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Optimizing Logistics Operations through Big Data in a Solar Panel Company

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Abstract

Logistics is a critical aspect of any manufacturing industry and, with the advent of the digital age, the amount of data generated in the logistics operations has grown exponentially. Companies are now facing challenges in making cost-effective use of the vast amount of data available from various sources with different levels of quality. This has led to a pressing need for appropriate tools and techniques to effectively manage and organize this colossal volume of data. In this context, the application of Big Data in logistics has gained immense significance in recent years. Proper use of Big Data can help manufacturing companies optimize their logistics operations and make informed decisions by prioritizing data based on its relevance and quality. The purpose of this research paper is to sort various strategies related to the use of Big Data in logistics operations through a multi-criteria decision-making approach, applied to the real case of a solar panel company. To evaluate their impact, the study considers different relevant factors such as lead time, quality, environmental impact, cost-effectiveness, and others. The proposed method categorizes each logistic strategy into three classes, namely "preferred", "acceptable", and "rejected", by assessing them against criteria. The results show that route optimization is the preferable strategy for the company, as confirmed by both the pessimistic and optimistic procedures. The logistics industry faces challenges in optimizing routes, especially when dealing with a large amount of data. However, the emergence of Big Data tools has revolutionized their approach to routing, allowing them to make informed and data-driven decisions that can help them save time, money, and resources.

Keywords: Big Data; Logistic Strategies; Multi-Criteria Decision-Making; Renewable Energy Industry

1. Motivation of Research

As time progresses, the world is witnessing an unprecedented and exponential growth in the sheer magnitude of data being generated and processed, surpassing all previous records. In today's digital age, we are inundated with an overwhelmingly vast amount of information that is predominantly generated through the use of the Internet and various communication systems. As a result, there is an urgent and compelling need for appropriate tools and techniques to effectively manage and organize this colossal volume of data. (Qi et al., 2023).

As Big Data continues to grow, it becomes increasingly challenging for firms to make cost-effective use of the vast amount of data available from various sources. To address this challenge, companies have made substantial investments in databases and analytical tools, aiming to empower themselves with the capability to make informed decisions based on data-driven insights. Prioritizing data based on its relevance and quality is a way to avoid the costs associated with producing uninformative reports and wasting valuable resources, which can ultimately negatively impact performance (Wilkin et al., 2020).

This paper proposes a Multi-Criteria Decision-Making (MCDM) approach to evaluate various strategies related to the application of Big Data and make recommendations with the aim of optimizing the logistics operations of a manufacturing company operating in the renewable energy industry. The study evaluates the impact of different strategic actions on logistics performance by considering factors such as lead time, quality, environmental impact, cost-effectiveness, and so on. The strategies tested include route optimization, demand forecasting, supply chain visibility, inventory management and green supplier selection, among others. By using MCDM, manufacturing companies can identify the best Big Data solutions to improve their logistics performance. In detail, we propose a MCDM-based approach to sort logistic strategies into recommendation categories based on various criteria from the literature. The literature review is presented in Section 2, followed by a description of the materials and the proposed methodological approach in Section 3. In Section 4, a real case study of a company manufacturing and marketing solar panels is presented, while Section 5 concludes the work by discussing potential avenues for future research.

2. Literature Review

Big data technologies aid business stakeholders in their decision-making process by integrating, analyzing, and interpreting data. This can lead to valuable insights being gained into customer behavior, market trends, operational inefficiencies, etc. These insights can then be used to make informed decisions that can positively impact the organization (Wang et al., 2020). For this reason, not only has Big Data become a pivotal factor in industry but also in various organizations and companies operating in different sectors. The field of Big Data offers a wide range of techniques and tools that can be used to extract meaningful insights from large volumes of data. To make data processing more manageable, it is crucial to structure and shape data appropriately. Data visualization is an essential aspect of this process, as it involves the representation of data in a visual format that captures the most critical information. By visualizing data, practitioners can easily understand and interpret complex data sets, making it a valuable tool in the analysis and decision-making process (Qi et al., 2023). Moreover, the use of new technologies like Big Data Analytics, has transformed many organizations by offering new possibilities to extract value from data. Such Big Data tools have the potential to improve customer management, supply chain management, risk management (Carpitella et al., 2021b), and help firms achieve a competitive advantage. Thus, companies are increasingly leveraging Big Data technologies to enhance their business management control and stay ahead of the competition (Dehbi et al., 2022). These technologies can handle a massive amount of data and are capable of processing it faster and more efficiently than traditional data management tools. Common Big Data technologies include:

- Hadoop: an open source software framework well-known for its ability to efficiently process large data sets (Usha and Jenil, 2014).
- Spark: software known for its fast and flexible computing capabilities, thanks to its in-memory system, which improves performance by storing data in memory rather than on disk (Acharjya and Ahmed, 2016).
- NoSQL databases: a type of database that is designed to handle unstructured and semi-structured data sets (Oussous et al., 2017).
- Apache Cassandra: distributed NoSQL database management system that can handle large amounts of structured and unstructured data with high scalability and availability (Chebotko et al., 2015).
- Machine learning tools: a set of algorithms and tools used to build predictive models and make predictions based on large data sets (Dehbi et al., 2022).
- Data visualization tools: a set of software tools used to represent complex data sets in an easily understandable format, such as graphs and charts (Oussous et al., 2018).

With the ever-increasing amount of data being generated, Big Data technologies will continue to play a vital role in helping organizations stay competitive and successful. Supply chain inefficiencies and waste can pose significant challenges to Logistics and Supply Chain Management (LSCM). Some of the major obstacles include slow shipments, escalating fuel prices, unreliable suppliers, and heightened consumer demands, among others (Barnaghi et al., 2013). Big Data has the potential to revolutionize the logistics industry, setting it apart from conventional practices. With vast amounts of information and by establishing stronger connections, the use of Big Data in logistics can be complex, but also rewarding. It may expedite processes, improve innovation management, guarantee service quality, and lower operational risk, ultimately leading to higher quality outcomes. To fully capitalize on these benefits, logistics companies must prioritize information management, meticulous attention to detail, standardized operations, and innovative business culture (Jin and Yang, 2020). With proper use and management of Big Data, informed decisions can be made in various logistic aspects. For instance, the transportation-related components of logistics need sound judgment, which Big Data may help with. Not only does intelligent transportation planning increase the effectiveness of distribution but it also lowers the expenses associated with distribution for logistics firms. Through the analysis and categorization of order information and inventory location data, the transportation decision-making process can factor in various circumstances faced by the distribution team, including traffic, weather, and other variables. Several types of material are included in logistics Big Data, such as logistics pricing, industry data, infrastructure, macroeconomic indicators, logistics parks, logistics firms, and other data of various types, systems, and formats (Jia and et al., 2018). Big Data serves as a strong foundation for establishing innovative business models, allowing service providers to streamline logistics procedures and enhance customer support. Information from stores, shipping companies, invoices, and other sources constitutes valuable data. An important part is also played by information from consumer profiles, social networking profiles, orders, market projections, and regional schemes. Retailers may fulfill the expectations of their consumers by foreseeing their behavior by using customer data to assess information from the delivery system. The majority of organizations, including logistics firms, strive to innovate in a number of areas to create value for clients who are requesting faster delivery, product availability, and dependability more frequently. Opportunities to address these client expectations and develop logistics are indeed provided by Big Data, which makes it a pivotal asset for these industries (Witkowski, 2017).

Prescriptive analytics plays a crucial role in recommending strategies for managing Big Data in sustainable logistics (Wang and Yan, 2022; Carpitella et al., 2022), given the vast amount of data to be collected, analyzed and interpreted in logistics operations (Mitroshin et al., 2022). This includes the use of MCDM methods, such as ELECTRE (Elimination Et Choix Traduisant la Realite) TRI, which can effectively allow logistics professionals to systematically evaluate and compare strategies considering the complex and dynamic nature of logistics operations (Carpitella et al., 2021a). ELECTRE TRI enables decision-makers to sort a set of alternatives under relevant criteria, considering both qualitative and quantitative factors. It allows for flexible definition of criteria and assignment of weights based on their importance (Ahmed et al., 2021b). By evaluating each logistic strategy against criteria, ELECTRE TRI generates categories for each strategy, such as "preferred", "acceptable", or "rejected". The use of ELECTRE TRI has been used in literature to pursue sustainable goals in logistics (Biluca et al., 2020), as it offers several advantages. It provides a structured and systematic approach for evaluating and selecting strategies, managing subjectivity in decision-making. It enables holistic evaluation of strategies by considering multiple criteria simultaneously. It offers flexibility by allowing decision-makers to adjust criteria weights and thresholds based on changing organizational needs or market conditions. Moreover, ELECTRE TRI facilitates transparency and communication among decision-makers, providing a clear visualization of the decision process and results (Galo et al., 2018).

3. Materials and method

Section 3 offers a comprehensive overview of the research approach undertaken in the study. This section starts by introducing the specific criteria and strategies that will be analyzed for optimizing logistic operations. To evaluate the impact of these strategies, the research employs an MCDM approach, specifically the ELECTRE TRI method, which effectively sorts the logistic strategies related to Big Data.

3.1. Definition of criteria and strategies

As mentioned above, this paper analyzes the impact of several strategies related to the use of Big Data as a tool to optimize logistic operations in a solar panel company. Logistics is a crucial aspect of any manufacturing industry, and careful consideration of multiple factors is necessary to ensure its effectiveness. An MCDM approach is herein used to evaluate the impact of these strategies on the logistics process. The criteria and strategies to be analyzed in this research are presented in this section, along with the proposed MCDM methodology. The set of relevant criteria aiming at optimizing logistics operations using Big Data has been identified in literature and presented in Table 1. With relation to these criteria, different logistic strategies have been discussed in literature. The most significant ones have been synthesized in Table 2.

Table 1. Relevant criteria analyzed in literature

ID	Criteria	Description and references
B_1	Lead Time Optimization	The capability of minimizing the amount of time it takes for a product to be delivered from the moment an order is placed to the time it arrives at its destination (Jing and Yang, 2022; Moh'd Anwer, 2022).
B_2	Customer Satisfaction	The extent to which customers feel their needs and expectations are met regarding the timely delivery, accuracy, quality, and overall performance of logistics services provided to them (Wu and Dong, 2023).
B_3	Reliability	The ability to deliver logistics services consistently and accurately as promised (Ozkan and Kilic, 2019; Moh'd Anwer, 2022).
B_4	Responsiveness	The willingness and ability to address and resolve customer inquiries or complaints promptly (Moh'd Anwer, 2022).
B_5	Cost-effectiveness	The ability to provide logistics services at a reasonable cost relative to the level of service provided (Shao et al., 2023).
B_6	Quality	The assurance of protecting customers' goods from damage, deterioration or loss during transportation and handling (Ren et al., 2022).
B_7	Eco-advancement	The capability of minimizing the effects of logistics operations on the natural environment, including aspects such as carbon emissions, waste generation, water consumption, air pollution, and biodiversity (Nogueira et al., 2022; Muñoz-Villamizar et al., 2021).

3.2. ELECTRE TRI method

As previously highlighted, ELECTRE TRI is advantageous for sorting logistic strategies related to Big Data due to its ability to handle multiple criteria with associated weights, accommodate imprecise information, and provide a clear assignment, making it suitable for complex decision-making in the renewable energy market, object of our case study. ELECTRE TRI can be implemented in two phases.

Table 2. Logistic strategies related to the use of Big Data

ID	Strategies	Description and references
A_1	Route optimization	Analyzing large data sets, including traffic patterns, weather conditions, and delivery schedules, can help optimize the routes for transportation fleets, reducing transportation costs, and improving delivery efficiency (Martikkala et al., 2023).
A_2	Demand forecasting	Processing historical sales data, market trends, and customer preferences can help accurately forecast demand, enabling optimized production planning, inventory management, and resource allocation (Zhao et al., 2018).
A_3	Supply chain visibility	Providing real-time visibility into the entire supply chain, allowing for better tracking and monitoring of goods, inventory levels, and transportation status, improving transparency and reducing supply chain disruptions (Dey, 2022).
A_4	Warehouse management	Assessing warehouse layouts and order volumes can optimize warehouse operations, including storage, picking, and packing, resulting in improved efficiency and reduced costs (Tiwari, 2023).
A_5	Last-mile delivery optimization	Evaluating customer locations, delivery preferences, and traffic conditions can help optimize last-mile delivery operations, reducing delivery time, and improving customer satisfaction (Silva et al., 2023).
A_6	Inventory optimization	Interpreting trends of inventory levels, demand patterns, and lead times can help optimize inventory management, reducing stockouts, overstocks, and holding costs (Tian and Wang, 2022).
A_7	Green supplier management	Reviewing suppliers under the perspective of reducing procurement cost and carbon emissions can help identify high-performing stakeholders (Lamba and Singh, 2019).
A_8	Risk management	Assessing potential risks, such as disruptions in transportation, weather events, or geopolitical factors, can help mitigate risks and develop contingency plans to ensure supply chain resilience (Gupta et al., 2022).
A_9	Eco-efficient management	Investigating on carbon emissions, energy consumption, and waste generation can help optimize logistics operations to reduce the environmental impact of transportation and warehousing activities (Raut et al., 2021).
A_{10}	Real-time tracking and monitoring	Using real-time data from IoT devices, sensors, and other sources can provide real-time tracking and monitoring of shipments, vehicles, and assets, enabling proactive decision-making and improving operational efficiency (Chen et al., 2021).

The first phase involves defining outranking relations between pairs of alternatives and reference profiles using concordance and discordance indices. The second phase proceeds to the assignment of alternatives to classes on the basis of the outranking relations established in the previous phase. Readers seeking further detailed information are encouraged to consult (Greco et al., 2016; Ahmed et al., 2021a; Carpitella et al., 2021a). It is necessary to define ordered classes without any intersection among the related reference profiles and collect the following input data for implementation:

- set of criteria $B_k, (k = 1, \dots, K)$ and related weights w_k, expressing theit mutual importance;
- set of reference profiles $P_j, (j = 1, \dots, J)$ corresponding to specific evaluations for each criterion;
- number $J + 1$ of classes C_h determined by the J reference profiles;
- set of alternatives $A_i, (i = 1, \dots, I)$ and their evaluations $B_k(A_i)$ under each criterion B_k;
- cutting value λ ranged between $[0.5, 1]$ (assumed as 0.75 in our case study);
- indifference (I_k), strong preference (S_k) and veto (V_k) thresholds characterising outranking relations.

Once accomplished the input data collection, the procedure is initialized with the first stage, i.e. establishing an outranking relation comparing each alternative with limits of classes (reference profiles). The first stage includes the following five steps.

- Calculating concordance indices for each criterion by means of formula 1.

$$C_k(A_i, P_j) = \begin{cases} 1 & if \quad [B_k(A_i) - B_j(P_j)] \leq I_k \\ \frac{B_k(P_j) - B_j(A_i) + S_k}{S_k - I_k} & if \quad I_k < [B_k(A_i) - B_j(P_j)] \leq S_k \\ 0 & if \quad [B_k(A_i) - B_j(P_j)] > S_k \end{cases} \quad (1)$$

- Calculating the aggregated concordance index matrix $C(A_i, P_j)$ by means of formula 2.

$$C(A_i, P_j) = \frac{\sum_{k=1}^{K} w_k \cdot C_k(A_i, P_j)}{\sum_{k=1}^{K} w_k}. \quad (2)$$

- Calculating discordance indices for each criterion by means of formula 3.

$$D_k(A_i, P_j) = \begin{cases} 1 & if \quad [B_k(A_i) - B_j(P_j)] \geq V_k \\ \frac{B_j(A_i) - B_k(P_j) - S_k}{V_k - S_k} & if \quad S_k \leq [B_k(A_i) - B_j(P_j)] < V_k \\ 0 & if \quad C_k(A_i, P_j) \neq 0 \end{cases} \quad (3)$$

- Calculating outranking credibility indices by means of formula 4.

$$\delta(A_i, P_j) = C(A_i, P_j) \cdot \prod_{k \in K^*} \frac{1 - D_k(A_i, P_j)}{1 - C(A_i, P_j)}. \quad (4)$$

If the veto threshold is not established (as it is the case of our case study), the credibility index $\delta(A_i, P_j)$ is equal to the aggregated concordance index $C(A_i, P_j)$.

- Using the cutting level λ to define the outranking relations (incompatibility, preference and indifference relations), as explained in (Ahmed et al., 2021a; Carpitella et al., 2021a).

The second stage is implemented to sort alternatives to classes by means of the pessimistic and the optimistic procedures. In general, the pessimistic procedure has to be preferred to the optimistic procedure, as it tends to assign alternatives to classes defined by a lower profile and achieve more conservative results.

- Pessimistic procedure: alternative A_i is assigned to the highest class C_h for which the condition that A_i outranks P_j is verified.
- Optimistic procedure: alternative A_i is assigned to the lowest class C_h for which the condition that A_i outranks P_j is verified.

4. Case Study

The company under study has a primary focus on manufacturing and marketing high-quality solar panels for the renewable energy industry. The solar panels are assembled using only high-quality components in a highly automated facility, adopting innovative technologies such as ribbon-less technology to achieve higher efficiency and reliability compared to traditional technologies. The company is constantly seeking optimized logistical solutions to ensure a consistent and easily programmable supply of modules over time. It offers a range of cutting-edge, next-generation products to meet the technical and design requirements demanded by the current market. The modules are available for sale with prompt delivery, and sales are primarily targeted at installers, designers, and photovoltaic material retailers. In recent years, the renewable energy market has experienced significant fluctuations, and one of the challenges encountered is the difficulty in sourcing solar panels that do not always meet the timelines required by customers. With the dynamic and fluctuating nature of the renewable energy market, including the challenges of timely sourcing of solar panels, optimizing logistics operations becomes essential. The efficient management of Big Data in logistics certainly plays a crucial role in the commercialization of solar panels for the company under study. By leveraging innovative technologies and data-driven solutions of supply chain analytics, the company would ensure smooth and reliable supply chain operations. This would allow for better planning, coordination, and synchronization of various processes involved in the commercialization of solar panels, resulting in improved customer service, reduced lead times, and enhanced overall operational efficiency.

We believe that providing a guide on which logistic strategy to prioritize from the alternatives presented in Table 2, to meet the criteria outlined in Table 1, would not only benefit the company under study but also other companies operating in the renewable energy market.

After implementing a brainstorming process with the company management, strategies have been evaluated under criteria by using a 10-point scale, for which higher values represent stronger beneficial impacts on criteria. Input evaluations are reported in Table 3 along with reference profiles, indifference and strong preference thresholds, namely I_k and S_k, and criteria weights w_k. No veto threshold has been established. As it is possible to observe, the company management suggested to attribute more importance to the eco-advancement criterion, while keeping the same weights for the other criteria. We now implement the ELECTRE TRI procedure by sorting strategies into three ordered classes, defined by the reference profiles b_1 and b_2: class C_1 (preferred), class C_2 (acceptable), class C_3 (rejected). We herein recall that the cutting value is assumed as $\lambda = 0.75$ in this application. Results derived from the application of the pessimistic and optimistic procedures are reported in Table 4 (and graphically displayed in Figure 1), having been validated by means of the J-Electre-v2.0 software for multi-criteria decision aid (https://sourceforge.net/projects/j-electre/files/).

Table 3. Input evaluations, reference profiles, thresholds and weights

	B_1	B_2	B_3	B_4	B_5	B_6	B_7
b_2	7	7	7	7	7	7	7
b_1	3	3	3	3	3	3	3
I_k	1	1	1	1	1	1	1
S_k	3	3	3	3	3	3	3
w_k	0.125	0.125	0.125	0.125	0.125	0.125	0.250
A_1	10	10	9	7	8	7	9
A_2	7	5	8	7	7	4	4
A_3	7	3	8	6	3	5	4
A_4	6	5	5	6	7	8	7
A_5	9	4	7	8	5	5	2
A_6	6	5	7	5	7	4	4
A_7	2	7	6	5	4	7	9
A_8	7	7	8	6	3	8	7
A_9	2	7	6	5	4	7	9
A_{10}	2	9	7	8	4	8	4

Table 4. Assignment of strategies to classes

ID	Pessimistic	Optimistic
A_1	C_1	C_1
A_2	C_2	C_2
A_3	C_2	C_2
A_4	C_2	C_1
A_5	C_2	C_2
A_6	C_2	C_2
A_7	C_2	C_2
A_8	C_2	C_2
A_9	C_2	C_2
A_{10}	C_2	C_2

Based on the application of ELECTRE TRI, it can be observed that route optimization (A_1) is the preferred strategy. As per the methodological explanation, results from the pessimistic procedure take precedence over results from the optimistic procedure. However, the optimistic procedure also indicates that apart from A_1, warehouse management (A_4) is also a favorable strategy. This suggests a potential order for the implementation of different strategies. It should be noted that these results are subjective and depend on the values attributed by the company

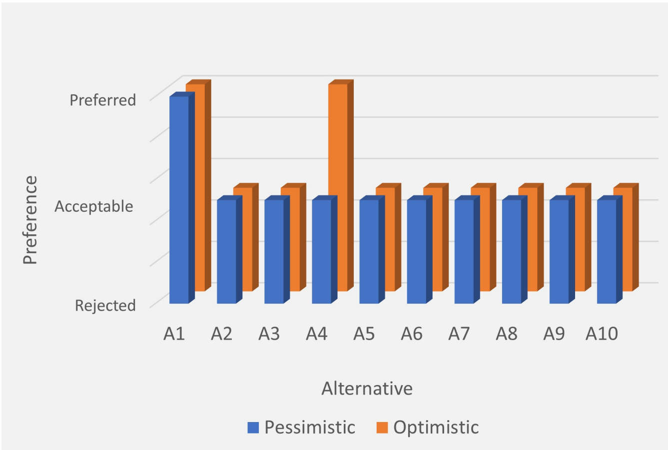

Figure 1. Assignment of strategies to classes

management, and may vary based on the context of reference, highlighting the flexibility of the proposed method.

Route optimization can be challenging, especially when dealing with a large amount of data. The transportation industry has been leveraging Intelligent Transportation Systems (ITS) to improve their services. The emerging technologies of the Internet of Things (IoT) and cloud computing have provided unprecedented opportunities for the development of innovative ITS, where sensors and mobile devices gather information for data-driven decision-making. However, to fully utilize the potential of these systems, Big Data Analytics is required to process and analyze the huge amount of data generated by millions of vehicles, traffic infrastructures, smartphones, weather stations, etc. By analyzing data from multiple sources, transportation companies can identify optimal routes, reduce congestion and emissions, improve safety, and optimize fleet management (Mohammed et al., 2020).

Logistics companies have traditionally relied on routing systems to determine the best time to start their transportation operations. However, the emergence of Big Data tools has revolutionized the industry's approach to routing, allowing companies to make data-driven decisions that can help them save time, money, and resources while improving the overall efficiency of their operations. Several potential solutions can be found in the literature such as the Standard Genetic Algorithm (SGA) II for solving multi-objective optimization Vehicle Routing Problems With Time Windows (VRPTW) (Qu and Li, 2022) or the Evolutionary Multi-objective Optimization (EMO) algorithm (Wang et al., 2011). Other studies present the use of data mining and delivery optimization models (Pan et al., 2017), as well as swarm intelligent optimization algorithm for vehicle path planning (Kyriakakis et al., 2021).

5. Conclusions and Future Lines

The importance of Big Data is already well known in different fields. This study emphasizes the value of channelizing Big Data, particularly using the ELECTRE TRI approach, to make decisions in the field of logistics of a company operating in the renewable energy market.

Based on the analysis using ELECTRE TRI, it appears that route optimization (A1) is the most desirable strategy. The method prioritizes the results obtained from the pessimistic procedure more than those from the optimistic procedure. Nevertheless, the optimistic procedure also highlights warehouse management (A4) as a favorable strategy alongside A1.

Moreover, this study contributes to the literature as the ELECTRE TRI application effectively deals with subjective evaluations of strategies related to Big Data, and decision makers can contemplate multiple criteria. This approach can support informed logistic decisions and the evaluation of risks related to preferred alternatives. The future studies of this research can be planned on situations where there is uncertainty even while assigning values to strategies. This is where studies in this direction can be done using the fuzzy set theory. Diving deep into the proper use of Big Data into logistics can open more avenues for industries and customers at a global level for satisfying multiple criteria and achieving benefits which were previously thought to be impossible.

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