Flexible Services and Manufacturing Journal (2024) 36:599–667
https://doi.org/10.1007/s10696-023-09502-0

Assessment of coal supply chain under carbon trade policy by extended exergy accounting method

Ali Roozbeh Nia[1] · Anjali Awasthi[1] · Nadia Bhuiyan[2]

Accepted: 20 May 2023 / Published online: 10 June 2023

Abstract

Within an uncertain environment and following carbon trade policies, this study uses the Extended Exergy Accounting (EEA) method for coal supply chains (SCs) in eight of the world's most significant coal consuming countries. The purpose is to improve the sustainability of coal SCs in terms of Joules rather than money while considering economic, environmental, and social aspects. This model is a multi-product economic production quantity (EPQ) with a single-vendor multi-buyer with shortage as a backorder. Within the SC, there are some real constraints, such as inventory turnover ratio, waste disposal to the environment, carbon dioxide emissions, and available budgets for customers. For optimization purposes, three recent metaheuristic algorithms, including Ant Lion Optimizer, Lion Optimization Algorithm, and Whale Optimization Algorithm, are suggested to determine a near-optimum solution to an "exergy fuzzy nonlinear integer-programming (EFNIP)." Moreover, an exact method (GAMS) is employed to validate the results of the suggested algorithms. Additionally, sensitivity analyses with different percentages of exergy parameters, such as capital, labor, and environmental remediation, are done to gain a deeper understanding of sustainability improvement in coal SCs. The results showed that sustainable coal SC in the USA has the lowest fuzzy total exergy, while Poland and China have the highest.

Keywords Extended exergy accounting (EEA) · Coal supply chain (SC) · Sustainability · Carbon emission · Fuzzy price · Inventory model

1 Introduction

Production systems rely heavily on traditional fossil fuels, mainly coal and oil (Wang et al. 2023). It is estimated that industrial sectors account for over 50% of global energy consumption (Safarian 2023). Almost all coal is composed of dead plant material. As a result of accumulated plant material being buried under anoxic conditions for millions of years,

Extended author information available on the last page of the article and being exposed to high temperatures and pressures over that time, coal was formed (Australian Government 2022). Coal is the world's largest source of energy for electricity generation and the production of steel, cement, and paper (U.S. Energy Information Administration (EIA), 2021). About 75% of coal is found in only 5 countries (USA, Russia, Australia, China, and India), while the biggest coal consumers are China (54%), India (18%), USA (6%), Japan (3%), and South Africa (2.3%) (Phengsaart et al. 2023). According to Notes from Poland (2022), Poland ranks 9th in the world in coal consumption to generate 70% of electricity, by far the highest figure in Europe. In terms of production, China tops the list supplying about 50% of global coal demand. Other key players in the global coal trade include India (9.9%), Indonesia (7.5%), USA (6.4%), Australia (5.9%), Russia (5.3%) and Poland (1.3%) (Phengsaart et al. 2023).

Moreover, coal-related SCs represent one of the major concerns for stakeholders (Mehmood et al. 2015) since these industries constitute a significant proportion of carbon dioxide (CO2) emissions (Sun and Yang 2021). Iron and steel manufacturing, for instance, emitted about 2,600 million tons of carbon in 2019. This number is expected to rise to 2,700 million tons by 2050 if no sustainable development *scenario* is applied (U.S. Energy Information Administration (EIA), 2022). As society becomes more aware of the value of the environment, waste disposal (imperfect quality items) and carbon dioxide emissions must become leading indicators of coal SC assessment. According to the European Union's Joint Research Centre, China is the largest emitter of CO2 in the world, with 11,680 Mt (11.680 GT) of carbon dioxide emissions in 2020. This is just over 32% of the world's total 2020 emissions. The United States and India released the second- and third-highest amount of carbon emissions at 4.535 and 2.411 GT (or roughly 12.6% and 6% of total global emissions). Moreover, Japan and Iran are the 5th and 6th CO2-emitting countries in the world. It should be mentioned that China, the USA, and India are also three of the most populous countries on Earth. In general, developed countries and major emerging markets lead in total carbon dioxide emissions.

Various countries worldwide have set impressive emission-cut goals in the outlook to tackle climate change and the function of sustainable development (Malladi and Sowlati 2020; Sun and Yang 2021). In this effort, environmental administrations around the globe agree that pricing carbon emissions is the most inexpensive and successful means to achieve their emission reduction goals (Environment and Climate Change Canada 2018). The primary carbon pricing strategies are carbon tax, carbon cap, carbon offset, and carbon trade (Malladi and Sowlati 2020), whereas each approach has different costs and carbon reductions. The benefits of applying each carbon emission policy are not equal for companies involved in coal SC. While some carbon policies are more environmentally friendly, others are more economically beneficial.

Moreover, emerging Industry 4.0 technologies and concerns about global warming show that decision-makers need to change their point of view in assessing the SC's performance (Roozbeh Nia et al. 2020). Shifting from traditional assessment methods to novel and more sustainable methods is one of the critical aspects of the fourth industrial revolution. Extended Exergy Accounting is an innovative method that can help SCs become more sustainable (Aghbashlo et al. 2018). This method integrates the effect of non-energetic manufacturing features into the complete loss assessment (Jawad et al. 2018; Sciubba 2011). The primary benefit of employing the extended exergy accounting method in the production system is that this method states all outcomes in Joules (instead of dollars); therefore, acceptable assessments among different products can be achieved (Naderi et al. 2021b; Jawad et al. 2018). Moreover, energy (in terms of Joules) is essential to operate all manufacturing and SC processes (Jawad et al. 2015).

It is true that the energy market (natural gas, oil, and coal) today tends to be maturing and unbalanced, characterized by increasing demand and fluctuating supply (Roozbeh Nia et al. 2021). There are tangible signs to verify that demand and price are not predetermined and can influence a broad collection of market influences and customer behaviors. While some scholars have focused on the direct issues, there are also unforeseen issues such as the economic environment, business events, and global politics (Su et al. 2021). For example, oil and gas prices have risen to their highest levels in nearly a decade because of Russia's unprovoked invasion of Ukraine. As a result, many countries have re-evaluated their energy sources. The fact is that uncertainties in demand and energy consumption significantly affect the total SC cost as the penalty cost of unsatisfied demand increases (Priyan et al. 2022). In response to this issue, Zadeh (1965) proposed "fuzzy set theory (FST)," which translates "ill-defined" data into mathematical terms.

Considering these issues, we can present the main research questions of this study as follows:

Q1. Is it possible to assess the sustainability of coal SC under a carbon reduction policy in terms of Joules rather than money to benefit the economy and the environment?

Q2. Generally speaking, coal SC in developing countries, or even China, has the lowest overall cost; however, considering sustainability aspects (social, economic, and environmental characteristics) in Joules, does this assumption still hold true?

Q3. Which country has the most sustainable coal SC in terms of Joules?

Q4. What is the best percentage of exergy components (social, economic, environmental characteristics) to achieve the most significant saving wherever coal SCs are working?

Consequently, the first goal of this study is to find the optimum total exergy of coal SC in different developed and developing countries under carbon trade policy in an uncertain environment (for carbon trade price and customer demand). The second objective is comparing the sustainability of coal SC in eight countries in terms of Joules rather than money. Finally, this research aims to improve the sustainability of coal SC by performing a sensitivity analysis on the three exergy parameters of sustainability (economic, environmental, and social) in the extended exergy accounting method.

2 Literature review

The leading publications related to carbon policies in coal-based industries such as cement, steel, etc. are shown in Table 1. Based on this table, there is no study that employs the extended exergy accounting method or considers uncertain environment for carbon. Therefore, in this section, the literature related to our study is reviewed in two categories: exergy analysis concepts, and the extended exergy accounting method. After that, research gaps and our contributions in this research compared to existing studies are presented.

2.1 Exergy analysis concepts

Although Rant (1956) first introduced the name "exergy," parallel denotations had previously been defined by other researchers. Exergy is the capability to produce work or adequate energy or a quantity of work (Liu et al. 2020). Jaber et al. (2004) tried to connect thermodynamics with inventory management and showed the pertinency of the first and second laws of thermodynamics to manufacture systems through the economic order (production) quantity (EOQ/EPQ) model. Later, Jaber et al. (2006) supposed that the performance of the production systems is like physical systems. Their results showed that the order quantity strategy is to order in more oversized lots less often than when the entropy cost is omitted considering entropy cost. Moreover, Jaber et al. (2009) established Jaber et al. (2004) 's research paper by extending an entropic mathematical model for deciding batch sizes for deteriorating goods. The outcomes of the entropy EOQ model indicated ordering in larger quantities than recommended by the traditional model. Later, Jaber et al. (2011) presented the notion of exergy (valuable energy) cost. The authors added exergy and entropy costs to the EOQ model and established it in a simple reverse logistics system. They supposed forward and backward product streams to be cost-related, and consequently, a revenue method is accepted.

In another study, Jawad and Jaber (2015) proposed using exergy-economics and exergetic costing when developing inventory models. The authors encourage that employing the suggested inventory modeling may be more effective for other sustainable industries. Additionally, Jaber et al. (2017) developed the traditional models of the economical manufacture quantity (EMQ) and Just-in-time (JIT) by comprising other issues. Their outcomes indicated that JIT, which produces items in small quantities more often, experiences lower costs than the EMQ model once associated stress and entropy costs were not counted. Afterward, Jawad et al. (2018) studied the chief issues that can impact the entire cost of an SC, for example, emissions, labor, energy, social effects of shipping, and entropy. The outcomes presented that optimizing the exergetic cost function grows the money significantly to society for a slight extra rise in cost on the section of the SC.

Moreover, in an industrial bread SC in the Netherlands, Banasik et al. (2017a) studied a multi-objective mixed-integer linear programming model to evaluate the collection of eco-efficient solutions relating to manufacturing planning decisions. The authors employed exergy analysis to state environmental performance of the SC. Their outcomes approve the results from the literature that avoidance is the most acceptable waste management policy from an ecological viewpoint. In another study for a mushroom SC, Banasik et al. (2017b) investigated a multi-objective mixed-integer linear programming model to calculate interchanges among financial and ecological gauges and investigate quantitatively substitute recycling tools. The total

Table 1 A short review of studies on carbon policies in heavy industries

Author/s (year)	Objective	Results	EEA method	Fuzzy price
Devlin and Yang (2022)	Focused on assessing potential green SCs for an Australia-Japan iron and steel case study	Suggested to reduce the green premium, a carbon tax of A$66–192/t CO2 would be required in 2030 and A$0–70/t CO2 in 2050	No	No
Kunche and Mielczarek (2021)	Presented a comparative overview of studies using the system dynamics approach to evaluate carbon mitigation strategies	This study included their scope, model description, test scenarios, and mitigation methods	No	No
Da et al. (2021)	Examined optimal inputs for clean coal technology in a coal enterprise and optimal carbon reduction quantities in a manufacturer	Focusing on the dominant mode, can affect carbon reduction under different leading models of cap-and-trade with government subsidies	No	No
Hančlová et al. (2020)	Identified and evaluated the interactions between the factors of the EU ETS (prices of emission allowances and grandfathering) and factors of the steel industry such as prices and production levels	Steel companies in the Czech Republic pass on the costs for emissions to their customers	No	No
Li et al. (2020)	Examined the impact of different carbon policies on coal SC networks	The government could guide organizations in reducing carbon by formulating reasonable emission policies	No	No
Da et al. (2019)	Developed a coal-electric power SC strategy that reduces carbon at two levels and operated with financial constraints	The government could encourage a low-carbon economy by controlling bank loan interest rates	No	No
Duan et al. (2019)	Explored the impact of emission reduction policies on China's steel production and economic level	The government should consider the overall and regional balance as well as benchmark values for carbon trading when deciding whether to implement a single or mixed policy	No	No
Gonela (2018)	Designed a hybrid electric SC (HESC) based on coal and biomass for electricity generation in a case study of North Dakota (ND) in the USA	coal-based electricity generation is preferred if the goal is to reduce costs, whereas biomass-based electricity generation is preferred if the goal is to reduce carbon emissions	No	No
Li et al. (2018)	Examined the carbon trading method's consequences in China's power sector	Using a carbon trade policy would negatively affect the entire economy, but the adverse effects would be removed in the future	No	No

Table 1 (continued)

Author/s (year)	Objective	Results	EEA method	Fuzzy price
Chaabane et al. (2012)	Provided a framework for designing a sustainable SC, in the aluminum industry	Top management will achieve sustainability goals through effective carbon management policies	No	No

exergy loss is used in this study as a single metric gauge for environmental performance. They discovered that accepting closing loop tools in modern mushroom manufacture can grow both the overall productivity of the SC and the environmental functioning. Naderi et al. (2021a) presented a mathematical model for enhancing sustainability involving the cost of exergy demolition (entropy) for a coal SC in Iran. The authors employed exergy analysis for a model that involves economic and wasted exergy costs. Their outcomes showed an extra-economic cost, but it will support managers to measure this added cost which is essential for other decisions.

2.2 Extended exergy accounting method

It was Sciubba (1998) who developed the traditional analysis of exergy and later introduced the "Extended Exergy Accounting" method (Sciubba 2003a, 2003b). The extended exergy accounting is expressed as the quantity of the main exergy aggregately exploited to manufacture and discard actual products or services (Song et al. 2019). This method contains energy and material's main aggregate exergy subject and cost corresponding to economic externality (labor and capital) and ecological externality (environmental remediation). The extended exergy accounting connects production systems' processes with surrounding systems (Song et al. 2019). Regarding the method, to the best of the authors' knowledge, only three studies employed this method for inventory management or SC. For example, Jawad et al. (2015) employed the notions of the extended exergy accounting method in inventory management for three factories in the USA, China, and Germany to involve the three aspects of sustainability: financial, ecological, and social. The outcomes presented that the order quantity in the companies is different since the corresponding exergy of money, labor and environment costs are not the same in each company. Later, Jawad et al. (2016) extended the traditional EPQ model by employing the extended exergy accounting method and thermodynamics laws to determine the degree of sustainability of a manufacture-inventory model. The outcomes revealed that an item's cost has a crucial function in diminishing the model's entropy creation (exergy lost). Moreover, for a conventional cement production SC in China, Song et al. (2019) utilized the extended exergy accounting method to estimate the cumulative exergy consumption (CExC), labor and money exergy, and ecological remediation exergy. They measured cement manufacture's environmental costs and the segments with exergy deficiencies. Finally, Naderi et al. (2021b) studied the utilized exergy for a sustainable SC through an extended exergy accounting method for a food SC in Iran. They suggested a hybrid global- and local-search metaheuristic algorithm to solve the model. Their findings revealed that exergy minimization substantially reduces the cost for society as different from raising the cost in some sections of the SC. For example, the recommended method delivers 4.48% savings in the utilized exergy of the SC through undertaking added economic costs.

To explore more about exergy components, exergy analysis and the extended exergy accounting method in detail, we suggest Arango-Miranda et al. (2018), Dincer and Rosen (2013), and Ehyaei et al. (2019) to interested readers. Additionally, a brief review of papers that used exergy analysis and the extended exergy accounting method (comparing with our proposed model) is available in Table 2. Based on this table, for example, no study considers carbon policy with the extended exergy accounting method.

2.3 Research gaps and our contributions

Regarding literature review, Tables 1 and 2, there are still several research gaps, including G1. There is a lack of research that assess a SC under carbon policy within an uncertain environment, for example, fuzzy carbon price or customer demand. G2. It is rare to find studies that assess a SC in terms of Joules instead of money (as traditional performance measures) and simultaneously evaluate all sustainability aspects, such as economic, labour, and environmental. G3. There is a lack of examinations that employ the extended exergy accounting method to assess a SC under any carbon reduction policy. As a matter of fact, no exergy analysis method in the literature takes into consideration carbon emission policy. G4. There is a scarcity of studies that compare the sustainability of coal SCs between developed and developing countries under carbon trade policy with the extended exergy accounting method. G5. There is a deficiency of investigation to find the best percentage of exergy components (social, economic, environmental aspects) in the extended exergy accounting method for a SC. G6. In addition, some real-world issues are ignored, such as considering the inventory turnover ratio for SC models, defective quality products discarded into the environment, shipping charges on the whole of coal SC (mining, railway transportation and steel making), vendor managed inventory (VMI) policy for coordinating SC, and the costs of loan/investment for budget limitation. In brief, the three contributions of this study to the literature are as follows:

- Improving the sustainability of coal SCs in terms of Joules (total exergy rather than traditional monetary objectives) in developed and developing countries under carbon trade policy and the uncertain environment by employing the extended exergy accounting method.
- Comparing the sustainability of coal SC in eight countries to determine which country has the most sustainable coal SC in terms of Joules.
- Finding the best value of exergy components (social, economic, environmental characteristics) for coal SC in both developed and developing countries which creates the highest sustainability.

The remainder of the study is structured as follows. In Sect. 3, the problem is outlined, the suppositions are stated, and the problem is mathematically expressed into a fuzzy nonlinear integer-programming model under emission trade policy. In Sect. 4, exergy modeling of fuzzy optimization using extended exergy accounting is presented. The proposed solution method is presented in Sect. 5 to solve the problem. Section 6 presents computational test problems and sensitivity analysis of exergy values to reveal the recommended solution methods' relevance. Finally, conclusions and potential studies are offered in Sect. 7.

Table 2 A brief review of research works in exergy analysis of supply chain

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Naderi et al. (2021a)	Provide a mathematical model for improving coal SC sustainability while minimizing the cost of exergy destruction (entropy) in SC	Single	Metaheuristic algorithm	No	No	No	No	No	No	No	No	No	No	No	Yes
Naderi et al. (2021b)	Provide an exergy analysis to model and minimize the consumed exergy for sustainable SC	Single	Metaheuristic algorithm	Branch & bound	No	No	Yes	No	No	No	No	No	No	No	Yes

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jawad et al. (2018)	Minimize the total cost of the developed SC model while focusing on the pillars of sustainable developments	Single	Exact method	N/A	No	Yes	No	No	No	No	No	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Banasik et al. (2017a)	Develop a mathematical model for quantitative assessment of alternative production options that are associated with different ways to deal with waste in food SCs	Multi	Exact method	N/A	No	No	No	No	No	No	Yes	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Banasik et al. (2017b)	Quantify trade-offs between economic and environmental indicators and explore quantitatively alternative recycling technologies	Multi	Exact method	N/A	No	No	No	No	No	No	No	No	No	No	Yes

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jawad et al. (2016)	Re-examines the economic production quantity (EPQ) model to reflect sustainability needs by using EEA and the laws of thermodynamics	Single	Exact method (EPQ formula)	N/A	N/A	Yes	Yes	No	No	No	No	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jawad et al. (2015)	Use an exergy model to determine the EOQ inventory policies for three firms operating in the USA, Germany, and China	Single	Exact method (EOQ formula)	N/A	N/A	Yes	Yes	No	No	No	No	No	No	No	No
Santhi and Karthikeyan (2015)	Determine the cycle length and the replenishment order quantity of an EOQ model to maximize the profit	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	Yes	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jawad and Jaber (2015)	Use exergoeconomics and exergetic costing when developing inventory models	Single	Exact method	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No
Jaber and Jawad (2015)	Estimate the entropy created in EPQ and JIT systems	Single	Exact method (EPQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jaber et al. (2009)	A mathematical model to determine batch sizes for deteriorating items while minimizing the entropy of the EOQ model	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jaber and Rosen (2008)	Improve production system performance by applying thermodynamics' first and second laws to reduce system entropy (or disorder)	Single	Exact method (EOQ formula)	N/A	No	Yes	No	No	No	No	No	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Jaber (2007)	Estimate the hidden costs of the EOQ model by applying the first and second laws of thermodynamics to reduce system entropy (or disorder) at a cost	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No

Table 2 (continued)

Authors (years)	Objective	Single objective / multi	Solving methods	Verification	Compare SCs	Inventory model	EEA technique	Carbon policy	Inventory turnover	Balanced budgeting	Waste discarding	Fuzzy	Shortage	VMI policy	Multi-buyer
Proposed model	Optimize the fuzzy exergy cost of an SC with the EEA method under trade emission policy	Single	Metaheuristic algorithm	GAMS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3 Problem description and model formulation

3.1 Problem description

Elevated energy market uncertainties (e.g., price and demand), disruptions (e.g., COVID-19 and global warming), and competition (e.g., global market and customer satisfaction) over current years have produced variations (negative and positive) to coal SC administration (Teerasoponpong and Sopadang 2022). It is true that coal is a low-cost and plentiful resource, but carbon dioxide (CO2) from coal usage in industries such as power plant, cement, steel and paper is responsible for about 40% of global greenhouse gas (GHG) emissions. Therefore, it is the responsibility of legislations and coal SC decision making to invest and innovate for cutting their carbon emissions.

This paper is inspired by the studies of Jawad et al. (2016) and Naderi et al. (2021a) and uses them to develop a multi-product multi-limitation EPQ model with backorder for a coal SC in eight countries under the fuzzy environment. Moreover, a VMI contract is employed for a single supplier and multi-buyer to coordinate the coal SC. The extended exergy accounting method with Mega-Joules (MJ) as a universal unit of measure is used to find the total exergy of the model. Besides, the buyers' demand, purchasing price per unit of product, cost of goods sold per unit of product, and carbon price of each unit of carbon are considered fuzzy. A famous carbon reduction policy, called carbon trade, is used to compare the model's performance as a sustainability measure and control the produced carbon emission of SC enterprises. Moreover, three recent metaheuristic algorithms are exercised to obtain a near-optimum solution of the developed exergy fuzzy nonlinear integer programming (EFNIP) to diminish the fuzzy total exergy of a coal SC. Additionally, ten numerical examples, including an actual case study in coal SC in Iran, were presented to display the pertinency of the proposed model. Likewise, the results are compared with the exact method (GAMS) to confirm the outcomes. Finally, a sensitivity analysis with changing the percentage of exergy parameters, including the capital, labor, and environmental remediation, has been done with seven different exergy sets of percentages (A-G) in eight developed and developing countries. Sensitivity analysis aims to find the best exergy values (capital, labour, and environmental remediation) of the extended exergy accounting method that create the highest sustainability for coal SC of Iran, Australia, China, India, Japan, Poland, the USA, and Zimbabwe.

3.2 Assumptions

Considering the purpose of this research to develop the sustainability of coal SC by integrating carbon trade policy and the extended exergy accounting method, we consider the succeeding assumptions for the mathematical preparation. More sophisticated assumptions are considered for future research in Sect. 7. There is a single supplier, multi-buyer coal SC with n products (different grades of coal) when stockout is permitted in the type of backorder for all products. The supplier's production rate for all products is fixed and known (EPQ model). In this model, quantity discount is not permitted, and the supplier pays the shipping cost whereas the setup and keeping costs are known. There are constraints on the capacity of the buyer's warehouse, budget and order quantity of a product and the total number of orderings. Additionally, all transportation between supplier and buyers are done by the railway system when distance between them is fixed and known. Moreover,

(a) Buyer's demand for the entire product, the price for all products and the price of carbon trade are fuzzy (trapezoidal fuzzy number).
(b) The linear backorder cost per unit per time unit is known for the entire products while the time-independent fixed backorder cost per unit is supposed to be zero.
(c) Orders are supposed to be immediate (lead time = 0).
(d) Coal Mining (supplier), shipping, and utilizing coal in the steel companies (buyers) produce carbon emission and waste (defective quality products) disposal to the environment.

4 Notations

The indices, factors, and decision variables of the SC model are described in Table 3.

The following subsections will develop a non-exergy mathematical model (a basic model) of the coal SC for carbon trade policy (Sect. 3.4). Then it has converted to a fuzzy model in Sect. 3.5.

4.1 A non-exergy modeling of coal SC under carbon trade policy

4.1.1 Objective function

Carbon trade integrates government regulations and market methods in a flexible policy that the Kyoto Protocol plans. With this policy, companies' carbon emissions are restricted (see Eq. 9); consequently, if a company generates carbon dioxide further than the launched cap, it must purchase extra carbon credits (e^{+}). In contrast, the company could sell its carbon credits (e^{-}) to other companies on the carbon market (Jiang et al. 2016), whereas the carbon price (C_{trade}) is determined by supply and demand in this market (Li et al. 2020). Although the price of carbon is considered known and fixed in the literature, this study considers it fuzzy (see Sect. 3.5). The trading strategy provides businesses with a great motivation to save money by reducing emissions in the most economical methods. This policy is employed in the European Union, Quebec province in Canada, California in the United States of America, and seven areas in China (Haites 2018). Consequently, the carbon trade cost is

$$Z_1 = \sum_{j}^{m} C_{trade} \times \left(e_j^{+} - e_j^{-} \right) \tag{1}$$

Table 3 Notations

Indices	
i : Index of the products;($i = 1, 2, \ldots, n$)	j : Index of buyers;($j = 1, 2, \ldots, m$)
Factors	
D_{ij}: Demand rate of product i for buyer j	t_f: Constant shipping cost of each order which is paid by the supplier (VMI contract)
P_i: Rate of production of the i^{th} product ($P_i \geq \sum_{j=1}^{m} D_{ij}$)	t_v: Variable shipping cost per unit of a product which is paid by the supplier (VMI contract)
Q_{Max}: Upper limit of transportation capacity on each order quantity	t_L: Labor cost for loading/unloading of coal per hour
N_{Max}: Max. total number of orders by all buyers	t_M: Machine/equipment cost for loading/unloading of coal
C_i: Buying price per unit of product i by buyers	Lo: Loading time of coal in a railcar (railway wagon)
C_o: Cost of goods sold per unit of product i by the supplier	Un: Unloading time of coal from a railcar
ITR_j : Inventory turnover ratio of buyer j	h_{ij}: Keeping cost per unit of product i held in the warehouse of buyer j in a period
C_{trade} : Emission trade price of each unit of produced carbon	s_1: fixed backorder cost per unit (time-independent)
X_j: Total available budget of all products for buyer j	s_2: Linear backorder cost per unit per time unit
int^-: The interest rate of the essential loan for buyer j	W_j : Available storage area of buyer j for all products
int^+: Interest (benefit) rate of new investment for buyer j	L_j: Distance between supplier and buyer j (km)
$K_{i,s}$: Supplier's fixed setup cost per unit of product i	θ_m: Emissions factor of mining (ton/unit)
$K_{ij,b}$: Constant ordering cost per unit of product i for buyer j	θ_t: Emissions factor of shipping (ton/unit)
δ_m: Proportion of imperfect quality items in mine process	θ_k: Emissions factor of furnace in steel manufacturer (ton/unit)
δ_t: Proportion of imperfect quality items in the transportation process	E_j: Upper limit on aggregate carbon emissions of all products of each buyer
δ_k: Proportion of imperfect quality items in steel manufacturer	F: Upper limit on total imperfect quality items disposal to the environment by all processes
Decision variables	
Q_{ij}: Order quantity of product i for buyer j	x_j^-: Total required loan for buyer j
b_{ij}: Maximum backorder level of product i for buyer j in a cycle	e_j^+: Emission credits that should be bought by buyer j
x_j^+: Total new investment for buyer j	e_j^-: Emission credits that could be sold by buyer j

The shipping costs accounted for about 40% of the entire delivered cost of coal in 2019 (U.S. Energy Information Administration (EIA), 2019). Transportation costs are also impacted by road distance, accessibility of shipping mode and supply source alternatives, and the competition among coal and other goods for shipping. Therefore, the total transportation cost of coal includes constant (t_f) and variable (t_v) costs, along with the cost of loading/unloading coal (t_L) in/from railcars and cost of equipment (t_M) is

$$Z_2 = \sum_i^n \sum_j^m \left[\left(\frac{D_{ij}}{Q_{ij}} . t_f \right) + \left(Q_{ij} . t_v \right) + \left(\frac{D_{ij}}{Q_{ij}} . (Lo + Un) . \left(t_L + t_M \right) \right) \right] \tag{2}$$

where (Lo, Un) are the loading/unloading time of coal in/from a railcar. The vendor-managed inventory (VMI) strategy is the regular inventory management in SC in which the upstream company completely controls the inventory at the downstream company's location (Giovanni 2021). In the VMI system, the determinations about scheduling and amount of buyer's replenishment are decided by the supplier that is assumed to have comprehensive information concerning the customers' requirements, to prevent stockouts (Çomez-Dolgan et al. 2021; Maio and Lagana 2020). Therefore, it is expected that the supplier gives the ordering, shipping, and keeping costs rather than the buyer as a part of the stated contract; the buyer gives no cost (Mateen et al. 2014; Yao et al. 2007; Razmi et al. 2010; Pasandideh et al. 2011; Roozbeh Nia et al. 2014, 2015). Furthermore, in an EPQ model with defective quality items and stockout as a backorder that utilizes the VMI strategy, the coal SC's total inventory cost is established by calculating the ordering/setup ($TC_{O_{ij}}$), keeping ($TC_{H_{ij}}$), stockout ($TC_{S_{ij}}$), and purchasing ($TC_{P_{ij}}$) costs as (Pasandideh et al. 2010, 2011)

$$Z_3 = TC_{O_{ij}} + TC_{H_{ij}} + TC_{S_{ij}} + TC_{P_{ij}} \tag{3}$$

where,

$$TC_{O_{ij}} = \sum_i^n \sum_j^m \frac{D_{ij}}{Q_{ij}} \left(K_{i,s} + K_{ij,b} \right) \tag{4}$$

$$TC_{H_{ij}} = \sum_i^n \sum_j^m \frac{h_{ij}}{2Q_{ij}\left(1 - \frac{D_{ij}}{P_i}\right)} \left(Q_{ij}(1 - \delta_m)\left(1 - \frac{D_{ij}}{P_i}\right) - b_{ij} \right)^2 \tag{5}$$

$$TC_{S_{ij}} = \sum_i^n \sum_j^m \left(\frac{s_1 . b_{ij}^2}{2Q_{ij}\left(1 - \frac{D_{ij}}{P_i}\right)} + \frac{s_2 . b_{ij} . D_{ij}}{Q_{ij}\left(1 - \frac{D_{ij}}{P_i}\right)} \right) \tag{6}$$

$$TC_{P_{ij}} = \sum_i^n \sum_j^m C_i . D_{ij} \tag{7}$$

where (D_{ij}, Q_{ij}, h_{ij}) are the demand rate, order quantity and holding cost per unit of coal i for buyer j, respectively. As mentioned previously, the existing budget of each buyer could be deposited in a bank account or invested in other projects to get profits. Now, we take into account a real-world balanced limitation (see Sect. 3.4.2) where the total amount of the existing budget for each buyer is restricted (see Eq. 8). To the best of the authors' knowledge, this type of objective function and limitation, have not been studied yet. On the one hand, each buyer's under-achievement budget (x_j^+ as a decision variable) is regarded as the benefit. It means this amount of money (x_j^+) may be invested in a new project with an actual interest rate (int^+) and make a profit (as a $int^+ \times x_j^+$) for the buyer. On the other hand, the over-achievement budget (x_j^- as a decision variable) is regarded as the cost. It means the buyer must get a loan with the amount of (x_j^-) and an interest rate of (int^-). After All, the buyer should pay this loan as well as the interest rate ($x_j^- + \left[int^- \times x_j^-\right]$) at the end of the period. Therefore, the total cost/benefit associated with the budget of all buyers is

$$Z_4 = \sum_j^m \left[x_j^- + \left(int^- \times x_j^-\right) - \left(int^+ \times x_j^+\right)\right] \tag{8}$$

wherever in Eq. (8), the first two components are linked to the cost functions, and the last part with a negative symbol is related to the benefit obtained. Moreover, under and over-achievement budgets (x_j^+, x_j^-) are not known parameters and are considered decision variables. Hence, the non-exergy total cost of coal SC under the carbon trade policy is the summation of $TC_{trade} = Z_1 + Z_2 + Z_3 + Z_4$.

4.1.2 The constraints

The constraints of this model are as follows:

$$\frac{\sum_i^n \sum_j^m C_0.D_{ij}}{\sum_i^n \sum_j^m \frac{C_0\cdot\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}} \geq ITR_j \tag{9}$$

$$\sum_i^n \left[\left(Q_{ij}.\theta_m\right) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.\theta_t\right) + \left(Q_{ij}.D_{ij}.\theta_k\right)\right] + \left(e_j^- - e_j^+\right) = E_j \tag{10}$$

$$\sum_i^n \sum_j^m \left[\left(Q_{ij}.\delta_m\right) + \left(Q_{ij}.\left(1-\delta_m\right).\delta_t\right) + \left(Q_{ij}\left(1-\delta_m\right).\left(1-\delta_t\right).\delta_k\right)\right] \leq F \tag{11}$$

$$\sum_i^n \left[Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right] \leq W_j \tag{12}$$

$$\sum_i^n \left[C_i.Q_{ij}(1-\delta_m)\right] + \left(x_j^+ - x_j^-\right) = X_j \tag{13}$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}} \le N_{Max} \tag{14}$$

$$Q_{ij} \le Q_{Max} \tag{15}$$

$$b_{ij} \le Q_{ij} \tag{16}$$

Equation (9) is an inventory turnover ratio (ITR_j) limitation. To the best of the authors' knowledge, this limitation has not been presented in SC literature before. The inventory turnover ratio is applied as a comparative measure of inventory performance between competitors and is crucial to control inventory (Beklari et al. 2018). This proportion is an economic index that merges the cost of goods sold with average inventories at cost (Kwak 2019). The inventory turnover ratio shows how often inventories are turned over a period. For Eq. (10), as mentioned before, with the policy of carbon trade, each buyer inside coal SC can only produce within an offered cap (E_j) of emission. If this actual emission amount goes above the emission limit, the company must purchase carbon credits (e^+). The company can vend these extra emission credits (e^-) if the actual emission amount runs under the emission limit (Li et al. 2020). Hence, with the emission trade policy, a new emission restriction is included in the model where Eq. (10) corresponds to the total generated carbon in mining, shipping, and steelmaking processes. In Eq. (10), ($\theta_m, \theta_t, \theta_k$) are emissions factors in mining, transportation, and steel manufacturer processes, respectively. Additionally, L_j is the distance between the coal vendor and buyer j. Equation (11) aims to make the model green since it considers a limitation (F) on total defective products (waste) disposal to the environment by all processes in coal SC. In this equation, ($\delta_m, \delta_t, \delta_k$) are the proportions of imperfect quality items in mining, transportation, and steel manufacturer processes, respectively. Furthermore, Eq. (12) expresses that the warehouse space of each buyer (W_j) is restricted, where (b_{ij}) is the backorder amount of coal i for buyer j in a cycle (a decision variable).

As shown before, a real-world contractual agreement grants balanced constraints (Eq. 13) for the existing budget of each buyer (X_j). To the best of the authors' knowledge, this type of limitation has not been given in SC literature in the past. Where Eq. (13) indicates that, on the one hand, if the total paid-out money of a buyer is below the existing budget ($\sum_i^n C_i.Q_{ij}(1-\delta_m) < X_j$), the buyer saves an amount of ($x_j^+ > 0$). It is possible the company invests this amount in a new project and makes a profit (see Eq. 8). On the other hand, if the total paid out money of a buyer is more than the existing budget ($\sum_i^n C_i.Q_{ij}(1-\delta_m) > X_j$), so the buyer demands to get a loan with the amount of ($x_j^- > 0$). The total cost/benefit linked to this balanced limitation is expressed in Eq. (8). In addition, Eq. (14) is related to the limitation on the total number of orders (N_{Max}) by all buyers. Additionally, there is a constraint for the shipping system (railway) while the Max. of shipping capacity (Q_{Max}) for each order quantity is stated in Eq. (15). Finally, based on Eq. (16), the quantity of backorder of product i for j^{th} buyer (b_{ij}) in a cycle should be fewer than or equal to its order amount (Q_{ij}). It should be mentioned that intending to simplify the mathematical model; we ignore the cost of purchasing (Eq. 7) in our model. Regarding Eqs. (1)–(16) and under carbon trade policy, the non-exergy crisp model of "multi-product" balanced limitations single-vendor multi-buyer (SVMB) EPQ can be easily achieved as

$$
\begin{aligned}
TC_{trade} = {} & \sum_{i}^{n}\sum_{j}^{m}\left[\frac{D_{ij}}{Q_{ij}}\left(K_{i,s}+K_{ij,b}\right)+\frac{h_{ij}}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\left(Q_{ij}\left(1-\delta_m\right)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)^2\right.\\
& \left.+\left(\frac{s_1.b_{ij}^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}+\frac{s_2.b_{ij}.D_{ij}}{Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\right)\right]+\sum_{j}^{m}C_{trade}\times\left(e_j^{+}-e_j^{-}\right)\\
& +\sum_{j}^{m}\left[x_j^{-}+\left(int^{-}\times x_j^{-}\right)-\left(int^{+}\times x_j^{+}\right)\right]+\sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{D_{ij}}{Q_{ij}}.t_f\right)+\left(Q_{ij}.t_v\right)+\left(\frac{D_{ij}}{Q_{ij}}.(Lo+Un).\left(t_L+t_M\right)\right)\right]\\
s.t. & \\
& \frac{\sum_i^n\sum_j^m C_0.D_{ij}}{\sum_i^n\sum_j^m\frac{C_0.\left(Q_{ij}\left(1-\delta_m\right)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}}\geq ITR_j\\
& \sum_{i}^{n}\left[\left(Q_{ij}.\theta_m\right)+\left(\frac{D_{ij}}{Q_{ij}}.L_j.\theta_t\right)+\left(Q_{ij}.D_{ij}.\theta_k\right)\right]+\left(e_j^{-}-e_j^{+}\right)=E_j\\
& \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\delta_m\right)+\left(Q_{ij}.\left(1-\delta_m\right).\delta_t\right)+\left(Q_{ij}\left(1-\delta_m\right).\left(1-\delta_t\right).\delta_k\right)\right]\leq F\\
& \sum_{i}^{n}\left(Q_{ij}\left(1-\delta_m\right)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)\leq W_j\\
& \sum_{i}^{n}C_i.Q_{ij}\left(1-\delta_m\right)+\left(x_j^{+}-x_j^{-}\right)=X_j\\
& \sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}}\leq N_{Max}\\
& Q_{ij}\leq Q_{Max} b_{ij}\leq Q_{ij}\\
& Q_{ij}>0, integer, i=1,2,\ldots,n\\
& b_{ij}\geq 0, integer, j=1,2,\ldots,m\\
& x_j^{+},x_j^{-},e_j^{+},e_j^{-}\geq 0,
\end{aligned}
\tag{17}
$$

In this non-exergy sustainable model, we are looking to optimize four objectives simultaneously: (a) the total inventory cost, (b) the entire cost associated with the additional required budget of all buyers, (c) the total coal transportation cost among SC members, (d) and the cost of produced carbon emission by all processes. Consequently, we have six decision variables, for example, the amount of required loan/investment for each buyer (x_j^-, x_j^+), the carbon credits for each buyer (e_j^+, e_j^-), the order quantity of each item for each buyer (Q_{ij}), and the amount of backorder of each item for each buyer (b_{ij}). The following subsection considers uncertainty to the non-exergy model in Eq. (17).

4.2 The inventory model in fuzzy environment

Stochastic modelling methods can solve the inventory model with sufficient historical data for ambiguous parameters (Aka and Akyüz, 2021). Despite this, it is problematic to have actual and exact random distributions because of the unavailability of historical data on the coal SC in Iran. Moreover, in the real coal SC business world, the market environments are full of ambiguities in a non-stochastic sense (Panja and Mondal 2019). Therefore, most inventory models in the literature consider an impractical assumption; all the inventory settings occur in a deterministic and particular condition. To cope with this unrealistic assumption, Zadeh (1965) proposed "fuzzy set theory (FST)," which converts "ill-defined" data to mathematical terminologies. Accordingly, the problem considered in this study is a fuzzy EPQ SVMB multi-product SC. As discussed in Hanss (2005), different types of fuzzy numbers exist, for example, triangular, trapezoidal, and Gaussian fuzzy numbers. Trapezoidal numbers are usually used to express ambiguous or uncertain information since they can deal with the ambiguity or uncertainty of complex fuzzy information (Wan et al. 2021). Moreover, the trapezoidal fuzzy number is a commonly used representation of uncertain information in real applications (He et al. 2018). Therefore, in this study, the buyer's demands, the unit price of products, the cost of goods sold per unit of product, and the carbon trade price are considered ill-defined and trapezoidal fuzzy numbers.

4.2.1 Graded mean integration representation technique

To figure out and employ the consequent responses from fuzzy SC, the results should be relevant for the top management of the companies. Therefore, defuzzification is necessary (Shekarian et al. 2017). As several techniques for the defuzzification of fuzzy numbers can be applied, one of the most employed, the "graded mean integration" technique (Chen and Hseih 1998), is used in this paper. In most circumstances employing the extension rule to get the membership function of the fuzzy total cost function is not easy. Because the membership function does not alter with fuzzy arithmetic procedures, it is probable to estimate the defuzzified amount immediately through the graded mean integration technique through arithmetic procedures (Mahata and Goswami 2013). Chen and Hseih (1998) method is helpful since it scores each point of support set of fuzzy numbers, and it is probable to determine the level of resemblance among fuzzy numbers concerning graded mean integration amounts. Suppose $\widetilde{A} = (a_1, a_2, a_3, a_4)$ is a trapezoidal fuzzy number and L^{-1}, R^{-1} are correspondingly the inverse functions of L and R. Describe the graded mean h-level amount of $\widetilde{A}$ as $\frac{h\left[L^{-1}(h)+R^{-1}(h)\right]}{2}$ (Mahata and Goswami 2013). So, the graded mean integration description of fuzzy number $\widetilde{A}$ can be calculated as

$$P\left(\widetilde{A}\right) = \frac{\int_0^1 \frac{h\left[L^{-1}(h)+R^{-1}(h)\right]}{2} dh}{\int_0^1 h.dh} = \int_0^1 h\left[L^{-1}(h) + R^{-1}(h)\right].dh \tag{18}$$

For trapezoidal fuzzy number $\widetilde{A} = (a_1, a_2, a_3, a_4)$, $L^{-1}(h) = a_1 + \left(a_2 - a_1\right)h$ and $R^{-1}(h) = a_4 + \left(a_4 - a_3\right)h$. Afterward, the graded mean integration depiction of trapezoidal fuzzy number $\widetilde{A} = (a_1, a_2, a_3, a_4)$ by Eq. (18) is given by

$$P(\widetilde{A}) = \frac{a_1 + 2a_2 + 2a_3 + a_4}{6} \tag{19}$$

Therefore, in this study the buyers' demand ($\widetilde{D_{ij}}$), purchasing price per unit of product i ($\widetilde{C_i}$), cost of goods sold per unit of product i ($\widetilde{C_0}$), and trade price of each unit of carbon ($\widetilde{C_{trade}}$) are considered trapezoidal fuzzy numbers i.e. $\widetilde{D_{ij}} = \left(D_{ij,1}, D_{ij,2}, D_{ij,3}, D_{ij,4}\right)$, $\widetilde{C}_i = \left(C_{i,1}, C_{i,2}, C_{i,3}, C_{i,4}\right)$, $\widetilde{C}_0 = \left(C_{0,1}, C_{0,2}, C_{0,3}, C_{0,4}\right)$, and $\widetilde{C_{trade}} = \left(C_{t,1}, C_{t,2}, C_{t,3}, C_{t,4}\right)$.

5 Exergy modeling of fuzzy optimization of multi-buyer coal SC

The earlier section presents a fuzzy monetary sustainable EPQ model (minimum Dollar or Euro) for a coal SC under a carbon trade policy. In this section, we consider three factors of hidden cost in a coal SC such as capital (*Cap*), labor (*L*), and environment (*Env.*) remediation by employing the extended exergy accounting method and then convert the monetary model (Eq. 17) to the equivalent exergy model.

5.1 Extended exergy accounting

Extended exergy accounting is the quantity of initial exergy (in Joules; J) aggregate consumed in the manufacture, operation, and discarding procedure of certain goods or services. This method delivers more information than an entirely financial method, which cannot support any suggestion about utilizing global resources (Jawad et al. 2016). The initial aggregate exergy includes material (*M*), and energy (*E*), corresponding exergy of labor (*L*), money (*Cap.*), and ecological (*Env.*) remediation costs, of which the last three components are counted as the cost correspondence of economic externality and ecological externality (Song et al. 2019). It can be expressed as (Naderi et al. 2021b)

$$EEA = ee_M + ee_E + ee_{Cap} + ee_L + ee_{Env} \tag{20}$$

where $(ee_M + ee_E)$ are the exergy of raw materials and energy flows, used in producing a product. The summation of these two exergies $(ee_M + ee_E)$ could be determined by transforming the summation of purchasing costs $(\sum_i^n \sum_j^m C_i D_{ij})$ in the inventory model to the exergy equivalents (Jawad et al. 2015). As mentioned in Sect. 3.4.2, for simplifying the mathematical model, we ignore the purchasing costs (and therefore exergy equivalents: $ee_M + ee_E$) since it does not affect the model's order quantity (Q_{ij} as decision variable). All related costs should be transformed into comparable exergetic amounts to employ the extended exergy accounting method in an inventory model. The setup (K), buying (C), and keeping (h) costs can be categorized into the summation of three exergetic amounts of capital, labor, and environment $\left(ee_{Cap,i} + ee_{L,i} + ee_{Env,i}\right)$, respectively (Jawad et al. 2018),

$$ee_{Cap,i} = \left(i_{Cap}\right) \times ee_{Cap} \tag{21}$$

$$ee_{L,i} = i_L \times ee_L / Labor\ cost \tag{22}$$

$$ee_{Env,i} = i_{Env} \times ee_{Env} \tag{23}$$

where $i = K, C, orh$ are calculated in J/order, J/unit, and J/unit/year, respectively. Concerning Eq. (23) for the exergy of environment characteristic, we accept the approach of Chen and Chen (2009), who respected ($ee_{Env} = ee_{Cap}$). Consequently, Eq. (23) is switched to ($ee_{Env,i} = i_{Env} \times ee_{Cap}$). It comprises any cost paid to get labor, capital, material, and other items used to reduce the damaging environmental effect of manufacturing a product, operating a SC, or delivering some other service (Jawad et al. 2015). Moreover (Jawad et al. 2015, 2018; Sciubba 2011; Naderi et al. 2021b),

$$ee_{Cap} = \alpha.\beta\left(\frac{Ex_{in}}{M_2}\right) \tag{24}$$

$$ee_L = \frac{\alpha.Ex_{in}}{(NWH)_{total}} \tag{25}$$

where (ee_{Cap}, ee_L) are the specific exergy equivalent of one monetary unit (€, \$, £, ¥) and the unit equivalent exergy of labor, respectively. Additionally, (Ex_{in}) is the total incoming exergy fluctuation (J/yr), can be defined based on the energy budget of the country under investigation. Based on Sciubba (2011), the extended exergy accounting method determines the exergy corresponding to Labour, Money, and Ecological remediation (Eqs. 24 and 25) in goods or services by elements of "α" and "β" and some financial factors like GDP. These aspects are highly inspired by population, labor statistics, regular and international income, and normal workload. The stated aspects and exergy counterparts were examined and figured out by Sciubba (2011) for some developed and developing countries. For example, if setup cost ($K = 30Euro$) and we consider the percentages of money, labor, and ecological remediation denote the order cost, e.g., 60%, 30%, and 10%, therefore, $K_{Cap} = 0.6 \times 30 = 18Euro$, $K_L = 0.3 \times 30 = 9Euro$ and $K_{Env} = 0.1 \times 30 = 3Euro$. Considering Eqs. (21)–(25), one can calculate the three exergetic values of capital, labor, and environment $\left(ee_{Cap,K} + ee_{L,K} + ee_{Env,K}\right)$ related to setup/order cost to achieve exergy $K_{(x)}$.

5.2 Applying extended exergy accounting to fuzzy optimization of multi-buyer coal SC

Under the carbon trade policy, the exergy equivalent of the total cost is ($TC_{(x)} = Z_{(x)1} + Z_{(x)2} + Z_{(x)3} + Z_{(x)4}$), These equivalents can be done with the following formulas (Jawad et al. 2015)

$$K_{(x)i,s} = \left(ee_{Cap,K(i,s)} + ee_{L,K(i,s)} + ee_{Env,K(i,s)}\right) \tag{26}$$

$$K_{(x)ij,b} = \left(ee_{Cap,K(ij,b)} + ee_{L,K(ij,b)} + ee_{Env,K(ij,b)}\right) \tag{27}$$

$$h_{(x)ij} = \left(ee_{Cap,h(ij)} + ee_{L,h(ij)} + ee_{Env,h(ij)}\right) \tag{28}$$

$$s_{(x)1} = s_1 \times \left(ee_{Cap}\right) \tag{29}$$

$$s_{(x)2} = s_2 \times \left(ee_{Cap}\right) \tag{30}$$

$$t_{(x)f} = t_f \times \left(ee_{Cap}\right) \tag{31}$$

$$t_{(x)v} = t_v \times \left(ee_{Cap}\right) \tag{32}$$

$$t_{(x)L} = t_L \times \left(ee_{Cap}\right) \tag{33}$$

$$t_{(x)M} = t_M \times \left(ee_{Cap}\right) \tag{34}$$

$$\widetilde{C_{(x)i}} = \left(ee_{Cap,\widetilde{C(i)}} + ee_{L,\widetilde{C(i)}} + ee_{Env,\widetilde{C(i)}}\right) \tag{35}$$

$$\widetilde{C_{(x)trade}} = \widetilde{C_{trade}} \times \left(ee_{Cap}\right) \tag{36}$$

$$X_{(x)j} = X_j \times \left(ee_{Cap}\right) \tag{37}$$

Therefore, by using the above formulas to the objective functions and limitations of the model in Eq. (17), it is converted to a fuzzy exergy model as follows:

5.3 A fuzzy exergy modeling of coal SC with carbon trade policy

$$
\begin{aligned}
TC_{(x)trade} &= \sum_{i}^{n}\sum_{j}^{m}\left[\frac{\widetilde{D_{ij}}}{Q_{ij}}\left(K_{(x)i,s}+K_{(x)ij,b}\right)+\frac{h_{(x)ij}}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}\left(Q_{ij}\left(1-\delta_m\right)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)^2\right.\\
&\left.+\left(\frac{s_{(x)1}.b_{ij}^2}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}+\frac{s_{(x)2}.b_{ij}.\widetilde{D_{ij}}}{Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}\right)\right]\sum_{j}^{m}\widetilde{C_{(x)trade}}\times\left(e_j^{+}-e_j^{-}\right)\\
&+\sum_{j}^{m}\left[x_{(x)j}^{-}+\left(int^{-}\times x_{(x)j}^{-}\right)-\left(int^{+}\times x_{(x)j}^{+}\right)\right]+\sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.t_{(x)f}\right)+\left(Q_{ij}.t_{(x)v}\right)+\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.(Lo+Un).\left(t_{(x)L}+t_{(x)M}\right)\right)\right]
\end{aligned}
$$

$$
\begin{aligned}
&s.t.\\
&\frac{\sum_i^n\sum_j^m C_{(x)0}.\widetilde{D_{ij}}}{\sum_i^n\sum_j^m\frac{C_{(x)0}.\left(Q_{ij}\left(1-\delta_m\right)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}}\geq ITR_j\\
&\sum_{i}^{n}\left[\left(Q_{ij}.\theta_m\right)+\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.L_j.\theta_t\right)+\left(Q_{ij}.\widetilde{D_{ij}}.\theta_k\right)\right]+\left(e_j^{-}-e_j^{+}\right)\leq E_j\\
&\sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\delta_m\right)+\left(Q_{ij}.\left(1-\delta_m\right).\delta_t\right)+\left(Q_{ij}\left(1-\delta_m\right).\left(1-\delta_t\right).\delta_k\right)\right]\leq F\\
&\sum_{i}^{n}\left(Q_{ij}\left(1-\delta_m\right)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)\leq W_j\\
&\sum_{i}^{n}\left(\widetilde{C_{(x)i}}.Q_{ij}\left(1-\delta_m\right)\right)+\left(x_{(x)j}^{+}-x_{(x)j}^{-}\right)=X_{(x)j}\\
&\sum_{i}^{n}\sum_{j}^{m}\frac{\widetilde{D_{ij}}}{Q_{ij}}\leq N_{Max}\\
&Q_{ij}\leq Q_{Max}\\
&b_{ij}\leq Q_{ij}\\
&Q_{ij}>0,\ integer,\ i=1,2,\ldots,n\\
&b_{ij}\geq 0,\ integer, j=1,2,\ldots,m\\
&x_{(x)j}^{+},x_{(x)j}^{-},e_j^{+},e_j^{-}\geq 0,
\end{aligned}
\tag{38}
$$

Under the extended exergy accounting technique, the following section suggests three recent metaheuristic algorithms to solve the fuzzy exergy model in Eq. (38).

6 A solution algorithm

In general, for solving optimization models like Eq. (38), there are three solution search methods such as exact (complete), heuristic, and metaheuristic (Shokouhifar and Jalali 2017). The weakness of "Exact" approaches, for instance, LINGO, CPLEX, and GAMS are primarily on demanded CPU running time, particularly in real-size problems (Diabat 2014; Zahedi et al. 2016), while "heuristics" approaches do not explore the search space effectively (Naderi et al. 2021b). In contrast, "metaheuristics" algorithms have enhanced the global search implementation slightly (Yan et al. 2021; Guo et al. 2020) and have the most precision results with a reasonable CPU running time (Stojanovic et al. 2017). Since the model in Eq. (38) is “nonlinear integer-programming (NIP)” and “NP-complete,” finding an “analytical solution” (if any) is demanding (Diabat 2014; Gen and Cheng 1997; Peng et al. 1998). The fact is that the objective function has a non-derivative arrangement, and the decision variables are integers (Roozbeh Nia et al. 2014). Optimization with metaheuristic algorithms is an influential and well-known method utilized in several engineering and real-world problems (Islam et al. 2021; Maier et al. 2019). These algorithms focus on improved reliability, enhanced system performance, efficient resources, superior system response, profit intensification, error, and cost reduction. (Maier et al. 2019).

Metaheuristic algorithms employ a stochastic manner for the optimization process created on random operators (Islam et al. 2021). Moreover, natural or biological phenomena have stimulated metaheuristic algorithms based on swarm intelligence and evolution (Abdullah and Ahmed 2020; Islam and Ahmed 2020) and applied them to various models (Wang et al. 2020a). Many researchers have successfully employed traditional swarm intelligence and evolutionary algorithms, for instance, ant colony optimization (ACO), particle swarm optimization (PSO), and genetic algorithm (GA) (Roozbeh Nia et al. 2017a, b). Despite these algorithms, there are some modern and attractive examples involving the Horse herd Optimization Algorithm (HOA) (MiarNaeimi et al. 2021; Moldovan 2020), Whale Optimization Algorithm (WOA) (Mirjalili and Lewis 2016; Islam et al. 2021; Yan et al. 2021; Zhang and Wen 2021; Wang et al. 2021b), Lion Optimization Algorithm (LOA) (Yazdani and Jolai 2016; Varshney et al. 2021; Selvi and Ramakrishnan 2020; Wang et al. 2020b; Gope et al. 2019), Ant Lion Optimizer (ALO) (Mirjalili 2015; Wang et al. 2020a; Bekakra et al. 2021; Singh et al. 2021; Chen et al. 2020a; Pradhan et al. 2020), and Grey wolf optimizer (GWO) (Mirjalili et al. 2014; Padhy and Panda 2021; Bekakra et al. 2021; Wang et al. 2021a; Liu et al. 2021; Tütüncü et al. 2021).

The GA and ACO presents a high risk of falling into local optimal, accordingly might lead to an inconsistent result thus needed more iteration to find the optimal solutions (Varshney et al. 2021). Moreover, GA, ACO and PSO have many factors, and it is complicated to decide on correct parameters (Shinoda and Miyata 2019). In this study we consider three recent metaheuristic algorithms: ALO, LOA, and WOA, to solve the “exergy fuzzy NIP (EFNIP) problem” modeled in Eq. (38). The reasons for selecting these three modern algorithms are as follows:

- ALO has been demonstrated as an efficient optimization algorithm in many areas (Mirjalili, 2015; Dubey et al. 2016; Ali et al. 2017; Wang et al. 2020a) and has a good performance in deciding global optimum (Pradhan et al. 2020; Mirjalili, 2015). The crucial aspect of selecting ALO is by reason of its efficient search space employing random walk and choice of search agents by chance. (Pradhan et al. 2020). ALO has drawn extensive interest because of its relatively adequate efficiency, flexibility, and simplicity (Wang et al. 2020a).
- In most circumstances, the outcomes achieved by LOA deliver outstanding solutions in fast convergence and global optima accomplishment (Yazdani and Jolai, 2016). This approach uses the local as well as global optima and thus gives the

optimal solution with minimum cost (fitness function) and takes less iteration (Varshney et al. 2021).

- WOA demands no added modification parameters to come to an outstanding balance between its exploration and exploitation (Aala Kalananda and Komanapalli, 2021). Study findings present that WOA is outstanding to other optimization methods, for instance, PSO, ACO, GA, differential evolution (DE), and gravitational search for solution precision and convergence speed (Chen et al. 2020c; Kaur and Arora, 2018; Mohammed et al. 2019, Jahromi et al. 2018). Since the benefits of effortless assumption, simple operation, straightforward application, few modification parameters, and strong robustness, the WOA algorithm has received widespread interest and has achieved many significant research outcomes (Du et al. 2021; Zhang et al. 2021; Long et al. 2020).

Based on the literature, metaheuristic algorithms' parameters substantially impact outcome quality and running time (Yang et al. 2009; Kao and Zahara 2008). Consequently, the algorithm's parameters employed are based on a pilot study, and the algorithm's results will be validated with GAMS output in small-size problems. In the following subsections, short explanations primarily supported three metaheuristic algorithms. Interested readers are encouraged to see referred studies about these algorithms in detail. Afterward, the phases concerned in the proposed solutions are described.

6.1 The ant lion optimization algorithm (ALO)

The Ant Lion Optimization algorithm, which Mirjalili (2015) proposed, is one of the nature-stimulated optimization procedures for solving one-dimensional and multidimensional optimization models (Pradhan et al. 2020). The algorithm is stimulated by the hunting behavior of antlions that catch their prey, ants, by digging a pit in the sand (Singh et al. 2021; Mirjalili 2015). A larva of an ant lion builds a conical-formed hole by going along a spherical route in the sand and putting the sand with its enormous jaw. After excavating the hole, larvae conceal at the bottom, stopping for ants to be stuck in the hole. When an ant has been stuck in the hole, the ant lion drops sand towards the outside, so it falls its target into the hole. Once an ant is stuck into the jaw, the ant lion draws the prey toward itself and eats (Mirjalili 2015; Chen et al. 2020a). Six main processes were planned in ALO to replicate communication between the ant and the ant lion in the hole, comprising of random walk of ants, getting caught in the ant lion's trap, the construction of a hole, descending ants towards the ant lion, sticking prey, re-construction of the hole, and elitism, respectively (Mirjalili 2015; Wang et al. 2020a). An analysis of all prior studies on ALO is newly offered by (Heidari et al. 2020; Abualigah et al. 2020; Abderazek et al. 2020). Moreover, Appendix Fig. 9. Presents pseudo-code of the ALO algorithm.

6.2 The lion optimization algorithm (LOA)

Yazdani and Jolai (2016) suggested Lion Optimization Algorithm (LOA) as a population-based metaheuristic approach. It is an optimization naturally motivated by the attributes of lions. It replicates lions' social and hunting performance, for instance, prey capturing, roaming, mating, and defence (Selvi and Ramakrishnan 2020). The lion has specific social behavior; hence it is the most powerful mammal globally. Lions have two forms of social behavior: inhabitants and travelers, and lions can switch over them. Inhabitants live in parties known as pride, in which resident females and males appear to give birth. The second structural behavior is so-called travelers, who occasionally move about in pairs or singularly. A detailed explanation of all LOA steps is presented in Yazdani and Jolai (2016). Moreover, Appendix Fig. 10. presents pseudo-code of the LOA algorithm.

6.3 The whale optimization algorithm (WOA)

The whale optimization algorithm (WOA) is a recent swarm intelligence optimization method suggested by Mirjalili and Lewis (2016). The WOA algorithm is motivated by the hunting method of humpback whales. Their predation process is called the bubble-net attacking method, and it has been seen that it is done by producing unique bubbles along a circle (Goldbogen et al. 2013). The hunting behavior primarily includes three stages: search for prey, diminishing encircling, and spiral revising location (Mirjalili and Lewis 2016; Wang et al. 2021b; Chen et al. 2020b, 2020c; Lee and Lu 2020). The WOA uses three operators that simulate these phases. Among them, the operator replicating the bubble-net hunting behavior of humpback whales is an essential process in WOA (Li et al. 2021). In WOA, the location of each humpback whale stands for a search agent. During the search process, the whales progressively acquire the proper location of the prey by encircling, twisting, and capturing it at the end (Zhang et al. 2021). The WOA obtains the best solution to the global optimization problem by continuously revising the search agent (Yan et al. 2021). Moreover, WOA depends on a linearly declining vector whose value reduces from 2 to 0 as the repetitions develop (Aala Kalananda and Komanapalli 2021). Appendix Fig. 11. Presents pseudo-code of the WOA algorithm.

At the end of this section, the main steps in the recommended solution process of Eq. (38) under carbon trade emission policy and uncertain environment are presented in Fig. 1. Moreover, an illustration of the chromosomes related to the order quantity (Q) and backorder amount (b) of a numerical example with one supplier and ten buyers who have four products are presented in Fig. 2, correspondingly.

7 Numerical examples

This section gives numerical test problems, including one real-world coal SC case study in Iran and nine arbitrary cases related to it. We are looking to optimize sustainability in a coal SC by considering the indirect (hidden) costs in Joules and

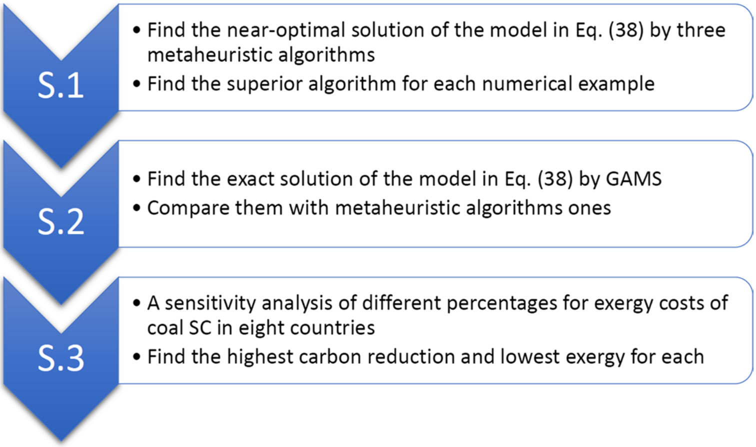

Fig. 1 Flow chart of the proposed solving procedure

Q_{i1}:	1590	1343	1162	2001	Q_{i2}:	1135	1619	1167	1341
Q_{i3}:	1187	1838	1192	1673	Q_{i4}:	1183	1055	1857	2101
Q_{i5}:	1320	2216	1310	1076	Q_{i6}	1470	1486	1877	558
Q_{i7}:	1013	1023	1151	689	Q_{i8}:	1935	2104	1566	805
Q_{i9}:	1461	1099	1797	1404	Q_{i10}	1216	1427	2074	606

b_{i1}:	36	1	40	32	b_{i2}:	16	48	13	17
b_{i3}:	70	56	35	15	b_{i4}:	0	11	3	94
b_{i5}:	18	27	12	17	b_{i6}	74	64	15	21
b_{i7}:	23	10	15	68	b_{i8}:	35	21	66	0
b_{i9}:	61	0	67	14	b_{i10}	16	14	20	60

Fig. 2 An example of the chromosomes for the numerical example with four products and ten buyers

including all three factors simultaneously (using the extended exergy accounting method) under a carbon trade policy in an uncertain environment. Based on the recommended solution steps in Fig. 1, we are examining to get the optimum value of six decision variables, such as the amount of required loan/investment for each buyer

(x_j^-, x_j^+), the required carbon credits for each buyer (e_j^+, e_j^-), order quantity of each product for each buyer (Q_{ij}), and amount of backorder of each product for each buyer (b_{ij}). Moreover, a sensitivity analysis considers different percentages for exergy costs in coal SC of eight countries: Iran, India, China, Australia, Japan, Poland, the USA, and Zimbabwe to find the best exergy values that great the highest sustainability in each country. These countries are ranked in the top 20 countries with the most coal consumption globally (Statista 2020).

7.1 Case study in Iran

The real-world case study includes one supplier and ten buyers of coal products in an SC in Iran. Tabas Parvadeh Coal Company (TPCCO), located in Tabas city, is the biggest coal producer in Iran. Consistent with the statistics printed by the Iranian Mines and Mining Industries Development and Renovation Organization (IMIDRO), TPCCO extracted 1.232 million tons of coal from March 21, 2019, to January 20, 2020. With about 1.15 billion tons of reserves, Iranian coal mines can deliver up to three million tons of coal concentrate yearly (IEA, clean coal center 2020). From another point of view, the production of steel in Iran is highly dependent on coal since metallurgical coal, or coking coal, is an essential part of steel-making operations. TPCCO produces four diverse types (grades) of coal, and this company has ten key customers (steel producers) in different cities in Iran. TPCCO and all buyers use the public rail transport system to transport coal orders. Since demand of each steel producer (buyer) for each type of coal, coal purchasing price, and carbon emission price is not stated precisely, we consider them trapezoidal fuzzy numbers (see Appendix Tables 10 & 11). Moreover, the initial data of the test problems (parameters and resource values) and their equivalent exergy parameters are presented in Appendix Tables 12, 13, 14, 15, 16, 17, 18 and 19, respectively. Moreover, all inventory costs and their equivalent exergy cost related to real case study in Iran are presented in Table 4. Consistent with the informed values in Sciubba (2011) as the only reference study for the extended exergy accounting method in the literature, we take equivalent exergy parameters of Egypt due to the resemblances between Iran and Egypt regarding economic development, population, religion, and culture. Therefore, exergy parameters of Iran and selected countries are presented in Table 5.

After consulting with SC managers of TPCCO, it was estimated that each cost of $K_{i,S}, K_{ij,b}, h_{ij} and C_i$ can be divided to $Cap = 30\%$ for capital, $L = 60\%$ for labor, and $Env = 10\%$ for ecological remediation. In Sect. 4.1, we described the method of extended exergy accounting and related formulas that we applied to our model. For example, in Table 4, the cost of $K_{i,S}$ is assumed €20 for the first product which includes €6 (20×0.30), €12 (20×0.60) and €2 (20×0.10) (monetary values) for capital ($Cap = 30\%$), labor ($L = 60\%$) and environmental ($Env = 10\%$) remediation, respectively. Moreover, these three numbers are converted to the exergy values of 34.08, 3.56, and 11.36 MJ, respectively (in total $K_{(x)i,S} = 49$ MJ). To show better the performance of our suggested modern metaheuristic algorithms in solving big-size test problems, besides the actual case study, we considered nine arbitrary numerical examples related to it with 10, 20, 40, 80, 160, 320, 640, 1280, and 2560 products in a sustainable coal SC in Iran with one supplier and 15 buyers. The initial data of all numerical examples are shown in Appendix Tables 12, 13, 14, 15, 16, 17, 18 and 19, respectively. As noted previously, a pilot study is used for the parameter tuning of all suggested metaheuristic algorithms, and the test problems are solved on a PC with an Intel Core i7-7500U CPU with 2.70 GHz and 8.00 GB RAM in Windows 10. The "MATLAB" 2017a software is also employed for coding all the algorithms.

7.2 Solving phases and related results

7.2.1 *Step one*—Metaheuristic algorithms

Based on solving procedure (Fig. 1), at the first step, all suggested metaheuristic algorithms are executed 15 times for the fuzzy exergy model with carbon trade policy (Eq. 38). The outputs of algorithms include the lowest fuzzy total exergy (*MJ*), and the CPU times (*seconds*) are presented in Tables 6 and 7, respectively. Based on the results, the superior metaheuristic algorithm for the smallest fuzzy total exergy (*MJ*) and running times (*seconds*) could be found for the model (Eq. 38).

Concerning the fuzzy total exergy and in line with the fallouts shown in Table 6, ALO is the best algorithm (with 32,753,094.69 and 122,319,654.35 MJ) in the actual case study in Iran with four products as well as the numerical test with ten products, while for test problems from 20 to 2560 products, WOA is the best. For our large size test problems (640, 1280 & 2560 products), WOA gets the lowest fuzzy total exergy cost (3,964,974,414.68; 8,490,424,760.63 & 20,715,326,512.04 MJ) followed by LOA, and ALO, respectively (see Fig. 3). Regarding Appendix Fig. 12, performance improvement between top two algorithms from 20 to 80 p test problems, are less since the results of them are very close together. But in large-size test problems the average performance enhancement between the results of WOA and LOA is about 90%, which means the results of WOA are outstanding. In opposition, ALO has the highest fuzzy total exergy (MJ) results in our medium and large-size test problems.

Considering the CPU time (Sec.), WOA is absolutely the best algorithm with the lowest running time in all test problems (see Fig. 4). For example, in our large-size test problems (640, 1280 & 2560 products), the WOA CPU times were 49.23, 78.89, and 154.47 (Sec.), respectively (see Table 7). Moreover, in large-size test problems, the average of WOA's performance improvement (%) with the second-best algorithm is about 700% which means WOA solves the models fast (see Appendix Fig. 13). Conversely, ALO has the highest CPU time among other algorithms in all test problems except for 1285 products, where LOA (with 829.7169 Sec.) is the worse algorithm (see Table 7). In Fig. 5, we presented some convergence diagrams of the smallest fuzzy total exergy by the proposed algorithms.

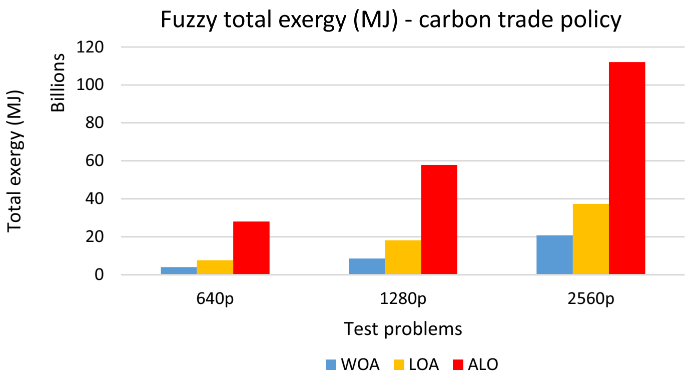

Fig. 3 The total fuzzy exergy comparisons of algorithms in large size test problems (step 1)

Table 4 Inventory costs and their equivalent exergy based on capital (30%), labor (60%), and environment (10%) values (Test with four products)

	Prod	value	Unit	Monetary values			Exergy values (MJ)			Total exergy	
				Cap	L	Env	$ee_{Cap,i}$	$ee_{L,i}$	$ee_{Env,i}$		
$K_{i,S}$	i	20	Euro/order	6	12	2	34.08	3.56	11.36	49	$K_{(x)i,S}$
$K_{ij,b}$	i	15	Euro/order	4.5	9	1.5	25.56	2.67	8.52	36.75	$K_{(x)ij,b}$
C_i	1	200	Euro/unit	60	120	20	340.8	35.6	113.6	490	$C_{(x)i}$
	2	170		51	102	17	289.68	30.26	96.56	416.50	
	3	140		42	84	14	238.56	24.92	79.52	343.00	
	4	100		30	60	10	170.40	17.80	56.80	245.00	
h_{ij}	1	5	Euro/unit/year	1.5	3	0.5	8.52	0.89	2.84	12.25	$h_{(x)ij}$
	2	4		1.2	2.4	0.4	6.82	0.71	2.27	9.80	
	3	3		0.9	1.8	0.3	5.11	0.53	1.70	7.35	
	4	3		0.9	1.8	0.3	5.11	0.53	1.70	7.35	

7.2.2 Step two—Exact method

A solution may be compared with an "exact method" to validate the results by suggested algorithms. Exact optimizer software, for example, "GAMS" or an optimization library in "Python," can find the "exact result." In this research, the proposed mathematical model (Eq. 38) under carbon trade strategy is solved in small size (test with four products) by GAMS. A contrast with the best metaheuristic algorithm is made in Table 8. Taking into account Eq. (38) for the 4-product test problem, the exact result for the fuzzy total exergy is 31,537,292.44 (MJ), while the outcome of the best metaheuristic algorithm (ALO) for this test is 32,753,094.69 (MJ). Therefore, the percentage penalty between the exact method and ALO is 3.86% (see

Table 5 The exergy parameters of selected countries (sensitivity analysis)

	Unit	Iran	Australia	China	India	Japan	Poland	USA	Zimbabwe
α_x	–	0.0121	0.018	0.0015	0.0419	0.773	0.55	0.145	0.0026
β_x	–	2.94	1.69	0.477	1.32	1.9	0.57	1.43	3.9
ee_{Cap}	MJ/Euro	5.68	3.56	14.01	4.34	3.35	14.02	2.85	3.35
ee_L	MJ/WH	3.56	71.21	48.66	1.64	70.18	76.55	72.82	70.18

Table 8). Because the percentage penalty is minor, suggesting the excellent dominance of the solutions got by the best-suggested algorithm (Cárdenas-Barrón et al. 2012) since it is remarkably close to the exact method (see Fig. 6). Concerning CPU running time and Table 8, the distinction between exact method and ALO is 1.21 (Sec.), but the percentage penalty is 39.48%. It shows that the metaheuristic algorithm (ALO) solved the carbon trade model more rapidly (see Appendix Fig. 14).

7.2.3 Step three- sensitivity analysis

In the earlier subsections, we studied the optimization of a sustainable fuzzy EPQ model of coal SC in Iran by taking into account different objectives simultaneously: the costs of the inventory system, an additional required budget of each buyer, coal transportation cost among SC members, and carbon emission cost. All goals in the models and related limitations under the emission trade strategy are in *MJ* in place of monetary values. This step tries to balance economic and sustainable advantages for coal SC companies. Considering that our proposed model is sustainable, we modify the exergy percentage for capital, labor, and environmental remediation by a sensitivity analysis to find the best values of exergy components that improve the sustainability of coal SC more than before. Additionally, to gain further insight into this adjustment, we evaluate sustainable coal SC in Iran as well as seven selected developing and developed countries with the world's most significant coal consumption. They are India, China, Australia, Japan, Poland, the USA, and Zimbabwe (Statista 2020). We assumed the same coal SC and products for all these countries to make a comparative analysis. In the previous section, we mentioned that in our numerical examples, it was assumed that each cost of $K_{i,S}, K_{ij,b}, h_{ij} and C_i$ can be allocated to $Cap = 30\%$ for capital, $L = 60\%$ for labor, and $Env = 10\%$ for ecological remediation (consider it as exergy Set A). In this section, to get more insight, we have changed these percentages to make seven different exergy sets (see Appendix Fig. 15), including A (30-60-10), B (60-20-20), C (20-50-30), D (20-40-40), E (20-30-50), F (30-10-60) and G (33-33-33). Considering each exergy set, we computed the fuzzy total exergy for a 4-item test problem under carbon trade policy for all countries by GAMS (see Table 9). For example, we consider coal SC in the USA and exergy Set C ($Cap = 20\%$, $L = 50\%$, and $Env = 30\%$), then employing extended exergy accounting method to convert all monetary costs of $K_{i,S}, K_{ij,b}, h_{ij} and C_i$ to equivalent (MJ). After that, we run model Eq. (38) with four product test problems using the Exact method (GAMS). Likewise, the same process was done for other exergy Sets (A-G) and considering other countries' coal SC. Finally, all results are presented in Table 9. In the following we explain the results in detail.

7.2.3.1 Analysis of each country Considering Table 9 and Fig. 7, for coal SC in each country, we have:

- **Australia:** For coal SC under the carbon trade policy in this country, the top exergy components are Set F (30-10-60) since more exergy percentage is assumed for Environment (60%) and less for Labor (10%). It created the minimum fuzzy total exergy of 24,251,604.43 (MJ) for coal SC. Besides, the worst exergy components are Set A (30-60-10) since Labor has 60% while Environment has only 10%, which created the highest fuzzy total exergy with 37,386,644.58 (MJ).
- **China:** The best exergy components are Set C (20-50-30) when Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. It created the minimum fuzzy total exergy of 83,731,242.82 (MJ) for coal SC. Likewise, the weakest exergy components are Set F (30-10-60) when more exergy percentage is assumed for Environment (60%) and only 10% for Labor, which generated the greatest fuzzy total exergy of 128,734,240.79 (MJ).
- **India:** Like China, the finest exergy components in India are Set C (20-50-30), when Labor has 50% weight, while Environment and Capital are 30% and 20%, respectively. It produced the minimum fuzzy total exergy of 24,826,136.13 (MJ) for coal SC. Moreover, the unpleasant exergy components are Set B (60-20-20) when more weight is expected for Capital (60%) and the same weights (20%) for Labor and Environment, which formed the maximum fuzzy total exergy of 56,664,303.08 (MJ).
- **Iran:** For coal SC in this country, the top exergy components are Set A (30-60-10) as Labor has 60% while Environment has only 10%. It made the minimum fuzzy total exergy of 31,537,292.44 (MJ). Like India, the unhealthiest exergy components in Iran are Set B (60-20-20) when more weight is assigned to Capital (60%) and the same weights for Labor and Environment (20%), which generated the maximum fuzzy total exergy of 50,042,180.33 (MJ).
- **Japan:** Like Australia, the best exergy components in Japan are Set F (30-10-60), while more exergy percentage is given to Environment (60%) and less to Labor (10%). It established the least amount of fuzzy total exergy with 22,873,547.02 (MJ) for coal SC. Furthermore, the unhealthiest exergy components are Set B (60-20-20) when more weight is provided to Capital (60%) and the same weights for Labor and Environment (20%), which generated the highest fuzzy total exergy of 40,279,208.50 (MJ).
- **Poland:** Like India and China, the excellent exergy components in Poland are Set C (20-50-30), when Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. It created the least possible fuzzy total exergy of 86,131,627.76 (MJ) for coal SC. Besides, the worst exergy components are Set F (30-10-60), when more exergy percentage is offered to Envi-

ronment (60%) and less on Labor (10%), which created the maximum fuzzy total exergy of 123,315,602.00 (MJ).

- **The USA:** Like Australia and Japan, the superior exergy components in the USA are Set F (30-10-60) as more exergy percentage is assumed to Environment (60%) and less on Labor (10%). It generated the minimum fuzzy total exergy of 19,675,609.14 (MJ) for coal SC. Additionally, the harmful exergy components are Set A (30-60-10) since Labor has 60% while Environment has only 10%, which established the highest fuzzy total exergy of 31,673,757.27 (MJ).
- **Zimbabwe:** Like Australia, Japan and the USA, the first-rate exergy components in Zimbabwe are Set F (30-10-60) because more exergy percentage is assumed to Environment (60%) and less on Labor (10%). It crafted the minimum fuzzy total exergy of 22,873,547.02 (MJ) for coal SC. Additionally, the weakest exergy components are Set A (30-60-10) since Labor has 60% while Environment has only 10%, which generated the greatest fuzzy total exergy of 31,803,458.12 (MJ).
- Considering Table 9, the best total exergy (MJ) in each country is as follow: Australia (24,251,604.43), China (83,731,242.82), India (24,826,136.13), Iran (31,537,292.44), Japan (22,873,547.02), Poland (86,131,627.76), the USA (19,675,609.14) and Zimbabwe (22,873,547.02).
- Among all presented countries, the coal SC in the USA has the smallest total exergy (19,675,609.14 MJ), followed by Japan, Zimbabwe, Australia, India, Iran, China, and Poland, respectively (see Fig. 7).
- Moreover, coal SC in China creates the highest total exergy for all exergy sets except for Set B (60-20-20) and Set C (20-50-30) related to Poland (see Fig. 8).

7.2.3.2 Analysis of each exergy set Considering Table 9, Fig. 8, and Appendix Fig. 15, for each exergy set, we have:

- **Exergy Set A (30%-60%-10%):** This exergy set has 60% for Labor, while for Environment, it is only 10%. Although this set works well for coal SC in Iran, with the minimum total exergy of 31,537,292.44 (MJ), in China, it is 121,884,457.74 (MJ).
- **Exergy Set B (60%-20%-20%):** In this set, more weight is assumed for Capital (60%) and the same for Labor and Environment (20%). Despite coal SC in Poland (110,155,055.08 MJ), exergy set B operates well in the USA with 22,604,564.59 (MJ).
- **Exergy Set C (20%-50%-30%):** In this set, Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. Exergy set C performs well in coal SC in India (24,826,136.13 MJ), even though in Poland, the total exergy is 86,131,627.76 (MJ).
- **Exergy Set D (20%-40%-40%):** In this set, Capital has only 20% while 40% is for both Labor and Environment. In spite of the high result in China with 94,201,685.52 (MJ), exergy set D runs well in Zimbabwe with 25,762,854.83 (MJ).

- **Exergy Set E (20%-30%-50%):** In this set, 50% is assigned to Environment and 20% and 30% to Capital and Labor, respectively. Exergy set E operates well in the USA with 25,320,951.45 (MJ), although the result is high in China (111,411,481.62 MJ).
- **Exergy Set F (30%-10%-60%):** In this set, 60% is allocated to Environment and only 10% Labor. Exergy set F performs well in the USA (19,675,609.14 MJ), despite the fact that the result is not healthy in China (128,734,240.79 MJ).
- **Exergy Set G (33%-33%-33%):** In this set, all three exergy components have equal 33% weight. Even though exergy set G does not perform well in China with 121,351,102.11 (MJ), it runs well in Zimbabwe with 24,146,338.65 (MJ).
- Moreover, exergy Sets B (30-60-10), E (20-30-50) and F (30-10-60) created the minimum total exergy for coal SC in the USA, while all exergy sets except Set B (30-60-10) and Set C (20-50-30) created the highest total exergy in China (see Fig. 8).

8 Conclusions and future work

According to the literature review, there is a lack of studies that assess a coal SC under a carbon trade policy with ambiguous parameters such as carbon price and customer demand. Likewise, it is scarce to obtain research that assesses a SC in terms of Joules (in place of traditional monetary measures of performance) and simultaneously evaluates all sustainability characteristics, such as economic, labour, and environmental. Similarly, to the best of the authors' knowledge, no exergy analysis method like the extended exergy accounting in the literature considers carbon policy in SC. Therefore, this study develops the work in the papers by Jawad et al. (2016) and Naderi et al. (2021a) to a multi-product multi-limitation inventory (EPQ) model with backorder for a coal SC in Iran under an uncertain environment. By applying the extended exergy accounting technique and Mega-Joules (*MJ*) as a universal unit of measure, the total exergy of the coal SC can be calculated. Moreover, a well-known carbon reduction strategy (carbon trade) is employed to evaluate the sustainability performance of the model. In this study, we presented four research questions (in Sect. 1) and attempted to answer them.

> **Q1**. Is it possible to assess the sustainability of coal SC under a carbon reduction policy in terms of Joules rather than money, to benefit both the economy and the environment?

In Sect. 3.4, we developed a non-exergy mathematical model of the coal SC for carbon trade policy. Then the model has converted to a fuzzy model in Sect. 3.5, and finally, a new SC assessment method called the extended exergy accounting (in terms of Joules) was employed in Sect. 4. This method contains energy and material's main aggregate exergy subject and costs corresponding to economic externality (labor and capital) and ecological externality (environmental remediation). Therefore, employing this method could benefit both the economy and the environment. After that, three recent metaheuristic algorithms (ALO, LOA, and WOA) are utilized. When contrasting the best algorithm outcomes in small-size test problems (four products) with the exact method (GAMS), there is a small percentage error (3.86%) under the carbon trade policy between them. Therefore, it could validate the results of metaheuristic algorithms in this study.

> **Q2**. Generally speaking, coal SC in developing countries, or even China, has the lowest overall cost; however, considering sustainability aspects (social, economic, and environmental characteristics) in terms of Joules, does this assumption still hold true?

Regarding the sensitivity analysis in Sect. 6.2.3, we compared the sustainability of coal SC in eight developed and developing countries, such as Iran, India, China, Australia, Japan, Poland, the USA, and Zimbabwe (see Table 9). They are the world's most significant coal-consuming countries (Statista 2020). It was observed that, Poland and China have the highest fuzzy total exergy of a sustainable coal SC (86,131,627.76 and 83,731,242.82 MJ, respectively) among eight selected countries. The reason behind this issue is that traditional assessment methods consider economic measures. In contrast, the method of extended exergy accounting (as mentioned in Sect. 4) considers all three aspects of sustainability (Labour, Money, and Ecological remediation) in goods or services. It determines the exergy corresponding to them (in terms of Joules) by some elements significantly affected by population, normal workload, labor statistics, and local and international wages in each country. Therefore, the extended exergy accounting results show the total number of Joules that coal SC utilized in Labour, Money, and Ecological aspects.

> **Q3**. Which country has the most sustainable coal SC in terms of Joules?

Based on Table 9, the lowest total exergy of a sustainable coal SC among all eight countries belongs to the USA (19,675,609.14 MJ) under the carbon trade policy. It means sustainable coal mining and related processes in the USA have economic and environmental advantages compared to China or developing countries such as Iran and Zimbabwe. Moreover, Japan, Zimbabwe, Australia, India, Iran, China, and Poland followed the USA (see Fig. 7).

> Q4. What is the best percentage of exergy components (social, economic, environmental characteristics) to achieve the greatest saving wherever coal SCs are working?

Considering Sect. 6.2.3 and Table 9, it is observed that under carbon trade policy, exergy Set F (30-10-60) percentages created the minimum fuzzy total exergy (highest carbon and exergy reduction) in coal SC of the countries such as Australia, Japan, the USA, and Zimbabwe. Set F (30-10-60) is given more weight (60%) to Environment, 30% to Capital and only 10% to Labor. Likewise, for coal SC in China, India, and Poland, exergy Set C (20-50-30) generated the least amount of fuzzy total exergy (83,731,242.82; 24,826,136.13 & 86,131,627.76 MJ respectively). In Set C (20-50-30), the emphasis is on Labor with 50% weight, while Capital and Environment have 20% and 30%, respectively. Finally, for coal SC in Iran, Set A (30-60-10) has the best exergy component with the minimum fuzzy total exergy of (31,537,292.44 MJ). Labor with 60% is the first weight in Set A (30-60-10), while only 10% was assigned to Environment and 30% to Capital.

Moreover, the theoretical and managerial implications of this work are presented as follows:

- It is important to note that the EEA method has the advantage of enabling meaningful comparisons between coal SCs in different countries that produce the same coal type. By comparing the amount of exergy consumed in the coal production process and related SC processes, it becomes easier to determine where a coal SC business should be located. Due to this, selecting a product from a country with low wages, such as China or India, may not always be beneficial as more exergy is required for its production. Using the EEA method provides an indication of the sustainability impact of coal SCs in an era when climate change concerns are increasing prevalent.
- The exergy equations in Sect. 4 (for instance, Eqs. 26–37) show that all exergy parameters in Table 5 are directly related to the cost elements of inventory models (such as setup, purchasing, and holding), and affect the exergy functioning of the coal SC in a significant way. It is therefore critical to decrease the cost elements of a coal SC's inventory model to improve sustainability. The managers could use stock classification and shorter order cycles, reducing the lead time of suppliers, eliminating obsolete inventory, implementing a Just-in-Time inventory system, and monitoring key performance indicators.
- Unlike conventional financial and commercial models, the results of our study found that despite assumptions that inventory parameters in coal SC are unchanged for all eight countries, more savings could be achieved through the tuning of exergy's inflows and outflows in each country. It means that no fixed amount of exergy components (Capital, Labor and Environment) can deliver the highest sustainability in all countries. According to our results in Table 9, set F (30-10-60) with 60% weight allocated to the environment and only 10% to labor generates the greatest sustainability for the USA (19,675,609.14 MJ) as well as the most unpleasant sustainability for China (128,734,240.79 MJ). Hence, finding the most appropriate values of the exergy components of the SC would be another task for decision makers.
- Another point is that, considering Table 5, one can conclude that the exergy parameter of Capital (ee_{Cap} = 2.85MJ/Euro) in the USA is less than the other countries. In contrast, China and Poland have the highest exergy parameter of Capital (ee_{Cap} = 14.01&14.02MJ/Euro) among other countries. This would be one of the reasons why the USA has the most sustainable coal SC in terms of Joules whereas China and Poland are the least sustainable. Therefore, a way to increase sustainability in each country is to find ways to decrease exergy parameters. If we look at Eqs. (24) and (25), exergy parameters of (ee_{Cap}, ee_L) are dependent on two econometric coefficients (α_x, β_x) as well as (Ex_{in}). Section 4.1 explains that these are influenced by the type of societal organization, the historical period, the technological level, the pro-capital resource consumption, and the geographical location of the country (Sciubba, 2011). All shareholders, govern-

Table 6 The fuzzy total exergy (MJ) observed by the algorithms under carbon trade policy in Iran (Eq. 38)

Test	ALO	LOA	WOA	Min. (MJ)	The bests	Performance improvement (%)
4p	32,753,094.69	56,130,526.91	48,504,010.50	32,753,094.69	ALO-WOA-LOA	48.09
10p	122,319,654.35	291,716,085.98	265,533,078.08	122,319,654.35	ALO-WOA-LOA	117.08
20p	620,356,160.82	464,274,771.96	444,387,816.87	444,387,816.87	WOA-LOA-ALO	4.48
40p	1,229,059,326.54	606,789,259.79	556,126,023.95	556,126,023.95	WOA-LOA-ALO	9.11
80p	2,772,002,306.09	950,139,646.13	887,480,983.66	887,480,983.66	WOA-LOA-ALO	7.06
160p	6,468,347,547.44	2,366,142,295.46	1,010,480,171.31	1,010,480,171.31	WOA-LOA-ALO	134.16
320p	12,809,569,710.57	5,295,722,151.09	2,409,465,266.86	2,409,465,266.86	WOA-LOA-ALO	119.79
640p	28,098,451,686.15	7,622,351,301.01	3,964,974,414.68	3,964,974,414.68	WOA-LOA-ALO	92.24
1280p	57,806,847,743.44	18,118,616,031.71	8,490,424,760.63	8,490,424,760.63	WOA-LOA-ALO	113.40
2560p	112,083,644,493.09	37,319,812,944.67	20,715,326,512.04	20,715,326,512.04	WOA-LOA-ALO	80.16

Table 7 The CPU times (Sec.) of solving numerical examples by the algorithms under carbon trade policy in Iran (Eq. 38)

Test	ALO	LOA	WOA	Min. (Sec.)	The bests	Performance improvement (%)
4p	3.07	3.23	0.97	0.97	WOA-ALO-LOA	214.90
10p	8.29	7.53	1.52	1.52	WOA-LOA-ALO	395.23
20p	14.71	12.62	2.60	2.60	WOA-LOA-ALO	384.68
40p	27.78	26.81	4.03	4.03	WOA-LOA-ALO	565.62
80p	53.99	51.63	5.57	5.57	WOA-LOA-ALO	826.17
160p	104.94	98.24	8.72	8.72	WOA-LOA-ALO	1026.17
320p	207.59	190.57	18.37	18.37	WOA-LOA-ALO	937.27
640p	406.38	339.40	49.23	49.23	WOA-LOA-ALO	589.36
1280p	801.43	829.72	78.89	78.89	WOA-ALO-LOA	915.85
2560p	1,606.61	1,442.98	154.47	154.47	WOA-LOA-ALO	834.17

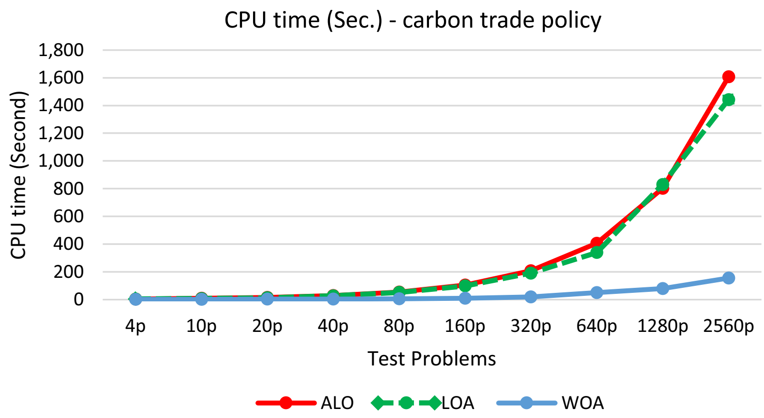

Fig. 4 The CPU time comparisons of all algorithms (step 1)

ments, individuals, societies, business organisations, scientists, etc., need to contribute significantly to adjusting parameters, if possible. An example is controlling the import and export of goods from and to the country or extracting ores and minerals. Promoting locally made goods can be a way for individuals, societies, and business organizations to support this cause. As a result, there would be more jobs available in the country, and increasing the labor force rate (Jawad et al. 2018). Additionally, effective productivity growth (output per hour worked) can boost a country's income and GDP per capita. For more information, readers are encouraged to consult Sciubba (2011).

- In addition, decision-makers should find ways to improve the sustainability of their coal SC by reducing waste, labor, material, and pollution, which will reduce the damaging effects of coal SC. When calculating energy costs, managers of SC would have more flexibility since they could use available resources rather than

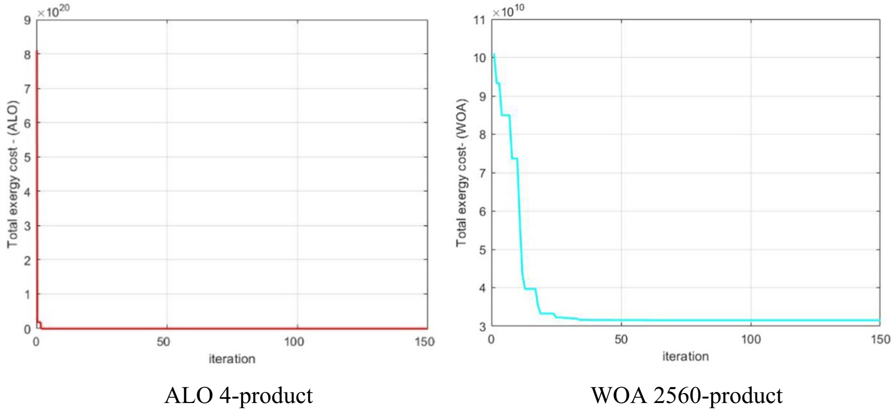

Fig. 5 The convergence diagram of the total fuzzy exergy by the proposed algorithms (step 1)

Table 8 Comparing the results of the exact method (GAMS) with the best algorithm (ALO)

	ALO	Exact	Difference	Penalty (%)
Fuzzy total exergy (MJ)	32,753,094.69	31,537,292.44	1,215,802.25	3.86
CPU time (Second)	3.07	4.28	1.21	39.48

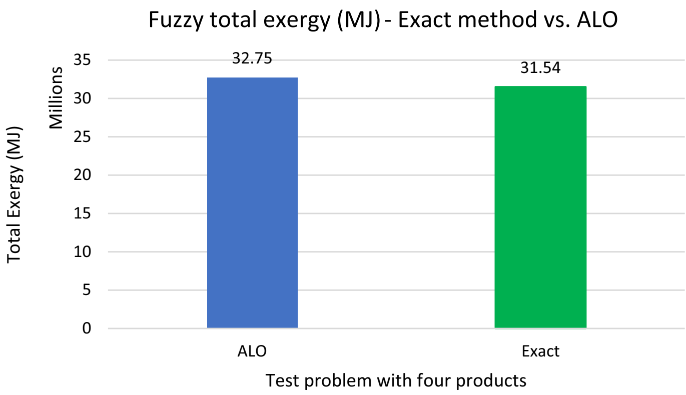

Fig. 6 Comparison of the total fuzzy exergy between exact method and the best metaheuristic algorithm for test problem with four products (step 2)

just capital to calculate the quantity. Furthermore, this research will also guide managers of international coal mining companies who wish to decide which country has more sustainable conditions for their business and investments.

Furthermore, the EEA method in this study is subject to some limitations, including the following:

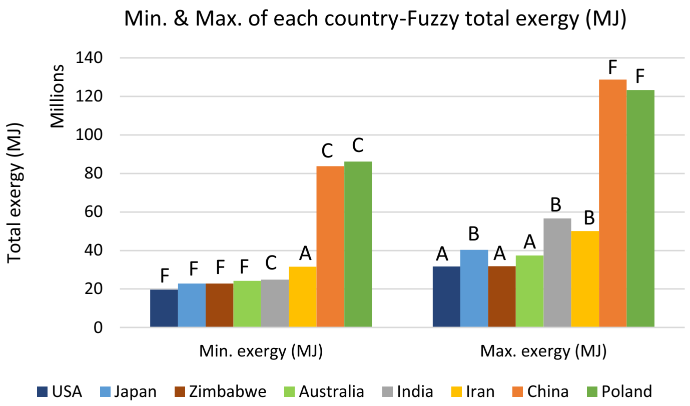

Fig. 7 Sensitivity analysis for each country—Min. & Max. of the total fuzzy exergy (step 3)

- When EEA is employed to a coal SC, the precision of the outcomes is dependent upon the assumptions made.
- It is possible that the EEA method in coal SCs may have limitations when more than one country is involved in the SC processes (international companies).
- Insufficient data regarding a country's total exergy input, the quantity of exergy represented in the workforce, the exergy of raw materials and energy consumed to supply a coal.

Finally, the following avenues for future research are suggested for consideration:

(a) A coal production system.
(b) An international coal SC model that works in more than one country at the same time.
(c) Comparing a global coal SC with a national one.
(d) A model with multi-objective (integrating inventory measures).
(e) The strategy of increasing carbon price with increasing the amount of carbon (price dependent on amount) by each company.
(f) The SC of coal power plants.
(g) Quantity discounts in cost per unit of products can be allowed.
(h) Multi-echelon SCs, for example, single-buyer multi-supplier and multi-buyer multi-supplier SCs, can be investigated.
(i) Lead times can be included.

Table 9 Sensitivity analysis of different percentages for exergy elements (example with four products)

Sets (%) *	Fuzzy total exergy (Emission trade) MJ								Min. (MJ)	Country min.	Max. (MJ)	Country max.
	AU**	CH	IN	IR	JA	PO	US	ZI				
A (30-60-10)	37,386,644.58	121,884,457.74	32,520,676.90	31,537,292.44	38,038,472.22	106,551,302.66	31,673,757.27	31,803,458.12	31,537,292.44	Iran	121,884,457.74	China
B (60-20-20)	27,362,603.27	109,229,963.03	56,664,303.08	50,042,180.33	40,279,208.50	110,155,055.08	22,604,564.59	23,779,747.58	22,604,564.59	USA	110,155,055.08	Poland
C (20-50-30)	36,172,081.05	83,731,242.82	24,826,136.13	35,822,252.13	30,489,673.91	86,131,627.76	29,064,237.19	26,772,135.64	24,826,136.13	India	86,131,627.76	Poland
D (20-40-40)	30,457,341.89	94,201,685.52	32,528,308.04	43,914,327.75	36,862,147.59	92,933,114.17	31,090,827.64	25,762,854.83	25,762,854.83	Zimbabwe	94,201,685.52	China
E (20-30-50)	35,641,776.33	111,411,481.62	43,026,717.09	43,802,295.45	36,228,006.97	109,302,825.19	25,320,951.45	28,886,560.45	25,320,951.45	USA	111,411,481.62	China
F (30-10-60)	24,251,604.43	128,734,240.79	29,354,458.87	49,114,885.31	22,873,547.02	123,315,602.00	19,675,609.14	22,873,547.02	19,675,609.14	USA	128,734,240.79	China
G (33-33-33)	33,163,723.31	121,351,102.11	31,623,790.11	44,552,827.66	32,432,070.96	118,125,544.27	29,934,368.36	24,146,338.65	24,146,338.65	Zimbabwe	121,351,102.11	China
Min. (MJ)	24,251,604.43	83,731,242.82	24,826,136.13	31,537,292.44	22,873,547.02	86,131,627.76	19,675,609.14	22,873,547.02	Min. Min. (MJ)		Max. Max. (MJ)	
Set Min.	F	C	C	A	F	C	F	F	19,675,609.14	USA	128,734,240.79	China
Max. (MJ)	37,386,644.58	128,734,240.79	56,664,303.08	50,042,180.33	40,279,208.50	123,315,602.00	31,673,757.27	31,803,458.12				
Set Max.	A	F	B	B	B	F	A	A				

*Set (Cap%-L%-Environment%); **AU: Australia, CH: China, IN: India, IR: Iran, JA: Japan, PO: Poland, US: the USA, ZI: Zimbabwe

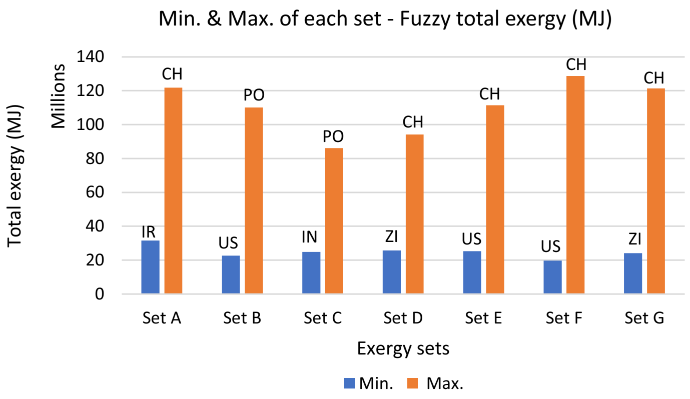

Fig. 8 Sensitivity analysis for each set—Min. & Max. of the total fuzzy exergy (step 3)

Appendix

See Figs. 9, 10, 11, 12, 13, 14 and 15.

Initialize the first population of ants and antlions randomly
Calculate the fitness of ants and antlions
Find the best antlions and assume it as the elite (determined optimum)
while *the end criterion is not satisfied*
  for *every ant*
    Select an antlion using Roulette wheel
    Update c and d
    Create a random walk and normalize it
    Update the position of ant
  end for
  Calculate the fitness of all ants
  Replace an antlion with its corresponding ant it if becomes fitter
  Update elite if an antlion becomes fitter than the elite
end while
Return *elite*

Fig. 9 Pseudo-code of the ALO algorithm (Mirjalili, 2015)

1. Generate random sample of Lions N_{pop}(N_{pop} is number of initial population).
2. Initiate prides and nomad lions
   i. Randomly select %N (Percent of lions that are nomad) of initial population as nomad lion. Partition remained lions into P (P is number of prides) prides randomly, and formed each pride's territory.
   ii. In each pride %S (Sex rate) of entire population are known as females and the rest as males. This rate in nomad lions is inversed.
3. For each pride do
   i. Some randomly selected female lion go hunting.
   ii. Each of remained female lion in pride go toward one of the best selected position from territory.
   iii. In pride, for each resident male; %R (Roaming percent) of territory randomly are selected and checked.
   %Ma (Mating probability) of females in pride mate with one or several resident male. → *New cubs become mature.*
   iv. Weakest male drive out from pride and become nomad.
4. For Nomad do
   i. Nomad lion (both male and female) moving randomly in search space.
   %Ma (Mating probability) of nomad Female mate with one of the best nomad male. → *New cubs become mature.*
   ii. Prides randomly attacked by nomad male.
5. For each pride do
   i. Some female with I rate ((Immigrate rate)) immigrate from pride and become nomad.
6. Do
   i. First, based on their fitness value each gender of the nomad lions are sorted. After that, the best females among them are selected and distributed to prides filling empty places of migrated females.
   ii. With respect to the maximum permitted number of each gender, nomad lions with the least fitness value will be removed.

If termination criterion is not satisfied, then go to step 3

Fig. 10 Pseudo-code of the LOA algorithm (Yazdani and Jolai, 2016)

```
Initialize the whales population Xi (i = 1, 2, ..., n)
Calculate the fitness of each search agent
X*=the best search agent
while (t < maximum number of iterations)
    for each search agent
    Update a, A, C, l, and p
        if1 (p<0.5)
            if2 (|A| < 1)
                Update the position of the current search agent
            else if2 (|A| ≥ 1)
                Select a random search agent (Xrand)
                Update the position of the current search agent
            end if2
        else if1 (p≥0.5)
                Update the position of the current search
        end if1
    end for
    Check if any search agent goes beyond the search space and amend it
    Calculate the fitness of each search agent
    Update X* if there is a better solution
    t=t+1
end while
return X*
```

Fig. 11 Pseudo-code of the WOA algorithm (Mirjalili and Lewis, 2016)

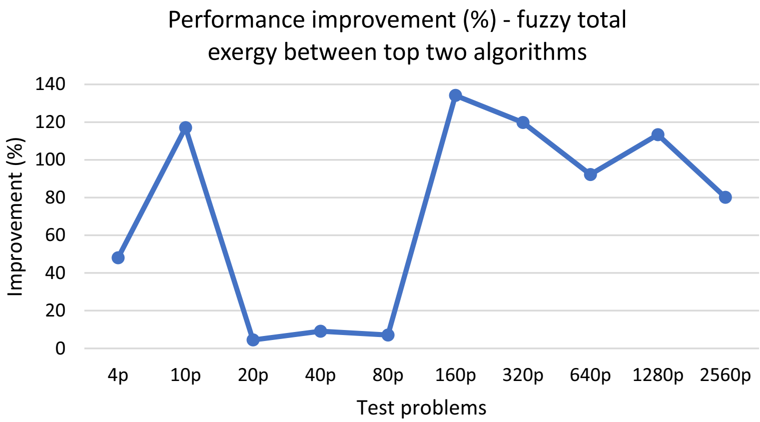

Fig. 12 Performance improvement (%) between top two algorithms in the total fuzzy exergy (step 1)

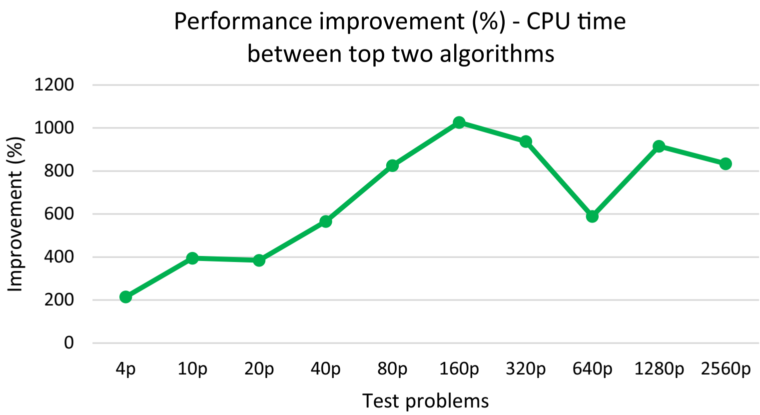

Fig. 13 Performance improvement (%) of CPU time between top two algorithms (step 1)

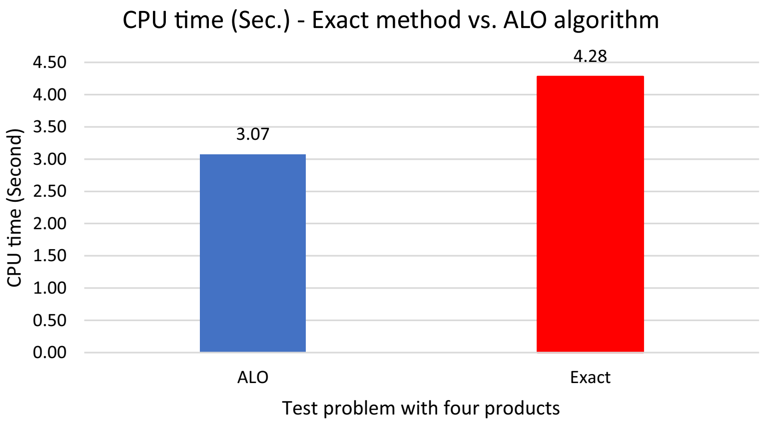

Fig. 14 Comparison of CPU time between exact method and ALO algorithm for test problem with four products (step 2)

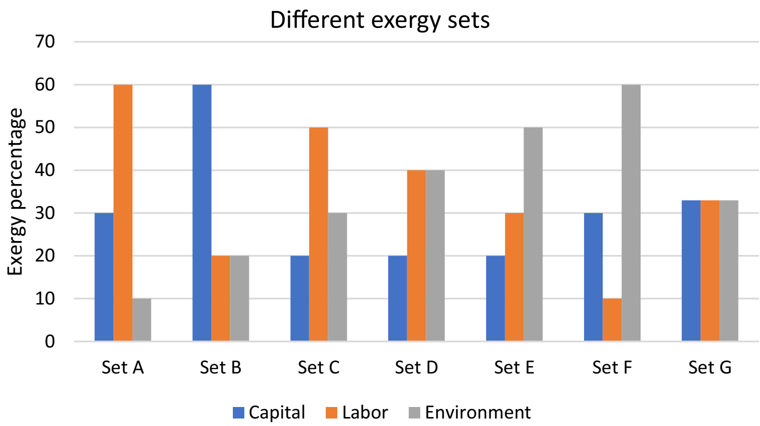

Fig. 15 Seven exergy sets (capital, labor & environment) for coal SC

See Tables 10, 11, 12, 13, 14, 15, 16, 17, 18 and 19.

Table 10 Fuzzy demands of 15 buyers (*j*) and 10 products (*i*) (values: *1000)

j	i = 1	i = 2	i = 3	i = 4	i = 5	i = 6	i = 7	i = 8	i = 9	i = 10
1	(100, 110, 125,150)	(70, 80, 95, 120)	(65, 68, 72, 75)	(16, 18, 21, 26)	(115, 118, 122, 125)	(85, 88, 91, 97)	(66, 68, 71, 76)	(16, 18, 21, 26)	(112, 118, 121, 130)	(82, 88, 91, 100)
2	(100, 110, 125,150)	(60, 70, 85, 110)	(55, 58, 62, 65)	(16, 18, 21, 26)	(115, 118, 122, 125)	(75, 78, 81, 87)	(56, 58, 61, 66)	(16, 18, 21, 26)	(112, 118, 121, 130)	(72, 78, 81, 90)
3	(90, 100, 115, 140)	(60, 70, 85, 110)	(55, 58, 62, 65)	(11, 13, 16, 21)	(105, 108, 112, 115)	(75, 78, 81, 87)	(56, 58, 61, 66)	(11, 13, 16, 21)	(102, 108, 111, 120)	(72, 78, 81, 90)
4	(70, 80, 95, 120)	(40, 50, 65, 90)	(35, 38, 42, 45)	(6, 8, 11, 16)	(85, 88, 92, 95)	(55, 58, 61,67)	(36, 38, 41, 46)	(6, 8, 11, 16)	(82, 88, 91, 100)	(52, 58, 61, 70)
5	(60, 70, 85, 110)	(40, 50, 65, 90)	(25, 28, 32, 35)	(5, 7, 10, 15)	(75, 78, 82, 85)	(55, 58, 61,67)	(26, 28, 31, 36)	(5, 7, 10, 15)	(72, 78, 81, 90)	(52, 58, 61, 70)
6	(50, 60, 75, 100)	(30, 40, 55, 80)	(15, 18, 22, 25)	(4, 6, 9, 14)	(65, 68, 72, 75)	(45, 48, 51, 57)	(16, 18, 21, 26)	(4, 6, 9, 14)	(62, 68, 71, 80)	(42, 48, 51, 60)
7	(40, 50, 65, 90)	(20, 30, 45, 70)	(10, 13, 17, 20)	(3, 5, 8, 13)	(55, 58, 62, 65)	(35, 38, 41, 47)	(11, 13, 16, 21)	(3, 5, 8, 13)	(52, 58, 61, 70)	(32, 38, 41, 50)
8	(30, 40, 55, 80)	(10, 20, 35, 60)	(5, 8, 12, 15)	(2, 4, 7, 12)	(45, 48, 52, 55)	(25, 28, 31, 37)	(6, 8, 11, 16)	(2, 4, 7, 12)	(42, 48, 51, 60)	(22, 28, 31, 40)
9	(20, 30, 45, 70)	(10, 20, 35, 60)	(3, 6, 10, 13)	(1, 3, 6, 11)	(35, 38, 42, 45)	(25, 28, 31, 37)	(4, 6, 9, 14)	(1, 3, 6, 11)	(32, 38, 41, 50)	(22, 28, 31, 40)
10	(10, 20, 35, 60)	(0, 10, 25, 50)	(0, 3, 7, 10)	(0, 2, 5, 10)	(25, 28, 32, 35)	(15, 18, 21, 27)	(1, 3, 6, 11)	(0, 2, 5, 10)	(22, 28, 31, 40)	(12, 18, 21, 30)
11	(100, 110, 125,150)	(70, 80, 95, 120)	(65, 68, 72, 75)	(16, 18, 21, 26)	(115, 118, 122, 125)	(85, 88, 91, 97)	(66, 68, 71, 76)	(16, 18, 21, 26)	(112, 118, 121, 130)	(82, 88, 91, 100)
12	(100, 110, 125,150)	(60, 70, 85, 110)	(55, 58, 62, 65)	(16, 18, 21, 26)	(115, 118, 122, 125)	(75, 78, 81, 87)	(56, 58, 61, 66)	(16, 18, 21, 26)	(112, 118, 121, 130)	(72, 78, 81, 90)
13	(90, 100, 115, 140)	(60, 70, 85, 110)	(55, 58, 62, 65)	(11, 13, 16, 21)	(105, 108, 112, 115)	(75, 78, 81, 87)	(56, 58, 61, 66)	(11, 13, 16, 21)	(102, 108, 111, 120)	(72, 78, 81, 90)
14	(70, 80, 95, 120)	(40, 50, 65, 90)	(35, 38, 42, 45)	(6, 8, 11, 16)	(85, 88, 92, 95)	(55, 58, 61,67)	(36, 38, 41, 46)	(6, 8, 11, 16)	(82, 88, 91, 100)	(52, 58, 61, 70)

Table 10 (continued)

j	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8	i=9	i=10
15	(60, 70, 85, 110)	(40, 50, 65, 90)	(25, 28, 32, 35)	(5, 7, 10, 15)	(75, 78, 82, 85)	(55, 58, 61,67)	(26, 28, 31, 36)	(5, 7, 10, 15)	(72, 78, 81, 90)	(52, 58, 61, 70)

*Demand values are repeated for test problems with greater than ten products

Table 11 Fuzzy parameters for 15 buyers (*j*) and 10 products (*i*) (values: *10)

	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8	i=9	i=10
$\widetilde{C}_i$:	(5, 8, 12, 15)	(9, 12, 16, 19)	(12, 15, 19, 22)	(15, 18, 22, 25)	(5, 8, 12, 15)	(9, 12, 16, 19)	(12, 15, 19, 22)	(15, 18, 22, 25)	(5, 8, 12, 15)	(9, 12, 16, 19)
$\widetilde{C_{trade}}$ =(33.6, 36.6, 40.6, 43.6)	$\widetilde{C_0}$ =(5, 8, 12, 15)									

*Parameter values are repeated for test problems with greater than ten products

Table 12 Initial data (monetary value) of test problem with ten products and their equivalent of exergy values (MJ)

Prod. (i)	Cost values				Exergy equivalent			
	$K_{i,S}$	$K_{ij,b}$	h_{ij}	C_i	$K_{(x)i,S}$	$K_{(x)ij,b}$	$h_{(x)ij}$	$C_{(x)i}$
1	20	15	5	200	49	36.75	14.94	597.67
2	20	15	4	170	49	36.75	11.95	508.02
3	20	15	3	140	49	36.75	8.97	418.37
4	20	15	3	100	49	36.75	8.97	298.83
5	20	15	5	200	49	36.75	14.94	597.67
6	20	15	4	170	49	36.75	11.95	508.02
7	20	15	3	140	49	36.75	8.97	418.37
8	20	15	3	100	49	36.75	8.97	298.83
9	20	15	5	200	49	36.75	14.94	597.67
10	20	15	4	170	49	36.75	11.95	508.02

*These values are repeated for test problems with greater than 10 products

Table 13 Initial data of the actual case study in Iran with four products (without exergy)

$Pi = (780{,}000, 550{,}000, 320{,}000, 110{,}000)$	$s1 = 3$, $s2 = 0$
$Lj = (635, 586, 1084, 1028, 763, 1102, 382, 688, 603, 877)$	$int- = 0.04$, $int+ = 0.02$
$Ej = (18{,}000, 16{,}800, 15{,}800, 12{,}000, 10{,}700, 8900, 7400, 5500, 5000, 3700)$	$\theta m = 3.18 \times 10-3$
$Xj = (290{,}000, 290{,}000, 300{,}000, 290{,}000, 300{,}000, 280{,}000, 280{,}000, 280{,}000, 280{,}000, 280{,}000)$	$\theta t = 1.4 \times 10-5$
$Wj = (6400, 6500, 6600, 6900, 7000, 7100, 7200, 7300, 7400, 7500)$	$\theta k = 5 \times 10-5$
$tf = 10$; $tv = 15$; $tl = 12$; $tm = 8$	$\delta m = 0.10$; $\delta t = 0.08$; $\delta k = 0.12$
$Nmax = 1300$; $F = 22{,}000$; $ITR = 17$; $Qmax = 2500$	$LO = 1$; $Un = 2.5$

Table 14 Equivalent exergy parameters of the actual case study in Iran with four products

$t_{(x)f} = 56.80; t_{(x)v} = 85.20; t_{(x)l} = 68.16; t_{(x)m} = 45.44$
$Laborcost = 12; C_{(x)trade} = 2192;$
$s_{(x)1} = 17.04; s_{(x)2} = 0$
$X_{(x)j} = (1647200, 1647200, 1704000, 1647200, 1704000, 1590400, 1590400, 1590400, 1590400, 1590400)$

Table 15 Warehouse space (W_j) of each buyer in all examples (10–2560 products)

	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Buyer 1	16,500	33,000	66,000	132,000	264,000	528,000	1,056,000	2,112,000	4,224,000
Buyer 2	16,600	33,200	66,400	132,800	265,600	531,200	1,062,400	2,124,800	4,249,600
Buyer 3	16,700	33,400	66,800	133,600	267,200	534,400	1,068,800	2,137,600	4,275,200
Buyer 4	17,200	34,400	68,800	137,600	275,200	550,400	1,100,800	2,201,600	4,403,200
Buyer 5	17,300	34,600	69,200	138,400	276,800	553,600	1,107,200	2,214,400	4,428,800
Buyer 6	17,500	35,000	70,000	140,000	280,000	560,000	1,120,000	2,240,000	4,480,000
Buyer 7	17,600	35,200	70,400	140,800	281,600	563,200	1,126,400	2,252,800	4,505,600
Buyer 8	17,800	35,600	71,200	142,400	284,800	569,600	1,139,200	2,278,400	4,556,800
Buyer 9	17,900	35,800	71,600	143,200	286,400	572,800	1,145,600	2,291,200	4,582,400
Buyer 10	18,000	36,000	72,000	144,000	288,000	576,000	1,152,000	2,304,000	4,608,000
Buyer 11	16,500	33,000	66,000	132,000	264,000	528,000	1,056,000	2,112,000	4,224,000
Buyer 12	16,600	33,200	66,400	132,800	265,600	531,200	1,062,400	2,124,800	4,249,600
Buyer 13	16,700	33,400	66,800	133,600	267,200	534,400	1,068,800	2,137,600	4,275,200
Buyer 14	17,200	34,400	68,800	137,600	275,200	550,400	1,100,800	2,201,600	4,403,200
Buyer 15	17,300	34,600	69,200	138,400	276,800	553,600	1,107,200	2,214,400	4,428,800

Table 16 Available budget (X_j) of each buyer (exergy values) in all examples (10–2560 products)

	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Buyer 1	4,260,000	8,520,000	17,040,000	28,400,000	56,800,000	113,600,000	221,520,000	443,040,000	886,080,000
Buyer 2	4,260,000	8,520,000	17,040,000	32,376,000	64,752,000	129,504,000	227,200,000	454,400,000	908,800,000
Buyer 3	3,976,000	7,952,000	15,904,000	30,672,000	61,344,000	122,688,000	227,200,000	454,400,000	908,800,000
Buyer 4	3,976,000	7,952,000	15,904,000	30,672,000	61,344,000	122,688,000	227,200,000	454,400,000	908,800,000
Buyer 5	3,805,600	7,611,200	15,222,400	30,444,800	60,889,600	121,779,200	227,200,000	454,400,000	908,800,000
Buyer 6	3,805,600	7,611,200	15,222,400	30,444,800	60,889,600	121,779,200	232,880,000	465,760,000	931,520,000
Buyer 7	3,805,600	7,611,200	15,222,400	30,444,800	60,889,600	121,779,200	224,360,000	448,720,000	897,440,000
Buyer 8	3,748,800	7,497,600	14,995,200	29,990,400	59,980,800	119,961,600	224,360,000	448,720,000	897,440,000
Buyer 9	3,748,800	7,497,600	14,995,200	29,990,400	59,980,800	119,961,600	232,880,000	465,760,000	931,520,000
Buyer 10	3,578,400	7,156,800	14,313,600	28,627,200	57,254,400	114,508,800	223,792,000	447,584,000	895,168,000
Buyer 11	3,578,400	7,156,800	14,313,600	28,627,200	57,254,400	114,508,800	219,248,000	438,496,000	876,992,000
Buyer 12	3,578,400	7,156,800	14,313,600	28,627,200	57,254,400	114,508,800	226,064,000	452,128,000	904,256,000
Buyer 13	3,521,600	7,043,200	14,086,400	28,172,800	56,345,600	112,691,200	223,792,000	447,584,000	895,168,000
Buyer 14	3,521,600	7,043,200	14,086,400	28,172,800	56,345,600	112,691,200	223,792,000	447,584,000	895,168,000
Buyer 15	3,521,600	7,043,200	14,086,400	28,172,800	56,345,600	112,691,200	223,792,000	447,584,000	895,168,000

Table 17 Permitted carbon emission (E_j) of each buyer in all examples (10–2560 products)

	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Buyer 1	41,000	82,000	164,000	270,000	530,000	1,060,000	2,080,000	4,160,000	8,320,000
Buyer 2	38,000	76,000	152,000	285,000	560,000	1,120,000	2,000,000	4,000,000	8,000,000
Buyer 3	36,000	72,000	144,000	255,000	500,000	1,000,000	1,900,000	3,800,000	7,600,000
Buyer 4	26,000	52,000	104,000	190,000	370,000	740,000	1,420,000	2,840,000	5,680,000
Buyer 5	23,000	46,000	92,000	184,000	365,000	730,000	1,320,000	2,640,000	5,280,000
Buyer 6	18,000	36,000	72,000	144,000	285,000	570,000	1,110,000	2,220,000	4,440,000
Buyer 7	13,000	26,000	52,000	104,000	200,000	400,000	800,000	1,600,000	3,200,000
Buyer 8	9,000	18,000	36,000	72,000	140,000	280,000	560,000	1,120,000	2,240,000
Buyer 9	7,000	14,000	28,000	56,000	110,000	220,000	440,000	880,000	1,760,000
Buyer 10	3,000	6,000	12,000	24,000	45,000	90,000	180,000	360,000	720,000
Buyer 11	41,000	82,000	164,000	295,000	580,000	1,160,000	2,170,000	4,340,000	8,680,000
Buyer 12	38,000	76,000	152,000	270,000	530,000	1,060,000	2,000,000	4,000,000	8,000,000
Buyer 13	36,000	72,000	144,000	270,000	530,000	1,060,000	1,850,000	3,700,000	7,400,000
Buyer 14	26,000	52,000	104,000	200,000	400,000	800,000	1,520,000	3,040,000	6,080,000
Buyer 15	23,000	46,000	92,000	184,000	365,000	730,000	1,400,000	2,800,000	5,600,000

Table 18 Initial data of the resources of all examples (4–2560 products)

	4p	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Nmax	1300	8200	19,000	43,000	96,000	192,000	405,000	840,000	1,680,000	3,500,000
ITR	17	17	20	20	20	20	20	20	20	20
F	22,000	82,000	164,000	328,000	656,000	1,312,000	2,624,000	5,248,000	10,496,000	20,992,000

Table 19 The exergy values of inventory parameters (values in MJ) for 1^{st} product ($i=1$)

Country		$ee_{Cap(i,s)}$	$ee_{L(i,s)}$	$ee_{Env(i,s)}$	Total
Iran	$K_{(x)i,S}$	34.08	3.56	11.36	49
	$K_{(x)ij,b}$	25.56	2.67	8.52	36.75
	$h_{(x)ij}$	8.52	0.89	2.84	12.25
	$C_{(x)i}$	340.80	35.60	113.60	490
Australia	$K_{(x)i,S}$	21.36	71.21	7.12	99.69
	$K_{(x)ij,b}$	16.02	53.41	5.34	74.77
	$h_{(x)ij}$	5.34	17.80	1.78	24.92
	$C_{(x)i}$	213.60	712.10	71.20	996.90
China	$K_{(x)i,S}$	84.06	48.66	28.02	160.74
	$K_{(x)ij,b}$	63.04	36.49	21.01	120.56
	$h_{(x)ij}$	21.02	12.17	7.01	40.19
	$C_{(x)i}$	840.60	486.60	280.20	1607.40
India	$K_{(x)i,S}$	26.04	1.64	8.68	36.36
	$K_{(x)ij,b}$	19.53	1.23	6.51	27.27
	$h_{(x)ij}$	6.51	0.41	2.17	9.09
	$C_{(x)i}$	260.40	16.40	86.80	363.60
Japan	$K_{(x)i,S}$	20.10	70.18	6.70	96.98
	$K_{(x)ij,b}$	15.07	52.63	5.02	72.74
	$h_{(x)ij}$	5.03	17.55	1.68	24.25
	$C_{(x)i}$	201	701.80	67	969.80
Poland	$K_{(x)i,S}$	84.12	76.55	28.04	188.71
	$K_{(x)ij,b}$	63.09	57.4125	21.03	141.53
	$h_{(x)ij}$	21.03	19.14	7.01	47.18
	$C_{(x)i}$	841.20	765.50	280.40	1887.10
The USA	$K_{(x)i,S}$	17.1	72.82	5.7	95.62
	$K_{(x)ij,b}$	12.82	54.61	4.27	71.72
	$h_{(x)ij}$	4.28	18.21	1.43	23.91
	$C_{(x)i}$	171.00	728.20	57.00	956.20
Zimbabwe	$K_{(x)i,S}$	20.1	70.18	6.7	96.98
	$K_{(x)ij,b}$	15.07	52.63	5.02	72.74
	$h_{(x)ij}$	5.03	17.55	1.68	24.25
	$C_{(x)i}$	201.00	701.80	67.00	969.80

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aala Kalananda VKR, Komanapalli VLN (2021) A combinatorial social group whale optimization algorithm for numerical and engineering optimization problems. Appl Soft Comput J 99:106903

Abderazek H, Yildiz AR, Mirjalili S (2020) Comparison of recent optimization algorithms for design optimization of a cam-follower mechanism. Knowl-Based Syst 191:105237

Abdullah SM, Ahmed A (2020) Hybrid bare bones fireworks algorithm for load flow analysis of islanded microgrids. In: Handbook of research on fireworks algorithms and swarm intelligence, IGI Global, pp 283–314

Abualigah LM, Shehab M, Alshinwan M, Mirjalili SM, Elaziz ME (2020) Ant lion optimizer: a comprehensive survey of its variants and applications. Archiv Comput Methods Eng 28:1397–1416

Aghbashlo M, Tabatabaei M, Hosseini SS, Dashti BB, Soufiyan MM (2018) Performance assessment of a wind power plant using standard exergy and extended exergy accounting (EEA) approaches. J Clean Prod 171:127–136

Aka S, Akyüz G (2021) An inventory and production model with fuzzy parameters for the food sector. Sustain Product Consumption 26:627–637

Ali E, Abd ES, Abdelaziz A (2017) Ant lion optimization algorithm for optimal location and sizing of renewable distributed generations. Renew Energy 101:1311–1324

Arango-Miranda R, Hausler R, Romero-Lopez R, Glaus M, Ibarra-Zavaleta SP (2018) An overview of energy and exergy analysis to the industrial sector, a contribution to sustainability. Sustainability 10(1):153

Australian Government (2022) Coal, https://www.ga.gov.au/digital-publication/aecr2022/coal

Banasik A, Kanellopoulos A, Claassen GDH, Bloemhof-Ruwaard JM, van der Vorst JG (2017a) Assessing alternative production options for eco-efficient food supply chains using multi-objective optimization. Ann Oper Res 250(2):341–362

Banasik A, Kanellopoulos A, Claassen GDH, Bloemhof-Ruwaard JM, van der Vorst JG (2017b) Closing loops in agricultural supply chains using multi-objective optimization: a case study of an industrial mushroom supply chain. Int J Prod Econ 183:409–420

Bekakra Y, Zellouma L, Malik O (2021) Improved predictive direct power control of shunt active power filter using GWO and ALO –Simulation and experimental study. Ain Shams Eng J 12(4):3859–3877

Beklari A, Nikabadi MS, Farsijani H, Mohtashami A (2018) A hybrid algorithm for solving vendors managed inventory (VMI) model with the goal of maximizing inventory turnover in producer warehouse. Ind Eng Manag Syst 17(3):570–587

Cárdenas-Barrón LE, Treviño-Garza G, Wee HM (2012) A simple and better algorithm to solve the vendor managed inventory control system of multi-product multi-constraint economic order quantity model. Expert Syst Appl 39:3888–3895

Chaabane A, Ramudhin A, Paquet M (2012) Design of sustainable supply chains under the emission trading scheme. Int J Prod Econ 135(1):37–49

Chen G, Chen B (2009) Extended-exergy analysis of the Chinese society. Energy 34(9):1127–1144

Chen J, Qi X, Chen L, Chen F, Cheng G (2020a) Quantum-inspired ant lion optimized hybrid k-means for cluster analysis and intrusion detection. Knowl-Based Syst 203:106167

Chen H, Li WD, Yang X (2020b) A whale optimization algorithm with chaos mechanism based on quasi-opposition for global optimization problems. Expert Syst Appl 158:113612

Chen X, Cheng L, Liu C, Liu QZ, Liu JW, Mao Y et al (2020c) A WOA-based optimization approach for task scheduling in cloud computing systems. IEEE Syst J 14(03):3117–3128

Chen SH, Hseih CH (1998) Graded mean integration representation of generalized fuzzy numbers. In: Proceedings of the sixth conference on fuzzy theory and its applications, Chinese fuzzy systems association, Taiwan, pp 1–6

Çomez-Dolgan N, Moussawi-Haidar L, Jaber MY (2021) A buyer-vendor system with untimely delivery costs: Traditional coordination vs. VMI Consign Stock Comput Ind Eng 154:107009

Da B, Liu C, Liu N, Xia Y, Xie F (2019) Coal-electric power supply chain reduction and operation strategy under the cap-and-trade model and green financial background. Sustainability 11:3021

Da B, Liu C, Liu N, Fan S (2021) Strategies of two-level green technology investments for coal supply chain under different dominant modes. Sustainability 13:3643

Devlin A, Yang A (2022) Regional supply chains for decarbonising steel: energy efficiency and green premium mitigation. Energy Convers Manag 254:115268

Diabat A (2014) Hybrid algorithm for a vendor managed inventory system in a two-echelon supply chain. Eur J Oper Res 238:114–121
Dincer I, Rosen MA (2013) Exergy: Energy, environment and sustainable development, 1st edn. Elsevier Science, Amsterdam
Du W, Zhang Q, Chen Y, Ye Z (2021) An urban short-term traffic flow prediction model based on wavelet neural network with improved whale optimization algorithm. Sustain Cities Soc 69:102858
Duan Y, Han Z, Mu H, Yang J, Li Y (2019) Research on the impact of various emission reduction policies on china's iron and steel industry production and economic level under the carbon trading mechanism. Energies 12(9):1624
Dubey HM, Pandit M, Panigrahi B (2016) Ant lion optimization for short-term wind integrated hydrothermal power generation scheduling. Int J Electr Power Energy Syst 83:158–174
Ehyaei MA, Ahmadi A, Rosen MA (2019) Energy, exergy, economic and advanced and extended exergy analyses of a wind turbine. Energy Convers Manag 183:369–381
Environment and Climate Change Canada (2018) Estimated impacts of the federal carbon pollution pricing system 2018. https://www.canada.ca/en/services/environment/weather/climatechange/climate-action/pricing-carbon-pollution/estimated-impacts-federal-system.html (Accessed July 3, 2019).
Gen, M., Cheng, R. (1997). Genetic algorithm and engineering design (1st ed.). John Wiley and Sons, New York, U.S.A; 1997.
Giovanni PD (2021) Smart Supply Chains with vendor managed inventory, coordination, and environmental performance. Eur J Oper Res 292:515–531
Goldbogen JA, Friedlaender AS, Calambokidis J, McKenna MF, Simon M, Nowacek DP (2013) Integrative approaches to the study of baleen whale diving behavior, feeding performance, and foraging ecology. Bioscience 63(2):90–100
Gonela V (2018) Stochastic optimization of hybrid electricity supply chain considering carbon emission schemes. Sustain Product Consum 14:136–151
Gope S, Dawn S, Mitra R, Goswami AK, Tiwari PK (2019) Transmission congestion relief with integration of photovoltaic power using lion optimization algorithm. In: Bansal J, Das K, Nagar A, Deep K, Ojha A (eds) Soft Computing for Problem Solving. Advances in Intelligent Systems and Computing. Springer, Singapore, p 816
Guo WY, Liu T, Dai F, Xu P (2020) An improved whale optimization algorithm for forecasting water resources demand. Appl Soft Comput 86:105925
Haites E (2018) Carbon taxes and greenhouse gas emissions trading systems: What have we learned? Climate Policy 18(8):955–966
Hančlová J, Zapletal F, Šmíd M (2020) On interaction between carbon spot prices and Czech steel industry. Carbon Manag 11(2):121–137
Hanss M (2005) Applied fuzzy arithmetic. Springer-Verlag, Berlin Heidelberg
He Y, Wei C, Long H, Ashfaq RAR, Huang JZ (2018) Random weight network-based fuzzy nonlinear regression for trapezoidal fuzzy number data. Appl Soft Comput 70:959–979
Heidari AA, Faris H, Mirjalili S, Aljarah I, Mafarja M (2020) Ant Lion Optimizer: Theory, Literature Review, and Application in Multi-layer Perceptron Neural Networks. In: Mirjalili S, Song Dong J, Lewis A (eds) Nature-Inspired Optimizers Studies in Computational Intelligence. Springer, Cham. https://doi.org/10.1007/978-3-030-12127-3_3
IEA, clean coal centre (2020), https://www.iea-coal.org/irans-10-month-coal-concentrate-output-over-555000-tons/
Islam QNU, Ahmed A, Abdullah SM (2021) Optimized controller design for islanded microgrid using nondominated sorting whale optimization algorithm (NSWOA). Ain Shams Eng J 12(4):3677–3689
Islam QNU, Ahmed A (2020) Optimized controller design for islanded microgrid employing nondominated sorting firefly algorithm. In: Nature-Inspired Computation and Swarm Intelligence, Elsevier, pp 247–272
Jaber MY (2007) Lot sizing with permissible delay in payments and entropy cost. Comput Ind Eng 52(1):78–88
Jaber MY, Rosen MA (2008) The economic order quantity repair and waste disposal model with entropy cost. Eur J Oper Res 188(2008):109–120
Jaber MY, Nuwayhid RY, Rosen MA (2004) Price-driven economic order systems from a thermodynamic point of view. Int J Prod Res 42(24):5167–5184
Jaber MY, Nuwayhid RY, Rosen MA (2006) A thermodynamic approach to modelling the economic order quantity. Appl Math Model 30(9):867–883

Jaber MY, Bonney M, Rosen MA, Moualek I (2009) Entropic order quantity (EnOQ) model for deteriorating items. Appl Math Model 33:564–578
Jaber MY, El Saadany AMA, Rosen MA (2011) Simple price-driven reverse logistics system with entropy and exergy costs. Int J Exergy 9(4):486–502
Jaber MY, Bonney M, Jawad H (2017) Comparison between economic order/manufacture quantity and just-in-time models from a thermodynamics point of view. Comput Ind Eng 112:503–510
Jaber MY, Jawad H (2015) An entropic comparison between the economic production quantity (EPQ) and Just-In-Time (JIT) models. In: Proceedings - CIE 45: 2015 international conference on computers and industrial engineering
Jahromi FS, Beheshti M, Rajabi RF (2018) Comparison between differential evolution algorithms and response surface methodology in ethylene plant optimization based on an extended combined energy - exergy analysis. Energy 164:1114–1134
Jawad H, Jaber MY, Bonney M (2015) The economic order quantity model revisited: an extended exergy accounting approach. J Clean Prod 105:64–73
Jawad H, Jaber MY, Bonney M, Rosen MA (2016) Deriving an exergetic economic production quantity model for better sustainability. Appl Math Model 40:6026–6039
Jawad H, Jaber MY, Nuwayhid RY (2018) Improving supply chain sustainability using exergy analysis. Eur J Oper Res 269(1):258–271
Jawad H, Jaber MY (2015) Exergy analysis: a new paradigm for modelling inventory systems. In: Proceedings - CIE 45: 2015 international conference on computers and industrial engineering
Jiang Y, Li B, Qu X, Cheng Y (2016) A green vendor-managed inventory analysis in supply chains under carbon emissions trading mechanism. Clean Technol Environ Policy 18(5):1369–1380
Kao YT, Zahara E (2008) A hybrid genetic algorithm and particle swarm optimization for multimodal functions. Appl Soft Comput 8(2):849–857
Kaur G, Arora S (2018) Chaotic whale optimization algorithm. J Comput Design Eng 05(03):275–284
Kunche A, Mielczarek B (2021) Application of system dynamic modelling for evaluation of carbon mitigation strategies in cement industries: a comparative overview of the current state of the art. Energies 14(5):1464
Kwak JK (2019) Analysis of inventory turnover as a performance measure in manufacturing industry. Processes 7:760. https://doi.org/10.3390/pr7100760
Lee KC, Lu PT (2020) Application of whale optimization algorithm to inverse scattering of an imperfect conductor with corners. Int J Antennas Propag 2020:8205797
Li W, Zhang Y, Lu C (2018) The impact on electric power industry under the implementation of national carbon trading market in China: a dynamic CGE analysis. J Clean Prod 200:511–523
Li J, Wang L, Tan X (2020) Sustainable design and optimization of coal supply chain network under different carbon emission policies. J Clean Prod 250:119548
Li SH, Luo XH, Wu LZ (2021) An improved whale optimization algorithm for locating critical slip surface of slopes. Adv Eng Softw 157–158:103009
Liu Z, Liu Z, Yang X, Zhai H, Yang X (2020) Advanced exergy and exergoeconomic analysis of a novel liquid carbon dioxide energy storage system. Energy Convers Manag 205:112391
Liu M, Luo K, Zhang J, Chen S (2021) A stock selection algorithm hybridizing grey wolf optimizer and support vector regression. Expert Syst Appl 179:115078
Long W, Wu TB, Jiao JJ, Tang MZ, Xu M (2020) Refraction-learning-based whale optimization algorithm for high-dimensional problems and parameter estimation of pv model. Eng Appl Artif Intell 89:103457
Mahata GC, Goswami A (2013) Fuzzy inventory models for items with imperfect quality and shortage backordering under crisp and fuzzy decision variables. Comput Ind Eng 64(1):190–199
Maier HR, Razavi S, Kapelan Z, Matott LS, Kasprzyk J, Tolson BA (2019) Introductory overview: optimization using evolutionary algorithms and other metaheuristics. Environ Model Softw 114:195–213
Maio AD, Lagana D (2020) The effectiveness of vendor managed inventory in the last-mile delivery: an industrial application. Procedia Manufact 42:462–466
Malladi KT, Sowlati T (2020) Impact of carbon pricing policies on the cost and emission of the biomass supply chain: optimization models and a case study. Appl Energy 267:115069
Mateen A, Chatterjee AK, Mitra S (2014) VMI for single-vendor multi-retailer supply chains under stochastic demand. Comput Ind Eng 79:95–102
Mehmood S, Reddy BV, Rosen MA (2015) Exergy analysis of a biomass co-firing based pulverized coal power generation system. Int J Green Energy 12(5):461–478

MiarNaeimi F, Azizyan G, Rashki M (2021) Horse herd optimization algorithm: A nature-inspired algorithm for high-dimensional optimization problems. Knowl-Based Syst 213:106711
Mirjalili S (2015) The ant lion optimizer. Adv Eng Softw 83:80–98
Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67
Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61
Mohammed HM, Umar SU, Rashid TA (2019) A systematic and meta-analysis survey of whale optimization algorithm. Computat Intell Neurosci 2019:8718571
Moldovan D (2020) Horse optimization algorithm: a novel bio-inspired algorithm for solving global optimization problems. In: Silhavy R (ed) Artificial intelligence and bioinspired computational methods. CSOC 2020. Advances in intelligent systems and computing. Springer, Cham. https://doi.org/10.1007/978-3-030-51971-1_16
Naderi R, Nikabadi MS, Alem-Tabriz A, Pishvaee MS (2021a) Sustainable coal supply chain management using exergy analysis and genetic algorithm. Manag Syst Product Eng 29(1):44–53
Naderi R, Nikabadi MS, Alem-Tabriz A, Pishvaee MS (2021b) Supply chain sustainability improvement using exergy analysis. Comput Ind Eng 154:107142
Notes from Poland (2022) Poland to delay coal phaseout and open more mines amid energy crisis, https://notesfrompoland.com/2022/11/07/poland-to-delay-coal-phaseout-and-open-more-mines-amid-energy-crisis/#:~:text=Poland%20uses%20coal%20to%20generate,have%20also%20sought%20to%20reduce
Padhy S, Panda S (2021) Application of a simplified Grey Wolf optimization technique for adaptive fuzzy PID controller design for frequency regulation of a distributed power generation system. Prot Control Modern Power Syst. https://doi.org/10.1186/s41601-021-00180-4
Panja S, Mondal SK (2019) Analyzing a four-layer green supply chain imperfect production inventory model for green products under type-2 fuzzy credit period. Comput Ind Eng 129:435–453
Pasandideh SHR, Niaki STA, Roozbeh Nia A (2010) An investigation of vendor-managed inventory application in supply chain: the EOQ model with shortage. Int J Adv Manufact Technol 49:329–339
Pasandideh SHR, Niaki STA, Roozbeh NA (2011) A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model. Expert Syst Appl 38:2708–2716
Peng T, Jian M, Dong-Mo Z (1998) Non-linear integer programming by Darwin and Boltzmann mixed strategy. Eur J Oper Res 105:224–235
Phengsaart T, Srichonphaisan P, Kertbundit C, Soonthornwiphat N, Sinthugoot S, Phumkokrux N, Juntarasakul O, Maneeintr K, Numprasanthai A, Park I, Tabelin CB, Hiroyoshi N, Ito M (2023) Conventional and recent advances in gravity separation technologies for coal cleaning: a systematic and critical review. HELIYON. https://doi.org/10.1016/j.heliyon.2023.e13083
Pradhan R, Majhi SK, Pradhan JK, Pati BB (2020) Optimal fractional order PID controller design using ant lion optimizer. Ain Shams Eng J 11:281–291
Priyan S, Udayakumar R, Mala P, Prabha M, Ghosh A (2022) A sustainable dual-channel inventory model with trapezoidal fuzzy demand and energy consumption. Clean Eng Technol 6:100400
Rant Z (1956) Exergy, a new word for technical available work. Forsch Ing Wis 22(1):36–37
Razmi J, Rad RH, Sangari MS (2010) Developing a two-echelon mathematical model for a vendor-managed inventory (VMI) system. Int J Adv Manufact Technol 48:773–783
Roozbeh NA, Hemmati FM, Niaki STA (2014) A fuzzy vendor managed inventory of multi item economic order quantity model under shortage: an ant colony optimization algorithm. Int J Prod Econ 155:259–271
Roozbeh NA, Hemmati FM, Niaki STA (2015) A hybrid genetic and imperialist competitive algorithm for green vendor managed inventory of multi-item multi-constraint EOQ model under shortage. Appl Soft Comput 30:353–364
Roozbeh NA, Haleh H, Saghaei A (2017a) Dual command cycle dynamic sequencing method to consider GHG efficiency in unit-load multiple-rack automated storage and retrieval systems. Comput Ind Eng 111:89–108
Roozbeh NA, Haleh H, Saghaei A (2017b) Energy-conscious dynamic sequencing method for dual command cycle unit-load multiple-rack automated storage and retrieval systems. Scientia Iranica E 24(6):3371–3393
Roozbeh Nia A, Awasthi A, Bhuiyan N (2021) Industry 4.0 and demand forecasting of the energy supply chain: A literature review. Comput Indust Eng 154:1071286

Roozbeh Nia A, Awasthi A, Bhuiyan N (2020) Management of sustainable supply chain and industry 4.0: A literature review. In: Ramanathan U, Ramanathan R (eds) Sustainable Supply Chains: Strategies, Issues, and Models. Springer, Cham
Safarian S (2023) To what extent could biochar replace coal and coke in steel industries? Fuel 339:127401
Santhi G, Karthikeyan K (2015) An entropic economic order quantity model for deterioration of perishable items with cubic demand rate and its fuzzy environment. Global J Pure Appl Math 11(5):3565–3581
Sciubba E (2003a) Cost analysis of energy conversion system via a novel resource-based quantifier. Energy 28:457–477
Sciubba E (2003b) Extended-exergy accounting applied to energy recovery from waste: the concept of total recycling. Energy 28:1316–1334
Sciubba E (2011) A revised calculation of the econometric factors α-and β for the extended exergy accounting method. Ecol Model 222(4):1060–1066
Sciubba E (1998) A novel exergetic costing method for determining the optimal allocation of scarce resources. In: Rudnicki et al. (eds.) Proceedings Contemporary problems in thermal engineering, gliwice
Selvi M, Ramakrishnan B (2020) Lion optimization algorithm (LOA)-based reliable emergency message broadcasting system in VANET. Soft Comput 24:10415–10432
Shekarian E, Kazemi N, Abdul-Rashid SH, Olugu EU (2017) Fuzzy inventory models: a comprehensive review. Appl Soft Comput 55:588–621
Shinoda M, Miyata Y (2019) PSO-based stability analysis of unreinforced and reinforced soil slopes using non-circular slip surface. Acta Geotech 14:907–919
Shokouhifar M, Jalali A (2017) Simplified symbolic transfer function factorization using combined artificial bee colony and simulated annealing. Appl Soft Comput 55:436–451
Singh D, Singh B, Kaur M (2021) Simultaneous feature weighting and parameter determination of neural networks using ant lion optimization for the classification of breast cancer. Biocybern Biomed Eng 40:337–351
Song D, Lin L, Wu Y (2019) Extended exergy accounting for a typical cement industry in China. Energy 174:678–686
Statista (2020) https://www.statista.com/statistics/265510/countries-with-the-largest-coal-consumption/
Stojanovic I, Brajevic I, Stanimirovic PS, Kazakovtsev LA, Zdravev Z (2017) Application of heuristic and metaheuristic algorithms in solving constrained weber problem with feasible region bounded by arcs. Math Probl Eng 2017:8306732
Su R, Weng M, Yang C (2021) Effects of corporate social responsibility activities in a two-stage assembly production system with multiple components and imperfect processes. Eur J Oper Res 293:469–480
Sun H, Yang J (2021) Optimal decisions for competitive manufacturers under carbon tax and cap-and-trade policies. Comput Ind Eng 156:107244
Teerasoponpong S, Sopadang A (2022) Decision support system for adaptive sourcing and inventory management in small- and medium-sized enterprises. Robot Comput Integr Manufact 73:102226
Tütüncü K, Şahman MA, Tuşat E (2021) A hybrid binary grey wolf optimizer for selection and reduction of reference points with extreme learning machine approach on local GNSS/leveling geoid determination. Appl Soft Comput J 108:107444
U.S. Energy Information Administration (EIA) (2019) Coal Transportation Rates to the Electric Power Sector. https://www.eia.gov/coal/data.php#transrate.
U.S. Energy Information Administration (EIA) (2021) Coal explained, https://www.eia.gov/energyexplained/coal/use-of-coal.php
U.S. Energy Information Administration (EIA) (2022) Direct CO2 emissions in the iron and steel sector by scenario, 2019-2050. Available from: https://www.iea.org/data-and-statistics/charts/direct-co2-emissions-in-the-iron-and-steel-sector-by-scenario-2019-2050, IEA. Licence: CC BY 4.0.
Varshney S, Kumar C, Swaroop A (2021) Lightning-based lion optimization algorithm for monitoring the pipelines using linear wireless sensor network. Wireless Pers Commun 117:2475–2494
Wan S-P, Chen Z-H, Dong J-Y (2021) Bi-objective trapezoidal fuzzy mixed integer linear program-based distribution center location decision for large-scale emergencies. Appl Soft Comput 110:107757
Wang M, Heidari AA, Chen M, Chen H, Zhao X, Cai X (2020a) Exploratory differential ant lion-based optimization. Expert Syst Appl 159:113548
Wang T, Manogaran G, Wang M (2020b) Framework for social tag recommendation using Lion Optimization Algorithm and collaborative filtering techniques. Clust Comput 23:2009–2019

Wang Y, Nie R, Ma X, Liu Z, Chi P, Wu W, Guo B, Yang X, Zhang L (2021a) A novel Hausdorff fractional NGMC (p, n) grey prediction model with grey wolf optimizer and its applications in forecasting energy production and conversion of China. Appl Math Model 97:381–397
Wang H, Wu F, Zhang L (2021b) Application of variational mode decomposition optimized with improved whale optimization algorithm in bearing failure diagnosis. Alex Eng J 60:4689–4699
Wang Q, Guo J, Li R, Jiang X (2023) Exploring the role of nuclear energy in the energy transition: a comparative perspective of the effects of coal, oil, natural gas, renewable energy, and nuclear power on economic growth and carbon emissions. Environ Res 221:115290
Yan Z, Zhang J, Zeng J, Tang J (2021) Nature-inspired approach: an enhanced whale optimization algorithm for global optimization. Math Comput Simul 185:17–46
Yang J, Xu M, Gao Z (2009) Sensitivity analysis of simulated annealing for continuous network design problems. J Transp Syst Eng Inf Technol 9(3):64–70
Yao Y, Evers PT, Dresner ME (2007) Supply chain integration in vendor managed inventory. Decis Support Syst 43:663–674
Yazdani M, Jolai F (2016) Lion optimization algorithm (LOA): a nature-inspired metaheuristic algorithm. J Comput Design Eng 3(1):24–36
Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353
Zahedi ZM, Akbari R, Shokouhifar M, Safaei F, Jalali A (2016) Swarm intelligence based fuzzy routing protocol for clustered wireless sensor networks. Expert Syst Appl 55:313–328
Zhang X, Wen S (2021) Hybrid whale optimization algorithm with gathering strategies for high-dimensional problems. Expert Syst Appl 179:115032
Zhang J, Hong L, Liu Q (2021) An improved whale optimization algorithm for the traveling salesman problem. Symmetry 13:48

Ali Roozbeh Nia is a PhD student of Information and Systems Engineering at at Concordia Institute for Information Systems Engineering (CIISE), in Concordia University, Montreal, Canada. He has published in the areas of Sustainable supply chain, Energy supply chain, and inventory management.

Anjali Awasthi is Full Professor and Concordia University Research Chair (Tier-II) in Connected Sustainable Mobility Systems at Concordia Institute for Information Systems Engineering (CIISE), in Concordia University, Montreal, Canada. Her areas of research are modeling and simulation, data mining, Information Technology and decision making, sustainable logistics planning, quality assurance in supply chain management and sustainable supply chain management.

Nadia Bhuiyan is Full Professor at department of Mechanical and Industrial Engineering Concordia University, Montreal, Canada. Her research focus is on product development processes, dealing with the design, development, production, and distribution of goods and services, with a focus on emerging tools and techniques for integrating design and manufacturing to improve process performance.

Authors and Affiliations

Ali Roozbeh Nia[1] · Anjali Awasthi[1] · Nadia Bhuiyan[2]

✉ Ali Roozbeh Nia
ali.roozbehnia@gmail.com; ali.roozbehnia@mail.concordia.ca

Anjali Awasthi
anjali.awasthi@concordia.ca

Nadia Bhuiyan
nadia.bhuiyan@concordia.ca

[1] Concordia Institute for Information Systems Engineering (CIISE), Concordia University, Montreal, Canada

[2] Department of Mechanical, Industrial and Aerospace Engineering (MIAE), Concordia University, Montreal, Canada