INDUSTRY 4.0 TECHNOLOGIES FOR REVERSE LOGISTICS: INTEGRATED BAYESIAN-BWM AND COBRA METHOD

Ajaygopal K.V.[1], *Rakesh Verma*[2#], *Saroj Koul*[3],

Highlights of this study

- Introduces a novel integration of the *Bayesian-Best-Worst Method* (Bayesian-BWM) with *COmprehensive-distance Based RAnking* (COBRA) for ranking alternatives.
- The Bayesian-BWM-COBRA method, based on 16 criteria identifies and evaluates ten different Industry 4.0 technologies employed for *Reverse Logistics* (RL).
- IoT is ranked highest for RL, followed by cloud computing and e/mobile marketplaces; autonomous vehicles rank lowest.
- Explores last-mile delivery scenarios, stakeholder-driven evaluations, and expanding COBRA for broader applications, hybrid models and fuzzy or interval environments.

ABSTRACT

The logistics sector is vital in the supply chain, ensuring freight transport is fast, flexible, safe, cost-effective, efficient, and environmentally sustainable. The circular economy (CE) emphasizes maintaining the highest utility and value of goods, components, and materials, highlighting the role of effective reverse logistics (RL) processes. Traditional RL methods often fall short in modern supply chains, necessitating Industry 4.0 technologies to enhance efficiency. This study assesses the applicability of various Industry 4.0 technologies in the RL sector, identifying the most suitable options. A novel "multicriteria decision-making (MCDM)" model was developed, combining the Bayesian Best-Worst Method (BWM) for criteria weights with the "Comprehensive Distance-Based Ranking (COBRA)" method for ranking technologies. The ranking of the proposed method is compared with other prominent MCDM methods to validate this innovative approach. Findings revealed that the most applicable technologies are the "Internet of Things (IoT)", cloud computing, and electronic-mobile marketplaces. These advancements are expected to significantly influence RL processes and CE systems, contributing to positive environmental and economic outcomes.

Keywords: Circular Economy; Reverse Logistics; Industry 4.0; MCDM; Bayesian-BWM; COBRA

[1] Ajaygopal KV, PhD Scholar, Operations and Supply Chain Management, Indian Institute of Management Mumbai, Mumbai, India, ajaygopal.2020@iimmumbai.ac.in (ORCID: 0000-0002-4119-7458).

[2#] Rakesh Verma, Professor, Analytics & Data Sciences, Indian Institute of Management Mumbai, Mumbai, India, Rakeshverma@iimmumbai.ac.in (ORCID: 0000-0002-3637-7788) Corresponding Author.

[3] Saroj Koul, Professor, Jindal Global Business School, OP Jindal Global University, Haryana, India, skoul@jgu.edu.in (ORCID: 0000-0002-3051-5625).

1. Introduction

With the spread of the circular economy (CE) paradigm, environmental, social, and economic challenges have gained prominence in decision-makers' agendas (**Geissdoerfer et al., 2017**), highlighting the fundamental role of the supply chain. The supply chain includes all activities and processes involved in producing goods, from raw materials to final customers (**CLM, 2013**). This study focuses on logistics, which involves the organization, planning, control, and realization of the flow of goods from the point of origin through production, distribution, and point of sale to end consumers, aiming to meet market demands with minimal costs and investment (**CLM, 2013**).

As the framework for all systems and processes, logistics enables the movement of material and non-material flows. Divided into two parts, it is 1) *Forward Logistics* comprising procuring raw materials, product development, manufacturing and distribution to end-consumers, and 2) *Reverse Logistics* involving backflows of returns and recalls for resale, reuse, repair, refurbishment, remanufacturing, recycling, or disposal.

Industry 4.0 solutions are identified as disruptive factors in closed-loop supply chains (CLSC) towards cleaner production processes (**Tjahjono et al., 2017; Mastos et al., 2021**). Businesses accelerate the implementation of CE and new technologies to meet sustainability goals (**Manavalan & Jayakrishna, 2019**). The opportunities and potential of Industry 4.0 for both CE and logistics have rarely been investigated simultaneously (**Birkel & Müller, 2020**). These technologies provide innovative solutions, enabling logistics service providers to address new challenges, restructure traditional supply chains, seek competitiveness, and transition to the digital age.

This study focuses on RL within supply chain management (SCM), highlighting its role in enhancing the efficiency of closed-loop supply chains (CLSC) (**Agnusdei et al., 2019**). By integrating Industry 4.0 and CE paradigms, the study evaluates the applicability of Industry 4.0 technologies in RL through a novel MCDM model based on COBRA. The study is structured as follows: the theoretical background, focusing on RL, the role of Industry 4.0 technologies in logistics, and an overview of MCDM methods (Section 2). The novel MCDM model and the final ranking of alternatives (Section 3). A case study application, the main results, and their validation (Section 4). Section 5 discusses the findings, and Section 6 concludes with suggestions for future research.

2. Literature Review

For the past few decades, the global population and living standards have continuously been growing, and with them has grown the consumption of a wide variety of products **(Prajapati et al., 2019).** In addition, consumer habits have been changing due to the expansion of internet use, electronic commerce, and more liberal returns policies, among other reasons (**Bernon & Cullen, 2007)**. This has led to significant amounts of leftover materials and products being returned and disposed of, thus raising several questions concerning the environment, sustainability, regulations, resource conservation, and social awareness **(Kazancoglu et al., 2021)**. The RL concept is developed and applied to address supply chain challenges.

Industry 4.0 amalgamates computer networks with tangible physical processes via sophisticated technologies, including "Internet of Things (IoT), blockchain, electronic and mobile marketplaces, cloud computing (CC), big data and data mining, artificial intelligence (AI), autonomous vehicles (AV), automated guided vehicles (AGV), augmented reality (AR), and cyber-physical systems (CPS)". Industry 4.0 is new as it integrates established solutions, applications, and technology into a complex network of interrelated components (**Tjahjono et al., 2017; Mastos et al., 2021**). Industry 4.0 has established a new framework for social, political, economic, and environmental initiatives, irrespective of its origin. Although many studies explore the implementation of Industry 4.0 technologies in logistics, there is a deficiency of thorough studies about these technologies in the RL sector. This study aims to fill these research gaps.

The criteria identified for evaluating the aptness of Industry 4.0 in RL are in **Annexure 1.** The domain of MCDM has experienced significant growth, particularly over the past ten years. More than fifty MCDM methods are available, classified into scoring (additive) methods (S), distance-based methods (DB), pairwise comparison methods (PC), and outranking methods (O) (**Penadés-Plà et al., 2016**).

This study primarily emphasizes distance-based approaches, including “TOPSIS, VIKOR, CODAS, EDAS, MOORA, WASPAS, and MARCOS”. These methods rank alternatives based on various distances from reference points (ideal, anti-ideal, average, etc.).

The literature has not yet defined a method that integrates several types of distances from various reference points, which is the research gap this study addresses. This study introduces a novel integration of Bayesian-BWM with the new COBRA to combine the advantages of existing distance-based methods. This integration eliminates the need to debate which distance and reference point should be used for ranking alternatives. The goal is to develop a technique that is more precise, credible, consistent, understandable, accessible, and less complex.

3. Research Design/Methodology

This study proposes a novel MCDM model based on COBRA method for evaluating and final ranking the alternatives. The model also includes the Bayesian-BWM method used to obtain the criteria weights. **Figure 1** outlines the proposed model's conceptual representation, which comprises thirteen steps.

4. Evaluation of Industry 4.0 Technologies in Reverse Logistics

The case study in this paper evaluates and ranks Industry 4.0 technologies to identify those most suitable for broader application in the RL sector. This MCDM problem evaluation utilizes a model based on the COBRA method, proving its application. The criteria set for this study are unique and explicitly developed by the authors for this issue.

The validity of the criteria was established via roundtables involving experts in reinforcement learning, Industry 4.0, academia, logistics service providers, stakeholders, public administrators, and residents.

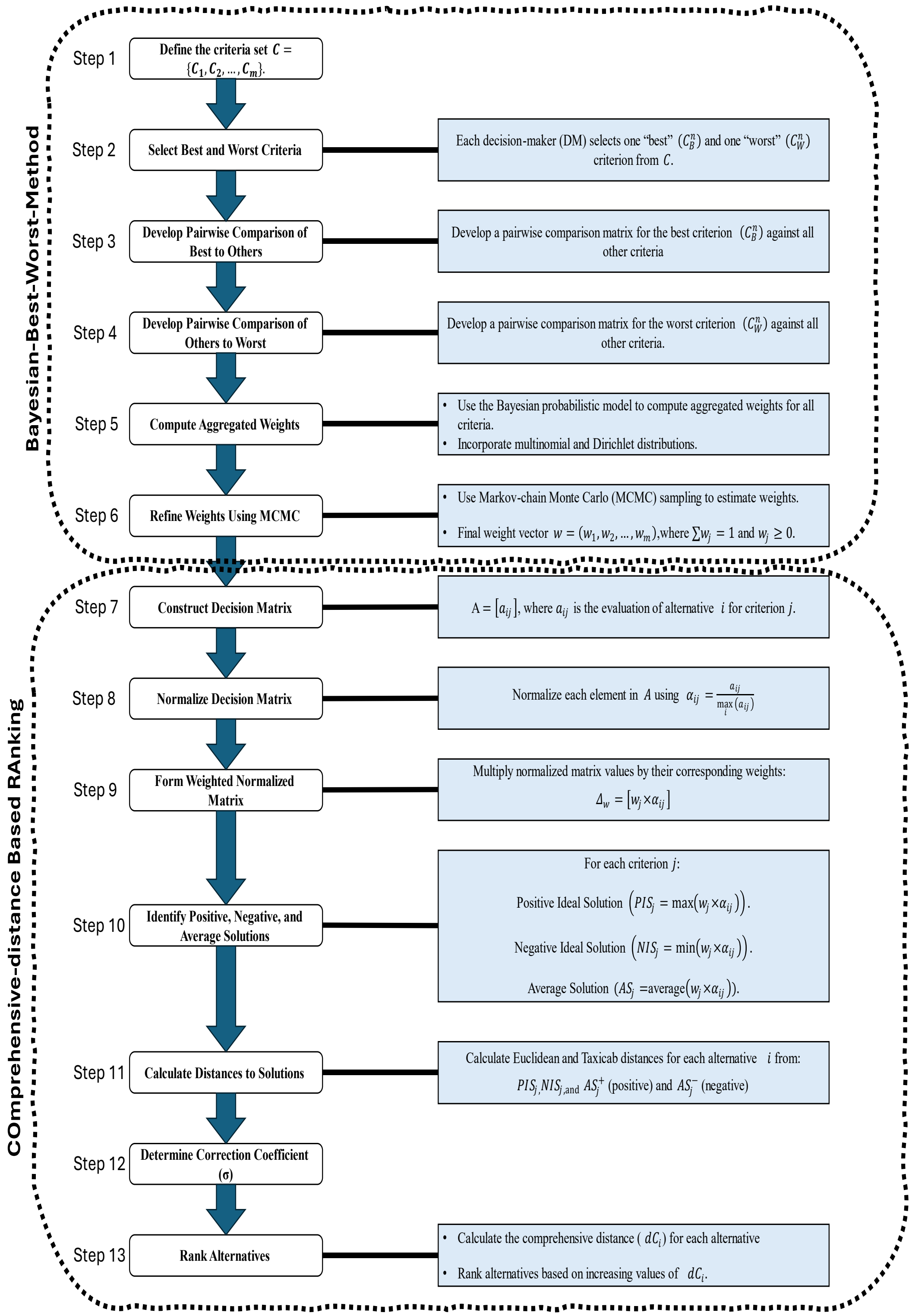

Figure 1. Conceptual framework of the MCDM model.

Table 1 presents the evaluations for the best and worst criteria relative to other criteria. Saaty's 9-point scale is used for all the evaluations **(Saaty and Peniwati, 2013).**

Table 1. Criteria Weights by using the Bayesian-BWM method.

Criterion	Best/Worst	Best over Other: e_{bj}		Other over Worst: e_{jw}		Weight
C_1		L	3	H	7	0.0657
C_2		FL	4	FH	6	0.0644
C_3		VL	2	VH	8	0.0669
C_4		EH	9	N	1	0.0581
C_5		VH	8	VL	2	0.0593
C_6		H	7	L	3	0.0606
C_7		FH	6	FL	4	0.0619
C_8		M	5	M	5	0.0631
C_9	CW	EH	9	/	1	0.0581
C_{10}		H	7	L	3	0.0606
C_{11}		FL	4	FH	6	0.0644
C_{12}	CB	/	1	EH	9	0.0682
C_{13}		M	5	M	5	0.0631
C_{14}		H	7	L	3	0.0606
C_{15}		EH	9	N	1	0.0581
C_{16}		VL	2	VH	8	0.0669

Following the same procedure as the criteria evaluations, the most frequent evaluations by respondents regarding the applicability of Industry 4.0 technologies in RL were adopted as representative evaluations, forming **Decision Matrix A**. These evaluations are in **Table 2.**

4.1. Validation of Results

The results were validated by applying the proposed integrated method and solving the same problem with other MCDM methods, including AHP, BWM-COBRA, TOPSIS, VIKOR, CODAS, EDAS, MOORA, WASPAS, and MARCOS. The results are in **Table 3.** The validation process excluded the ANP method due to its complexity in analyzing interdependencies and feedback loops where criteria and alternatives are interrelated **(Jorge-García and Estruch-Guitart, 2022).** It requires extensive computations and data compared to AHP (which is designed for simple decision-making scenarios with independent criteria).

Bayesian-BWM-COBRA ranked T1 significantly lower (10th) than other methods (1st). Similarly, the ranking for T4 diverges, being ranked 1st by Bayesian-BWM-COBRA but consistently ranked around 7th by different methods. This difference suggests that Bayesian-BWM-COBRA strongly emphasizes specific criteria or weighting factors, potentially prioritizing less dominant dimensions in traditional models.

Table 2. Decision Matrix A (Step 7 of Methodology): Evaluations of the technologies.

	T 1	T_2	T_3	T4	T_5	T	T_7	T8	T_9	T_{10}
C_1	H	VH	VL	L	M	H	FH	EH	FL	M
C_2	EH	VL	L	H	H	VH	H	M	FL	VL
C_3	H	L	VL	FL	VH	H	VH	VH	FH	L
C_4	M	H	FH	VL	M	FH	FH	FH	L	M
C_5	VH	VL	L	FH	VH	EH	FH	FH	FL	VL
C_6	H	FH	L	FH	L	FL	M	M	M	EH
C_7	VH	L	M	FL	H	VH	FH	L	L	N
C_8	H	L	FH	FH	VL	VL	VL	FL	FH	VL
C_9	FL	FH	L	L	M	VH	H	EH	FH	L
C_{10}	FH	M	M	H	M	M	H	VH	M	FL
C_{11}	H	VH	VL	FL	H	FH	EH	VH	H	VH
C_{12}	H	VL	N	FL	H	VH	VH	H	M	L
C_{13}	VH	H	FH	H	H	VL	VL	H	FH	M
C_{14}	FL	FL	VL	FH	FH	EH	FH	FH	M	FL
C_{15}	FH	M	L	FH	H	VH	H	FH	M	FL
C_{16}	EH	M	FH	H	VH	M	VH	VH	M	L

Table 3. Comparison of Bayesian-BWM-COBRA with prominent MCDM methods.

Method	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Bayesian-BWM-COBRA	10	9	5	1	3	4	2	7	6	8
AHP	1	7	10	6	5	2	4	3	8	9
BWM-COBRA	1	8	10	7	4	5	2	3	6	9
TOPSIS	1	9	10	7	4	5	3	2	6	9
VIKOR	1	8	10	7	4	5	3	2	6	9
CODAS	1	8	10	7	5	4	3	2	6	9
EDAS	1	8	10	6	5	4	3	2	7	9
MOORA	1	8	10	7	5	4	3	2	6	9
WASPAS	1	8	10	7	4	5	3	2	6	9
MARCOS	1	8	10	7	4	5	3	2	6	9

These variations may arise from the Bayesian approach to capturing subjective preferences and integrating them with the COBRA ranking process, which differs fundamentally in how criteria weights and distances are handled. The differences indicate that Bayesian-BWM-COBRA might provide a unique perspective, emphasizing alternative aspects of the decision-making problem that other methods might underrepresent or overlook. This highlights the method's potential to offer innovative insights but also underscores the need for a deeper understanding of the specific criteria driving the differences in rankings.

5. Discussion

The results of this study suggest that the most applicable Industry 4.0 technologies used in RL are IoT, CC and electronic/mobile marketplaces (**Table A1.2**). IoT is considered the foundational technology for establishing cyber-physical systems and is the primary driver of Industry 4.0 development. It is the best-ranked technology as it initiates, stimulates, and accelerates the development of other Industry 4.0 technologies. Cloud computing offers companies and organizations increased adaptability, business stability, and cost reduction, especially under the new reality imposed by the COVID-19 pandemic.

In the past two years, 19-52% of people in selected European countries have shopped online more often than in previous years **(Statista, 2024).** Applying these technologies will significantly impact the development of a CE, bringing positive effects such as cost reduction, additional value creation, risk reduction, and the completion of the product life cycle **(Patyal et al., 2022; Javaid et al., 2022).** While the applications of Industry 4.0 technologies in RL have been investigated individually in the literature, no research has comprehensively analyzed and ranked various Industry 4.0 technologies in the RL sector concerning their pertinence. The literature lacks studies that effectively address Industry 4.0 technologies and attempt to structure and construct them.

The practical implications of this study include establishing a framework that experts, decision-makers, policy creators, and practitioners in RL sector can use to make informed decisions about implementing Industry 4.0 technologies in their core business processes. The study identifies the most promising Industry 4.0 technologies in terms of their potential in RL, establishing the course for further development and implementation.

6. Conclusions

This study evaluated and ranked Industry 4.0 technologies for their pertinence in RL activities. Ten leading technologies were identified and evaluated using 16 criteria points. A novel MCDM model was used, combining the Bayesian-BWM method for criteria weights and the newly developed COBRA method for ranking alternatives.

The results identified IoT as the most applicable Industry 4.0 technology, followed by CC and electronic/mobile marketplaces. Autonomous vehicles were the least relevant. The proposed method was validated by comparing its results with other well-known distance-based MCDM methods, which showed high conformity and proved its competitiveness.

One potential approach is establishing and evaluating scenarios for RL operations based on the application blend for Industry 4.0 technologies in executing various activities and processes. Future research could explore scenarios for RL operations using Industry 4.0 technologies and integrate them with last-mile delivery in cities. This could also be employed across different areas, expanded to intuitive or interval sets (e.g., fuzzy, rough, grey) and combined with other MCDM methods to create new hybrid models.

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ANNEXURE 1.

Table A1.1: Criteria for evaluation of Industry 4.0 technology applicability in RL.

Criteria Group	**Criterion**	**References**
Technological	C1-Degree of development	(Si et al., 2016); (Jamwal et al., 2021)
	C2-Possibility of integration (modularity)	(Kumar et al., 2022); (Chang et al., 2021)
	C3-Complexity of implementation	(Amoozad Mahdiraji et al., 2020)
	C4-Possibility of standardization	(Moktadir et al., 2018); (Kumar et al., 2022)
	C5-Adaptability	(Kaya et al., 2020); (Si et al., 2016)
Socio-political	C6-Safety	(Kaya et al., 2020)
	C7-Labour market impact	(Moktadir et al., 2018); (Chang et al., 2021)
	C8-Environmental impact	(Jamwal et al., 2021); (Amoozad Mahdiraji et al., 2020)
	C9 - Cultural framework	(Amoozad Mahdiraji et al., 2020); (Si et al., 2016)
	C10-Political framework	(Kaya et al., 2020); (Moktadir et al., 2018)
	C11-Regulatory framework	(Kumar et al., 2022); (Chang et al., 2021)
Economic-operational	C12-Implementation costs	(Sriram & Vinodh, 2021)
	C13-Energy consumption efficiency	(Jamwal et al., 2021); (Kumar et al., 2022)
	C14-Security	(Kaya et al., 2020); (Si et al., 2016)
	C15-Organizational readiness	(Amoozad Mahdiraji et al., 2020); (Chang et al., 2021)
	C16-Logistics service quality	(Si et al., 2016);

Table A1.2: Alternatives of Industry 4.0 technology for application in RL.

Alternative	**Code**	**References**
Artificial Intelligence	T1	(Copeland, 2020); (Wilson et.al., 2021); (Xing et al. 2010).
Automated Guided Vehicles	T2	(Krstić & Tadić., 2021); (Sathiya et al., 2021).
Autonomous Vehicles	T3	(Christensen, 2021); (Le Moigne, 2020)
Internet of Things	T4	(Krstić & Tadić., 2021); (Lu, et.al., 2018)
The E/M-Marketplaces	T5	(Kokkinaki et al., 2004).
Blockchain	T6	(Pilkington, 2016); (Farouk & Darwish, 2020)
Cloud Computing	T7	(Mell & Grance, 2011)
Big Data	T8	(Wu et al., 2014); (Clifton, 2019).
3D Printing	T9	(McKinnon, 2016); (Królikowski, et al., 2020).
Advanced Robotics	T10	DHL. (2016); (Alvarez & Renteria, 2017).