Journal of Cleaner Production 384 (2023) 135628

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Enabling the circular economy of bio-supply chains employing integrated biomass logistics centers - A multi-stage approach integrating supply and production activities

Victoria Muerza [a], Luca Urciuoli [b,c,*], Sebastián Zapata Habas [d]

[a] Department of Applied Economics - Area of Quantitative Methods for Economics and Business, University of Zaragoza, Zaragoza, Spain
[b] Department of Industrial Management and Economics, KTH Royal Institute of Technology, Stockholm, Sweden
[c] MIT International Logistics Program, Zaragoza Logistics Center, Zaragoza, Spain
[d] CIRCE - Research Centre for Energy Resources and Consumption, Parque Empresarial Dinamiza, Zaragoza, Spain

A R T I C L E I N F O

Handling Editor: Sunil Luthra

Keywords:
Circular economy
Multi-criteria decision making
Biomass supply chain
Simulation
Supplier selection

A B S T R A C T

Studies in the agro-industry sector have shown the importance to evaluate the feasibility of an IBLC (a multi-product transformation plant). This paper develops a model to simulate the performance of an IBLC in Spain, using a combined approach: AHP, TOPSIS, and a hybrid simulation model. Results show that profits can be incremented by about 55.7% and environmental emissions of KgCO2e per tonne of bio-commodity produced, reduced by 24.2%. The scientific contribution covers the development of a simulation model that dynamically select suppliers based on a combination of social, environmental, and economic criteria. In addition, the model can be used to evaluate the economic and environmental feasibility of the IBLC by integrating the suppliers selection with the operations of a multi-product transformation plant.

1. Introduction

The European Commission's objective is to transform the EU economy into a Circular Economy (CE) by 2030 and to achieve climate neutrality by 2050 (EC, 2020). A CE is based on the principle of "*closing the life cycle*", extending the value of waste, materials, goods, services, energy, and water (Kowalski and Makara, 2021). Agricultural processing industries denote an industrial sector that is transitioning towards a CE, entailing the opportunity to boost the use of agricultural residues for biomass supply chains (Atashbar et al., 2016).

Agro-industries face diverse challenges, e.g. maintaining competitive advantage, ensuring the cost-efficiency of supply operations, modifying consumption patterns, and guaranteeing financial assets and technical know-how for SMEs (Kowalski and Makara, 2021; Rezaei et al., 2020). Other challenges include developing the circular business model (Barros et al., 2020) while ensuring 1) its robustness against uncertain factors such as quality and seasonality (Aghalari et al., 2021), 2) transparency in waste availability and waste streams (Brandão et al., 2021), and 3) prioritization of the local economy to minimize logistics costs (Salvador et al., 2021).

To overcome these challenges, the Integrated Biomass Logistics Centre (IBLC) concept has been coined within the AgroInLog EU project. An IBLC refers to an agro-industrial center in which food production activities (feed and fodder), carried out in existing facilities of the agricultural processing industry, are combined with new non-food activities taking advantage of idle times and available residuals from the agricultural sector (Annevelink et al., 2017; Muerza et al., 2020). Previous research on the IBLC concept has considered SC optimization (Guo et al., 2020), and analysis of maximum distances to suppliers to demonstrate economic feasibility (Suardi et al., 2019).

The purchasing function of the IBLC is expected to select suppliers and thereby determine the optimal quantity and timing of the orders (Rezaei et al., 2020). The complexity of this task raises due to diverse factors (Khemiri et al., 2017): (i) the rapid market changes; (ii) a high degree of uncertainty in the planning decisions; and (iii) accessibility to some input data and preferences, sometimes only available through human judgments. In addition, supplier selection must respond to several criteria including social, economic, quality, environmental, etc. aspects (Kazantzi et al., 2013). This process is of utmost importance to ensure that the quality of the final bio-commodities will be as expected, i.e., matching market demand while reducing environmental impacts.

The selection of biomass suppliers has been studied from different

* Corresponding author. KTH Royal Institute of Technology, Lindstedsvägen 30, 11428 Stockholm, Sweden.
E-mail address: urciuoli@kth.se (L. Urciuoli).

https://doi.org/10.1016/j.jclepro.2022.135628
Received 24 May 2022; Received in revised form 11 December 2022; Accepted 13 December 2022
Available online 16 December 2022

perspectives. For instance, the model provided by Kazantzi et al. (2013) allows for optimally combining suppliers and select quantities to be purchased in different periods. Scott et al. (2013) integrate stakeholders' requirements into the selection process in the UK context. More recently, Nguyen and Chen (2018) integrate supplier selection and operation planning problems to minimize the total cost of a biomass SC, without considering the environmental analysis of the solution. Lu et al. (2019) propose green supplier selection in the straw biomass industry based on green and traditional indicators, taking into account uncertainty and fuzziness. Another model provided by El Amrani et al. (2021) focuses only on sustainability aspect, but not on the economic feasibility of production activities. Sun et al. (2020) integrate the supply process with strategic and tactical decisions to build a cost-effective logistics system, yet production processes are neglected. In summary, it seems that biomass supply selection models do not align supply and production activities with environmental and economic feasibility, and, to our knowledge, no integrated simulation models have been developed within the framework of an IBLC.

This paper answers two main research questions:

1. What are the main decision criteria that affect an IBLC's supplier selection decision considering quality, seasonality, and availability of the raw material?
2. Will an IBLC be economically and environmentally feasible?

To answer these questions, this paper aims to develop a Decision Support System (DSS) for the sustainable procurement of agricultural waste in an IBLC. In addition, it aims to demonstrate that adopting a sustainable purchasing strategy may lead to benefits for companies. It proposes a multi-stage approach in a case study of an agricultural processing industry in Spain. It uses the Analytic Hierarchy Process (AHP) for weighting the criteria to be considered in the selection problem, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank the alternatives, and a hybrid simulation (agent-based and discrete event modeling) to evaluate and compare the financial performance when the agro-industry engages in the CE business. The DSS helps decision-makers distinguish which suppliers have these characteristics and rank them accordingly. This ultimately facilitates the supplier selection process, improving its agility and flexibility in terms of cost-effectiveness.

After this introduction, Section 2 elaborates on the CE and IBLC concepts, as well as the supplier selection problem; Section 3 describes the methodology; Section 4 the main results. Section 5 discusses implications of results and Section 6 concludes the paper.

2. Background

2.1. The CE and the integration with the IBLC concept

A CE requires the maximization of the value of residues. Biomass use strategies differ in value and conflicts between different uses increase the social debate about agriculture and food (Berbel and Posadillo, 2018). Agricultural residues, available in a certain area, determine the type of bio-products that can be produced by a CE business (Sherwood, 2020). In the agri-food sector, a CE is driven by innovations in business models to close material loops by creating new configurations (Donner and de Vries, 2021). The valorization of agricultural waste is linked to several risk factors (Donner et al., 2021): specificities of the residues, affecting conversion activities and resources; price of new products, which affects economic feasibility of the CE transition; availability of space for the transformation process; management regulations; and resistance of third parties. The effective use of agricultural waste to foster CE requires a cross-sectoral valorization vision (Donner et al., 2020).

The transition of agricultural processing industries towards CE forces the transformation of existing SC. Sometimes this transformation considers the adoption of alternative biowaste treatment units to optimally manage agricultural residues (Vlachokostas et al., 2020), and the reengineering of pre-treatment processes (Bakan et al., 2022). Capital goods and facilities in many agro-industries cannot be used year-round due to the seasonal availability of the primary feedstocks (Muerza et al., 2020). Hence, some authors have focused on the definition of efficient biomass SCs where intermediate facilities are used. Lautala et al. (2015) use distributed depots for the supply of uniform feedstock "commodities". A similar concept is defined by Eranki et al. (2011) and Maheshwari et al. (2017), which use regional depots for pre-processing and pre-treatment to produce densified biomass. Similarly, Sharma et al. (2018) consider a network of biomass depots for storing and pre-processing. Lamers et al. (2015) differentiate between Standard Depots and Quality Depots and perform a techno-economic analysis of decentralized biomass processing depots. Annevelink et al. (2017) coin the concept of IBLC that is adopted in this paper. The difference from previous literature is that the IBLC focuses on the transformation process, also considering supplies, treatment and storage operations.

The adaptation of the SC to CE allows for achieving economic growth and environmental conservation through the utilization of agricultural residues, but also entails overcoming several logistics costs (Iakovou et al., 2010) and challenges (Roy et al., 2022) like seasonality, location, climatic, biophysical, and socio-economic environments (Guo et al., 2020). Challenges are linked to the complexity of the decisions to be made upstream and downstream of the SC (Sharma et al., 2013), but also the need to ensure continuous feedstock supply (Mafakheri and Nasiri, 2014), and optimally design biomass processing planning (Guo et al., 2020). Hence, the IBLC is revealed as a key echelon of the SC towards this transformation as it relies heavily on the creation of synergies between biomass feedstock purchasing, transportation, logistics, and manufacturing functions.

2.2. Purchasing function and supplier selection problem

The purchasing function in the agroindustry that intends to redesign the SC into a circular one is linked to the optimization of production, transport, inventory, and purchasing costs. In this regard, the supplier selection problem must be integrated into the purchasing process, and each decision should consider specific features of biomass SCs (Al-Wesabi et al., 2022), as these decisions have an impact on the quality and availability of biomass feedstock. Previous studies have addressed the problem from different perspectives and methodologies (Gören, 2018; Mohammed et al., 2018; Sureeyatanapas et al., 2018). For instance, Kazantzi et al. (2013) proposed an Intuitionistic Fuzzy Sets based algorithm to assess biomass supplier alternatives to maximize total purchasing values. Palak et al. (2014) used the classical economic lot sizing model to select the suppliers and transportation modes in a biofuel SC. Scott et al. (2013) combined a literature review and semi-structured industry interviews to determine the most important stakeholder groups in biomass supplier selection. Later on, Scott et al. (2015) combined AHP-Quality Function Deployment and chance-constrained optimization algorithm approach to select and allocate orders optimally.

More recently, Nguyen and Chen (2018) combined a two-stage stochastic programming model and operation planning in a biomass SC. Lu et al. (2019) advanced a decision-making framework based on the Cloud model, possibility degree, and Fuzzy AHP for green supplier selection. A challenge identified by Malladi and Sowlati (2018) consists in incorporating supplier-driven biomass collection and developing models that can integrate supply replenishments with production and transportation processes.

3. Methodology

A case study has been defined in collaboration with a Spanish agro-industry, region of Aragon. The company's plant collects alfalfa and processes it to manufacture compound feed (April to November). The company has agreed to experiment with the IBLC concept, i.e., to collect additional wheat straw residuals from farmers, blend them with wood chips and thereby manufacture pellets for the Energy Market (Fig. 1). This transition implies a review of the company's policies to select suppliers, determining optimal quantities of raw materials to purchase, and, finally, the creation of a new production line to be activated from December to March, exploiting the idle time of the compound feed production (Fig. 1).

The multi-stage model developed in this study focuses on a two-echelon SC, with three sets of TIER I suppliers delivering: (i) straw for pellets (Energy Market), (ii) straw for compound feed (Feed and Fodder Market), (iii) wood chips, to the transformation plant, and two combined production lines manufacturing bales and pellets (Fig. 1). The methodology starts with (i) identification and selection of criteria for supplier selection, (ii) valuation, prioritization, and synthesis of criteria based on the AHP. Thereafter, (iii) a hybrid simulation model is developed based on discrete and agent-based simulation, in which a ranking of alternatives is performed using TOPSIS.

3.1. Identification and selection of criteria

To identify suppliers' selection criteria a literature review was performed, focusing on studies that use multicriteria decision-making or hybrids methodologies published during the last ten years (Table Annex 1). From the literature review, a preliminary list of criteria was identified: transport costs, delivery terms, on-time delivery, supplier stability, control mechanisms in place, and environment. In the second step, a group of nine experts (three from a Spanish agroindustry company, three researchers in biomass and bioenergy, and managers selected amongst the three largest companies supplying straw in Spain) was created. The experts were selected in the framework of the AGROinLOG EU project. Participants from the agro-industry case company included the general manager, the quality manager, and the production manager. The three researchers in biomass and bioenergy have more than 15 years of experience and have participated in different EU projects in this area of research. Three managers from the three largest suppliers of straw in Spain were also involved in the group of experts. Experts were surveyed to validate the lists of criteria identified from the literature. The experts agreed that the criteria depend on the final product, and therefore two lists of criteria were identified and agreed upon during a telematic discussion (Table Annex 2). For the Feed and Fodder Market (FFM): Social (C1), Protein content (C2), % ash content (C3), % moisture content (C4), Supply stability (C5), Delivery time (C6), Color of the material (C7), Purchase price (C8), Operative (C9); for the Energy market (EM): % chlorine (C1′), % ash content (C2′), % moisture content (C3′), Supply stability (C4′), Delivery time (C5′), Purchase price (C6′), Distance (C7').

3.2. Valuation, prioritization, and synthesis of criteria based on the AHP

The AHP is a multicriteria decision-making methodology that allows transferring human perceptions into numerical values. It is used for the selection of a set of alternatives in a situation where multiple scenarios, actors, and criteria are involved (Saaty, 1980). Three stages are used (Saaty, 1980): (1) modeling the problem as a hierarchy of different levels (goal, criteria, subcriteria, alternatives), (2) valuation (the preferences of the experts are incorporated using pairwise comparisons between the elements that hang from the same node of the hierarchy), and (3) prioritization and synthesis to determine the local and global priorities of the elements and the total priorities for the alternatives. Different methods are used for this. The most common are Saaty's EigenVector method (EGV) and the Row Geometric mean Method (RGM).

AHP has been used in supplier selection, e.g. Levary (2008), Bruno et al. (2012), because of its capability to integrate multiple scenarios, actors, and criteria (Muerza et al., 2017). It provides mechanisms to monitor the consistency of the experts' judgments, allowing the combination with other approaches (Bruno et al., 2012). In this paper, AHP is used to weigh the criteria for supplier selection.

Importance scores (α) were assigned to the experts (E) for the energy market (EM) and feed and fodder market (FFM) (Table 1). Since the model has been applied to a case study, the highest importance scores in the current activity (FFM) were assigned to company experts based on process knowledge. For the EM (new activity), the highest importance scores were assigned to the biomass and bioenergy researchers due to their extensive expertise.

A questionnaire was used to gather the judgments from each expert. Preferences were assigned using the scale of Saaty (1980) and individual priorities of the experts were obtained using the EGV (Saaty, 1980). The consistency analysis (using the Consistency Ratio index, CR) of each comparison matrix was performed. When it was found unacceptable (CR>10%) a linearization procedure was applied to identify the closest consistent matrix to the one provided by the expert (Benítez et al., 2011). Afterward, the analysis was presented to each expert to get the acceptance of the changes carried out in the initial judgments. Finally,

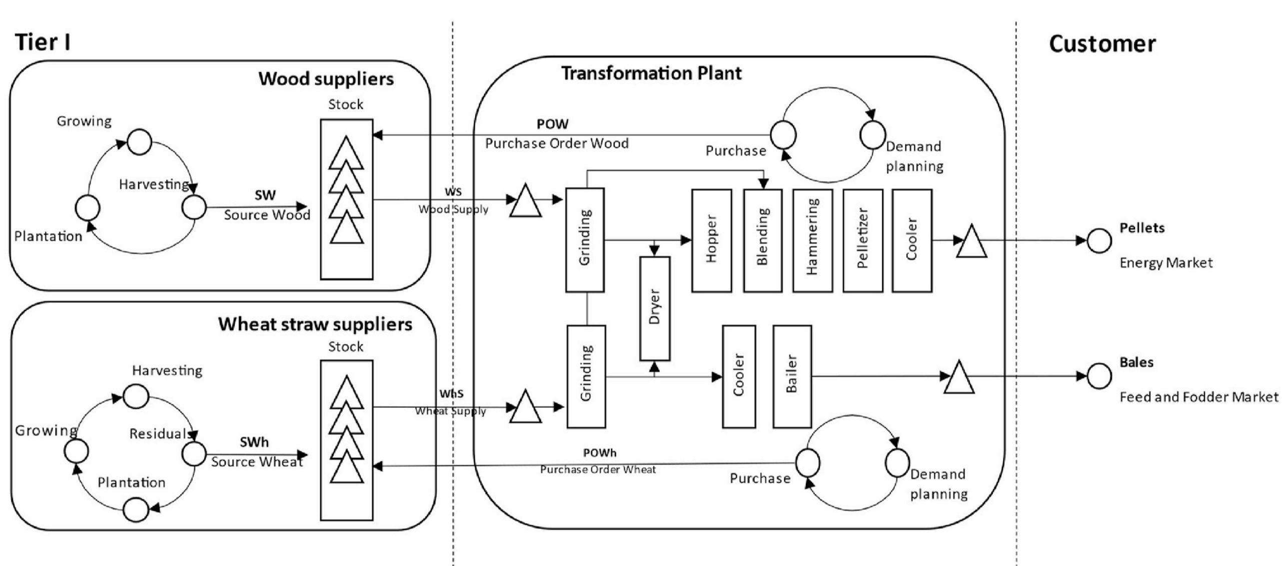


Fig. 1. Two-echelon SC producing compound feed and pellets.

Table 1
Importance scores assigned to the experts (decimals).

	E1	E2	E3	E4	E5	E6	E7	E8	E9
FFM (α)	0.3500	0.2500	0.1200	0.0400	0.1000	0.0400	0.0330	0.0330	0.0330
EM (α)	0.0666	0.0666	0.0666	0.2334	0.2334	0.2334	0.0333	0.0333	0.0333

NOTE: E1 currently works as a manager in a company of the characteristics of the study; E2 is working in the production department; E3 performs quality activities; E4, E5, and E6 are researchers and technicians in a technology center and research institute in renewables energies, energy efficiency, and CE in Spain; E7, E8, and E9 are logistics representatives from three big suppliers of straw.

the aggregation of individual priorities (AIP) was performed using the AIP-weighted geometric mean method ($w_{AIP-WGMM}$) (Forman and Peniwati, 1998) to obtain the group judgment for each criterion, expressed as:

$$w_{AIP-WGMM} = [w_1 \quad w_2 \quad \dots \quad w_n] = \left[\prod_{k=1}^{m} (w_{1,k})^{\alpha_k} \quad \prod_{k=1}^{m} (w_{2,k})^{\alpha_k} \quad \dots \quad \prod_{k=1}^{m} (w_{n,k})^{\alpha_k} \right]^{1/\sum_{k=1}^{m}\alpha_k}, \quad (1)$$

$k = 1, 2, \dots, m$ experts and $1, \dots, n$ criteria

Table 2 shows the priorities normalized considering the two production activities: bales of compound feed (FFM) and pellets (EM).

3.3. The hybrid simulation model

A model combining agent-based and discrete event simulation was used to compute the financial performance of the CE business and evluate the feasibility of the integrated supply-production activities. The agent-based model required the decomposition of the systems into agents, and thereafter the programming of their actions, defining how they interact with each other in the given environment, and the expected emergent behavior (Chen and Zhan, 2014; Gunasekaren et al., 2000). Next, discrete event simulation was used to simulate the production lines transforming the raw materials into bio-commodities.

3.3.1. Agents' definition

Five agents were created: TIER I suppliers (both for FFM and EM), trucks moving the wheat straw (respectively for pellets and compound), and a single agent representing the buyer, receiving the material, and transforming it into final bio-products:

$\{F_e\}$: set of suppliers for pellets production , $e = 1 \dots n_e$

$\{F_f\}$: set of suppliers used for compound feed production , $f = 1 \dots n_f$

$\{T_e\}$: set of trucks moving straw for pellets production , $e = 1 \dots n_e$

$\{T_f\}$: set of trucks moving straw compund feed production , $f = 1 \dots n_f$

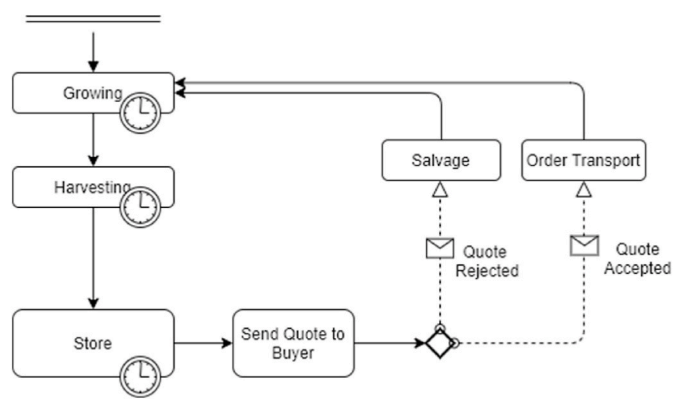


Fig. 2. Actions performed by suppliers selling raw materials respectively for the energy and feed markets.

Table 2
Individual (w(Ex)), aggregated and normalized priorities for each FFM and EM criteria.

Criteria FFM	w(E1)	w(E2)	w(E3)	w(E4)	w(E5)	w(E6)	w(E7)	w(E8)	w(E9)	$w_{AIP-WGMM}$	$w_{AIP-WGMM\ Normalized}$
C1	0.087	0.017	0.028	0.023	0.148	0.067	0.025	0.025	0.019	0.0439	0.0608
C2	0.291	0.269	0.344	0.166	0.268	0.276	0.317	0.048	0.271	0.2659	0.3688
C3	0.166	0.023	0.081	0.129	0.076	0.094	0.088	0.062	0.049	0.0759	0.1052
C4	0.115	0.055	0.155	0.13	0.105	0.024	0.148	0.319	0.092	0.0962	0.1334
C5	0.094	0.052	0.055	0.081	0.071	0.063	0.083	0.127	0.139	0.0739	0.1024
C6	0.013	0.045	0.028	0.035	0.028	0.008	0.019	0.142	0.038	0.0244	0.0339
C7	0.139	0.319	0.062	0.03	0.185	0.259	0.065	0.046	0.057	0.1409	0.1955
C8	0.054	0.131	0.22	0.381	0.092	0.194	0.208	0.194	0.271	0.1104	0.1532
C9	0.041	0.089	0.027	0.025	0.027	0.015	0.047	0.037	0.064	0.0436	0.0604
Criteria EM	**w(E1)**	**w(E2)**	**w(E3)**	**w(E4)**	**w(E5)**	**w(E6)**	**w(E7)**	**w(E8)**	**w(E9)**	**$w_{AIP-WGMM}$**	**$w_{AIP-WGMM\ Normalized}$**
C1′	0.2288	0.0595	0.4473	0.1761	0.3864	0.4970	0.2725	0.1886	0.2216	0.2782	0.3072
C2′	0.2288	0.3478	0.1212	0.1692	0.2215	0.1595	0.1182	0.0800	0.0985	0.1761	0.1945
C3′	0.2762	0.1898	0.1024	0.1692	0.1548	0.0916	0.1086	0.1499	0.0883	0.1389	0.1534
C4′	0.0522	0.1491	0.0601	0.0590	0.0635	0.0600	0.0929	0.1499	0.0812	0.0674	0.0744
C5′	0.0518	0.0514	0.0298	0.0261	0.0384	0.0257	0.0316	0.1191	0.0371	0.0337	0.0372
C6′	0.1250	0.1622	0.1852	0.3545	0.1138	0.0961	0.3224	0.2581	0.4261	0.1688	0.1864
C7′	0.0372	0.0404	0.0539	0.0459	0.0216	0.0702	0.0539	0.0543	0.0472	0.0425	0.0470

$\{P_1\}$: Buyer or Transformation plant

$n_e = 62$, number of farmers used for energy production

$n_f = 22$, number of farmers used for food production

3.3.2. Agents' actions

3.3.2.1. Suppliers - Action 1: produce wheat straw, send quotes, and adapt to the buyer's response. The suppliers' actions start by simulating the growing and harvesting processes for all TIER I suppliers ($\{F_e\}$, and $\{F_f\}$.). Growing, harvesting, and storage time are modeled as triangular distributions. Data related to annual quantities produced stemmed from statistical data provided by the case company. The growing of wheat for the feed and energy market starts in April and has an expected total time duration of 5 months, after which the harvested straw is collected and stored in bales (Fig. 2).

Suppliers receive a Request For Quotation (RFQ) from the buyer and respond by sending the quote with all information requested. Table 3 shows the list of data that is included in the quote emitted by suppliers used for the animal food market (FFM) and energy (EM).

Once the quotes are received, the buyer ranks the suppliers and sends orders to the suppliers selected. If the quote is accepted, the supplier proceeds by ordering transport and shipping the material to the buyer. If the quote is rejected, the supplier will resell the material to a salvage market.

3.3.2.2. Buyer - Action 1: Receive quotes from suppliers, perform ranking and send orders. The buyer reviews all the offers of wheat straw for the energy market performs a selection of suppliers, and thereby sends orders. The selection of suppliers is simulated by using an AHP-TOPSIS-based algorithm as shown in (Fig. 3). The algorithm gathers the following information: the criteria and weights for the selection of straw suppliers assigned by AHP, the quantity of straw to be purchased for the EM and FFM markets, and the quotes from the suppliers. Next, the TOPSIS ranking is performed, returning the ranked list of suppliers (Urciuoli and Hintsa, 2018). A final loop selects suppliers until the necessary material quantities are purchased.

Following the TOPSIS approach, two pairs of alternatives, S and S′, and criteria, C and C', are created:

$S = \{e = 1, \ldots, 62\}$, EM suppliers

$S' = \{f = 1, \ldots, 22\}$, FFM suppliers

$C = \{ec = 1, \ldots, 8\}$, criteria to select EM suppliers

$C' = \{fc = 1, \ldots, 10\}$, criteria to select FFM suppliers

A performance rating vector, $X = \{e = 1, \ldots, 62; ec = 1, \ldots, 8\}$ and $X' = \{f = 1, \ldots, 22; fc = 1, \ldots, 10\}$, is assigned to each of the alternatives/suppliers. The rating represents how the supplier score on the selected criteria (generated by the agents in action 1). A weight vector, based on the weights assigned to the AHP, is generated.

		Criteria
		$[C_1 \;\; C_2 \;\; \ldots \;\; C_m]$
Alternatives	$\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_n \\ W \end{bmatrix}$	$\begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1m} \\ x_{12} & x_{22} & \ldots & x_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ x_{n1} & x_{n2} & \ldots & x_{nm} \\ w_1 & w_2 & \ldots & w_m \end{bmatrix}$

The algorithm proceeds with the ranking of the suppliers: it calculates normalized rankings (r_{kj}), weighs the rankings (v_{kj}), and finally, compute positive (PIS,A^+) and negative (NIS,A^-) ideal points (J_1 and J_2 represent benefits and costs) using the following formulas (Salmon et al., 2015):

$$r_{kj} = \frac{x_{kj}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}}, k = 1, \ldots, n; j = 1, \ldots, m \quad (2)$$

$$v_{kj} = w_j r_{kj}\ (x), k = 1, \ldots, n; j = 1, \ldots, m \quad (3)$$

$$PIS = A^+ = \{v_1^+(x), v_2^+\ (x), \ldots, v_m^+\ (x)\} = \{k = 1, \ldots n\} \quad (4)$$

$$NIS = A^- = \{v_1^-(x), v_2^-\ (x), \ldots, v_m^-\ (x)\} = \{k = 1, \ldots n\} \quad (5)$$

The Positive Ideal Solution (PIS) is made of v_{kj} values maximizing benefits and minimizing costs. On the opposite, benefits are minimized, and costs are maximized in the Negative Ideal Solution (NIS). A Euclidean distance, between the weighted normalized ratings v_{kj} and the respective ratings composing the PIS and NIS vectors of ideal solutions are computed to understand how each alternative differs from the negative and positive ideal solutions:

$$D_k^+ = \sqrt{\sum_{j=1}^{m} \left[v_{kj}\ (x) - v_j^+(x)\right]^2}, k = 1, \ldots, n \quad (6)$$

$$D_k^- = \sqrt{\sum_{j=1}^{m} \left[v_{kj}\ (x) - v_j^-(x)\right]^2}, k = 1, \ldots, n \quad (7)$$

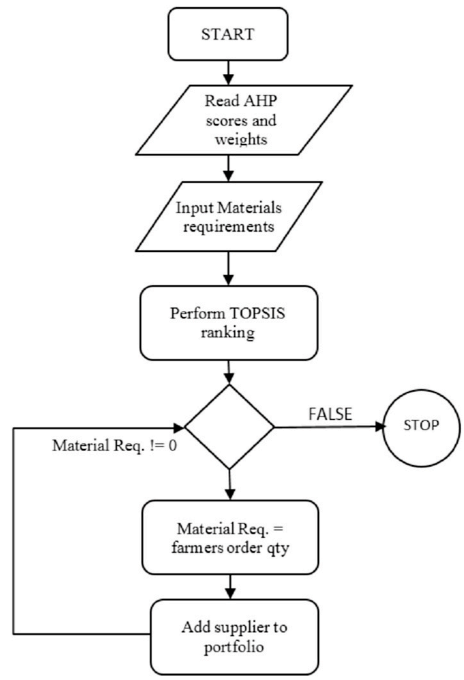


Fig. 3. Flowchart to perform TOPSIS and selection of suppliers.

Table 3
Data included in the quote requested by the buyer (e = 62, f = 22).

Feed and Fodder Market (f = 1 … 22)	Energy Market (e = 1 … 62)
Quantity	Quantity
Purchase price (C8)	Purchase price (C6′)
Social level (C1)	% Chlorine (C1′)
Protein content (C2)	% Ash (C2′)
Ash content (C3)	Moisture content (C3′)
Moisture content (C4)	Supply stability (C4′)
Supply stability (C5)	Delivery time (C5′)
Delivery time (C6)	Distance (C7′)
Colour of the material (C7)	
Size/format of straw supplied (bale or bulk) (C9)	

Given the two separation values, a final ranking factor is calculated (Urciuoli and Hintsa, 2018):

$$f_k^+ = \frac{D_k^-}{(D_k^+ + D_k^-)}, \forall k = 1, \ldots, n; \; C_k^+ \in [0, 1] \tag{8}$$

Low values of f_k^+ are solutions closer to the less ideal solution, and high values closer to the positive ideal solution. By sorting on descending values of f_k^+ the ranks of the preferred choices (first places on the list) and the less favorable (last places on the list) are identified.

3.3.2.3. Buyer Action 3: Receive ordered shipments and run production. Supplies are received by the buyer and stored inbound until production starts. The production process consists of two lines. The first produces bales of wheat to be sold to the animal feed market, running from April to November every year, and is made of the following processes/equipment (Fig. 4):

- **Source wheat (bales production).** Production line point of entry.
- **Storage wheat (bales production).** The temporary storage of material before processing.
- **Tub Grinder.** Grinding process reducing the size of the collected wheat.
- **Rotary dryer.** Drying process to reduce/minimize the liquid moisture content.
- **Cooler.** Temperature is reduced to bring it down to the optimal one for bailing.
- **Bailer.** The dried material is compressed into bales.
- **Storage of bales.** Bales are stored waiting for a sale on the market.

The second produces pellets from a mixture of wheat and wood, running from December to March. This line shares two machines with the bales production line, i.e., the tub grinder and rotary dryer. The line runs are made of the following processes/equipment (Fig. 4):

- **Source alfalfa.** Alfalfa point of entry.
- **Source of wood.** Wood is to be mixed with wheat to produce pellets.
- **Tub grinder.** Alfalfa is fed into a dedicated mill and ground in smaller pieces.
- **Tub grinder.** Using the tub grinder shared with the production of alfalfa bales for the animal feed market, wood is ground into wood chips.
- **Wood chips storage.** The wood chips must be stored for a minimum of 4 h before entering the rotary dryer.
- **Rotary Dryer.** The dryer is used to reduce/minimize the amount of moisture content in the wood.
- **Storage dry wood.** The dried wood is piled waiting to enter the next machine.
- **Wood hopper.** The hopper is used to convey wood into dedicated containers.
- **Merge.** Wood and wheat are merged in proportions (60% wheat and 40% wood). This blend was selected to optimize the composition of the pellets and maximize the energy released when burning the pellets.
- **Hammer mill.** Wood and wheat are shredded, crushed into even-sized feedstock, and aggregated into smaller pieces.
- **Mixer.** Material is further mixed to control the optimal moisture (to be maintained between 12% and 14%).
- **Pelletizer.** Material is compressed or molded into the shape of pellets.
- **Cooler.** The temperature of pellets is lowered to let them become rigid and lose moisture.
- **Storage and disposal.** The produced pellets are temporarily stored until sold to the energy market.

3.4. Financial performance metrics

Financial indicators, i.e., profits, revenues and cost metrics are computed to compare the outcomes of the simulations:

$$P = \sum_{t=0}^{4} (R_t - C_t) = \sum_{t=0}^{4} \left[\left(\sum_{bc} Q_{bc}^t \cdot sp_{bc} \right) - C_t \right]$$
$$= \sum_{t=0}^{4} \left[\sum_{bc} Q_{bc}^t \cdot sp_{bc} - \sum_{rm} (IC_{rm}^t + PU_{rm}) - \sum_{bc} PC_{bc}^t \right]$$

where,

$P = \text{Profits } [€ \cdot y^{-1}]$

$R_t = \text{Revenues } [€ \cdot y^{-1}]$

$C_t = \text{Total Costs } [€ \cdot y^{-1}]$

$t = 0 \ldots 4$, years simulated

$Q_{bc}^t = \text{quantity of bio} - \text{commodity produced during year t}, [Mg]$

$bc : \{\text{pellets, wheat bales}\}$, set of bio − commodities produced

$IC_{rm}^t = \underline{Q}_{rm}^t \cdot hc \cdot pp_{rm}^t = \text{Inventory Costs}, [€ \cdot y^{-1}]$

$\underline{Q}_{rm}^t = \text{average annual quantity of raw material kept in inbound storage}, [Mg]$

$hc = \text{holding costs} = 30\%$

$rm : \{\text{FFM Wheat, EM Wheat, Wood}\}$

$PU_{rm} = \text{cumulative purchase costs for raw materials}$

$PC_{bc}^t = \text{production costs of bio} - \text{commodities bc}, [€ \cdot y^{-1}]$

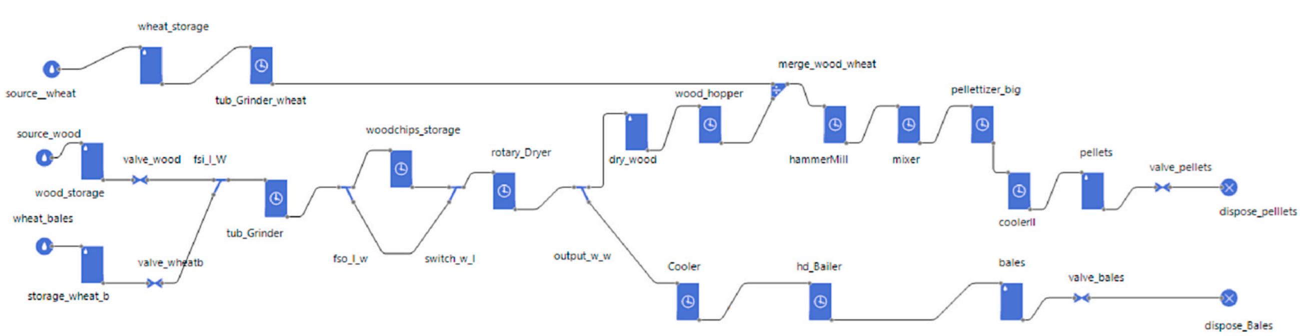


Fig. 4. Production lines for pellets and bales.

3.5. Model scenarios assumptions

To run the simulation, the following assumptions were made based on data provided by the Spanish Research Centre for Energy Resources and Consumption:

- All produced bio-commodities are sold to the market and no excess or stock-out costs are considered.
- Data for each supplier, representing the amount of produced wheat annually, was collected in 2 databases (one for EM suppliers and one for FFM suppliers). Triangular distributions were used to simulate the produced wheat.
- Suppliers' offered prices were also available in the database. Triangular distributions were used in the simulation.
- Suppliers' addresses were geocoded to determine the geographic position and route distances to the transformation plant. A cost per km has been set to 1.3785 €/km to derive transportation costs on the computed distances.
- Production cost per ton was 66.5 €/ton-year for pellets, and 52.5 €/ton-year for the compound feed (bales).
- Inventory costs are assumed to be 30% of the purchase price.
- The purchase price of wood is modeled as a uniform distribution with values between 80 and 90 €/ton.
- The sale price of final bio-commodity products is 150 €/ton (feed bales) and 170 €/ton (pellets).
- Switching the production cost of bales (food) to pellets (non-food) (or vice versa) is €210 per switch (three employees involved are considered).
- Production of pellets takes place every year from December to March, and production of bales from April to the end of November.

The simulation is used to assess two scenarios:

(1) A base scenario where the transformation plant, aims to satisfy the demand for compound feed in bales by purchasing all the available wheat straws from FFM suppliers.
(2) In the second scenario, the buyer purchases wood, and wheat straw both from the EM and FFM suppliers. Two production lines are used, one to convert the straw into compound feed and one to blend the wheat straw and wood in pellets.

4. Results

Results from the simulation show that on average, the available wheat for bales production from suppliers is on average 2,656.31, while wheat for the energy market is tons/year 44,013.18 tons/year (Fig. 5).

Table Annex 3 and Table Annex 4 (suppliers' names anonymized) show how the wheat suppliers were ranked when using the AHP criteria weights and scores in the simulated TOPSIS. The tables contain extracted scores and ranking for a random year from the ones simulated in the model.

4.1. Scenario 1: one production line

In this scenario, only FFM wheat suppliers are selected. A farmer produces on average 43.7 t/year of wheat, transported along an average distance of 77.7 km, and generates an expected revenue of 1,684 €/year from the bio-commodity business. The expected CO_2 emissions are about 84.4 $KgCO_2e$ per supplier/year (Fig. 6). Considering the whole set of suppliers, system-level emissions go up to about 5,234.04 $KgCO_2e$ per year and about 1.98 $KgCO_2e$ per produced ton of bales. The linear model fitting the relationship between available wheat and km-traveled shows a high concentration of raw material close to the plant. The raw materials linearly diminish at longer distances, up to a maximum distance of 800 km from the plant (Fig. 7).

When simulating the production lines, the amount of produced compound feed is between 2,587 and 2,736 tons of bales per year. Purchasing costs sum up to about 99,965–105,701 €/year. Production costs are between 138,126 and 145,768 €/year. Transportation costs are stable at around 6,560 €/year and inventory costs are the lowest figures, with values between 106 and 160 €/year (Fig. 7). This means that all the available straw is promptly processed by the transformation plant. Fig. 8 shows that the transformation plant has positive profits already after year 1 of simulation, reaching an average value of 150,150 €/year after 4 years.

4.2. Scenario 2: two production lines

In this scenario, a new line to produce pellets is used during the idle time of the line producing compound feed. The new line is replenished with 1,339 tons/year of wheat straw, and 893 tons/year of wood chips. In addition to all FFM suppliers, this scenario ranks and selects one additional supplier from the EM portfolio. EM wheat suppliers produce on average about 2,000 t/year of wheat, transported along an average

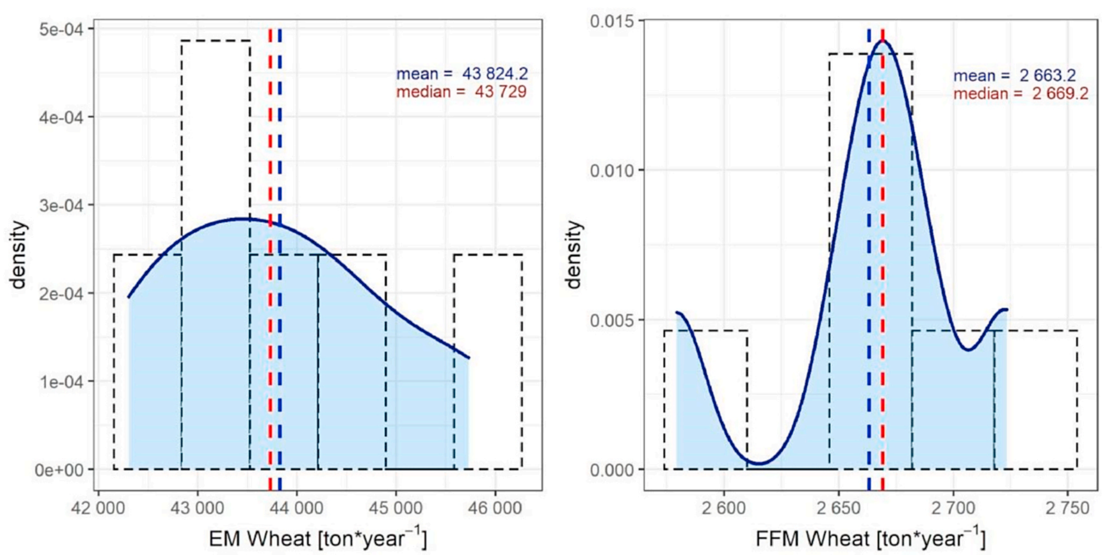


Fig. 5. Available wheat straw from suppliers in Spain (ton/year) (mean = dashed blue line, median = dashed red line).

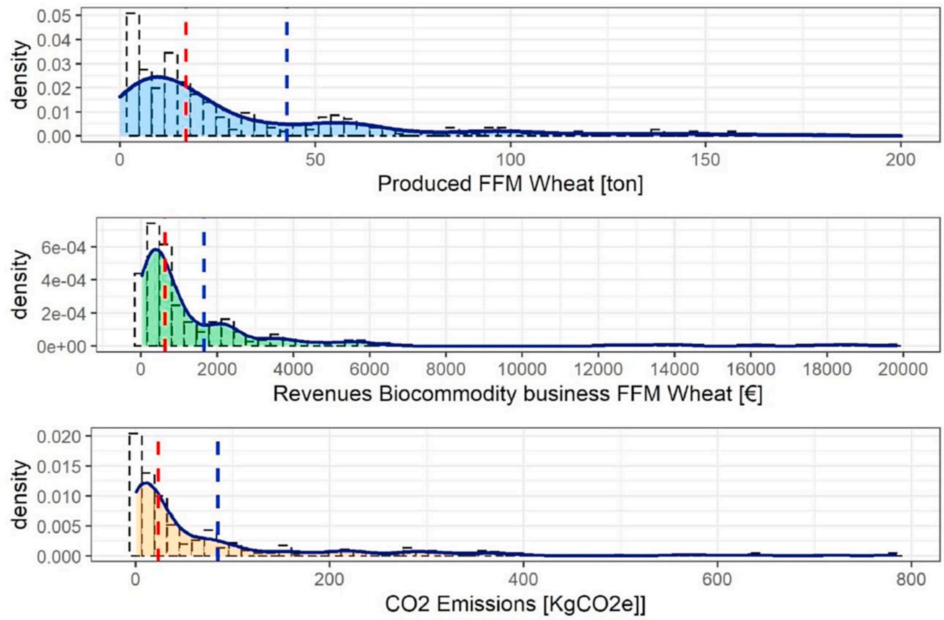


Fig. 6. Kernel density distribution estimates of produced FFM wheat [ton], revenues [€] and CO2 emissions [kgCO2e] per farmer (bins = 62, mean = blue vertical line, median = red vertical line).

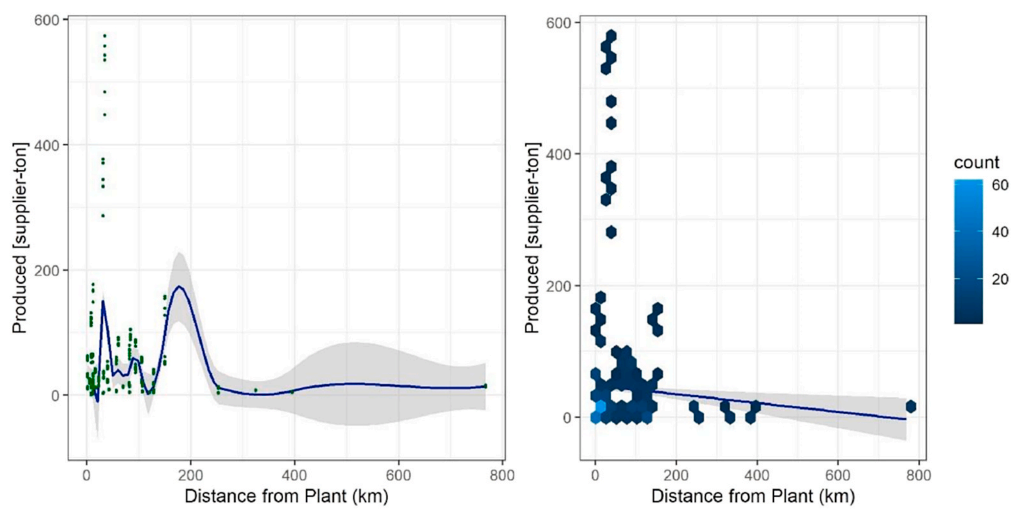


Fig. 7. Fitted local polynomial regression (left), 2d hexagonal heatmap, and linear model (right) for average produced wheat for the animal market (supplier-ton) and distance from plant (km), confidence interval 0.8.

distance of 84.1 km the expected revenue for the single supplier selected amounts to 54,635 €/year (Fig. 9). Emissions increased by 1,478 $KgCO_2e$ (6,712.04 $KgCO_2e$, with bales activities), but reduced to 1.50 $KgCO_2e$ per ton of bio-commodity produced (bales and pellets).

Inventory and production costs increase substantially, up to respectively 19,387 €/year and 292,965 €/year. Transportation costs increase slightly to 6,580 €/year. The production line can still produce the same quantities of bales as in the previous scenario, about 2,625 tons/year. In addition, pellets are now produced, reaching a maximum of 2,239 tons/year. Purchasing costs are between 226,274 and 233,206 €/year. Consequently, profits can now reach a maximum of about 233,782 €/year, an increment of 83,632 €/year compared to the previous scenario (+55.7%) (Fig. 10).

To evaluate the stability of the above results the simulation was iterated with a random seed to initialize the pseudo-random number generator, and average profits were computed (Fig. 11). In addition, a sensitivity analysis using the prices of bales and pellets as main parameters varied was performed (Fig. 12). Results show that (i) all the iterated outcomes report positive profits, and (ii) the range of prices selected generates positive profits in 71% of the simulated outcomes.

5. Discussion

This study collects and expounds criteria relevant to select suppliers of biomass material. Existing literature about the supplier selection problem (Table Annex 1) focuses primarily on the manufacturing sector. Other studies investigate the problem of selecting suppliers of biomass, yet these focus on single indicators, e.g., green indicators, (Lu et al., 2019), or country-specific criteria, e.g., UK context (Scott et al. (2013). In our approach, criteria are market-diversified: feed and food criteria include social factors, protein content, the color of the material, and transport format (bales or bulk). Criteria relevant for the energy market are % chlorine and distance supplier-buyer. Common criteria are the purchase price, delivery time, supply stability, % ash, and % moisture.

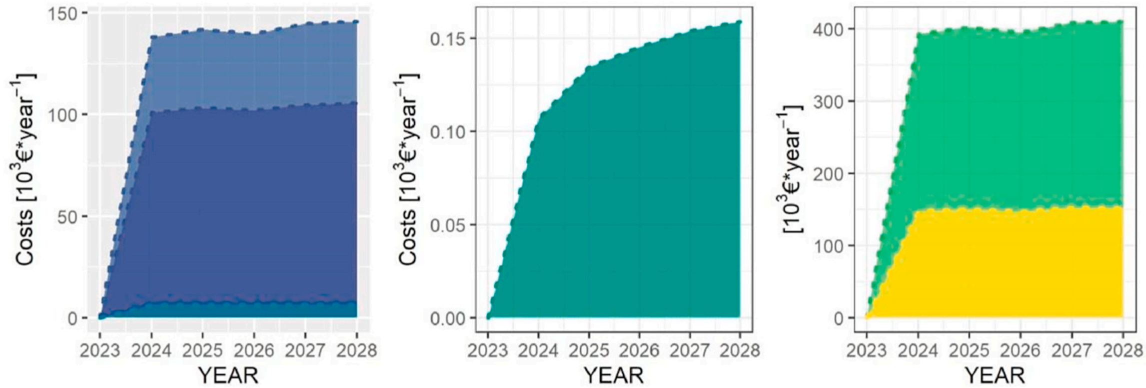


Fig. 8. Left diagram: purchasing (light blue), production (blue), transportation costs (green). Centre diagram: inventory costs. Right diagram: revenues (green), profits (yellow).

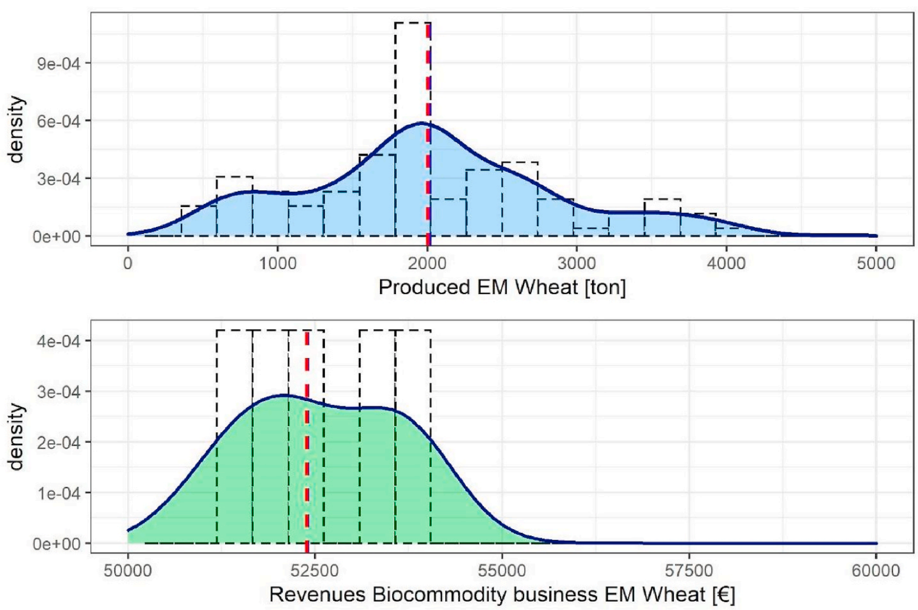


Fig. 9. Kernel density distribution estimates of produced EM wheat [ton], and revenues [€] per farmer (bins = 22, mean = blue vertical line, median = red vertical line).

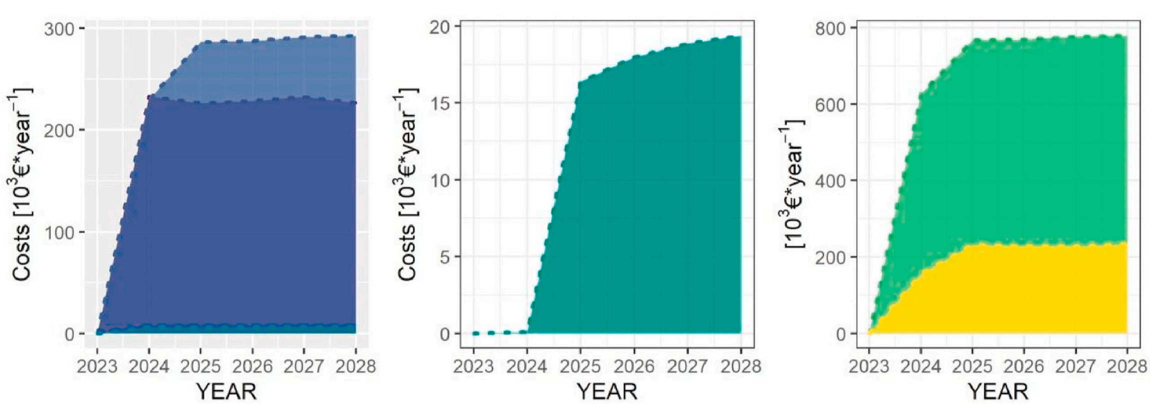


Fig. 10. Left diagram: purchasing (light blue), production (blue), transportation costs (green). Centre diagram: inventory costs. Right diagram: revenues (light green), profits (yellow).

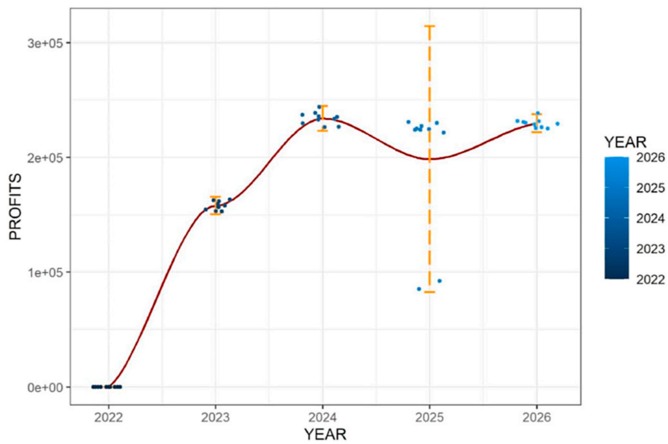


Fig. 11. Yearly profits from iterated simulation runs (random seed initialization) (blue), fitted polynomial regression on annual means (red), and error bars (Orange, $Max = \mu + 2\sigma, min = \mu - 2\sigma$).

Another important finding concerns the economic and environmental feasibility of the IBLC. The results of the simulation show that when using the combined production lines, higher profits may be realized with an increment of 83,632 €/year compared to the base scenario, where only bales are produced (+55.7%). In addition, emissions of CO2 are reduced to 1.50 $KgCO_2e$ per ton of bio-commodity produced (−24.2%). Hence, the establishment of IBLC where supply and production can be optimally coordinated can be seen as a feasible enabler of the CE bio-business, economically and environmentally. Previous literature has indicated that integrated planning and coordination of supply–production activities can contribute to efficiency gains (Annevelink et al., 2017), but there is a lack of empirical studies proving the concept. Nguyen and Chen (2018) propose a two-stage stochastic programming model and numerical studies to show how suppliers' criteria impacts expected costs. Yet, revenues and profits calculations are not considered. In addition, the study does not consider the problem of dealing with seasonal raw materials as an input to a single production line. Other studies focus on suppliers' selection costs, neglecting the optimal integration with production activities (Kazantzi et al., 2013; Lu et al., 2019; Palak et al., 2014).

5.1. Research implications

Our methodology and empirical study show that supply-production activities, integrated into IBLCs, have the potential to profitably transform biomass into energy and other bio-commodities while reducing waste from agriculture and contributing to lowered environmental emissions. The introduction of these practices on a global scale could establish robust and profitable circular economies by valorizing agricultural residues and contributing to the establishment of a profitable CE business. These activities are also aligned with the objectives set by the REPower EU Plan (ensuring that 45% of Europe's energy supply comes from renewable sources by 2030) and carbon-neutral Europe by 2050.

6. Conclusions

In the agroindustry, the use of residues as an input for new processes pursuing a CE has put the basis for the creation of a new concept in the framework of the AGROinLOG project: the Integrated Biomass Logistics Centre (IBLC). IBLCs aim to increase the use of existing facilities in the agroindustry, (i) taking advantage of idle periods, and (ii) allowing diversification of the business activity. This paper focuses on the purchase problem of agricultural residues for building an integrated supply-production system for a feed and fodder agroindustry located in Spain, planning to operate as an IBLC; diversifying the activities to produce fodder and pellets from straw respectively for two markets: animal feed and energy market (Annevelink et al., 2017).

The following contributions to literature can be highlighted: (i) the development of a novel methodology based on AHP, TOPSIS, and simulation that can be used by agro-industries planning to operate as an IBLC. This approach can be used to dynamically select suppliers, responding to the volatility of market demand and supplies. (ii) A specific list of criteria based on literature review and discussion with a group of experts that can be applied with minor modifications to other agro-industries. As suggested by the literature, the application of the methodology allows a quantification of the most suitable suppliers for the agroindustry transformation, considering specific features of biomass SCs (Al-Wesabi et al., 2022). (iii) The demonstration that an IBLC using biomass straw as raw material is economically and environmentally feasible, supporting the CE transformation.

The novelty of the work is based on the following aspects: (i) there are few methodologies and empirical studies incorporating the supplier selection problem to evaluate the performance of integrated logistics

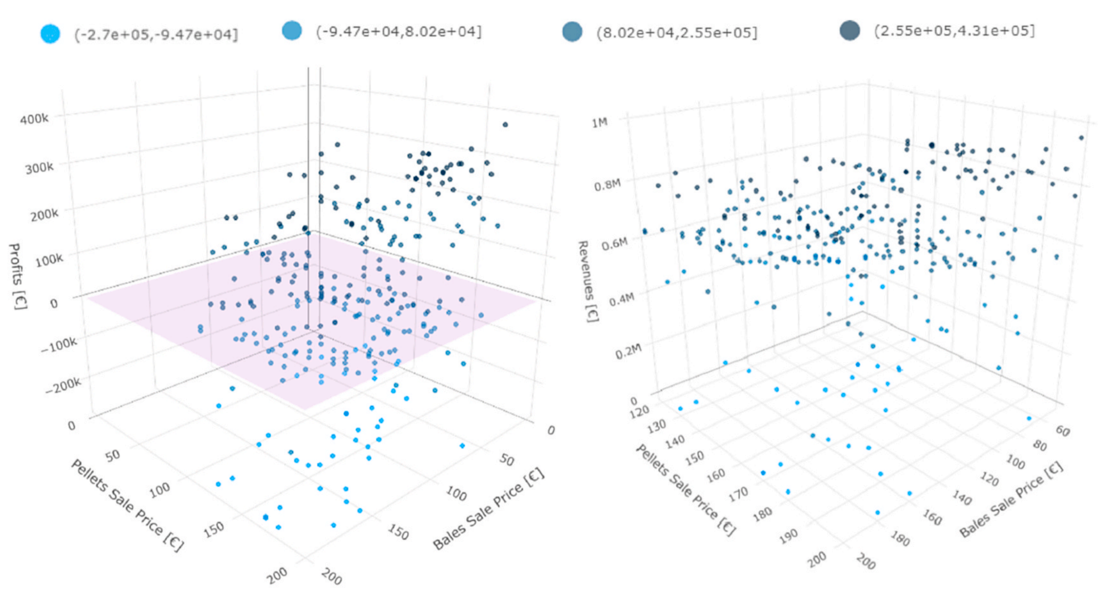


Fig. 12. Sensitivity analysis: bales (€50-€200, step €10) and pellet prices (€120-€200, step €10), profits (left), and revenues (right).

systems. Previous studies have developed simulation tools or mathematical models to evaluate the performance of biomass supply operations (Kazantzi et al., 2013; Lu et al., 2019; Nguyen and Chen, 2018). Yet, these studies consider demand as fulfilled, and do not focus on the problem of dynamically selecting suppliers and integrating supply with production activities (Malladi and Sowlati, 2018). (ii) The proposed methodology is focused on a novel concept, the IBLC, integrating both food and bio-based (non-food) value chains. The existing system for supplying food products (feed and fodder) in the case study provided is combined with supplying bio-based (intermediate) products (pellets for the energy market). Agricultural production with the suppliers of biomass feedstock is an important part of the value chain. The IBLC addresses one of the challenges identified by Salvador et al. (2021): the seasonal availability of resources, and the prioritization of the local economy allowing the minimization of logistics costs. The model developed allows exploring the transformation of biomass-to-pellet SCs considering key criteria such as quality and seasonality of biomass, one of the challenges identified by (Aghalari et al., 2021). The simulation provided can help frame the economic, social, and environmental viability of the IBLC. This will support future research that delves into the business model at a greater level of detail, as claimed by Barros et al. (2020).

Agribusiness managers and practitioners will benefit from a better understanding of how the agricultural residue procurement process and the production process influence the economic and environmental feasibility of the IBLC. The proposed methodology can be applied with minor modifications to other agroindustries (e.g., fruit and vegetables, vegetable and animal oils and fats, grain mill, etc.). Future research should focus on the purchase problem of agricultural residues for building an IBLC to foster CE in agroindustries that use other types of residues, e.g. olive prunings, leaves, straw, stalks, etc. in other European and non-European countries, exploring the suitability of the criteria used and the weight assigned according to the residue typology.

CRediT authorship contribution statement

Victoria Muerza: Conceptualization, Methodology, Data curation, Formal analysis, Writing – review & editing. **Luca Urciuoli:** Conceptualization, Formal analysis, Software, Validation, Visualization, Data curation, Funding acquisition, Methodology, Writing – review & editing. **Sebastián Zapata Habas:** Resources, Writing – review & editing.

Declaration of competing 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.

Data availability

The data that has been used is confidential.

Acknowledgments

The authors are grateful for the research funding received from the European Union's Horizon 2020 research and innovation program under Grant Agreement No 727961.

ANNEX.

Table Annex 1
Literature on supplier selection based on multicriteria or hybrids methods

Authors	Method	Criteria	Gap covered
Banaeian et al. (2018)	Comparison of TOPSIS, VIKOR, and GRA methods in a fuzzy environment.	*Service level*: on-time delivery, after-sales service, and supply capacity; *Price*: product/service price, capital, and financial power; *Quality*: quality of material, labor expertise and operation excellence; *Environmental Management Systems*: Environmental prerequisite, planning and certificates.	Incorporation of environmental criteria in the supplier selection model. Application to the agri-food sector.
Bruno et al. (2012)	AHP	*Process and Product Quality*: Non-Defect Rate, Corrective actions, Throughput Time; *Service Level*: Punctuality, Flexibility, Price Fairness; *Management and Innovation*: Human Resources, Relationships with Large Enterprises, R&D Investments; *Financial Position*: Profit Margin, Assets, Liquidity.	It provides empirical evidence of the practical usefulness of the supplier selection model in a railway manufacturer.
Gören (2018)	Fuzzy DEMATEL and Taguchi loss functions	*Economic*: Price, Productivity, Capacity of the supplier, Long-term relationship-Continuity, Lead time, Quality, Production technology, Responsiveness; *Social*: Occupational health and safety management system, Supportive activities; *Environmental*: Environmental management system, Environmental friendly product design, Resource consumption.	Integration of supplier selection and order allocation problems considering lost sales in the context of an online retailer company.
(Hadian et al., 2020)	VIKOR-AHP-BOCR model	*Benefits*: Quality, Delivery, Flexibility; *Opportunities*: Supplier's technology, Joint growth, Relationship building; *Costs*: Cost of product, Cost of relationship; *Risks*: Buyer-supplier risks; Supplier Risks, Supplier's profile risks.	The selection model considers both the advantages and disadvantages of outsourcing in a case study of the automotive sector in Iran.
Kazantzi et al. (2013)	Multicriteria decision-making based on Intuitionistic Fuzzy Sets (IFS)	Reliability; Responsiveness; Flexibility; Cost aspects; Quality; Assets and infrastructure; Environmental and safety-related issues.	The model assesses the imprecise and uncertain profiles of biomass suppliers.
(Kellner et al., 2019)	Multi-objective optimization and the Analytic network process	*Economic dimension*: Profitability, Financial position, Physical assets including capacities, Know-how & Innovations, Reputation, Geographic proximity, Flexibility/Response to changes, after-sales support, Delivery time; *Environmental dimension:* Energy, Raw materials, Greenhouse gas, Water pollution, Waste; *Social dimension:* Health & Safety standards, Ethics & Human	The developed model considers risks and sustainability for supplier selection. It is applied to an automotive OEM in Germany.

(*continued on next page*)

Table Annex 1 (*continued*)

Authors	Method	Criteria	Gap covered
		rights, Training & development programs, Contribution to Cultural development, Contribution to Economic Development.	
Khan et al. (2018)	Multicriteria Decision Making model integrating Fuzzy Shannon entropy and Fuzzy inference system	*Economic*: Cost, Quality, Delivery, Service Reliability, Capacity, Flexibility, Financial Capability; *Environmental*: Emission, Resource consumption, Environmental Management System, Use of environmentally friendly material, Cleaner technology availability, Recycled material, Green packaging, Green policy; *Social*: Employment practice, Health, and safety, Employer rights, Information disclosure, Social commitment, Business ethics.	Develops a novel methodology for the evaluation of supplier sustainability performance applied to supplier classification in a manufacturing company.
Lu et al. (2019)	Cloud model and Fuzzy AHP	*Economy*: Production price of biomass briquette, Transportation cost; *Delivery capability*: Flexible batch order, Available supply, Lead time, On-time delivery, Shortfall; *Fuel quality*: Calorific value, Fuel safety; *Environment*: Carbon emission reduction per unit fuel, Green certification, Bad environmental record, Good environmental awareness.	Selection of green suppliers in the straw biomass industry based on green and traditional indicators, taking into account uncertainty and fuzziness.
Mohammed et al. (2018)	Fuzzy AHP, TOPSIS, and multi-objective programming model	*Conventional criteria*: Costs, Livestock healthiness, Technology capability, Delivery reliability; *Green criteria*: Environment management system, Waste Management, Pollution production; *Social criteria*: Safety, rights, and health of employees, Staff development, Information disclosure.	Integration of supplier selection and order allocation problems considering the pillars of sustainability in the context of the food supply chain.
Scott et al. (2013)	QFD–AHP method	Financially robust or credible counterparty, Track record, Rural jobs created or safeguarded, CO2/MW h, Base cost of material, Fixed price, Take or play clauses, Guarantee of fuel quality available, SME employment created, Diversion of material from landfill, Distance from the buyer, Quality control mechanisms in place, Biodiversity change, Supplier stability, Environmental regulatory, Dependency on imports, Personal relationship, Contract has PFI back up, Visibility.	Identifies the most important stakeholders in the UK bioenergy industry, the requirements that these stakeholders have to meet in the supply of biomass, and the criteria to be considered in the UK context.
Scott et al. (2015)	AHP-Quality Function Deployment and chance constrained optimization algorithm approach	Long-term contracts, Take or pay clauses, Track record, Personal relationship, Contract has PFI back up, Fixed price, Traceable (chain of custody), Base cost of material (pound/MWh), Clear definition of fuel, Visibility, Quality control mechanism in place, Guarantee of fuel quality available, Supplier stability, Distance from buyer, CO2/MWh, Land use change, FSC accreditation, Alternative end use, Diversion of material from landfill, Environmental regulatory environment in which the supplier operates, Performance against sustainability assurance certificate indicators, Credit strength, Size of the balance sheet, Financially robust or credible counterparty, Rural jobs created or safeguarded, Dependency of imports, SME employment created, Biodiversity change.	The proposed method optimizes the selection of multiple suppliers under uncertain multicriteria constraints that integrate stakeholder requirements.
Sureeyatanapas et al. (2018)	TOPSIS and Rank order Centroid method	Certifications, Price, Cleaner production, Procedural compliance, Cultural congruence, Process control capability, Customer satisfaction and impression, Product appearance, Delivery performance, Product knowledge, Domestic political stability, Product quality, Ease of use, Product reliability, Environmentally friendly products, Product Safety, Financial status, Production capacity, Geographical location, Production facilities and technology, Image and experience of suppliers, Quick response to emergency, problem, or special request, Information technology and communication systems, Safety awareness, Innovation and R&D, Sale policies, Inventory and warehousing, Social responsibility, Invoicing, Serviceability, Labour relations record, Warranties and claim policies, Maintainability, Willingness to change their products and services to meet buyer's needs, Management and organisation, Willingness to participate in buyer's new product development and R&D, Packaging quality, Willingness to share sensitive information, Payment terms.	Selection of suppliers under conditions of uncertainty and unavailability of evaluation information. Application to the agri-food sector.

Table Annex 2
List of criteria for supplier selection in IBLCs.

Feed and Fodder Market (FFM)	Reference	Energy Market (EM)	Reference
C1: Social. The degree of activities performed to promote business with local suppliers.	Gören (2018), Kellner et al. (2019), Khan et al. (2018), Mohammed et al. (2018)	**C1': % chlorine.** % of chlorine in raw material supplied. The amount of chlorine affects the quantity of wood added to the mixture in the pelletizing process. Therefore, this can be stabilized by controlling the % chlorine in materials from suppliers.	Authors contribution
C2: Protein content. The quality of the straw for animal feeding	Authors contribution	**C2': % ash content.** Higher ash content lowers the heating value of the pellet decreasing quality of the product	Scott et al. (2015)
C3: % ash content. It correlates with nutritional value and therefore indicates the quality of the straw. In straw ash, the optimal percentage is expected to be in the range of 5–11%.	Scott et al. (2015)	**C3': % moisture content.** It has a significant effect on fuel pellets. Low moisture content (<10%) allows high energy conversion efficiency	Kazantzi et al. (2013), Scott et al. (2015)
C4: % Moisture content. It affects the quality of the bale and provides safer warehousing. Furthermore, a high level of humidity produces both fungal attacks and putrefaction. At a humidity level, higher than 20% straw must be rejected.	Kazantzi et al. (2013), Scott et al. (2015)	**C4': Supply stability.** Capacity to provide the required amounts of material	Scott et al. (2013), Scott et al. (2015)
C5: Supply stability. The capacity to reliably provide the required amounts of material	Scott et al. (2013), Scott et al. (2015)	**C5': Delivery time.** Time to deliver to the destination.	Banaeian et al. (2018), Hadian et al. (2020), Kellner et al. (2019), Khan et al., 82018), Lu et al. (2019), Sureeyatanapas et al. (2018)
C6: Delivery time. Time to deliver to the destination.	Banaeian et al. (2018), Hadian et al. (2020), Kellner et al. (2019), Khan et al., 82018), Lu et al. (2019), Sureeyatanapas et al. (2018)	**C6': Purchase price.** Set by the agroindustry, depends on the year, the purchase volume, the month of purchase	Banaeian et al. (2018), Bruno et al. (2012), Gören (2018), Lu et al. (2019), Scott et al. (2013), Scott et al. (2015), Sureeyatanapas et al. (2018)
C7: Color of the material. The color indicates the tannins in the straw and thereby the digestibility for animals. It also affects the marketability of the product (the whiter the more attractive)	Authors contribution	**C7': Distance.** Distance between processing plant and farm delivering the raw material.	Scott et al. (2013), Scott et al. (2015)
C8: Purchase price. It is set by the agroindustry. It is affected by seasonal factors and purchased volumes.	Banaeian et al. (2018), Bruno et al. (2012), Gören (2018), Lu et al. (2019), Scott et al. (2013), Scott et al. (2015), Sureeyatanapas et al. (2018)		
C9: Operative. Size/format of straw supplied (bales or bulk)	Authors contribution		

Table Annex 3
Ranking of food wheat suppliers ($n = 62$).

Supplier	C1	C2	C3	C4	C5	C6	C7	C8	C9	Quantity	Rank
Supplier 4	0.007	0.053	0.018	0.017	0.020	0.005	0.026	0.020	0.007	486,033	1
Supplier 17	0.008	0.050	0.012	0.017	0.024	0.004	0.026	0.020	0.008	127,490	2
Supplier 56	0.008	0.044	0.020	0.017	0.017	0.004	0.026	0.020	0.008	18,913	3
Supplier 60	0.008	0.047	0.014	0.018	0.022	0.004	0.026	0.019	0.008	2,083	4
Supplier 28	0.008	0.048	0.018	0.017	0.015	0.004	0.026	0.020	0.008	22,073	5
Supplier 30	0.008	0.043	0.017	0.017	0.018	0.004	0.026	0.020	0.008	4,417	6
Supplier 3	0.007	0.052	0.012	0.017	0.018	0.004	0.026	0.022	0.007	52,930	7
Supplier 34	0.008	0.053	0.020	0.017	0.010	0.004	0.026	0.018	0.008	33,837	8
Supplier 42	0.006	0.050	0.016	0.017	0.014	0.004	0.026	0.020	0.006	142,260	9
Supplier 22	0.008	0.047	0.013	0.017	0.018	0.003	0.026	0.020	0.008	13,490	10
Supplier 49	0.008	0.046	0.012	0.017	0.023	0.004	0.017	0.019	0.008	12,920	11
Supplier 27	0.006	0.048	0.014	0.017	0.016	0.004	0.026	0.020	0.006	35,993	12
Supplier 52	0.008	0.051	0.008	0.017	0.021	0.004	0.026	0.020	0.008	3,380	13
Supplier 55	0.008	0.051	0.009	0.017	0.017	0.005	0.026	0.020	0.008	61,003	14
Supplier 58	0.008	0.050	0.016	0.017	0.010	0.004	0.026	0.020	0.008	22,297	15
Supplier 24	0.008	0.050	0.028	0.017	0.003	0.005	0.026	0.019	0.008	4,037	16
Supplier 31	0.008	0.051	0.018	0.017	0.010	0.005	0.017	0.020	0.008	15,093	17
Supplier 50	0.008	0.038	0.014	0.017	0.019	0.005	0.026	0.020	0.008	19,210	18
Supplier 36	0.008	0.045	0.011	0.017	0.017	0.005	0.026	0.018	0.008	32,863	19
Supplier 25	0.007	0.048	0.015	0.017	0.014	0.004	0.017	0.019	0.007	95,443	20
Supplier 19	0.007	0.050	0.017	0.017	0.009	0.004	0.026	0.020	0.007	4,690	21
Supplier 46	0.008	0.049	0.010	0.017	0.015	0.005	0.026	0.020	0.008	4,790	22
Supplier 40	0.008	0.041	0.019	0.017	0.011	0.004	0.026	0.020	0.008	8,580	23
Supplier 15	0.008	0.043	0.006	0.017	0.021	0.005	0.026	0.020	0.008	7,870	24
Supplier 26	0.008	0.039	0.012	0.017	0.021	0.004	0.017	0.020	0.008	61,957	25
Supplier 35	0.008	0.046	0.012	0.017	0.013	0.005	0.026	0.018	0.008	11,613	26

(continued on next page)

Table Annex 3 (*continued*)

Supplier	C1	C2	C3	C4	C5	C6	C7	C8	C9	Quantity	Rank
Supplier 21	0.008	0.049	0.014	0.017	0.010	0.004	0.026	0.019	0.008	11,993	27
Supplier 39	0.006	0.053	0.009	0.017	0.012	0.005	0.026	0.020	0.006	5,813	28
Supplier 61	0.008	0.046	0.011	0.017	0.014	0.004	0.026	0.020	0.008	54,140	29
Supplier 1	0.008	0.046	0.006	0.017	0.018	0.005	0.026	0.020	0.008	339,180	30
Supplier 9	0.007	0.045	0.007	0.017	0.020	0.005	0.017	0.020	0.007	3,607	31
Supplier 10	0.008	0.049	0.010	0.017	0.012	0.004	0.026	0.020	0.008	6,587	32
Supplier 62	0.007	0.048	0.019	0.017	0.008	0.005	0.017	0.020	0.007	4,483	33
Supplier 32	0.008	0.043	0.009	0.017	0.015	0.004	0.026	0.019	0.008	62,650	34
Supplier 37	0.008	0.044	0.019	0.017	0.006	0.004	0.026	0.018	0.008	2,483	35
Supplier 59	0.008	0.046	0.016	0.017	0.007	0.003	0.026	0.020	0.008	0,900	36
Supplier 6	0.008	0.050	0.007	0.017	0.012	0.004	0.026	0.018	0.008	158,983	37
Supplier 16	0.008	0.052	0.015	0.017	0.005	0.004	0.026	0.018	0.008	12,223	38
Supplier 7	0.006	0.046	0.010	0.017	0.012	0.004	0.026	0.019	0.006	16,963	39
Supplier 57	0.007	0.047	0.015	0.017	0.006	0.004	0.026	0.020	0.007	69,620	40
Supplier 33	0.008	0.051	0.012	0.017	0.009	0.005	0.017	0.018	0.008	16,747	41
Supplier 13	0.008	0.041	0.007	0.017	0.016	0.004	0.017	0.018	0.008	13,260	42
Supplier 23	0.008	0.040	0.015	0.017	0.008	0.004	0.026	0.020	0.008	10,257	43
Supplier 20	0.007	0.039	0.004	0.016	0.016	0.004	0.026	0.020	0.007	87,997	44
Supplier 51	0.008	0.053	0.008	0.017	0.007	0.004	0.026	0.020	0.008	8,970	45
Supplier 12	0.008	0.040	0.011	0.017	0.010	0.005	0.026	0.019	0.008	23,457	46
Supplier 47	0.004	0.049	0.010	0.017	0.006	0.004	0.026	0.020	0.004	5,060	47
Supplier 2	0.008	0.048	0.010	0.017	0.005	0.004	0.026	0.020	0.008	26,553	48
Supplier 18	0.006	0.052	0.013	0.017	0.004	0.004	0.017	0.020	0.006	13,753	49
Supplier 14	0.008	0.050	0.010	0.016	0.004	0.005	0.026	0.020	0.008	1,900	50
Supplier 48	0.008	0.043	0.005	0.017	0.010	0.003	0.026	0.019	0.008	4,623	51
Supplier 44	0.007	0.046	0.015	0.017	0.002	0.004	0.026	0.020	0.007	42,810	52
Supplier 41	0.006	0.048	0.015	0.017	0.001	0.004	0.026	0.020	0.006	14,833	53
Supplier 53	0.008	0.045	0.012	0.017	0.003	0.004	0.026	0.018	0.008	59,010	54
Supplier 38	0.008	0.042	0.016	0.017	0.000	0.005	0.026	0.020	0.008	38,943	55
Supplier 29	0.008	0.044	0.014	0.017	0.001	0.003	0.026	0.020	0.008	22,327	56
Supplier 5	0.007	0.044	0.009	0.017	0.004	0.005	0.026	0.018	0.007	48,633	57
Supplier 11	0.007	0.049	0.014	0.017	0.000	0.004	0.017	0.020	0.007	18,430	58
Supplier 54	0.007	0.038	0.007	0.017	0.006	0.005	0.026	0.018	0.007	90,523	59
Supplier 45	0.008	0.042	0.011	0.017	0.004	0.005	0.017	0.018	0.008	16,653	60
Supplier 43	0.008	0.045	0.009	0.017	0.000	0.005	0.026	0.020	0.008	1,293	61
Supplier 8	0.008	0.049	0.010	0.017	0.008	0.004	0.026	0.020	0.008	32,853	62

Table Annex 4
Ranking of energy wheat suppliers ($n = 22$).

Supplier	C1′	C2′	C3′	C4′	C5′	C6′	C7′	Quantity	Rank
Supplier 13	0.556	0.220	0.153	0.106	0.043	0.186	0.063	2,000	1
Supplier 16	0.475	0.220	0.153	0.074	0.037	0.185	0.063	1,500	2
Supplier 5	0.478	0.220	0.153	0.013	0.037	0.192	0.063	3,000	3
Supplier 10	0.475	0.220	0.153	0.001	0.032	0.189	0.063	2,500	4
Supplier 7	0.363	0.169	0.153	0.013	0.037	0.185	0.028	3,000	5
Supplier 19	0.363	0.169	0.153	0.004	0.032	0.188	0.028	1,500	6
Supplier 14	0.307	0.195	0.153	0.106	0.043	0.195	0.036	2,000	7
Supplier 21	0.307	0.195	0.153	0.074	0.037	0.186	0.047	750	8
Supplier 15	0.307	0.195	0.153	0.074	0.037	0.192	0.036	1,500	9
Supplier 22	0.307	0.195	0.153	0.074	0.037	0.184	0.027	750	10
Supplier 9	0.307	0.195	0.153	0.069	0.032	0.189	0.036	2,500	11
Supplier 20	0.307	0.195	0.153	0.074	0.037	0.182	0.020	750	12
Supplier 4	0.307	0.195	0.153	0.013	0.037	0.185	0.036	3,000	13
Supplier 18	0.307	0.195	0.153	0.004	0.032	0.191	0.036	1,500	14
Supplier 17	0.279	0.130	0.153	0.074	0.037	0.183	0.064	1,500	15
Supplier 6	0.279	0.130	0.153	0.013	0.037	0.183	0.064	3,000	16
Supplier 1	0.195	0.079	0.153	0.032	0.043	0.176	0.028	2,000	17
Supplier 11	0.112	0.065	0.153	0.096	0.043	0.187	0.011	2,000	18
Supplier 8	0.140	0.078	0.153	0.036	0.032	0.167	0.018	2,500	19
Supplier 12	0.028	0.078	0.153	0.096	0.043	0.192	0.016	2,000	20
Supplier 2	0.056	0.078	0.153	0.032	0.043	0.173	0.014	2,000	21
Supplier 3	0.028	0.078	0.153	0.032	0.043	0.176	0.016	2,000	22

References

Aghalari, A., Aladwan, B.S., Marufuzzaman, M., Tanger, S., Da Silva, B.K., Gude, V.G., 2021. Optimizing a pellet supply system: market-specific pellet production with biomass quality considerations. Comput. Chem. Eng. 153, 107417.

Al-Wesabi, F.N., Malibari, A.A., Hilal, A.M., Nemri, N., Kumar, A., Gupta, D., 2022. Intelligent ensemble of voting based solid fuel classification model for energy harvesting from agricultural residues. Sustain. Energy Technol. Assessments 52, 102040.

Annevelink, B., van Gogh, B., Nogués, F.S., Espatolero, S., De la Cruz, T., Luzzini, D., Karampinis, M., Kougioumtzis, M., Olsson, J., 2017. Conceptual Description of an Integrated Biomass Logistics Centre (IBLC). European Biomass Conference & Exhibition 2017, Stockholm, Sweden.

Atashbar, N.Z., Labadie, N., Prins, C., 2016. Modeling and optimization of biomass supply chains: a review and a critical look. IFAC-PapersOnLine 49 (12), 604–615.

Bakan, B., Bernet, N., Bouchez, T., Boutrou, R., Choubert, J.-M., Dabert, P., Duquennoi, C., Ferraro, V., Garcia-Bernet, D., Gillot, S., 2022. Circular economy applied to organic residues and wastewater: research challenges. Waste Biomass Valorization 13 (2), 1267–1276.

Banaeian, N., Mobli, H., Fahimnia, B., Nielsen, I.E., Omid, M., 2018. Green supplier selection using fuzzy group decision making methods: a case study from the agri-food industry. Comput. Oper. Res. 89, 337–347.

Barros, M.V., Salvador, R., de Francisco, A.C., Piekarski, C.M., 2020. Mapping of research lines on circular economy practices in agriculture: from waste to energy. Renew. Sustain. Energy Rev. 131, 109958.

Benítez, J., Delgado-Galván, X., Izquierdo, J., Pérez-García, R., 2011. Achieving matrix consistency in AHP through linearization. Appl. Math. Model. 35 (9), 4449–4457.

Berbel, J., Posadillo, A., 2018. Review and analysis of alternatives for the valorisation of agro-industrial olive oil by-products. Sustainability 10 (1), 237.

Brandão, A.S., Goncalves, A., Santos, J.M., 2021. Circular bioeconomy strategies: from scientific research to commercially viable products. J. Clean. Prod. 295, 126407.

Bruno, G., Esposito, E., Genovese, A., Passaro, R., 2012. AHP-based approaches for supplier evaluation: problems and perspectives. J. Purch. Supply Manag. 18 (3), 159–172.

Chen, X., Zhan, F.B., 2014. Agent-based Modeling and Simulation of Urban Evacuation: Relative Effectiveness of Simultaneous and Staged Evacuation Strategies, Agent-Based Modeling and Simulation. Springer, pp. 78–96.

Donner, M., de Vries, H., 2021. How to innovate business models for a circular bio-economy? Bus. Strat. Environ. 30 (4), 1932–1947.

Donner, M., Gohier, R., de Vries, H., 2020. A new circular business model typology for creating value from agro-waste. Sci. Total Environ. 716, 137065.

Donner, M., Verniquet, A., Broeze, J., Kayser, K., De Vries, H., 2021. Critical success and risk factors for circular business models valorising agricultural waste and by-products. Resour. Conserv. Recycl. 165, 105236.

EC, 2020. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT. THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS, A new Circular Economy Action Plan, For a cleaner and more competitive Europe. THE COUNCIL. Accessed April 2022. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52020DC0098&from=EN.

El Amrani, Safae, Niamat Ullah, Ibne Hossain, Karam, Sofia, Jaradat, Raed, Nur, Farjana, Hamilton, Michael A., Ma, Junfeng, 2021. Modelling and assessing sustainability of a supply chain network leveraging multi–Echelon Bayesian Network. J. Clean. Prod. 302.

Eranki, P.L., Bals, B.D., Dale, B.E., 2011. Advanced regional biomass processing depots: a key to the logistical challenges of the cellulosic biofuel industry. Biofuels, Bioproducts and Biorefining 5 (6), 621–630.

Forman, E., Peniwati, K., 1998. Aggregating individual judgments and priorities with the analytic hierarchy process. Eur. J. Oper. Res. 108 (1), 165–169.

Gören, H.G., 2018. A decision framework for sustainable supplier selection and order allocation with lost sales. J. Clean. Prod. 183, 1156–1169.

Gunasekaren, A., Macbeth, D., Lamming, R., 2000. Modelling and analysis of supply chain management systems: an editorial overview. J. Oper. Res. Soc. 51 (10), 1112–1115.

Guo, X., Voogt, J., Annevelink, B., Snels, J., Kanellopoulos, A., 2020. Optimizing resource utilization in biomass supply chains by creating integrated biomass logistics centers. Energies 13 (22), 6153.

Hadian, H., Chahardoli, S., Golmohammadi, A.-M., Mostafaeipour, A., 2020. A practical framework for supplier selection decisions with an application to the automotive sector. Int. J. Prod. Res. 58 (10), 2997–3014.

Iakovou, E., Karagiannidis, A., Vlachos, D., Toka, A., Malamakis, A., 2010. Waste biomass-to-energy supply chain management: a critical synthesis. Waste Manag. 30 (10), 1860–1870.

Kazantzi, V., Gerogiannis, V., Anthopoulos, L., 2013. Multi-Criteria Decision Making for Supplier Selection in Biomass Supply Networks for Bioenergy Production, Outsourcing Management for Supply Chain Operations and Logistics Service. IGI Global, pp. 313–343.

Kellner, F., Lienland, B., Utz, S., 2019. An a posteriori decision support methodology for solving the multi-criteria supplier selection problem. Eur. J. Oper. Res. 272 (2), 505–522.

Khan, S.A., Kusi-Sarpong, S., Arhin, F.K., Kusi-Sarpong, H., 2018. Supplier sustainability performance evaluation and selection: a framework and methodology. J. Clean. Prod. 205, 964–979.

Khemiri, R., Elbedoui-Maktouf, K., Grabot, B., Zouari, B., 2017. A fuzzy multi-criteria decision-making approach for managing performance and risk in integrated procurement–production planning. Int. J. Prod. Res. 55 (18), 5305–5329.

Kowalski, Z., Makara, A., 2021. The circular economy model used in the polish agro-food consortium: a case study. J. Clean. Prod. 284, 124751.

Lamers, P., Roni, M.S., Tumuluru, J.S., Jacobson, J.J., Cafferty, K.G., Hansen, J.K., Kenney, K., Teymouri, F., Bals, B., 2015. Techno-economic analysis of decentralized biomass processing depots. Bioresour. Technol. 194, 205–213.

Lautala, P.T., Hilliard, M.R., Webb, E., Busch, I., Hess, J.R., Roni, M.S., Hilbert, J., Handler, R.M., Bittencourt, R., Valente, A., 2015. Opportunities and challenges in the design and analysis of biomass supply chains. Environ. Manag. 56 (6), 1397–1415.

Levary, R.R., 2008. Using the analytic hierarchy process to rank foreign suppliers based on supply risks. Comput. Ind. Eng. 55 (2), 535–542.

Lu, Z., Sun, X., Wang, Y., Xu, C., 2019. Green supplier selection in straw biomass industry based on cloud model and possibility degree. J. Clean. Prod. 209, 995–1005.

Mafakheri, F., Nasiri, F., 2014. Modeling of biomass-to-energy supply chain operations: applications, challenges and research directions. Energy Pol. 67, 116–126.

Maheshwari, P., Singla, S., Shastri, Y., 2017. Resiliency optimization of biomass to biofuel supply chain incorporating regional biomass pre-processing depots. Biomass Bioenergy 97, 116–131.

Malladi, K.T., Sowlati, T., 2018. Biomass logistics: a review of important features, optimization modeling and the new trends. Renew. Sustain. Energy Rev. 94, 587–599.

Mohammed, A., Setchi, R., Filip, M., Harris, I., Li, X., 2018. An integrated methodology for a sustainable two-stage supplier selection and order allocation problem. J. Clean. Prod. 192, 99–114.

Muerza, V., Larrodé, E., Moreno-Jiménez, J.M., 2017. Identification and selection of ICTs for freight transport in product service supply chain diversification. Ind. Manag. Data Syst. 117 (7), 1469–1484.

Muerza, V., Urciuoli, L., Annevelink, B.E., Snels, J., van Dam, J.E.G., 2020. Managing biomass supply chains: the importance of strategic leadership. In: Dwivedi, A., Alshamrani, M. (Eds.), Leadership Strategies for Global Supply Chain Management in Emerging Markets. IGI Global, pp. 1–27.

Nguyen, D.H., Chen, H., 2018. Supplier selection and operation planning in biomass supply chains with supply uncertainty. Comput. Chem. Eng. 118, 103–117.

Palak, G., Ekşioğlu, S.D., Geunes, J., 2014. Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: an application to a biofuel supply chain. Int. J. Prod. Econ. 154, 198–216.

Rezaei, J., Pourmohammadzia, N., Dimitropoulos, C., Tavasszy, L., Duinkerken, M., 2020. Co-procurement: making the most of collaborative procurement. Int. J. Prod. Res. 58 (15), 4529–4540.

Roy, T., Garza-Reyes, J.A., Kumar, V., Kumar, A., Agrawal, R., 2022. Redesigning traditional linear supply chains into circular supply chains–A study into its challenges. Sustain. Prod. Consum. 31, 113–126.

Saaty, T., 1980. The Analytic Hierarchy Process. McGraw Hill, reprinted by RWS Publication, New York, NY. Pittsburgh.

Salmon, C., Mobin, M., Roshani, A., 2015. TOPSIS as a Method to Populate Risk Matrix Axes. In: IIE Annual Conference. Proceedings. Institute of Industrial Engineers-Publisher, p. 1504.

Salvador, R., Puglieri, F.N., Halog, A., de Andrade, F.G., Piekarski, C.M., Antonio, C., 2021. Key aspects for designing business models for a circular bioeconomy. J. Clean. Prod. 278, 124341.

Scott, J.A., Ho, W., Dey, P.K., 2013. Strategic sourcing in the UK bioenergy industry. Int. J. Prod. Econ. 146 (2), 478–490.

Scott, J., Ho, W., Dey, P.K., Talluri, S., 2015. A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments. Int. J. Prod. Econ. 166, 226–237.

Sharma, B., Ingalls, R.G., Jones, C.L., Khanchi, A., 2013. Biomass supply chain design and analysis: basis, overview, modeling, challenges, and future. Renew. Sustain. Energy Rev. 24, 608–627.

Sharma, B., Clark, R., Hilliard, M.R., Webb, E.G., 2018. Simulation modeling for reliable biomass supply chain design under operational disruptions. Front. Energy Res. 6, 100.

Sherwood, J., 2020. The significance of biomass in a circular economy. Bioresour. Technol. 300, 122755.

Suardi, A., Bergonzoli, S., Alfano, V., Scarfone, A., Pari, L., 2019. Economic distance to gather agricultural residues from the field to the integrated biomass logistic centre: a Spanish case-study. Energies 12 (16), 3086.

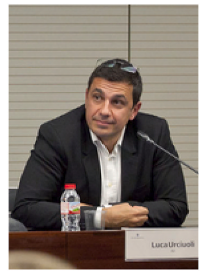
Sun, Fangzhou, Sarin, Subhash C., Cundiff, John S., Ozan Sert, I., 2020. Design of Cost-Effective Sorghum Biomass Feedstock Logistics-A Comparison of Different Systems, 143. Biomass and Bioenergy.

Sureeyatanapas, P., Sriwattananusart, K., Niyamosoth, T., Sessomboon, W., Arunyanart, S., 2018. Supplier selection towards uncertain and unavailable information: an extension of TOPSIS method. Operations Res. Perspect. 5, 69–79.

Urciuoli, L., Hintsa, J., 2018. Improving supply chain risk management – can additional data help? Int. J. Logist. Syst. Manag. 30 (2), 195–224.

Vlachokostas, C., Achillas, C., Agnantiaris, I., Michailidou, A.V., Pallas, C., Feleki, E., Moussiopoulos, N., 2020. Decision support system to implement units of alternative biowaste treatment for producing bioenergy and boosting local bioeconomy. Energies 13 (9), 2306.

Dr. Victoria Muerza Victoria Muerza is an Assistant Professor at the University of Zaragoza, area of Quantitative Methods for Business and Economy. She holds a BSc in Electronics Engineering, a MSc in Industrial Engineering, and a Ph.D. in Industrial Engineering from the University of Zaragoza. She has been certified as a Risk Management Expert and a Quality Management Expert by the National Distance Education University (UNED). Dr. Muerza's main research interests include multi-criteria decision-making, decision-making optimization, Transport and Logistics in the Supply Chain, the analysis and development of industrial and technological diversification processes, the analysis of the technological competitiveness of firms and regions, the management of technology and innovation, and technology evaluation. Dr. Muerza has previously been employed as a research engineer in the "Council for Competitiveness and Industrial and Technological Diversification of the University of Zaragoza", the "Aragon Institute of Engineering Research (i3A)" in the Transport and Logistics area, and as a Postdoctoral researcher at "Zaragoza Logistics Center" in the MIT International Logistics Program.



Dr. Luca Urciuoli Luca Urciuoli is an Associate Professor (Docent) at KTH Royal Institute of Technology, Department of Industrial Economics and Management. Currently, he is also Adjunct Professor at the MIT - Zaragoza Logistics Center (Zaragoza, Spain), and a research affiliate at the MIT Center for Transportation and Logistics (Boston, US). In the past, he has been working at the research unit of the Volvo Group, the Cross-border Research Association in Switzerland, and collaborated in several consultancy and EU FP7/H2020 research projects, with a focus on topics like e-Customs, trade facilitation, supply chain security, waste, bio-mass, digitalization, and postal supply chains. Dr. Urciuoli has a patent granted in the US in 2012 and his publications have appeared in several prestigious peer-reviewed journals. He has participated in ALICE activities related to the development and establishment of the Physical Internet initiative as vice chair of the working group for transport sustainability, safety, and security. In addition, he has been an invited speaker to several conferences and roundtables organized by international organizations like the World Customs Organization, the World Bank Group, OSCE-UNECE, European Shippers Council, PostEurop, etc.

MSc, Sebastian Zapata MSc Zapata has a master's degree in chemical engineering from the University of Granada and a master in Renewable Energy from the University of Córdoba. He has experience as a Process/Quality and R&D Engineer in an innovation company focusing on the transformation of biomass into energy applications. Since 2017 he has been working at CIRCE Foundation as a researcher first and after 2020 as Technology Project Manager, in the Technologies for Bioeconomy team, a part of the Industry and Energy Department. During his time at CIRCE he has been developing different technical innovative projects based on the energetic use of lignocellulosic biomass both at the European and National scale, mainly focused on developing new value chains, assessing ways for the decarbonization of energy-intensive industries, characterization of the biomass, combustion test, verification of boilers, feasibility studies and business models.