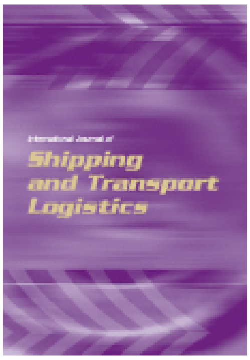


International Journal of Shipping and Transport Logistics

ISSN online: 1756-6525 - ISSN print: 1756-6517
https://www.inderscience.com/ijstl

Global and local supply chain sourcing design: cost and delivery reliability comparison in unimodal and intermodal transportation

Rizwan Shoukat, Xiaoqiang Zhang

Article History:

Received:	22 November 2020
Last revised:	09 October 2021
Accepted:	03 November 2021
Published online:	30 September 2022

Global and local supply chain sourcing design: cost and delivery reliability comparison in unimodal and intermodal transportation

Rizwan Shoukat and Xiaoqiang Zhang*

School of Transportation and Logistics,
Southwest Jiaotong University,
Chengdu, China
and
National Engineering Laboratory of Integrated
Transportation Big Data Application Technology,
Chengdu, China
and
Lab of National United Engineering Laboratory of
Integrated and Intelligent Transportation,
No. 111, North Second Ring Road, Chengdu, China
Email: Rizwanshoukat08@gmail.com
Email: xqzhang@swjtu.edu.cn
*Corresponding author

Abstract: The design of the sourcing strategy is key to gain a competitive advantage. In recent times, supplier failure is one of the most crucial risks of supply chains. The purpose of this study is to investigate the cost of local and global sources of the supply chain (SC) with the comparison of delivery reliability. The approach of this study applied data from one of the largest paper and board industries in Asia. We used a bi-objective mixed-integer linear programming (BOMILP) model for the formulation of the problem. Pareto optimal solutions are generated by implementing the multi-objective genetic algorithm (MOGA) to facilitate decision-makers to trade-off between cost and delivery reliability. The results reveal significant savings of 138.51 million Pkr per year by contracting with local suppliers (Pakistan) as compared to global suppliers from Turkey, China and Vietnam. However, the delivery reliability of global suppliers is higher than local suppliers. Further, this study can be developed by investigating the performance, wastage, and quality of the supplies provided by local and global suppliers.

Keywords: supply chain; genetic algorithm; Pareto solutions; mixed-integer linear programming; local and global sources.

Reference to this paper should be made as follows: Shoukat, R. and Zhang, X. (2022) 'Global and local supply chain sourcing design: cost and delivery reliability comparison in unimodal and intermodal transportation', *Int. J. Shipping and Transport Logistics*, Vol. 15, Nos. 1/2, pp.164–190.

Biographical notes: Rizwan Shoukat is a research scholar and PhD student of Logistics Engineering at the Southwest Jiaotong University, Chengdu, China. He received his MS in Total Quality Management from the University of the Punjab, Pakistan, in 2017. Cost reductions, green logistics, deep learning, intermodal and multimodal freight transportation are among his primary research interests. He has 12 years of experience in several industrial sectors in Pakistan, including production and operations, research and development, quality assurance, supply chain and total productive maintenance.

Xiaoqiang Zhang is a PhD Supervisor and Associate Professor in the School of Transportation and Logistics, Southwest Jiaotong University, Chengdu, China. He received his PhD in Communication and Information System at the Southwest Jiaotong University, in 2006. He worked as a Post-doctor at the Georgia Institute of Technology, Atlanta, USA, from 2009 to 2010. He worked as a Visiting Scholar at the Georgia Mason University, Fairfax, Virginia, USA, from July to September 2015. His research interest includes management of railway transportation, optimisation, supply chain management and deep learning. He has published more than 50 academic papers, six of which were retrieved by SCI, and more than 20 were retrieved by EI, ISTP, etc.

1 Introduction

As customer expectations increase year after year, multinational corporations have significant challenges in modernising and streamlining their supply networks to meet the expectations. Global competitiveness, the expansion of corporate information systems, and shorter product life cycles all contribute to these challenges, resulting in more complicated supply chains (SCs) that necessitate more sophisticated management techniques (Yu et al., 2019). Today, SC management efficiency is characterised by how well its members are coordinated to compete in the global market. At the moment, there are various ways to manage and increase the efficiency of logistics service coordination (for example, information systems, workgroups, a balanced scorecard, information systems, etc.). It should be noted, however, that the SC management system also incorporates the cost control subsystem of the SC members. Businesses continually want to know how effective their logistics network will be. Despite the importance of logistics services in accomplishing the company's objectives, there are presently no effective methods for objectively evaluating their quality. As a result, it can only be evaluated after the supplies have been received. During the research and design of the logistics system, the quality of the logistics chain should be examined using consumer criteria. Customers compare the actual values of quality 'measuring parameters' to the predicted values when assessing a logistics service. If all of these indications agree, the quality is deemed good (Hariga and Al-Ahmari, 2013; Eren and Chan, 2015; Ling and Yumashev, 2018). Several techniques for creating supplier criteria, assessments, and selection have been published in peer-reviewed publications. In the evaluation and selection of environmentally friendly suppliers, multi-criteria decision-making methods have been successfully used. As a result, the subject of supplier selection is a hot topic in both scientific study and real-world applications (Govindan et al., 2015). Choosing a supplier is a complex strategic choice, but few studies have taken into account aspects such as sustainability and risk. The supplier selection process may be exceedingly complex, especially if the selection criteria are subjective and need the decision-makers' judgement, and if each supplier candidate has a unique selection criterion that prevails (Alikhani et al., 2019).

In addition to selection criteria and sourcing strategy, previous researches have largely used mathematical programming techniques such as mixed-integer programming and dynamic programming to address optimum multimodal routing challenges in supplier selection (Ayar and Yaman, 2012; Cho et al., 2012; Xie et al., 2012; Xing and Zhong, 2017). These studies make several assumptions to simulate multimodal transportation networks that must conform to certain routes or sectors (Wang and Yeo, 2018). Multi-criteria decision analysis (MCDA) models are extensively used to assist decision-makers in solving sustainability-related decision-making issues. However, the MCDA technique has numerous shortcomings when it comes to scientific and practical elements of sustainability evaluation. Researchers have used a variety of approaches to decrease decision-making mistakes, including combining the PROMETHEE and FAHP processes (Liao et al., 2018; Wang et al., 2018a). An integrated MCDM model is created for supplier evaluation and selection. In this study, Shannon's entropy is utilised to establish the weights of the assessment criteria, and PROMETHEE is used to rank the potential providers in the final phase. A multi-criteria supplier selection model has been developed using a fuzzy PROMETHEE model. The proposed method might be used to assist SC decision-makers who face similar selection challenges (Safari et al., 2012). By contrasting traditional and non-traditional techniques, a practical solution for complicated selection issues is established. The authors of this study selected a set of major criteria, which included quality, delivery, pricing, environmental health, financial status, management competencies, and working circumstances and investigated their interrelationships, and assessed the relevance of each component (Sari and Timor, 2016). An MCDM approach for selecting the location of solid waste to energy plant is presented, which includes the fuzzy analytic network process (FANP) and the technique for order of preference by similarity to ideal solution (TOPSIS) model (Wang et al., 2018c). The MCDM model is used to choose vendors in the rice SC (Wang et al., 2018b).

Along with the approaches used for sourcing strategies, many solution methods are utilised to get the best possible results while selecting global and local suppliers. Metaheuristic algorithms have recently been applied to tackle real-world issues in economics, engineering, politics, management and engineering (Kumar et al., 2014). A metaheuristic algorithm's two most crucial components are intensification and variety. To properly address the real-life issue, a correct combination of these elements is necessary. Most metaheuristic algorithms are based on biological evolution, swarm behaviour, and physical principles (Webb, 2002). The genetic algorithm is a well-known population-based metaheuristic algorithm (Michalewicz, 1996). There are two types of metaheuristic algorithms: single-solution and population-based. Single-solution metaheuristic algorithms are metaheuristic algorithms that use a single candidate solution and use local search. The solution supplied by single-solution-based metaheuristics, on the other hand, may become trapped in local optima (Kumar and Kumar, 2017). Simulated annealing, tabu search (TS), microcanonical annealing (MA), and guided local search are some well-known single-solution-based metaheuristics. Throughout the search phase, population-based metaheuristics employ many potential solutions. These metaheuristics preserve population variety and prevent solutions from becoming trapped in local optima.

In the literature, the themes of dependability, transportation cost, responsiveness, IT orientation, and communication have been explored as strategies for selecting a shipping line. When choosing a container shipping company, dependability, after-sales support, service quality, pricing, and perceived capabilities are all important considerations (Yeung et al., 2012; Yuen and Thai, 2015). The qualities of shipping business service quality are identified, and their impact on customer satisfaction is investigated. Customer satisfaction is influenced by service quality variables such as speed, dependability, responsiveness, and value, according to the research (Yuen and Thai, 2015). Liner shipping includes a solution on container routing with repacking (Wang et al., 2017). Logistical hazards in container shipping operations are examined and analysed (Chang et al., 2015). The cost of transportation, as well as the reliability of delivery, is important considerations. The bulk of the criteria used to select a carrier are based on a low delivery cost or a shorter transit time (Chung and Citation, 2007). Several aspects' competitiveness and effect in freight forwarding are recognised and investigated. In every example, there are statistically significant and favourable correlations (Fanam et al., 2016). A study approach with four constructs and six hypotheses is proposed to explore how switching fees help customers avoid switching shipping lines. The effect of perceived service quality on customer loyalty is shown to be significant for consumers with high levels of satisfaction (Chao and Chen, 2015). A benchmarking technique for freight rates has been developed, and the causes of different shipping prices for shippers and their transportation outsourcing strategies have been identified (Joo et al., 2017).

Supplier failure has been listed as one of the top SC risks in recent years, with vulnerabilities increasing dramatically in recent years. Researchers try to limit the negative effects of supplier failure by implementing strategies such as local versus global sourcing, single versus multiple sourcing, performance-based supply contracts, and optimising order distribution across suppliers. Global sourcing is a well-known business approach that entails a trade-off between dependable, high-cost local suppliers and untrustworthy, low-cost overseas vendors. Global procurement carries the hazards of currency rate volatility, trade restrictions, and longer lead times. The creation of sourcing strategies that take into account pricing, currency rate risks, and supplier delivery reliability is an essential research area that requires attention.

In this study, we present a mixed-integer linear programming model to solve the bi-objective problem of minimising total procurement costs while maximising the delivery reliability of local and global (L&G) vendors. We solved the problem by using a multi-objective genetic algorithm (MOGA) to provide a Pareto front solution. This research will assist logistics service providers, shipping lines, decision-makers, and policymakers in the selection of suppliers, as well as in the export and import of goods. Second, this research will help transportation planners make better freight movement decisions. Our investigation made the following significant contributions:

- To analyse the cost and delivery reliability of global (China, Turkey and Vietnam) and local (Pakistan) suppliers.
- To provide Pareto solutions generated by MOGA of the bi-objective problem and share with the decision-makers.
- To evaluate the cost of shipping from the shipper to the consignee in unimodal and intermodal transportation.
- To highlighting the essential parameters affecting the total cost of procurement and delivery reliability and providing managerial insights for justifying the impact of sensitivity analysis.

This paper has been divided into five sections. Section 2 shows the important technical context of the real-life cases and formulation of the bi-objective MILP model. This section will also provide information for the solution methodology with details about assumptions for the mathematical model of the bi-objective suppliers' selection problem. Section 3 gives information about some parameters and initial data which are applied in the calculations. Section 4 illustrates results and a discussion of the real-life problem. Lastly, Section 5 presents the conclusions and further research ideas.

2 Problem statement

In this section, we will provide the design and definition of the bi-objective problem of selecting suppliers. We will provide the formulation of bi-objective mixed-integer linear programming (BOMILP) model that will examine cost and reliability objectives in the supplier's selection. The MILP problem is solved by creating Pareto front solutions generated by the MOGA.

2.1 Problem definition

In this investigation, we explained the subject as a BOMILP problem. In this problem, our prime objective is to minimise the cost of suppliers in the purchase and delivery of calcium carbonate ($CaCO_3$) in the paper and board industry in Pakistan. Our second objective is to maximise the reliability in the case of domestic or global suppliers.

The problem in this study is from one of the largest paper and board manufacturing industries in Asia. They coat white duplex board, white bleach board, and tetra duplex board and export worldwide. The coating is the process of making the surface of paper and board too smooth for good printing. $CaCO_3$ is applied as a whitening chemical on the surface for two-layers or three-layers coating with chemicals for binding, strength, brightness, and other important properties. There are limited suppliers in the domestic market for the raw material ($CaCO_3$), who charge monopolistic prices of chemicals. Suppliers authenticate the manufactures by obligating them to sign the contract for the procurement of a specific quantity of the raw material, no matter what is the demand for supplies in the market. As a response, they offer a discount on the prices. Suppliers seldom offer a discount to all other non-contract manufacturers in the market. The international market rules prices of the raw material. Due to the economic condition of Pakistan, the prices of imported chemicals are higher as compared to domestic chemicals. The gap between the prices of local and imported $CaCO_3$ is wider because of fluctuating exchange rates, long lead times, quality of the raw materials, safety issues due to terrorism, diseases like COVID-19, and other disasters. For global purchases, manufacturers have to buy large quantities of raw materials with the maintenance of higher inventories at warehouses, which cause a higher cost of working capital and end at less profitability.

In our problem, we assumed four local suppliers with a single type of product ($CaCO_3$), from the Punjab and Sindh regions of Pakistan. A single type of product with 40 feet containers unit capacity for transport is considered for this study. Four global suppliers are also included for this research that operates from China, Turkey, and Vietnam with the same product and 40-feet shipping containers, as shown in Figure 2.

Figure 1 Flowchart of research methodology (see online version for colours)

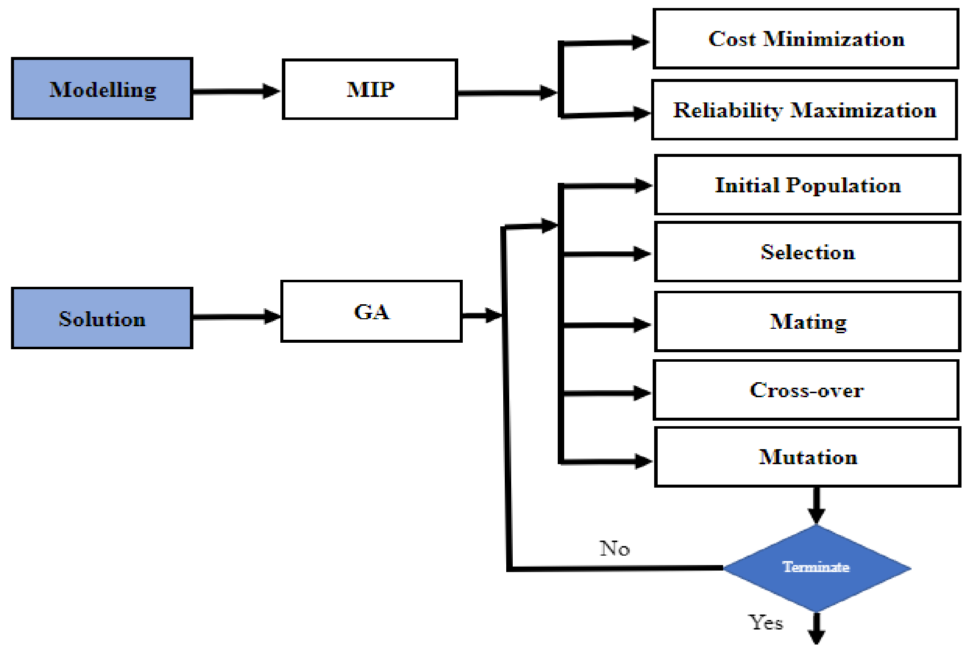
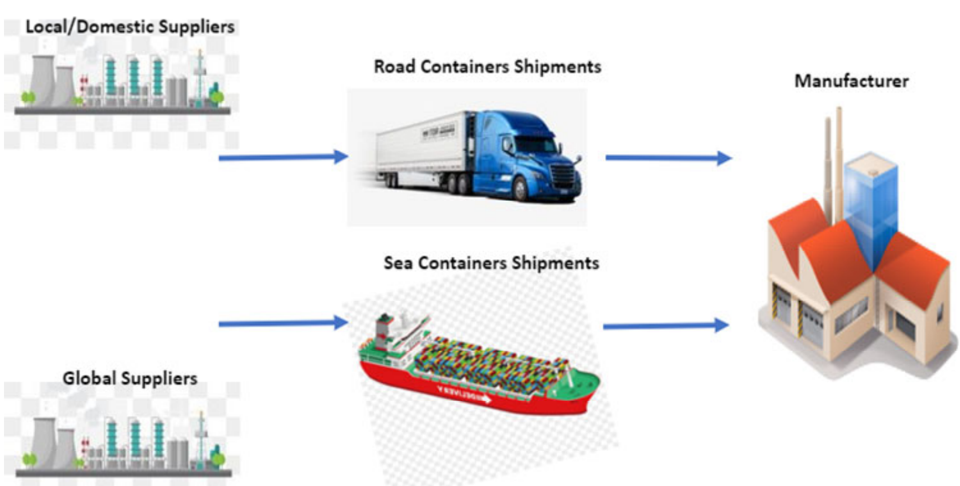


Figure 2 Graphical illustration for L&G supplies (supplier to manufacturer) (see online version for colours)



2.2 Model formulation

A BOMILP model has been formulated to select the best vendors. This model has the primary objective of minimisation the total procurement cost of suppliers. Our secondary objective is to maximise the delivery reliability of the suppliers. Total cost includes the acquisition cost of raw material ($CaCO_3$) from suppliers, transportation cost, and cost of stock out. Reliability includes quantity supplied and demand of the raw material with the delivery reliability index.

2.2.1 Assumptions

The assumptions of our model are:

- single product with multi-planning periods
- fixed and known manufacturers, suppliers, retailers, and their locations with capacities
- ordering to the vendors at the beginning of every period
- treating stock out as a loss of sales.

2.2.2 Indices

s supplier s ∈ (1, 2, 3, …, S)

p plant p ∈ (1, 2, 3, …, P)

t time period t ∈ (1, 2, 3, …, T).

2.2.3 Parameters

C_s the capacity of the supplier s in any given period (13,823 tonnes per year)

C_p the capacity of plant p for production in any given period (13,823 tonnes per year)

D_{pt} the demand at plant p for the raw material in period t (13,823 tonnes per year)

P_{spt} the cost of acquisition of raw material to plant p from the supplier s in period t (Pkr 37,965 per ton for global suppliers and Pkr 29,930 per ton for local suppliers)

Tr_{spt} transportation cost from the supplier s to plant p in period t (Pkr 912.3 per ton for local supplies and Pkr 10,924 per ton for global supplies)

Sh_{pt} the cost of the shortage of material at plant p in period t (Pkr 3,796.5 per ton for global suppliers and Pkr 2,993 per ton for local suppliers)

Dr_s the index of supplier delivery reliability (0.78, 0.80, 0.82, 0.84, and 0.86 and 0.92, 0.94, 0.96, 0.94, and 0.90 for global suppliers)

U_s the upper bound on the total number of suppliers (4 + 4)

R utilisation of raw material per unit of the product (1 ton)

J transport of raw material per unit of the product (1 ton).

2.2.4 Decision variable

q_s 1, if supplier s is selected; 0 otherwise

Q_{spt} quantity of raw material from the supplier s shipped to plant p in period t

T_{spt} transportation of raw material in tons shipped from supplier s to plant p in period t

S_{pt} quantity of raw material shortage at plant p in period t

$$\text{Min } f_1 = \sum_s \sum_p \sum_t P_{spt} Q_{spt} + \sum_s \sum_p \sum_t Tr_{spt} T_{spt} + \sum_p \sum_t S_{pt} Sh_{pt} \tag{1}$$

$$\text{Min } f_2 = \sum_s \left(\sum_p \sum_t Q_{spt} \Big/ \sum_p \sum_t D_{pt} \right) * Dr_s \tag{2}$$

subjected to

$$\sum_p Q_{spt} \le C_s, \quad \forall s, t \tag{3}$$

$$R \sum_s Q_{spt} \le C_p, \quad \forall p, t \tag{4}$$

$$\sum_p \sum_t Q_{spt} \ge \sum_t D_{pt}, \quad \forall p \tag{5}$$

$$J \sum_s T_{spt} \le C_p, \quad \forall p, t \tag{6}$$

$$\sum_s \sum_t T_{spt} \ge \sum_t D_{pt}, \quad \forall p \tag{7}$$

$$\sum_s q_s \le U_s \tag{8}$$

$$Q_{spt} \ge 0, \quad \forall s, p, t \tag{9}$$

$$Tr_{spt} \ge 0, \quad \forall s, p, t \tag{10}$$

$$S_{pt} \ge 0, \quad \forall p, t \tag{11}$$

Equation (1) shows the objective function of minimising the total cost of procurement. The first summation indicates the cost of raw material, the second summation shows the cost of transportation, and the last summation presents the cost of raw material shortage at the plant. Equation (2) indicates the maximisation of the delivery reliability of L&G suppliers for the manufactures of the paper and board industry in Pakistan as our second objective function. The summation shows the fraction between the raw material and demand at the plant with the supplier delivery reliability index. Equations (3)–(4) show the constraints of capacity for suppliers and plant. Equation (5) shows that the total quantity of the raw material arriving at the plant must be greater than or equal to the total demand of the plant. Equation (6) indicates that material transfer at the plant must be less than the capacity of the plant. Equation (7) shows that the transfer of the material should be greater than or equal to the demand of the plant. Equation (8) depicts the upper limit of the suppliers. Equations (9)–(11) indicate the non-negativity restrictions on the constraints.

2.3 Solution methodology

In our study, we applied Pareto fronts to solve the bi-objective problem of sourcing design with the help of a genetic algorithm proposed by Deb (2011).

The genetic algorithm is very famous these days to get the solutions to optimisation problems. It works with three main operators which are selection, crossover and mutation. The genetic algorithm works as a universal optimiser to optimise any kind of problem. GA is very easy to use, implement, and create a proper balance between exploitation and exploration. The parameters can be set properly with logical reasoning.

In the genetic algorithm terminology, a solution vector which is denoted by $x \in X$ is called a chromosome. These chromosomes are based on the discrete unit which are named genes. Genes are responsible for controlling the features of chromosomes. The genes are considered binary digits in the execution of the GA. The GA operates with the population. Generally, the population is initialised randomly. As the search progresses, the population starts including the most fitting solution and converges finally with a single dominating solution.

The genetic algorithm works with two lead operators which are crossover and mutation. These operators are important because the new solutions from the existing ones are provided by these operators' workings. The selection of the parents is carried out in the population. So, it is assumed that offspring will inherit better genes to make better and fit parents. The genes with good chromosomes appear more frequently in the population and coverage ultimately with a good solution.

The mutation operator is responsible for providing the random changes in the chromosomes' features. In the execution of the genetic algorithm, the selection of the mutation rate depends upon the length of chromosomes. So, newly provided chromosomes generated by mutation cannot be very different from originals. In this research, the developed mathematical model with GA application is written as M-files using MATLAB software. Steps in the implementation of the GA are as follows:

1 The evaluation of each individual in the targeted population.

2 Best and fittest parents' selection out of the given population.

3 Performing the crossover by combining the individuals from parents again to produce their children as a new generation.

4 Mutation of the newly created generation.

5 If no termination, repeat Step 2 until the operation's termination and return to the best-found individual in the present population.

Bi-objective genetic algorithm pseudocode

```
Begin
    t = 0
Initiate the population for chromosomes Pop(gg);
        Evaluating the initialised population by calculating its measure of fitness
        Pop(gg);
    While not termination criteria do
    gg := gg + 1;
```

Select Pop(gg + 1) from Pop(gg);
Crossover Pop(gg + 1)
Mutate Pop(gg + 1);
Evaluate Pop(gg + 1);
End While
Output results to external archive
End

In the implementation of GA, a set of solutions with a good spread within a given range is identified. The fitness function is created during multi-objective optimisation using GA. The fitness function uses model equations to optimise two objective functions at the same time using MATLAB'S optimisation toolbox. The single objective, on the other hand, can also be optimised using MATLAB'S toolbox. In terms of Pareto, all of the options are optimal. Variable 'x' values $x_1, x_2, x_3, \ldots, x_n$ are used as inputs. In the fitness function, the GA solver takes one input value x, where x is a row vector with as many elements as the number of variables in the problem. The fitness function calculates the value of each objective function and returns it as a single vector output y.

A minimum of two input parameters, such as the number of variables and fitness function, should be provided when using the MATLAB toolbox to solve the MOGA optimisation problem. The first two output arguments returned by MOGA are x and fval, which display the objective function's Pareto front points and values. A minimum of two input parameters, such as the number of variables and fitness function, should be provided when using the MATLAB toolbox to solve the MOGA optimisation issue. The first two output arguments returned by the MOGA are x and fval, which show the objective function's Pareto front points and values.

A population of initial solutions is formed once decision variables or parameters are encoded in GA. At the same time, GA affects the whole population. The appropriate number of initial individuals or population within the required range is generated using a random generator. The binary string representation is the most popular, in which each vector is encoded as a binary string before being concatenated to create chromosomes. We can choose any population between bit string and double vector to select the chromosomes in the population. The solver automatically decodes the data in the bit string if we choose the bit string option in the population. The selection of the chromosomes by using the bit string option is shown in Table 5.

Iterations begin after the optimisation is performed, and the solver toolbox displays the functions and decision variables. Other optimisation options include population type (double vector, bit string), crossover (constraint dependent, single point, double point, intermediate and scattered), mutation (uniform, constraint dependent and Gaussian), and mutation (uniform, constraint dependent and Gaussian).

3 Computational experiments

In this section, we will discuss the data used for the model with an overview of real-life cases with their applicability in this investigation. In our problem, we applied data from one of the largest paper and board industries in Asia. Our data include L&G suppliers which differ the rate of $CaCO_3$, the quantity of the raw material used for production, the capacity of the plant, the demand of the customers, annual sales, total weight of $CaCO_3$ added on the uncoated baseboard, consumption of raw material per month, delivery time of raw material, taxes applied on transports, locations of suppliers, feedback by managers about the supplies, historical data of delivery of supplies, labour cost, utility cost and cost of raw material.

4 Results and discussion

In this section, we will look at our MILP model for bi-objective problems in a variety of scenarios, using both domestic and international vendors. The pricing of raw materials and delivery reliability are the key differences between L&G suppliers.

In the first case, raw materials are delivered to the plant from vendors in Punjab and Sindh. In the second example, raw materials are ordered at the plants from worldwide vendors in China, Turkey and Vietnam. The pricing difference for $CaCO_3$ of L&G suppliers is shown in Tables 1 and 2. Exchange rates 2020–2021 is also given to compare the prices of global from local suppliers. We obtained Pareto solutions for cost and delivery reliability between L&G suppliers. For each of the scenarios, sensitivity analysis is offered to assist decision-makers in determining the appropriate sourcing method. BOMILP is run on a computer with an Intel (R) core (TM) M-5Y10c CPU at 0.80 GHz, 2 core(s), 4 logical processor(s) and 4 gigabytes of RAM.

Table 1 Raw material prices (local suppliers)

Period	*Demand for raw material (tons)*	*Raw material (local price Pkr per ton)*			
		Lahore (Punjab)	*Kasur (Punjab)*	*Karachi (Sindh)*	*Hyderabad (Sindh)*
1	930	20,543	39,205	29,953	27,130
2	930	20,410	38,950	29,758	26,953
3	899	20,364	38,863	29,691	26,893
4	1,020	20,436	39,000	29,796	26,988
5	1,302	20,298	38,738	29,595	26,806
6	1,260	20,255	38,655	29,532	26,749
7	1,209	20,960	40,000	30,560	27,680
8	1,240	21,877	41,750	31,897	28,891
9	1,230	21,424	40,885	31,236	28,292
10	1,333	22,028	42,038	32,117	29,090
11	1,230	21,936	41,863	31,983	28,969
12	1,240	22,087	42,150	32,203	29,168

The proposed MOGA is used to provide Pareto front solutions for the BOMILP problem. 100 separate Pareto sets are taking into consideration the cost of procurement as well as the delivery reliability of L&G providers.

Table 2 Raw material prices (global suppliers)

Period	*Demand for raw material (tons)*	*Raw material at global price dollar per ton*				*Exchange rate (Pkr)*
		Tianjin China	*Shanghai China*	*Ho Chi Minh Vietnam*	*Nigde Turkey*	
1	930	15,682	27,444	26,659	78,410	156.82
2	930	15,580	27,265	26,486	77,900	155.8
3	899	15,545	27,204	26,427	77,725	155.45
4	1,020	15,600	27,300	26,520	78,000	156
5	1,302	15,495	27,116	26,342	77,475	154.95
6	1,260	15,462	27,059	26,285	77,310	154.62
7	1,209	16,000	28,000	27,200	80,000	160
8	1,240	16,700	29,225	28,390	83,500	167
9	1,230	16,354	28,620	27,802	81,770	163.54
10	1,333	16,815	29,426	28,586	84,075	168.15
11	1,230	16,745	29,304	28,467	83,725	167.45
12	1,240	16,860	29,505	28,662	84,300	168.6

4.1 Sample #1 (S1)

Figure 3 depicts the trade-off between procurement cost and delivery reliability of local suppliers for the Pakistani paper and board sector. Figure 4 depicts the required findings of this comparison, such as:

a the average distance between individuals

b selection function

c distance of individuals

d genealogy

e stopping criteria

f rank histogram

g score histogram

h Pareto front

i average spread.

These findings support the study of both objective functions of suppliers at the local level.

In this process, four local suppliers from Lahore, Kasur from the Punjab Province of Pakistan and Karachi, and Hyderabad from the province of Sindh in Pakistan receive the raw material ($CaCO_3$) order. Consignment is transported on 40-foot container trucks. The orders at the facility are expected to be delivered in less than a week. The overall annual demand at the facility is 13,823 tonnes per year as shown in Table 1 (month-wise demand of the customer is given for one year). The cost of raw material from local suppliers is given in Table 1. The distance between supplier and customer cities is also shown in Table 3. We took the average cost of buying the raw materials from all the local suppliers which is Pkr 359,161 (Pkr 0.35 million) after converting all the $ rate prices in Pkr according to the exchange rate of consecutive months. The transportation cost of delivering from Lahore, Karachi, Hyderabad, and Kasur is Pkr 1.5 per ton per kilometre. The total cost of transportation from Karachi to Kasur (including loading and unloading, toll tax, and other highway charges) is Pkr 83,556 in the delivery of 44 tons of material. The cost from Lahore to Kasur is Pkr 3,240, Hyderabad to Kasur is Pkr 72,793, and Kasur to the customer's facility in Kasur is Pkr 991. The average cost of transportation at the local level of four suppliers in Pakistan is Pkr 40,145 for 44 tons (one container delivery cost) delivery whereas the average cost of delivering 13,823 tonnes is 40,145 $*$ 314 = 12.6 million – Pkr (13,823 tons carried by 314 containers if one container carries approximate 44 tons then 44 $*$ 314.15 = 13,822.6 tons). The cost of stock out is 10% of the cost of raw material which would be Pkr 0.035 million. Thus, the total cost of supplying the material is 12.6 + 0.35 + 0.035 = Pkr 12.98 million from local suppliers.

Figure 3 Total procurement cost and delivery reliability of local suppliers (see online version for colours)

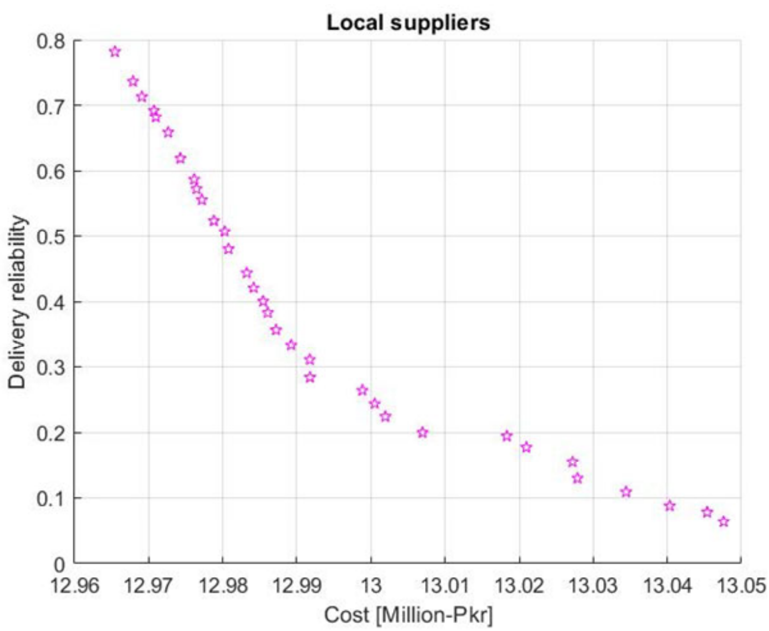


Table 3 Distance between L&G cities of suppliers

Cities	*Kasur (km)*	*Lahore (km)*	*Karachi (km)*	*Hyderabad (km)*
Kasur	15	49	1266	1101
Global cities	Tianjin, China (km)	Shanghai, China (km)	Ho Chi Minh, Vietnam (km)	Nigde, Turkey (km)
Karachi (seaport)	12,273	10,891	8,932	8,021

Figure 4 MOGA optimisation results of cost and delivery reliability (local suppliers) (see online version for colours)

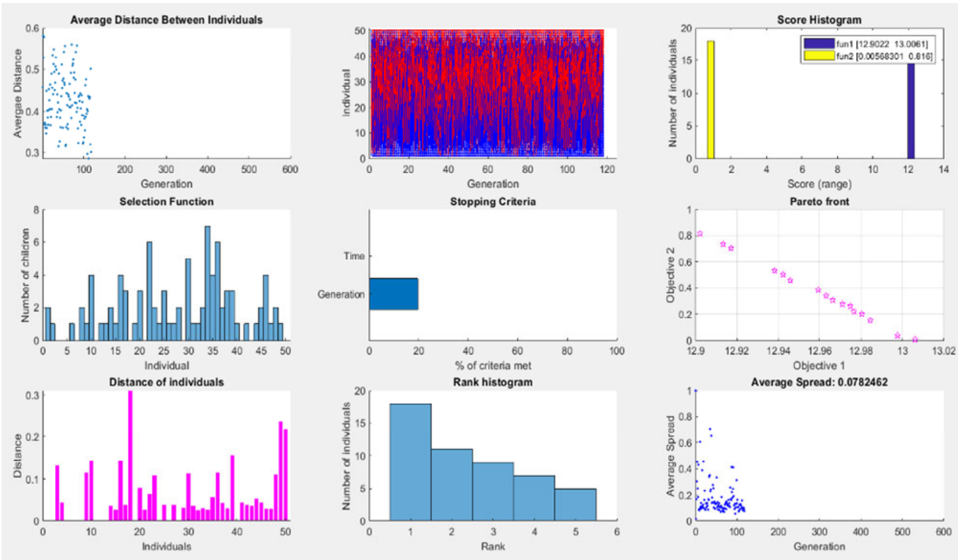


Table 4 Parameter settings of MOGA

Parameters (MOGA)	*Values*
Population size	100
Population type	Double vector
Number of iterations	166
Crossover rate	0.72
Creation function	Constraint dependent
Mutation	Uniform
Crossover	Constraint dependent
Selection function	Tournament
Crossover fraction	0.7
Migration direction	Forward
Number of variables	3

Domestic delivery reliability index values are 0.78, 0.80, 0.82, 0.84, and 0.86, depending on the supplier's capacity, infrastructure, economic situation, place of origin, mode of transport and delivery lead time. The reliability index values are determined through interaction with the manufacturer and are based on supplier delivery performance in the past. Figures 4 and 6 show the results of the genetic algorithm as follows:

a the average distance between individuals

b selection function

c distance of individuals

d genealogy

e stopping criteria

f rank histogram

g score histogram

h Pareto front

i average spread.

These findings support the study of both objective functions of suppliers at the local level.

Table 5 MOGA results for global suppliers cost and reliability (initial score and initial population matrix)

Index	*Initial score matrix*		*Initial population matrix*		
	f_1	f_2	x_1	x_2	x_3
1	152.8302	0.30054	0.111233	0.741528	0.023553
2	151.1178	0.887232	0.864748	0.016879	0.155886
3	151.1178	0.887232	0.864748	0.016879	0.155886
4	151.1178	0.887232	0.864749	0.016879	0.155886
5	151.1178	0.887232	0.864749	0.016879	0.155886
6	151.1178	0.887232	0.864749	0.016879	0.155886
7	152.8302	0.30054	0.111233	0.741528	0.023553
8	151.1178	0.887232	0.864749	0.016879	0.155886
9	152.8302	0.30054	0.111233	0.741528	0.023553
10	152.8302	0.30054	0.111233	0.741528	0.023553
11	152.8302	0.30054	0.111233	0.741528	0.023553
12	152.8302	0.30054	0.111233	0.741528	0.023553
13	152.8302	0.30054	0.111233	0.741528	0.023553
14	151.1178	0.887232	0.864749	0.016879	0.155886
15	151.1178	0.887232	0.864749	0.016879	0.155886
16	152.4663	0.331401	0.176044	0.587679	0.042221
17	152.1638	0.35046	0.223219	0.459799	0.057077
18	151.1361	0.844551	0.819709	0.024688	0.150784
19	151.1394	0.767406	0.741039	0.026233	0.142824
20	151.1371	0.854113	0.829324	0.025117	0.151709
21	151.4387	0.442784	0.383732	0.153267	0.097242
22	151.3879	0.468879	0.414921	0.13174	0.102041
23	152.6097	0.364651	0.196648	0.648223	0.039437
24	152.6317	0.365078	0.195059	0.657512	0.038544
25	152.1089	0.370056	0.248193	0.436552	0.061368
26	152.8302	0.30054	0.111233	0.741528	0.023553
27	151.1588	0.661125	0.631295	0.034615	0.131231
28	152.8302	0.30054	0.111233	0.741528	0.023553

Table 5 MOGA results for global suppliers cost and reliability (initial score and initial population matrix) (continued)

Index	*Initial score matrix*		*Initial population matrix*		
	f_1	f_2	x_1	x_2	x_3
29	151.1497	0.732327	0.704458	0.030645	0.138833
30	151.6318	0.420135	0.34295	0.234851	0.086775
31	151.963	0.523742	0.417754	0.374667	0.083082
32	151.1356	0.788306	0.762622	0.024577	0.145105
33	151.2386	0.522966	0.483608	0.06857	0.113848
34	151.1691	0.620894	0.589485	0.039021	0.126719
35	151.2956	0.506282	0.461417	0.092664	0.109741
36	151.1763	0.562547	0.529546	0.042197	0.120497
37	151.1499	0.776018	0.748819	0.030662	0.143251
38	151.1178	0.887232	0.864749	0.016879	0.155886
39	151.4064	0.47628	0.420734	0.139549	0.102007
40	151.2288	0.625657	0.58882	0.064256	0.12467
41	151.7879	0.406484	0.314722	0.300879	0.078723
42	151.1585	0.718569	0.689674	0.034381	0.137065
43	151.6591	0.424396	0.344783	0.246396	0.086001
44	151.1623	0.641853	0.611397	0.036123	0.12913
45	151.3853	0.481803	0.428292	0.130604	0.103461
46	151.2052	0.682329	0.64856	0.054185	0.131414
47	151.2317	0.543934	0.505547	0.065594	0.116268
48	151.1689	0.72722	0.697506	0.038756	0.137502
49	151.191	0.640171	0.60705	0.048241	0.127742
50	151.1544	0.687024	0.658006	0.03272	0.134041
51	152.2806	0.432938	0.29629	0.509014	0.060383
52	151.1436	0.796603	0.770312	0.027945	0.145607
53	151.1178	0.887232	0.864748	0.016879	0.155886
54	151.1517	0.782832	0.755582	0.031374	0.143869
55	151.1666	0.618116	0.586889	0.037986	0.126542
56	151.4539	0.523624	0.464475	0.159531	0.104744
57	151.173	0.587446	0.555148	0.040731	0.123163
58	152.368	0.407134	0.262035	0.546036	0.054026
59	152.5833	0.341191	0.175239	0.637123	0.038189
60	152.8302	0.30054	0.111233	0.741528	0.023553
61	151.181	0.709529	0.67842	0.043902	0.135196
62	151.1328	0.804349	0.779171	0.023386	0.146848
63	151.1178	0.887232	0.864748	0.016879	0.155886
64	151.1532	0.792129	0.764881	0.032018	0.144746
65	151.369	0.490974	0.439107	0.123722	0.105072

Table 5 MOGA results for global suppliers cost and reliability (initial score and initial population matrix) (continued)

Index	Initial score matrix		Initial population matrix		
	f_1	f_2	x_1	x_2	x_3
66	151.1261	0.842154	0.818192	0.020478	0.150964
67	151.476	0.549946	0.48916	0.168838	0.106502
68	151.1502	0.714837	0.686652	0.030863	0.137041
69	151.1451	0.751977	0.724843	0.028664	0.141019
70	151.4632	0.446123	0.384876	0.163585	0.096541
71	152.022	0.400067	0.286671	0.399805	0.0681
72	151.1245	0.858958	0.835413	0.019752	0.152737
73	151.1485	0.723546	0.695649	0.030157	0.137993
74	151.1748	0.857471	0.829268	0.041029	0.150447
75	151.1734	0.773581	0.744181	0.040591	0.142008
76	151.1308	0.815534	0.790722	0.022497	0.148068
77	151.1733	0.65425	0.622974	0.040766	0.129918
78	151.3149	0.512518	0.465968	0.100833	0.109556
79	151.1725	0.607611	0.575672	0.040508	0.125226
80	151.2385	0.544713	0.505712	0.068478	0.116052
81	152.5559	0.338471	0.174997	0.625552	0.039079
82	151.1433	0.780225	0.753699	0.027869	0.143957
83	152.2543	0.363071	0.227724	0.498033	0.054449
84	151.1749	0.672942	0.641815	0.041402	0.131746
85	151.3092	0.5822	0.537281	0.098268	0.116863
86	151.1974	0.568905	0.534063	0.051097	0.120248
87	151.1512	0.702851	0.674378	0.031339	0.135781
88	152.0847	0.429601	0.310924	0.426281	0.068362
89	151.6165	0.431116	0.355523	0.228411	0.088492
90	152.5241	0.331657	0.171	0.612105	0.039757
91	151.1904	0.725797	0.694076	0.047859	0.136446
92	151.2336	0.639137	0.602078	0.066234	0.125834
93	151.5737	0.464298	0.393179	0.210264	0.093653
94	151.9132	0.393584	0.290103	0.353816	0.072075
95	151.1196	0.877179	0.854366	0.017683	0.154788
96	151.4036	0.503688	0.448835	0.138337	0.104885
97	152.3538	0.435363	0.292022	0.539959	0.057494
98	151.1592	0.673436	0.643766	0.034749	0.132463
99	152.3233	0.398303	0.257182	0.527142	0.055037
100	151.2106	0.732642	0.699175	0.056351	0.136287

Table 6 MOGA results for local suppliers cost and reliability (initial score and initial population matrix)

Index	*Initial score matrix*		*Initial population matrix*		
	f_1	f_2	x_1	x_2	x_3
1	13.0476	0.063724	0.01898	0.027356	0.826436
2	12.96544	0.781889	0.88871	0.028799	0.918927
3	13.04762	0.063734	0.018982	0.027396	0.826394
4	12.9835	0.56473	0.634333	0.03029	0.740091
5	13.04776	0.063823	0.019003	0.027759	0.826026
6	12.9757	0.694634	0.78416	0.034044	0.862236
7	13.0476	0.063726	0.01898	0.027364	0.826428
8	12.96792	0.772639	0.879956	0.0442	0.800502
9	13.0476	0.063725	0.01898	0.02736	0.826431
10	13.04732	0.122815	0.088711	0.04944	0.754237
11	13.02721	0.154509	0.141466	0.029758	0.62135
12	13.0476	0.063725	0.01898	0.027359	0.826433
13	12.96997	0.739305	0.837572	0.028784	0.905999
14	12.98032	0.618467	0.698706	0.040972	0.705701
15	12.98257	0.560628	0.63112	0.030588	0.709255
16	13.00761	0.372364	0.398637	0.029077	0.764254
17	12.98608	0.382879	0.436776	0.033346	0.327741
18	13.02788	0.129596	0.113973	0.030012	0.572696
19	12.98779	0.36301	0.413361	0.033237	0.3149
20	12.96665	0.766305	0.870661	0.029287	0.900815
21	12.98062	0.649166	0.727977	0.028533	0.901834
22	13.02784	0.227446	0.218551	0.02792	0.825077
23	12.98027	0.507273	0.577186	0.032903	0.515083
24	12.98416	0.420989	0.479815	0.032701	0.387302
25	13.02324	0.224187	0.220923	0.029363	0.713797
26	13.0476	0.063725	0.01898	0.02736	0.826432
27	12.97718	0.555262	0.632003	0.031372	0.58354
28	13.00195	0.223638	0.246735	0.033044	0.261089
29	13.03444	0.109065	0.083837	0.029061	0.661058
30	13.00249	0.236448	0.259747	0.032687	0.305672
31	12.98777	0.362587	0.412947	0.033315	0.312842
32	12.98568	0.414765	0.471302	0.032622	0.402837
33	13.04441	0.155596	0.128734	0.05446	0.728383
34	13.04147	0.094424	0.059435	0.027959	0.773964
35	12.97672	0.574332	0.652927	0.030992	0.623665
36	12.98927	0.377028	0.426463	0.032545	0.383844
37	13.01046	0.268353	0.283948	0.030633	0.557153

Table 6 MOGA results for local suppliers cost and reliability (initial score and initial population matrix) (continued)

Index	*Initial score matrix*		*Initial population matrix*		
	f_1	f_2	x_1	x_2	x_3
38	12.96908	0.712859	0.810467	0.029674	0.817154
39	12.98078	0.480436	0.547493	0.031933	0.470168
40	12.99174	0.310909	0.352775	0.033555	0.264883
41	13.04033	0.088008	0.053997	0.028328	0.732966
42	12.97551	0.690876	0.778923	0.028688	0.899736
43	12.97489	0.678215	0.769469	0.041402	0.737999
44	13.00051	0.243594	0.269862	0.032959	0.281352
45	13.0476	0.063725	0.01898	0.02736	0.826431
46	12.97319	0.649446	0.737758	0.030789	0.735754
47	12.99282	0.43434	0.483278	0.030684	0.607621
48	13.0476	0.063724	0.01898	0.027356	0.826436
49	12.97071	0.691654	0.78576	0.029746	0.79788
50	12.99177	0.28395	0.323929	0.034081	0.196165
51	12.99165	0.338835	0.382668	0.032783	0.337039
52	13.00697	0.199447	0.214693	0.032788	0.304033
53	12.98324	0.443938	0.505525	0.032547	0.42542
54	12.97565	0.610682	0.693221	0.030903	0.690307
55	12.97091	0.754615	0.860915	0.058697	0.679809
56	12.9788	0.523479	0.596024	0.031744	0.536058
57	12.98612	0.602959	0.678187	0.052346	0.675183
58	12.97615	0.585958	0.666097	0.031002	0.640155
59	12.98097	0.529004	0.599834	0.033452	0.575555
60	12.99884	0.264265	0.294068	0.033024	0.29747
61	12.98923	0.333327	0.379823	0.033451	0.270204
62	12.97586	0.610717	0.692885	0.030451	0.698755
63	12.99872	0.277653	0.308536	0.032838	0.328871
64	13.03937	0.179495	0.159891	0.052516	0.705104
65	13.03108	0.149404	0.131141	0.028964	0.692556
66	12.98835	0.416226	0.469543	0.032101	0.463516
67	12.98946	0.434447	0.487865	0.032377	0.526079
68	12.97513	0.686545	0.775306	0.03085	0.861637
69	12.98868	0.363292	0.41264	0.033381	0.331627
70	12.9885	0.443838	0.498921	0.031745	0.535736
71	13.00801	0.262831	0.282624	0.036891	0.437125
72	13.01106	0.341758	0.361701	0.029244	0.757041
73	12.96789	0.735935	0.836597	0.029392	0.851552

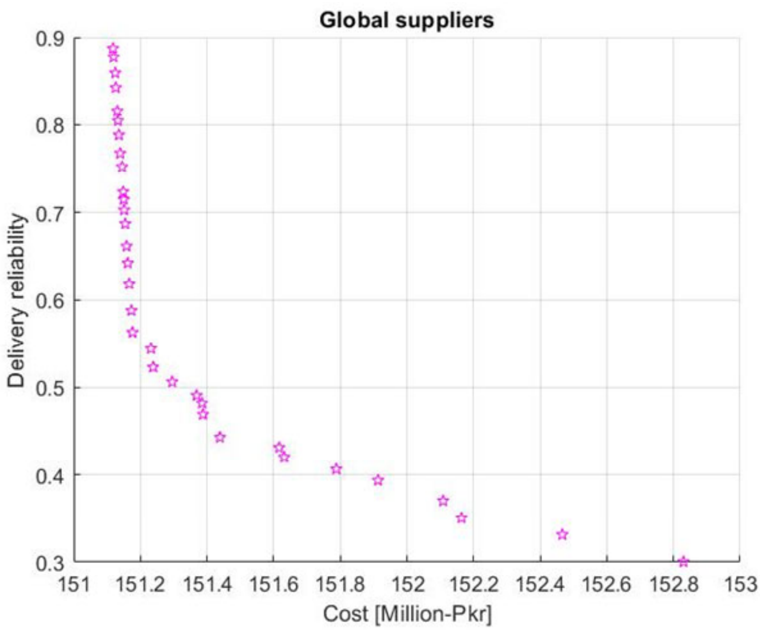
Table 6 MOGA results for local suppliers cost and reliability (initial score and initial population matrix) (continued)

Index	*Initial score matrix*		*Initial population matrix*		
	f_1	f_2	x_1	x_2	x_3
74	12.97507	0.609032	0.692141	0.030924	0.674899
75	12.99182	0.31055	0.352299	0.033547	0.265572
76	12.99506	0.316962	0.355104	0.032769	0.351695
77	12.97428	0.618464	0.703158	0.030698	0.683998
78	12.97097	0.681473	0.774627	0.030159	0.774788
79	13.02096	0.177012	0.173277	0.030465	0.54617
80	13.01832	0.194159	0.194874	0.030603	0.534239
81	13.03108	0.131698	0.11222	0.02928	0.647141
82	12.98036	0.516463	0.586837	0.032502	0.542635
83	13.02828	0.190974	0.179124	0.028947	0.737111
84	12.96544	0.781889	0.88871	0.028799	0.918927
85	12.98934	0.40918	0.460773	0.032018	0.466848
86	12.98445	0.454908	0.51712	0.037255	0.43111
87	13.04538	0.07838	0.037423	0.027543	0.816145
88	13.0476	0.063725	0.01898	0.02736	0.826432
89	12.98771	0.503919	0.564088	0.030635	0.674168
90	12.97301	0.701892	0.800604	0.054259	0.636638
91	12.98802	0.53032	0.59187	0.029863	0.750411
92	12.98545	0.400161	0.455968	0.03292	0.360747
93	12.98719	0.356674	0.407314	0.033386	0.286607
94	13.00014	0.325562	0.359051	0.035645	0.444573
95	12.97646	0.571693	0.650441	0.031141	0.610916
96	12.99115	0.408681	0.457907	0.031378	0.507051
97	13.02949	0.20098	0.188236	0.028202	0.791519
98	12.98659	0.384362	0.437687	0.033114	0.343601
99	13.03786	0.146793	0.124802	0.045905	0.659584
100	12.97264	0.658076	0.748931	0.035443	0.70184

4.2 Sample #2 (S2)

Figure 5 depicts the trade-off between global suppliers' procurement costs and delivery reliability. Figure 6 illustrates all of the essential comparison results. These findings support the global analysis of both objective functions of suppliers. Four global suppliers from Tianjin and Shanghai in China, Ho Chi Minh in Vietnam, and Nigde in Turkey accept the raw material order at the prices shown in Table 2, and 40-foot containers transport the supplies to the manufacturer in Kasur, Punjab, Pakistan. The shipment is expected to arrive at the factory within a month. For imports, the firm must pay taxes such as 17% sales tax, 1% additional sales tax, 1% income tax, 1% additional customs duty, 1% insurance tax, 5% customs duty, and 1% landing costs. The plant's entire annual requirement is 13,823 tonnes. The average cost of raw materials received from one global vendor to meet the requirement of 13,823 tonnes per year is 0.45 million Pakistani rupees. The average cost of transporting 13,823 tonnes of material from suppliers in Tianjin, China, Shanghai, China, Ho Chi Minh, Vietnam, and Nigde, Turkey to the port of Karachi, Pakistan is Pkr 151 million. For global providers, we converted dollar values into Pakistani rupees based on the month of purchase and supply. Pkr 0.045 million is 10% of the cost of raw material stock. Purchasing raw materials from global vendors costs 0.45 + 151 + 0.045 = Pkr 151.495 million each year.

Figure 5 Total procurement cost and delivery reliability of global suppliers (see online version for colours)

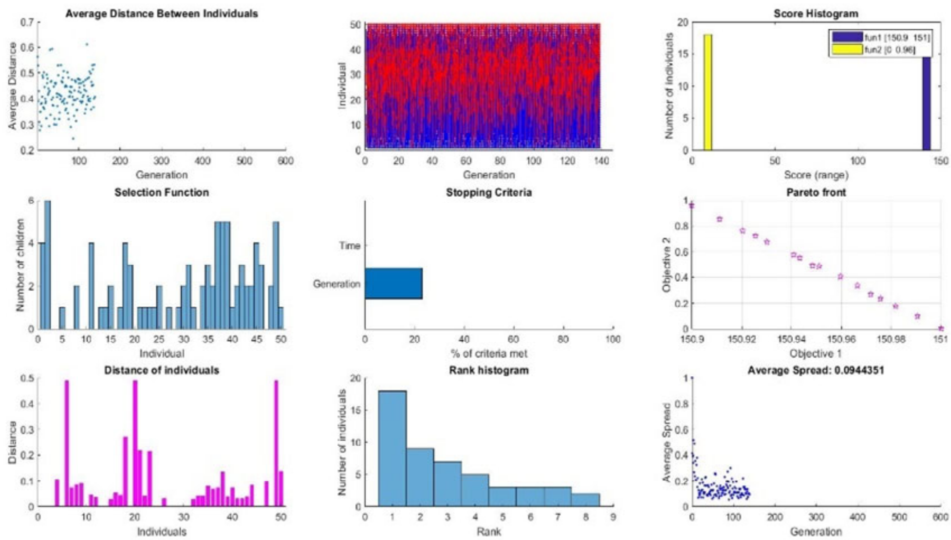


For local providers, the delivery reliability index values are 0.92, 0.94, 0.96, 0.94 and 0.90. Figures 5 and 6 show the delivery reliability for global suppliers, and the average value is 0.94 based on the judgements and experience of the coating plant's managerial staff.

The findings from the problem of determining the appropriate SC sourcing strategy backed local providers as a more cost-effective method than global suppliers. Local supply has the lowest raw material, transportation and material shortage costs. In terms of procurement costs, the difference between L&G supplies is 151.495 – 12.985 = Pkr 138.51 million per year, representing a 91% savings by local suppliers. However, the global supplier's delivery reliability is preferable. The difference between global and local providers' delivery reliability is 0.94 – 0.84 = 0.1.

The most challenging component in the purchase cost is shipping duty cost and currency rate. A total of 34% of import tariffs are too high for SCs to meet customer demands, as they directly affect the price of the product, as stated by Ghodsypour and Brien (2001). Second, due to Pakistan's unpredictable economy, the raw material exchange rate is critical when purchasing imported materials. The worldwide raw material's delivery reliability is higher due to the fine and standard particle size of $CaCO_3$, which gives the best result when compared to local raw material. However, the lead time for global raw materials is longer, which poses a risk to manufacturers.

Figure 6 MOGA optimisation results of cost and delivery reliability (global suppliers) (see online version for colours)

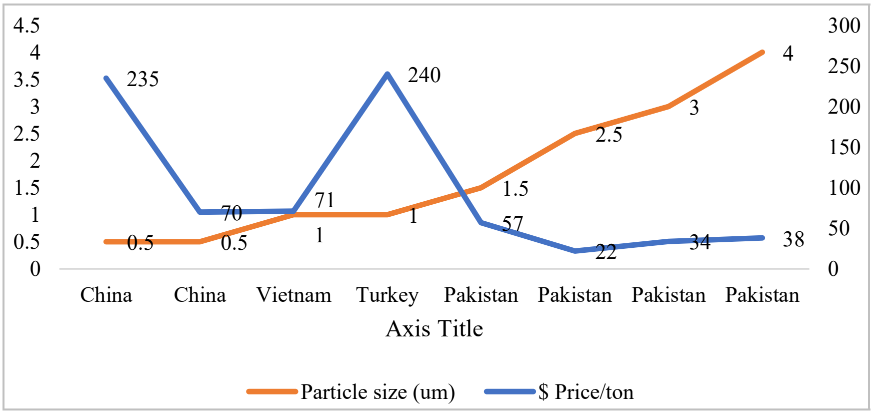


4.3 Sensitivity analysis

For the SC sourcing design problem, the study is applied to both L&G suppliers. The primary purpose of this research is to minimise the total procurement cost of L&G suppliers. Our second objective is to improve the reliability of our suppliers. We perform the following sensitivity analysis.

As Figure 7 demonstrates the cost variations between domestic and international vendors, the average cost of procurement from global vendors to supply chemicals at the facility on an annual basis is Pkr 151.49 million. The average annual purchase cost of local suppliers in Pakistan is 12.985 million Pakistani rupees. Annually, the difference is 138.51 million Pakistani rupees. The cost of raw material due to the difference in the quality of the raw material, the 34% duty on imports per tonne, and transportation expenses are the key factors for the higher global supply costs and lower delivery reliability of local suppliers. Imported $CaCO_3$ produces the greatest results due to its uniform particle size. As a result, this quality feature separates the product from its competitors in the local market. However, because of the scarcity of modern grinding plants, it boosts the market price of the product because very fine grinding raises the cost of raw material. The failure of suppliers to establish modern grinding plants at the local level is due to domestic consumers' lack of purchasing power. As a result, many large-scale manufacturing firms have decided to establish grinding plants. Figure 7 demonstrates the effect of standard particle size accessible internationally and locally, as well as the price shift in Pkr.

Figure 7 Change in particle size of $CaCO_3$ effect on cost (L&G suppliers) (see online version for colours)



Second, as the value of the dollar rises, the cost of imported raw materials, shipment charges, custom clearance charges, first-mile delivery cost, and other hidden costs rise. Figure 8 displays the changes in the dollar rate. The dollar rate has been raised from 156 to 168 Pkr/$ in 2019–2020. Pakistani firms are unable to obtain $CaCO_3$ from global providers due to changes in the economic condition.

Figure 8 Effect of changing dollar rate on Pkr (see online version for colours)

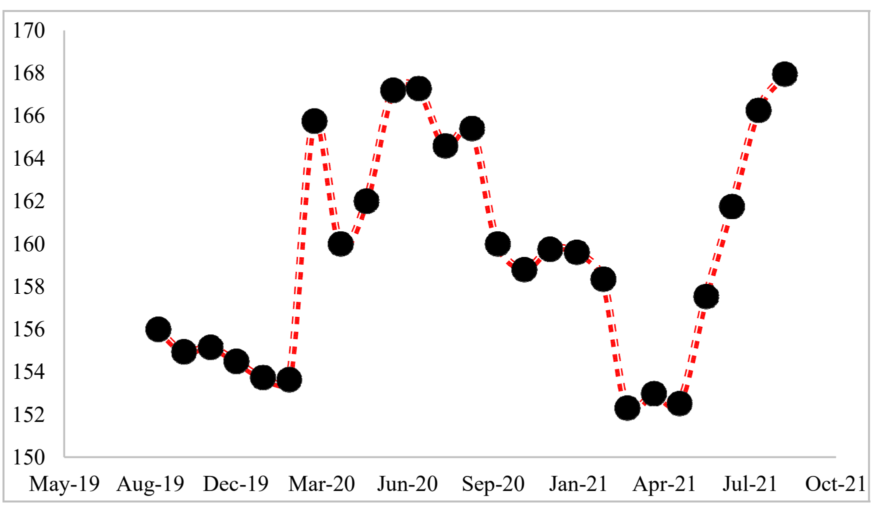
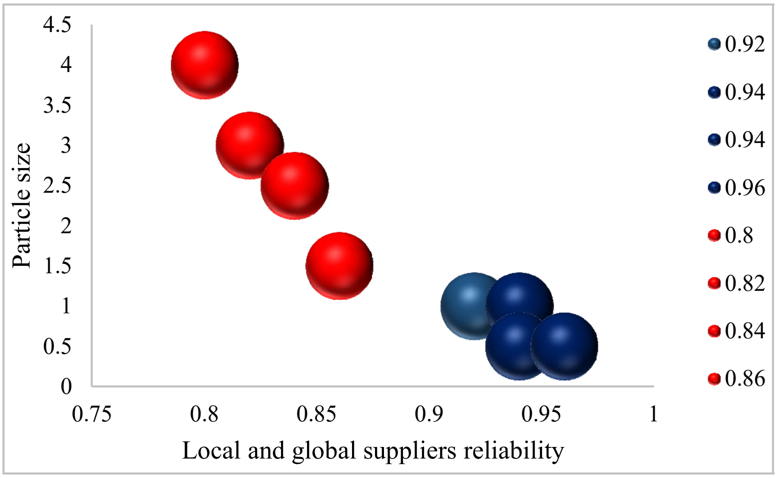


Figure 9 depicts the shift in delivery dependability from local to global suppliers. Imported materials have higher delivery reliability due to their higher quality such as standard particle size as shown in Figure 7, which produces a good surface for printing. Figure 7 shows the impact of changing particle size from 0.5 um to 4 um on the cost of raw materials. The delivery time from local suppliers is less than one week, but the quality of the $CaCO_3$ is not as good as that of imported chemicals.

Figure 9 Particle size impact of delivery reliability of L&G suppliers (see online version for colours)



5 Conclusions

The bi-objective problem of procurement cost and delivery reliability for L&G suppliers' for finding the best sourcing strategy in the SC is an important topic of research. Suppliers play a critical role at every stage of the product lifecycle. Companies must work closely with their suppliers to get the most out of their products, from procuring raw materials to assisting with ramping up production and discovering better raw material choices when the market becomes saturated.

In our work, we implemented the mixed-integer linear programming model to formulate the problem. The genetic algorithm is used to get the Pareto front solutions to compare procurement cost and delivery reliability between L&G suppliers for one of the largest paper and board industries in Asia. In our study, the cargo is provided by intermodal transportation from global suppliers of China, Vietnam and Turkey. Truck shipment is used for local suppliers to deliver from various suppliers to the customer in Pakistan. We used real-life data to check the robustness of sourcing strategies under price, reliability, exchange rates, and demands of the plant in Pakistan. The results of our investigation show that cost of delivering the raw material from global suppliers to the customer in Kasur, Pakistan is 91% higher than the global suppliers. The customs duty on imports is 34% and increasing dollar rates are the main reasons for higher procurement costs. Our second objective was to increase the delivery reliability of suppliers. Our results show that the delivery reliability of global suppliers is 10% better than local suppliers. Due to the standard particle size of $CaCO_3$ provided by global suppliers, manufacturers ensure the best surface quality of the paper board in the process of applying coating (a paper process before printing the paper to make the surface of paper smooth). So, the satisfaction of manufacturers can be increased at the local level improving the standard size of particles in Pakistan.

This study will help decision-makers, freight forwarders, policymakers, and researchers to understand the impact of producing good quality products on the cost and reliability of the product (by providing standard particle sizes), and differences in global and local procurement. This study will support understanding the impact of custom duty and change in the dollar rates on imports. Moreover, our study also helps in economical modes of transportation as compared to intermodal and unipersonal transportation costs in our study.

This research has a few limitations as well. First, factors affecting the delivery reliability other than cost and quality could be included. Secondly, transportation cost investigations do not include rail transportation. Thirdly, transit time factors could be included to make this research more impactful.

CO_2 emissions in unimodal, intermodal, and multimodal transportation in the delivery of items from L&G vendors might be investigated further in this study. To understand the contribution of each mode of transportation to emissions, the percentage of emissions in each mode of transportation will be useful. Second, this research can be expanded upon by looking into the CO_2 emissions produced during the conversion of raw materials to final commodities.

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