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Fuzzy Logic Approach to Circular Economy Maturity Assessment of Manufacturing Companies †

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Abstract: The transition from linear to circular value creation is leading to a fundamental transformation in all areas of manufacturing organisations. Maturity models are used to analyse and support the transformation, but these have deficiencies regarding holism and the ability to process fuzziness. To address these deficiencies, a holistic Fuzzy Logic approach to Circular Economy maturity assessment is proposed. Circular Economy maturity indicators are processed in a multi-stage fuzzy system. This allows for the identification of potential for change in all areas of the organisation to derive actions to improve the organisation's circularity.

Keywords: circular economy; maturity assessment; fuzzy logic; manufacturing

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1. Introduction

The Circular Economy (CE) is an economic model that aims to minimise the consumption of resources and to establish closed resource loops [1]. Through the progressive implementation of economic activities to reduce waste and the consumption of limited resources, a systemic change in production chains and consumer behaviour and a fundamental reorientation of industrial systems are being pursued [2]. To achieve a far-reaching establishment of the Circular Economy principle, manufacturing companies must be shown ways and strategies to implement a change in their structures and processes to this end [3]. Successful participation by companies, therefore, requires a comprehensive corporate transformation, as all areas of the company are affected.

Maturity models are structured frameworks and tools to guide this transformation, as they help organisations assess their current state of development in certain areas and plan improvements [4]. They provide a graduated representation of different levels of maturity or development, typically measured by criteria such as processes, capabilities or performance [5]. The purpose of maturity models is to help organisations define their transformation goals, identify bottlenecks and implement best practices to improve their organisational transformation performance continuously [5,6].

A maturity assessment is associated with various uncertainties [7]. The comparison between requirements and reality always uses subjective opinions and non-quantifiable variables [8,9]. However, the determination of the maturity level leads to a quantified level that suggests a supposed accuracy [8]. Taking uncertainties into account is a suitable way of generating data that are as valid and differentiable as possible [7,9].

There are various approaches in the literature for assessing the current CE maturity of companies. Most existing approaches include self-assessments using Likert scales (e.g., "strongly agree" to "strongly disagree"), which contain a high uncertainty factor in terms of subjectivity [10].

This paper aims to present and describe a new approach to CE maturity assessment for manufacturing companies, considering uncertainty factors. The approach includes the separate and aggregated assessment of business units and both quantitative and qualitative Circular Economy maturity indicators.

The following Section 2 provides a current overview of uncertainty factors in maturity models and Fuzzy Logic theory. Section 3 presents the proposed approach, which is finally discussed, and conclusions are drawn in Section 4.

2. State of the Art

2.1. Fuzzy Logic Theory

Fuzzy Logic is based on the principle that objects can only be partially assigned to a set but can be assigned to different sets at the same time [11]. In contrast to classical set theory, in which an element belongs completely to a set and fulfils all of its properties, the assignment is, therefore, not necessarily unambiguous [11]. Instead, the set can be described as fuzzy. The Boolean logic, in which the object is either present (value 1) or not present (value 0) in the set, is extended to the entire interval [0, 1] [12].

Fuzzy Logic can be used to mathematically record and quantitatively process qualitative statements, such as those generally expressed by humans for evaluation purposes. This is particularly helpful when qualitative and quantitative values are analysed simultaneously and in relation to each other [8,13].

Fuzzy set theory enables the representation, modelling and data processing of both uncertain numerical and fuzzy linguistic input information. Fuzzy precise output information can be generated through the processing procedure. Natural language terms that are difficult to define precisely, such as "warm", "tall" or "young", and that depend to a large extent on subjective judgements can be formulated mathematically. This facilitates the computer-aided processing of unstructured knowledge [13].

2.2. Existing Fuzzy Logic Approaches for Maturity Models

Fuzzy Logic can be used to develop standardised maturity models that are easy to use and applicable to any type of process. The method provides opportunities to assess the maturity of an organisation as it allows for flexibility in diagnosing the maturity level and mitigates subjective elements [9,14].

In the scientific literature, the first authors have already used Fuzzy Logic in the creation of maturity models to model the uncertainties in the quantitative interpretation of vaguely defined terms of human language and the assignment of these to a maturity level [9]. Chen et al. use Fuzzy Logic, for example, to build a maturity model for digital transformation [14]. In contrast, Kahraman et al. use Fuzzy Logic to build a maturity model for the energy industry [15]. In addition, Caiado et al. depict uncertainty in a hierarchical, cascaded maturity model for Industry 4.0 [16]. However, there is currently no Circular Economy maturity model for manufacturing companies that takes uncertainties and subjectivity into account.

3. Fuzzy Logic Approach for Circular Economy Maturity Model

The proposed approach to Circular Economy maturity assessment is partly based on the multi-level Fuzzy Logic approach. It includes the stepwise, cascaded and pairwise aggregation of Circular Economy maturity indicators into dimensional indicators and an overall CE maturity index. The hierarchical structure was used here, which Caiado et al. also propose for maturity models with a Fuzzy Logic approach [16]. Bernerstätter and Jording also see the maturity level as a multi-factorial, hierarchical overall result based on various indicators [6,17]. The further design is also based on the work of Bitter et al., Kouloumpis et al., Liu and Phillis and Kouikoglou, who have extensively dealt with and documented hierarchical fuzzy systems in the context of sustainability assessments [18–21]. Figure 1 shows the process of the Fuzzy Logic Circular Economy maturity model approach.

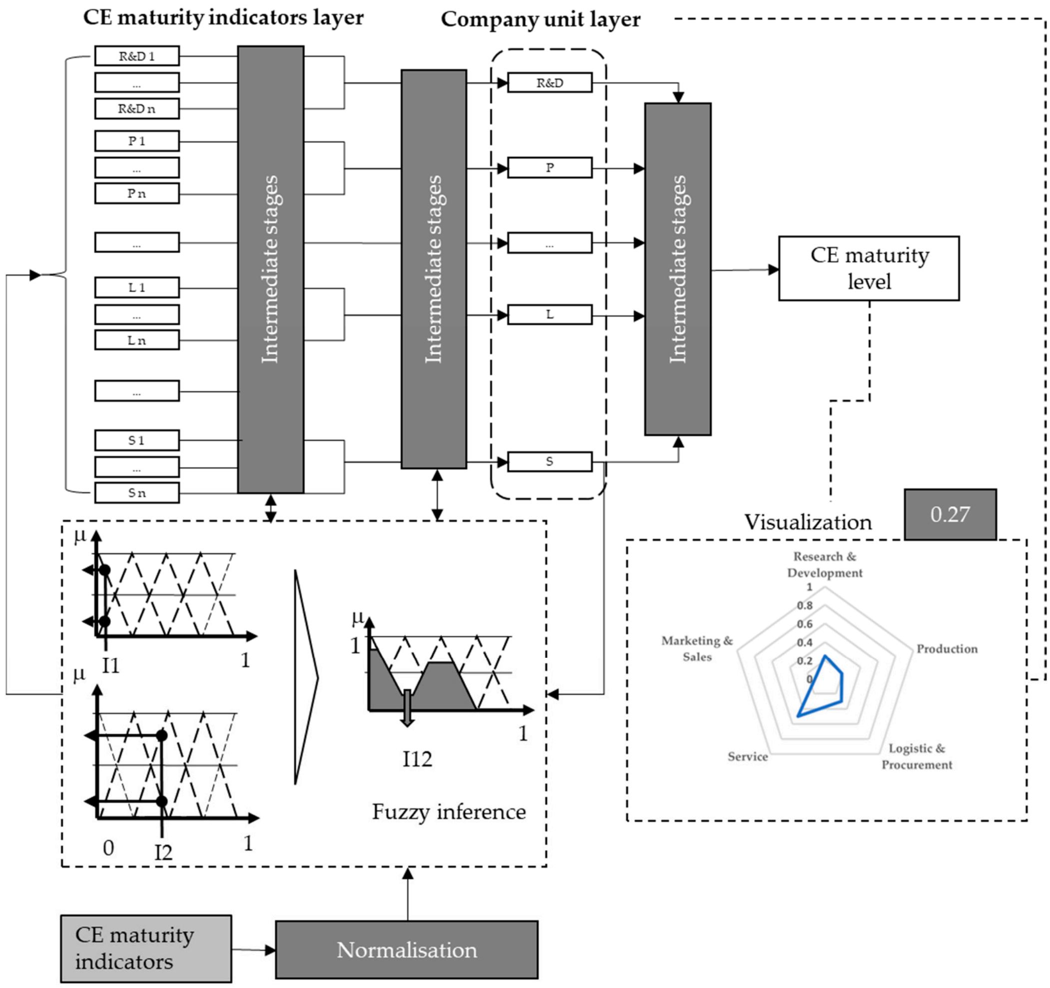

Figure 1. Process of the Fuzzy Logic Circular Economy maturity model approach.

3.1. Indicator Selection and Normalisation

The basis for the selection of CE maturity indicators is the review paper by Kreutzer et al., who derived CE maturity indicators for manufacturing companies from sixteen existing Circular Economy maturity levels and eight readiness models from the literature [22]. Table 1 shows two examples of Circular Economy maturity indicators.

As shown in Table 1, the indicators have both qualitative (e.g., no, planned, initiated, standard) and quantitative measures (e.g., %). Normalisation is necessary to make these indicators comparable with each other. Normalisation serves to improve comparability and avoids the formation of inconsistencies [23]. Equations (1) and (2) are used to normalise the input value x to a scale of [0, 1] [21]:

$$x_{norm,high} = \frac{x - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$$x_{norm,low} = \frac{X_{max} - x}{X_{max} - X_{min}} \quad (2)$$

Equation (1) is applied when a high input value x is favourably conditioned, whereas Equation (2) is applied when a low input value is favourably conditioned. Normalisation is only necessary at the first hierarchy level, as the subsequent fuzzy interference systems (FIS) are defined on the scale [0, 1]. The further mathematical structure of the individual FIS is described below.

Table 1. Example of Circular Economy maturity indicators and threshold for normalisation.

Circular Economy Maturity Indicator	Unit	Reference	X_{min} [1]	X_{max}	Eq.
Share of toxic materials	%	[24]	0	100	(2)
Documentation of maintenance and repair	No, Planned, Initiated, Standard	[25]	1 (No)	4 (Standard)	(1)

[1] X_{min}: Lower threshold, X_{max}: Upper threshold, Eq.: Equation.

3.2. Scales and Membership Functions

The next step is to assign scales and membership functions to each indicator. By using normalised indicators, the interval of the scale for each indicator is naturally [0, 1]. For each scale, there are several discrete sets described by linguistic terms and overlapping triangular membership functions [21].

The terms and membership functions indicate the extent to which the input value is assigned to the discrete sets. The overlap between the membership functions represents the assignment of the input values to two neighbouring groups (see Figure 2). In the model set-up, a five-level linguistic scale is used for all indicators, which represent the maturity levels (Level 1–5) and are evenly distributed over the interval [0, 1].

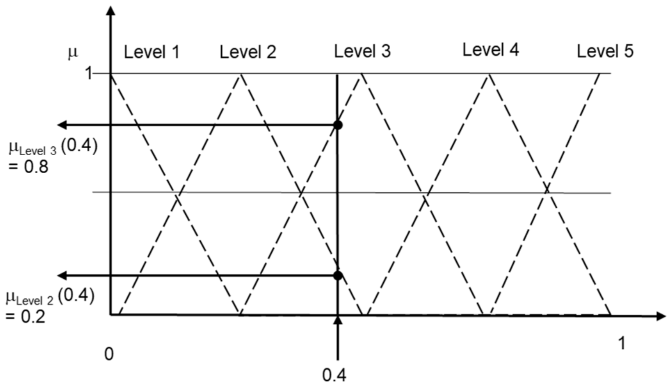

Figure 2. Fuzzification of an indicator.

3.3. Rule Base

Once the scales and membership functions have been determined, the rules for aggregating the indicators are listed. A rule consists of a premise (IF X_1) that is linked via an operator (AND, OR) with the premise of another indicator (IF X_2) and, from this, forms the conclusion (THEN Y):

$$\text{IF } (X_1 \text{ is A}) \text{ AND } (X_2 \text{ is B}), \text{ THEN } (Y_1 \text{ is C}) \tag{3}$$

It is possible to process any number of linguistic variables together via the rule bank. Under certain circumstances, this can lead to a so-called "rule explosion". The number of rules n increases exponentially with the number of linguistic characteristics k of the input variables and the number of indicators per aggregation step m (basis):

$$n = m^k \tag{4}$$

To counteract an explosion of rules, a limited number of membership functions are generally used; three to five characteristics are often found in the literature [8]. The number of rules also decreases with the number of hierarchy levels or aggregation levels and can, therefore, also be controlled by the modelling of these [8]. In general, however, a trade-off must always be made between the level of detail and the associated computational effort [11]. In addition, a kind of weighting can also be applied through the formulation of the rules; the rule-based system can be designed asymmetrically in this way [20]. Rules can also be evaluated with a confidence factor, which expresses the confidence of the modeller in the validity of the rule [12].

According to Akkasoglu, a maximum of four indicators should be included per aggregation level, as the number of rules is otherwise no longer manageable [8]. In addition, the evaluation effort increases with an increasing number of indicators. The number of rules depends both on the number of indicator values and on the number of indicators to be aggregated in one step. For an aggregation of two indicators with five values each, this results in 25 rules. As a rule, the rules are listed. A more compact representation for two indicators is a matrix-shaped rule bank [21] (see Table 2). For the proposed approach, a fixed number of two input values and one output value are, therefore, defined for each FIS.

Table 2. Symmetrical rule bank for the aggregation of two indicators.

Rule Base		**Indicator 2**				
		Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Indicator 1	**Level 1**	Level 1 (0.0)	Level 2 (0.25)	Level 2 (0.25)	Level 3 (0.5)	Level 3 (0.5)
	Level 2	Level 2 (0.25)	Level 2 (0.25)	Level 3 (0.5)	Level 3 (0.5)	Level 3 (0.5)
	Level 3	Level 2 (0.25)	Level 3 (0.5)	Level 3 (0.5)	Level 3 (0.5)	Level 4 (0.75)
	Level 4	Level 3 (0.5)	Level 3 (0.5)	Level 3 (0.5)	Level 4 (0.75)	Level 5 (1.00)
	Level 5	Level 3 (0.5)	Level 3 (0.5)	Level 4 (0.75)	Level 5 (1.00)	Level 5 (1.00)

3.4. Fuzzification, Inference and Defuzzification

The fuzzification of a maturity indicator (X_i) translates the sharp input value into a linguistic term ($T_{i,p}$) using the defined membership functions. This allows for a degree of affiliation of μ_p (X_i) to a maturity level to be identified, which is a real number in the interval [0, 1] [13]. An example of fuzzification is shown in Figure 2.

Fuzzy inference is then used to aggregate two indicators with the defined rule banks. The Takagi–Sugeno–Kang (TSK) inference is used in the presented approach, which is also frequently used in Fuzzy Logic approaches in sustainability assessment (e.g., [18]). All aggregation steps with the TSK inference are monotonic, meaning that any changes made to a lower level automatically affect the levels above it. For rules with a conjunction (AND-operator), the algebraic product rule from (5) is used. For adjunction (OR-operator), an algebraic sum rule as shown in (6) is used. If more than one rule assigns the same linguistic variable (T) to the input value (x_{n+1}), the degree of membership μ_T (x_{n+1}) is calculated using (7) [21].

$$\mu_{n+1,p}(x_{n+1}) = \prod_{i=1}^{n} \mu_{i,p}(x_i) \tag{5}$$

$$\mu_{n+1,p}(x_{n+1}) = 1 - \prod_{i=1}^{n} 1 - \mu_{i,p}(x_i) \tag{6}$$

$$\mu_T(x_{n+1}) = \sum_{p:\ T_{n+1}=T} \mu_{n+1,p}(x_{n+1}) \tag{7}$$

In the final defuzzification step, distinct outputs are generated from the membership values of the aggregated inputs. There are several types of defuzzification, but in the proposed approach, the Singleton defuzzification method is used because it provides unambiguous output values with minimal computation. The output value (x_{n+1}) is calculated as in (8). A_T is the numerical value of the linguistic variable (T) when μ_T = 1 [26].

$$x_{n+1} = \frac{\sum_T A_T \mu_T(x_{n+1})}{\sum_T \mu_T(x_{n+1})} \tag{8}$$

The three steps of fuzzification, inference and defuzzification are carried out hierarchically for all maturity indicators. As a result, the indicators are aggregated to the individual company processes that, in turn, are aggregated to the General Circular Economy Maturity Index (GCEMI). Figure 3 below shows an example of the visualisation of the results for company processes and GCEMI.

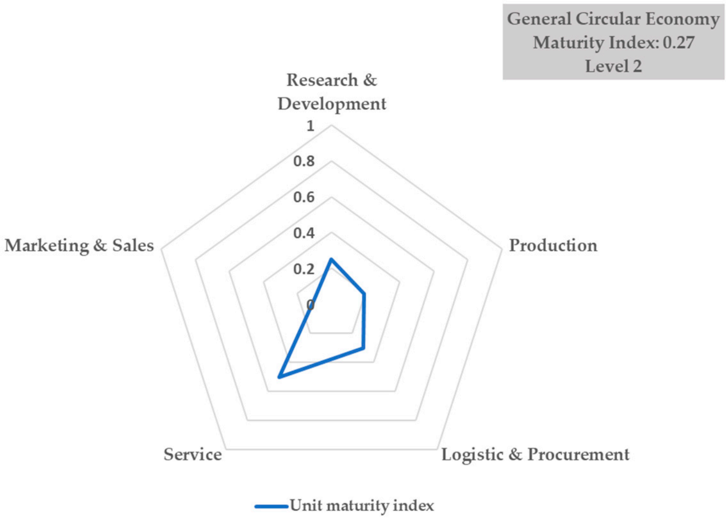

Figure 3. Exemplary visualisation of the General Circular Economy Maturity Index.

4. Results and Discussion

The presented Fuzzy Logic approach for Circular Economy maturity models for manufacturing companies allows for a separate and aggregated maturity assessment of individual company divisions and the entire company. This enables decision-makers to assess the current status of the company's transformation to a Circular Economy and derive the next steps from this. In addition, the Fuzzy Logic approach allows for the processing of qualitative and quantitative indicators under uncertainty and subjectivity. This can be used to create a framework that uses the Fuzzy Logic approach to consider the uncertainty factors in the assessment of current Circular Economy maturity. To develop this framework, a complex, holistic set of indicators for assessing the circular maturity of manufacturing companies is required as well as a basic structure that maps the structures of manufacturing companies.

The exemplary implementation of the Fuzzy Logic approach shows basic applicability of Circular Economy maturity models, but relevant information could be lost due to the compromise between aggregation steps and the number of rules, which requires more detailed research here. In addition, all indicators and dimensions were equally weighted in the approach, and interactions between the indicators were not considered. It should, therefore, be investigated what influence the weighting, e.g., through asymmetric rule banks, has on the individual results and how the indicators relate to each other.

5. Conclusions

The described Fuzzy Logic approach provides a model for measuring the circular maturity of manufacturing companies. It considers both the uncertainty and subjectivity in the assessment process as well as the aggregation of maturity indicators of different metrics. This offers companies an important decision-making aid in the further transformation process. However, due to the limitations of the authors, further research is required to validate and optimise the approach. On the one hand, this includes the development of the framework model in which the approach could be used. On the other hand, the approach itself should also be further analysed and validated regarding individual weighting methods and the number of rules.

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