>

4.3 modeFRONTIER® implementation

This section relates to the "solution phase" of Fig. 2. The AHP integrated mixed-integer programming model for the low-carbon location-routing optimisation is strictly computationally NP-hard in nature. It is difficult to achieve an exact solution space for such NP-hard models. Therefore, an optimiser capable of achieving a precise feasible solution space should be employed to solve the NP-hard model. Selection of such an optimiser is critical. One of the important criteria for achieving a fast Pareto convergence is that the optimiser should have the capability of escaping local optima. Additionally, the optimiser should be able to generate the best set of non-dominated solutions close to the true Pareto front. In terms of diversity of the non-dominated solutions, MOPSO is the only meta-heuristic algorithm that is able to cover the entire Pareto front (Coello et al. 2004). Further, MOPSO is a powerful optimiser and superior to other optimisers in converging to the true Pareto front (Raquel and Naval 2005). Hence MOPSO is selected as an optimiser for solving the NP-hard low-carbon location-routing model. PSO is motivated from the simulation of social behaviour of bird flocking. Each single solution is a 'bird' in the search space with a velocity which directs the flight of all the particles through the problem space. The principle features of the scheduler based on MOPSO are (i) it allows involvement of both the continuous and discrete variables, (ii) the constraint handling method does not make use of penalty parameters and (iii) a clustering method is used to prune non-dominated sets.

In order to implement the proposed low-carbon location-routing method, the modeFRONTIER® solver is employed. A logical solution-design of the location-routing problem is generated using the modeFRONTIER® solver (Fig. 3). DoPs are linked to the objective function, constraints and decision variables of the integrated 0-1 programming model, Design of Experiments (DoE) and MOPSO optimiser. The objectives are to optimise both the CO_2 emission and costs along with the traversed routes of the vehicles.

DoE is employed while implementing the green location-routing approach through MOPSO. As seen from Fig. 3 the DoE is called at the starting-point of the optimisation process. Use of the DoE assists in the avoidance of solutions which have good performance within the design space but poor off-design characteristics (Esteco 2012; Lewis 2009). The MOPSO optimiser details of Table 9 are considered in the solution design of the location-routing problem (Fig. 3).

<INSERT Fig. 3 ABOUT HERE>
<**INSERT TABLE 9 ABOUT HERE**>

5. Results and Discussion

N number of entries in the DoE table are used as the initial population of the low-carbon LRP. This population on the DoE table produces 61 different designs comprising 10 DoE sequences based on a custom user sequence, 10 random designs, 10 Sobol designs, 10 uniform Latin hypercube, 10 incremental space filler designs and 1 design on constraint satisfaction. Once the DoE table is generated, the mixed-integer programming is executed using the MOPSO optimiser on a maximum of 50 generations and 2,600 real feasible design solutions. The 'realistic designs table' refines this 'designs table' and results in only 1,132 realistic designs. These designs are sorted in two phases to select the 30 best designs as feasible realistic designs. A statistical summary of the maximum and minimum levels of CO_2 emission and costs based on the different DoE tables for the MOPSO optimiser is tabulated in Table 10. The selected designs are based on the two lower-most rows in the 4D bubble plots for F1 (Fig. 5) and F2 (Fig. 4) objective functions. F2 indicates the cost objective function while F1 refers to the CO_2 emission. Thirty realistic designs are selected from the designs table for further evaluation through TOPSIS.

<**INSERT TABLE 10 ABOUT HERE**>

The selected optimal designs are further evaluated using TOPSIS. The selected solutions have the lowest values satisfying both the objective functions of the low-carbon location-routing problem. The design IDs with the lowest possible CO_2 emission with the highest cost factor and the lowest CO_2 emission with low costs are selected for further evaluation.

<INSERT Fig. 4 ABOUT HERE>
<INSERT Fig. 5 ABOUT HERE>

Using DoE one-way ANOVA is computed for both the total CO_2 emission and total costs of location-routing. This compares the means of two or more groups of the optimised output. The function of ANOVA is to determine the p-value for the null hypothesis to detect if data from several groups have a common mean (Walpole et al. 2006). Table 11 and Table 12 show the ANOVA outcomes. ANOVA computes the source of the variation in the design, sum of squares (SS) due to each source, degrees of freedom (Df) associated with each source, mean squares (MS) for each source (SS/Df ratio), F-ratio (ratio of two MS) and p-value given by the cdf of F. The most important assumption requested by ANOVA is that the standard deviations within each group are the same.

<INSERT TABLE 11 ABOUT HERE>
<INSERT TABLE 12 ABOUT HERE>

The p-value of the ANOVA table for the CO_2 emission (Table 11) using the MOPSO optimiser is zero suggesting significant differences 'between the groups'. It signifies that at least one sample mean is considerably different than the other sample means.

The MOPSO optimiser generates a feasible space of solution guided by DoE tables. The MOPSO optimiser's performance is analysed from the convergence plots for the CO_2 emissions (Fig. 6) and costs (Fig. 7). Figs. 6 and 7 show that the solutions from the MOPSO optimiser converge in a comparatively steady rate for CO_2 emissions when compared with costs of location-routing.

Table 13 shows the selected realistic designs, corresponding design IDs, CO_2 emissions and costs. This table is generated based on the history plots. Fig. 8 illustrates a graphical representation of the Pareto dominance for the two-objective low-carbon location-routing problem based on the selected realistic results of Table 13.

<INSERT Fig. 6 ABOUT HERE>
<INSERT Fig. 7 ABOUT HERE>

<INSERT TABLE 13 ABOUT HERE>

It is noticed that design ID #1092 of Table 13 has the lowest CO_2 emission with the highest costs. This situation represents an extreme decision concerned only about CO_2 emissions while sacrificing costs. Thus, this specific design offers the lowest value for CO_2 emission but the highest value for costs. This typical situation is not acceptable and this optimal and feasible design ID does not lie on the Pareto front. Therefore, the Pareto front covers only 29 design IDs as indicated in Fig. 8. The design IDs are indicated on the Pareto dominance plot.

<INSERT Fig. 8 ABOUT HERE>

The solution from the MOPSO optimiser is compared with a similarly constructed Multiple-Objective Simulated Annealing (MOSA) optimiser (Table 14). From Table 14 it can be seen that the MOPSO is able to generate better solution space than the MOSA optimiser in all the four types of design tables. Therefore, the elitism of the MOPSO optimiser outperforms the solution from the MOSA optimiser.

<INSERT TABLE 14 ABOUT HERE>

5.1 Evaluation and ranking of the results using TOPSIS

This section relates to the "analysis phase" of Fig. 2. The solutions, as illustrated in Table 13, are evaluated further using TOPSIS. Detailed steps of the TOPSIS methodology are found in Hwang and Yoon (1981). TOPSIS is selected to facilitate the strategic decision-making procedure in the low-carbon location-routing optimisation. In the case of strategic decision-making it is desirable to prioritise the set of solutions using an analytical approach. Therefore, the set of thirty selected feasible optimal solutions are ranked according to the DMs' preferences using TOPSIS. A decision matrix is generated using the results with two attributes adopted from the objective function of the integrated 0-1 programming, viz., costs and CO_2 emissions.

A weight matrix $W_1 = (0.1 \quad 0.9)$ shows the least weight to CO_2 emission as compared to the cost attribute while $W_9 = (0.9 \quad 0.1)$ represents the most weight to CO_2 emission as compared with the cost attribute. Therefore, these two matrices indicate extreme DMs' preferences that seem not to be very realistic in nature. Nine weight matrices are used to compare the TOPSIS results. These weight matrices are:
$W_1 = (0.1 \quad 0.9), W_3 = (0.3 \quad 0.7), W_5 = (0.5 \quad 0.5), W_7 = (0.7 \quad 0.3), W_9 = (0.9 \quad 0.1)$ and $W_2 = (0.2 \quad 0.8), W_4 = (0.4 \quad 0.6), W_6 = (0.6 \quad 0.4), W_8 = (0.8 \quad 0.2)$. TOPSIS aids prioritisation of the thirty optimum results generated by the MOPSO optimiser with the nine different weight matrices covering different types of preferences of the DMs. The weight matrix $W_5 = (0.5 \quad 0.5)$ contains moderate preferences of DMs.

As a representative evaluation technique three different designs are selected using these nine matrices in TOPSIS. Figs. 9 and 10 illustrate CO_2 emission and costs corresponding to the DMs' preferences. In these figures the design IDs are ranked. It is noticed that the ranking through TOPSIS considering the two objective function attributes vary depending on the characteristics of the weight matrices. Therefore, to facilitate the decision-making procedure a DM should use the outcome of an analysis for these two objective functions with all possible weight matrices. Fig. 9 and Fig. 10 show two plots reflecting the DMs' preferences for the ranking process based on the two objective functions. Fig. 9 and Fig. 10 analyse the DMs' preferences (i.e., weight matrices of TOPSIS) in order to monitor the changes in the controlling parameters with respect to the changes in the decision-weights of TOPSIS.

<INSERT Fig. 9 ABOUT HERE>

<INSERT Fig. 10 ABOUT HERE>

Table 15 provides a synopsis of the results from TOPSIS for $W_5 = (0.5 \quad 0.5)$ matrix. From Figs. 9 and 10 it is noticed that for the weight matrix $W_9 = (0.9 \quad 0.1)$ the design generates low CO_2 emission with a high cost. The highest cost and lowest CO_2 emission (Figs. 9 & 10) comes from the trading-off mechanism of TOPSIS for the weight matrix W_9 thereby representing the case of an extreme decision-making process for the weight matrix.

5.2 Scenario analysis of the realistic solutions

Scenario analysis provides the details of open and closed routes for different design IDs. A scenario analysis is conducted with moderate preferences of the DMs using $W_5 = \left(0.5 \quad 0.5\right)$ weight matrix. Table 16 represents the scenario analysis for $W_5 = \left(0.5 \quad 0.5\right)$ TOPSIS weight matrix. There are different scenario analysis solutions on the basis of the TOPSIS weight matrices and design IDs. Once a particular TOPSIS weight matrix is selected by a DM the same should be used for scenario analysis in order to identify the relevant open and closed routes. Further to this, a scenario analysis provides the information on the CO_2 emission and costs if a closed route on the demand side of the supply chain is forcibly opened. Therefore, a DM should conduct a scenario analysis after selecting the most appropriate design ID and the respective solutions from TOPSIS.

<INSERT TABLE 16 ABOUT HERE>

Once the scenario analysis is performed the routes are geographically mapped. This is illustrated in Fig. 11. This figure shows the routes from the two plants to the twenty-two DoPs based in Ireland. The routes are mapped based on the design ID #1781 and TOPSIS weight matrix (0.5 0.5). The routes are different for the different design IDs and TOPSIS weight matrices.

<INSERT Fig. 11 ABOUT HERE>

6. Conclusions

This paper delineates a novel low-carbon location-routing model, its solution approach through a robust DoE-guided MOPSO optimiser and analysis of the solution for the demand side of a supply chain. An integrated 0-1 programming is proposed to optimise the CO_2 emissions, costs associated and the routes of the vehicles. The MOPSO optimiser coupled with DoE is employed to implement the NP-hard integrated mathematical programming approach. TOPSIS is employed to prioritise and rank the solutions. The proposed integrated low-carbon location-routing model allocates drop-off points to the facilities, i.e., plants. Further, it has been evidenced that the proposed method aids in routing vehicles for serving the demand-side of the supply-chain with reduced levels of CO_2 emissions from the vehicles during transportation and optimises the costs involved. The optimal vehicle routes on the demand side of the supply chain are located and geographically mapped for the low-carbon vehicle routes. Additionally, the methodology aids in identifying the open and closed drop-off points for different design IDs. The incurred costs and carbon emission quantities for the closed routes are determined if those are forced to open. The novel model and its solution approach are implemented in a dairy manufacturing supply chain based in Ireland. However, the model, its unique solution approach and analysis can be extended to any two-layer SC.

Future scope of research includes development of a low-carbon capacitated dynamic location-routing methodology using MOPSO optimiser. A comparative analysis of a group of meta-heuristic based optimisers is another scope for future research in the arena of low-carbon location-routing. The proposed NP-hard mathematical programming methodology can be extended to three-layer low-carbon location-routing on the demand side of the supply chain. Variability of demand at the drop-off points and consumer locations is another issue that can be considered as a scope for future research. However, from the methodological perspective the complexity of these NP-hard models would be compounded. In order to tackle such complexities in the methodologies the solution procedures may be considered in multi stages. An efficient simulation package may be engaged in order to facilitate simulation of physical routes on the maps for strategic decision-makers and managers.

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