Contemporary Mathematics
https://ojs.wiserpub.com/index.php/CM/

Research Article

Application of Neutrosophic Case-Based Reasoning and Neutrosophic Best-Worst Method for Product Cost Estimation

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Received: 15 August 2024; **Revised:** 24 September 2024; **Accepted:** 25 October 2024

Abstract: The problem of product cost estimation is one of the crucial issues in contemporary manufacturing systems when new products arrive as customer orders. Product cost estimation determines the success of manufacturers. An overestimation causes them to lose sales and competitiveness and an underestimation results in a financial crisis. This should be done at the early of production to reduce the potential costs that can be incurred in the production, distribution, consumption, and disposal of products. In previous studies, this problem was addressed using different mathematical, heuristics, multiple-criteria decision-making (MCDM), and artificial intelligence (AI) methods. These methods have their advantages and disadvantages as stated by several studies. Referring to the previous studies, the integration of neutrosophic case-based reasoning (N-CBR) and neutrosophic best-worst method (N-BWM) was not applied to solve the problem of product cost estimation. This study aims to develop a decision support system (DSS) by integrating the neutrosophic versions of CBR and BWM to solve the problem of product cost estimation at the early production stage. This implies that the proposed system contributes additional knowledge to the current literature in product cost estimation and decision-making. This is because, nowadays, neutrosophic set theory (NST) is getting more attention to represent the knowledge of experts in MCDM. In this study, product orders were treated as multiple-attributed cases incorporating neutrosophic-based verbal terms, and numeric and categorical cost drivers as case attributes. In addition, this study applied an object-oriented programming (OOP) approach to represent part-order arrivals as cases with multiple attributes. Optimal weights of case attributes were determined using a group-based N-BWM. Neutrosophic-based verbal terms of cost drivers and neutrosophic BWM terms were converted into equivalent single-valued trapezoidal neutrosophic numbers (SVTNNs). From managerial implication, the proposed system can be applied to estimate the cost of new product orders at the early production stage in real manufacturing environments by integrating the proposed methodological approaches. In this study, a numerical example was illustrated in a simulated machining environment to test the soundness of the proposed system.

Keywords: decision support system, neutrosophic set, case-based reasoning, best-worst method, cost estimate, decision-making, object-oriented programming

MSC: 03B52, 68T37, 68T30, 90B50

DOI: https://doi.org/10.37256/cm.6220255503

1. Introduction

The problem of product cost estimation is very significant due to the paradigm shift from mass production to mass customization in modern manufacturing systems [1–3]. Fierce and intense competition in stochastic and dynamic situations, manufacturers must be responsive and agile to respond quickly to the changes in customer preferences [4, 5]. One of the requirements in such manufacturing environments is developing the right product cost estimation model and framework [3, 6–8]. This is because product cost estimation has a great effect on product price and supply lead time [9–12]. Most previous studies recommended that such models should be applied at the early stages of production [3, 7, 13, 14]. The reason is that the early stage of product development contributes only around 15% of the total production cost. However, nearly 75% of the total product cycle cost savings are met at this early stage of product development [14–20]. This indicates a large amount of product lifecycle cost savings can be achieved by reducing modifications and reworks during production and consumption stages [21–23].

Customers often demand products with excellent quality dimensions, lower prices, and short supply lead time (SLT). To meet this challenge in competitive market situations, manufacturers are required to develop an appropriate cost estimation framework [17, 20, 24, 25]. The proposed cost estimation systems must incorporate structured and unstructured data of product attributes [3]. If the costs of products are inaccurate and imprecise, misleading decisions can be made by decision-makers [5, 21, 23, 26, 27]. An overestimation of product costs causes companies to lose sales and competitiveness and an underestimation results in a financial crisis [6, 16, 28, 29].

Based on the stated problem, the paper aims to develop a decision support system (DSS) that works as a cost estimator when new product orders are introduced into machining operations. Specifically, it focuses on estimating the cost of cylindrical products on turning machining operations. The proposed system can retrieve the most similar prior cases. As a new product order is introduced it finds the past product order with the most similar production cost and adapts the retrieved solutions to the current problem. The DSS utilizes neutrosophic case-based reasoning (N-CBR) and neutrosophic best-worst method (N-BWM) for this estimation process to address the truth, indeterminacy, and falsity membership functions in decision-making. The neutrosophic version of CBR was used to apply unstructured and structured data of product features to construct cases and measure similarities with hybrid case features. In addition, the N-BWM component of the proposed DSS was applied to determine the optimal weights of case attributes by soliciting the knowledge and experiences from a group of experts. This was used as input to measure the similarities between new product orders as new cases and previous product orders as prior cases.

As an academic contribution, the combination of N-CBR and N-BWM was not implemented in previous studies to solve the problems of product estimation. This study addressed this literature gap in DSS theories for estimating new product costs. In this regard, this paper provided new insights into integrating CBR and BWM in a neutrosophic environment to estimate production costs for new product orders. This bridges the current knowledge gaps in DSS and decision-making. In addition, according to the survey of previous studies in DSS, the integration of N-CBR and N-BWM has not been applied to solve any industrial problems. The reason to integrate these two methods was selected, they could be easily implemented in manufacturing environments where limited past data are available to apply other machine learning (ML) methods.

The remaining part of this paper contains five sections. Section 2, reviews related studies. Section 3 explains the methodological approach for developing the DSS. Section 4 illustrates a numerical example for estimating the cost of cylindrical products. In Section 5, the findings are briefly discussed. In the last section, conclusions are articulated.

2. Review of related studies

This part reviews related studies and identifies study gaps in the problem of product cost estimation using different methodological approaches. In addition, this section reviews the limitations of the existing product cost estimation methods. In general, it theoretically capitalizes on the problem and the study gaps stated in the previous section.

According to a review by Zhao et al. [30], several cost estimation methods were proposed with different limitations such as labor and time intensiveness, specified design changes, low reusability, and traceability and accuracy. Additional limitations of the proposed methods were discussed in other studies [19, 31, 32]. These proposed models were classified in different ways. For example, Shehab and Abdalla [10] categorized different estimation methods as intuitive, parametric, variant-based, and generative frameworks. Qian and Ben-Arieh, [33] classified the methods of product cost estimation into intuitive, analogical, parametric, and analytical models. In other studies, the methods were classified as quantitative and qualitative approaches (e.g., see [8, 13, 28, 29, 31, 32]). In addition, more classifications are shown in other studies [7, 9, 19, 34, 35].

The review of related studies in product cost estimation is summarized in Table 1. It incorporates the authors, proposed estimation models/frameworks, and applied methods for developing models.

Table 1. Summary of related studies

SN	Author(s)	Framework/model	Method	Production area
1	Weustink et al. [18]	Generic analytical framework	Hierarchical method at assembly, component, and feature levels	Assembly line
2	Molcho et al. [17]	Analytical decision support tool	Linear regression using seven input cost factors	Abrasive parts
3	Wouters and Stecher [36]	Analytical real-time cost estimation model	Analysis of real-time machine and labor hours	Machining mechanical parts
4	H'mida et al. [16]	Knowledge-based integrated product and costgrammes model	Analysis of part, material, and process features as constraint satisfaction from CAD	Machining mechanical parts
5	Park and Simpson [37]	Knowledge-based Product family cost estimation	Activity-based costing (ABC)	Cordless power screwdriver
6	Zhang and Fuh [38] Zhang et al. [39]	Machine learning (ML) based model	Featured-based artificial neural network (ANN)	Packaging
7	Wang [21]	ML-based model	Featured-based ANN	Plastic injection
8	Duran et al. [1]	ML model	ANN	Piping elements
9	Bode [24, 40]	ML-based decision support	ANN	Bearing products development
10	Cavalieri et al. [27]	ML-based predictive model	ANN	Automotive industry
11	Loyer et al. [25]	ML-based model	Support vector regression and gradient-boosted trees	Jet engine components
12	Caputo and pelagagge	ML-based model	ANN	Complex pressure vessels
13	Duverlie and Castelain [19]	CBR-oriented ML model	Parametric and CBR	Piston parts
14	Zhao et al. [30]	Comprehensive framework	Knowledge-based engineering	Aircraft component
15	Wang et al. [5]	ML model	Integration of ANN and particle swarm optimization (PSO)	Plastic injection molding
16	Karaoglan and Karademir [12]	ML model	ANN-forward and backward propagation	Electromechanical/ transformer
17	Relich and Świć [22]	Decision support framework	Integration of parametric, constraint programming, and simulation	Generic new product development
18	Tyagi et al. [41]	Analytical life-cycle cost estimation model	Analytical methods to estimate development, service, and risk costs	Gas turbine

Table 1. (Cont.)

SN	Author(s)	Framework/model	Method	Production area
19	Tu et al. [9]	Cost index structure	Generative and variant cost estimation method	Generic mass customization
20	Chougule and Ravi [20]	Web-based intelligent collaborative engineering system	Parametric using material, geometric, quality, and production attributes	Casting
21	Chan et al. [2]	ML-based predictive framework	Big data analytics	Additive manufacturing
22	Letaief et al. [26]	Feature-based ML framework	Feature-based CAD/ CAM data reuse	CAD/CAM-based machining
23	Jung [42]	Featured-oriented analytical model	Featured-based machining parts	Machining
24	Shehab and Abdalla [10]	Knowledge-based DSS	Feature-oriented CAD	CAD/CAM-based machining
25	Özbayrak et al. [43]	Mathematical/ simulation model	Activity-based costing (ABC)	Advanced manufacturing systems
26	Yeh and Deng [8]	ML-based product life cycle cost estimation	ANN and support vector machine (SVM)	Airframe structure manufacturing
27	Campi et al. [44]	Analytical models	Feature-based	Open-die forging
28	Mandolini et al. [14]	Knowledge-based analytical framework	Rule-based reasoning	Open-die forging
29	Wasim et al. [6]	Knowledge-based DSS	Feature-based method	Lean system
30	Ning et al. [23]	ML model	Feature-based deep learning	Machining
31	Koonce et al. [45]	Hierarchy-based analytical framework	Hierarchical structure	Concurrent engineering (CE) Manufacturing
32	Defersha et al. [35]	Analytical model	Data envelopment analysis (DEA)	Landing gears of aircraft
33	Ou-Yang and Lin [46]	Analytical framework	Feature-based CAD/CAM	CE machining
34	Qian and Ben-Arieh [33]	ABC-oriented analytical model	Combined parametric and ABC methods	Machining rotational parts
35	Smith and Mason [47]	Predictive ML model	Regression and ANN	Generic production
36	Hooshmand et al. [11]	Generic analytical model	Combined new and standard variants of cost driver attributes	Engineer-to-order (ETO)
37	Juan et al. [48]	ML-based DSS	Integrated CBR and genetic algorism (GA)	Housing customization
38	Chang et al. [49]	ML-based product predictor	Integrated CBR and ANN	Mobile phone products
39	An et al. [50]	CBR-oriented ML	Integrated CBR and analytic hierarchy process (AHP)	Construction
40	Sajadfar and Ma [51]	Feature-oriented ML	Linear regression and data mining	Welding
41	Kasie and Bright [3]	CBR-oriented ML	Integrated fuzzy CBR and fuzzy AHP	Machining
42	Matel et al. [52]	ML	ANN	Construction consultancy service

The review of related studies indicates that the problems of product cost estimation were addressed using different methods. This includes analytical, heuristics, multiple-criteria decision-making (MCDM), machine learning (ML), simulation, and knowledge-based systems in various problem areas. However, the integration of N-CBR and N-BWM has not been applied to this problem. Cost estimation can be utilized in neutrosophic environments for case representation and weighing case features/cost drivers. For instance, if we ask ten customers to state their acceptance of the specific price (say $ 100) of a product; six customers may accept, three may reject and one of them may be indeterminate. The situation is expressed using a dependent single-valued neutrosophic set (SVNS) using three membership values (0.6, 0.3, 0.1). This finding may change over time if we conduct other surveys because of uncertainty [53]. This situation indicates that the membership values in SVNS can be expressed by fuzzy theory [54, 55]. An individual or a group of experts can independently evaluate the membership values in neutrosophic environments in MCDM [56–59]. The objective of this research is to address this knowledge gap in DSS and product cost estimation research. It gives new insights into integrating CBR and BWM in neutrosophic environments to solve the problem of product estimation.

3. Methodological approach

This section explains the theories, preliminaries, and methodological procedures applied in this study.

3.1 *Integration of NS, CBR, and BWM*

The decision-making process in modern manufacturing systems should include uncertainty, incompleteness, and vagueness to cope with human thoughts [60, 61]. Decision support models using a CBR methodology can be applied in such situations [3, 62]. CBR is a popular ML methodology in AI, which solves the target problems by reusing and adapting the prior similar solutions retained as cases [63, 64]. Some of the recent applications in different problem domains are present in various studies (see [3, 62, 65–67]). The advantages of CBR over other ML systems are its training capability by employing a few historical datasets [65–68], and its accuracy improvement accumulated experiences as many problems are solved over time [3, 66, 67].

According to Aamodt and Plaza [63], a CBR methodology has four major phases for decision-making

(1) *Retrieving* the most similar prior case to the current problem;

(2) *Reusing* the concrete knowledge and experiences from the retrieved case to the new problem;

(3) *Revising* the retrieved case for adapting it as a solution to the current problem; and,

(4) *Retaining* the final solution for future retrieval in case a similar problem will be encountered in the future.

Human experts make decisions in uncertain, vagueness and inconsistent situations expertise is well represented in terms of neutrosophic sets (NS) [55, 62]. An NS is the generalization of fuzzy sets (FS) and intuitionistic fuzzy sets (IFS) [55, 62, 69]. A case is defined as a neutrosophic case as one or more case features are described using NS versions [62]. Smarandache [70] introduced NS using three membership functions such as truth, indeterminacy, and falsity membership functions that generalize FS and IFS. Al-Omeri et al. [71] defined a cone metric space in the context of the NST and basic findings regarding fixed points for weakly compatible mapping. In addition, Wang et al. [72] defined single-valued neutrosophic sets (SVNS). SVNS and its extensions were widely applied in multiple-criteria decision-making (MCDM) and DSS research as presented by the following recent studies. Garg [73] developed a multiple-attribute group decision-making (MAGDM) algorithm using new exponential-logarithm-based SVNS to handle the uncertainties in group decision-making. Nafei et al. [74] presented a multiple-attribute group decision-making (MAGDM) framework using a neutrosophic fuzzy set (NFS) for selecting machine tools in manufacturing industries. Al-Omeri et al. [75] presented the application of a neutrosophic graph to identify the location of an Internet streaming service with the help of Hamming distance. Other applications were presented in the following studies (e.g., see [53, 55–57, 59, 62, 76, 77]). SVNS can be applied for case representation in CBR to describe case attributes or cost drivers using the three membership functions as neutrosophic numbers [53, 62]. The situation of SVNS is defined as a single-valued neutrosophic number (SVNN) [54–59, 62].

Cases are often represented in terms of hybrid multiple features of MCDM to find distance-based similarity measures between target and alternative cases for retrieving the most similar case [3, 65–67, 78, 79]. On the other hand, determining optimal weights for case features is very useful in case-based MCDM [62, 79]. For optimal weight determination, the BWM is a popular pairwise comparison approach, initially proposed by Rezaei [80] and improved by Rezaei [81]. The BWM is easily extended into its neutrosophic version to articulate vagueness, uncertainty, and incompleteness as studied by Vafadarnikjoo et al. [82], Yucesan and Gul [83], Liou et al. [54]. The BWM is more reliable, flexible, and easier than other pairwise comparison approaches such as the analytic hierarchy process (AHP) and analytic network process (ANP) [62, 80–82].

3.2 *Preliminaries*

The preliminary concepts and basic arithmetic operation of SVTNN, which were applied in this study, are explained in this subsection. The definitions and membership functions of NS by Smarandache [70], SVNS by Wang et al. [72], SVNN by Abdel-Basset et al. [56], Abdel-Basset et al. [55, 57] and Chai et al. [84], and single-valued trapezoidal neutrosophic number (SVTNN) by Deli and Subas [58], Abdel-Basset et al. [55], and Liou et al. [54] were applied in this paper. The SVTNN applied in this study is shown in Figure 1.

Definition 1 The three membership functions of an SVTNN such as the truth $T_{\widetilde{A}}(x)$, indeterminacy $I_{\widetilde{A}}(x)$, and falsity $F_{\widetilde{A}}(x)$ membership functions are presented from Equations (1)-(3) respectively.

$$T_{\widetilde{A}}(x) = \begin{cases} \alpha_{\widetilde{A}} \left(\dfrac{x-\widetilde{a}_1}{\widetilde{a}_2-\widetilde{a}_1} \right), & \widetilde{a}_1 \le x \le \widetilde{a}_2 \\ \alpha_{\widetilde{A}}, & \widetilde{a}_2 \le x \le \widetilde{a}_3 \\ \alpha_{\widetilde{A}} \left(\dfrac{\widetilde{a}_4-x}{\widetilde{a}_4-\widetilde{a}_3} \right), & \widetilde{a}_3 \le x \le \widetilde{a}_4 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$I_{\widetilde{A}}(x) = \begin{cases} \dfrac{(\widetilde{a}_2-x) + \theta_{\widetilde{A}}(x-\widetilde{a}_1)}{\widetilde{a}_2-\widetilde{a}_1}, & \widetilde{a}_1 \le x \le \widetilde{a}_2 \\ \theta_{\widetilde{A}}, & \widetilde{a}_2 \le x \le \widetilde{a}_3 \\ \dfrac{(x-\widetilde{a}_3) + \theta_{\widetilde{A}}(\widetilde{a}_4-x)}{\widetilde{a}_4-\widetilde{a}_3}, & \widetilde{a}_3 \le x \le \widetilde{a}_4 \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

$$F_{\widetilde{A}}(x) = \begin{cases} \dfrac{(\widetilde{a}_2-x) + \beta_{\widetilde{A}}(x-\widetilde{a}_1)}{\widetilde{a}_2-\widetilde{a}_1}, & \widetilde{a}_1 \le x \le \widetilde{a}_2 \\ \beta_{\widetilde{A}}, & \widetilde{a}_2 \le x \le \widetilde{a}_3 \\ \dfrac{(x-\widetilde{a}_3) + \beta_{\widetilde{A}}(\widetilde{a}_4-x)}{\widetilde{a}_4-\widetilde{a}_3}, & \widetilde{a}_3 \le x \le \widetilde{a}_4 \\ 1, & \text{otherwise} \end{cases} \tag{3}$$

where $\alpha_{\widetilde{A}}$, $\theta_{\widetilde{A}}$, *and* $\beta_{\widetilde{A}}$ are the maximum value of $T_{\widetilde{A}}(x)$, the minimum value of $I_{\widetilde{A}}(x)$, and the minimum value of $F_{\widetilde{A}}(x)$ respectively.

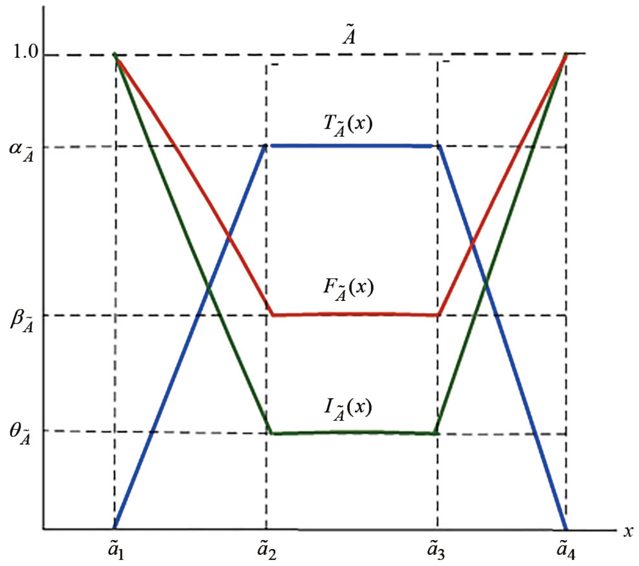

Figure 1. Representation of single-valued trapezoidal neutrosophic number (SVTNN) $\widetilde{A}$ [54]

Definition 2 According to Deli and Subas [58], Abdel-Basset et al. [55, 56], Yucesan and Gul [83]; let $\widetilde{A} = ((\widetilde{a}_1, \widetilde{a}_2, \widetilde{a}_3, \widetilde{a}_4); \alpha_{\widetilde{A}}, \theta_{\widetilde{A}}, \beta_{\widetilde{A}})$ and $\widetilde{B} = \left(\left(\widetilde{b}_1, \widetilde{b}_2, \widetilde{b}_3, \widetilde{b}_4\right); \alpha_{\widetilde{B}}, \theta_{\widetilde{B}}, \beta_{\widetilde{B}}\right)$ are two positive SVTNNs, this study applied the following basic arithmetic operations.

1. **Addition**

$$\widetilde{A}+\widetilde{B} = \left(\left(\widetilde{a}_1+\widetilde{b}_1, \widetilde{a}_2+\widetilde{b}_2, \widetilde{a}_3+\widetilde{b}_3, \widetilde{a}_4+\widetilde{b}_4\right); \min\left(\alpha_{\widetilde{A}}, \alpha_{\widetilde{B}}\right), \max\left(\theta_{\widetilde{A}}, \theta_{\widetilde{B}}\right), \max\left(\beta_{\widetilde{A}}, \beta_{\widetilde{B}}\right)\right). \tag{4}$$

2. **Subtraction**

$$\widetilde{A}-\widetilde{B} = \left(\left(\widetilde{a}_1-\widetilde{b}_1, \widetilde{a}_2-\widetilde{b}_2, \widetilde{a}_3-\widetilde{b}_3, \widetilde{a}_4-\widetilde{b}_4\right); \min\left(\alpha_{\widetilde{A}}, \alpha_{\widetilde{B}}\right), \max\left(\theta_{\widetilde{A}}, \theta_{\widetilde{B}}\right), \max\left(\beta_{\widetilde{A}}, \beta_{\widetilde{B}}\right)\right). \tag{5}$$

3. **Multiplication of two positive SVTNNs**

$$\widetilde{A}\times\widetilde{B} = \left(\left(\widetilde{a}_1\widetilde{b}_1, \widetilde{a}_2\widetilde{b}_2, \widetilde{a}_3\widetilde{b}_3, \widetilde{a}_4\widetilde{b}_4\right); \min\left(\alpha_{\widetilde{A}}, \alpha_{\widetilde{B}}\right), \max\left(\theta_{\widetilde{A}}, \theta_{\widetilde{B}}\right), \max\left(\beta_{\widetilde{A}}, \beta_{\widetilde{B}}\right)\right). \tag{6}$$

4. **Division of two positive SVTNNs**

$$\widetilde{A}\div\widetilde{B} = \left(\left(\widetilde{a}_1/\widetilde{b}_4, \widetilde{a}_2/\widetilde{b}_4, \widetilde{a}_3/\widetilde{b}_2, \widetilde{a}_4/\widetilde{b}_1\right); \min\left(\alpha_{\widetilde{A}}, \alpha_{\widetilde{B}}\right), \max\left(\theta_{\widetilde{A}}, \theta_{\widetilde{B}}\right), \max\left(\beta_{\widetilde{A}}, \beta_{\widetilde{B}}\right)\right). \tag{7}$$

5. **The inverse of a positive SVTNN $\widetilde{\mathrm{A}}$**

$$\widetilde{A}^{-1} = \left(\left(\frac{1}{\widetilde{a}_4}, \frac{1}{\widetilde{a}_3}, \frac{1}{\widetilde{a}_2}, \frac{1}{\widetilde{a}_1}\right); \alpha_{\widetilde{A}}, \theta_{\widetilde{A}}, \beta_{\widetilde{A}}\right). \tag{8}$$

6. **Multiplying a positive SVTNN $\widetilde{\mathrm{A}}$ by a positive constant k**

$$k\widetilde{A} = \left((k\widetilde{a}_1, k\widetilde{a}_2, k\widetilde{a}_3, k\widetilde{a}_4); \alpha_{\widetilde{A}}, \theta_{\widetilde{A}}, \beta_{\widetilde{A}}\right). \tag{9}$$

Definition 3 According to Liou et al. [54] and Kasie and Bright [62], for an SVTNN $\widetilde{A}$, the crisp score of $\widetilde{A}$ is estimated as follows:

$$CSc\left(\widetilde{A}\right) = \frac{(\widetilde{a}_1 + 2\widetilde{a}_2 + 2\widetilde{a}_3 + \widetilde{a}_4)(2 + \alpha_{\widetilde{B}} - \theta_{\widetilde{B}} - \beta_{\widetilde{B}})}{18}. \tag{10}$$

Definition 4 In addition, a single-valued triangular neutrosophic number, a special kind of SVTNN that can be represented as $\widetilde{A} = ((\widetilde{a}_1, \widetilde{a}_2, \widetilde{a}_3); \alpha_{\widetilde{A}}, \theta_{\widetilde{A}}, \beta_{\widetilde{A}})$, when $\widetilde{a}_2 = \widetilde{a}_3$ in a general SVTNN [56, 62, 83]

3.3 *Methodological procedure proposed DSS*

The methodological procedure and integration of the proposed DSS of this paper are indicated in Figure 2. This study integrates N-CBR and N-BWM to develop the proposed system for solving the problem of product cost estimation. The methodological procedure incorporates four main phases (a) Data cleaning and case representation phase; (b) Similarity measure and case retrieval phase; (c) Case reuse and adaptation phase; and (d) Case retraining and indexing phase.

3.3.1 *Data cleaning and neutrosophic case representation*

In real industrial situations, the specifications of product orders from the customers are usually unstructured with many outliers and noisy data. To address this problem, the proposed system should use an appropriate data-cleaning strategy. Different rules are required to organize the unstructured data from the customers. This study specifically applied data cleaning methods to omit and edit outliers and noisy data for cost driver attributes by referring to the descriptions of simulated product orders from the customers. The researchers implemented several rules to handle the outliers of cost-driving features. For example, the cost driver features of the workpieces beyond the capability of the machining operations were prevented by those rules. After cleaning the noises from the cost drivers, cases were represented by organizing cleaned cost driving features as multiple case attributes. To identify crucial cost drivers as multiple case/product order attributes, the researchers selected knowledgeable and experienced experts. The selected cost drivers of product orders were used to construct cases and determine similarities between target and prior cases. Object-oriented programming (OOP) was applied to represent cases on the Java platform which is a freely available OPP platform.

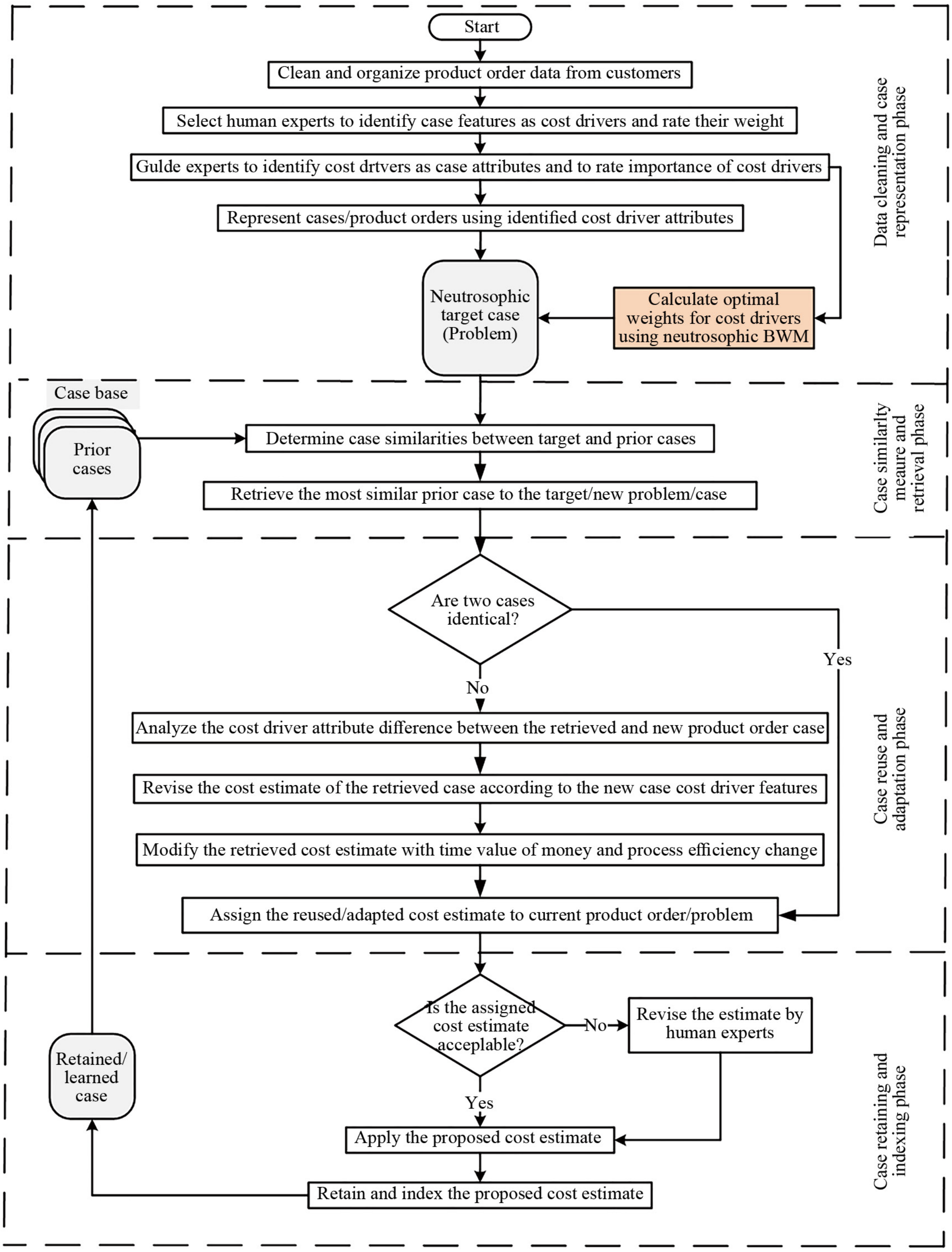

Figure 2. Procedures of proposed cost estimating DSS

In total, fourteen cost drivers were identified to represent product orders as cases using multiple cost-driving attributes. The cost drivers were included from three major product features such as work-piece size and material, finished product quality, and typed machining operations. These features were selected using the recommendation from human experts and reviews of related studies [3, 7, 11, 14, 18, 26, 44]. The cost drivers of multiple case attributes were expressed using numerical, categorical, and linguistic case attributes to make the reasoning and decision-making process more flexible [65–67].

To represent products using multiple cost-driving attributes, various neutrosophic-based linguistic terms were transformed into their equivalent SVTNNs according to the proposal by Abdel-Basset et al. [55, 59] and Kasie and Bright [62]. Finally, the crisp score (CSc) of the SVTNNs was estimated using Equation (10). The results of these conversions are presented in Table 2.

Table 2. Proposed neutrosophic conversion scale of linguistic terms (see [55, 59, 62])

Linguistic terms	SVTNN $\widetilde{A}$	Estimated $CSc(\widetilde{A})$
Extremely minimum (EMi)	((0.0, 0.0, 0.1, 0.2); 0.8, 0.2, 0.15)	0.041
Highly minimum (HMi)	((0.0, 0.1, 0.2, 0.3); 0.85, 0.2, 0.1)	0.128
Minimum (Min)	((0.1, 0.2, 0.3, 0.4); 0.9, 0.1, 0.15)	0.221
Fairly minimum (FMi)	((0.2, 0.3, 0.4, 0.5); 0.9, 0.15, 0.1)	0.309
Medium minimum (MMi)	((0.3, 0.4, 0.5, 0.6); 0.85, 0.0, 0.1)	0.413
Medium (Med)	((0.4, 0.5, 0.6, 0.7); 0.95, 0.15, 0.1)	0.495
Medium maximum (MMa)	((0.5, 0.6, 0.7, 0.8); 0.9, 0.1, 0.1)	0.585
Fairly maximum (FMa)	((0.6, 0.7, 0.8, 0.9); (0.95, 0.1, 0.15)	0.675
Maximum (Max)	((0.7, 0.8, 0.9, 1.0); (0.9, 0.1, 0.0)	0.793
Highly maximum (HMa)	((0.8, 0.9, 1.0, 1.0); (0.95, 0.1, 0.1)	0.856
Extremely maximum (EMa)	((0.9, 1.0, 1.0, 1.0); (1.0, 0.0, 0.1)	0.951

3.3.2 *Determination of optimal weights cost driving case attributes*

After the selection of cost-driving multiple attributes of cases, the researchers determined the optimal weights of cost-driving attributes using the neutrosophic version of the BWM. The contribution of each cost driver was evaluated by a group of experts using BWM-based neutrosophic linguistic terms. These terms were converted into their proposed BWM-based SVTNNs and the average values of expert ratings were calculated using Equation (9). Finally, the estimated crisp of the average SVTNN was determined by applying Equation (10). The conversion scales from linguistic terms into SVTNNs and their estimated crisp values are presented in Table 3. Similar approaches were applied in some recent studies in other problem domains [54, 59, 83].

Table 3. Conversion scale of BWM-linguistic terms into SVTNNs and estimated crisp scores

BWM-based linguistic preference	BWM-based SVTNN $\widetilde{A}$	Estimated $CSc(\widetilde{A})$
Equally preferred (EP)	((1, 1, 1, 1); 1.0, 0.0, 0.0)	1.000
Nearly equally preferred (NEP)	((1, 1, 1.5, 2); 0.95, 0.1, 0.0)	1.267
Intermediate between equal and moderate (IEM)	((1, 2, 2.5, 3); 0.9, 0.1, 0.1)	1.950
Moderately preferred (MP)	((2, 3, 3.5, 4); 0.85, 0.1, 0.0)	2.903
Intermediate between moderate and high (IMH)	((3, 4, 4.5, 5); 0.9, 0.15, 0.1)	3.681
Highly preferred (HP)	((4, 5, 5.5, 6); 0.9, 0.05, 0.15)	4.650
Intermediate between high and very high (IHVH)	((5, 6, 6.5, 7); 0.95, 0.1, 0.1)	5.653
Very highly preferred (VHP)	((6, 7, 7.5, 8); 0.9, 0.15, 0.1)	6.570
Intermediate between very high and extreme (IVHE)	((7, 8, 8.5, 9); 0.95, 0.1, 0.15)	7.350
Extremely preferred (ExP)	((8, 9, 9.5, 9); 1.0, 0.05, 0.05)	8.539

To apply the neutrosophic version of BWM; the researchers followed eight steps.

Step 1: Select m experts that can evaluate pairwise the importance of cost-driving case attributes at three levels depending on the BWM-based linguistic terms presented in Table 3.

Step 2: Guide your experts to identify n cost drivers at their respective hierarchical levels.

Step 3: Consult your experts to select the best and the worst cost drivers at each level.

Step 4: Guide the experts to evaluate the cost drivers independently based on the best over others and generate a preference matrix of the equivalent BWM-based SVTNNs.

$$\widetilde{A}_B = \begin{bmatrix} \widetilde{A}_{B1}^1 & \cdots & \widetilde{A}_{Bn}^1 \\ \vdots & \ddots & \vdots \\ \widetilde{A}_{B1}^m & \cdots & \widetilde{A}_{Bn}^m \end{bmatrix} \tag{11}$$

where $\widetilde{A}_{Bj}^i$ is the preference of the best cost driver over a cost driver j $(j = 1,\ 2,\ \ldots n)$ by an expert i $(i = 1,\ 2,\ \ldots,\ m)$.

Step 5: Guide the experts to evaluate the cost drivers independently based on others to the worst and generate a preference matrix of the equivalent BWM-based SVTNNs.

$$\widetilde{A}_W = \begin{bmatrix} \widetilde{A}_{1W}^1 & \cdots & \widetilde{A}_{nW}^1 \\ \vdots & \ddots & \vdots \\ \widetilde{A}_{1W}^m & \cdots & \widetilde{A}_{nW}^m \end{bmatrix}^T \tag{12}$$

where $\widetilde{A}_{jW}^i$ is the preference of a cost driver j $(j = 1,\ 2,\ \ldots n)$ over the worst cost driver by an expert i $(i = 1,\ 2,\ \ldots,\ m)$.

Step 6: Calculate the averages of individual ratings of preferences from the matrices generated from Step 4 and Step 5. To apply Equations (13) and (14), the preliminary neutrosophic operations from Equations (1) and (9) were utilized and different SVTNNs were obtained.

$$\overline{\widetilde{A}}_B = \frac{\sum_{i=1}^m \widetilde{A}_{Bj}^i}{m} = \left[\overline{\widetilde{A}}_{B1},\ \overline{\widetilde{A}}_{B2},\ \ldots,\ \overline{\widetilde{A}}_{Bn}\right] \tag{13}$$

$$\overline{\widetilde{A}}_W = \frac{\sum_{i=1}^m \widetilde{A}_{jW}^i}{m} = \left[\overline{\widetilde{A}}_{1W},\ \overline{\widetilde{A}}_{2W},\ \ldots,\ \overline{\widetilde{A}}_{nW}\right]^T \tag{14}$$

where $j = 1,\ 2,\ \ldots n$.

Step 7: Calculate the estimated crisp scores of SVTNNs from Step 6 using Equation (13) as $CSc\left(\overline{\widetilde{A}}_{Bj}\right) = \overline{a}_{Bj}$ and $CSc\left(\overline{\widetilde{A}}_{jW}\right) = \overline{a}_{jW}$.

Step 8: Determine the optimal weights of cost drivers of multiple case attributes $(w_1^*,\ w_2^*,\ \ldots,\ w_n^*)$ using the optimization models of BWM. According to Rezaei [81], a linear programming optimization model can be applied to the results of Step 7 as follows:

$$\mathrm{Min}\,\xi^L$$

subject to

$$\left|\overline{w}_B - \overline{a}_{Bj}\overline{w}_j\right| \leq \xi^L, \text{ for all } j$$

$$\left|\overline{w}_j - \overline{a}_{jW}\overline{w}_W\right| \leq \xi^L, \text{ for all } j$$

$$\sum_{j=1}^{n} \overline{w}_j = 1$$

$$\overline{w}_j \geq 0 \text{ for all } j \tag{15}$$

where ξ^L is a consistency index of the linear optimization model. The index $\xi^L \approx 0$ shows a good level of consistency.

3.3.3 *Case similarity measure and retrieval*

After case representation and determining the optimal contributions/weights of the selected cost drivers, a case similarity is required to retrieve the most similar prior case to the current problem. The weighted Euclidean distance is the most recognized function based on the nearest neighbor (NN) pattern recognition [3, 65]. This study used this pattern recognition function. The researchers applied this function using the two steps. Firstly, the linear distances between pairs of each cost-driving attribute were calculated. Lastly, the cumulative weighted Euclidean distances between the prior and new two cases were determined. Similar approaches were applied by several recent studies (e.g., [3, 65–67]). The optimal weights of cost drivers, which were determined by N-BWM were normalized. To calculate the cumulated weighted Euclidean distance between any target product order/case T and a prior product order/case P; the following equation was applied.

$$D_{Euc}(T,\ P) = \sqrt{\sum_{j=1}^{n}\left[w_j(D_{lin}(a_j^T,\ a_j^P))\right]^2},\ \ 0 \leq D_{lin}\left(a_j^T,\ a_j^P\right)\ \leq 1 \tag{16}$$

where:

n is the number of cost drivers of a multiple attribute case.

w_j is the normalized optimal weight of a jth cost driver.

$D_{lin}\left(a_j^T,\ a_j^P\right)$ is the linear distance between individual pair-values of cost-driving attributes of target and prior cases.

$a_j^T,\ a_j^P$ are the values of the jth cost driver for target and prior product orders respectively.

An individual linear distance, $D_{lin}\left(a_j^T,\ a_j^P\right)$, for specific types of cost drivers such as numeric, categorical, and linguistic attributes, used different approaches. For numeric and categorical cost-driving attributes, the study used a similar approach to the functions applied by Kasie and Bright [3] and Kasie and Bright [65].

Neutrosophic linguistic cost drivers, the linguistic terms were converted into equivalent SVTNNs using the conversion scales presented in Table 2. Then the crisp score of the SVTNNs was estimated using Equation (7). Finally, the estimated scores were treated as numeric cost-driving attributes [62] using Equation (14).

In pattern recognition, distance and similarity measures are inversely related, the weighted similarity measure between target and prior product orders/cases, $S_{Euc}(T,\ P)$, was found by applying the inverse of an exponential function [66, 67]:

$$S_{Euc}(T,\ P) = \frac{1}{\exp(D_{Euc}(T,\ P))},\ 0 \leq S_{Euc}(T,\ P)\ \leq 1 \tag{17}$$

Using this similarity measure between the target and prior cases, the most similar case to the target problem was the retrieved case for reuse and adaptation to the current product order or target problem.

3.3.4 *Case reuse and adaptation*

After retrieving the best prior case to the target product order, the next crucial activity is reusing and adapting the cost estimates of the retrieved product order to the target problem [3]. Depending on the similarity measure between the two cases, different rules were proposed for reuse and adaptation of the retrieved cost estimate. If the retrieved and target product orders are highly similar i.e., $S_{Euc}(T,\ P) \approx 1$, the retrieved cost estimate has a great chance for direct reuse except for minor adjustments if there are significant changes in time value of money and process efficiency. If there are important variations between the two cases, $S_{Euc}(T,\ P) < 1$, an adaptation of the retrieved cost estimate from the retrieved case is highly applicable. For example, if parameter differences are encountered between the two cases, the retrieved cost estimate can be modified using parametric cost estimation methods. Similarly, if the removal and/or addition of new features is considered, feature-oriented cost estimation methods can be applied for adaptations (see [3]).

3.3.5 *Case retaining and indexing*

This phase is used to retain and index the current (reused and revised) cost estimate with its cost-driving case attributes for future retrieval as similar new product orders arrive. These indexed cases will serve as solutions for future similar order arrivals. In addition, the proposed DSS provides an opportunity for human experts to interact with the proposed decision of the system. If human experts accept the proposed decision from the DSS, they can implement the decisions. Otherwise, they can modify the proposal before its application.

4. Analysis of numerical example

This part illustrates the integration of CBR and BWM in neutrosophic environments using the methodological procedure presented in Figure 2. The four phases presented in Section 3 are numerically illustrated in this section. The methodological integration of the proposed system was applied in a simulated environment of a machining process. A turning machining process was simulated to machine various types of cylindrical products.

4.1 *Data cleaning and case representation*

Initially, order arrival descriptions by customers were cleaned by using data cleaning methods to omit and edit outliers and noisy data of cost-driving attributes. Different rules were implemented to handle the outliers of cost-driving features. For example, the dimensions (length and diameter) of the work-pieces beyond the capability of the machining operations were prevented by those rules. After cleaning the noises from the cost drivers, cases were represented by organizing cleaned cost driving features as multiple case attributes.

The researchers selected four human experts to identify crucial cost-driving case attributes. The experts were identified depending on their capabilities for estimating the production costs of machining processes. In total, the human experts identified fourteen cost drivers to construct multiple-attributed cases from new and prior product order arrivals. The researchers clustered the proposed cost drivers into three major hierarchical product features such as work-piece characteristics (*WPC*), finished product quality (*FPQ*), and required machining operations (*RMO*). The three classifications were done based on the recommendation of experts and reviews of related studies as stated in the previous section. The cost drivers of the multiple-attributed case were expressed using numerical, categorical, and neutrosophic linguistic terms. The researchers used the linguistic terms presented in Table 2.

Under the hierarchy of *WPC*, three cost drivers were included such as the length (*Len*), diameter (*Dia*), and composition (*Com*) of the work-piece/raw material. The first two dimensions of the workpiece are often measured by numerical values commonly in millimeters (mm). They are usually used as parametric cost estimators [3, 10, 22, 33]. In this study, they were considered as numeric cost-driving attributes of cases. The composition of the raw material can be expressed using either its alloy type (e.g., carbon steel, stainless steel, cast iron, etc.) or the expensiveness of the input raw material. In this regard, the expensiveness of the workpiece was preferred to describe the cost of products. This cost driver was best described using linguistic terms presented in Table 2 to indicate the expensiveness/cheapness of construction materials.

In the case of *FPQ* features, the precision (*Pre*), reliability (*Rel*), and durability (*Dur*) of finished product attributes were incorporated as cost drivers for case construction. All cost drivers under this cluster were described using neutrosophic linguistic terms to indicate the quality of products since they are difficult to measure using specific units. The required machining operations were sub-clustered into external and internal features of cost drivers. Under external features of machining operation, four basic turning operations such as turning (*Tur*), facing (*Fac*), grooving (*Gro*), and threading (*Thr*) were considered. Similarly, under internal operations, four fundamental operations such as drilling (*Dri*), boring (*Bor*), reaming (Rea), and tapping (*Tap*) were included as cost-driving attributes. All external and internal cost drivers were expressed using categorical attributes of {0, 1} binary integer values. This implies a product order requires a specific operation, its value for that cost driver is '1'; otherwise, it is '0'. Similar case representation approaches were applied by recent studies in other problem domains [3, 65–67]

The researchers represented the simulated prior and target product orders using OOP in the freely available Java platform. Target product arrivals (*Ta*1-*Ta*7) were generated as new cases or target problems and three prior order arrivals (*Pa*1-*Pa*3) were generated as prior case or solution alternatives with assigned production cost estimates (*PCE*). The generated cases incorporating their fourteen cost drivers are presented in Table 4. The prior *PCE*s were used as retrieved solutions that could be reused/and or adapted for target product orders.

Table 4. Neutrosophic cases of product orders

Ta or *Pa*	Cost-driving attributes of product orders/cases														*PCE*
	Len	*Dia*	*Com*	*Pre*	*Rel*	*Dur*	*Tur*	*Fac*	*Gro*	*Thr*	*Dri*	*Bor*	*Rea*	*Tap*	
*Ta*1	730	320	MMa	Med	FMa	FMi	1	1	0	0	1	1	0	1	
*Ta*2	920	430	FMi	Max	MMi	FMa	1	0	1	0	1	0	1	1	
*Ta*3	570	200	Max	MMi	EMa	FMa	1	0	0	1	0	1	0	0	
*Ta*4	720	330	MMa	MMi	FMa	FMi	1	1	0	0	1	1	0	1	
*Ta*5	580	200	Max	MMi	EMa	FMa	1	0	0	1	0	1	0	0	
*Ta*6	920	440	FMi	Max	MMi	FMa	1	1	1	0	1	0	1	1	
*Ta*7	710	330	MMa	MMi	FMa	FMi	1	1	0	0	1	1	0	1	
*Pa*1	900	430	MMi	Max	Med	FMa	1	0	1	0	1	0	1	1	*PCE1*
*Pa*2	560	220	HMa	FMi	EMa	HMa	1	0	1	1	0	1	0	0	*PCE*2
*Pa*3	740	310	MMa	MMa	FMa	FMi	1	1	0	0	1	0	1	1	*PCE*3

4.2 *Determination of optimal weights for cost drivers*

The cost drivers of multiple-attributed cases were hierarchically rated by the selected four experts using BMM-based terms presented in Table 3. In general, steps 2-8 in Section 3.3.2 were applied for optimal weight determinations of cost drivers. At three levels of clustered cost drivers, the best and the worst cost drivers were selected. The experts independently rated the cost drivers based on the concept of BWM i.e., the best to others and others to the worst rating approaches. The researchers converted the expert ratings in the linguistic terms into their equivalent SVTNNs using the conversion scale in Table 2 and Equation (11) (best to others) and Equation (12) (others to worst). The average values of group-based expert ratings were determined using Equation (13) (best to others) and Equation (14) (others to worst). Using the outputs from Equations (13) and (14), the optimal weights of cost drivers were determined using Equation (15) at the respective clustered levels.

The three major cost drivers ($n = 3$) were evaluated by the selected four experts ($m = 4$). In this case, the *WPC* was identified as the best cost driver, and the *FPQ* was considered the worst cost driver by a group of experts. The group evaluation of the best to others is presented in Table 5 and others to the worst are shown in Table 6 respectively.

Table 5. The best to others for major cost drivers using N-BWM

Ex/CD	*WPC*	*RMO*	*FPQ*
Ex1	EP	IEM	MP
Ex2	EP	NEP	IEM
Ex3	EP	MP	IMH
Ex4	EP	NEP	MP
Average, $\overline{a}_{Bj}$	1.000	1.847	2.859

Note Ex = Expert, CD = Cost driver

Table 6. Others to the worst for major cost drivers using N-BWM

CD/Ex	Ex1	Ex2	Ex3	Ex4	Average, $\overline{a}_{jW}$
WPC	MP	IEM	IMH	MP	2.859
RMO	IEM	NEP	MP	IEM	2.016
FPQ	EP	EP	EP	EP	1.000

Using Equation (15), the optimal weights were found as $\overline{w}_B = \overline{w}_1$ = 0.541 for *WPC*, $\overline{w}_2$ = 0.292 for *RMO*, $\overline{w}_W = \overline{w}_3$ = 0.167 for *FPQ*, and $\xi^L = 0.097$.

Under the cluster of *WPC* cost drivers, *Len* was selected as the best cost driver and *Com* was taken as the worst cost driver. The rating of the best to others is indicated in Table 7 and others to the worst are presented in Table 8 respectively.

Table 7. The best to others for cost drivers under *WPC* using N-BWM

Ex/CD	*Len*	*Dia*	*Com*
Ex1	EP	NEP	IMH
Ex2	EP	EP	IEM
Ex3	EP	NEP	MP
Ex4	EP	EP	IMH
Average, $\overline{a}_{Bj}$	1.000	1.134	3.054

Table 8. Others to the worst for cost drivers under *WPC* using N-BWM

CD/Ex	Ex1	Ex2	Ex3	Ex4	Average, $\overline{a}_{jW}$
Len	IMH	IEM	MP	IMH	3.054
Dia	MP	IEM	MP	IMH	2.859
Com	EP	EP	EP	EP	1.000

The optimal weights were determined as $\overline{w}_B = \overline{w}_1 = 0.430$ for *Len*, $\overline{w}_2 = 0.427$ for *Dia*, $\overline{w}_W = \overline{w}_3 = 0.143$ for *Com*, and $\xi^L = 0.0$ by applying Equation (15).

For the cost driver under cluster *FPQ*, *Pre* was selected as the best cost driver and *Dur* was taken as the worst cost driver. The ratings of the best to others and others to the worst are shown in Tables 9 and 10 respectively.

Table 9. The best to others for cost drivers under *FPQ* using N-BWM

Ex/CD	*Pre*	*Rel*	*Dur*
Ex1	EP	MP	HP
Ex2	EP	IEM	IMH
Ex3	EP	NEP	MP
Ex4	EP	MP	IMH
Average, $\overline{a}_{Bj}$	1.000	2.256	3.729

Table 10. Others to the worst for cost drivers under *FPQ* using N-BWM

CD/Ex	Ex1	Ex2	Ex3	Ex4	Average, $\overline{a}_{jW}$
Pre	HP	IMH	MP	IMH	3.729
Rel	MP	MP	NEP	IEM	2.256
Dur	EP	EP	EP	EP	1.000

With the help of Equation (15), the optimal weights were determined as $\overline{w}_B = \overline{w}_1 = 0.538$ for *Pre*, $\overline{w}_2 = 0.308$ for *Rel*, $\overline{w}_W = \overline{w}_3 = 0.154$ for *Dur*, and $\xi^L = 0.0$.

For the two cost drivers under cluster *RMO*, an external operation (*ExO*) was considered the best cost driver, and an internal operation (*InO*) was taken as the worst cost driver. The ratings of the best to others and others to the worst are shown in Tables 11 and 12 respectively.

Table 11. The best to others for cost drivers under *FPQ* using N-BWM

Ex/CD	*InO*	*ExO*
Ex1	EP	EP
Ex2	NEP	EP
Ex3	EP	EP
Ex4	IEM	EP
Average, $\overline{a}_{Bj}$	1.304	1.000

Table 12. Others to the worst for cost drivers under *FPQ* using N-BWM

CD/Ex	Ex1	Ex2	Ex3	Ex4	Average, $\overline{a}_{jW}$
emphInO	EP	EP	EP	EP	1.000
ExO	EP	NEP	EP	IEM	1.304

Similarly, the optimal weights were determined as $\overline{w}_B = \overline{w}_2 = 0.566$ for *ExO*, $\overline{w}_W = \overline{w}_1 = 0.434$ for *InO*, and $\xi^L = 0.0$. For the cost drivers under cluster *ExO*, *Tur* was considered as the best cost driver and *Gro* was taken as the worst cost driver. The ratings of the best to others and others to the worst are shown in Tables 13 and 14 respectively.

Table 13. The best to others for cost drivers under *ExO* using N-BWM

Ex/CD	*Tur*	*Fac*	*Gro*	*Thr*
Ex1	EP	VP	ExP	HP
Ex2	EP	IMH	VP	MP
Ex3	EP	MP	IVHE	IMH
Ex4	EP	IMH	VHP	HP
Average, $\overline{a}_{Bj}$	1.000	4.209	7.257	3.971

Table 14. Others to the worst for cost drivers under ExO using N-BWM

CD/Ex	Ex1	Ex2	Ex3	Ex4	Average, $\overline{a}_{jW}$
Tur	ExP	VHP	IVHE	VHP	7.257
Fac	MP	IMH	IMH	MP	3.292
Gro	EP	EP	EP	EP	1.000
Thr	MP	HP	IMH	MP	3.534

Using Equation (15), the optimal weights were determined as $\overline{w}_B = \overline{w}_1 = 0.595$ for *Tur*, $\overline{w}_2 = 0.164$ for *Fac*, $\overline{w}_W = \overline{w}_3 = 0.076$ for *Gro*, $\overline{w}_4 = 0.165$ for *Thr*, and $\xi^L = 0.093$.

Similarly, for the cost drivers under cluster *InO*, *Dri* was selected as the best cost driver and *Tap* was taken as the worst cost driver. The ratings of the best to others and others to the worst are shown in Tables 15 and 16.

Table 15. The best to others for cost drivers under *InO* using N-BWM

emphEx/CD	*Dri*	*Bor*	*Rea*	*Tap*
Ex1	EP	IEM	MP	HP
Ex2	EP	NEP	MP	IMH
Ex3	EP	MP	HP	IHVH
Ex4	EP	MP	IMH	HP
Average, $\overline{a}_{Bj}$	1.000	2.256	3.534	4.659

Table 16. Others to the worst for cost drivers under *InO* using N-BWM

CD/Ex	Ex1	Ex2	Ex3	Ex4	Average, $\overline{a}_{jW}$
Dri	HP	IMH	IHVH	HP	4.659
Bor	MP	IMH	MP	IEM	2.860
Rea	IEM	NEP	MP	IEM	2.018
Tap	EP	EP	EP	EP	1.000

Finally, the optimal weights were determined as $\overline{w}_B = \overline{w}_1 = 0.500$ for *Dri*, $\overline{w}_2 = 0.273$ for *Bor*, $\overline{w}_3 = 0.136$ for *Rea*, $\overline{w}_W = \overline{w}_4 = 0.091$ for *Tap*, and $\xi^L = 0.081$.

The optimal weights from Tables 5-16 are compiled in Table 17. The local optimal weight of every cost driver at its clustered level is indicated in (.). The global optimal weight of each cost driver was determined from the product's optimal local weights. In all evaluations, the value of ξ^L was at an acceptable level.

Table 17. Hierarchical clusters of cost drivers with their optimal local and global weights

Levels of cost drivers from top to bottom			Optimal weight	
Top/First	Second	Bottom/Third	Global weight determination	Global weight (w_i)
WPC (0.541)	-	*Len* (0.430)	(0.541) (0.430)	0.232
		Dia (0.427)	(0.541) (0.427)	0.230
		Com (0.143)	(0.541) (0.143)	0.078
RMO (0.292)	*ExO* (0.566)	*Tur* (0.595)	(0.292) (0.566) (0.595)	0.098
		Fac (0.164)	(0.292) (0.566) (0.164)	0.027
		Gro (0.076)	(0.292) (0.566) (0.076)	0.013
		Thr (0.165)	(0.292) (0.566) (0.165)	0.027
	InO (0.434)	*Dri* (0.500)	(0.292) (0.434) (0.500)	0.063
		Bor (0.273)	(0.292) (0.434) (0.273)	0.035
		Rea (0.136)	(0.292) (0.434) (0.136)	0.017
		Tap (0.091)	(0.292) (0.434) (0.091)	0.012
FPQ (0.167)	-	*Pre* (0.538)	(0.167) (0.538)	0.090
		Rel (0.308)	(0.167) (0.308)	0.051
		Dur (0.154)	(0.167) (0.154)	0.026

4.3 *Case similarity and retrieval*

Using the values of cost drivers for cases/product orders presented in Table 4, and the optimal weights of cost-driving attributes of cases shown in Table 17, the similarity measure between prior and target cases $S_{Eul}(T,\ P)$ was determined by applying Equation (16). For determining the similarity measure, Equation (16) was utilized to calculate the weighted Euclidean distance between new and prior product orders, $D_{Eul}(T,\ P)$. For the case of neutrosophic terms such as *Com*, *Pre*, *Rel*, and *Dur*, the terms were converted into the equivalent SVTNNs according to the scales presented in Table 2, and their crisp scores were estimated using Equation (10). Finally, they were treated as numeric cost drivers using the neutrosophic term EMi (0.041) as the minimum and EMa (0.951) as the maximum cost driver values (see Table 2). By combining $D_{lin}\left(a_j^T,\ a_j^P\right)$, and the optimal global weight of each cost driver, the weighted Euclidean was calculated between each target problem and all prior alternative cases using Equation (16). Finally, by considering the inverse relationships between distance and similarity, Equation (17) was employed to estimate the similarity between the target problem and all previously solved problems. The outputs of this similarity measure are compiled in Table 18. The maximum value represents the best similarity between the target product order and the most similar prior order which is the retrieved case. In this study, this maximum similarity measure is designated as $S_{Euc}(T,\ R)$. R is a special prior order/case, which has the most similarity with the current order, called a retrieved product order/case. The cost estimate for this retrieved case is used as an initial solution that can be reused and revised based on the similarity and the difference between the target and retrieved product order. The bold values in Table 18 indicate the values of $S_{Euc}(T,\ R)$.

Table 18. Similarity between new and alternative prior orders, $S_{Euc}(T,\ P)$

Ta/Pa	*Pa*1	*Pa*2	*Pa*3	*Pa*4/*Ta*1	*Pa*5/*Ta*2	*Pa*6/*Ta*3	*Pa*7/*Ta*4	*Pa*8/*Ta*5	*Pa*9/*Ta*6
*Ta*1	0.878	0.865	**0.956**						
*Ta*2	**0.991**	0.784	0.879	0.874					
*Ta*3	0.783	**0.981**	0.857	0.861	0.779				
*Ta*4	0.879	0.864	0.951	**0.988**	0.874	0.857			
*Ta*5	0.784	0.980	0.858	0.862	0.781	**0.996**	0.859		
*Ta*6	0.988	0.780	0.874	0.870	**0.992**	0.775	0.871	0.776	
*Ta*7	0.877	0.865	0.951	0.986	0.872	0.859	**0.997**	0.860	0.869

Moreover, Table 19 shows the retried prior orders for the target problems, the similarity between the target and retrieved orders, and the *PCE*s that should be reused and revised for the target problems. In addition, this table indicates the number of prior alternatives with their corresponding *PCE*s as a new target problem arrives in the system. This figure increases when several production costs are estimated since *PCE*s are retained for future retrieval. This was observed when problems (*Ta*4-*Ta*7) were arrived. The previous product arrivals *Ta*1, *Ta*3, *Ta*2, and *Ta*4 were retrieved for new product arrivals *Ta*4, *Ta*5, *Ta*6 and *Ta*7 respectively.

Table 19. Summary similarity measure and retrieval

Ta	Retrieved prior order R	$S_{Euc}(T,\ R)$	Retrieved PCE for adaptation	Number of alternatives	Remark
*Ta*1	*Pa*3	0.956	*PCE*3	3	
*Ta*2	*Pa*1	0.991	*PCE*1	4	
*Ta*3	*Pa*2	0.981	*PCE*2	5	
*Ta*4	*Pa*4/*Ta*1	0.988	*PCE*4	6	Retained *PCE* of *Ta*1
*Ta*5	*Pa*6/*Ta*3	0.996	*PCE*6	7	Retained *PCE* of *Ta*3
*Ta*6	*Pa*5/*Ta*2	0.992	*PCE*5	8	Retained *PCE* of *Ta*2
*Ta*7	*Pa*7/*Ta*4	0.997	*PCE*7	9	Retained *PCE* of *Ta*4

4.4 *Case reuse and adaptation*

Table 19 indicates that the values of $S_{Euc}(T,\ R) < 1.0$, which indicates that the retrieved *PCE*s should be revised for adapting to new problem situations. The adaptions were done depending on the differences in the values of cost-driving attributes between target and retrieved order arrivals. Considering the first product, the similarity measure between the new arrival *Ta*1 and the retrieved *Pa*3 was calculated as $S_{Eul}(Ta1,\ Pa3) = 0.956 < 1.0$. In this case, the adaptation of the retrieved production cost estimate, *PCE*3 was mandatory. This was done by analyzing the difference in the values of cost-driving attributes between the target and retrieved product orders. Under *WPC* cost drivers, parameter variations are shown in the dimensions of workpieces (length and diameter). These variations were addressed using parametric cost estimation methods by estimating the cost of construction per unit volume change [3, 10, 33]. A small difference is indicated in the precision of the cluster of *FPQ* cost drivers. This situation was intuitively articulated by experienced experts. Other important variations were shown in the cluster of cost drivers under *RMO*. In this regard, there are variations i.e., the addition or omission of boring and reaming operations between the target and retrieved product orders. The operations are usually required to add some features to product order arrivals. These changes were articulated using feature-oriented cost estimation methods [3, 10].

The same approach was applied to the remaining six product order arrivals to adapt the retrieved *PCE*s according to their target requirements. The recommended case adaptation methods in this study are presented in Table 20. In general, the combinations of three methods were proposed by the DSS researched and developed in this study. They are parametric, feature-oriented, and expert-based intuitive methods.

Table 20. Recommended *PCE* adaptation methods

Target	*PCE* adaptation/revision methods		
	Parametric	Feature-oriented	Expert-based intuitive
*Ta*1	Applicable	Applicable	Applicable
*Ta*2	Applicable	Not applicable	Applicable
*Ta*3	Applicable	Applicable	Applicable
*Ta*4	Applicable	Not applicable	Applicable
*Ta*5	Applicable	Not applicable	Not applicable
*Ta*6	Applicable	Applicable	Not applicable
*Ta*7	Applicable	Not applicable	Not applicable

4.5 *Case retaining and indexing*

The revised *PCE*s from the retrieved product orders were retained and indexed as learned cases for future retrieval. Their *PCE*s were retrieved and adapted for similar problem situations. This action was applied for new product arrivals *Ta4*, *Ta*5, *Ta*6, and *Ta7* (see Table 18). The previous PCEs (*PCE*1, *PCE*3, *PCE*2 and *PCE*4) assigned to *Ta*1, *Ta*3, *Ta*2 and *Ta*4 were retrieved, revised and assigned to target arrivals *Ta*4, *Ta*5, *Ta*6, and *Ta*7 respectively.

5. Discussion

This part explains the importance of this study over previous related studies, the managerial implications, and the limitations of this study.

5.1 *Comparison with related studies*

As stated in Section 2, specifically in Table 2, the problems of product cost estimation were addressed using different approaches in previous studies. The previous studies used different ML, analytical (parametric and feature-oriented), MCDM, intuitive or heuristics, and CAD/CAM methods to solve cost estimation problems. However, the integration of N-CBR and N-BWM has not been applied to estimate the cost of new products in the existing literature. In comparison to related studies, the proposed DSS in this study has many advantages over other similar previous studies. For example, comparing it with similar studies like Kasie and Bright [3] and other CBR-oriented cost estimation approaches, this study has many improvements for decision-making: (1) This paper introduced the concept of a group decision-making approach while determining the optimal weights of cost drivers using N-BWM. (2) It incorporated neutrosophic cases specifically SVTNN cost-driving case attributes rather than fuzzy cases. The SVTNN components are more flexible by incorporating three membership functions further to a single membership for fuzzy function since a neutrosophic set is a generalization of a fuzzy set as stated in Section 3. As compared with frameworks proposed using ANNs, the ANN-based frameworks require a huge amount of training and testing datasets to implement them as explained by other studies in different problem domains [62, 65, 68, 78]. However, CBR frameworks can be implemented with a few prior cases and their performance can be improved over time as many product orders are processed (see Table 19). This implies that the proposed system is highly applicable when a few prior datasets are available in manufacturing systems due to unforeseen reasons.

5.2 *Managerial implication*

From a managerial implication perspective, production planning and control managers can use the proposed to estimate the production cost of new product orders at the early phase of a product lifecycle. This reduces quality failure costs in the production and service phases of a new product. Although the proposed DSS was illustrated for estimating the cost of cylindrical products, it can be modified and applied for any complicated products by incorporating other important cost-driving attributes of new products.

In a similar approach to the simulated example, experts can apply the proposed cost estimator at the early production stage to the other complex manufacturing operations. For instance, they can utilize a milling operation center by identifying the most important cost drivers of milling operations that can be used to manufacture the expected or planned product orders. These identified cost drivers can be used to create neutrosophic cases as presented in Table 4. In addition, they should be hierarchically evaluated and weighted by group experts for group decisions using N-BWM as shown in Section 4.2. Depending on the nature of the machining process some cost drivers can be added to/removed from the case construction process. For example, the geometric feature/shape of the workpiece is an important cost driver for milling operations, which was not considered in the simulated numerical example (turning operations. This implies that the effectiveness of the proposed systems is highly dependent on the knowledge and skills of system developers to acquire experts' judgments and experiences in a group decision-making process using N-CBR and N-BWM. This means the cost estimators are flexible and adaptable depending on manufacturing situations.

5.3 *Limitation*

As the main limitation, the proposed system was not implemented in real industrial situations to test its validity. It was tested only in a simulated machining environment. In addition, in the case of adaptation/revision, only three cost estimation methods such as parametric, feature-oriented, and expert-based intuitive methods were recommended. However, in real situations, only the three methods may not be adequate, and other complex approaches may be required. This study implemented the proposed DSS in a simulated manufacturing environment to illustrate the system's soundness. To enhance the system's soundness, the researchers will work to test the proposed system in actual manufacturing environments.

6. Conclusions

This paper proposed a novel DSS in group-oriented decision-making by combining CBR and BWM in neutrosophic environments. This integration was applied for the first time to address the problem of production cost estimation in this study. The proposed approach can be considered an alternative solution to these problems in manufacturing processes. Integrating N-CBR and N-BWM can be a new contribution to the current literature in group-oriented decision-making and DSS development.

This study applied an N-CBR methodology to construct product orders as cases by incorporating uncertain, imprecise, and inconsistent knowledge with the help of truth, indeterminacy, and falsity membership functions respectively as presented in Table 4. As shown in the simulated numerical analysis, describing some cost drivers using neutrosophic linguistic terms was more meaningful than measuring them in numeric data. Such linguistic terms were converted into equivalent SVTNNs to include uncertain, vague, and inconsistent experiences using three membership functions, which are the common phenomena in natural human reasoning and decision-making situations.

Further, an N-BWM was applied to formalize the judgments from a group of experts to determine the optimal weights of fourteen cost drivers under different clusters (see Tables 5-16). Combining the results from this N-BWM and N-cases (Table 4), the similarity measure between target problems and alternative prior cases was found using Equations (13)-(16). From this measure, a previous order with the best similarity was selected as a retrieved case or an initial solution to the target problem (Tables 18 and 19). For adapting the retrieved cost estimates for the target problems, the proposed DSS recommended three cost adaptation methods depending on the similarity and the difference between the target and retrieved order arrivals (Table 20). This kind of DSS framework has not been applied in the current literature on DSS and product cost estimation.

In the future, the limitation of the proposed DSS stated in Section 5.3 will be addressed by implementing the proposed approach in real situations. Additional cost revision methods will be considered to revise the cost of more complex products in actual manufacturing environments.

Acknowledgment

The authors thank the editors and reviewers for their constructive comments for improving our paper.

Conflict of interest

The authors declare that they have no conflict of interest.

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