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Fuzzy Logic-Based Assessment of Circular Economy Maturity in Manufacturing Companies

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Abstract:
The shift from linear to circular value creation is driving a fundamental transformation across all sectors of manufacturing organizations. While maturity models are commonly used to assess and support this transition, they often lack comprehensiveness and the capacity to handle uncertainty. To overcome these limitations, this paper proposes a holistic Fuzzy Logic-based approach for assessing Circular Economy maturity. Circular Economy maturity indicators are processed through a multi-stage fuzzy system, enabling the identification of potential areas for change within the organization. This approach provides actionable insights to enhance the organization's circularity.
Keywords: Circular Economy, Maturity Assessment, Fuzzy Logic, Manufacturing

1. Introduction

The Circular Economy (CE) is an economic model that focuses on minimizing resource consumption while establishing closed-loop systems for resource management [1]. By promoting activities that reduce waste and optimize the use of limited resources, the CE seeks a systemic transformation in production chains, consumer behavior, and industrial systems [2]. For the widespread adoption of Circular Economy principles, it is essential to guide manufacturing companies on strategies and methods to restructure and optimize their processes and operations [3]. To successfully engage in this transformation, companies must undergo a comprehensive organizational shift, as all areas within the organization are impacted.

Maturity models offer structured frameworks and tools to guide this transformation. These models help organizations assess their current development stages in various domains and plan improvements accordingly [4]. Maturity models typically outline different levels of progress, which are evaluated based on criteria such as processes, capabilities, or performance [5]. Their primary purpose is to assist organizations in defining transformation objectives, identifying obstacles, and implementing best practices to enhance organizational performance over time [5,6].

However, maturity assessments are often linked to significant uncertainties [7]. The comparison between theoretical requirements and actual outcomes involves subjective evaluations and non-quantifiable factors [8,9]. Despite this, maturity assessments provide a quantified level, which may give an impression of precision [8]. Accounting for uncertainties is crucial to generating reliable and differentiable data [7,9].

Several existing approaches to assessing the Circular Economy maturity of companies are presented in the literature. Most of these approaches rely on self-assessments using Likert scales (e.g., from "strongly agree" to "strongly disagree"), which introduce high levels of uncertainty due to their subjective nature [10].

This paper proposes a new approach to CE maturity assessment for manufacturing companies, which takes into account uncertainty factors. The proposed approach combines both separate and aggregated assessments of business units, integrating both quantitative and qualitative indicators of Circular Economy maturity.

Section 2 provides an overview of the uncertainty factors in maturity models and introduces Fuzzy Logic theory. Section 3 presents the proposed assessment approach, followed by a discussion in Section 4, where conclusions are drawn.

2. State of the Art

2.1. Fuzzy Logic Theory

Fuzzy Logic is based on the principle that objects can only partially belong to a set, and can simultaneously belong to multiple sets. Unlike classical set theory, where an element either completely belongs to a set and satisfies all its properties, the assignment in Fuzzy Logic is not necessarily clear-cut. The set is described as fuzzy, and the traditional

Boolean logic (where an object is either present or not, i.e., a value of 1 or 0) is extended to the continuous interval [0, 1]. This allows for a more nuanced representation of membership in a set.

Fuzzy Logic enables the mathematical representation and quantitative processing of qualitative statements, which are often used in evaluations. This is especially useful when analyzing both qualitative and quantitative data in relation to each other. Fuzzy set theory provides a method for handling uncertain numerical and linguistic data, enabling the generation of precise output information. Terms from natural language, such as "warm," "tall," or "young," which are difficult to define precisely and are often subject to personal judgment, can be mathematically modeled. This allows for the computer-aided processing of unstructured knowledge and facilitates a more flexible analysis of complex, imprecise information.

2.2. Existing Fuzzy Logic Approaches for Maturity Models

Fuzzy Logic is increasingly being used to develop standardized maturity models that are both easy to use and applicable to a variety of processes. This approach offers flexibility in assessing organizational maturity and helps to mitigate the subjective elements inherent in traditional evaluation methods.

The application of Fuzzy Logic to maturity models can be traced back to several studies, where it was used to model uncertainties in the interpretation of human language, particularly in the assignment of vague terms to maturity levels. For instance, Chen et al. utilized Fuzzy Logic to construct a maturity model for digital transformation. Similarly, Kahraman et al. applied Fuzzy Logic to develop a maturity model for the energy sector. Caiado et al. presented a hierarchical, cascaded maturity model for Industry 4.0, incorporating uncertainty. However, to date, no Circular Economy maturity model exists for manufacturing companies that explicitly accounts for the inherent uncertainties and subjectivity involved. **3. Fuzzy Logic Approach for Circular Economy Maturity Model**

The proposed Circular Economy (CE) maturity assessment method is grounded in a multi-level Fuzzy Logic approach, which is designed to handle the inherent complexity and uncertainty in measuring the maturity of manufacturing companies' adoption of Circular Economy practices. The methodology involves several steps, including the stepwise, cascaded, and pairwise aggregation of CE maturity indicators into dimensional indicators, which are further combined into an overall CE maturity index. This hierarchical structure aligns with the frameworks outlined by Caiado et al., who suggest that a Fuzzy Logic-based maturity model should be hierarchical and multi-dimensional [16]. Furthermore, Bernerstätter and Jording highlight that maturity levels should be seen as a multi-factorial result, incorporating a variety of indicators to provide a comprehensive assessment of CE adoption [6,17].

This approach builds on several key works in the field of sustainability assessments, including those of Bitter et al., Kouloumpis et al., Liu and Phillis, and Kouikoglou, who have developed and documented hierarchical fuzzy systems for evaluating sustainability in various contexts [18–21]. These works emphasize the utility of Fuzzy Logic in dealing with vague, qualitative data and transforming it into actionable insights for decision-making.

In this model, the CE maturity indicators are categorized into several dimensions, which are then aggregated at each level of the hierarchy. The aggregation is performed through Fuzzy Logic operations, which account for the uncertainty and imprecision inherent in the assessment process. By employing a fuzzy approach, the model can integrate qualitative assessments (such as "planned" or "initiated") and quantitative measures (such as percentage values) in a way that reflects the true complexity of assessing maturity levels in Circular Economy practices.

Figure 1 demonstrates the process of the Fuzzy Logic Circular Economy maturity model approach. It depicts the flow from the individual CE maturity indicators to the final aggregated CE maturity index. The process includes several steps, including data collection, normalization, fuzzification, aggregation, and defuzzification, with each step contributing to the final assessment of maturity.

3.1. Indicator Selection and Normalization

The foundation for selecting CE maturity indicators comes from a comprehensive review conducted by Kreutzer et al., who identified a set of relevant indicators derived from sixteen existing Circular Economy maturity models and eight readiness models used in manufacturing companies [22]. These indicators span a range of dimensions, from environmental performance and waste reduction to resource efficiency and supply chain sustainability.

Table 1 provides examples of two Circular Economy maturity indicators: one qualitative and one quantitative. The qualitative indicators describe the status of CE practices using descriptors like "no," "planned," "initiated," and "standard," representing varying levels of implementation or integration of Circular Economy practices. The quantitative indicators, on the other hand, may include measures such as the percentage of material recycled, energy savings, or waste reduction in a given period.

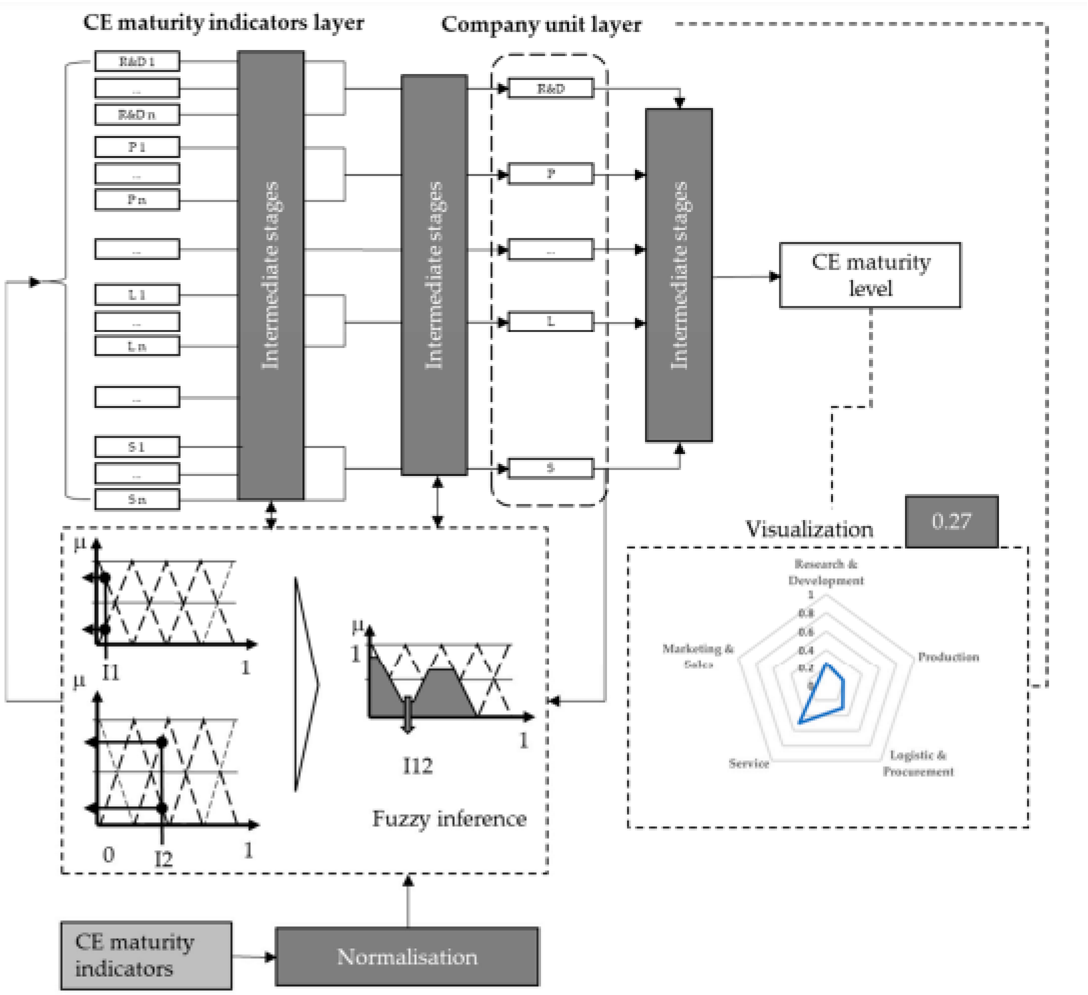

Figure 1. Process of the Fuzzy Logic Circular Economy maturity model approach.

Since these indicators come in different forms—qualitative (e.g., categorical levels) and quantitative (e.g., percentages)—they need to be normalized to make them comparable. Normalization transforms all indicators into a common scale, typically between 0 and 1, which makes it possible to compare disparate data types without introducing bias due to differences in scale or unit of measurement.

The normalization process is essential because it allows for a consistent comparison of indicators with differing units or scales, ensuring that no single indicator disproportionately influences the overall maturity index. Normalization also helps in handling outliers and inconsistencies in the data, which are common when collecting data from multiple sources or when the data contains subjective assessments.

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

Here, xnorm is the normalized value, and xxx is the original indicator value. The parameters xmin and xmax are the minimum and maximum values for each indicator across the dataset. This formula ensures that the values of all indicators are scaled to a uniform range, which is critical for effective aggregation and decision-making in the subsequent stages of the Fuzzy Logic model.

The process of normalization serves multiple purposes:

1. **Standardization of units:** Indicators that originally have different units (e.g., percentages, counts, or qualitative labels) are transformed into a comparable range, ensuring that no single indicator dominates the aggregation process.
2. **Prevention of bias:** Without normalization, indicators with larger scales (such as percentages or quantities) would exert more influence over the overall maturity assessment, potentially skewing the results.

3. **Improved consistency:** By ensuring that all indicators are on the same scale, normalization enhances the consistency and reliability of the maturity assessment process.

Once the indicators are normalized, they are ready for the next steps in the Fuzzy Logic process, which include fuzzification, aggregation, and defuzzification, all of which contribute to the overall assessment of Circular Economy maturity in the manufacturing company.

In summary, the fuzzy approach presented in this paper offers a comprehensive and nuanced method for assessing the maturity of manufacturing companies in adopting Circular Economy practices. By combining qualitative and quantitative indicators, and utilizing normalization techniques, this approach ensures that companies can be evaluated on their CE maturity in a systematic, transparent, and adaptable manner.

3.2. Scales and Membership Functions

In the process of developing a fuzzy logic model for Circular Economy maturity assessment, the next critical step is to assign scales and membership functions to each indicator. By normalizing the indicators, the scale interval for each indicator becomes naturally constrained within the range [0, 1]. For each indicator, several discrete sets are defined using linguistic terms, which represent the different maturity levels. These sets are often represented by overlapping triangular membership functions, as shown in Figure 2.

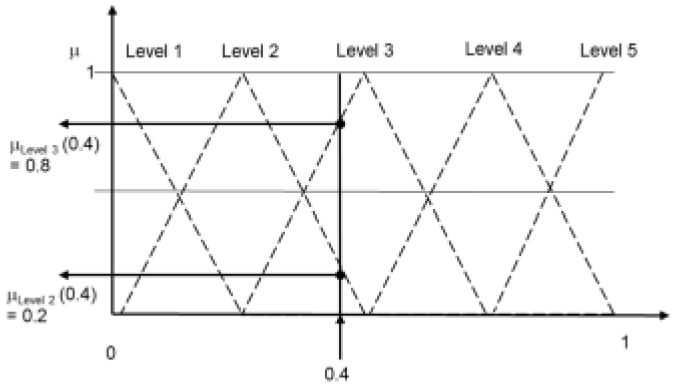

Figure 2. Fuzzification of an indicator.

The membership functions provide a way to measure the degree to which a particular input value belongs to each of the discrete sets. The overlap between these functions indicates the extent to which an input value can simultaneously belong to two neighboring sets, allowing for flexibility in the representation of imprecise data. This fuzzification process enables a more nuanced evaluation of the maturity level of an indicator, rather than assigning it to a single, exact value.

In the proposed approach, a five-level linguistic scale is used for all indicators, representing the different maturity levels (Level 1 to Level 5). These levels are evenly distributed over the interval [0, 1], ensuring that the entire range of values is captured and categorized appropriately. The use of a five-level scale allows for a balance between the granularity of the assessment and the simplicity of interpretation, providing a clear but flexible framework for maturity evaluation.

3.3. Rule Base

After defining the scales and membership functions, the next step is to establish the rule base, which consists of a set of rules for aggregating the indicators. These rules are structured in the form of conditional statements, commonly known as IF-THEN rules. A typical rule may look like the following:

IF (X1 is A) AND (X2 is B), THEN (Y1 is C)

In this context, X1 and X2 represent different indicators, A and B are the linguistic terms assigned to those indicators, and Y1 is the resulting outcome. The rules are designed to process the input indicators and generate conclusions based on the defined relationships between them.

The rule base can involve multiple linguistic variables, processed together using various operators such as AND or OR. However, this approach can lead to a "rule explosion," where the number of rules increases exponentially with the number of linguistic variables and the number of indicators in each aggregation step. The total number of rules (n) is determined by the formula:

$$n = m^k$$

Where mmm is the number of indicators to be aggregated in a given step, and k is the number of linguistic terms used for each input variable. To avoid this rule explosion, it is common to limit the number of membership functions to three to five characteristics per indicator. Additionally, the number of rules can be reduced by structuring the model with fewer hierarchy levels, which also helps control the computational complexity.

Another technique to manage the rule base is to apply weighting factors to the rules, which can be used to prioritize certain indicators over others. Furthermore, a confidence factor may be assigned to each rule, representing the degree of certainty in the validity of the rule. This allows for more flexibility and control in the aggregation process, ensuring that rules with higher confidence can have a greater impact on the final output.

3.4. Fuzzification, Inference, and Defuzzification

The fuzzification step involves converting sharp input values into linguistic terms using the defined membership functions. This process determines the degree to which each input belongs to a specific maturity level, yielding a real number between 0 and 1. An example of fuzzification is shown in Figure 2.

Once the inputs are fuzzified, fuzzy inference is used to aggregate the indicators using the established rule base. In this approach, the Takagi-Sugeno-Kang (TSK) inference method is employed, which is commonly used in fuzzy logic models for sustainability assessments. The TSK inference method ensures that all aggregation steps are monotonic, meaning that any changes made at a lower level will automatically affect the higher levels. For rules with a conjunction (AND operator), the algebraic product rule is applied:

$$\mu_{n+1,p}(x_{n+1}) = \prod_{i=1}^{n} \mu_{i,p}(x_i)$$

For rules with an adjunction (OR operator), the algebraic sum rule is used:

$$\mu_{n+1,p}(x_{n+1}) = 1 - \prod_{i=1}^{n}(1 - \mu_{i,p}(x_i))$$

When multiple rules assign the same linguistic term (T) to an input value, the degree of membership is calculated by summing the individual membership values:

$$\mu_T(x_{n+1}) = \sum_{p:T_{n+1}=T} \mu_{n+1,p}(x_{n+1})$$

The entire process of fuzzification, inference, and defuzzification is carried out hierarchically for all maturity indicators. Ultimately, the indicators are aggregated at the company process level, and these are further aggregated to form the General Circular Economy Maturity Index (GCEMI). Figure 3 provides an example of how the results for individual company processes and the GCEMI are visualized. This hierarchical aggregation enables a comprehensive and systematic evaluation of an organization's circular economy maturity, taking into account the fuzziness and uncertainty of the indicators.

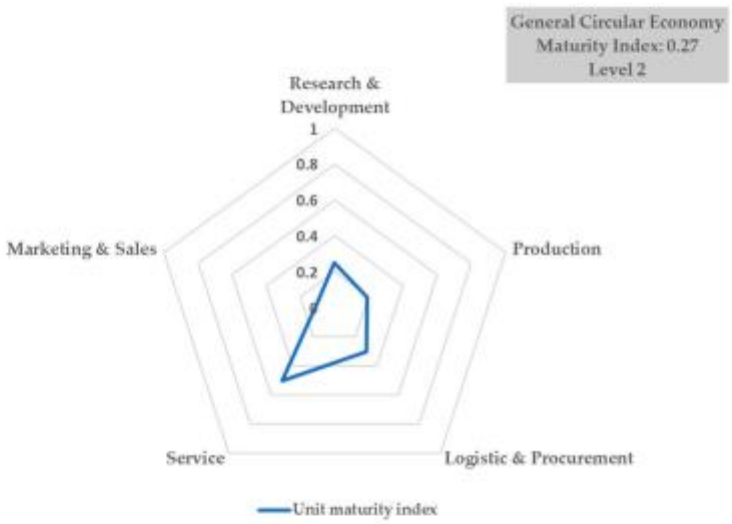

Figure 3. Exemplary visualisation of the General Circular Economy Maturity Index.

4. Results and Discussion

The Fuzzy Logic approach presented for assessing Circular Economy (CE) maturity in manufacturing companies provides a structured and flexible framework for evaluating both individual business divisions and the company as a whole. By allowing the separate and aggregated assessment of CE maturity, this model empowers decision-makers to understand the current status of the company's transition to a Circular Economy and strategically plan the next steps. The ability to process both qualitative and quantitative indicators under conditions of uncertainty and subjectivity enhances the robustness of the model, as it mirrors real-world complexities often encountered in CE maturity assessments.

The framework developed through this approach serves as a useful tool to handle the uncertainty factors present in CE maturity evaluations. In many cases, manufacturing companies face challenges in assessing their CE maturity due to the qualitative nature of some of the indicators, as well as the difficulty in measuring certain aspects of sustainability and resource efficiency. The proposed model integrates these uncertainties, allowing a more accurate and actionable assessment of the current maturity level. This capability is especially relevant in industries where decision-making relies on both objective data and subjective assessments (e.g., company-specific strategies, readiness, or initiatives), which are inherently uncertain.

To build this framework, a complex and holistic set of indicators was used to assess the circular maturity of manufacturing companies. These indicators encompass various dimensions of Circular Economy practices, such as resource efficiency, waste reduction, closed-loop systems, and environmental impact. The holistic approach takes into account the varied and often interdependent nature of CE implementation across different areas of a manufacturing company. Additionally, the basic structure of the framework reflects the organizational structures typically found in manufacturing companies, ensuring that the maturity model is adaptable and relevant to a wide range of industries.

The exemplary implementation of the Fuzzy Logic approach demonstrates the fundamental applicability of Circular Economy maturity models. It shows how the proposed model can be used to evaluate the CE maturity of manufacturing companies in a structured, data-driven way. However, there are limitations that need to be addressed. One key challenge is the potential loss of relevant information due to the aggregation steps involved in the model. These steps combine multiple indicators into a single score, which can result in the oversimplification of complex data. This trade-off between aggregation and detail necessitates further research to refine the aggregation process and determine the optimal balance between data granularity and interpretability.

Additionally, the approach presented here assumes that all indicators and dimensions are equally weighted in the aggregation process, which may not always be appropriate. In reality, some dimensions of Circular Economy practices may hold greater significance than others depending on the context, industry, or company priorities. A more nuanced approach, where the relative importance of each indicator is taken into account, could improve the accuracy and relevance of the assessment. Furthermore, the interactions between indicators were not considered in the current model. The relationships between different dimensions of Circular Economy practices—such as how improvements in one area (e.g., energy efficiency) might influence others (e.g., waste management)—could provide valuable insights and improve the model's predictive power. Including these interactions could result in a more dynamic and holistic maturity model that reflects the complex and interconnected nature of Circular Economy strategies.

Overall, while the proposed Fuzzy Logic approach offers significant advantages in terms of flexibility and handling uncertainty, further work is needed to address these limitations. Future research should focus on refining the aggregation process, incorporating weighted indicators, and exploring the interactions between various dimensions of Circular Economy maturity. Such improvements would enhance the applicability of this model across different industries and contribute to more accurate, actionable assessments of Circular Economy maturity in manufacturing companies.

5.Conclusion

The proposed fuzzy logic-based approach for Circular Economy (CE) maturity assessment provides a comprehensive and flexible framework for evaluating the maturity of manufacturing organizations transitioning towards circular practices. By incorporating fuzzy logic, this method overcomes the limitations of traditional maturity models that often fail to capture the complexities and uncertainties inherent in evaluating qualitative and quantitative indicators.

This model addresses key challenges such as the vagueness and fuzziness of the data, as well as the need for a holistic assessment of multiple indicators. The use of normalized indicators, linguistic terms, and overlapping triangular membership functions ensures that the model can handle both precise and imprecise data while maintaining flexibility in evaluating organizational maturity. The integration of fuzzification, inference, and defuzzification stages provides a systematic approach to aggregating and processing the indicators at various levels of hierarchy, ultimately yielding a

General Circular Economy Maturity Index (GCEMI) that reflects the organization's progress in adopting circular practices.

The approach further contributes to the field by offering a rule-based system where the aggregation of indicators is guided by a set of IF-THEN rules. This allows for the inclusion of multiple indicators and their relationships while controlling the complexity of the rule base through careful management of membership functions and rule hierarchy. The use of the Takagi-Sugeno-Kang (TSK) inference method ensures that the aggregation process is both efficient and consistent, with the ability to automatically adjust the results based on changes at lower levels.

One of the key advantages of this model is its ability to handle uncertainties and subjective elements commonly found in the evaluation of circular economy maturity. By allowing for the assessment of maturity across multiple dimensions, the fuzzy logic approach provides a more accurate and nuanced understanding of an organization's current state and its potential for improvement. Additionally, the inclusion of a confidence factor in the rule base helps prioritize more reliable and relevant rules, enhancing the robustness and applicability of the model.

However, there are still opportunities for further refinement and application of the model. For example, the current model assumes a relatively simple rule base with a limited number of indicators per aggregation step. Future work could explore the use of more advanced techniques such as machine learning or artificial intelligence to optimize the rule generation process and further improve the model's adaptability. Additionally, expanding the model to incorporate more specific sectoral or industry-specific indicators could enhance its relevance and precision for different types of manufacturing organizations.

In conclusion, this fuzzy logic-based approach offers a valuable tool for organizations seeking to assess and improve their circular economy practices. By providing a clear, systematic, and flexible methodology for maturity evaluation, this model can support decision-making, identify areas for improvement, and guide organizations in their transition towards a more sustainable and circular economic model. The framework's capacity to integrate both qualitative and quantitative indicators, along with its ability to handle uncertainty, makes it a powerful tool for advancing the principles of the Circular Economy in manufacturing organizations.

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